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Stock market trend behaviour and continuation and reversal effects in stock market returns

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STOCK MARKET TREND BEHAVIOUR AND CONTINUATION AND REVERSAL EFFECTS IN STOCK MARKET RETURNS

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by

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SUMMARY

This thesis considers the existence of, and potential causes of, continuation and reversal effects in stock market returns. In the first part of the research, a time-series approach is used to consider the profitability of momentum trading strategies on fourteen major stock market indices. Momentum trading strategies exploit continuation in returns, and evidence of significant profits to such strategies therefore implies the presence of continuation effects in the data samples. Significant losses to momentum strategies, on the other hand, are indicative of reversal effects in returns. This part of the research identifies continuation effects in stock index returns over periods of 1 trading day and 10 through 252 trading days.

The second part of the research explores the various behavioural and non-behavioural theories proposed in the literature for the existence of continuation and reversal effects in returns. Such effects imply that stock market trends differ systematically from trends in random data with the same underlying distribution of daily returns. An algorithm from the information technology literature is adapted and used to identify turning points in trends in the fourteen data sets, and the statistical properties of daily returns within stock market trends are analysed. Important patterns are observed in the steepness of trends and the volatility of returns within trends as they develop. These patterns enable some inferences to be drawn as to the most probable factors driving the continuation effects observed in the first part of the research, with nonsynchronous trading and investor loss aversion highlighted as potential causes of very short-term and medium-term effects respectively.

TABLE OF CONTENTS

Chapter 1

Introduction

Chapter 2

Behavioural Theories of Stock Market Continuation and Reversal Effects

Chapter 3

Alternative Theories of Stock Market Continuation and Reversal Effects

Chapter 4

Empirical Evidence of Stock Market Continuation and Reversal Effects

Chapter 5

Data

Chapter 6

Momentum Study Methodology

Chapter 7

Momentum Study Results

Chapter 8

Trend Analysis Methodology

Chapter 9

Trend Analysis Results

Chapter 10

Main Findings and Interpretation

Chapter 11

Summary and Conclusions

Appendices

LIST OF TABLES

LIST OF FIGURES

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Chapter 1

Introduction

1.1 Background and Structure of Thesis

This thesis documents two main bodies of research which approach from different angles the question of the existence and nature of continuation and reversal effects in stock market returns. Continuation effects in financial market returns occur when periods of positive returns are followed by further positive returns and negative returns are followed by negative returns. Reversal effects, on the other hand, occur when positive returns are followed by negative returns and negative returns by positive returns.

The existence of continuation and reversal effects is an important issue in finance. If such effects can be shown to be a feature of stock market returns, then this would imply that stock markets are not efficient in the manner suggested by Fama (1970) and that suitably constructed trading strategies will generate excess returns which are not accounted for by risk. Jones and Netter (1993) identify three perspectives from which the issue of stock market efficiency is important. Firstly, from an economy-wide perspective, stock market efficiency implies that the market is functioning effectively in channelling financial resources between savers and borrowers. Market inefficiency may therefore imply a non-optimal allocation of resources at the economy-wide level. At an individual level, small investors might be deterred from entering a market which they believe to be inefficient since inefficiency may favour large investors with access to extensive research resources. Stock market efficiency is therefore considered to be desirable since it is expected to generate the widest possible participation in the stock market. Finally, market efficiency has important implications for regulation, with a higher level of regulation typically considered necessary to control less efficient markets.

If continuation and reversal effects are shown to occur in stock market returns, then the appropriate response on the part of policy-makers will depend on the factors driving such effects. A number of different explanations of continuation and reversal effects in stock market returns have been proposed in the literature. These fall into two broad categories. Behavioural biases, reviewed in Chapter 2, relate to research in psychology which suggests that the way in which individuals approach decision-making situations can introduce bias to the resulting decision. Decision-making heuristics, or rules of thumb, as well as emotional factors affecting decision-making may lead investors to make biased predictions of future returns. If such biases affect investors in a systematic manner and their effect is not cancelled out by arbitrage activity, then anomalies in individual behaviour may feed through to anomalies in market returns. Alternative explanations, discussed in Chapter 3, concentrate on non-behavioural reasons for the findings of the empirical literature. The nature of the data used in these studies may be responsible for short-term anomalies, with bid-ask bounce and the effects of nonsynchronous trading on recorded prices driving short-term serial correlation effects. Secondly, the additive rather than multiplicative methods of aggregating short-term returns used in most studies may also introduce bias to their results. Thirdly, the models of expected returns typically used to calculate abnormal returns do not necessarily reflect the returns available to investors, and so findings of continuation and reversal effects in the empirical literature may not imply the availability of excess returns in the real world. Finally, even if such returns were shown to be available to real-world investors, they may simply reflect the risk inherent to the trading strategies required to exploit them.

In order to reflect the existence of both behavioural and alternative explanations for the return anomalies reported in the empirical literature, this thesis uses the terms continuation and reversal effects throughout in preference to the terms underreaction and overreaction which are commonly employed in the literature. Similarly, a consistent terminology is applied throughout in describing the research methodologies employed by previous studies, although individual authors use slightly different terms[1].

Chapter 4 provides a detailed review of the findings of previous studies which have examined empirically the existence of continuation and reversal effects in stock market returns. The structure of Chapters 2 through 4 might be

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[1] A range of terms has been used in the literature for formation and test period, for example, as well as for the various models of expected returns and methods of cumulating returns reviewed in Chapter 3.

considered unorthodox in that the possible explanations proposed in the literature, discussed in Chapters 2 and 3, for empirical findings of continuation and reversal are presented in advance of a review of the findings themselves. This structure is adopted in order that the findings of individual studies can be critically reviewed with reference to the potential pitfalls of the methodologies employed. In addition, many empirical studies have gone on to propose specific behavioural factors as potential explanations for their empirical findings. These can only be commented on in depth following the review of the behavioural literature provided in Chapter 2.

Chapter 4 documents a large body of previous empirical research on the existence of continuation and reversal effects in financial market returns. This body of work is categorised for the purposes of review into three sections: short-term, medium-term, and long-term studies.

Studies of short-term stock market continuation and reversal effects examine returns following large price changes over periods from one day to one week. In general, studies tend to find evidence of short-term reversal in returns with periods of poor returns following large short-term price increases, and high returns following large short-term decreases in price (see, for example, Atkins and Dyl, 1990, and Otchere and Chan, 2000).

Studies of medium-term continuation and reversal effects identify stocks with particularly high and low returns over periods ranging from one to twelve months and go on to examine returns over subsequent periods of similar length. Overall, the empirical evidence from studies such as Jegadeesh and Titman (1993 and 2001) and Hon and Tonks (2003) suggests that significant continuation effects occur in stock market returns over horizons lasting up to around 12 months. That is to say, stocks which perform well over periods of up to 12 months tend to continue to perform well over subsequent periods of similar length, and vice versa for stocks with poor performance.

Studies of long-term stock market continuation and reversal effects follow the seminal work of DeBondt and Thaler (1985) who consider the returns of New York Stock Exchange (NYSE) stocks between January 1926 and December 1982 and conclude that extreme "winners" over a three/five year period show a consistent tendency to become "losers" over the following three/five year period and vice versa. That is to say, extremely high and low return stocks tend to experience a "reversal of fortunes" over the long term. Whilst the focus of the current study is on short-term and medium-term continuation and reversal effects, long-term effects can be seen as a combination of shorter-term effects and as such, the results of previous research into long-term continuation and reversal in stock market returns are of relevance to the current study and are therefore reviewed in Chapter 4.

Chapter 5 goes on to describe the data used in both parts of the research documented in this thesis and to provide descriptive statistics. FTSE All-World country index data (daily price index and total return index data) was downloaded from Datastream for the period January 1994 through December 2002[2] for the stock markets of Australia, Belgium, Canada, Denmark, France, Germany, Hong Kong, Japan, Italy, the Netherlands, Spain, Switzerland, the UK, and the USA. Chapter 5 also describes the calculation of the daily price returns, total returns and funded returns on which the empirical research documented in this thesis is based.

Fama (1998) contends that, with an appropriate change in methodology, the anomalies of continuation and reversal in stock market returns identified in the literature and described in detail in Chapter 4 will tend to disappear. The main objective of the first part of the research documented in this thesis is to investigate whether short-term reversal and medium-term continuation effects persist when measured using a time series methodology and where the measure of abnormal returns is the profitability of momentum and contrarian trading strategies. These profits reflect the excess returns available to investors after taking into account funding costs but before transactions costs[3]. The availability of excess profits to such strategies is an important issue since, if found, they imply that investors are "leaving money on the table". That is to say,

[2] January 1994 being the earliest date for which total return index data is available for each country.

[3] Transactions costs are not explicitly considered in the research documented in this thesis since they may vary widely from investor to investor. Any excess profits must, therefore, be sufficiently large to cover transaction costs at the level relevant to the individual investor before investment in such strategies can be expected to yield positive returns.

anomalies have not been fully arbitraged away by the market, and investors may be able to achieve persistent profits from suitably specified trading strategies. The use of returns to investors as the appropriate measure of returns allows the risk inherent to such strategies, that is to say the volatility of returns, to be explicitly considered. In addition to the profitability of such strategies, therefore, this section of the research explicitly examines whether the risk of the strategies considered is empirically related to their returns.

Chapter 6 discusses the research methodology employed in this part of the research. Trading strategies are derived which buy the relevant stock market index following rises in the market and sell following market declines. Such strategies can be expected to generate significant excess profits in markets that are subject to continuation effects and significant losses in markets subject to reversal. Eleven strategies are considered for each of the fourteen data sets (one for each of the countries considered) based on holding periods ranging from one day to one year. The excess returns to each strategy are calculated as the returns to a funded position in the relevant index. That is to say, the returns calculated reflect the returns available to real-world investors before transactions costs[4]. Returns are decomposed into the returns from long and short positions for each strategy, and the annual returns to each strategy are also considered. Sharpe Ratios, which measure the relationship between returns and risk, are calculated for each strategy. A non-parametric bootstrap approach is used to assess the impact of serial correlation in the data on the returns achieved. As Fama (1998) argues, positive returns may simply occur as a result of chance resulting in a fortuitous choice of data sample. The bootstrap method attempts to control for this problem by isolating the impact of the serial correlation properties of the data, rather than the statistical distribution of the data sample, on strategy returns.

The properties of the returns to each of the 154 strategies derived in Chapter 6 are discussed in Chapter 7. Positive excess returns are found for strategies based on holding periods of one trading day and 10 to 252 trading days. The returns to individual strategies are highly inconsistent over time, and trading strategy profitability is not generally significant once risk is taken into account. In addition, the returns are driven almost exclusively by high returns to long

[4] Including capital gains and dividend income as well as funding costs.

positions which may be a simple result of generally rising prices over the period covered by the data. This finding provided the initial motivations for the second part of the research documented in this thesis which considers the issue of stock market continuation and reversal effects from a different angle – what features of the underlying price series would drive findings of continuation and reversal in returns, are these features present in the data sets considered, and how can such features be reconciled with the possible explanations discussed in Chapters 2 and 3?

The second part of the research aims to explore the possible driving forces behind empirical findings of continuation and reversal effects in stock market index data. One limitation of the prior literature is that although it has generated evidence of return anomalies together with an extensive menu of possible causes, it is difficult to distinguish empirically between those possible causes. Findings of one-day reversals in returns, for example, may reflect methodological issues or equally may be a result of investor overreaction to new information entering the market. This part of the research begins with a discussion of the types of patterns in market prices required to drive findings of continuation and reversal effects, and concludes that such findings imply that market trends differ in a systematic way from random trends. The focus of this part of the research is therefore on an exploratory analysis of the properties of trends in the data sets used in the first part of the research with the aim of shedding further light on which, if any, of the behavioural and alternative explanations proposed in the literature may be responsible for empirical findings of continuation and reversal effects.

Chapter 8 discusses the methodology used to consider the empirical properties of trends in each of the fourteen data sets. An algorithm from the information technology literature (Fink and Pratt, 2004) is used to identify trends in each data set and descriptive statistics are calculated for the properties of bull (upwards) and bear (downwards) trends for each data set. Bootstrap analysis is then used to assess the ways in which these properties of stock market trends differ systematically from random trends based on the same distribution of daily returns.

Chapter 9 presents the results of this analysis. Trends in the fourteen data sets do not differ systematically from random trends in terms of their duration or their total amplitude. Significant patterns are, however, observed in the steepness of trends as they develop. In particular, the final quarter of bear trends is particularly steep. Patterns are also observed in the volatility of prices through the bull-bear cycle.

Chapter 10 brings together the results of the two main bodies of research documented in this thesis and describes the relationship between the two sets of results. The consistency of these results with the findings of previous research is discussed, and the consistency of the results with each of the main behavioural and alternative explanations described in Chapters 2 and 3 is explored. This leads into a summary of the main implications of the research documented in this thesis for the broader literature, together with a number of specific avenues for further research.

Chapter 11 summarises the motivation behind the current study and the rationale for the methodology employed. The principal results of the study are presented together with their main implications for the literature. Finally, the limitations of the research are discussed and a framework for further research presented.

1.2 Significance and Contribution of the Research

The research documented in this thesis contributes to the existing body of knowledge in two main ways. The focus of the first part of the research is a study of momentum strategy profitability based on a time series methodology and a measure of excess returns which has practical applicability. This approach is used in order to examine the contention of Fama (1998) that with a suitable change of methodology, anomalies will disappear. In addition, the use of directly comparable data sets across 14 major stock markets offers an international perspective which has received only limited attention from previous research (Rouwenhorst, 1998 being the main exception).

The second part of the research documented in this thesis does not directly build on any previous research and as such adds a new strand to the literature. Whilst related to previous work on the properties of the business cycle, and a limited amount of prior research on identifying trends in financial market prices, this research introduces a new dating algorithm from the information technology literature. This algorithm, which is based on amplitude, is more closely suited to dating stock market trends than are the duration-based approaches typically used for dating the business cycle[5]. The analysis of the features of stock market trends as they develop is, to the author's knowledge, new.

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[5] Previous studies in this area, such as that of Pagan and Sossounov (2003), have used duration-based algorithms such as that of Bry and Boschan (1971), designed for use in dating the business cycle, to date stock market trends. In order to force the algorithms to "correctly" identify short-term market shocks (such as the market crash of October 1987) as trends, researchers have needed to add additional censoring rules to the initial algorithm. As Chapter 8 discusses, the way in which this is done can have an important influence on the results obtained. The amplitude-based algorithm employed in the current study, on the other hand, can be successfully applied to a range of different financial market data sets without modification.

Chapter 2

Behavioural Theories of Stock Market Continuation and Reversal Effects

2.1 Introduction

Price changes in a financial market can be regarded as a product of the pricing and trading decisions of the individuals and entities trading within that market. In the simplest terms, if on aggregate investors are buyers of a commodity, its price will tend to increase and vice versa when investors are net sellers. According to Edwards and Magee (1948, reprinted 2001, p4-5),

> "The market price reflects not only the differing value opinions of many orthodox security appraisers, but also the hopes and fears and guesses and moods, rational and irrational, of hundreds of potential buyers and sellers, as well as their needs and their resources – in total, factors which defy analysis and for which no statistics are obtainable, but which are nevertheless all synthesized, weighed, and finally expressed in the one precise figure at which a buyer and a seller get together and make a deal... This is the only figure that counts"

Research in psychology has identified a wide range of biases in the decision-making behaviour of individuals. These may result from the way in which decision problems are simplified in order to make them more manageable, or from emotional factors affecting decision outcomes. If these biases can be shown to influence decision-making within a financial markets context in such a way that anomalous individual behaviour feeds through to anomalous market behaviour and hence to anomalous market prices, empirical phenomena such as medium-term market continuation and very short-term and long-term market reversal might be at least partly explained.

The main objective of prior research in this area has been the identification of those decision-making biases which are systematic among individuals within the context of trading and investment decisions. As Barber and Odean (1999, p41) observe, "although departures from rationality are sometimes random, they are often systematic". Whilst random departures from rationality among investors might be expected to cancel out in the aggregate, systematic departures, in which most individuals err in the same direction, will not (Camerer, 1987). Three main investigative approaches have been taken. In the first, experimental environments are designed to enable specific biases to be tested for. A second body of work uses a questionnaire approach to survey real-world investors about the way in which they reach investment decisions. Finally, a number of studies have examined actual transactions data from stock trading accounts in an attempt to identify empirically whether the behavioural traits identified in the literature have any clear bearing on trading and investment decisions.

Taking into account potential biases in the way in which individuals reach decisions may lead to a better understanding of the way in which market prices, which are a function of the overall price-setting and trading behaviour of individuals within that market, behave. The remainder of this chapter builds up a picture of how this may occur, from the biases displayed by individual investors through to the way in which these may affect the behaviour of market prices. Section 2.2 sets a framework for the decision-making process and provides a categorisation of the behavioural traits discussed in the literature into two groups; these are considered in detail in sections 2.3 and 2.4. Section 2.5 discusses the possible links between behavioural biases in investor decision-making and the return anomalies documented in the literature. Section 2.6 considers the circumstances in which the investor behaviour described in earlier sections may feed through to anomalies in market prices. Section 2.7 concludes.

2.2 The Decision-Making Process and Behavioural Biases

Carroll and Johnson (1990, p19) define decision-making as "a process by which a person, group, or organization identifies a choice or judgement to be made, gathers and evaluates information about alternatives, and selects from among the alternatives".

The concept of decision-making therefore encompasses the full range of mental activities from the moment we realise a decision needs to be made right through until the final decision is reached and acted upon. The process may be almost instantaneous, or it may be spread out over a period of time.

In a financial markets context, the recognition that a decision needs to be made may form part of an ongoing process of evaluating opportunities and revisiting current market exposures, or may be prompted by new information entering the market. The objectives of decision-making will typically incorporate considerations of expected return, risk, and diversification, whilst constraints might include time constraints on research and limits on market positions due to risk and/or funding constraints. When considering the available information, investors may take into account qualitative data such as market sentiment and the tone of reports published by financial institutions in addition to quantitative data such as the recent performance of the market under consideration. Biases can occur in any of these stages, or indeed at the point of evaluating and choosing between alternatives. Furthermore, biases in the interpretation of feedback may have an impact on future decisions.

Researchers have used a number of different categorisations when assessing the empirical evidence relating to behavioural biases in investor decision-making. Raghubir and Das (1999), for example, separate biases in financial decision-making into five groups based on the stage in the decision-making process where they occur: perception, memory retrieval, information integration, judgement making, and behaviour. Their approach is similar in many ways to that of Carroll and Johnson (1990), discussed earlier in this section. Stracca (2002) separates biases into four categories centred on cognitive limitations, the interference of emotional states, choice bracketing, and a lack of pre-determined preferences. In this thesis, behavioural biases are considered within two broad categories: decision-making heuristics and emotional factors affecting decision-making.

Traditional models in finance assume that the human brain has infinite computational capacity. This is clearly not the case. Research in psychology has identified a number of rules-of-thumb or heuristics used to simplify decision-making problems. By simplifying the problem, the investor is able to consider the alternatives and reach a decision within an acceptable time frame.

Importantly, research[6] has shown that the use of decision-making heuristics can in itself introduce bias to the resulting decision. Section 2.3 describes decision-making heuristics in more detail.

Emotional factors can also introduce bias into the decision-making process. These may involve a degree of self-deception on the part of the investor in order to control emotional responses. For example, financial decisions may be biased by investors' need to maintain their own self esteem, which results in overconfidence in their own abilities. Section 2.4 discusses the biases identified in the literature which stem from emotional factors.

One of the fundamental problems encountered by the behavioural finance literature to date is that investors appear to succumb to different biases in different situations. One strong influence on the types of bias exhibited and therefore the eventual outcome of decision-making scenarios has been shown to be the way in which the scenario is framed. Minsky (1977, p355) describes a frame as "a data-structure for representing a stereotyped situation like being in a certain-type of living room or going to a child's birthday party". Tversky and Kahneman (1981), for example, show that by framing an identical decision situation in terms of losses rather than gains, investor preferences of one gamble over another can be reversed. Whilst a huge range of individual behavioural traits has been documented, therefore, the difficulties in identifying which traits will be foremost in different situations means that these traits have not been brought together into a unified theory of investor behaviour which could be tested empirically. Stracca (2002, p3) notes that

> "So far, the behavioural finance literature has not reached a level of maturity which would allow it to provide a coherent, unified theory of human behaviour in market contexts in the same way expected utility and mainstream economics and finance have done".

In addition, it may be very difficult to identify empirically which of the biases described in Sections 2.3. and 2.4 are at work in any given situation. For example, many of the biases described in Sections 2.3 and 2.4 lead investors to erroneously place too much or too little weight on different types of

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[6] Barberis and Thaler (2002) provide a thorough review.

information when making financial decisions. Kahneman and Tversky (1973) describe three types of information that are relevant to statistical prediction:

- Base rate evidence (such as the population likelihood of an event occurring)
- Specific evidence relating to the individual case
- The expected accuracy of prediction

Within this context, the expected accuracy of prediction controls the relative weight to be placed on base rate and specific evidence. Both overconfidence and representativeness, described in detail in Sections 2.3 and 2.4, could cause an investor to overweight specific evidence relative to base rate evidence in a particular decision-making scenario. Different behavioural biases may be triggered as a result of very subtle differences in decision-making situations, and different biases can produce the same outcome in terms of investor behaviour, making the identification of those biases at work in any particular situation extremely difficult. Whilst research in psychology has produced a veritable shopping list of individual biases, therefore, and research in finance has identified a range of different anomalies in financial market returns, a direct causal link between individual behavioural biases and specific anomalies in market pricing has been difficult to prove.

2.3 Decision-Making Heuristics

When reaching investment decisions, the human brain does not possess sufficient processing power to perform many of the calculations suggested by traditional finance models. Even if it did, the computation costs (in terms of time and effort) would be excessively high for most decision situations. Research has shown that individuals use heuristics, or rules-of-thumb, to simplify decision situations and make the decision-making process more manageable. An investor wishing to construct a diversified portfolio might, for example, rely on selecting stocks from different industry sectors rather than attempting to analyse the covariance of individual stock returns.

Different individuals may have slightly different sets of decision rules which have either been taught to them or which they have developed through personal experience. This offers one explanation for the fact that investors will reach different decisions in response to the same situation. In general, however, researchers have identified a number of heuristics which are used to simplify analysis and aid decision-making across a wide range of scenarios. Whilst these heuristics are useful in helping individuals to reach decisions efficiently, they can often in themselves introduce bias to the results of the decision-making process. This section discusses mental accounting, representativeness, availability and anchoring.

2.3.1 Mental Accounting

The use of mental accounting to simplify decision-making is introduced to the literature by Thaler (1985). Individual portions of wealth are considered separately in different "mental accounts". Thus, decisions relating to saving for pensions are likely to be taken in complete isolation to decisions regarding the weekly groceries budget, for example. Thaler (1999) shows how mental accounting violates the concept of fungibility (that is to say, money in one account is no longer regarded as a perfect substitute for money in another account) and hence can result in irrational decision-making on the part of investors.

The mental accounting used by individuals is one example of framing, described in Section 2.2, in which the decisions reached by individuals are heavily influenced by the way in which the decision scenario is presented to them. Statman (1999, p19) cites the example of individual investors' use of mental accounting to distinguish between the different aims of a portfolio:

> "Many investors still divide their money into a mental account for downside protection (containing cash and bonds) and a mental account for upside potential (containing stocks, options, and lottery tickets)".

Research has demonstrated that the use of mental accounting to compartmentalise decisions can lead to inconsistencies such as the commonly quoted anomaly that a large proportion of the population buy both insurance policies and lottery tickets[7].

[7] This anomaly is discussed by Friedman and Savage (1948)

Barberis and Huang (2001) consider how investors frame gains and losses, and in particular whether investors consider the gains and losses on individual stocks (individual stock accounting) or on their overall portfolio of stocks (portfolio accounting).

Under individual stock accounting, changes in the discount rate used by investors to value stocks depend on the past performance of the stock. Following a gain, Barberis and Huang hypothesise, an investor will become less concerned about future performance and so will lower the discount rate at which he values the stock (this reflects the reduced risk subjectively associated with the stock). Following a loss the investor recognises the stock to be risky and increases the discount rate. Simulated stock values using this framework are found to be consistent with many of the empirically identified characteristics of stock returns including high mean returns, excess volatility, and high cross-sectional differences in returns between stocks.

Under portfolio accounting, on the other hand, the same discount rate is used for all stocks and is driven by the past return of the investor's overall portfolio. In simulated tests, the mean returns of individual stocks are lower and less volatile than under individual stock accounting, and stock returns are more highly correlated. In addition, whilst three-year reversal effects of the type identified by De Bondt and Thaler (1985)[8] are replicated in the simulated values using individual stock accounting, this is not the case under portfolio accounting.

Barberis and Huang conclude that in general, individual stock accounting appears to be more successful than portfolio accounting in reproducing the empirical features of stock market returns and mental accounting on the part of investors may therefore play an important role in driving empirically observed anomalies in stock market returns.

[8] These findings are discussed in detail in Chapter 4.

2.3.2 Representativeness

Individuals commonly simplify decision situations by considering the extent to which a given item is similar to, or representative of, known groups of items. Tversky and Kahneman (1974) give the example of an experiment in which subjects were asked to predict the future stock price of a company. If shown a positive description of the company, subjects tended to produce a high stock value since the description given was highly representative of a successful company. If a less favourable description was shown, a low predicted stock value was obtained reflecting the representativeness of the description to a failing company. The representativeness heuristic may be used in different ways based on the decision scenario in question.

Exact representativeness describes a situation which is seen to exactly represent a known stereotypical image. Camerer (1987) uses a simulated financial market (trading game) to consider the biases exhibited by participants. Assessed probabilities of future prices are broadly in line with the Bayesian prediction except where the price history <u>exactly</u> reflects a known scenario (this could be a repeated pattern of prices, for example). Exact representativeness may therefore play an important role in the price formation process in situations where the recent path of prices exactly represents a "known" feature such as a bull or bear trend or a commonly followed technical trading pattern.

The tendency for investors to extrapolate past price trends (Daniel et al, 2002) may be related to the concept of exact representativeness. Shleifer and Summers (1990, p28) state that

> "one of the strongest investor tendencies documented in both experimental and survey evidence is the tendency to extrapolate or to chase the trend".

If investors perceive that the pattern of recent prices forms a trend, future prices may be predicted using representativeness. That is to say, if a positive trend is observed in the recent price history, investors predict future prices based on the assumption of a continued positive trend.

Benartzi (2001) shows that employees of firms with good past price performance make higher discretionary 401K contributions to company stock than do employees of companies with poor past price performance. The level of discretionary contributions does not predict future performance, however, hence it does not appear to be the case that employees make higher contributions to their own company's stock as a result of superior information in relation to the company's future prospects. Rather, employees appear to be predicting high future performance on the basis of good past performance.

Similarly, investment flows into US mutual funds have been shown to be concentrated into those funds with the highest past performance (Sirri and Tufano, 1998) although as shown by Carhart (1997), a high past performance among mutual funds is not a significant indicator of high future performance.

Kahneman and Tversky (1973) identify the concept of local representativeness (also commonly referred to as the law of small numbers or the gambler's fallacy), which leads individuals to expect that a short sequence of events will be representative of the characteristics of the underlying process . If a coin is tossed six times, for example, the sequence of outcomes "HTHTHT" is generally considered to be much more likely than the sequence "TTTTTT". In the context of financial markets, local representativeness might lead investors to believe that if a market has risen for four days in a row, it is highly likely to fall on the fifth day. According to Tversky and Kahneman (1974, reprinted 1982, p7),

> "Chance is commonly viewed as a self-correcting process in which a deviation in one direction induces a deviation in the opposite direction to restore the equilibrium".

Investors often overlook the importance of sample size, taking small samples to be as informative as large samples[9]. In the short-term, local representativeness may lead investors to expect reversals in market prices, with recent runs of price increases expected to be followed by a fall and vice versa following periods of declining market prices.

The phenomenon known as regression towards the mean also has its roots in the representativeness heuristic. Investors commonly expect extreme market movements to be followed by equally large price changes (positive or negative)

[9] See, for example, Tversky and Kahneman (1971) and Rabin (2000).

in the following period. Based on the normative laws of probability, however, if we take any particularly extreme observation it is highly probable that the next observation will be less extreme. Kahneman and Tversky (1973) argue that the reason regression is a difficult concept is due to the influence of representativeness. Investors expect inputs to be representative of outcomes. Given a large market move on one day, therefore, they expect the move on the following day to be just as extreme. A lack of understanding of regression towards the mean may help to explain the observed phenomenon of volatility clustering in financial markets[10]. Investors expect large market movements to be followed by similarly large movements, and small market movements to be followed by similarly small movements.

When assessing the representativeness of a situation, individuals have been shown to place too little emphasis on the quality and relevance of the information used. In Kahneman and Tversky (1973), subjects were asked to assess the probability of individuals within a sample group being engineers or lawyers. If no description of the individual was provided, the subjects assessed the probability correctly based on the number of engineers and lawyers in the sample group. If a description was given, however, the subjects appeared to assess the probabilities using representativeness, regardless of the relevance of the information provided. The information provided, including worthless information such as an individual's marital status and number of children, was compared to the subjects' stereotypes pertaining to each occupation in order to gauge the probability of the individual in question being an engineer. The representativeness heuristic may therefore result in reliance being placed on largely irrelevant information when assessing the prospects for future market prices. If investors can be shown to react systematically in this way, biased predictions based on irrelevant information may be a driving force behind anomalous patterns in financial market returns.

Representativeness may lead to price continuation if investors extrapolate past trends, or indeed to price reversal if they are subject to local representativeness. Different tendencies may be more common in certain types of investor. De Bondt (1998), for example, finds that whilst strategists tend to suffer from gambler's fallacy (expecting reversals), individual investors are

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[10] The literature on volatility clustering is reviewed in Jacobsen and Dannenburg (2003)

more susceptible to extrapolating trends. In addition, different tendencies may be prevalent in different situations. The degree to which the data is representative of a given situation (for example, a bull market) may have an important influence, with exact representativeness becoming dominant where a close match is found between the underlying data and the stereotypical scenario to which it is compared. It is also important to consider the different types of information which may be used by investors in this regard. Whilst it would be reasonable to expect financial information and past price performance to play a role, the findings of Kahneman and Tversky (1973), among others, tend to suggest that investor expectation may also be influenced to a large extent by 'soft' information such as media coverage.

2.3.3 Availability

Under the Availability Heuristic, decision-makers assess the probability of an outcome based on the ease with which similar instances can be brought to mind.

A class of outcomes which is easier to recall will generally be allocated a higher probability of occurrence than an equally likely class of outcomes which is less easy to recall. More salient events are typically easier to recall (extreme price movements are easier to recall than small price movements, for example), as are more recent events (price movements last week are easier to recall than price movements last year).

Under the Availability Heuristic, investors can therefore be expected to overestimate the probability of market movements which are extreme, recent, or on some other way memorable, and to correspondingly underestimate the probability of small or "ordinary" market movements. This can lead to biases in decision-making.

Tversky and Kahneman (1973, reprinted 1982) describe a number of experimental situations in which subjects are shown to make decisions based on availability. In one, subjects are shown a six by six grid of noughts and crosses, reproduced in Figure 2.1, and asked to estimate the number of paths containing six Xs and no Os, five Xs and one O, and so on. A path is defined for this purpose as any descending line (not necessarily a straight line) starting at the top row, ending at the bottom row, and passing through exactly one symbol in each row.

Figure 2.1 Grid from Tversky and Kahneman (1973)

X	X	O	X	X	X
X	X	X	X	O	X
X	O	X	X	X	X
X	X	X	O	X	X
X	X	X	X	X	O
O	X	X	X	X	X

In this situation, subjects are seen to estimate the frequency of occurrence of each type of path by the ease with which they can be seen in the grid. Since there are far more Xs than Os at each stage, it is much easier to construct paths of six Xs than five Xs and one O, even though these are in fact more numerous. Subjects erroneously infer that there must be more paths of six Xs and no Os than five Xs and one O.

Tversky and Kahneman go on to repeat the experiment framing the problem in a different way. Subjects are given a description of a card game with six players. Each player draws one card blindly in each round of the game. Five sixths of the cards are marked X and one sixth are marked O. Subjects are asked to estimate, after many rounds of the game have been played, the percentage of rounds in which six players receive X and no player receives O, 5 players receive X and one player receives O, and so on. Although this is the same problem as the one involving the grid, the first experiment places emphasis on the grid whilst the second places emphasis on the population parameter. In the second experiment, subjects are seen to make judgements using representativeness rather than availability.

This experiment highlights the importance of framing, introduced in Section 2.2, in determining the way in which individuals respond to decision-making scenarios. In general, Tversky and Kahneman note (p174), "... the frequency of a class is likely to be judged by availability if the individual instances are emphasized and by representativeness if generic features are made salient".

The use of the availability heuristic leads investors to place too much weight on recent and salient information. In the case of recent information, this will reinforce the tendency to chase trends, as described in Section 2.3.2.

2.3.4 Anchoring

The anchoring heuristic affects individuals' ability to make accurate numerical predictions. Rather than starting "from scratch", predictions are typically made by taking a known initial value (the "anchor") and adjusting it upwards or downwards to reach a predicted value.

Empirical research suggests that, in general, the adjustments made to the anchor to reach a predicted value are insufficient (Slovic and Lichtenstein, 1971). Different starting points result in different predictions, all biased towards the choice of the initial anchor. In one commonly cited experiment, individuals were asked whether the percentage of African countries in the United Nations was higher or lower than a given level before being asked for their estimate of the true percentage. Those given a level of 10 produced subsequent estimates of 25, whilst those given a level of 60 produced estimates of 45. In each case, anchoring on the level suggested by the task biases the estimate towards the anchor.

The use of different anchors will result in different predicted values. When assessing the importance of anchoring in financial decision-making, therefore, a key goal is the identification of those scenarios in which investors will systematically choose anchors in the same way.

The current market price may be used as an anchor. In empirical experiments involving problems similar to this, subjects generally produce predicted market levels which are too close to the current level (Tversky and Kahneman, 1974). If asked to assess the probability of the market exceeding a particular level (the "target level") over the next week, on the other hand, investors have been shown to be much more likely to anchor on the target market level, or possibly on a point halfway between the current level and the target level. Given the higher level of the anchor, they are likely to produce a correspondingly high probability of the target level being reached. This conclusion is supported by empirical research involving questions of a similar nature - in general subjects overestimate the probability of the market exceeding the given level than is actually the case (Tversky and Kahneman, 1974). This may lead investors to overestimate the probability of large market movements.

De Bondt (1998, p834) notes that past returns are generally used as an anchor when forming short-term expectations, whereas past price levels are an important anchor for longer-term expectations:

> "It is as if investors predict the near future with an eye towards recent price changes but that past price levels anchor their longer-term forecasts.... Investors who think long-term tend to subscribe to regressive expectations and those who think short-term have static expectations"

Investors' overestimation of the likelihood of low probability events, and corresponding underestimation of the likelihood of high probability events, results in a tendency to overestimate the probability of conjunctive events (such as tossing a coin six times and obtaining a head on each throw) and underestimate the probability of disjunctive events (such as obtaining a head at least once from six throws). In each case, the subjective probability of success in one stage is used as an anchor for subsequent stages. Given insufficient adjustment, decision-makers may therefore underestimate the likelihood of high probability compound events, such as a run of small price changes, and overestimate the likelihood of low probability compound events such as a run of large price changes.

Conservatism has its roots in the anchoring heuristic. When forming predictions, individuals may use the base rate frequency of outcomes as an anchor. Insufficient adjustment means that the specific evidence relating to the decision to be made is underweighted relative to the base rate evidence. If investors form predictions based on conservatism, overweighting base rate information relative to specific information relating to the current situation, then prices may not initially fully adjust to new information entering the market. Instead, prices may adjust only slowly. Conservatism, based on the anchoring heuristic, has therefore been identified in the literature as one of the possible factors behind continuation effects in stock market returns. Ritter (2003) notes that conservatism can be seen as being at war with representativeness. If a decision scenario is closely representative of a known scenario, then individuals will form predictions based on exact representativeness, leading to an overweighting of specific evidence relative to the base-rate information. In other scenarios, conservatism may prevail.

2.4 Emotional Factors affecting Decision-Making

Emotional factors can also result in biases in investor decision-making. A simple example is provided by the ultimatum game described by Thaler (2000). The ultimatum game is a controlled experiment involving two individuals. Player One is given a sum of money (10 US dollars, say) and must offer a share of the total to Player Two who can accept, in which case he receives the amount offered, or reject, in which case neither player receives anything. Experimental evidence shows that although it is clearly rational for Player Two to accept any amount offered, low offers of less that 20 percent of the total available are commonly rejected. In such cases, Player Two's non-rational behaviour is driven by emotional factors (and in particular a sense of indignation) if they are offered what they see as a derisory share of the overall financial gain. Similar experimental situations have been widely used to highlight other areas in which financial decision-making may deviate from rationality as a result of emotional factors affecting decision-making. This section discusses overconfidence, aversion to loss, and aversion to ambiguity in further detail.

2.4.1 Overconfidence

Investors are typically overconfident in relation to their own ability. In the Canoles et al (1998) study of commodity speculators in Alabama, for example, approximately half of the speculators surveyed considered themselves to be successful, despite only around 10 percent having made a net profit over the time they had been trading.

Barber and Odean (2000) conclude that overconfidence on the part of investors can explain both high levels of trading activity and poor performance. In their study of 66,465 households in the United States over a six year period ending in January 1997, the average household was seen to turn over 75 percent of its portfolio annually. This is attributed to excess confidence among investors, the results of which can be extremely costly. The average gross returns achieved were comparable to the return on a value-weighted market index. When the impact of the bid-ask spread and commissions are taken into account, however, households significantly underperform the market, achieving a 1.1 percent underperformance compared to the value-weighted market index, or 3.7 percent after the tendency among households to skew their portfolios towards smaller-cap, higher-risk stocks is accounted for. Men trade on average 45 percent more often than women, and earn 1.4 percent less. Overconfidence results in high levels of trading activity, with the associated trading costs presenting a significant drag on profitability.

De Bondt (1998) studies the forecasting behaviour of 45 investors in Wisconsin. Between October 1994 and March 1995, each investor made weekly two- and four-week forecasts and interval estimates (levels beyond which they thought the market had only a one in ten chance of ending the two or four week period). Each investor made forecasts of the Dow Jones Industrial Average in addition to a single stock of their choice from among their main equity holdings. The investors were seen to make overly optimistic predictions relating to their own holdings but not relating to the Dow Jones index. The predictions of the performance of the Dow Jones index were statistically indistinguishable from the actual performance of the index. On average, however, the predicted outperformance of the individual stocks over the Dow Jones index was 0.86 percent compared to an actual outperformance of only 0.28 percent. The confidence interval estimates were too narrow in all cases (forecast values were too close to the values at the time the predictions were made), with this problem being greater for longer forecasting horizons. In addition, the confidence intervals were asymmetric. High predicted returns were combined with negatively skewed confidence intervals and vice versa, implying that the confidence intervals were formed using the initial value as an anchor.

Research indicates that subjects are generally more confident in their predictions the greater the degree of representativeness (the greater the degree with which the input to the decision process fits the stereotypical image relating to the prediction). This occurs regardless of the quality or accuracy of the information on which the prediction is made, resulting in often unwarranted confidence known as the "illusion of validity". Overconfidence may interact with representativeness in the formation of market bubbles.

According to Shiller (2001, p3),

> "The essence of a speculative bubble is a sort of feedback, from price increases, to increased investor enthusiasm, to increased demand, and hence further price increases. The high demand for the asset is generated by the public memory of high past returns, and the optimism those high returns generate for the future. The feedback can amplify positive forces affecting the market, making the market reach higher levels than it would if it were responding only directly to these positive forces."

In addition, confidence in predictions increases where all of the input information is consistent. For example, if each piece of information provided on a company is mediocre, subjects will be much more confident in predicting an unchanged share price than if the information provided is a mixture of good and bad signals. Adding redundant but consistent information, such as different measures of sales growth, can therefore increase predictive confidence. The typically high degree of correlation between redundant data, however, actually reduces accuracy relative to that obtained from the same number of independent pieces of information. Providing decision-makers with large quantities of redundant data therefore results in increased confidence combined with decreased accuracy. This may be relevant to the prediction of future stock prices, where the correlation between individual stocks and stock markets may not be taken into account by investors. Rising prices across a number of stocks or markets may therefore be interpreted as stronger evidence for future price rises than is warranted in reality.

Kahneman and Tversky (1973) note that under normative principles of prediction, expected accuracy controls the relative weights to be placed on prior (base-rate) information and specific evidence concerning the case in question. When predictive accuracy is low, predictions should be weighted towards the base-case evidence alone. In such a scenario, an appropriate prediction of a future market price would be the current price. When predictive accuracy is high, relatively more weight should be placed on specific evidence relating to the case in question. Overconfident investors overestimate the accuracy of their own predictions, and as a result place too much emphasis on specific rather than base-rate information. In a financial markets context, overconfidence therefore leads individuals to exaggerate the expected size of future returns.

2.4.2 Aversion to Loss

Survey evidence supports the theory that significant loss aversion exists among financial market participants

Canoles et al (1998) survey the motivations of 114 retail commodity futures speculators in Alabama and find that whether a gain or loss was made on a particular trade is more important to the individual speculator than the size of the gain or loss. The investors considered won more often than they lost (51 percent of trades were profitable), however 90 percent of them were net losers in dollar terms. In spite of recurring losses, the typical investor had never made any fundamental changes to his/her trading style. Investors were more concerned about missing out on a profit by not having a market position than they were about losing money by being on the wrong side of a market move. This encouraged continual position-taking rather than selective taking of a market position based on perceived opportunity for gain[11].

The Prospect Theory of Kahneman and Tversky (1979) has loss aversion among investors as one of its main components. Under prospect theory, values are multiplied by decision weights to arrive at decisions in much the same way as described by normative theories of decision-making. In prospect theory, values are assigned to gains and losses relative to a fixed reference point (current wealth) rather than to measures of final wealth, however, reflecting the concept that individuals obtain utility from gains and losses in wealth rather than absolute levels of wealth. In addition, the value function is generally concave for gains and convex for losses, with investors experiencing a reducing marginal pleasure from higher gains and an increasing marginal discomfort to higher losses. The steepest part of the value curve is close to the reference point (implying that investors are most sensitive to small gains and losses from their current wealth) and the value curve is non-linear through the origin. A fourfold pattern of risk attitudes is obtained: risk averse for high-probability gains and low probability losses, and risk-seeking for high probability losses and low probability gains.

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[11] Loss aversion may therefore contribute to the excessive trading volume attributed to overconfidence in some studies (see, for example, Barber and Odean, 2000).

The value function is specified as

$$v(x) = x^{\alpha} \qquad \text{if } x >= 0, \text{ or}$$
$$-\lambda(-x)^{\beta} \qquad \text{if } x < 0$$

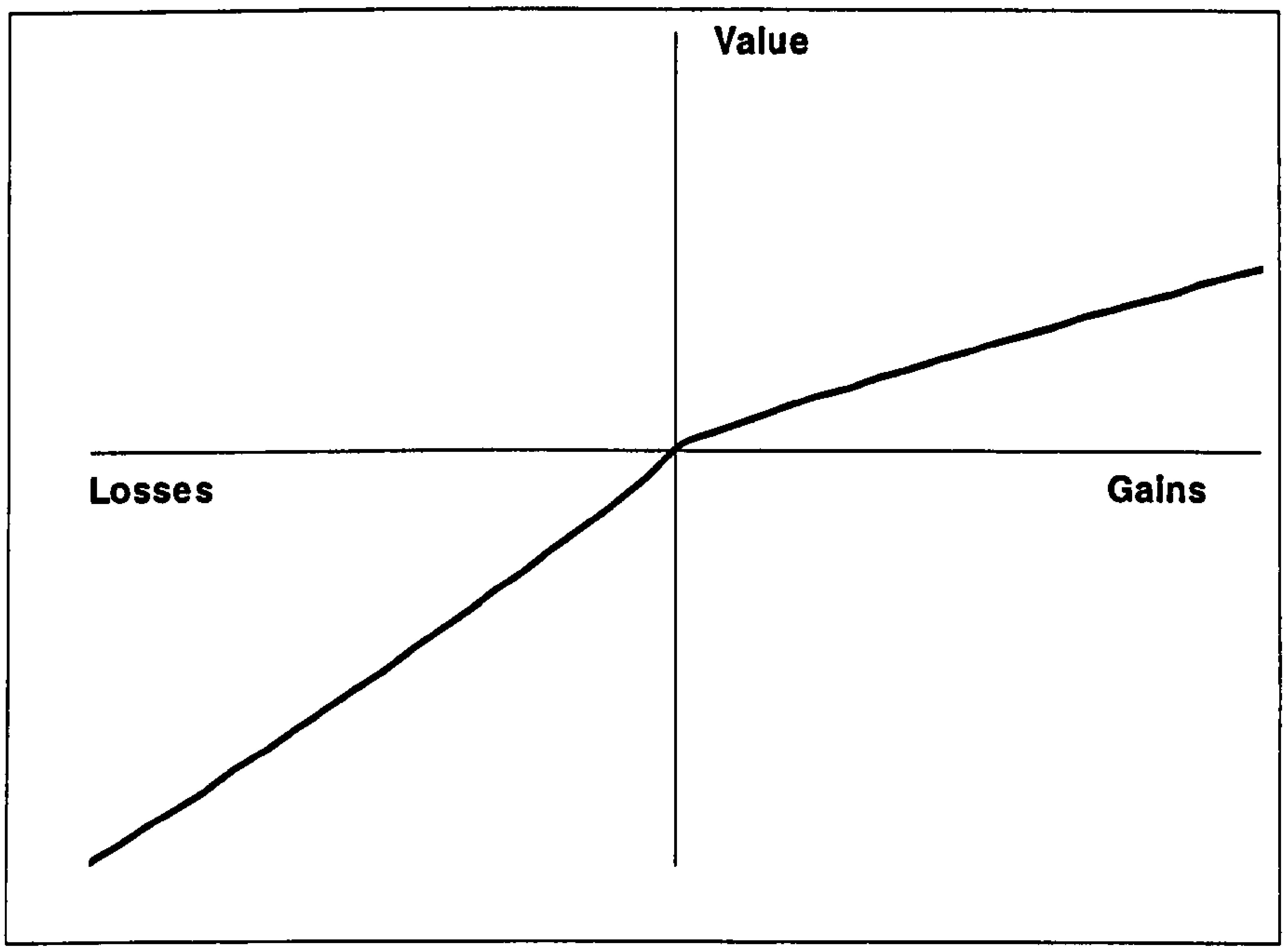
The degree of loss aversion is reflected in the parameter λ and diminishing sensitivity to gains and losses via the parameters α and β respectively. Experimental work by Tversky and Kahneman suggests values of α, β, and λ of 0.88, 0.88, and 2.25 respectively. Panel A of Figure 2.2 shows the value function obtained using the parameter values suggested by Kahneman and Tversky, and also demonstrates the impact of a change in each of the three individual parameters on this value function.

The parameter α controls the degree of curvature of the value function in the region of gains, with a reduction in α resulting in an increased sensitivity to small gains relative to large gains, as illustrated in Panel B. Similarly, the parameter β controls the degree of curvature of the value function in the region of losses. Panel C shows the impact of reducing β in terms of an increased sensitivity to small losses. Finally, the parameter λ controls the relative value of gains and losses, with a reduction in λ reducing the degree to which losses are assigned higher value than gains. Panel D shows the effect of a reduction in λ.

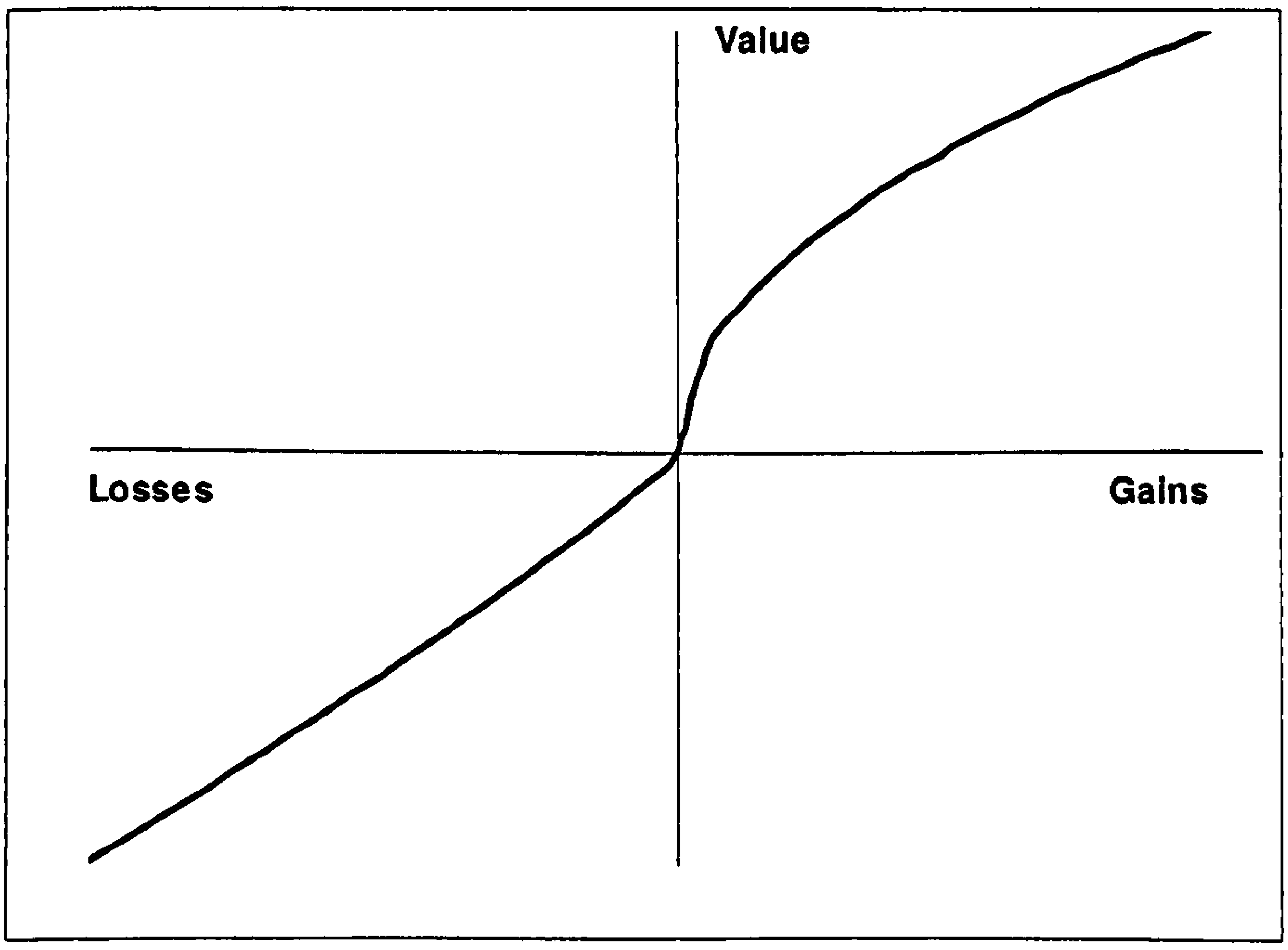
The decision weights used in conjunction with the value curve reflect biases in probability assessment by individuals. These probabilities are generally lower than normative probabilities in all situations except for very small probabilities, where decision weights may be higher than the associated normative probability. That is to say, individuals overestimate the probability of extreme events and correspondingly underestimate the probability of non-extreme events. Kahneman and Tversky note that this may occur as a result of anchoring, described in Section 2.3.4. Whilst normative theories of decision-making assume that individuals make decisions using the correct probability distribution of returns, therefore, prospect theory suggests that this may not be the case and that the decision weights used by individuals may deviate systematically from actual probabilities. Figure 2.3 shows hypothetical prospect theory decision weights.

Figure 2.2 Prospect Theory: Value Function

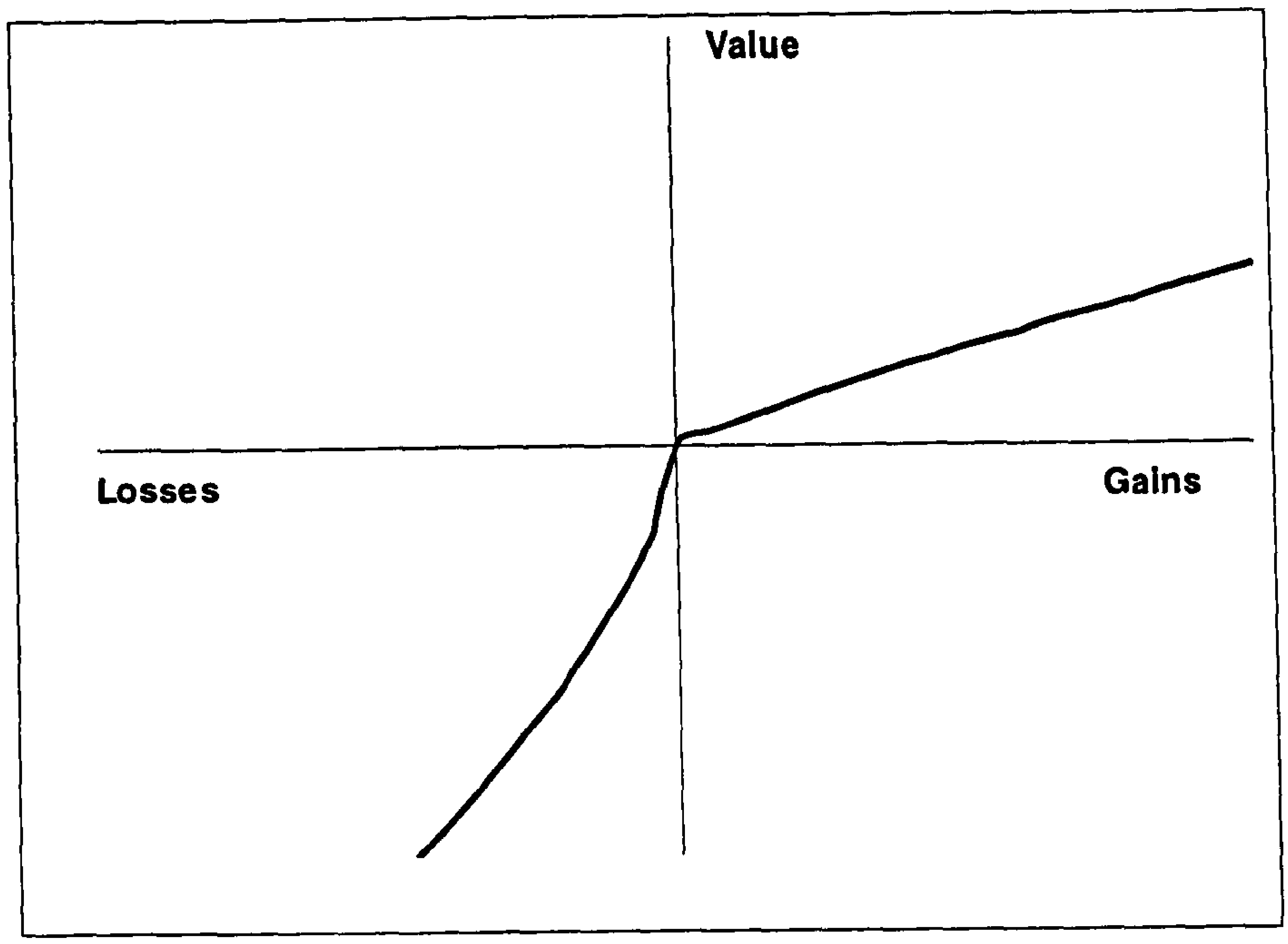
A. Value Function with $\alpha = 0.88$, $\beta = 0.88$, and $\lambda = 2.25$



B. Value Function with $\alpha = 0.50$ ($\beta = 0.88$, and $\lambda = 2.25$)



C. Value Function with $\beta = 0.65$ ($\alpha = 0.88$, and $\lambda = 2.25$)



D. Value Function with $\lambda = 1.00$ ($\alpha = 0.88$, and $\beta = 0.88$)

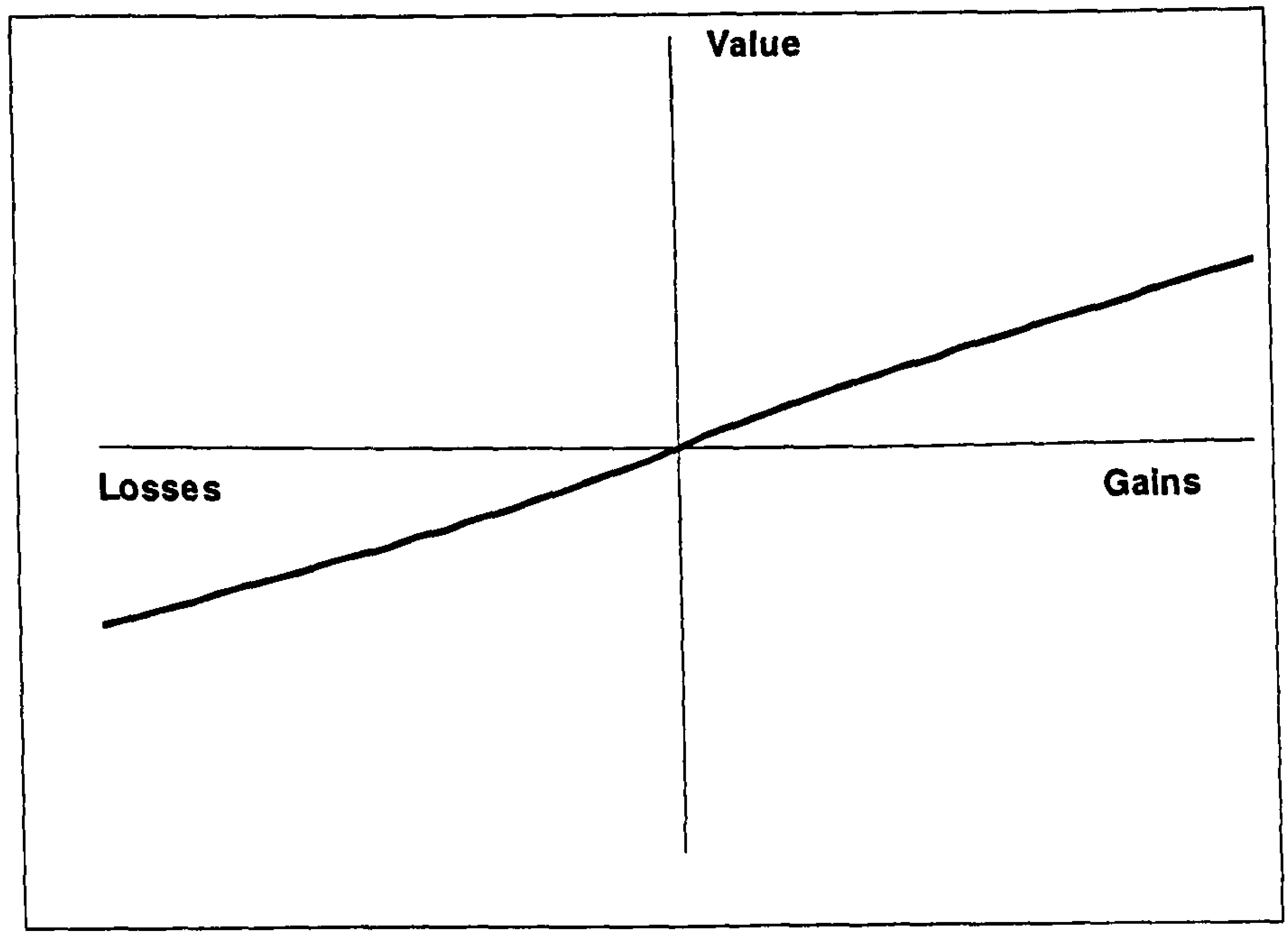
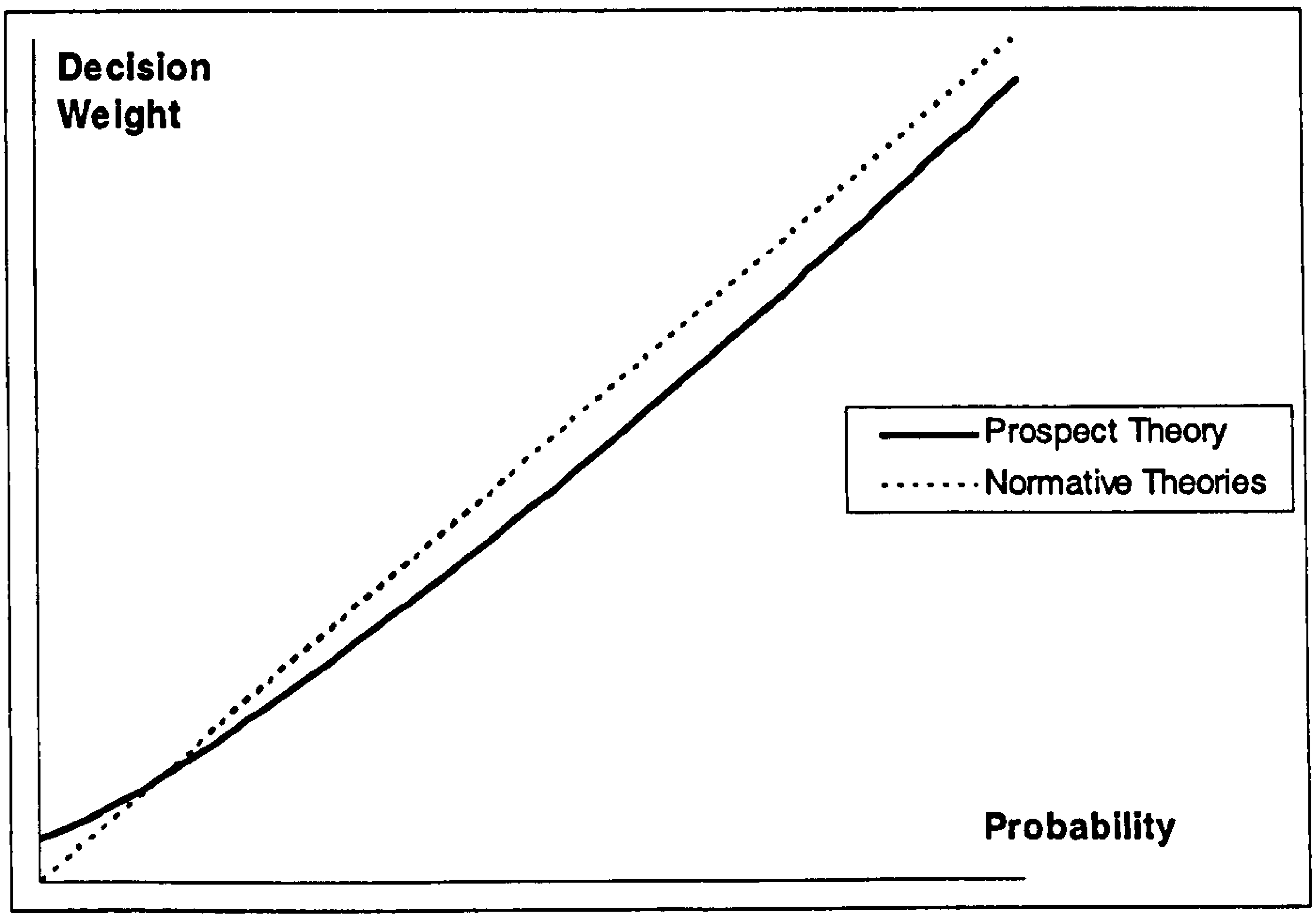


Figure 2.3 Prospect Theory: Decision Weights



Shefrin and Statman (1985) place aversion to realising losses into a wider theoretical framework, describing a "disposition effect" whereby investors display a general disposition to sell winners too early and hold losers too long[12].

Odean (1998) studies 163,000 accounts at a discount brokerage house in the USA, and compares the fractions of all capital gains and capital losses realised each day. From January through November, gains are realised 1.68 times more often than losses except in December when losses are 1.02 times more likely to be realised than gains, which Odean attributes to a tax effect. In general, small losses tend to be realised whereas large losses are held, generating poor subsequent returns.

In their study of 10,000 randomly-selected accounts from a US discount brokerage, Barber and Odean (1999) find evidence to support the disposition

[12] Related tendencies have been identified in other decision-making scenarios. Drummond (2003, p39), for example, describes the phenomenon of escalation in business decision-making whereby managers may "make matters worse by persisting with failing ventures and end up throwing good money after bad". London's Millennium Dome project is cited as an example.

effect of Shefrin and Statman (1985), with holdings of stocks that show an unrealised profit 50 percent more likely to be sold on any given day than stocks showing an unrealised loss.

Grinblatt and Keloharju (2001) use Finnish Central Securities Depository (FCSD) data from 27 December 1994 through 10 January 1997 on stock transactions in the Finnish market to investigate the propensity to sell or hold equity investments[13]. Logit regression is used to analyse influences on the daily sell versus hold decision for stock investors. Positive market-adjusted returns during the previous month are found to be significantly correlated with the decision to sell. Generally speaking, the more recent the positive returns, the more likely the investor is to sell. Strongly negative market-adjusted returns up to a week in the past moderately reduce the tendency to sell, whereas the more distant returns history of the stock has little impact on the sell versus hold decision. Large capital losses of over 30 percent significantly reduce the probability of a sale, by 32 percent. Smaller capital losses have a somewhat reduced, although still significant, effect on the propensity to sell, reducing the chance of a sale by 21 percent on average. Loss aversion among investors, as described by prospect theory and the disposition effect, may therefore have important implications for investor behaviour and hence also for stock market prices.

In addition to simply being averse to realising losses, investor behaviour may also be influenced by gains and losses realised in the past. The house money effect of Thaler and Johnson (1990) describes the phenomenon that when faced with sequential gambles people risk more if they won on previous gambles than they do if they lost. In other words, individuals are risk taking following gains and risk averse following losses. Stock market investment is not a single-period scenario, and it is reasonable to expect that the degree of loss aversion experienced by investors may be related to the level of returns experienced in the recent past, with risk aversion therefore negatively correlated with recent market performance. For example, if an investor buys a share and sells it six months later at a profit of 10 percent, he is likely to have a

[13] This data set is unique in that it includes details of the shareholdings and transactions of almost all Finnish investors, both retail and institutional, during this period.

greater tolerance for risk when selecting a second stock in which to invest than he would be if he had lost 10 percent on the first investment. The house money effect may therefore be related to overconfidence, with past gains increasing the level of overconfidence and therefore resulting in exaggerated expectations of future returns.

Barberis et al (2001, p2) describe a model which incorporates elements of both prospect theory and the house money effect. Investors are loss averse to a lesser extent following prior gains than following prior losses:

> "After a run-up in stock prices, our agent is less risk averse because those gains will cushion any subsequent loss. After a fall in stock prices, he becomes more wary of further losses and hence more risk averse".

The model is seen to predict phenomena seen in historical stock market data, namely high average returns, excess volatility, and time series predictability[14].

The regularity with which investors review performance may also have an impact on the degree of loss aversion they experience. Myopic loss aversion, introduced to the literature by Benartzi and Thaler (1995), describes the tendency for loss-averse investors to be less willing to accept risk if outcomes are evaluated more frequently. The asymmetric valuation of losses and gains described in prospect theory means that whilst losses may be valued over gains over a single investment period, gains may be valued more highly than losses over multiple periods. Investments which are attractive over a long horizon can therefore appear unattractive over short horizons. This is reflected in the empirical observation that individuals display reduced loss aversion when faced with gambles which are repeated over time. Samuelson (1963) describes his experience that one of his colleagues rejected the chance to enter into a bet with a 50 percent chance of winning US$ 200 and a 50 percent chance of losing US$ 100, even though the expected outcome was positive. He was, however, prepared to enter into a series of 100 such bets.

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[14] Specifically, reversals in returns over three year periods of the type identified empirically by De Bondt and Thaler (1985)

Langer and Weber (2003) show that myopic loss aversion can also work in the opposite direction. A series of junk bond investments with a low probability of default but high losses in the event of default, for example, may become more attractive in the short-term as a result of myopic loss aversion. Willingness to invest may not therefore be strictly negatively related to the degree of myopia as had been suggested in some previous studies.

Haigh and List (2002) study myopic loss aversion in professional traders on the Chicago Board of Trade and undergraduate students at the University of Maryland. In an experimental environment, both groups display evidence of myopic loss aversion, with the degree of myopic loss aversion of professional traders actually greater than that of undergraduate students exposed to the same test.

Fielding & Stracca (2003) model expected returns under aversion to loss and to regret and suggest that a combination of myopic loss aversion over very short investment horizons and disappointment aversion over longer horizons may provide an attractive explanation of the equity premium puzzle[15]. Their results suggest that unrealistically short investment horizon of less than three years is required for the historical equity premium to be explained by loss aversion alone. Disappointment aversion on the other hand can explain the historical equity premium for much longer investment horizons of up to ten years.

Aversion to loss describes the phenomenon whereby investors value losses more highly than gains. This may lead to the rejection of opportunities which traditional Net Present Value (NPV) analysis would lead one to believe would be accepted. The degree of loss aversion displayed by investors may be related to the extent of previously realised losses and gains or the frequency with which future losses and gains are to be evaluated.

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[15] Aversion to disappointment and regret is discussed by, for example, Loomes and Sugden (1987) and Inman et al (1997). Investors not only derive utility from realised outcomes (investments they hold), but also from investment opportunities they chose to forego.

2.4.3 Aversion to Ambiguity

Empirical evidence suggests that individuals are averse to ambiguity. In other words, they prefer choices where the probabilities of outcomes are known rather than unknown. Camerer and Weber (1992, p326) state that "ambiguity about probability creates a kind of risk... – the risk of having the wrong belief".

Aversion to ambiguity is raised in the literature by Ellsberg (1961). In an experimental setting, Ellsberg shows, via a series of tests, that individuals prefer bets with a known probability of winning to equivalent bets where the probability of winning is unknown. In one test, the subject has to bet on the outcome of a single draw from an urn containing 30 red balls and 60 black and yellow balls in an unknown combination. Participants show a clear preference for betting on red over betting on black, and prefer betting on "yellow or black" to betting on "yellow or red". In each case, the bet with a known probability of success is preferred, and the examples can be constructed in such a way that participants' choices violate axiomatic theories of choice under uncertainty.

Other sources of ambiguity may be based on the perceived credibility of information sources such as analysts' reports, or the "weight of evidence", which Camerer and Weber (1992, p331) define as the "amount of available information relative to the amount of conceivable information".

Heath and Tversky (1991) note that aversion to ambiguity is inversely linked to overconfidence. If an individual is made to feel less confident about his predictive ability, he becomes more averse to ambiguity.

Aversion to ambiguity may also be linked to a preference for the familiar. Benartzi (2001), for example, notes that about a third of 401(k) account assets in the USA are invested in the stock of the employing company, as are about a quarter of discretionary contributions. This clearly implies insufficient diversification and may be a result of investor preference for the familiar.

Viscusi and Magat (1992, p373) consider that "ambiguity creates an aversion to incurring a loss and decreases the attractiveness of potentially winning a prize". Aversion to ambiguity can therefore be seen as exaggerating the effects of aversion to loss described in the previous section.

Sections 2.3 and 2.4 discuss research in psychology which has identified a broad range of biases in investor behaviour, any one or more of which may be relevant in individual decision-making situations. The following section goes on to consider how such biases may relate to empirically observed patterns in stock market returns.

2.5 Behavioural Biases and Continuation and Reversal Effects in Stock Market Returns

Table 2.1 provides a broad categorisation of the sources of behavioural bias described in Sections 2.3 and 2.4 according to their relevance to the empirical phenomena of very short-term reversal and medium-term continuation which are the focus of this study.

Findings of reversal in stock market returns over the very short-term may be driven by local representativeness, with investors expecting a large market move in one direction to be followed by a "balancing" move in the opposite direction. Alternatively, if investors anchor on recent market prices rather than returns, they may equally expect a reversal following a large price change.

A broad range of behavioural biases can be identified as being potential driving forces behind medium-term continuation effects in stock market returns. Exact representativeness, and the related tendency to extrapolate past trends, may lead investors to expect recent high or low returns to persist in the future. Similarly, recent high or low returns may be expected to persist as a result of the availability heuristic, or as a result of anchoring if investors anchor on past returns rather than past prices. Conservatism, whereby investors place too much weight on base case evidence rather than the individual case, may result in a slow adjustment of prices in response to new information entering the market.

Behavioural influences may also help to explain some of the statistical properties of financial time series[16]. If investors overestimate the probability of

[16] These properties are reviewed by Cont (1999).

Table 2.1 Behavioural Biases and Continuation and Reversal Effects in Stock Market Returns

Empirically Observed Phenomenon	Potentially Contributing Behavioural Factors	
Very Short-Term Reversal	local representativeness	following a large one-day movement, investors expect a movement in the opposite direction
	anchoring	investors anchor on recent market prices
Medium-Term Continuation	exact representativeness extrapolation of past trends	if investors identify a trend in recent prices, representativeness leads them to expect the trend to continue
	availability	if the recent trend in prices is positive, positive price changes will be more easily brought to mind, and investors will expect future price changes to reflect this
	anchoring	investors anchor on recent market returns
	conservatism	investors overweight base-case information, and therefore adapt expectations slowly to new information
Leptokurtotic Distribution of Returns	availability	investors overestimate the probability of very large (salient) price movements
	overconfidence	investors exaggerate the expected magnitude of future returns
Volatility Clustering	regression towards the mean	investors expect large price changes to be followed by large price changes and small price changes to be followed by small price changes, causing volatility to persist

very large price movements, as a result of availability or overconfidence for example, then this may result in the typical "fat-tailed" distributions of financial time series. Similarly, a lack of understanding of regression towards the mean may help to explain why volatility clustering occurs.

A number of models of investor behaviour have been proposed in the literature. These typically combine one or two known biases in models which seek to replicate the empirical phenomena of medium-term continuation and long-term reversals in returns.

Barberis, Shleifer and Vishny (1998) present a model in which investors see the market as subject to two competing regimes. When the market is in regime 1, earnings are mean-reverting, whereas when the market is subject to regime 2, earnings trend.

Investors within the Barberis et al model are subject to both conservatism and the representativeness heuristic. Investors are slow to update their expectations in the light of new information. As information arrives in the form of new prices, investors revise their subjective probabilities of being in each regime. For example, if the market does particularly well over a short period, investors will increase the probability of their being in regime 2. If, on the other hand, positive and negative returns are more mixed over a subsection of the data then the probability of being in regime 1 will be increased. That is to say, investors subjectively assess the probability of being in regime 1 or regime 2 base on representativeness, with probabilities updated slowly as a result of conservatism.

Barberis et al show that their model of investor sentiment generates prices which are consistent with the medium-term continuation and long-term reversal effects documented in the literature.

Daniel, Hirshleifer and Subrahmanyam (1998) present an alternative model of investor behaviour in which investors are seen to suffer from both overconfidence and biased self-attribution. The overconfident investor overestimates his own ability to generate market information and thus underestimates his own forecast errors. Biased self-attribution concerns the investor's reactions to the results from his investment decisions. If a trade is profitable, the investor's self confidence increases further. If a trade is loss-making, it is largely discounted. Successes are seen as a result of the investor's superior foresight whereas losses are put down to chance. Overconfidence and biased self-attribution lead to short-term momentum in prices as investors overweight private information relative to public information. Over the longer term, however, public information prevails and prices are drawn back towards the value implied by fundamentals (reversal).

The model of Hong and Stein (1999) uses the interaction between heterogeneous groups of investors to generate patterns in market returns. The Hong and Stein world is populated by two types of investor, "news watchers" and "momentum traders". Each is rational in a bounded sense, in that they use only part of the universe of available information when making investment decisions.

News watchers make decisions based solely on information concerning market fundamentals; they take no notice of current and past price levels. When new information enters the market, it diffuses slowly across the population of news watchers. If no momentum traders are active in the market, prices gradually adjust to reflect the new information, and the market displays evidence of continuation in returns.

Momentum traders are simple trend chasers in the Hong and Stein model. As new information enters the market, it begins to disperse among the news watchers and the price slowly starts to adjust. At a given point, momentum traders will enter the market in an attempt to profit from the slow price adjustment process caused by the news watchers. Their transactions accelerate the price change, causing more momentum traders to enter the market. The price is pushed beyond the full information price and a reversal in returns occurs.

The three behavioural models outlined above predict slightly different financial market behaviour. In the Barberis et. al. model, investors' perceptions as to the state of the market (regime 1 or regime 2) result in short-term continuation or reversal depending which regime is favoured at the time. In the Daniel et. al. and Hong and Stein models, short-term continuation in returns is accompanied by long-term reversal. One limitation of such models is that observed patterns in returns could be explained by any number of combinations of individual behavioural biases; causality between individual biases and patterns in market prices is difficult to identify.

If behavioural biases result in biased decision-making on the part of investors then anomalies in market prices, and hence market inefficiency, may result. The implications of behavioural biases for market efficiency depend, however, on the ability of arbitrage to cancel out the effect of behavioural biases and force prices to fundamental (unbiased) levels. The following section discusses the conditions in which behavioural biases may drive market prices.

2.6 Behavioural Finance, Arbitrage, and Market Prices

It is important to recognise that the behavioural biases in the decision-making of individual investors that have been identified in the literature and discussed in Sections 2.3 and 2.4 do not in themselves result in biases in market pricing. Irrational decision-making on the part of the individual investor may result in irrational market prices in some, but not all, circumstances.

Shefrin and Statman (2000) note that behavioural finance rests on two pillars: psychology and the limits of arbitrage. Markets may be irrational if four key points hold:

- Investors are irrational
- Biases in investor decision-making are systematic, that is to say they do not cancel out
- Irrational investors survive
- Biases are not arbitraged away. The actions of irrational investors can therefore cause mispricing without rational investors trading to exploit, and therefore eradicate, this mispricing

This section reviews these issues in detail. Section 2.6.1 considers the issues of investor irrationality and systematic bias. Section 2.6.2 addresses the question of whether irrational investors can be expected to survive in the marketplace. Finally, Section 2.6.3 examines whether arbitrage can be expected to cancel out the potential impact of such biases on market prices.

2.6.1 Investor Irrationality

Barberis and Thaler (2002) define rational investors as those who:

- Update beliefs in accordance with Bayes' Theorem[17] when new information is received
- Make choices consistent with Subjective Expected Utility[18] (Savage, 1954)
- Make forecasts using the correct probability distribution of returns

For investors to be strictly rational, all three criteria must be met. Bounded rationality, on the other hand, assumes only that the first two criteria are met.

The empirical evidence presented in Sections 2.4 and 2.5 makes a compelling case for investor irrationality among some if not all investors. Investors who are subject to conservatism may not update beliefs quickly on receipt of new information, for example, whilst the availability heuristic may lead investors to make decisions based on an incorrect probability distribution of returns. Whilst it is reasonable to assume a continuum of rationality, with some investors acting more rationally than others, research suggests that there are a number of biases which are common to all investors to some extent, such as the use of decision-making heuristics.

Clearly, the rationality of investors has implications for the rationality of the market as a whole. Rubinstein (2000) defines three levels of rational market. A maximally rational market is defined as one in which all investors are rational. A rational market is one in which prices are set as though all investors were rational. Finally, a minimally rational market is one in which prices are not set as though all investors were rational, but there are no abnormal profits available to those who are. Any evidence to support the existence of excess

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[17] Bayes' theorem relates prior, conditional, and posterior probabilities of outcomes. The updating of beliefs in accordance with Bayes' theorem ensures that subjective probabilities are mathematically consistent.

[18] Under Subjective Expected Utility (SEU), subjective probabilities are multiplied by outcomes in terms of utility to calculate the subjective expected utility for a given decision scenario.

profits to momentum and contrarian trading strategies would therefore be sufficient to imply market irrationality within Rubinstein's framework.

In summary, irrational investors clearly do exist, and some investors are more irrational than others. Section 2.6.2 goes on to consider whether irrational investors are able to survive within a financial market over prolonged periods of time.

2.6.2 Survival of Irrational Investors

Critics of behavioural finance cite two main reasons why irrational investors may not survive in financial markets over long periods of time, and will not therefore have any prolonged impact on market pricing. Firstly, irrational investors will become bankrupt very quickly when transacting in a rational market, and secondly, any irrational investors who are not bankrupted will learn from their mistakes and become more rational.

Friedman (1953) argues that irrational investors will consistently lose money, and will not therefore survive. As a result, irrational investors will not influence long-term asset prices. If rational traders control most of the wealth they will control prices. Fama (1965) argues that rational investors will trade against irrational investors and force prices to levels that reflect fundamental values.

The arguments of both Friedman and Fama can, in a certain sense, be regarded as circular. If markets are rational, that is to say market prices are rational, then irrational traders will lose money and prices will remain rational. If, on the other hand, markets are irrational, then there is no reason to expect that irrational investors will necessary lose money or that prices will be forced towards rational values. On the contrary, rational investors may consistently lose money and be forced out of the market and prices forced to irrational levels[19].

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[19] In such circumstances, the concept of rationality becomes somewhat muddled. In an irrational market, it might be considered rational for an investor to trade irrationally.

De Long et al (1990) argue that irrational traders may choose investments with higher expected returns and hence higher risk as a result of overconfidence, and may therefore even displace rational traders.

Kogan et al (2003) point out that survival and influence on prices are two separate issues. Irrational traders can have an impact on prices even with very low wealth.

There is no clear evidence, therefore, to suggest that irrational investors will in fact be wiped out by the actions of rational investors. The impact of irrational traders on financial market prices is driven by the extent to which the marginal investor is irrational rather than simply by the presence of irrational investors in the marketplace.

Critics of behavioural finance have argued that since irrationality does not necessarily imply a lack of basic intelligence, it would be reasonable to expect that irrational investors will learn over time and therefore become more rational[20]. Brailsford (1992, p226) says

> "It is difficult to understand how this type of myopic investor behaviour, formalised in the overreaction hypothesis, can persist over time. It implies continued irrational behaviour of share market participants".

Three key arguments emerge in the literature and are addressed in turn below:

- Individuals learn through repetition
- Experts can be expected to make fewer errors than the average investor, and it is reasonable to expect the marginal trader in financial markets to be a professional investor
- With incentives, learning is accelerated, and biases will disappear

Empirical evidence suggests that in reality, people learn much more slowly than economic models predict. Thaler (2000, p135) notes that "The problem with many economic models of learning is that they seem to apply to a very static environment". In reality, the same situation rarely occurs twice in exactly the same way, making learning more difficult.

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[20] Camerer and Hogarth (1999) provide a comprehensive review.

Thaler goes on to give an example (p136):

> "This means that models of saving for retirement (a hard problem with few opportunities for learning) should be very different from models of frequency of milk purchases (easier, with many learning chances)".

Learning in a financial environment may therefore be made difficult by the fact that situations do not reoccur in exactly the same way, and that some decisions do not offer the opportunity for repetition.

Whilst experts, who have much greater opportunity to make repeated financial decisions, might reasonably be expected to learn more quickly than amateur investors, empirical evidence suggests that this is not necessarily the case. Heisler (1994), for example, studies the disposition effect among treasury bond off-floor traders on the Chicago Board of Trade (CBOT), finding that traders do in fact hold initial losses longer than initial gains regardless of the fact that they are supposed experts. Similarly, group decision-making might be expected to display the benefits of learning to a greater extent than individual decision-making, whereas in fact, group decision-making has been shown empirically to be no more rational than individual decision-making (Carroll & Johnson, 1990, p 28).

Critics of the empirical evidence on learning argue that the experimental scenarios used in many studies do not offer incentives for subjects to learn. In real-life financial decision-making scenarios, investors do have incentives and therefore will learn more quickly. Kachelmeier and Shehata (1992) find evidence to counter this argument. Recognising that the incentives offered to students to participate in experiments are generally low, Kachelmeier and Shehata recruited a group of Masters students at Beijing University in addition to a group at a Canadian university. The incentives offered were large from the point of view of the Chinese students, reflecting three times average monthly income in one experiment.

The experiment involved a simple bet scenario, where students were told the payoff of the bet and the associated probabilities and were asked to give a value for the bet. The main finding of the research is a tendency towards massive risk seeking for low probability bets (around 3 times the expected value of the bet in some cases). There was no evidence to suggest that incentives improved performance. These results hold for Chinese students both with high and low incentives and for Canadian students with low incentives (high incentives were not available to the Canadian students). Kachelmeier and Shehata conclude that whilst incentives may improve attention and reduce carelessness, they do not remove irrational behavioural traits.

To summarise, there is no clear evidence to suggest that irrational investors will necessarily be bankrupted by the actions of rational investors. Similarly, irrational investors need not learn the be more rational over time. The impact of irrational investors on market prices is not strictly dependent on the level of wealth controlled by irrational investors, and irrational investors can influence prices even at very low levels of wealth. Without an effective arbitrage mechanism, therefore, the actions of irrational investors may have a significant impact on market prices.

2.6.3 Arbitrage

Mispricing in financial markets may result in an asset being wrongly priced relative to its fundamental value or relative to the prices of other assets. Whilst testing for mispricing relative to fundamentals is difficult[21], investors are in a position to identify mispricing between different assets (or indeed between the same asset in different markets). Arbitrage is the simultaneous purchase and sale of two assets which are mispriced relative to one another in order to profit from the price discrepancy. The act of buying the underpriced asset and selling the overpriced asset will tend to eradicate the initial mispricing. Even where behavioural factors are systematic, therefore, arbitrage may prevent such factors from influencing market prices.

Arguments that arbitrage does not eradicate market mispricing are commonly made by counterexample. Shiller (2000, p176), for example, discusses the example of eToys, and points out that the market valuation following its IPO in

[21] A dual hypothesis problem arises for most assets where the model of fundamental value to be used is tested in conjunction with the relevant research hypothesis.

1999 was clearly absurd relative to the valuations of other toy retailers such as Toys"R"Us[22].

Lamont and Thaler (2001) describe the clear mispricing of Palm stock compared to that of its parent company 3Com following the spin-off of Palm in 2000. At the time of the spin-off, 3Com retained 95 percent of the shares in Palm but expressed their intention to spin off the remainder later that year following regulatory approval. Shareholders in 3Com would receive 1.5 Palm shares for each 3Com share held. Since each 3Com share offered a claim on 1.5 Palm shares, the share price of 3Com should have been at least 1.5 times the share price of Palm, even if the other holdings of 3Com were assigned zero value. At the end of the first day's trading, March 2nd 2000, Palm shares closed at $95.06 whilst 3Com shares closed at $81.81, reflecting a valuation of 3Com's remaining assets of minus 22 billion dollars. As Lamont and Thaler point out, this was not a simple case of enthusiasm on the first day of trading; rather, the mispricing took months to be eradicated despite receiving significant press attention.

Shefrin (2002) provides the similar example of Royal Dutch and Shell, whose cash flows are split by charter such that Royal Dutch receives 1.5 times the cash flow received by Shell. Neverthless, the share prices of the two companies frequently diverge from this 1.5 times ratio.

Lamont and Thaler (2001) point out that one reason why arbitrage may not occur is that the cost of shorting stocks can be excessive. Whilst this explains why arbitrage may not quickly eradicate mispricing betwen undervalued and overvalued stocks, it does not explain why investors would buy the overpriced security. In the case of Palm and 3Com, Lamont and Thaler say (p8-9),

> *"the demand for certain shares by irrational investors was too large relative to the ability of the market to supply these shares via short sales, creating a price that was too high"*

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[22] At the time, Toys"R"Us had sales of $11.2 billion and profits of $376 million (together with an ideal starting position for entry into the internet retailing sector), whilst eToys had much smaller sales of $30 million and losses of $28.6 million. Remarkably, eToys had a market value of $8 billion compared to that of Toys"R"Us at $6 billion.

Barberis & Thaler (2002) discuss a number of reasons why arbitrage may not prove effective in eradicating market mispricing. As stated above, arbitrage involves the purchase and sale of correlated assets in order to take advantage of mispricing. Such a strategy is not, however, without risk. Arbitrage strategies are subject to fundamental risk, such as new information entering the market relating to only one of the supposedly correlated assets. In addition, noise trader risk may mean that the mispricing between assets actually increases in the short-term in which case an arbitrage strategy may have to be cut out at a loss before the mispricing is eradicated. In general, this type of arbitrage can be extremely risky. Shefrin (2002, p42) says

> "The departure of price from fundamental value does not automatically lead to risk-free profit opportunities. In fact, the 'smart money' may avoid some trades, even though they have identified mispricing. Why? Because of nonfundamental risk, meaning risk associated with unpredictable sentiment".

Shleifer and Vishny (1997) note that arbitrage requires the use of capital and also involves risk. These two factors are likely to constrain arbitrage activity. In addition, most arbitrageurs are professionals who manage the funds of other investors. Given the documented tendency for investors to follow past performance when selecting funds, fund managers are likely to be hesitant to take on high risk arbitrage strategies, particularly in markets where fundamental values are opaque such as stock markets, or where the manager's track record is short. There may also be a tendency, given the need to be able to "explain" performance to investors, to wait until a pricing anomaly is well known before seeking to exploit it. This in itself may explain why some of the anomalies identified in the empirical literature have appeared to be remarkably persistent over time.

Of course, the identification of profitable investment strategies in past data does not necessarily mean that financial markets do not function effectively in eventually arbitraging away anomalies. Lo and MacKinlay (2001, p16) note that their variance ratio results from the 1980s were exploited by investors to make profits, and these profits are now disappearing. Similar effects have been noted with some day-of-the-week anomalies, where investor attention subsequent to their identification has caused them to be all but removed.

Fama (1970) notes that the Efficient Markets Hypothesis is consistent with abnormal profits as long as such profits are not available over long periods of time. In financial markets, mispricing may occur from time to time and it may take some time before opportunities are spotted by market participants. Even at this stage, considerations of risk may not make it rational to arbitrage them away.

Daniel et al (2002, p150) consider the changing nature of stock market anomalies over time:

> "Existing models of psychology and the stock market would have permanent descriptive power if, in the long run, patterns of stock return predictability were to stabilize permanently. However, we suspect this is unlikely to occur. Individual learning about profitable trading strategies, and arbitrage activity can over time attenuate or reverse a given mispricing effect, or even... strengthen it. We therefore suggest that a key challenge for future asset pricing models is to capture the process by which investors adopt new theories about market pricing".

Arbitrage may therefore act to cancel out the effects of behavioural biases on market prices given certain conditions. Although clear examples of extreme market mispricing are commonly cited in the literature, there is some evidence to suggest that anomalies do tend to disappear once they have been identified and widely publicised.

2.7 Summary

This chapter considers the behavioural explanations proposed in the literature for continuation and reversal effects in financial market returns. These are considered within two broad categories; decision-making heuristics, and emotional factors affecting decision-making. The possible impact of these biases on market prices is considered, as are the conditions required for behavioural factors to exert the predicted influence on prices. Chapter 3 goes on to discuss the non-behavioural alternative explanations proposed in the literature for continuation and reversal effects in financial market returns.

Chapter 3

Alternative Theories of Stock Market Continuation and Reversal Effects

3.1 Introduction

A broad range of explanations has been proposed to explain empirical findings of continuation and reversal effects in financial market returns[23]. Whilst Chapter 2 discussed behavioural theories of financial market continuation and reversal effects, this chapter goes on to consider the non-behavioural alternative arguments put forward in the literature.

Criticisms of the empirical research conducted in this field typically argue that the momentum and contrarian profits identified by many studies are not achievable by investors under real-world conditions and/or merely reflect compensation to investors for increased levels of risk[24]. The principal arguments fall into three main categories. Firstly, profits may be driven by errors in the measurement of the prices used in empirical work due to market microstructure issues such as bid-ask bounce and nonsynchronous trading. Secondly, even if the underlying price data used in studies is correctly specified, methodological issues such as the choice of model of expected returns and the methodology used to cumulate returns may lead to spurious results. Finally, notwithstanding market microstructure and methodological issues which may be responsible for the results of previous empirical work in this field, the excess profits identified by previous research may simply reflect cross-sectional dispersion in the risk and expected returns of individual stocks and/or time-varying risk properties of financial market returns.

These alternative theories are discussed in this chapter. Section 3.2 explores market microstructure issues which may influence the recorded prices on which

[23] These empirical findings were briefly introduced in Chapter 1 and are considered in detail in Chapter 4.

[24] Momentum trading strategies seek to exploit continuation effects in financial market returns, whilst contrarian trading strategies exploit reversals in returns. Momentum and contrarian trading strategies are discussed in more detail in Chapter 6.

empirical work is based. Section 3.3 goes on to consider methodological issues which may bias the results of cross-sectional studies of stock market continuation and reversal effects. Section 3.4 discusses ways in which the cross-sectional and time-varying properties of the risk and expected returns of individual stocks may be responsible for the findings of prior research in this field. Section 3.5 concludes.

3.2 Market Microstructure Issues

Market microstructure issues such as bid-ask bounce and nonsynchronous trading may have an impact on the recorded daily closing prices which form the source data for the majority of studies in this field of finance. Bid-ask bounce can be expected to result in negative short term autocorrelation in returns, with nonsynchronous trading generating spurious negative short-term autocorrelation in returns for single stocks and positive short-term autocorrelation in returns for stock market indices. Section 3.2.1 discusses bid-ask bounce, whilst Section 3.2.2 considers the issue of nonsynchronous trading.

3.2.1 Bid-Ask Bounce

The impact of bid-ask spread on the short-term serial correlation of stock market returns is introduced to the literature by Roll (1984), who develops a model of bid-ask spread which predicts negative serial correlation in returns measured over adjacent intervals.

This effect is easily explained in the context of daily closing stock prices. The closing price recorded for any given day will be on either the bid side or the offer side of the market[25]. Following a sharp market fall, it is likely that the last recorded price will be a bid price (the lower of the two prices). Conversely, following a market rise, the recorded price is likely to be an offer price (the higher of the two prices). This has the effect of introducing an upward bias to

[25] A bid price is the price at which a market maker buys, whilst the offer price is the price at which the market maker is prepared to sell the same asset. The ask price is by definition higher than the bid price, with the difference between the two prices (the bid-ask spread) reflecting the spread earned by the market maker.

the recorded size of market movements. On the following business day, in the absence of further movement in prices, this bias will be, on average, corrected. Bid-ask bounce can therefore be expected to induce negative serial correlation in returns over very short horizons.

Although negative serial correlation over short horizons has been identified by a number of studies[26], many researchers find that controlling for bid-ask bounce using skip-day returns (that is, missing a day between formation and test periods in order to remove the effect of the 'bounce') does not reduce the profits available to contrarian strategies. Jegadeesh (1990), for example, finds positive profits from a strategy set up to exploit negative serial correlation in monthly stock returns, whilst Lehmann (1990) obtains similar results for weekly returns.

Although the impact of bid-ask bounce may continue beyond one trading day, it can reasonably be expected to remain limited to the very short term. Evidence to suggest the presence of bid-ask bounce is likely to be negative serial correlation in short-term returns which largely dissipates over a further period of one or two trading days. The data used in this study is taken from broad stock market indices covering approximately 90 per cent of the total market capitalisation in each of the countries considered. As a result, the impact of bid-ask bounce is likely to be reduced by diversification although bid-ask bounce may still have an impact on index values following large price changes affecting a high proportion of the largest stocks (general economic or political news items, for example).

3.2.2 Nonsynchronous Trading

Nonsynchronous trading may introduce spurious short-term serial correlation effects into the closing stock prices used in empirical studies of stock market continuation and reversal effects.

The reported closing price for a stock is typically based on the last trade price which, for some less liquid stocks, may have occurred several hours prior to the close. Alternatively, some exchanges may report the average of the quoted

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[26] see, for example, Gaunt and Gray (2003)

indicative bid and ask prices at the close. For some stocks, these prices may not have been updated for several hours, or even for a number of days.
Stock prices typically respond in the same direction to new information affecting the market as a whole (macroeconomic data releases, for example). Stocks whose closing prices are not up-to-date will see their prices "catch up" when they are next traded or market quotations are updated. This effect may cause the short-term positive serial correlation in index returns observed empirically by some studies[27].

Cohen et al (1986) consider how nonsynchronous trading can produce spurious autocorrelations and cross correlations in the empirically observed return structures of individual stocks and stock market indices. Their models suggest that the first-order autocorrelations for single stocks will be slightly negative with cross-correlations between stocks generally positive[28]. Stock index returns will have positive first-order autocorrelation with the degree of autocorrelation positively related to the influence of thinly traded stocks in the index.

Atchison et al (1987) compare the theoretical size of stock index total return autocorrelations due to nonsynchronous trading with that observed empirically. For a sample of 280 randomly selected NYSE firms over the period January 1978 through December 1981, data on the distribution of total returns and the frequency of transactions for each stock are used to model the theoretical autocorrelation of returns due to nonsynchronous trading. The theoretical levels of autocorrelation estimated from the model are significantly lower than those observed empirically. For a value-weighted portfolio, for example, the theoretical autocorrelation of 0.0172 is much smaller than the empirical autocorrelation of 0.1286. The equally-weighted autocorrelations are higher than the value-weighted autocorrelations, consistent with the predictions of the Cohen et al model, but the theoretical value of 0.0408 remains small compared to the empirical autocorrelation of 0.2586. These findings imply that only a

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[27] see, for example, Säfvenblad (1997)

[28] Lo and MacKinlay (1990a) similarly model stock returns under nonsynchronous trading and demonstrate negative one-lag serial correlation for single stocks, positive one-lag cross-correlation between stocks, and positive one-lag serial correlation for portfolios of stocks.

small portion of the empirically-observed autocorrelation in stock returns can be explained by nonsynchronous trading.

Boudoukh et al (1994), on the other hand, show that the impact of nonsynchronous trading on autocorrelation in stock index returns may have been understated. Using the patterns of nontrading over different days of the week estimated empirically by Keim (1989), Boudoukh et al show that the theoretical impact of nontrading on autocorrelation can be 2 to 3 times higher than that estimated by prior research on the basis of a uniform distribution of nontrading. Spurious autocorrelation is driven principally by the degree of mismatch between severe nontrading in some stocks and frequent trading in others. Where high-beta stocks are those which are subject to nontrading, the effect on autocorrelation is magnified further. Nevertheless, the theoretical autocorrelations obtained by Boudoukh et al are still not high enough to explain all of the autocorrelation observed empirically.

Ahn et al (2002) consider the short-term autocorrelation structures of 24 major stock market indices and their associated futures contracts. Since the price of a stock index and its futures contract are linked by no-arbitrage assumptions, the autocorrelation structures of the two should be very similar. Any major differences between the two would imply some kind of market microstructure bias affecting the price series. Positive one-day autocorrelations are found for 23 of the 24 stock market indices considered. Autocorrelations are generally greater for indices with less liquid stocks (such as the Russell 2000 in the USA and the FTSE 250 in the UK) than for indices of the most liquid stocks (such as the S&P 500 index in the USA). In addition, the autocorrelations of the stock market indices are in all cases greater than the autocorrelations of the corresponding futures market prices. The difference between the spot and futures market autocorrelations are both economically and statistically significant, pointing to market microstructure biases such as nonsynchronous trading as the most likely drivers of positive short-term autocorrelations in empirical studies of stock market returns.

The impact of nonsynchronous trading on historical stock price data is again likely to remain limited to the very short term. Evidence to suggest that nonsynchronous trading may have an impact on results would include negative serial correlation in short-term stock returns combined with positive serial correlation in short-term index returns, in each case largely dissipating over a period of one or two trading days. The results of Ahn et al (2002) in particular suggest that nonsynchronous trading may prove a more serious issue for the broad stock market index data used in the current study than for more well-known stock market indices comprising exclusively liquid stocks (such as the FTSE 100 index in the UK or the CAC 40 index in France).

3.3 Methodological Issues

Problems inherent to the methodologies used by previous cross-sectional studies of continuation and reversal effects in financial market returns may be at least partly responsible for the results of these studies. Fama (1998) argues that the lack of consistency in the results of previous empirical studies indicates that the anomalies found may simply be chance results. Importantly, Fama adds that most such anomalies "tend to disappear with reasonable changes in technique" (p283). Section 3.3.1 reviews the basic methodologies used by studies of continuation and reversal effects in stock market returns.

The majority of cross-sectional studies of stock market continuation and reversal effects have used the market-adjusted model of expected returns to calculate abnormal returns to individual stocks within the data samples[29]. Section 3.3.2 discusses the market-adjusted model together with the alternative models of expected returns used by some studies, and discusses how the use of such models may be responsible for seemingly anomalous results which nevertheless may not be replicable under real-world conditions.

Section 3.3.3 goes on to consider how the methods commonly used to cumulate single-period returns may produce spurious results. Finally, Section 3.3.4 describes how direct comparisons between formation and test period returns can in themselves prove misleading.

3.3.1 Research Methodologies

Much of the empirical literature on continuation and reversal effects in financial market returns follows the methodology used in De Bondt and Thaler (1985).

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[29] The specific methodologies used by each study are discussed in Chapter 4.

De Bondt and Thaler study the returns of New York Stock Exchange (NYSE) stocks between January 1926 and December 1982 and conclude that extreme "winners" over a three/five year period show a consistent tendency to become "losers" over the following three/five year period and vice versa. That is to say, extremely high and low return stocks tend to experience a "reversal of fortunes" over the long term.

Figure 3.1 shows the standard cross-sectional approach introduced by De Bondt and Thaler in the form of a time line.

The first step in this methodology is to calculate the abnormal return of each stock in the data sample relative to a benchmark (the "expected return") over an initial period (the "formation period"). In De Bondt and Thaler's study, non-overlapping formation periods of three and five years are considered, and the expected return is the market return (with the unweighted average return on the stocks included in the study taken as a proxy for the market). The abnormal return for each stock is then simply the excess of the actual (realised) return over the expected return, which has already been calculated. An estimation period may be required prior to the formation period where the model of expected returns chosen has parameters which must be estimated in advance[30].

Individual stocks are then ranked according to their abnormal return over the formation period. "Winner" and "loser" portfolios are formed, in De Bondt and Thaler's case from the top- and bottom-performing decile of stocks respectively. The abnormal return of each portfolio over the formation period can then be calculated and is simply the mean abnormal return of the stocks in that portfolio.

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[30] For example, if expected returns are to be calculated using the Capital Asset Pricing Model (CAPM), then the β coefficient for each stock would be calculated over a prior estimation period, with this parameter then be used to calculate expected returns over the required formation period.

Figure 3.1 Standard Cross-Sectional Methodology

Estimation Period

- estimation of parameters of model of expected returns
- length of estimation period generally independent of the length of formation and test periods

Formation Period

- calculation of formation period abnormal returns for all stocks
- formation of winner and loser portfolios
- calculation of formation period abnormal returns of winner and loser portfolios

Test Period

- calculation of test period abnormal returns of winner and loser portfolios

The abnormal return of each portfolio is then calculated over a subsequent period (the "test period") in the same way. In De Bondt and Thaler's study, the test period has the same length as the formation period (i.e. a three year test period is used in conjunction with a three year formation period, and a five year test period with a five year formation period).

The abnormal returns of the winner and loser portfolios across the formation and test periods are then compared. If winners continue to perform well over the test period and losers perform badly, then this is taken as evidence of continuation in returns. Conversely, if winners perform poorly over the test period and losers perform well, this provides evidence of reversal. In determining "good" and "bad" performance for the purposes of this analysis, studies may consider whether test period performance is positive or negative, or may consider whether test period performance is better than or worse than formation period performance. The performance of the winner portfolio minus that of the loser portfolio over the test period is also reported in many studies. This represents the return to a strategy of buying past winners and selling past losers.

A small number of studies (see, for example, Cox and Peterson, 1994) have used regression analysis to examine short-term continuation and reversal effects. In this approach, abnormal test period returns for individual stocks are regressed on formation period returns to estimate the relationship between formation and test period returns for a given subsection of stocks (in Cox and Peterson's case, those which had experienced one-day formation period declines in price of 10 percent or more).

In addition, some studies have estimated directly the serial correlation properties (Poterba and Summers, 1998, for example) or variance ratios (Jegadeesh, 1990, for example) of stock returns and used their results to infer continuation and/or reversal effects in returns.

The following sections discuss ways in which the standard cross-sectional methodology described in this section may in itself be responsible for many of the empirical results reported in the research literature.

3.3.2 Models of Expected Returns

Previous research has tended to use an event study approach, comparing the abnormal returns to a portfolio of stocks (winner and/or loser) during an initial event window (the formation period) to the abnormal performance of the same portfolio during a subsequent post-event window (the test period). In this context, the abnormal performance of a stock is simply the realised return minus the expected return, where the expected return is typically calculated using one or more of the mean-adjusted model, market model, market-adjusted model, capital asset pricing model (CAPM), or Fama-French three-factor model.

The choice of model of expected returns will have an impact on the abnormal returns obtained and may therefore bias the results of empirical studies of this type. Authors such as Fama (1998) have noted that this issue is most serious for studies of long-term market continuation and reversal effects. Over very short time horizons, expected returns will be small and the difference between the expected returns obtained using different models is likely to be insignificant. Over long time periods, on the other hand, where expected returns may be large, the choice of model of expected returns may have a significant impact on the results of empirical studies.

This section provides a brief review of the models of expected returns commonly used in the empirical literature; these models are referred to in Chapter 4 where the methodologies and results of previous studies are discussed in detail.

In the Mean-Adjusted Model, the expected daily return is a constant calculated by averaging the actual daily returns on the stock over a specified estimation period prior to the formation period. Using an estimation period of k days, for example,

$$ER_{it} = \frac{1}{k} \times \sum_{n=t-k}^{n=t-1} R_{it} + \varepsilon_{it}$$

where

ER_{it} is the expected return for security i on day t

R_{it} is the observed return for security i on day t

ε_{it} is an error term with expected value zero (i.e. white noise)

Brown and Warner (1985) find that, although simple, the mean-adjusted method produces results that are very similar to those obtained using more complex models.

The Market Model[31] specifies a linear relationship between the performance of a given stock and the performance of the market over the same period.

$$ER_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where

R_{mt} is the observed market return on day t

Regression analysis is used over an estimation period calculate the intercept and slope coefficients of this relationship (α_i and β_i). The expected return of the

[31] also known as Sharpe's Single Index Market Model (Sharpe, 1963)

stock over the formation period can then be calculated as a function of the actual market performance over the same period. A broad market index is commonly used as a proxy for the market when implementing the Market Model.

The Market-Adjusted Model is the model of expected returns most commonly employed in studies of stock market continuation and reversal effects. In the market-adjusted model, the expected return for all stocks is simply the market return over the same period.

$$ER_{it} = R_{mt} + \varepsilon_{it}$$

The main advantage of the market-adjusted model is that no parameters need to be estimated in order to implement it. A major drawback of the model, however, is that no allowance is made for differential risk, and hence differential expected returns, across stocks.

The market-adjusted model is clearly equivalent to the market model with $\alpha_i = 0$ and $\beta_i = 1$, whilst the mean-adjusted model can be seen to be equivalent to the market model with $\beta_i = 0$.

In the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), the expected daily return is calculated as the risk-free return plus a proportion of the excess market return over this risk-free return.

$$ER_{it} = r_{ft} + \beta_i(R_{mt} - r_{ft}) + \varepsilon_{it}$$

where

r_{ft} is the risk-free return on day t

The beta of the stock (the proportion of excess market returns which the stock returns) is generally estimated using regression analysis over an estimation period prior to the formation period.

The Fama-French Three Factor Model (Fama and French, 1992) has also been used in the empirical literature on continuation and reversal effects in financial market returns. This model aims to take into account the empirical observation that small stocks and stocks with high book to market ratios typically enjoy higher returns than larger stocks or stocks with lower book to market ratios.

$$ER_{it} = r_{ft} + \beta_{1i}(R_{mt} - r_{ft}) + \beta_{2i}SB_t + \beta_{3i}HL_t + \varepsilon_{it}$$

where

SB_t is the difference in returns between the smallest and biggest stocks at time t (the size premium)

HL_t is the difference in returns between the highest book to value and lowest book to value stocks at time t (the value premium)

Again, the parameters of the return model are typically calculated over an estimation period prior to the formation period.

One of the main issues surrounding the choice of model of expected returns in the empirical literature is the presence of a dual hypothesis issue. When testing for continuation effects using abnormal returns calculated using the market-adjusted model, for example, the results are subject to two distinct hypotheses. The first is the hypothesis that the market-adjusted model correctly specifies the returns generating process, and the second is that the hypothesised continuation and reversal effects are present in the data.

A second issue relates to the implications of empirical findings of continuation and reversal effects based on measures of abnormal returns which may not be easily replicable by investors. If strong evidence of continuation and/or reversal effects is found using abnormal returns calculated using the market-adjusted model, then this has clear implications for market efficiency. The abnormal returns to a stock calculated using the market-adjusted model are easily replicated by investors (by buying the relevant stock and short-selling the market), hence investors could easily devise strategies to profit from continuation and reversal effects in stock returns measured using the market-adjusted model. If these effects persist, this therefore implies that investors are "leaving money on the table", and the market's failure to arbitrage away such opportunities provides a clear argument against market efficiency.

If evidence of continuation and/or reversal effects is found using abnormal returns calculated using more complex models such as the Fama-French Three Factor model, on the other hand, then this must be weighed against the difficulty facing investors in exploiting such effects (this would require a much more complex strategy transacting not only in the stock in question and the market but also in portfolios of large-sized, small-sized, high book-to-value and low book-to value stocks). The complexity of such a strategy, the additional risks it may entail, potential liquidity issues, as well as high transactions costs may explain any apparent failure on the part of the market to arbitrage away the apparent excess returns available from such strategies.

3.3.3 Calculation of Cumulative Returns

Cumulative return calculations involve the calculation of multi-period returns using the returns already available for shorter time periods, for example the calculation of a twelve month return using monthly returns data.

A number of different specifications of cumulative returns have been used in the literature. Within these, some studies use discrete returns whilst others use logarithmic returns. Gray and McAllister (2001) show that the choice of discrete or logarithmic (continuously compounded) returns can have a significant impact on the findings of empirical studies in this field. As some studies, such as De Bondt and Thaler (1985) use discrete returns and others, such as Brailsford (1992) use logarithmic returns, the results of these studies can prove difficult to compare[32].

3.3.3.1 Cumulative Average Returns (CARs)

The Cumulative Average Return (CAR) approach sums separately the realised return and the expected return to the relevant portfolio of stocks for each sub-period. The total expected return is then subtracted from the total actual return to give the portfolio abnormal return.

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[32] As discussed in Chapter 5, the current study uses discrete returns throughout since these correspond to the returns which would be achieved by a real-world investor.

The CAR method is given by

$$\overline{R}_{CAR} = \sum_{t=0}^{T}\left(\sum_{1}^{N}\frac{R_{it}}{N}\right) - \sum_{t=0}^{T}\left(\sum_{1}^{N}\frac{ER_{it}}{N}\right)$$

where

N	is the total number of stocks in the portfolio
T	is the total number of time periods (e.g. months)
R_{it}	is the return on security i in time period t
ER_{it}	is the expected return on security i in time period t

The CAR method has the advantage of computational speed, although Dissanaike (1994) notes that the returns obtained bear little relation to those actually available to investors. One implication of the CAR method is that portfolios are rebalanced each time period. A 12 month return cumulated from daily returns would, for example, imply daily portfolio rebalancing. Although a CAR return could theoretically be replicated by investors, the costs of doing so may be prohibitively high. Dissanaike also shows that the differences between returns calculated using the CAR approach and those actually achieved by investors will be exacerbated in the case of high price-volatility markets.

Nevertheless, the CAR approach is used in a wide range of studies of stock market continuation and reversal effects, including De Bondt and Thaler (1985) and Alonso and Rubio (1990).

3.3.3.2 Periodically Rebalanced Returns (PRRs)

The Periodically Rebalanced Returns (PRR) approach cumulates the actual return and the expected return to the relevant portfolio of stocks before subtracting one from the other in the same way as the CAR approach. Rather than adding the sub-period returns, however, the PRR approach takes the product of sub-period returns. This again assumes that the portfolio is rebalanced to equal weights at the beginning of each time period, but the use of a product rather than a summation more closely reflects the returns available to investors[33].

The PRR method is given by

$$\overline{R}_{PRR} = \prod_{t=0}^{T} \left(\sum_{i}^{N} \frac{R_{it}}{N} + 1 \right) - \prod_{t=0}^{T} \left(\sum_{i}^{N} \frac{ER_{it}}{N} + 1 \right)$$

where

N	is the total number of stocks in the portfolio
T	is the total number of time periods (e.g. months)
R_{it}	is the return on security i in time period t
ER_{it}	is the expected return on security i in time period t

Whilst the PRR method has the advantage of being more closely related than the CAR approach to the real-world returns available to investors, rebalancing does in itself imply transactions costs. These costs may outweigh any evidence of significant profits arising from continuation and reversal effects in financial market returns from studies based on Cumulative Average Returns (CARs) or Periodically Rebalanced Returns (PRRs).

3.3.3.3 Holding Period Returns (HPRs)

The use of Holding Period Returns (HPRs), commonly referred to in the literature as buy-and-hold returns, assumes equal initial investment in each stock with no subsequent rebalancing.

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[33] The PRR approach takes a product of single-period returns, implying that profits (or losses) are reinvested each time the portfolio is rebalanced. The CAR approach, in contrast, takes the arithmetic mean of single-period returns. This not only assumes that the portfolio is rebalanced each period, but also that the portfolio value is reinstated to its original level each time. The CAR approach therefore does not reflect the experience of most investors, who do not extract profits and make good losses on a regular basis.

The HPR method is given by:

$$\overline{R}_{HPR} = \frac{1}{N}\sum_{i}^{N}\left(\prod_{t=0}^{T}(R_{it}+1)-\prod_{t=0}^{T}(ER_{it}+1)\right)$$

Whilst the holding period return approach provides a measure of returns which reflects the experience of investors without incurring excessive transactions costs, one argument against the use of holding period returns in cross-sectional studies of stock market continuation and reversal effects is that portfolios can become very unbalanced in the event that there is a large variation in performance between stocks (Dissanaike, 1994).

It should be noted that the HPR method described above produces returns which are equivalent to calculating returns over a single (longer) period as advocated by some researchers (see, for example, Conrad and Kaul, 1993).

In order to illustrate the implications of the three different methods of calculating multi-period returns, an example is considered below. Table 3.1 shows prices taken at monthly intervals for three different stocks together with the return to each stock over the 2 monthly periods. For example, the return shown for stock A in the first month is calculated using the prices shown at t=0 and t=1 as (55/50 – 1)%, or 10.0%. For simplicity, it is assumed that the expected return on each stock is zero and that there are no dividends reinvested.

Table 3.1 Impact of Cumulation Method on Measured Returns

	Stock		
Price	A	B	C
t=0	50.0	20.0	30.0
t=1	55.0	60.0	27.0
t=2	60.5	15.0	35.1

	Stock		
% Return	A	B	C
1	10.0%	200.0%	-10.0%
2	10.0%	-75.0%	30.0%

The portfolio returns calculated using the three methods are:

CAR: (10%+200%-10%)/3 + (10%-75%+30%)/3 = 55.00%

PRR: [(10%+200%-10%)/3 + 1] × [(10%-75%+30%)/3 + 1] – 1 = 47.22%

HPR: [(1+10%) × (1+10%)]/3 + [(1+200%) × (1–75%)]/3 +[(1–10%) × (1+30%)]/3 = 4.33%

The three methods of calculating portfolio returns produce very different results. Both the CAR and PRR method imply rebalancing of the portfolio each period. After the first month, therefore, both methods imply a reduction in the holding of Stock B to rebalance the portfolio. This results in a substantially higher return to the CAR and PRR approaches than the HPR approach. Clearly, examples can be constructed where the CAR and PRR methods substantially underperform the HPR method. In addition, the transactions costs associated with rebalancing in the CAR and PRR methods are difficult to determine explicitly.

As the above example demonstrates, the choice of method used to cumulate returns may have a significant impact on the results of previous empirical studies. The following section discusses arguments against the use of cumulative returns in general.

3.3.3.4 Arguments against the Use of Cumulative Returns

Conrad and Kaul (1993) show that any noise in prices due to factors such as bid-ask bounce and nonsynchronous trading can be statistically shown to introduce an upward bias to single-period returns[34]. This bias is not dependent on the length of the period over which returns are calculated, and so the cumulation of many single-period returns using, for example, the CAR or PRR method, can greatly exaggerate the bias.

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[34] Jakobsen and Voetmann (2000) show how returns are upwardly biased as a result of the compounding effect. This bias is driven by the volatility of returns and occurs even where the distribution of single-period returns is normal. These results can be related back to the argument of Conrad and Kaul. Noise in short-term returns (daily or hourly, for example) introduces an upwards bias to returns over longer periods.

This upward bias in calculated returns may also be responsible for the empirical findings of anomalies between the performance of winners and losers noted in some studies using the market model. If losers have generally lower prices than the average and winners higher prices than the average, noise items such as bid-ask spread will have a proportionally greater impact on losers than the market, and a greater impact on the market than on winners. The upward bias is therefore greater for losers than for the market, exaggerating reversals for losers, and greater for the market than winners, thus reducing any reversals in the winner portfolio.

Conrad and Kaul use both CARs and holding period returns[35] to investigate the evidence of return reversals in NYSE stocks over non-overlapping three-year formation and test periods from 1929 to 1988. The CAR method is used to form the winner and loser portfolios, but then the subsequent performance of the portfolios is evaluated using both methods. The results using the CAR method are consistent with those of De Bondt and Thaler (1985). Using the buy-and-hold method reduces formation period returns in all instances, however, eliminating all non-January returns to the contrarian strategy of buying past losers and selling past winners. Conrad and Kaul conclude that the results of previous studies suggesting long-run reversal in stock market returns could therefore be due to a combination of cumulated measurement errors and the January effect, with findings of reversal consistent with those of De Bondt and Thaler (1985) absent in their data set when buy-and-hold returns are used and the January effect is controlled for.

Dissanaike (1994) considers the impact of using the CAR and PRR methods on the results of previous empirical studies using data from the London Share Price Database from January 1981 to January 1990 and a typical cross-sectional methodology based on 3 year formation and test periods. Whilst the two methods yield very different results both in terms of performance and the composition of the winner and loser portfolios, the author notes that the direction of the overall bias is difficult to specify.

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[35] Conrad and Kaul calculate their holding period returns directly over three year periods rather than cumulating from shorter-term returns. As discussed in Section 3.3.3.3, however, the same results would be obtained using the HPR method described in that section.

3.3.4 Comparison of Formation and Test Period Returns

Studies of continuation and reversal effects in stock market returns typically form winner and loser portfolios based on stock performance during a given formation period using a choice of model of expected returns and method for cumulating returns, as described above. They then use the same methodology to track the performance of the winner and loser portfolios over a subsequent test period. This methodology may result in unintended biases in the results of empirical studies.

Dissanaike (1996) notes that using test period returns to measure the strength of continuation and reversal effects is unreliable. Symmetric price reversals do not imply symmetric return reversals. Dissanaike gives the example of two stocks each with a price of 100 at the start of the formation period. The winner stock increases in value to 150 over the formation period before falling to 125 by the end of the test period. The loser stock falls to 50 by the end of the formation period before rising to 75 at the end of the test period. The formation and test period price reversals are symmetric, whilst the return reversals are not. For the winner stock, a 50% return in the formation period is followed by a 16.6% fall in the test period. For the loser stock, a 50% fall in the formation period is followed by a 50% test period gain. In typical studies of stock market continuation and reversal effects, such a pattern would be interpreted as an asymmetry between winners and losers. Dissanaike proposes a new measure, the reversal coefficient, to correct for this bias in cross-sectional stock market studies[36].

Dissanaike (1998) uses monthly returns data from the London Share Price Database from 1st January 1981 to 1st January 1988 inclusive and considers the returns to winner and loser portfolios using 48 month formation and test periods using the FTSE 500 return index as a proxy for the market in calculating expected returns using the market-adjusted model. The average test period abnormal return is 67% for the loser portfolio and -58.3% for the winner portfolio, seemingly confirming findings of winner-loser asymmetry in

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[36] The reversal coefficient, which compares the magnitude of price changes rather than returns over the formation and test periods, has not, to the author's knowledge, been used in empirical work in this field other than by Dissanaike, and it is therefore difficult to assess the impact its use would have on the results of the existing literature.

earlier studies using US data. The effect is not as strong as found in previous studies, however, and the reversal for losers exceeds that for winners in only 4 of the 8 test periods considered. Use of the reversal coefficient proposed by Dissanaike (1996), however, shows that the reversals for winners are stronger than for losers in all test periods with winners falling 33% on average and losers gaining 8.5%.

3.4 Risk and Expected Returns

Even if the price series used in previous studies of continuation and reversal effects in financial market returns are not affected by issues such as bid-ask bounce and nonsynchronous trading, and methodological issues cannot be shown to be responsible for the significant profits to momentum and contrarian trading strategies identified by previous research, these profits may simply reflect a fair reward to investors for the risks inherent to such strategies.

The existing literature suffers from an important joint hypothesis problem, in that the measure of expected returns used to calculate the abnormal returns on which the analysis is based may be invalid. The market-adjusted model in particular does not take into account differences in risk across stocks. A number of researchers have considered ways in which the risk and return characteristics of different stocks may be responsible for the findings of the empirical literature. These include differences in the risk and expected return of stocks in the cross-section, discussed in Section 3.4.1, and the time-varying properties of risk and expected returns, covered in Section 3.4.2.

3.4.1 Cross-Sectional Dispersion in Risk and Expected Returns

Cross-sectional dispersion in the risk and expected returns of individual stocks may be responsible for the medium-term momentum effects documented by studies such as that of Jegadeesh and Titman (1993). Profits to momentum strategies may therefore simply reflect the risk borne by such strategies.

Conrad and Kaul (1998) argue that momentum strategies should prove profitable where there is cross-sectional dispersion between the mean returns of stocks, even where the price formation process is a random walk. Momentum strategies involve buying past winners and selling past losers. On average, past winners are stocks with high mean returns, whereas past losers are stocks with low mean returns. Momentum profits can therefore be consistent with efficient markets where the dispersion of expected returns is large relative to the variance in unexpected returns. That is to say, if the difference between returns achieved by the highest return stocks and lowest return stocks is large and the volatility of these returns is relatively small, then our high-return stocks will remain high-return and our low-return stocks will remain low-return. Momentum strategies will generate positive profits over time, but these profits reflect cross-sectional differences in the risk and expected returns of stocks and may not necessarily be inconsistent with market efficiency[37].

In their study, Conrad and Kaul carry out a decomposition of the returns to momentum strategies in the US stock market to examine to what extent returns are driven by the time series properties of returns and to what extent by cross-sectional variations in the mean returns of individual stocks. Weights are assigned to each stock depending on its performance relative to the market performance (where the market performance is an average of all the stocks under consideration). Stocks which outperformed the market are bought, and stocks which underperformed are sold. The strategies therefore hold a position in each stock, and by construction each strategy is a zero-cost investment [38].

The momentum strategies use holding periods of 1 week, 3 months, 6 months, 9 months, 12 months, 24 months and 36 months, and consider the performance of each stock over a preceding period of the same length as the holding period to be used (so 3 month returns are used to form portfolios which are held for 3 months, 6 month returns for 6 month holding periods, and so on). The data used is the entire sample of NYSE/AMEX stocks over the period 1926-1989, with 5 subsets considered.

Of the 36 profitable strategies discovered, 18 are momentum strategies and 18 contrarian. Statistically significant returns are achieved by 21 of the 36

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[37] If the dispersion of stock returns is smaller and/or the volatility of individual stock returns higher, on the other hand, then momentum strategies may not generate significant excess profits over time.

[38] This trading strategy specification is that proposed by Lo and MacKinlay (1990b).

profitable strategies. Of these, 11 are contrarian strategies and 10 are momentum strategies. Momentum strategies with 3 to 12 month holding periods are profitable across all periods excluding 1927-1947, which is consistent with the results of Jegadeesh and Titman (1993) and similar studies. Contrarian strategies are only successful in the 1927-1947 period.

The profits to the successful momentum studies are decomposed into profits accruing from the time series predictability of returns and those accruing from cross-sectional dispersion in returns. Of the 18 profitable momentum strategies, only 2 benefit significantly from price continuation effects. In the others, the returns are almost entirely driven by cross-sectional variation in mean stock returns. Conrad and Kaul conclude that momentum profits may therefore simply be a result of holding high return, high risk stocks and selling low return, low risk stocks.

Connolly and Stivers (1998) find that the degree of autocorrelation in equity index returns in the US, UK, and Japan is related to unexpected changes in the dispersion of the previous week's firm-level returns. When the previous week's returns show abnormally high dispersion, continuation effects are observed whilst reversal follows abnormally low dispersion in firm-level returns. These results are consistent with the arguments of Conrad and Kaul.

Jegadeesh and Titman (2002), on the other hand, find that very little of the observed return to momentum strategies is explained by cross-sectional differences in expected returns, and attribute Conrad and Kaul's results to small sample biases in their empirical tests as a result of the use of non-overlapping periods. Using a momentum strategy specification identical to that of Conrad and Kaul for six month holding periods and a data sample of all NYSE and AMEX stocks over the period 1965 to 1997, Jegadeesh and Titman show that the zero-cost momentum strategy does produce significantly positive profits and that cross-sectional differences in expected returns contribute little to explaining these profits.

The effect of risk on the cross-section of stock returns may be asymmetric. Ang et al (2001) note that stocks with high downside risk, that is to say stocks which are highly correlated with the market during market downturns, generate relatively high expected returns. This is illustrated using data on all

NYSE/AMEX stocks over the period 1964 through 1999 and NASDAQ firms over the period 1972 through 1999. After controlling for market beta, size, and book-to-market effects, the portfolio of stocks with highest downside risk was found to outperform the portfolio with the lowest downside risk by 6.55 percent per annum[39]. Momentum strategies involve buying past winners and selling past losers. Past winners will tend to be stocks with high expected returns, high betas, and thus high downside risk in the event of a fall in the market. Part of the profitability of momentum strategies may therefore reflect compensation for taking on this additional risk.

3.4.2 Time-Varying Risk and Expected Returns

In addition to cross-sectional dispersion in the risk and return characteristics of individual stocks, a number of authors have noted that the risk and expected returns of individual stocks also vary over time.

Chan (1988) argues that the use of past data to calculate expected returns is inappropriate. The risks associated with winner and loser stocks are not constant over time. Other things equal, the risk of loser stocks can be expected to increase as their prices fall and hence their leverage increases. The converse is true for winner stocks, whose risk can be expected to fall following a price rise. Measures of expected returns based on past data will therefore be biased, upwards in the case of winners and downwards for losers. This will tend to exaggerate any evidence of return reversals. In order to avoid such biases, separate estimation periods should be used to generate the betas to be used in calculating formation and test period returns. Although this assumes that beta is constant over each of these periods, this is considered preferable to estimating a single beta over a long horizon such as the 60 months used in De Bondt and Thaler (1985). Chan illustrates the point by testing the returns to the contrarian strategy of selling past winners and buying past losers based on the CRSP data set used by De Bondt and Thaler (1985) and expected returns calculated using the CAPM. The returns to the contrarian strategy once market betas are allowed to vary over time are small, producing an average return of 0.133 percent per month compared to 0.586 percent per month in the De Bondt

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[39] Stocks are allocated to six portfolios based on their downside correlation. Portfolio returns are value-weighted.

and Thaler study. The excess return available from contrarian strategies may therefore simply reflect suitable compensation for the risk involved in such a strategy.

Ball and Kothari (1989) present evidence that negative long-term serial correlation in firm-level returns may be due to expected returns which vary over time as a result of changes in risk. Serial correlation in realised and expected returns is calculated using data on all stocks on the CRSP tape from 1930 through 1981. At the start of each calendar year, 20 portfolios are formed on the basis of realised returns over the previous 5 years and also on the basis of firm size. The returns realised by each portfolio over the years t-4 through t+5 are then calculated for each portfolio, with holding period returns used throughout. Regression analysis is used to estimate the parameters of the market model for each combination of event year (t-4 through t+5) and portfolio (1 through 20). These parameters are then used to calculate abnormal returns for each portfolio and year. Whilst there is evidence of negative serial correlation in realised returns, Ball and Kothari also find significant changes in risk over time, and the negative serial correlation effect is greatly reduced once these changes are accounted for by considering abnormal rather than realised returns.

Berk et al (1999) demonstrate how the expected returns to a stock and its systematic risk vary dynamically as the profile of the firm's assets and growth options changes over time. Shocks to firm value occur as a result of the adoption or abandonment of projects with, other things equal, positive shocks caused by the adoption of low risk projects or the abandonment of high-risk projects and conversely, negative shocks caused by the adoption of high risk projects or the abandonment of low risk projects. Such shocks to firm value impact on the firm's systematic risk and hence its expected future return. Berk et al find that expected future returns are positively correlated with past expected returns (since a firm's asset mix is persistent over time) but negatively correlated with past realised returns.

The evidence of short-term contrarian strategy profits and medium-term momentum profits documented by previous research may therefore be a result of ignoring the time-varying properties of expected returns. In the very short-term, for example, a large positive price change (a positive shock to firm value) will be accompanied by a reduction in systematic risk and therefore expected returns are lower since less compensation for risk is required. Berk et al note that failing to take into account this drop in expected returns will result in an understating of subsequent abnormal returns thus driving findings of reversal. Over the longer-term, a single shock to firm value becomes less important in determining returns over the period and momentum effects begin to appear.

Berk et al show by simulation that this model is capable of explaining much of the empirically-observed variation in cross-sectional stock market returns as well as stock market return anomalies documented in the literature including those of short-term return reversals and medium-term continuation. Contrarian strategies produce profits up to horizons of 9 months, after which momentum strategies are profitable out to 5 year horizons. Although these time periods are somewhat longer than those identified in the empirical literature, the magnitude of profits are broadly consistent with those of studies such as Conrad and Kaul (1998).

Chordia and Shivakumar (2002) similarly find evidence to suggest that momentum profits may reflect time-varying risk and expected returns. Chordia and Shivakumar demonstrate that momentum profits can be explained by a set of lagged macroeconomic variables: the 3 month T Bill yield as a proxy for expectations of future economic activity, dividend yield as a proxy for time variation in unobservable risk premia (since a high dividend yield for a given stock price indicates that dividends are being discounted at a higher rate), default spreads to capture the effect of default premia and term spread (which has been shown to be closely related to the short-term business cycle).

The data set is identical to that of Jegadeesh and Titman (1993), and business cycle dates for the US economy are taken from the National Bureau of Economic Research (NBER). Overall, Chordia and Shivakumar find that momentum returns are only significantly positive during economic expansions. During economic contractions, momentum profits are negative although not significantly so. This indicates that the source of momentum profits is linked in some way to the business cycle. The authors note that a common cause of momentum profits is suggestive of rational risk-based explanations rather than behavioural biases.

Ahn et al (2003) use a different approach to consider the extent to which medium-term momentum profits can be explained by risk. A stochastic discount factor is constructed from industry portfolios as basis assets and used to assess the significance of risk-adjusted momentum profits[40]. If momentum strategies produce significant risk-adjusted returns, then they will enhance the investor's opportunity set, that is to say the returns to strategies will not be 'priced' by a combination of the basis assets. The momentum strategies are formulated as per Jegadeesh and Titman (1993) using decile portfolios and formation and test periods of 3, 6, 9, and 21 months. The data used for the momentum strategies is NYSE and AMEX stock prices over the period 31 January 1965 through 31 December 1997, and the basis assets are twenty equally-weighted industry portfolios of NYSE and AMEX stocks.

As in Jegadeesh and Titman's study, the returns to the momentum strategies vary widely but are generally increasing with the length of the formation period. The returns are not adequately explained by either the CAPM or Fama and French Three Factor Model. Using an unconditional performance measure based on the 20 industry portfolios reduces the abnormal performance of the momentum strategies to around half the level originally measured, although the residual profits remain statistically significant at the 5% level for 8 of the 16 strategies considered. Ahn et al conclude that up to a half of momentum strategy profits may be attributable to risk inherent in the strategies.

3.5 Summary

This chapter discusses the non-behavioural explanations proposed in the literature for empirical findings of continuation and reversal effects in financial market returns. Market microstructure biases such as bid-ask bounce and nonsynchronous trading have a clear potential impact on the short-term autocorrelation structure of returns. The impact of methodological issues such as the choice of model of expected returns and the use of cumulative returns is not immediately clear. In general, however, it should be noted that the market-

[40] The Stochastic Discount Frontier (SDF) approach is used to assess the returns to an investment strategy with respect to the universe of alternative investments available to the investor rather than a single benchmark return such as the return on a stock index. Farnsworth et al (2002) provide an explanation of this approach.

adjusted method of calculating abnormal returns, used in the majority of studies of continuation and reversal effects, does not take into account differential risk in the cross-section of stocks. In addition, the time-varying nature of risk and expected returns may not be adequately captured in some studies.

Chapter 2 described the behavioural explanations put forward in the literature for continuation and reversal effects in financial market returns. This chapter has examined a range of non-behavioural alternative explanations based on the data and methodologies used in empirical studies. Chapter 4 goes on to consider, in the light of these behavioural and alternative explanations, the methodologies and results of individual empirical studies of continuation and reversal effects in stock market returns.

Chapter 4

Empirical Evidence of Stock Market Continuation and Reversal Effects

4.1 Introduction

This chapter considers the empirical evidence of continuation and reversal effects in stock market returns. Whilst the broad pattern of empirical results can be summarised as reflecting very short-term reversal, medium-term continuation and long-term reversal, the results of individual studies are often inconsistent and the different methodologies employed can make these differences difficult to reconcile. Some observers have gone so far as to suggest that findings of continuation and reversal may simply be a result of excessive data-mining on the part of researchers. Fama (1998, p287), for example, says

> "I doubt that the literature presents a random sample of events. Splashy results get more attention, and this creates an incentive to find them. ... The same authors, viewing different events, are often content with overreaction or underreaction, and are willing to infer that both warrant rejecting market efficiency"

This chapter reviews in turn the evidence of predictability in returns over the short-term, medium-term, and long-term. Section 4.2 examines studies focusing on short-term effects over periods ranging from one day to a week. Section 4.3 goes on to consider medium-term effects over periods up to two years[41]. A review of the literature on long-term effects is provided in Section 4.4.

Whilst the research documented in this thesis concentrates on short-term and medium-term effects, it is possible that the long-term effects identified in the literature may be driven by short-term and medium-term phenomena. Nagel (2002), for example, postulates that medium-term continuation in returns may be a direct consequence of short-term reversals. In a similar fashion, the

[41] Studies are categorised in this thesis as being short-term or medium-term based on the length of the formation period considered.

results of long-term studies in this field may have implications for returns in the short- and medium-term.

4.2 Short-Term Studies

A number of studies have considered stock market returns following large price changes over periods ranging from one day to one week.

Howe (1986) considers CRSP stocks with one-week price changes of 50 percent or more over the period 1963 through 1981 and finds that winners underperform the market by 30 percent over the 12 month period following the price event, with this underperformance consistent and statistically significant across all time frames up to 12 months. Losers, however, appear to rebound in the first 5 weeks following the price event, with much of this reversal occurring in the first week. After 40 weeks, cumulative returns relative to the market once again turn negative for losers. Howe notes that the price event appears to have little impact on the market betas of the stocks under consideration, and the results are not explained by the January effect.

Atkins and Dyl (1990) use data on the three largest percentage winners and losers among NYSE stocks each day over the period January 1975 through December 1984. These are published daily in the Wall Street Journal. From this data set, 300 trading days are chosen at random, and the average performance of the winners (14.94 percent) and losers (-10.28 percent) calculated. The performance of these stocks is then examined using both the mean-adjusted and market-adjusted models to calculate abnormal returns over test periods of between 1 and 10 days. Losers appear to produce significantly positive returns over days 1 and 2 following the initial price event, and cumulative returns are positive out to 8 days. Interestingly, losers also generate significantly positive returns on average over the four days prior to the price event, a phenomenon which had not been specifically addressed in the literature. Winners experience slightly negative returns on average over 1 through 7 days following the price event, although these are not significantly different from zero. The results are similar using the mean-adjusted and market-adjusted models. Atkins and Dyl conclude that their study shows evidence of strong reversals following a negative price event, combined with slight reversals following a positive price event.

Bremer and Sweeney (1991) examine returns following one-day abnormal price declines of 10 percent or more in Fortune 500 stocks listed on the CRSP tape between 1962 and 1986. They find significant positive abnormal returns, with average cumulative returns of 1.773 percent after 1 day, 2.215 percent after 2 days and 2.641 percent after 3 days. Whereas 55.28 percent of stocks show a positive performance on day 1, this figure reduces to 46.05 percent over day 2 and 41.19 percent over day 3, suggesting that most stocks have completed their price adjustment after day 1 but that some stocks continue to rise in value over a longer period. This is inconsistent with the notion that market prices quickly change to reflect relevant information. The results are robust to the January effect and day of the week effects.

Cox and Peterson (1994) similarly study price changes in US stocks following one-day declines of 10 percent or more. Data from January 1963 through June 1991 is taken for all 2776 NYSE, 2287 AMEX, and 1436 NMS firms that are included in the CRSP data files. Regression analysis is used to examine the relationship between test period abnormal returns over 1 to 20 days and the initial one-day abnormal drop in price, firm size, and the market on which the stock is traded.

The study finds significant reversals for all markets over 1 to 3 days following the initial one-day decline, although for NYSE and AMEX firms, short term reversals gradually diminish over time and no reversals are found after October 1987. For NMS firms, reversals continue, but after controlling for the bid-ask spread no reversals are found after October 1987. The lack of reversals for all markets after 1987 is consistent with the hypothesis that market liquidity and bid-ask bounce are the driving factors behind the initial short-term reversals, with increases in market liquidity over time resulting in smaller price reversals. Additionally, if behavioural factors were the cause of reversal following one-day declines, one would expect larger declines to result in larger subsequent reversals, a hypothesis for which Cox and Peterson find no empirical evidence. Continuation is observed over a period between 4 and 20 days following the large one-day drop for all time periods and markets.

Overall, therefore, Cox and Peterson find evidence of price reversals among losers over a 1 to 3 day period following a large one-day decline in stock price, followed by evidence of continued poor performance over longer test periods up to 20 days. There is evidence to suggest that the short-term reversals may be due to liquidity effects rather than behavioural factors.

Akhigbe et al (1998) consider the greatest percentage loser and winner announced in the Wall Street Journal for each trading day during 1992. Returns data from the CRSP database and average closing bid-ask spread data from the ISSM tape are used for the sample of 203 losers and 210 winners. Losers exhibit strong reversals over 1 and 2 days following the price event, whilst winners show continuation behaviour over the first day following the price event before undergoing a reversal over days 2 through 4. Whilst the cumulative reversal for losers over the first two days following the price event greatly exceeds the average bid-ask spread, the average return from a strategy of buying extreme losers at the offer price following the price event and selling at the bid price one or two days later is negative. Even though the market appears to experience a reversal following a large price event, Akhigbe et al conclude, this is not inconsistent with weak-form market efficiency.

Ratner and Leal (1999) examine returns following large one-day movements in the major stock market indices of Argentina, Brazil, Chile, India, Korea, Malaysia, Mexico, the Philippines, Taiwan, Thailand, the USA, and Japan as well as the Morgan Stanley World Index. The data covers the period January 1982 through March 1995, with the month of October excluded to avoid the volatility surrounding the crash of 1987. Expected returns are calculated using the mean-adjusted and market models over 105 through 6 trading days prior to the large one-day movement and 21 through 121 days afterwards. A large one-day movement is defined as one which exceeds three standard deviations from the mean daily return.

Evidence of significant reversal following a large one-day decline is found for only Japan (day 2), Malaysia (days 4-20) and the USA (days 1-3), whilst evidence of significant continuation is found only for India (day 1) and the Philippines (day 3)[42]. No significant continuation or reversal effects are found following large one-day increases in the indices considered.

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[42] all at the 5 percent significance level.

Otchere and Chan (2000) consider the evidence from short-term returns to Hong Kong Stock Exchange (HKSE) stocks over the periods 25 March 1996 to 31 July 1997 and from 1 August 1997 to 30 June 1998 (the period of the Asian Financial Crisis). The earlier sample consists of data on 432 stocks and the later sample contains data on 474 stocks.

On each trading day, a winner and loser stock is chosen, these being the stocks with the highest and lowest abnormal return over that trading day respectively, and the subsequent abnormal return over test periods of 1 to 7 trading days is calculated. Over the earlier period, evidence of reversal in returns is found over 2 to 4 trading days following the designation of stocks as a winner and 3 days following designation as a loser, with the size of the reversals more pronounced for winners than for losers. After accounting for transactions costs, however, profits from a trading strategy designed to exploit these reversals are generally insignificant. This is consistent with the results of Akhigbe et al. Over the period of the Asian Financial Crisis, the results are mixed. Otchere and Chan note that their results appear robust to factors such as bid-ask bounce, size effects, and day-of-the-week effects.

Schnusenberg and Madura (2001) use a time-series approach to investigate the short term returns behaviour of six US stock market indices: the Dow Jones Industrial Average (1st October 1928 to 31st December 1997), the S&P 500 (1st January 1928 to 31st December 1997), the Nasdaq Composite (5th February 1971 to 31st December 1997), the NYSE Composite (1st January 1966 to 31st December 1997), the Russell 3000 (2nd January 1979 to 31st December 1997), and the Wilshire 5000 (1st December 1979 to 31st December 1997).

Portfolios of winning and losing days are formed based on the abnormal index performance on that day. Both a mean-adjusted return model, in which expected returns are based on the average actual return over the previous 60 days, and an ARIMA model are used in the calculation of abnormal returns. In the case of the ARIMA model, the model is fitted using the first 100 days of data to obtain the necessary model coefficients, and is re-estimated for each decade of data in the sample.

The winner and loser portfolios are formed from the top and bottom deciles of daily returns, with each portfolio therefore containing a list of trading days rather than of individual stocks. Cumulative abnormal test period returns are computed for 1, 2, 3, 5, 10 , 30, and 60 days following the trading days in the winner and loser portfolios, and a mean return calculated for each winner and loser portfolio. Schnusenberg and Madura thus consider combinations of a one-day formation period with test periods of length from 1 to 60 days.

Using the mean-adjusted model, the returns on the day following the market event show strong evidence of continuation for both winners and losers. For example for winners, an average Dow increase of 1.93 percent is followed by an increase of 0.21 percent (t=5.73) on the following trading day whilst for losers, an average Dow decrease of 1.91 percent is followed by a further decrease of 0.12 percent on the following trading day. This short-term continuation is statistically significant for both winners and losers across all six indices.

For longer periods, abnormal returns to winners are consistently positive and increasing with time period. For losers, however, once we go beyond a one-day test period, the subsequent abnormal return is significantly negative only for the NYSE out to 5 days and the Nasdaq out to 30 days. For test periods of 60 days, the abnormal returns to the loser portfolio become significantly positive for all indices other than the Russell 3000 and Wilshire 5000, indicating reversal among losers over the medium term.

For the one-day test period, the results from the ARIMA model are different to those using the mean-adjusted model, with no significant abnormal test-period returns for either winners (with the exception of the S&P 500 and Nasdaq) or losers. The results obtained for longer periods are similar to those using the mean-adjusted model.

Overall, Schnusenberg and Madura's study provides mixed-evidence of market behaviour on the day following a large one-day movement. Over periods from 2 to 30 days following such a move, evidence of market continuation is observed. Over a 60 day period following a large one-day market movement, asymmetry is seen between winners and losers, with reversal among winners and continuation among losers.

Lasfer et al (2003) examine the price behaviour of 40 stock market indices over 1 to 10 days following large one-day price changes. The data covers the period 1989 through 1997 and is grouped into developed and emerging markets indices based on the Financial Times and Morgan Stanley classifications. Large price changes are defined as those exceeding two standard deviations from the mean daily return, where both the mean and standard deviation are calculated over a 50 day window ending 10 days before the price event. This mean return is similarly used in the calculation of abnormal returns in the post-event period.

For developed markets, the abnormal test period returns display continuation over 1, 3, 5, and 10 days following both positive and negative initial shocks, with the results significant at the 1 percent level throughout. Following positive shocks, abnormal returns increase monotonically from 0.29 percent over 1 day to 0.916 percent over 10 days. Following negative shocks, abnormal returns follow the opposite path, declining monotonically from –0.12 percent over one day to –0.872 percent over 10 days.

The results are similar for emerging markets, with statistically significant positive returns of 0.651 percent over one day rising to 1.951 percent over 10 days following initial positive shocks. Following negative shocks, returns are negative and statistically significant over 1 day (-0.31 percent), 5 days (-0.398 percent) and 10 days (-0.872 percent).

To summarise, Bremer and Sweeney (1991) and Cox and Peterson (1994) each study the returns to losers following one-day price declines of 10 percent or more. Both studies find evidence of reversal in returns over periods of 1 to 3 days, with similar results reported by Atkins and Dyl (1990) and Akhigbe et al (1998) for US stocks and Otchere and Chan (2000) for Hong Kong Stock Exchange stocks. Cox and Peterson note that the size of their reversals declines markedly through the data samples. This is taken to be an indicator that bid-ask bounce may be responsible for findings of short-term reversal, with increased market liquidity in recent years reducing the magnitude of the effect. Howe (1986) finds evidence of return reversals continuing out to 12 months for winners and 5 weeks for losers.

Table 4.1 summarises the research methodology and results of each of the studies reviewed in this section. It is worth noting that slightly different results are obtained by studies which consider the short-term return characteristics of stock market indices rather than individual stocks. Ratner and Leal (1999) find mixed evidence of continuation (2 indices) and reversal (2 indices) for losers among the 12 indices considered in their study, with no evidence of either continuation or reversal effects found for winners. Both Schnusenberg and Madura (2001) and Lasfer et al (2003) find evidence of continuation for winners over test periods lasting up to 10 days (Lasfer et al) and 60 days (Schnusenberg and Madura). For losers, Schnusenberg and Madura find continuation over 1 day using mean-adjusted but not ARIMA expected returns, whilst Lasfer et al find evidence of return reversals out to 10 days.

For single stocks, therefore, the empirical evidence supports strong reversal among losers with mixed evidence for winners. There is some evidence to support bid-ask bounce as a possible driver of these effects. For stock market indices, the evidence is more mixed.

4.3 Medium-Term Studies

Poterba and Summers (1988) use a variance ratio test to examine the serial correlation properties of the stock market indices of 18 countries[43]. Monthly returns data is considered for Canada (1919 - 1986), the UK (1939 – 1986), Austria, Belgium, Germany, Finland, France, India, Japan, the Netherlands, Norway, the Philippines, South Africa, Sweden, Switzerland, and the USA (1957 - 1986), Columbia (1959 – 1983), and Spain (1961 – 1986). The NYSE, TSE, and FTSE indices are used for the USA, Canada and the UK respectively, with indices published by the IMF used in all other cases.

[43] If stock market returns follow a random walk, then the variance of returns will be proportional to the return horizon. That is to say, the variance of 6 month returns will be half that of 12 month returns, which will be one third that of three year returns, and so on. The variance ratio statistic relates the variance of returns at different horizons to the variance of 12 month returns.

Table 4.1 Short-Term Studies

Study	Country	Data Sample	Stock Selection Criteria	Basic Methodology[44]	Model of Expected Returns[45]	Formation Period	Test Period	Method of Cumulating Returns[46]	Overlapp-ing Events?	Control for	Significant Findings
Howe (1986)	USA	CRSP Stocks 1963-1981	one-week price change of at least 50 percent	standard cross-sectional	market-adjusted and market model	1 week	up to 12 months	not specified	no	January Effect	winners: reversal out to 12 months losers: reversal to 5 weeks then continuation to 12 months
Atkins and Dyl (1990)	USA	NYSE Stocks 1975-1984	3 largest daily winners and losers from Wall Street Journal	standard cross-sectional	mean-adjusted and market-adjusted models	1 day	1 to 10 days	not specified	no	-	winners: possible reversal (not significant) losers: reversal over 1-3 days
Bremer and Sweeney (1991)	USA	Fortune 500 Stocks 1962-1986	one-day price decline of at least 10 percent	standard cross-sectional	market-adjusted	1 day	1 to 20 days	not specified	no	January day of week	losers: reversals over 1-3 days
Cox and Peterson (1994)	USA	CRSP Stocks 1963-1991	one-day price decline of at least 10 percent	regression analysis	market-adjusted	1 day	1 to 20 days	not specified	no	size market	losers: reversals over 1-3 days, diminishing through time consistent with liquidity and bid-ask bounce theories

[44] These are reviewed in Section 3.3.1

[45] These are reviewed in Section 3.3.2

[46] These are reviewed in Section 3.3.3

Table 4.1 Short-Term Studies (continued)

Study	Country	Data Sample	Stock Selection Criteria	Basic Methodology	Model of Expected Returns	Formation Period	Test Period	Method of Cumulating Returns	Overlapping Events?	Control for	Significant Findings
Akhigbe et al (1998)	USA	CRSP Stocks 1992	largest daily winner and loser from Wall Street Journal	standard cross-sectional	not specified	1 day	1 to 4 days	not specified	no	-	winners: continuation over day 1, then reversal losers: reversal over days 1 and 2
Ratner and Leal (1999)	International (12 countries)	market indices 1982-1995	one-day price movements of at least 3 standard deviations	standard cross-sectional	mean-adjusted and market model	1 day	21 to 121 days	not specified	no	-	losers: mixed evidence (limited) winners: no evidence of continuation or reversal
Otchere and Chan (2000)	Hong Kong	HKSE Stocks 1996-1998	highest and lowest performing stocks daily	standard cross-sectional	not specified	1 day	1 to 7 days	not specified	no	size day of week bid-ask bounce	winners: reversal over 2 to 4 days losers: reversal over 3 days
Schnusenberg and Madura (2001)	USA	6 indices various periods	top and bottom 10 percent	time series	mean-adjusted and ARIMA	1 day	1 to 60 days	CAR	no	-	winners: continuation losers: continuation over 1 day (not ARIMA), reversal over longer periods (typically > 30 days)
Lasfer et al (2003)	40 countries	market indices 1989-1997	one-day price movements of at least 2 standard deviations	time series	market-adjusted	1 day	1 to 10 days	not specified	no	-	winners: continuation losers: continuation

Evidence of positive serial correlation in returns over a one-month horizon is found in all but one country (Columbia), with negative serial correlation over longer periods. Although the short data samples and associated high standard errors make it difficult to reject the null hypothesis of zero serial correlation, Poterba and Summers report, the consistency of the results is persuasive.

Jegadeesh (1990) finds evidence of significant serial correlation in CRSP stocks, with negative serial correlation over one month and positive serial correlation over 2 to 36 months but most notably over a 12 month horizon. A trading strategy is devised which uses one month serial correlations estimated using prior data to rank stocks in terms of expected performance over the following month. The strategy then buys the decile of stocks with the highest expected performance and sells that with the lowest expected performance. This strategy realises an average abnormal return of 1.99 percent per month over the period 1934 to 1987. A similar strategy using the 12 month serial correlation estimate realises an average 0.93 percent per month over the same period, whilst one which uses all of the estimated serial correlations from 1 to 36 months realises 2.49 percent per month.

Jegadeesh reports that the pattern of returns is different in January, but this does not explain the overall findings. Similarly, possible explanations such as size-based risk, time-varying risk and the effects of the bid-ask spread and nonsynchronous trading are unable to fully explain the observed empirical results.

Kryzanowski and Zhang (1992) consider the evidence of continuation and reversal behaviour among Toronto Stock Exchange (TSE) stocks between 1950 and 1988 using formation and test periods of equal length ranging from 12 and 24 months up to 10 years. Evidence is found of significant price continuation up to 24 months. Over longer periods, small reversals in returns are observed although these are not statistically significant. Their results are robust to the January effect and size effect.

Jegadeesh and Titman (1993) find that momentum strategies which buy US stocks with strong past performance and sell stocks with poor past performance generate significant positive abnormal returns over 3 to 12 month holding periods but negative abnormal returns over the subsequent two year period. These results are consistent with medium-term market continuation but longer-term market reversal. For example, a strategy based on a six month formation period generates average returns of 9.5 percent over a 12 month test period but loses over half of this return over the following 24 months. These later losses indicate that the strategies are not simply selecting stocks with high unconditional expected returns, rather that price changes during the holding period are at least partially temporary.

Data from 1965 to 1989 is used for AMEX and NYSE stocks with formation periods and test periods of between 1 and 4 quarters. Strategies are considered where the test period follows on immediately from the formation period and where a one week gap exists between formation and test periods, giving 32 strategies in all. Stocks are ranked at the beginning of each month on the basis of their return during the formation period, and portfolios formed based on the top and bottom deciles. The strategies examined involve buying the winner portfolio and selling the loser portfolio each month, and also carry forward positions from the previous K-1 months where K is the length of the holding period. Thus, each strategy makes use of overlapping holding periods based on previous months' winner and loser portfolios.

The returns from all the strategies considered by Jegadeesh and Titman are positive and statistically significant except for that of the 3 month/3 month strategy that does not skip a week, where returns are positive but not statistically significant. Importantly, both the buy and sell sides of the strategy generate a positive contribution to returns in all cases. The most successful strategy uses a 12 month formation period and 3 month holding period.

The 6 month formation / 6 month holding period strategy is analysed in further detail. Over the 1965 to 1989 period, the strategy realises a compound excess return of 12.01 percent per annum on average. Average losses of about 7 percent occur in each January but positive abnormal returns averaging 1.66 percent per month are found in all other months. The magnitude of the January losses is found to be inversely related to firm size. Seasonal effects occur outside January, with fairly low returns in August and particularly high returns in April, November and December.

Jegadeesh and Titman (2001) respond to criticisms that their earlier results may have been a result of data snooping bias by retesting the 6 month formation / 6 month holding period strategy used in the 1993 study using data from 1990 to 1998. The results of this out-of-sample analysis indicate that momentum strategies continue to be profitable throughout the 1990-1998 period and that past winners outperform past losers by a similar amount to that found in the earlier study. The authors conclude that momentum profits arise due to time-series variations in stock returns caused by behavioural factors.

Chang et al (1995) use one month formation periods and test periods of between one and six months to examine the profitability of contrarian strategies using data on Tokyo Stock Exchange-listed firms between 1975 and 1991. The short term contrarian strategy produces significant profits for holding periods of up to four months, although returns are negative over five and six month holding periods. The results are not affected by adjusting for firm size, systematic risk, or the January effect. Additionally, a strong symmetry in returns is observed between the winner and loser portfolios.

Rouwenhorst (1998) considers the profitability of Deutschmark-based momentum strategies in twelve European countries (Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the UK) over the period 1980 to 1995. The methodology is that of Jegadeesh and Titman (1993), and the results are similar. Significant continuation effects are observed in all twelve countries and last for about a year, with a portfolio of internationally diversified winners outperforming the loser portfolio by approximately 1 percent per month, on average, after controlling for risk. Irrespective of the length of the formation period, returns tend to reduce as the holding period is increased. Country-neutral and size-neutral momentum strategies are also found to be profitable in all cases. Whilst continuation is negatively correlated with firm size, it is not limited to small firms. International returns are found to be correlated (with a positive correlation of 43 percent) with those of the USA, suggesting that the profitability of momentum strategies in different countries is driven by a common factor.

Chan et al (1999) consider the profitability of a simple strategy of buying past six-month winners and selling past six-month losers using data on all NYSE, Amex and Nasdaq stocks between January 1973 and December 1993. Their results suggest that the arbitrage portfolio is profitable, earning an average 8.8 percent over six month holding periods and 15.4 percent over 12 month holding periods. Returns over 2 and 3 years are similar for the winner and loser portfolios, with the portfolio of buying past winners and selling past losers producing insignificant returns. These results are broadly in line with those of Jegadeesh and Titman (1993) using a very similar data sample. Whilst the earlier study found that momentum profits were eroded over longer time horizons, however, Chan et al find no evidence of any such longer-term price reversals.

Schiereck et al (1999) use data on all companies listed on the Frankfurt Stock Exchange between January 1961 and December 1991 to consider the issue of momentum and contrarian strategy profitability in the German stock market. To test the profitability of momentum strategies, winner and loser portfolios are formed from the best and worst 10, 20, or 40 performing stocks respectively over formation periods of 1, 3, 6, and 12 months, and the performance of these portfolios are tracked over the following 12 months.

The momentum strategies considered are generally profitable. With a formation period of one month and portfolios formed from the top and bottom 20 stocks, for example, the mean monthly return is a small but statistically significant 1.49 percent. The authors note that the profitability of the momentum strategies considered increases over time through the three decades covered by the data. The five year contrarian strategies based on portfolios of 20 stocks earn positive returns in 15 of the 22 samples considered. Controlling for beta, risk, and firm size does not account for the findings of the study.

Pan and Hsueh (2001) argue that the significant momentum profits found by studies such as Rouwenhorst (1998) may be empirical illusions caused by the use of overlapping data. Trading strategies are constructed using a data set comprising the stock market indices of twelve European countries and the USA. The strategy generates a zero-cost portfolio comprising long and short investments in each index where the portfolio weights assigned to each index are based on the excess of that index's performance over a prior period relative to the average performance of the indices. Indices which outperform the average over the prior period are therefore assigned positive weights, and vice versa for indices which underperform the average[47]. The data sample covers the period from January 6th 1988 to December 29th 1999.

The momentum strategy is implemented for five different time horizons: one week, two weeks, four weeks, twelve weeks, and 26 weeks, with average profits of –0.00096 cents, 0.032 cents, 0.099 cents, 0.358 cents, and 0.824 cents respectively. The profits appear to increase with longer formation and test periods, and are significant at the 1 percent level across all horizons except one week. These results suggest the existence of international momentum effects in stock market indices similar to those reported by Rouwenhorst using data on single stocks. Repeating the test using non-overlapping data however generates profit estimates, none of which are significantly different from zero, whilst a variance ratio test shows little evidence of serial correlation in any of the thirteen indices. Much of the evidence for momentum profitability may therefore be attributable to biases introduced by the use of overlapping time periods.

Wilson and Pinfold (2001) find evidence in favour of the profitability of both momentum and contrarian strategies using data on the New Zealand stock market from June 1989 to June 2000 and a standard methodology using buy-and-hold returns and the market model. Contrarian strategies with formation periods of 12 and 26 weeks and a test period of 52 weeks generate statistically significant excess returns of 13.5 percent and 15.6 percent respectively, whilst a momentum strategy with a formation period of one week and a test period of four weeks generates a significant excess return of 2.3 percent. The two profitable contrarian strategies are no better than chance, however, at picking test period winners; rather, profits are generated by a small number of formation period losers which produce particularly high test period returns.

Hameed and Kusnadi (2002) investigate the profitability of momentum strategies in Hong Kong, Malaysia, Singapore, South Korea, Taiwan, and Thailand over the period 1981 through 1994. The methodology employed is similar to that of Rouwenhorst (1998) with sixteen combinations of 3, 6, 9, and 12 month formation and test periods. Whilst the returns achieved by these

[47] This methodology is introduced by Lo and MacKinlay (1990b) and is also used by Conrad and Kaul (1993).

strategies are generally positive, they are small (the most profitable strategy, using a 9 month formation and 12 month test period, generates an average annual return of 9.48 percent) and none of the results are statistically significant.

Hon and Tonks (2003) use the methodology of Jegadeesh and Titman (1993) to investigate the profitability of short term momentum strategies in the UK stock market based on data from the London Business School London Share Price Database (LSPD) tape. Using formation periods and test periods ranging from 3 to 24 months in 3 month intervals (i.e. a total of 64 combinations of formation and test period), positive mean returns are found to most strategies over the period January 1955 to December 1996 with 24 of the 64 strategies generating significantly positive returns at the 90 percent confidence level.

In terms of formation period, returns tend to increase with the length of the formation period up to 12 months, subsequently decreasing towards zero. None of the strategies using a 24 month formation period generate significantly positive returns, and a number of the average returns are in fact negative. In terms of test period, strategies with 6 to 9 month test periods generate the highest returns, with returns again subsequently tailing off towards zero. The highest overall return is produced by the 12 × 6 (12 month formation period, 6 month test period) strategy with an annualised return of 16.2 percent. These results are consistent with those of Jegadeesh and Titman (1993).

Hon and Tonks go on to report that splitting the data set into two subsamples from January 1955 to December 1976 and January 1977 to December 1996 generates very different results, with the returns generally positive but insignificant over the period 1955 to 1976. Over the period 1977 to 1996, returns increase with the length of the formation period up to 9 months before decreasing with longer formation periods, but are generally positive and significant throughout. Most of the profits generated from the whole sample are therefore concentrated in the second half of the data, and the authors conclude that momentum was not a general feature of the UK stock market during the period as a whole.

Forner and Marhuenda (2003) consider the returns to 6 month and 12 month momentum strategies in the Spanish stock market[48]. Significant positive returns are found only for the 12 month strategy, and these returns remain after adjusting for risk.

Table 4.2 summarises the methodology and findings of the empirical studies of medium-term continuation and reversal effects in stock market returns reviewed in this section. Overall, the empirical evidence suggests that significant continuation effects are present in stock market returns over horizons lasting up to around 12 months. Within this, returns appear to increase with the length of the formation period as noted by Hon and Tonks (2003), among others. The majority of studies consider the profitability of momentum strategies based on buying a portfolio of past winners and simultaneously selling a portfolio of past losers. Whilst some studies, such as Jegadeesh and Titman (1993), note that both winner and losers contribute to momentum strategy returns, further information on the relative performance of the winner and loser investments may help to shed light on the potential driving forces behind the momentum effect. Similarly, whilst some studies, such as Jegadeesh and Titman (1993, 2001) consider the returns to strategies over different subsets of the total available data, further research into the time-varying nature of momentum strategy returns may indicate the extent to which these are persistent over time. Whilst Jegadeesh and Titman (2001) obtain returns which are broadly consistent with those of their 1993 study, for example, Hon and Tonks (2003) find that the momentum profits identified in their study are concentrated almost exclusively in the second half of the period covered by their data.

[48] 3 and 5 year contrarian strategies are also considered using the same methodology; the results for these strategies are reviewed in Section 4.4.

Table 4.2 Medium-Term Studies

Study	Country	Data Sample	Stocks Examined	Basic Methodology	Model of Expected Returns	Formation Period	Test Period	Method of Cumulating Returns	Overlapping Events?	Control for	Significant Findings
Poterba and Summers (1988)	International (18 countries)	market indices to 1986 (various starting dates)	not applicable	variance ratio test	not applicable	not applicable	1 month 2,3,4,5,6,7,8 years	not applicable	not applicable	-	positive one-month serial correlation negative serial correlation over longer periods
Jegadeesh (1990)	USA	CRSP Stocks 1934-1987	all	serial correlation	market model	not applicable	1 to 36 months	not specified	not applicable	January effect risk bid-ask spread	negative serial correlation in one-month returns positive serial correlation at longer lags particularly 12 months
Kryzanowski and Zhang (1992)	Canada	Toronto Stock Exchange Stocks 1950-1988	portfolios of top and bottom 20%	standard cross-sectional	market-adjusted model	12 and 24 months	12 and 24 months	CAR	no	risk, January effect	significant continuation over 1 and 2 years (see also Table 4.3 for long term results)
Jegadeesh and Titman (1993, 2001)	USA	CRSP Stocks 1965-1998	decile portfolios	standard cross-sectional	not applicable	3, 6, 9, 12 months	3, 6, 9, 12 months	HPR	yes	not applicable	medium-term continuation up to 12 months followed by reversal

Table 4.2 Medium-Term Studies (continued)

Study	Country	Data Sample	Stocks Examined	Basic Methodology	Model of Expected Returns	Formation Period	Test Period	Method of Cumulating Returns	Overlapping Events?	Control for	Significant Findings
Chang et al (1995)	Japan	Tokyo Stock Exchange Stocks 1975-1991	decile portfolios	standard cross-sectional	not applicable	1 month	1 to 6 months	not applicable	yes	January effect, size risk	losers outperform winners over 1 to 4 months winners outperform losers in months 5 and 6
Rouwenhorst (1998)	International (12 countries)	single stocks 1980 through 1995	decile portfolios	standard cross-sectional	not applicable	3, 6, 9, 12 months	3, 6, 9, 12 months	HPR	yes	-	significant continuation effects up to 12 months
Chan et al (1999)	USA	CRSP Stocks 1973 through 1993	decile portfolios	standard cross-sectional	not applicable	6 months	6 months 1, 2, and 3 years	HPR	yes	-	winners outperform losers over 6 and 12 months
Schiereck et al (1999)	Germany	Frankfurt Stock Exchange Stocks 1961 through 1991	portfolios of best- and worst-performing 10, 20, and 40 stocks	standard cross-sectional	market-adjusted	1, 3, 6, and 12 months	12 months	CAR HPR	no	beta risk size	winners outperform losers, with momentum returns increasing over time
Pan and Hsueh (2001)	International (13 countries)	market indices 1988 through 1999	zero-cost weighted portfolio of all indices	As per Conrad and Kaul (1998)	not specified	1, 2, 4, 12, and 26 weeks	1, 2, 4, 12, and 26 weeks	not specified	no	-	profits disappear when non-overlapping periods are considered

Table 4.2 Medium-Term Studies (continued)

Study	Country	Data Sample	Stocks Examined	Basic Methodology	Model of Expected Returns	Formation Period	Test Period	Method of Cumulating Returns	Overlapping Events?	Control for	Significant Findings
Wilson and Pinfold (2001)	New Zealand	Stocks on Datastream Jun 1989 to June 2000	portfolios of 15 stocks	standard cross-sectional	market-adjusted	1, 4, 12, 26, weeks	1, 4, 12, 26, 52, 78, 104, 156, 208 weeks	HPR	no	size	excess returns to momentum and contrarian strategies, not explained by size
Hameed and Kusnadi (2002)	6 Asian countries	Stocks on PACAP database 1981 through 1994	decile portfolios	standard cross-sectional	not applicable	3, 6, 9, and 12 months	3, 6, 9, and 12 months	not specified	no	-	no significant momentum effects found
Hon and Tonks (2003)	UK	LSPD Tape Stocks 1955 through 1996	decile portfolios	standard cross-sectional	not applicable	1 to 8 quarters	1 to 8 quarters	HPR	yes	size beta	winners outperform losers, profits concentrated in second half of data sample
Forner and Marhuenda (2003)	Spain	All Listed Stocks 1963-1997	portfolios of 5 stocks	standard cross-sectional	market-adjusted	6 and 12 months	6 and 12 months	CAR and buy and hold	no	risk	momentum returns to 12 month strategy not explained by risk

4.4 Long-Term Studies

Using data on NYSE stocks between January 1926 and December 1982, De Bondt and Thaler (1985) find evidence of significant reversals in returns over formation and test periods of 3 and 5 years. They report that over 3 years, a contrarian strategy which buys past losers and sells past winners earns an average return of 24.6 percent, for example, whilst the equivalent 5 year strategy earns an average return of 31.9 percent. Subsequent studies have tended to use a similar methodology with broadly consistent results.

Alonso and Rubio (1990) examine the evidence of price reversals in the Spanish stock market between 1967 and 1984. Formation periods of 36 months are used with holding periods of between 1 month and 36 months. For each choice of holding period, losers outperform winners with cumulative returns to the contrarian strategy of buying past losers and selling past winners increasing over time. With a holding period of 10 months, for example, losers outperform winners by a cumulative 31.2 percent. The authors note that the results are symmetrical for losers and winners and that the January effect does not appear to be significant in this sample.

Brailsford (1992) also uses a 36 month formation period and test periods of 1 to 36 months, in this case to consider the evidence from Australian stock prices from 1958 to 1987 inclusive. The market-adjusted model and cumulative average returns (CARs) are used to calculate abnormal returns for each stock over a 36 month formation period and winner and loser portfolios formed based on the top-performing and bottom-performing decile of stocks respectively.

Over a 36 month test period, winners undergo a significant price reversal with an average return of -69.6 percent whilst losers continue to perform poorly with an average return of -52.6 percent. The difference between the returns of winners and losers during the test period is not statistically significant, and no single calendar month produces any consistent significant return behaviour for either winners or losers. The results are robust to the size effect, and do not appear to be influenced by the industrial classification of stocks. Results using 5 year formation and test periods are consistent with those of the three year periods described above.

Chopra et al (1992) find significant profits to the 5 year contrarian strategy using CRSP tape data from 1926 to 1986. Using 5 year formation and test periods together with buy and hold returns, losers appear to outperform winners by 6.5 percent per annum on average. Adjusting for risk using empirically estimated betas does not explain these excess returns. Return reversals are strongest among small firms, with only very weak effects observed among the largest firms.

Kryzanowski and Zhang (1992) consider formation and test periods of 36, 60, 96, and 120 months in addition to the shorter periods described in Section 4.3. No significant evidence of reversal is found over these longer periods for the Toronto Stock Exchange Stocks which are the focus of their study.

Allen and Prince (1995) consider the evidence from Australian stock prices between 1974 and 1991 using 36 month formation and test periods and additionally controlling for time-varying risk using the approach proposed by Chan (1988). The winner and loser portfolios are constructed from the best-performing and worst-performing 35 stocks respectively with data taken from the Centre for Research in Finance (CRIF) database. The initial results, using cumulative abnormal returns and the market model, are broadly consistent with those of Brailsford (1992). Cumulative formation period returns of 166.10 percent for winners are followed by 39.97 percent falls over the test period, whilst losers fall 192.90 percent on average over the formation period and fall a further 57.95 percent over the test period. The picture is somewhat different once time-varying betas are taken into account. Winners show evidence of strong continuation effects in contrast to the previous findings, whilst losers continue to perform poorly.

Clare and Thomas (1995) use monthly data on UK stock returns from 1955 to 1990 to examine the evidence of long-term reversal effects in UK stock prices. The data is taken from the London Business School LSPD tapes and consists of the month-end dividend-adjusted returns of all stocks quoted on the London Stock Exchange over the period. In each analysis, up to 1000 stocks are chosen at random from the data sample, and winner and loser portfolios are formed on the basis of this subsample only. Stocks are required to survive for the formation and test period to be analysed but need not be present throughout the entire data sample.

Non-overlapping one, two and three-year formation periods together with CAR returns calculated using the market-adjusted model are used to form winner and loser portfolios comprising the top- and bottom-performing quintile of stocks respectively. The performance of these portfolios is then tracked over a test period of the same length as the original formation period. Using one-year formation and test periods therefore generates a total of 18 non-overlapping observations, two year periods give 9 non-overlapping observations, and three year periods provide 6 non-overlapping observations.

Using one year formation and test periods, the difference between the performance of winners and losers over the test period is not significantly different from zero. Winners produce an abnormal return of 0.36 percent per month and losers 0.328 percent per month, equivalent to an annualised difference of 0.37 percent.

Clare and Thomas report evidence of reversals for formation and test periods of 2 and 3 years, however, with losers seen to outperform past winners by a statistically significant 1.68 percent per annum over 2 years (based on average monthly returns of 0.11 percent for losers and -0.03 percent for winners) and 1.56 percent per annum over 3 years (based on average monthly returns of 1.29 percent for losers and 1.15 percent for winners). Controlling for size using the approach proposed by Zarowin (1990), however, reveals a size effect over 2 and 3 years which may be the cause of the observed price reversals.

Chen and Sauer (1997) re-examine the findings of De Bondt and Thaler (1985) and Chopra et al (1992) using data from the CRSP tape from 1926 through 1992. Five-year formation periods and buy-and-hold returns are used to form winner and loser portfolios consisting of the top and bottom 5 percent of stocks respectively. The loser portfolio generates an average annual test period return of 23.74 percent whilst the winner portfolio yields an average annual return of 12.43 percent. Test period returns are seen to fall gradually as one moves from the extreme loser portfolio through to the extreme winner portfolio. The returns to the contrarian strategy of buying past losers and selling past winners are not stationary through time, however, with periods of very high returns (such as the late 1930s and early 1940s), periods when the strategy earns negative returns (the mid to late 1930s for example), and periods where returns are negligible (from the mid 1940s to the mid 1950s for example).

Considering the standard deviation of test period returns produces a U shaped relationship. Extreme winners and losers do not always become extreme losers and winners respectively. Lower standard deviations for the mid-rank portfolios imply that these are more likely to remain mid-rank portfolios over time. Plotting arbitrage portfolio returns against the market risk premium reveals a close positive relationship. Contrarian profits may therefore be a simple result of economic cycles. During downturns, losers fall faster than winners (resulting in negative profits to the contrarian strategy), whilst during economic upturns, losers rise faster than winners (producing positive profits to the contrarian strategy). During periods of economic stability, there is little difference in the performance of winners and losers.

Dissanaike (1997) examines long-term reversal effects in the UK stock market using monthly returns data from the London Share Price Database for 925 constituent companies of the FTSE 500 index during the period from 1st January 1975 to 1st January 1991 inclusive. Aggregate abnormal returns over 48 month formation and test periods are calculated using the market-adjusted model with the FTSE 500 index as a proxy for the market, and using buy-and-hold returns as well as periodically rebalanced returns[49]. Ten overlapping formation periods spaced 12 months apart are considered. On average, extreme winners (the top-performing decile of stocks over the formation period) fall 69.1 percent over the test period whilst extreme losers (the worst-performing decile of stocks over the formation period) gain 25.5 percent using buy-and-hold returns. Using monthly rebalancing returns, extreme winners suffer a fall of 57.9 percent whilst extreme losers gain 14.63 percent. The results appear robust to the arguments of differential risk for winners and losers proposed by Chan (1988).

Baytas and Cakici (1999) use Conrad and Kaul (1993)'s methodology to test for long term reversal effects in the stock markets of seven industrialised countries (Canada, France, Germany, Italy, Japan, the UK, and the USA). Data from 1982 to 1991 is used from the Worldscope Disclosure Database and winner and loser portfolios formed over five year formation periods using holding period returns and the market-adjusted model. Moving on one year, another (overlapping) formation period is considered, and so on. Test periods of one,

[49] The calculation of these returns is discussed in Section 3.3.3.

two, and three years are considered. In all countries except the USA and Canada, losers consistently outperform winners over all three test periods.

The three year return to the contrarian strategy (buying losers and selling winners) is positive and statistically significant for all countries except the USA, with average returns over the three-year period of 94.5 percent in Japan, 62.9 percent in France, 58.5 percent in the UK, 50.5 percent in Germany, 21.6 percent in Italy, and 12.4 percent in Canada.

Strong asymmetries are found in some markets, for example Japan where the reversal is much stronger for winners than for losers. In the UK, Germany, and France, the reaction is less pronounced and the magnitude of the reversal for losers is only slightly less than that for winners.

Whilst the results seem to indicate the presence of return reversals in the markets studied, Baytas and Cakici note that this may be due to the influence of factors such as price and firm size on performance. Across all countries, winners have higher average prices and market values than losers. Using pooled regressions of holding period returns on both price and size (approach as per Fama and MacBeth, 1973) in the USA, Canada and Japan, the price coefficient is negative and statistically significant whilst the market value coefficient is insignificant. Returns increase as price declines, and reversal effects in stock market returns may be a low price phenomenon.

In Europe the results are more mixed. In Italy, France and Germany the price coefficient is negative and statistically significant for losers. In Italy the market size coefficient is positive and significant for winners. In Germany both price and market size coefficients are significant for winners. In the UK, the market value coefficient is significant in some regressions.

Baytas and Cakici also consider their results in the context of the profitability of contrarian trading strategies in the relevant markets. Given the results of the regression analysis, the strategy of buying the lowest price stocks and selling the highest price stocks (regardless of past performance) is considered and outperforms the market across all time periods and markets except Italy. In all markets except Germany, the returns from this strategy are greater than for strategies based on past performance (buy losers and sell winners) or market value. In all countries except Italy, the market value strategy also outperforms the past performance strategy.

Baytas and Cakici conclude that although returns to long term contrarian strategies are generally significant, returns to arbitrage portfolios based on price are higher than those based on size, and those based on size do still generally outperform the winner / loser arbitrage portfolio. Perceived reversal effects in stock markets may therefore be a result of relationships between price and/or market value and the performance of individual stock prices.

Forner and Marhuenda (2000) use the methodology of De Bondt and Thaler (1985) to consider the evidence of long term return reversals in the Spanish equity market using 36 month formation and test periods. Whilst formation period winners do produce negative test period returns and formation period losers positive test period returns, these effects disappear when adjusting for risk as per the methodology proposed by Chan (1988).

Ahmad and Hussain (2001) consider the empirical evidence of reversal effects in returns among Kuala Lumpur Stock Exchange (KLSE) stocks using three year formation and test periods. Daily price data on 166 companies from 1986 to 1996 inclusive is used. Of these companies, 66 were constituents of the KLSE Composite Index in 1996, representing approximately 50 percent of the value of the main board at that date, and every sector in the board is included in the sample. There is a potential issue of survivorship bias, since companies for whom data was not available throughout the period under consideration are omitted from the study.

Three year formation periods are considered starting in January each year from 1986 to 1991 inclusive (6 non-overlapping formation periods in total), followed in each case by a three year test period. Expected returns are calculated using the market-adjusted model with the KLSE Composite Index used as a proxy for the market, and the winner and loser portfolios are based on the top- and bottom-performing decile of stocks during the formation period.

Ahmad and Hussain find that the performance of winners worsens significantly from the formation period to the test period whilst the performance of losers improves, with the choice of returns measure having no significant impact on the results obtained. The results display some asymmetry - the underperformance of winners in the test period is not as dramatic as the outperformance of losers. Also, the return to the loser portfolio is generally greater than that of the winner portfolio indicating the availability of contrarian profits from selling winners and buying losers, although these results are not all significant. Any potential profits may therefore not be worth exploiting once transaction costs are taken into account.

Forner and Marhuenda (2003) consider the returns to 3 and 5 year contrarian strategies in the Spanish stock market in addition to the 6 and 12 month momentum strategies discussed in Section 4.3. Significant contrarian profits are found for the 5 year strategy but not for the 3 year strategy. The differences in results between this study and that of Alonso and Rubio (1990) appear to be due to differences in the methodologies used to calculate abnormal returns. Whilst Forner and Marhuenda calculate betas individually for the formation period and the test period and use these, together with the market model, to generate expected returns, Alonso and Rubio calculate betas on a rolling month-by month basis using the previous 60 months' returns.

Table 4.3 summarises the methodologies used by the empirical studies of long-term continuation and reversal effects reviewed in this section, together with their main findings. Studies have tended to find evidence of significant profits to the contrarian strategy of buying past losers and selling past winners. Whilst some studies, such as Alonso and Rubio (1990) argue that size does not explain these returns, others, such as Clare and Thomas (1995), argue that size does have an important role to play. Similarly, studies such as that of Dissanaike (1997) note that contrarian profits are not explained by considerations of risk, whilst the study of Forner and Marhuenda (2000) finds that profits disappear after controlling for risk.

Table 4.3 Long-Term Studies

Study	Country	Data Sample	Stocks Examined	Basic Methodology	Model of Expected Returns	Formation Period	Test Period	Method of Cumulating Returns	Overlapping Events?	Control for	Significant Findings
De Bondt and Thaler (1985)	USA	NYSE Stocks 1926 through 1982	decile portfolios	standard cross-sectional	market-adjusted market model CAPM	3 and 5 years	3 and 5 years	CAR	no	-	losers outperform winners over 3 and 5 years
Alonso and Rubio (1990)	Spain	All Listed Stocks 1967-1984	decile portfolios	standard cross-sectional	CAPM	36 months	36 months	CAR	no	size	significant contrarian profits, not explained by size
Brailsford (1992)	Australia	CRIF file stocks 1958-1987	decile portfolios	standard cross-sectional	market-adjusted	36 months	36 months	CAR	no	size risk	winners: reversal losers: continuation no significant contrarian profits
Chopra et al (1992)	USA	CRSP tape stocks 1926-1986	portfolios formed from top and bottom 5 percent	standard cross-sectional	market model	5 years	5 years	HPR	yes	beta size	significant contrarian profits, not due to the size effect
Kryzanowski and Zhang (1992)	Canada	TSE stocks 1950-1988	portfolios formed from top and bottom 20 percent	standard cross-sectional	market-adjusted	36,60,96, and 120 months	36,60,96, and 120 months	CAR	no	risk, January effect	no evidence of significant reversal (see Section 4.3 for further details of this study)
Allen and Prince (1995)	Australia	CRIF file stocks 1974-1991	portfolios of top and bottom 35 stocks	standard cross-sectional	market-adjusted	36 months	36 months	CAR	no	risk	results consistent with Brailsford (1992)
Clare and Thomas (1995)	UK	LSPD tape stocks 1955 - 1990	portfolios formed from top and bottom 20 percent	standard cross-sectional	market-adjusted	1, 2, 3 years	1, 2, 3 years	CAR	no	size, seasonality	contrarian profits, support for size effect

Table 4.3 Long-Term Studies (continued)

Study	Country	Data Sample	Stocks Examined	Basic Methodology	Model of Expected Returns	Formation Period	Test Period	Method of Cumulating Returns	Overlapping Events?	Control for	Significant Findings
Chen and Sauer (1997)	USA	CRSP tape stocks 1926-1999	portfolios formed from top and bottom 5 percent	standard cross-sectional	market model	5 years	5 years	HPR	yes	-	contrarian profits are not stationary
Dissanaike (1997)	UK	LSPD tape stocks 1975-1991	decile portfolios	standard cross-sectional	market-adjusted	48 months	48 months	HPR	yes	risk	contrarian profits not explained by risk
Baytas and Cakici (1999)	Intrenational (7 countries)	Stocks on Worldscope Database 1982-1991	portfolios of top and bottom 35 stocks	standard cross-sectional	market-adjusted	36 months	12, 24, 36 months	HPR	yes	size	3 year contrarian profits, asymmetry - greater reversal for winners than losers
Forner and Marhuenda (2000)	Spain	All listed stocks 1963-1997	portfolios of top and bottom 5 stocks	standard cross-sectional	market-adjusted	36 months	36 months	CAR and HPR	no	risk	contrarian profits disappear after adjusting for risk
Ahmad and Hussain (2001)	Malaysia	KLSE stocks 1986-1996	decile portfolios	standard cross-sectional	market-adjusted	36 months	36 months	CAR and HPR	yes	seasonality, size	strong reversal for losers, contrarian profits Chinese New Year effect
Forner and Marhuenda (2003)	Spain	All listed stocks 1963-1997	portfolios of top and bottom 5 stocks	standard cross-sectional	market-adjusted	3 and 5 years	3 and 5 years	CAR and HPR	no	risk	contrarian profits to 5 year strategy asymmetric – significant reversal only for losers not explained by risk

4.5 Summary

This chapter reviews the empirical evidence of continuation and reversal effects in stock market returns. In the short-term, empirical evidence of reversal effects has been reported for single stocks and in particular following large one-day price declines. The evidence of short-term continuation and reversal effects for stock indices, rather than single stocks, is mixed. In the medium-term, momentum strategies which buy past winners and sell past losers appear to be profitable for single stocks, whilst in the long-term, contrarian strategies generate significant profits in many studies. Very few studies have considered medium-term and long-term continuation and reversal effects in stock market indices. The two exceptions reviewed in this chapter are Poterba and Summers (1998), who find continuation effects over periods lasting only up to one month, and Pan and Hsueh (2001), who find no significant excess profits to a portfolio of stock indices weighted by past performance.

The current study considers whether short-term and medium-term continuation and reversal effects occur in international stock indices. The time-series approach used builds on Schnusenberg and Madura (2001) who consider the abnormal returns to market indices over 1 to 20 days following a large price movement. The current study extends this approach to consider formation and test periods ranging from 1 to 252 trading days, with returns measured as the excess return to an investor from a fully funded market position[50].

This chapter has reviewed the empirical evidence of continuation and reversal effects in stock market returns. Chapter 5 introduces the data used in the current study before Chapter 6 describes the methodology used to identify continuation and reversal effects in the data.

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[50] This is similar to the approach taken by Conrad and Kaul (1998) and is described in detail in Chapter 5.

Chapter 5

Data

5.1 Introduction

The research documented in this thesis is in two main parts. The first part considers the profitability of short- and medium-term momentum trading strategies whilst the second examines the statistical properties of stock market trends. Each part of the research is carried out in the context of an international study of fourteen major stock markets.

The stock market data used in each study is taken from the country indices of the FTSE All-World Index Series for Australia, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Spain, Switzerland, the UK, and the USA. The fourteen markets chosen are all those in the developed markets category of the FTSE All-World Index Series for which daily data is available (price return, total return and interest rate data) over the required period for each study.

The methodologies employed in each part of the research are discussed in detail in subsequent chapters. This chapter considers the choice of data and provides descriptive statistics. Section 5.2 discusses the choice of data samples. Section 5.3 describes the background to, and construction of, the FTSE All-World Index Series. Section 5.4 discusses the sources of the data. Section 5.5 considers the calculation of daily returns for each trading day in the data samples. Section 5.6 presents descriptive statistics, whilst Sections 5.7 and 5.8 go on to consider the correlations between data series and the autocorrelation structure of returns for each individual data series. Section 5.9 concludes.

5.2 Choice of Data Samples

This study uses stock market data in preference to data from other financial markets such as the markets for foreign exchange or commodities. The main reason for this is that previous empirical studies of continuation and reversal effects in financial market returns concentrate on stock market data. One major limitation of the literature to date has been a lack of consistency in results. The application of a revised methodology across 14 international stock markets may enable such differences to be at least partly reconciled.

Stock index data together with a time-series approach is chosen in preference to individual stock data and a cross-sectional approach. One main benefit of the use of stock market indices is that an international comparison of the way in which different national stock markets behave becomes possible without the need to consider, and control for, the individual characteristics of many thousands of individual stocks.

The use of index data raises issues in terms of the potential impact of bid-ask bounce and nonsynchronous trading on the daily closing levels of the stock market indices employed in the current study and therefore on the empirical results. As discussed in Sections 3.2.1 and 3.2.2 respectively, bid-ask bounce might be expected to induce spurious negative short-term correlation in returns, with nonsynchronous trading conversely inducing positive short-term autocorrelation in returns.

A number of possible choices of stock market index exist for each of the fourteen countries considered in this study. The country indices of the FTSE All-World Index Series were chosen in preference to well-known national indices (such as the S&P 500 index in the USA, the FTSE 100 index in the UK, and the Nikkei 225 index in Japan) since the FTSE indices are broad market indices which are comparable in their scope and calculation methodology across countries.

The well-known national stock market indices are in general not directly comparable. They cover different proportions of the investible stock market universe in each country. For example, only 40 stocks are included in France's CAC 40 index whereas 500 are included in the USA's S&P 500 index. In addition, calculation methods may differ between indices. The calculation of performance indices such as the German DAX, for example, includes reinvested dividends; most other well-known indices are price indices, which exclude dividends. In addition, indices may incorporate only stocks of a particular type (sector indices) which may have different characteristics to those of the stock market as a whole. One example would be the Nasdaq 100 index of technology stocks in the USA.

The FTSE All-World country indices consider the entire universe of stocks in each country which meet minimum standards of size and liquidity, thus offering a much broader base than the alternatives, which generally only consider those stocks with the highest market capitalisation in each country. They offer a consistent methodology across all markets, enabling like-for-like comparison of results. The FTSE indices are preferred over the (similar) country indices calculated by Morgan Stanley Capital International (MSCI) due to the availability of total return data over a longer period for each country.

One argument in favour of using well-known national indices is that the indices can generally be traded in their own right through liquid futures contracts. Although one of the main stated aims of the FTSE indices is that they are replicable by investors, the costs of replication may be difficult to determine and will almost certainly differ markedly across investors. For the purposes of this study, however, it is considered that the benefits of using broad market indices in terms of consistency across national stock markets more than offset any costs in terms of the difficulty of explicitly taking into account transactions costs.

The fourteen stock markets considered are taken exclusively from the developed market category of the FTSE All-World Index Series. One reason for this is that the required total return and interest rate data is generally not available for developing markets. In addition, market microstructure effects and liquidity issues are likely to be more pronounced in emerging market data and this may contaminate results.

5.3 The FTSE All-World Index Series

The FTSE All-World Index Series™ was launched in 1987 and is owned by FTSE International Ltd. The objective of the Index is to

> "... create and maintain a series of high quality indices of the international equity markets for use as a benchmark by the global investment community" (FTSE, 2004, p4)

The index series comprises 49 country indices divided into 3 categories: developed, advanced emerging, and emerging. Stocks are classified by their country of incorporation in principle, unless the individual case warrants alternative consideration.

The FTSE All-World country indices are broad market indices, the aim being to capture 90 percent of the investible universe (total market capitalisation) in each country after the application of three investibility screens designed to ensure that each index is easily replicable by investors without excessive cost. Liquidity and size screens exclude very small and/or illiquid stocks. Similarly, screens based on free float / cross-holdings and foreign ownership limits ensure that investors have access to all stocks included in the index. In practice, a range of 85 percent - 95 percent of the investible universe in any given country is considered acceptable (FTSE, 2001). The constituents of each index are regularly reviewed, as is the industry distribution, the aim being to ensure that the industry distribution of each index closely reflects that of the investible universe of the country in question. As a general rule, unnecessary turnover of stocks is avoided to minimise cost of replication. FTSE (2001) describes these procedures in detail.

The construction of the FTSE All-World Index Series follows a chained Paasche methodology, which is defined by Deutsches Aktieninstitut (2000) as follows:

$$I(t) = \frac{\sum_{i=1}^{n} p_{it} \times q_{it}}{\sum_{i=1}^{n} p_{i0} \times q_{it}} \times B$$

Where

I(t) = index value at time t

p = market price for stock i at time t

q = weighting of stock i at time t

0 = base date of the index

B = base value of the index

Each country index of the FTSE All-World Index Series has a base value of 100 as at 31st December 1986. Index values are calculated once daily using actual closing mid-market or last trade prices.

A review by the Deutsches Aktieninstitut (2000) notes that different index construction methodologies are used by well-known stock market indices. The Dow Jones Industrial Average, for example, is calculated as an unweighted arithmetic mean, the Dax and Eurostoxx indices are Laspeyres indices, whilst the S&P 500 index is a value index. Indices also differ in the way in which stocks are weighted, with some indices weighted by price and others on the basis of market capitalisation. The review concludes that the choice of index methodology does not generally have a significant impact on reported index values and returns. It is possible that the index calculation methodology used in the construction of the FTSE All-World Indices may have an influence on the time series behaviour of the resulting data sets, although this issue is not explored further in the current study.

One advantage of the chained Paasche methodology is that the index calculation only requires the current weights and prices for each stock in the index. All required adjustments to the index, for example following capital changes, are handled by adjusting the weights of the stock(s) in question. FTSE (2002) provides full details of the calculation methodologies for the price and total return indices as well as adjustments to the indices to take account of free float percentage for individual stocks, capital changes, mergers, and other corporate events. The details are not reproduced in this thesis for reasons of brevity.

The total return index series for each country similarly has a base value of 100 as at 31st December 1986, but incorporates dividends reinvested as at their effective date. These are grossed up to reflect the position of an international investor with benefit of double taxation agreements, if any. It is therefore necessary to bear in mind that any excess returns to investment strategies considered based on this data may be subject to taxation implications based on circumstances of individual investors in addition to transactions costs. The methodology used to adjust the price index series for dividends may introduce a further source of bias to the time series behaviour of the total return indices used in the current study, although this issue is not explored further within this thesis.

The research documented in this thesis uses all of the country indices in the developed category for which daily price return, total return and short-term interest rate data is available over the period 31st December 1993 to 31st December 2002 inclusive. The local currency series are used throughout, and all returns calculated are therefore local currency returns.

5.4 Data Sources

The calculation of the daily returns used in the two parts of the research requires daily price index and total return index values for each of the stock markets considered, together with short-term interest rates in the domestic currency of each stock market.

This data was downloaded from Datastream for the period 31st December 1993 to 31st December 2002 inclusive, this being the maximum period for which total return index as well as price index data was available for each of the separate country indices.

Where available, the short-term interest rate data consists of the overnight deposit rate in the relevant currency. For some countries, where overnight rates were not available, call rates were used. In all cases, the interest rates used are mid-market prices. Appendix A gives the Datastream codes for the data employed in this study.

The conversion to the Euro for those countries participating in the first round of European Monetary Union (EMU) does not have a direct impact on the stock index levels provided by Datastream. Although some data series (such as individual stock prices) prior to 1st January 1999 are recalculated by Datastream using fixed conversion rates for those currencies to the Euro, this does not impact on the values of the FTSE All-World Index Series.

Appendix B provides charts of the price index and total return index data for each of the 14 stock markets considered in this study.

5.5 Calculation of Daily Returns

Discrete returns are used in preference to logarithmic (continuously compounded) returns throughout this study. Logarithmic returns are commonly used in studies of stock market continuation and reversal effects due to the simplicity of calculating multi-period returns from single-period returns. A further benefit of using logarithmic returns is that if single period returns are assumed to be normally distributed then multi-period returns will also be normally distributed (Savage, 2003). Empirical evidence suggests, however, that the return distributions of financial time series are not normal (they have 'fat tails', for example)[51], and since the methodology used in this study is "model-free", logarithmic returns do not offer significant advantages over discrete returns. The use of discrete returns ensures that the returns from the momentum study are replicable and reflect the actual returns to a real-world investor, which may not be the case for logarithmic returns[52].

Daily returns are calculated for each trading day in each of the fourteen data series. In all cases, returns are measured at the published closing price, that is to say the return over trading day t is measured from the closing price on the previous trading day t-1 to the closing price on trading day t. Price returns, total returns, and funded returns are calculated for each trading day in each of the 14 data samples using the daily price index, total return index, and short-term interest rate data as described below.

Daily price returns measure the capital gain to an investor from holding a given index for one day. For a single unit of currency invested in the index at the close on trading day t-1, the daily price return for index i on trading day t is calculated as:

$$PR_{i,t} = \frac{PI_{i,t} - PI_{i,t-1}}{PI_{i,t-1}} - 1$$

[51] Cont (1999) provides a review of the statistical properties of financial time series.

[52] Whilst logarithmic returns are good approximations of discrete returns in the region of zero, the errors are not symmetric and can become large for extreme values, for example.

where

$PR_{i,t}$ = price return for index i on trading day t

$PI_{i,t}$ = price index for index i on trading day t

Daily total returns measure the returns to an investor from dividend income as well as capital gains. Since dividends are, by definition, positive, the total return will always be greater than the price return for any given trading day in the data samples. For a single unit of currency invested in the index at the close on trading day t-1, the daily total return for index i on trading day t is calculated as:

$$TR_{i,t} = \frac{PI_{i,t} + D_{i,t} - PI_{i,t-1}}{PI_{i,t-1}} - 1 = PR_{i,t} + \frac{D_{i,t}}{PI_{i,t-1}}$$

where

$TR_{i,t}$ = total return for index i on trading day t

$D_{i,t}$ = effective dividend for index i on trading day t

Alternatively, the total return can be calculated directly from the total return index series downloaded from Datastream (as in this study), in which case

$$TR_{i,t} = \frac{RI_{i,t} - RI_{i,t-1}}{RI_{i,t-1}} - 1$$

where

$RI_{i,t}$ = total return index for index i on trading day t

Total return index data is used in preference to dividend yield data in the current study for the calculation of total returns. Dividends are highly seasonal in most countries (see Deutsches Aktieninstitut, 2000, for examples). The total return index enables the effective dividend relating to each individual trading day in the data samples to be isolated. An equivalent degree of accuracy would not be possible using annualised dividend yield data.

The total returns described above are not employed directly in the remainder of this thesis, but are used in the calculation of funded returns. Descriptive statistics are, however, presented in this chapter for total returns since this enables an insight to be drawn into the different properties of the three measures of returns.

Daily funded returns measure the return to an investor from holding the index on a fully funded basis, that is to say borrowing the necessary funds to finance the purchase of the index which then pays a return in the form of dividends and capital gains. For a single unit of currency invested in the index at the close on trading day t-1, the funded return for trading day t is calculated as:

$$FR_{i,t} = TR_{i,t} - \left(r_{i,t-1} \times \frac{calendardays_{i,t-1,t}}{basis_i} \right)$$

where

$FR_{i,t}$ = funded return for index i on trading day t

$r_{i,t-1}$ = closing overnight domestic currency interest rate for index i on trading day t-1

$calendardays_{i,t-1,t}$ = number of calendar days from trading day t-1 to trading day t for index i

$basis_i$ = interest rate basis for money market rates in the domestic currency of index i

The difference between the calculation of total return and funded return for any particular trading day lies in the calculation of the funding cost of holding a position in the index. In order to fund a single unit of currency invested in the index at the close on trading day t-1, the investor must borrow 1 unit of currency at the then-prevailing short term interest rate r_{t-1}. The number of days over which interest must be paid is based on the number of calendar days between trading day t-1 and trading day t, as per market convention. The basis on which interest is calculated is also taken from market convention. For US Dollars, interest is calculated on an Actual/360 basis, so 3 calendar days' interest at 5 percent equates to a cost of 5 percent × 3/360 or 0.041667 percent, or example. For Sterling, the calculation is on an Actual/365 day basis, so 3 calendar days' interest at 5 percent equates to a cost of 5 percent × 3/365 or 0.041096 percent, for example.

An investor who is long the index on any trading day receives the returns (price, total, or funded) described above. Similarly, an investor who is short the market on any trading day pays these returns, that is to say the return accruing to the investor who is short the index is the negative of the return accruing to the investor who is long the index.

The methodology employed in the current study to investigate the existence of continuation and reversal effects in the 14 data samples is model-free in that the return metric used is the return to an investor taking into account dividends and funding costs as well as capital gains. As such, it should be recognised that the returns to the trading strategies considered in Chapters 6 and 7 will be excess returns. This is in contrast to many prior studies in this field, which have considered abnormal returns calculated using one of the models of expected returns discussed in Section 3.3.2.

This analysis does not take into account bid-ask spreads or other transactions costs and also assumes that it is possible for investors to short stocks without excessive cost or other penalty. Where results rely on returns from short positions in stock market indices, these are explicitly highlighted and the potential impact of any restrictions on short selling is considered.

5.6 Descriptive Statistics

Tables 5.1, 5.2, and 5.3 present basic descriptive statistics for the daily price returns, total returns, and funded returns calculated for each index, whilst Appendix B reproduces the funded returns for each index in chart form.

The number of daily observations for the 14 stock market indices ranges from 2222 (Japan) to 2296 (Hong Kong and the Netherlands), with the differences in the number of observations accounted for by the different numbers of public holidays in each country.

Table 5.1 Summary Statistics: Daily Price Returns

	Number of Observations	Mean (%)	Maximum (%)	Minimum (%)	% Positive	Median (%)	Annualised Standard Deviation (%)	Skewness	Kurtosis	Jarque-Bera Statistic
Australia	2276	0.0209%	5.65%	-6.48%	51.36%	0.0236%	13.52%	-0.26	6.40	1121.4
Belgium	2277	0.0218%	6.99%	-5.14%	51.78%	0.0309%	17.01%	0.10	7.35	1795.8
Canada	2266	0.0313%	5.40%	-7.83%	53.13%	0.0635%	17.16%	-0.43	7.74	2191.4
Denmark	2279	0.0273%	5.25%	-6.22%	51.12%	0.0238%	17.02%	-0.24	5.66	696.5
France	2260	0.0266%	6.79%	-7.01%	51.46%	0.0377%	21.55%	-0.07	5.63	652.1
Germany	2269	0.0170%	7.76%	-8.11%	52.23%	0.0768%	23.77%	-0.19	6.25	1014.4
Hong Kong	2296	-0.0121%	16.35%	-12.63%	49.04%	-0.0131%	28.55%	0.38	11.97	7758.2
Italy	2286	0.0349%	7.89%	-7.60%	49.91%	0.0000%	24.45%	0.01	4.66	261.5
Japan	2222	-0.0130%	7.19%	-6.23%	47.25%	-0.0441%	20.31%	0.22	5.43	563.9
Netherlands	2296	0.0320%	7.33%	-7.56%	51.96%	0.0434%	22.26%	-0.09	6.87	1438.0
Spain	2265	0.0384%	6.54%	-7.17%	51.83%	0.0740%	23.07%	-0.05	5.28	491.7
Switzerland	2261	0.0297%	8.12%	-7.34%	52.76%	0.0603%	19.69%	-0.07	8.11	2459.4
UK	2272	0.0119%	5.04%	-5.57%	52.11%	0.0562%	17.31%	-0.16	5.55	623.6
USA	2269	0.0347%	5.47%	-6.77%	52.27%	0.0387%	18.21%	-0.04	6.34	1052.6

Table 5.2 Summary Statistics: Daily Total Returns

	Number of Observations	Mean (%)	Maximum (%)	Minimum (%)	% Positive	Median (%)	Annualised Standard Deviation (%)	Skewness	Kurtosis	Jarque-Bera Statistic
Australia	2276	0.0353%	5.66%	-6.46%	52.50%	0.0414%	13.53%	-0.26	6.39	1115.4
Belgium	2277	0.0340%	7.00%	-5.13%	53.32%	0.0455%	17.00%	0.09	7.36	1805.4
Canada	2266	0.0390%	5.41%	-7.82%	53.62%	0.0729%	17.16%	-0.44	7.74	2192.1
Denmark	2279	0.0333%	5.25%	-6.22%	51.95%	0.0292%	17.02%	-0.24	5.67	699.3
France	2260	0.0365%	6.79%	-7.00%	51.73%	0.0501%	21.55%	-0.07	5.63	651.9
Germany	2269	0.0236%	7.76%	-8.10%	52.49%	0.0820%	23.77%	-0.20	6.26	1017.1
Hong Kong	2296	0.0012%	16.37%	-12.61%	50.13%	0.0022%	28.55%	0.38	11.98	7775.6
Italy	2286	0.0428%	7.89%	-7.59%	50.70%	0.0094%	24.43%	0.01	4.66	264.0
Japan	2222	-0.0097%	7.19%	-6.23%	47.61%	-0.0413%	20.30%	0.22	5.43	566.7
Netherlands	2296	0.0422%	7.33%	-7.56%	52.96%	0.0556%	22.25%	-0.10	6.88	1442.1
Spain	2265	0.0487%	6.54%	-7.16%	52.63%	0.0852%	23.07%	-0.06	5.28	491.7
Switzerland	2261	0.0352%	7.37%	-7.12%	53.12%	0.0636%	19.36%	-0.11	7.22	1678.7
UK	2272	0.0246%	5.05%	-5.56%	52.86%	0.0699%	17.30%	-0.17	5.55	624.8
USA	2269	0.0418%	5.47%	-6.76%	52.67%	0.0480%	18.21%	-0.04	6.33	1051.2

Table 5.3 Summary Statistics: Daily Funded Returns

	Number of Observations	Mean (%)	Maximum (%)	Minimum (%)	% Positive	Median (%)	Annualised Standard Deviation (%)	Skewness	Kurtosis	Jarque-Bera Statistic
Australia	2276	0.0128%	5.65%	-6.47%	51.36%	0.0221%	13.53%	-0.26	6.41	1128.5
Belgium	2277	0.0185%	6.99%	-5.14%	52.22%	0.0308%	17.00%	0.09	7.36	1805.2
Canada	2266	0.0209%	5.40%	-7.84%	52.56%	0.0546%	17.15%	-0.44	7.75	2206.8
Denmark	2279	0.0161%	5.25%	-6.25%	50.55%	0.0139%	17.02%	-0.24	5.67	699.2
France	2260	0.0199%	6.76%	-7.02%	51.46%	0.0357%	21.55%	-0.07	5.62	650.6
Germany	2269	0.0084%	7.73%	-8.12%	52.27%	0.0669%	23.76%	-0.20	6.25	1015.3
Hong Kong	2296	-0.0164%	16.35%	-12.64%	48.87%	-0.0225%	28.56%	0.37	11.98	7767.4
Italy	2286	0.0190%	7.86%	-7.60%	49.34%	-0.0111%	24.43%	0.01	4.65	258.9
Japan	2222	-0.0121%	7.19%	-6.23%	47.52%	-0.0458%	20.30%	0.22	5.43	565.7
Netherlands	2296	0.0276%	7.32%	-7.59%	52.00%	0.0399%	22.25%	-0.10	6.88	1446.4
Spain	2265	0.0270%	6.53%	-7.17%	51.57%	0.0575%	23.07%	-0.05	5.28	491.2
Switzerland	2261	0.0268%	7.37%	-7.13%	52.59%	0.0567%	19.36%	-0.10	7.22	1679.0
UK	2272	0.0021%	5.03%	-5.58%	51.80%	0.0479%	17.30%	-0.17	5.54	623.15
USA	2269	0.0225%	5.46%	-6.81%	51.74%	0.0321%	18.20%	-0.04	6.36	1069.4

The mean daily price return and funded return is positive for all countries with the exception of Hong Kong and Japan. This reflects the strong performance of most of the stock markets considered in this study during the first 5 years of the data sample. Similarly, the mean total return, which includes dividends but does not deduct funding costs, is positive for all markets except Japan.

The maximum and minimum daily returns are very similar for price, total, and funded returns. Maximum daily returns fall in the region of 5 percent to 8 percent with the exception of Hong Kong. Minimum daily funded returns fall in the region -5 percent to -8.5 percent, again with the exception of Hong Kong.

For Hong Kong, Italy, and Japan, slightly less than 50 percent of the observed daily price and funded returns are positive; for the other 11 countries, just over 50 percent are positive. All countries have positive total returns on over 50 percent of the observations in the data, with the sole exception of Japan. For Italy, less than 50 percent of observations are positive yet the mean price return and funded return are positive, suggesting positive skewness in the data. The percentage of negative funded returns is not reproduced since, to two decimal places, this simply equates to 100 percent minus the percentage of positive funded returns (the data contains very few zero return observations).

Not surprisingly given the statistics described above, the median daily price return is positive for all countries except Hong Kong and Japan. The median daily total return is positive with the exception of Japan, and the median daily funded return is positive with the exception of Hong Kong, Italy, and Japan. For these countries, the median return is lower (more negative) than the mean return.

Tables 5.1 through 5.3 also show annualised (252 trading day) standard deviations of daily returns together with the coefficients of skewness and kurtosis and values of the Jarque-Bera (1980) test for normality.

A comparison of the mean levels of price returns, total returns, and funded returns in each data sample reveals that almost all of the daily variation in returns is driven by price changes rather than changes in dividends or interest rates. For this reason, the standard deviations, coefficients of skewness and kurtosis, and Jarque-Bera statistics calculated for price returns, total returns, and funded returns are very similar. The remainder of this section discusses the values obtained for funded returns; the same conclusions can be drawn for price returns and total returns.

The annualised (252 trading day) standard deviations of daily returns shown in tables 5.1 through 5.3 are calculated as:

$$StDev_i = \frac{\sum_{t=1}^{N}\left(R_{i,t} - \overline{R}_i\right)^2}{(N_i - 1)} \times \sqrt{252}$$

where

$StDev_i$	= 252 trading day standard deviation of daily returns over the data sample for index i
N_i	= total number of daily observations for index i
$R_{i,t}$	= daily return (price / total / funded, as appropriate) for index i on trading day t
$\overline{R}_i$	= the average daily return (price / total / funded, as appropriate) over the data sample for index i

For funded returns, the values obtained range from 13.53 percent (Australia) to 28.56 percent (Hong Kong), with most values falling in the range from 17 percent to 24 percent.

The use of the square root of time to scale the standard deviations reported in this section may be questioned on the basis that the underlying distributions of daily returns are not normal. Since the distributions of these returns are not known, the appropriate scaling rule is also unknown, and the square root of time is therefore used as an approximation in order to calculate an intuitively tractable metric across the 14 data sets. The limitations of this approach are acknowledged.

The coefficients of skewness are calculated as follows:

$$Skew_i = \frac{\sum_{t=1}^{T}\left(R_{i,t} - \overline{R}_i\right)^3}{(N_i - 1)\times Stdev_i^3}$$

where

$Skew_i$ = the skewness of daily returns over the data sample for index i

Normally-distributed data has skewness of zero. The coefficients obtained are negative in most cases, with positive skewness in daily returns obtained for only four countries (Belgium, Hong Kong, Italy and Japan).

The coefficients of kurtosis are calculated as follows:

$$Kurt_i = \frac{\sum_{t=1}^{T}\left(R_{i,t} - \overline{R}_i\right)^4}{(N_i - 1)\times Stdev_i^4}$$

where

$Kurt_i$ = the kurtosis of daily returns over the data sample for index i

Normally distributed data has kurtosis of 3.00. The coefficients of kurtosis obtained fall in the region 4.65 to 7.75 for all countries except Hong Kong, which has kurtosis of 11.98. All countries in the sample therefore display leptokurtosis (a 'fat-tailed' distribution) in daily returns.

The Jarque-Bera statistic follows a chi-square distribution with 2 degrees of freedom. A comparison of the value obtained for each index with the critical value from the chi-square distribution results in a clear rejection of the null hypothesis of normality for all fourteen time series[53]. The values obtained fall in the range between 258.9 (Italy) and 7767.4 (Hong Kong). Five countries

[53] The test statistic is based on two independent variables (skewness and kurtosis), both of which are squared. The square of a normal variable is distributed as chi-square with one degree of freedom, giving a total of two degrees of freedom for the Jarque-Bera statistic. The critical values of the chi-square distribution for a 2 tailed test with 2 degrees of freedom are 5.991 at the 5% significance level and 9.210 at the 1% significance level.

(Denmark, France, Japan, Spain, and the UK) have values in the region 490 to 700. The remaining seven values range from 1069.4 (USA) to 2206.8 (Canada).

5.7 Correlations

Table 5.4 shows the pairwise correlations between the 14 data samples based on daily funded returns. The correlations obtained from price returns and total returns are extremely similar to those for funded returns and hence are not reproduced.

In order to calculate these correlations, the data sets were cleaned in a pairwise fashion, that is to say the correlation between Italy and Spain is based on returns on those trading days where both the Spanish and Italian markets were open, the Spain/Germany correlation is based on days where data is available for both Spain and Germany, and so on.

It is apparent from the correlation coefficients in Table 5.4 that the fourteen data samples can be split into 3 natural groups, with each country having higher correlations with members of its own group than with other countries.

The first group, consisting of the continental European countries (Belgium, Denmark, France, Germany, Italy, the Netherlands, Spain, and Switzerland) plus the UK has relatively high correlations between daily stock market returns, ranging from 49.1% (Denmark/Italy) to 83.4% (France/Netherlands). Australia, Hong Kong, and Japan have higher correlations with each other than with any other countries, ranging from 36.8% (Hong Kong/Japan) to 47.5% (Australia/Japan). Similarly, Canada and the USA have a higher correlation with each other (70.1%) than with other countries.

Table 5.4 Pairwise Correlations between Data Samples

	Belgium	Canada	Denmark	France	Germany	Hong Kong	Italy	Japan	Netherlands	Spain	Switzerland	UK	USA
Australia	29.6%	18.0%	30.3%	25.2%	28.1%	47.5%	21.4%	40.8%	29.1%	24.8%	26.6%	26.4%	10.1%
Belgium		35.8%	51.5%	69.2%	65.7%	25.6%	55.8%	21.9%	73.4%	61.4%	69.4%	64.9%	38.1%
Canada			31.3%	44.7%	47.7%	18.9%	36.4%	16.1%	41.4%	42.3%	40.0%	43.1%	70.1%
Denmark				56.4%	56.4%	31.8%	49.1%	24.6%	58.1%	53.6%	55.7%	54.5%	25.9%
France					77.1%	28.9%	71.9%	23.1%	83.4%	78.6%	75.3%	80.1%	43.1%
Germany						32.7%	64.5%	22.0%	77.0%	69.4%	73.0%	70.8%	46.4%
Hong Kong							23.6%	36.8%	30.5%	27.1%	28.0%	31.6%	12.3%
Italy								18.8%	68.2%	69.4%	65.0%	65.0%	34.9%
Japan									23.7%	19.5%	22.7%	23.6%	11.1%
Netherlands										74.3%	78.0%	78.8%	40.8%
Spain											69.9%	70.4%	40.3%
Switzerland												73.2%	39.6%
UK													42.6%

5.8 Autocorrelations

Table 5.5 shows the autocorrelation coefficients of daily funded returns for lags of 1, 2, 3, 4, 5, 10, 21, 42, 63, 126, and 252 trading days, scaled to fall in the range –100 to +100.

The h-lag autocorrelation for each index i is calculated as:

$$Autocorrelation_{i,h} = \frac{\sum_{t=1}^{N-h}\left(FR_{i,t} - \overline{FR_i}\right)\left(FR_{i,t+h} - \overline{FR_i}\right)}{\sum_{t=1}^{N}\left(FR_{i,t} - \overline{FR_i}\right)^2} \times 100$$

where

$Autocorrelation_{i,h}$ = the autocorrelation coefficient calculated for index i based on a lag of h trading days

Table 5.5 Autocorrelations of Daily Funded Returns

	Lag Length (trading days)										
	1	2	3	4	5	10	21	42	63	126	252
Australia	0.92	-3.65	2.38	-4.52	-3.48	-1.97	-0.97	0.89	-1.51	1.73	-1.52
Belgium	16.74	0.34	-6.66	0.18	-5.89	0.02	-1.06	-2.21	1.37	0.59	0.90
Canada	6.77	-3.75	1.27	-5.86	-0.16	0.93	-3.89	-7.68	-0.08	-0.25	0.28
Denmark	5.36	-2.33	-2.78	3.38	-1.24	0.08	-4.00	-2.93	0.70	-1.54	0.16
France	3.15	-2.81	-5.74	1.43	-4.62	-2.13	0.39	0.58	2.35	0.93	4.57
Germany	-0.87	-3.33	-1.13	3.91	-2.03	-3.25	-0.98	-1.69	0.18	-0.29	3.21
Hong Kong	5.04	-4.30	7.64	-3.04	-3.23	1.84	0.28	1.23	1.21	1.48	-0.85
Italy	1.59	1.19	-0.54	5.11	-4.06	2.68	-0.60	-1.26	3.62	-1.76	4.60
Japan	3.45	-6.04	-0.59	-6.39	-3.58	1.12	-2.15	0.70	-0.62	0.34	-1.36
Netherlands	0.49	-4.19	-6.53	2.84	-4.75	-0.38	0.53	-0.31	6.98	0.45	0.04
Spain	4.22	-5.55	-2.99	1.32	-2.48	-0.47	0.07	1.36	1.88	-2.81	-1.81
Switzerland	4.86	-1.26	-1.73	1.43	-6.53	0.58	0.88	0.16	-0.46	0.89	2.77
UK	2.36	-6.15	-7.61	1.34	-3.00	-4.80	-3.59	-1.45	1.64	-0.03	1.44
USA	0.73	-3.46	-3.27	0.12	-4.03	2.39	-2.89	-2.99	2.01	-0.16	-1.89

All figures are percentage values. 0.92 = 0.92% and so on

The autocorrelation coefficients calculated are generally small. With a time lag of one trading day, the coefficients range from –0.87 (Germany) to 16.74 (Hong Kong). Excluding these two countries, all values are positive and lie in the region of 0.49 to 6.77.

For a lag of two trading days, 12 of the 14 autocorrelation coefficients are negative, as are 11 coefficients for a lag of 3 trading days, 4 coefficients for a lag of 4 trading days, and all 14 coefficients for a lag of 5 trading days. Over longer horizons, no clear pattern emerges in the autocorrelation coefficients and the coefficients themselves are small.

5.9 Summary

This chapter explains the choice of the FTSE All-World Index Series as the basis for the research described in this thesis. The composition and calculation of the Index Series is explained, as is the methodology used to calculate daily returns for each country based on daily data downloaded from Datastream. Descriptive statistics are presented for each index together with the correlations between data samples, and the autocorrelation structure of data samples is also considered.

The information presented in this chapter is fundamental to the analysis conducted in the remainder of the thesis. Chapter 6 describes how the daily funded returns described in this chapter are used to consider the existence of momentum effects in the fourteen data samples. Similarly, Chapter 8 explains how daily price returns are used to examine the properties of stock market trends.

Chapter 6

Momentum Study Methodology

6.1 Introduction

This chapter describes the methodology employed in this study to identify continuation and reversal effects in the fourteen data sets described in detail in Chapter 5.

The medium-term continuation effects identified in the literature by studies such as that of Jegadeesh and Titman (1993) attribute their results to investors' underreaction to new information entering the market. Underreaction, as described in the behavioural finance literature, is very much a time series phenomenon. Investors place too little weight on new information entering the market in relation to a particular asset. As a result, prices adjust slowly towards the "full information" price, and continuation effects occur. In the model of Hong and Stein (1999), for example, new information entering the market diffuses slowly across the population of news watchers and prices gradually adjust to reflect the new information. As the price adjusts, momentum traders enter the market, pushing the price beyond the full information price. This produces the patterns of continuation and reversal in returns which are commonly referred to in the literature as underreaction and overreaction.

Previous studies of continuation and reversal effects in stock market returns typically perform a cross-sectional analysis of the returns to individual stocks. Cross-sectional studies are effectively selecting stocks in different phases of the underreaction / overreaction cycle. If the best-performing decile of stocks over a given period is taken to form a winner portfolio, for example, some of these stocks may be in the phase of underreacting to new positive information, whilst others may be in the stage of correcting an overreaction to previous negative information. There is likely to be an aggregation effect in results which may make true patterns of underreaction and overreaction difficult to isolate, and may therefore be at least partially responsible for the inconsistency in the results of previous research.

The time series methodology employed in this study allows patterns in market returns through time to be more easily identified, and may therefore shed more light on behavioural theories than a cross-sectional approach. In order to test this, suitably-specified momentum strategies are defined which will generate a buy signal following a rise in the market and a sell signal following a fall. The returns to these strategies are then tracked to assess the extent to which significant excess profits or losses are produced. This approach ensures that the results of the current study reflect the returns which would be available to a real-world investor, before considering the impact of transaction costs.

A further benefit of the time series methodology employed in the current study is that it avoids a number of important potential modelling problems. Previous research into continuation and reversal effects in stock market returns using a cross-sectional methodology may suffer from a dual hypothesis problem in that the measures of expected returns used (the market model, for example), may not reflect the true returns-generating process. In the current study, excess returns are used to measure any significant continuation and reversal effects identified in the data, and provide a measure of the actual return an investor would achieve, taking into account the returns from dividends and capital gains as well as funding costs. In addition, the trading rule profitability measure used in this study makes full use of each data sample whilst avoiding the methodological issues associated with overlapping returns in cross-sectional studies[54].

The methodology described in the remainder of this chapter is applied consistently to each of the fourteen stock markets considered. Only a small number of previous studies have applied a consistent methodology in an international study of stock market continuation and reversal effects[55], and the consistency of results across countries is in itself of value in assessing the most probable sources of any such effects discovered.

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[54] Richardson and Smith (1991) discuss in detail the advantages and limitations of the use of overlapping return observations in empirical studies.

[55] See, for example, Rouwenhorst (1998).

6.2 Momentum and Contrarian Trading Strategies

This study considers the profitability of momentum strategies on the fourteen stock market indices described in Chapter 5. Momentum strategies involve buying assets which have performed well in the past and selling those which have performed badly. If continuation is a fundamental feature of financial time series, appropriately constructed momentum trading strategies can be expected to generate positive returns over time.

Contrarian trading strategies, on the other hand, involve buying assets which have performed poorly in the past and selling those which have performed well. If reversal is a fundamental feature of financial time series, then appropriately constructed contrarian strategies can be expected to generate positive returns over time.

A contrarian strategy is the opposite of a momentum strategy. For any specific momentum trading strategy, there exists a contrarian strategy which generates exactly opposite signals. It is therefore not necessary to consider both momentum and contrarian strategies in order to assess the evidence of continuation and reversal effects in financial market returns. Whilst significantly positive momentum profits indicate continuation, significantly negative momentum profits are in themselves sufficient to indicate reversal.

This section describes the construction of the momentum strategies implemented for each of the fourteen stock market indices. In the context of a time series analysis, a momentum strategy will buy following a period of good performance and sell following a period of poor performance. The key features of a strategy that must be defined include:

1. the measure of returns used to judge 'good' and 'poor' performance
2. the time period over which the strategy judges 'good' and 'poor' performance
3. the level of returns that constitutes 'good' and 'poor' performance
4. the transaction that will be executed on receipt of a buy or sell signal

These features are discussed in the following subsections.

6.2.1 Measure of Returns used to Generate Signals

Chapter 5 describes the calculation of price returns, total returns, and funded returns for each of the data sets. Any of these three measures could be used as the appropriate measure of past returns on which to base trading signals[56]. The choice of price returns, total returns, or funded returns as the measure of past returns used to generate trading signals within a strategy depends largely on the nature of the process which is assumed to drive continuation and reversal effects in stock market returns.

For example, if continuation effects are considered to be driven by extrapolation of past price trends by investors (a symptom of representativeness), then signals based on price returns can be expected to generate the most successful results since they most closely reflect the returns generating process. Similarly, if investors extrapolate based on total returns or on the excess performance of a market over the cost of funding, then total returns or funded returns respectively may be considered the most appropriate measure on which to base signals. The process driving continuation and reversal effects in stock market returns is not known, and funded returns are therefore used both to generate trading signals and to calculate the returns to each of the momentum strategies considered in this part of the research[57].

To summarise, in this study, funded returns are used to generate signals in momentum strategies. Each strategy considers the cumulative funded return over a given past period, buying the market index if that return is high and selling the market index if it is low.

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[56] Funded returns are clearly the appropriate measure to use when calculating and comparing the profitability of momentum strategies, however.

[57] The analysis described in this chapter and in Chapter 7 was repeated using price returns and total returns, rather than funded returns, as the measure of past returns on which signals are based. The results, which are consistent with those based on funded returns, are reproduced in Appendix D (price returns) and Appendix E (total returns). Chapter 7 discusses in detail the results obtained using signals based on funded returns.

6.2.2 Length of Price History used to Generate Signals

In this study, a range of momentum strategies is considered for each stock market index. Strategies are differentiated based on the period over which market positions are held. Eleven holding periods are considered ranging from 1 to 252 trading days, as follows:

1 trading day	
2 trading days	
3 trading days	
4 trading days	
5 trading days	(analogous to 1 week)
10 trading days	(analogous to 2 weeks)
21 trading days	(analogous to 1 month)
42 trading days	(analogous to 2 months)
63 trading days	(analogous to 3 months)
126 trading days	(analogous to 6 months)
252 trading days	(analogous to 12 months)

A total of eleven strategies is therefore considered for each of the 14 stock markets which are the focus of this study.

In each case, the length of prior price history used to generate trading signals is the same as the holding period of the strategy. A strategy with a holding period of 5 trading days, for example, generates signals based on the funded return over the previous 5 trading days. Once transactions are entered into, they are held for the specified horizon regardless of actual price movements in the interim. That is to say, no stop-loss mechanism is incorporated into the simple strategies considered.

6.2.3 Level of Returns required to Generate Signals

Previous studies using cross-sectional data samples have tended to form 'winner' portfolios based on the top-performing decile of stocks and 'loser' portfolios based on the worst-performing decile of stocks.

In a time series scenario, this might translate to the strategy generating a buy signal on 10 percent of decision days within the data sample and a sell signal on a further 10 percent of decision days. Given that each strategy is only permitted to generate signals based on the available information at the time, it will not be known whether, on any decision day, the previous market move is sufficiently large to place it in the top or bottom 10 percent. A hurdle rate must therefore be set against which prior returns are evaluated.

Some previous studies into returns following large short-term price changes have used hurdle rates. Howe (1986) considers CRSP stocks with one-week price changes of 50 percent or more, for example, whilst Bremer and Sweeney (1991) consider returns following one-day abnormal price declines of 10 percent or more in Fortune 500 stocks. Fixed hurdle rates do not provide a "level playing field" on which to compare the results from markets with potentially different volatility, however. In volatile markets, prices might reasonably be expected to move further in percentage terms before a transaction is initiated than would be the case in less volatile markets. In addition, market volatility changes over time, hence the effective level of any fixed hurdle rate will also fluctuate over time through each data sample.

The current study therefore defines a hurdle rate based on the standard deviation of the underlying price series. For consistency with previous research using cross-sectional data, an appropriate frequency of signals is taken to be 10 percent of decision days. If daily price changes were normally distributed then a hurdle rate of approximately 1.28 times the standard deviation of the underlying return series should generate buy/sell signals 10 percent of the time respectively[58].

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[58] This is somewhat simplistic given that the null hypothesis of normality in daily returns was rejected using the Jarque-Bera skewness-kurtosis test (see Chapter 5 for details).

For the purposes of calculation, the strategy estimates the standard deviation of the underlying funded returns using the previous twelve months' data. This is then scaled to the appropriate number of business days (multiplied by square root of number of days) and multiplied by 1.28 to find the appropriate percentage hurdle rate to apply. The purpose of the hurdle rate is to ensure that a small subset of periods are chosen from each data sample representing periods of particularly high and particularly low excess returns. The rejection of the null hypothesis of normality in funded returns for each data sample, described in Chapter 5, is acknowledged as a potential issue in the use of the square root of time to scale standard deviations.

The actual funded return over the appropriate time period is then calculated. If this is greater than the hurdle, a buy signal is generated. If it is lower than the negative of the hurdle, a sell signal is generated.

For example, if the standard deviation of daily funded returns over the previous 12 months is 0.65 percent, the investor will buy under the 5 day strategy if the total funded return over the previous 5 trading days exceeds 1.86 percent (0.65 percent $\times \sqrt{5} \times 1.28$) and sell if the total funded return over the previous 5 trading days is lower than −1.86%.

6.2.4 Transactions Executed based on Signals

All transactions entered into by each of the 154 momentum trading strategies considered in this study (11 strategies for each of the 14 stock markets) are deemed to occur at the market close on the day the signal is generated. This is by definition the case since the data used in the construction of each strategy is closing price data. All transactions occur at the closing price obtained from Datastream, and no bid-ask spread or other transactions costs are taken into account.

There are three main ways in which a strategy could be set up to take advantage of the buy and sell signals generated on the basis of past performance as described in the preceding sections:

1. a strategy could buy or sell a fixed number of units of the index in each transaction. This is akin to a strategy which trades a single stock buying

or selling 1000 shares in each transaction, for example. The main disadvantage of this approach is that transactions are larger in monetary terms when prices are high than when prices are low. The level of risk undertaken by the strategy at any point in time becomes dependent on the level of the index, which may in itself influence the results obtained.

2. a strategy could start with a fixed monetary value and reinvest the proceeds of each transaction into the next. For example, a strategy with a starting capital of £100 would buy or sell units of the index with a value of £100 for the first transaction. If a loss of £10 is made on the first transaction, the second transaction would be for a value of £90, and so on. The disadvantage of this approach is that cumulative returns over the data sample as a whole are highly influenced by returns to the first few transactions. If the first few transactions are loss-making, for example, remaining transactions will be small and will have only a limited impact on overall cumulative returns even if they prove highly profitable in percentage terms.

3. a strategy could buy or sell units in the index with a fixed currency value for each transaction. This is the approach used in this study. Each transaction is the same size in monetary value rather than in terms of units of the index as in the first alternative. The main advantage of this approach is that a given percentage return generates the same monetary gain or loss regardless of the actual level of the relevant stock market index.

Once transactions have been initiated, they are held for the appropriate length of time (1, 2, 3, 4, 5, 10, 21, 42, 63, 126, or 252 trading days) based on the specification of the strategy, regardless of the performance of the market over this period. That is to say, no new signals are generated by the strategies whilst another position is being held. Similarly, transactions are not rebalanced during the holding period.

Consider the example of a 5 trading-day strategy with a monetary value of £1 million per transaction for which a buy signal is generated on trading day t. The strategy buys the index at the closing price of 5000 on trading day t, thus buying 200 units of the index. If the market falls substantially over the period (t, t+5), the strategy will not generate a sell signal whilst it is holding a position in the market (although a sell signal may be likely on trading day t+5 when the current position expires). The monetary value of the 200 units of the index held will fluctuate over the 5 days for which the position is held since no rebalancing takes place[59].

6.3 Calculation of Returns

The calculation of the return for each transaction entered into for the 154 strategies considered in the current study is carried out on the basis of the daily funded returns described in Chapter 5[60]. These daily returns must be cumulated to produce returns over longer periods (2, 3, 4, 5, 10, 21, 42, 63, 126, or 252 trading days, depending on the strategy considered), taking into account that no rebalancing takes place during the holding period.

Returns are calculated in two ways. The first enables the total return to each transaction to be easily calculated. In the second, returns are calculated daily for each strategy, thus providing an analogous measure to the mark-to-market profit accruing to an investor each day. These two measures produce the same total profit or loss for each transaction and for each data sample as a whole; the daily profit figures are calculated for ease of compiling annual profit figures for each strategy, as described later in this Chapter.

6.3.1 Transaction Profit and Loss

Recalling from Chapter 5 that the funded return on each trading day in the data sample is calculated as:

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[59] This is in contrast to some cross-sectional methodologies which imply daily or monthly rebalancing.

[60] Appendices D and E reproduce the results of the current analysis using price returns and total returns as the measure of past returns used to generate trading signals. This does not affect the use of funded returns in calculating the performance of these strategies, and the description provided in this section of the calculation of returns is directly applicable to the strategies discussed in the appendices.

$$FR_{i,t} = \frac{RI_t - RI_{t-1}}{RI_{t-1}} - 1 - \left(r_{i,t-1} \times \frac{calendardays_{i,t-1,t}}{basis_i} \right)$$

where

$FR_{i,t}$ = funded return for index i on trading day t

$RI_{i,t}$ = total return index for index i on trading day t

$r_{i,t-1}$ = closing overnight domestic currency interest rate for index i on trading day t-1

$calendardays_{i,t-1,t}$ = number of calendar days from trading day t-1 to trading day t for index i

$basis_i$ = interest rate basis for money market rates in the domestic currency of index i

The transaction profit for each unit of transaction size for index i strategy j based on an x-trading day strategy entered into at the closing price on trading day t is then

$$TP_{i,j,t,t+x} = \prod_{n=1}^{n=x} \left(1 + FR_{t+n}\right) - 1$$

The transaction profit for a 5 trading day strategy initiated on day t, for example, is a function of the funded return on trading days t+1 (which is based on the return from the close on trading day t to the close on trading day t+1), t+2, t+3, t+4, and t+5. Note that since the profit is calculated per unit of transaction size, this is equivalent to a percentage return.

A key assumption of this method of calculating holding period returns is that investors do not fund the entire transaction at initiation of the position, but fund on a rolling basis each trading day.

The cumulative profit for each strategy is simply the sum of the profit or loss for each individual transaction entered into by that strategy. In practice, interest would be earned on positive returns to transactions, and further funding costs would become due on negative returns. These returns to realised profits during the period covered by the data are not taken into account in the current study[61].

6.3.2 Daily Profit and Loss

For the purposes of the analysis described in the remainder of this chapter, the returns to each strategy are also calculated for each trading day in the data samples. This enables the returns to "incomplete" transactions to be included in the analysis. In this way, the results reported for strategies with different holding periods cover the same amount of data. In addition, reporting profits daily enables the profitability of trading strategies over each calendar year in the data samples to be calculated, allowing an examination of the consistency of momentum strategy profitability over time.

The reported profit per currency unit of transaction size on each trading day in the data sample is zero for all trading days on which a strategy does not hold a market position. For the first day on which any market position is held, the daily profit is simply the funded return already calculated for that day. For all other days, the reported profit is calculated based on the transaction profit to date for the current transaction and the transaction profit to date at the close on the previous day[62].

The daily profit on the k^{th} trading day of a position entered into at the closing price on day t and maturing at the close on day t+x is then

$$DP_{i,j,k,t,t+x} = TP_{i,j,t,t+k} - TP_{i,j,t,t+k-1}$$

and

$$TP_{i,j,t,t+x} = \sum_{n=1}^{x} DP_{i,j,k,t,t+x}$$

[61] The reason for this is the difficulty of including such funding costs in the calculation of returns based on the 4999 bootstrap time series for each strategy.

[62] Within the context of this study, a loss is simply a negative profit and the text therefore refers to profits throughout.

For example, the daily profit on the second day of a transaction initiated on day t for the 5 trading day strategy, is calculated by subtracting the profit over the first day of the transaction from that calculated over the first two days.

Summing the daily profits reported for each trading day covered by a given transaction simply gives the total transaction profit described in the previous section. The daily profits can be considered as analogous to a simple mark-to-market return for each trading day in the data sample.

For example, consider a 5 trading day transaction with funded returns calculated for days t+1 through t+5 of 1.00 percent, 0.73 percent, -0.50 percent, -0.80 percent, and 1.22 percent.

The transaction profit is (1.0100 × 1.0073 × 0.9950 × 0.9920 × 1.0122) - 1 or 0.0164 per currency unit of transaction size (rounded to 4 decimal places). Transaction profits to date for the first 2, 3, and 4 trading days of the strategy can be calculated in the same way. These are reproduced in Table 6.1.

Table 6.1 Calculation of Transaction Profit and Daily Profit

Trading Day	Funded Return	Transaction Profit to Date	Daily Profit
t+1	1.00%	1.00%	1.00%
t+2	0.73%	1.74% (=1.0100 x 1.0073 - 1)	0.74% (=1.74% - 1.00%)
t+3	-0.50%	1.23% (=1.0100 x 1.0073 x 0.9950 - 1)	-0.51% (=1.23% - 1.00% - 0.74%)
t+4	-0.80%	0.42% (=1.0100 x 1.0073 x 0.9950 x 0.9920 - 1)	-0.81% (=1.23% - 1.00% - 0.74% + 0.51%)
t+5	1.22%	1.64% (=1.0100 x 1.0073 x 0.9950 x 0.9920 x 1.0122- 1)	1.23% (=1.23% - 1.00% - 0.74% + 0.51% + 0.81%)
		Overall Transaction Profit: 1.64%	Total Daily Profit: 1.64%

For trading day t+1, the reported daily profit is 1.00 percent, the same as the funded return. For trading day t+2, the funded return on trading day t+1 has already been reported. The transaction profit produced so far by the strategy is 1.74 percent, hence the daily profit remaining to be reported on trading day t+2 is 0.74 percent. For day t+3, the transaction profit to date is 1.23 percent, or which 1.74 percent has already been reported, hence the reported daily profit for day t+3 is -0.51 percent, and so on.

All strategies transact over the period 1st January 1995 through 31st December 2002. Data from 1994 is used to calculate the past returns on which to generate signals during 1995 and to calculate initial values for the standard deviation of returns over the past 12 months. Transactions need not be completed by the end of the data sample. If the 252 trading day strategy, for example, obtains a buy signal on 1st September 2002, then only the first four months' of returns for the final transaction will be included in the cumulative profit over the data sample.

The following example summarises using the example of the 5 trading-day strategy. Similar examples can easily be constructed for the other ten strategies considered for each stock market index.

On the first available trading day in the data set (the first trading day in 1995), the strategy considers the funded return over the previous 5 trading days. The trigger level for initiating a position is calculated as 1.28 times the standard deviation of daily funded returns over the previous 12 months. A position is initiated only if the absolute value of the funded return over the past 5 days exceeds the trigger level. If it does not, no trade is initiated and the same calculation is performed on the following trading day and each subsequent trading day until a signal is received.

Once a signal is received (that is to say the absolute value of the funded return over the previous 5 trading days exceeds the trigger level), the strategy enters into a market position. If the funded return is positive, the strategy goes long the market in a notional amount of one unit of currency. If the return is negative, the strategy goes short the market in the same notional amount. The strategy is therefore simply following the recent market trend.

Once initiated, the position will be held for 5 days regardless of market movements in the interim, and no additional positions will be entered into during these 5 days. On each trading day within the data samples, the daily profit to the position is calculated with reference to the price change, dividend return and cost of funding the position for that day. Positions are not rebalanced over the 5 day holding period.

6.4 Performance Measures

As discussed in Section 6.1, significant positive momentum strategy profitability is indicative of continuation effects within the data sample. Similarly, findings of significant negative profits to momentum strategies indicate price reversal.

If any one of the alternative explanations discussed in Chapters 2 and 3, or indeed a combination of these explanations, drives systematic continuation and reversal effects in stock market returns, then it is reasonable to expect that the performance of any particular momentum strategy (the 2 trading day strategy for example) will be broadly consistent across markets and across time. A substantial lack of consistency in the results would be supportive of chance, or another as yet unidentified factor, as the most probable driving force behind patterns in stock market returns.

Perhaps the most important indicator of the performance of any momentum strategy is its profitability. For each strategy, cumulative returns across the data sample are calculated covering the eight year period from January 1995 through December 2002 by summing the daily profits generated by the strategy over the data sample[63]. In addition, cumulative returns are calculated by calendar year. Mean transaction profits are also reported and reflect the average profitability of each individual transaction entered into by a particular strategy. The cumulative return by year enables the consistency of each strategy's performance to be assessed[64]. The mean transaction profit across

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[63] These daily profits are calculated per unit of currency invested and are therefore analogous to percentage returns.

[64] This is important since many professional investors are assessed on annual returns. Within this context, annual returns should ideally be consistently positive, with no large

the data sample enables an assessment of whether a strategy is likely to be worthwhile after allowing for transaction costs.

The profitability measures described above are also reported separately for buy and sell transactions. Some types of investor may be precluded from taking short stock market positions, for example pension funds in the UK, whilst others, such as individual investors, may not be in a position to short-sell stocks on a cost-effective basis. For these investors, only buy-side returns may be relevant. Additionally, the relative contribution of long and short positions to total profitability may be important in assessing the potential driving forces behind any significant findings.

Some observers have argued that significant momentum strategy profitability may simply compensate investors for the increased risk inherent to such strategies. Whilst the cumulative returns to each strategy by year provide some indication of the consistency of a strategy's performance, more formal measures are also reported in the form of the standard deviation of daily strategy returns and the Sharpe ratio of each strategy over the data sample.

The Sharpe ratio, developed in the literature by Sharpe (1966 and 1975), is a performance measure for hedge funds based on the ratio of profitability (mean return) to risk (variance of returns). The Sharpe ratio is calculated as

$$S_{i,j} = \sqrt{252} \times \frac{\overline{DP_{i,j}}}{\sigma_{DP,i,j}}$$

where

$S_{i,j}$ = the Annualised Sharpe ratio for index i, strategy j

$\overline{DP}_{i,j}$ = the mean daily profit for index i strategy j, calculated as

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drawdowns reported. In this study, annual returns are calculated based on the calendar year. As Birniyi (1993, p27) says,

> "Fact is that most seasonal tendencies are only 'statistically significant' – meaning you can write a dissertation on the subject, but don't try to make money on it ... Institutions, unlike most of you, close their books at the end of the year and tally up their gains and losses so they can prepare their report cards".

$$\overline{DP_{i,j}} = \frac{\sum_{t=1}^{N} DP_{i,j,1,t,t+1}}{N_i}$$

N_i = the number of daily funded returns in the data sample for index i

$\sigma_{DP,i,j}$ = the standard deviation of daily profits for index i strategy j, calculated as

$$\sigma_{DP,i,j} = \sqrt{\frac{\sum_{t=1}^{N}\left(DP_{i,j,1,t,t+1} - \overline{DP}_{i,j}\right)^2}{N_i - 1}}$$

Profitable strategies will have positive Sharpe ratios and vice versa for unprofitable strategies (although these reflect positive Sharpe ratios to the equivalent contrarian strategy). A higher Sharpe ratio indicates a higher return per unit of risk.

6.5 Statistical Inference

The trading strategy methodology used in this study enables some insight to be drawn as to the availability of excess profits to momentum strategies, and therefore the existence of continuation and reversal effects in the markets and over the time periods considered.

Appropriate statistical tests are required to assess the significance of any momentum profits identified. Traditional parametric methods of statistical inference require a knowledge of the distribution of the test statistic, which is not available for many of the performance measures described in Section 6.5 such as the cumulative returns to, and Sharpe ratios of, momentum trading strategies. The Central Limit Theorem provides that the distribution of a sample mean is normal so long as the sample size is large or the underlying variable is normally distributed, and the mean and standard distribution of the sample provide unbiased point estimates of the population mean and standard deviation. These conditions are not typically met for the test statistics calculated in this part of the research.

A non-parametric bootstrap approach is therefore used to assess the significance of the performance measures described in the previous section. The bootstrap methodology employed in this study not only permits the calculation of reliable significance levels for momentum strategy returns but may also provide an insight into the potential sources of such returns. Section 6.5.1 provides a background to bootstrap methodologies, whilst Section 6.5.2 describes the specific approach used in this study.

6.5.1 Bootstrap Methodologies

Traditional parametric approaches to statistical inference assume that the sampling distribution of the statistic in which the researcher is interested is known. The sampling distribution of a statistic is simply the distribution of the values of that statistic obtained by drawing an infinite number of samples of a given size from the population.

For a parametric approach to provide accurate results, both the shape and location of the sampling distribution must be specified. These variables are known for a number of the most commonly employed statistics such as ordinary least squares regression coefficients. Other statistics in which researchers may be interested, such as the difference in median between two samples, have sampling distributions which are not known, and the assumptions of the parametric approach are thus violated. This is the case for many of the trading rule profitability statistics which form the basis of this study.

The implications of using parametric statistics in situations where the assumptions of the parametric approach are violated are that the accuracy of any rejection or non-rejection of the null hypothesis may be compromised. In addition, the probability of making Type I errors (rejection of a true hypothesis) and Type II errors (failure to reject a false hypothesis) will be unknown in advance. Non-parametric methods are often preferred in such situations.

The bootstrap methodology is a non-parametric approach to statistical inference based on the analogy between a sample and the population from which it is drawn. Where the sampling distribution of the statistic under consideration is unknown, it may be preferable to base statistical analysis on the information contained in the known data sample rather than making potentially incorrect assumptions about the possible shape and location of the sampling distribution.

The bootstrap methodology involves resampling the available data, with replacement, many times to generate an empirical estimate of the sampling distribution of the statistic in which the researcher is interested. This empirical sampling distribution can be used for the construction of confidence intervals and for hypothesis testing in much the same way as for parametric methods. Whereas the relevant cut-off points for parametric methods are typically taken from tables based on the assumed sampling distribution, however, the bootstrap methodology bases confidence levels on the empirical sampling distribution.

The theoretical justification for the bootstrap methodology rests on two key results. As the sample size approaches the population size, the empirical sampling distribution converges to the population sampling distribution (Bickel and Freedman, 1981). Similarly, so long as the sample size is large enough to permit this, as the number of resamples increases the empirical sampling distribution converges to the population sampling distribution (Babu and Singh, 1983). The success of the bootstrap methodology therefore rests on ensuring that the sample size and number of resamples are sufficiently large to ensure convergence. Mooney and Duval (1993) suggest a sample size of 30-50 and 1000 resamples as being adequate in most cases[65].

The most obvious potential difficulty arising from the use of the bootstrap methodology occurs where the data sample is not representative of the population from which it is drawn. In such cases, the empirical sampling distribution obtained from the bootstrap will not converge to the population sampling distribution regardless of the number of resamples. In financial markets research, this could occur where the original data covers a short period of extreme market behaviour. This study employs a consistent methodology across data covering nine years and fourteen major stock markets in an attempt to control for the "bad sample" problem. Although stock markets have been shown to be positively correlated in the short term, as the

[65] In this study, 4999 resamples are taken for each strategy based on sample sizes of between 2222 and 2296 observations.

descriptive statistics in Chapter 5 and charts in Appendix B suggest, the actual paths taken by the various markets over the period of the data samples have been quite varied. Any specific circumstances which may contribute to a bad sample problem are unlikely to affect all markets, hence consistency in results will tend to indicate that no 'bad data sample' problem has occurred.

6.5.2 Methodology used in this Study

In this part of the research, trading rules are devised to profit from any continuation and reversal patterns present in the returns of 14 major stock market indices.

Simple bootstrap methodologies, such as that used in this study, do not preserve the serial correlation structure of the underlying returns data. This has proved problematic for some applications of bootstrap methodologies to time series data, leading to the more recent development of new bootstrap approaches which aim to preserve serial correlation in the data, such as the sieve bootstrap (see, for example, Bühlmann, 1997) and block bootstrap (see, for example, Gorener et al, 2001).

The simple bootstrap approach employed in the current study destroys serial correlation in the data whilst retaining the distributional properties of the original data sample. Continuation effects may be observed empirically as a simple result of skewness in the distribution of daily returns within a data sample. In a sample characterised by predominantly rising prices, for example, momentum profits will occur as a simple result of the nature of the data (positive returns will tend to be followed by further positive returns). The bootstrap, which shares the same distribution of funded returns as the original data, will show a similar degree of momentum profits. Where returns are generated by serial correlation in the data rather than the distribution of the underlying data sample, on the other hand, then differences will occur between the two values since the serial correlation properties of the data sample are destroyed by the bootstrap process. Any significant difference between the profits calculated using the original data and the bootstrapped value can therefore be interpreted as indicating a significant contribution of serial correlation in driving the observed returns.

If no significant serial correlation effects are present in the original data which have an important impact on momentum strategy profitability (for example, if momentum profits in the original data occur purely by chance), therefore, then there will be no reason to expect that the bootstrap test statistics will be significantly different from the statistics based on the original data and the profit measures from the original data will not prove statistically significant based on the bootstrap test. Where serial correlation in returns does drive momentum strategy profitability, these profits can be expected to disappear when the same strategy is applied to the bootstrap data and the bootstrap test indicates that the results from the original data are statistically significant.

The approach employed in this study creates 4999 bootstrap runs for each data sample by sampling with replacement from the daily funded returns in the original data. Any individual bootstrap run may contain a given point in the original data once, more than once, or not at all. The descriptive statistics for any single bootstrap run may therefore be different to those for the original data, although the mean value over a large number of bootstrap runs converges to the parameters of the original data and the empirical sampling distribution therefore preserves the characteristics of returns presented in Tables 5.1 through 5.3 and described in Section 5.6.

Each of the 4999 bootstrap runs for each strategy is used to calculate performance measures in exactly the same way as for the original data. This gives, for each of the 154 combinations of index and momentum strategy, 4999 sets of performance measures.

Mackinnon (2002) suggests that the number of bootstrap simulations B be chosen such that α (B+1) is an integer for all levels of α considered. The value of Mackinnon's approach to choosing the number of bootstrap simulations is that critical values from the empirical distribution correspond exactly with individual observations from the empirical sampling distribution, removing the need for interpolation. For each performance measure, the 4999 bootstrap values form an empirical sampling distribution to which the corresponding value from the original data is compared. Using the percentile method of deriving confidence intervals from empirical sampling distributions, the 99 percent confidence interval of a statistic is its value at the 99.5th and 0.5th percentiles of the sampling distribution. In this study, two-tailed tests are used at the 5 percent and 1 percent significance levels, giving α levels of 0.005, 0.025, 0.975, and 0.995. With B of 4999, this gives values of α (B+1) of 25, 125, 4875, and 4975[66]. These values can be easily looked up from the 4999 bootstrap runs and used to test the hypothesis that the value from the original data is taken from the empirical sampling distribution. That is to say, serial correlation in returns does not contribute significantly to momentum strategy profitability. If the profitability of a strategy is significantly different from the mean profitability from the bootstrap, we conclude that serial correlation is an important driving force behind momentum strategy profits.

6.6 Summary

This chapter describes the methodology employed in this study to consider the existence of continuation and reversal effects in stock market returns. The returns to 11 different strategies are considered for each of the 14 stock market indices described in Chapter 5, and a range of performance measures calculated for each. A non-parametric bootstrap approach is used to assess the significance of the test statistics calculated for each strategy.

Chapter 7 presents the results of the analysis described in this chapter.

[66] This contrasts with a choice of 5000 bootstrap runs, for example, where the required test values fall between observations in the empirical sampling distribution and must be estimated by interpolation.

Chapter 7

Momentum Study Results

7.1 Introduction

This chapter presents the results of the analysis described in Chapter 6 of the profitability of momentum strategies in the 14 stock market data sets introduced in Chapter 5.

The principal aim of this part of the research is to identify any significant continuation and reversal patterns in the time series of 14 major stock market indices. The second part of the research, described in Chapters 8 and 9, then goes on to examine the potential sources of such effects by conducting an analysis of the statistical properties of trends within the data.

Section 7.2 describes the cumulative returns to each of the 154 strategies over each data sample. Section 7.3 considers the pattern of returns across calendar years. Section 7.4 examines the contribution of long and short positions, both in terms of their contribution to the cumulative profits introduced in Section 7.2 and in terms of their consistency throughout the data samples. Section 7.5 moves on to consider the mean transaction profit achieved by each strategy. Sections 7.6 and 7.7 discuss the standard deviation of daily profits and the Sharpe ratios for each strategy. Section 7.8 concludes.

7.2 Cumulative Returns

Table 7.1 presents the cumulative returns across the 8 years of data of the 11 momentum trading strategies on each of the 14 stock market data sets. A total of 154 cumulative return values are therefore reported. It is recognised that in reporting 154 values for each test statistic, a multiple comparison issue may occur in that the significance level of individual statistical tests may understate the overall experimental error rate.

The returns shown are from strategies which generate trading signals based on daily funded returns and are in the form of a percentage of the monetary value of each transaction. For example, the one trading day momentum strategy in the Australian market implemented with a transaction size of AUD 10 million would produce a cumulative profit of 11.03% or AUD 1.103 million over the 8 year period from January 1995 through December 2002.

As discussed in Section 6.2.1, momentum trading strategies may use funded returns, price returns, or total returns as the appropriate measure of past returns on which to base trading signals. In the current study, the same broad pattern of returns is obtained for all three measures. As a result, this chapter describes in detail the results for the 154 strategies which generate signals based on funded returns (11 strategies for each of the 14 data sets); the equivalent results using price returns and total returns can be obtained from Appendices C and D respectively and the conclusions drawn in this chapter and subsequent chapters remain valid for each.

The second figure provided for each strategy is the mean cumulative return generated by the 4999 bootstrap runs. The calculation methodology is exactly the same as that employed for the original data, but the strategy is run over 4999 new data series constructed by resampling with replacement the daily funded returns from the original data. This procedure is described in Section 6.5.

The one trading day strategy generates positive cumulative returns for all countries with the exception of Germany, where a negative cumulative return of –11.42% is recorded. Positive returns range from 11.03% (Australia) to 128.36% (Belgium). These returns reflect the excess returns over and above the cost of funding. The bootstrap cumulative returns are small in all cases, ranging from –1.74% (Switzerland) through 1.83% (the Netherlands) and are statistically significant in only four cases for the one day trading strategy (at the 1% level for Belgium and Canada, and at the 5% level for Hong Kong and Switzerland), reflecting the wide dispersion of the bootstrap returns.

As discussed in Chapter 6, the bootstrap values shown in the tables in this chapter are the mean values of the relevant statistic across 4999 time series generated by sampling with replacement from the daily funded returns calculated for the original data.

The cumulative returns for the 2 trading day strategies differ markedly from those of the 1 trading day strategies. The cumulative return is positive for only 6 of the 14 countries considered, ranging from –74.61% (the Netherlands) to 80.72% (Belgium). Only the return for Belgium is significantly different from the bootstrap, at the 1% significance level. This pattern of returns continues over the 3 day, 4 day, and 5 day strategies where only 4, 4, and 5 of the 14 data sets generate positive cumulative returns respectively and very few results are statistically significant. The lack of significant excess returns to these strategies suggests that the positive excess returns observed to the 1 trading day strategies may be due to nonsynchronous trading, which can introduce a spurious positive bias to the very short-term serial correlation behaviour of stock market indices as discussed in Section 3.2.2.

For the 10 through 252 trading day strategies, 61 of the 84 strategies produce positive cumulative returns, with 6 of the 23 negative cumulative returns contributed by the Australian data alone. Six strategies produce cumulative returns that are significantly different to the bootstrap at the 1% level, and a further 9 strategies at the 5% level.

Overall, 21 of the 154 strategies considered produce statistically significant cumulative returns based on the two-tailed bootstrap test. All of these returns are significantly larger than the bootstrap returns. There are no strategies which produce cumulative returns which are significantly lower than the bootstrap values. No clear pattern is observed in these significant positive excess returns, however, either in terms of a significant profitability of specific strategy specifications or strategies implemented in specific stock markets.

Table 7.1 Cumulative Returns

PANEL A: 1-10 Trading Day Strategies	**1**	**2**	**3**	**4**	**5**	**10**
Australia	11.03% *-0.51%*	-21.50% *0.13%*	-21.76% *-0.67%*	-43.44% *-5.69%*	-29.17% *-6.16%*	-48.47% *-3.75%*
Belgium	128.36% *-0.71%* SIG 1%	80.72% *0.50%* SIG 1%	27.23% *-0.16%*	21.44% *-1.17%*	-20.33% *5.03%*	8.59% *10.98%*
Canada	76.86% *-0.32%* SIG 1%	21.03% *-0.38%*	14.42% *0.79%*	-13.82% *0.73%*	9.37% *2.11%*	46.90% *1.83%*
Denmark	35.99% *0.46%*	4.00% *-0.08%*	3.42% *-1.29%*	40.11% *-2.44%*	49.71% *-0.71%*	33.37% *0.82%*
France	21.37% *-1.04%*	-68.61% *1.26%*	-52.64% *0.95%*	-56.92% *-0.67%*	-84.45% *2.08%*	-10.61% *2.85%*
Germany	-11.42% *-1.67%*	-51.41% *-1.86%*	-53.47% *-1.53%*	-3.96% *1.05%*	16.92% *0.21%*	-17.41% *1.11%*
Hong Kong	71.06% *0.64%* SIG 5%	66.85% *0.63%*	41.46% *3.38%*	15.02% *-0.48%*	9.45% *-0.16%*	36.91% *-4.04%*
Italy	14.06% *-0.06%*	-34.07% *1.26%*	-20.96% *17.52%*	52.75% *9.02%* SIG 5%	-4.09% *9.71%*	104.49% *19.24%* SIG 1%
Japan	23.29% *-0.17%*	6.89% *0.30%*	-51.99% *-0.17%*	-126.43% *0.45%*	-109.94% *4.46%*	-19.60% *0.18%*
Netherlands	21.81% *1.83%*	-74.61% *-11.65%*	-72.75% *-0.12%*	-92.90% *1.60%*	-58.92% *1.22%*	70.55% *5.16%*
Spain	32.37% *-1.74%*	-42.43% *-0.89%*	-31.67% *-0.58%*	-18.49% *1.23%*	16.41% *-1.21%*	73.65% *-1.83%*
Switzerland	46.53% *1.14%* SIG 5%	3.58% *3.29%*	-41.02% *1.38%*	-15.84% *1.45%*	-36.97% *1.30%*	72.75% *4.48%* SIG 5%
UK	38.92% *0.10%*	-51.69% *-0.58%*	-65.61% *0.76%*	-63.12% *-1.07%*	-79.69% *-0.95%*	3.46% *-0.49%*
USA	23.54% *-1.03%*	-38.05% *0.44%*	-65.34% *1.69%*	-51.98% *2.72%*	-79.05% *2.46%*	-12.07% *3.87%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.1 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-36.79% *1.50%*	-34.86% *2.82%*	-44.06% *4.23%*	-12.53% *5.25%*	-3.69% *5.14%*
Belgium	-1.18% *21.25%*	71.35% *24.73%* SIG 1%	25.55% *4.05%*	62.82% *4.80%*	71.39% *7.24%*
Canada	11.80% *3.28%*	71.41% *5.09%* SIG 5%	8.22% *5.53%*	3.74% *9.77%*	54.18% *13.12%*
Denmark	-2.41% *0.51%*	32.44% *-5.88%*	74.23% *-1.22%* SIG 1%	108.87% *-2.85%* SIG 1%	76.22% *5.38%*
France	35.95% *1.03%*	75.10% *2.72%*	70.73% *3.58%*	-23.76% *5.67%*	91.55% *9.83%* SIG 5%
Germany	20.79% *-2.80%*	58.91% *-0.32%*	80.66% *2.50%*	-4.75% *2.42%*	90.98% *2.45%*
Hong Kong	78.21% *-4.69%*	37.00% *19.82%*	-26.17% *5.91%*	14.49% *4.28%*	-94.22% *6.35%*
Italy	-2.08% *24.11%*	0.97% *-12.82%*	51.82% *3.19%*	51.24% *-13.07%*	64.97% *-14.09%*
Japan	-21.83% *-2.28%*	26.76% *1.42%*	32.23% *2.27%*	1.97% *2.97%*	-14.44% *2.34%*
Netherlands	13.04% *3.10%*	112.07% *2.96%* SIG 5%	106.03% *6.44%* SIG 5%	19.19% *11.30%*	124.28% *17.17%* SIG 5%
Spain	82.60% *4.29%* SIG 5%	59.69% *7.43%*	60.31% *17.70%*	81.55% *11.75%*	127.62% *14.96%* SIG 5%
Switzerland	18.15% *7.19%*	19.65% *7.43%*	101.03% *10.91%* SIG 1%	35.69% *11.16%*	88.46% *17.66%* SIG 5%
UK	-48.07% *0.13%*	-17.28% *2.38%*	30.97% *0.39%*	-31.67% *-1.02%*	36.24% *-2.14%*
USA	6.74% *1.62%*	-15.71% *4.71%*	11.37% *6.55%*	52.76% *8.12%*	109.07% *10.51%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

7.3 Returns by Calendar Year

The overall cumulative returns described in the previous section provide only very limited evidence of momentum strategy profitability. Positive excess returns to 1 trading day strategies may be due to nonsynchronous trading affecting the index time series. For the longer strategies, no clear pattern is observed in the significant positive returns obtained.

For investors, the consistency of returns is as important, if not more important, than the absolute magnitude of returns. Given that the returns considered in this chapter are all excess returns over and above the cost of funding, investors can employ leverage to increase the magnitude of small but consistent returns. Inconsistent returns, on the other hand, cannot be financially engineered into consistent excess returns.

This section considers how the cumulative profitability reported in Table 7.1 relates to the returns of each strategy in the calendar years 1995 to 2002 inclusive. Table 7.3 shows, for each strategy, the number of years in the data sample (from a maximum of 8) over which the strategy produces a positive return, the maximum annual return achieved, and the minimum annual return generated.

As can be seen from the Table 7.2, very few strategies produce returns of a consistent sign (positive or negative) across all 8 calendar years. Those which do produce positive returns across all 8 years are the 1 trading day strategy (Belgium), and the 63 trading day strategy (Switzerland). These strategies also generate significant positive cumulative returns across the entire data sample, as shown in Table 7.1. Those strategies which produce a consistently negative return (indicating consistent positive returns to the equivalent contrarian strategy) are the 5 trading day strategy (USA) and the 10 trading day strategy (Australia). The cumulative returns across the entire data sample are not significant at the 5% level for either strategy, however, indicating that although annual returns are negative for these two strategies throughout, they tend to be small. No clear patterns are identified in the minimum and maximum annual returns achieved by the 154 strategies considered in this part of the research.

Table 7.2 Consistency of Cumulative Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	4	3	3	2	1	0
	9.61%	4.05%	5.94%	0.40%	7.45%	-0.57%
	-5.28%	-20.40%	-14.36%	-15.81%	-14.65%	-12.05%
Belgium	8	6	6	5	4	4
	32.00%	23.15%	18.60%	19.47%	20.43%	22.98%
	6.14%	-3.92%	-14.60%	-13.15%	-30.99%	-25.01%
Canada	7	6	5	4	5	6
	16.24%	13.81%	23.51%	23.32%	10.88%	14.47%
	-0.20%	-14.49%	-19.44%	-49.16%	-11.49%	-12.83%
Denmark	7	5	5	6	6	5
	14.67%	15.76%	15.88%	32.49%	26.63%	17.51%
	-17.71%	-20.85%	-18.67%	-21.35%	-13.68%	-12.41%
France	6	3	3	3	2	5
	16.72%	9.54%	8.14%	12.17%	8.81%	14.47%
	-6.07%	-25.07%	-20.43%	-37.01%	-46.88%	-23.19%
Germany	3	3	2	4	4	4
	10.91%	13.76%	4.65%	14.36%	20.13%	23.43%
	-16.51%	-22.02%	-20.35%	-30.37%	-18.23%	-32.56%
Hong Kong	5	6	4	5	5	4
	28.84%	32.31%	45.95%	24.23%	10.44%	38.83%
	-9.04%	-9.81%	-10.06%	-25.29%	-10.46%	-19.66%
Italy	5	4	6	4	3	7
	12.37%	17.33%	19.52%	24.99%	20.72%	23.83%
	-12.67%	-25.59%	-60.81%	-6.73%	-14.48%	-11.38%
Japan	6	4	3	2	2	3
	14.10%	13.15%	4.48%	11.54%	3.41%	10.30%
	-13.07%	-15.61%	-30.02%	-38.93%	-33.75%	-26.52%
Netherlands	4	3	3	3	3	6
	23.19%	5.19%	13.29%	10.00%	17.19%	41.11%
	-10.51%	-31.13%	-34.07%	-47.66%	-29.52%	-13.97%
Spain	7	4	4	4	4	6
	10.60%	8.17%	13.11%	12.94%	23.35%	33.65%
	-16.58%	-20.74%	-23.10%	-27.13%	-11.40%	-7.93%
Switzerland	6	5	3	4	2	6
	25.78%	18.49%	6.68%	12.74%	12.45%	36.07%
	-3.50%	-16.55%	-26.02%	-23.23%	-17.61%	-6.90%
UK	6	4	1	1	1	4
	19.53%	4.78%	11.21%	0.56%	5.98%	9.04%
	-5.98%	-27.18%	-31.77%	-20.49%	-17.75%	-12.27%
USA	6	1	2	3	0	4
	13.73%	20.05%	5.61%	8.31%	-0.86%	9.68%
	-2.11%	-24.73%	-21.52%	-23.98%	-25.34%	-29.45%

Table shows the number of calendar years over the period 1995 to 2002 inclusive over which each strategy produced a return greater than or equal to zero, together with the maximum and minimum annual return achieved.

Table 7.2 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	1 2.84% -8.99%	2 4.43% -15.54%	1 4.82% -14.93%	4 8.73% -9.56%	5 6.71% -14.24%
Belgium	5 39.06% -40.36%	5 42.25% -18.04%	4 27.43% -15.32%	4 45.80% -21.76%	4 50.42% -14.69%
Canada	3 16.62% -4.95%	6 28.99% -14.92%	5 15.28% -13.45%	6 16.89% -30.95%	6 25.11% -32.54%
Denmark	4 10.20% -15.30%	5 27.18% -13.78%	7 39.16% -9.72%	7 41.27% -16.86%	6 43.80% -24.02%
France	4 29.97% -14.42%	5 44.69% -12.69%	7 27.05% -7.94%	4 23.42% -38.19%	7 46.49% -32.71%
Germany	4 22.44% -18.62%	5 37.88% -16.81%	7 30.95% -4.05%	4 25.00% -36.07%	6 37.76% -2.38%
Hong Kong	4 42.65% -13.21%	5 27.52% -24.53%	4 9.23% -46.34%	5 34.04% -37.45%	3 20.43% -40.56%
Italy	3 33.90% -17.29%	5 38.83% -38.43%	6 18.38% -13.23%	4 35.86% -21.31%	7 43.01% -53.50%
Japan	3 22.04% -25.06%	5 29.78% -16.42%	5 23.6% -10.45%	4 26.24% -27.65%	3 12.73% -17.54%
Netherlands	3 20.76% -11.98%	7 33.22% -7.21%	7 33.92% -1.28%	6 40.84% -33.86%	6 48.31% -33.97%
Spain	6 24.82% -6.00%	5 47.59% -42.00%	5 27.62% -10.37%	5 35.14% -4.75%	5 40.31% -12.99%
Switzerland	4 22.85% -12.93%	4 34.41% -24.78%	8 21.08% 0.24%	4 51.31% -27.58%	7 52.92% -29.30%
UK	2 4.26% -26.97%	4 9.61% -24.78%	6 14.90% -7.28%	5 18.29% -32.98%	6 22.48% -21.08%
USA	3 17.68% -12.91%	4 21.64% -23.30%	4 20.30% -15.85%	6 18.27% -8.97%	6 25.35% -0.36%

Table shows the number of calendar years over the period 1995 to 2002 inclusive over which each strategy produced a return greater than or equal to zero, together with the maximum and minimum annual return achieved.

Appendix C charts the annual cumulative returns to the eleven momentum strategies considered for each stock market over the calendar years 1995 to 2002 inclusive, in addition to identifying years in which the returns achieved were significantly different to the mean annual bootstrap return for that strategy. In general, the returns achieved by individual strategies vary quite considerably from year to year. For the short-term (1 to 10 trading day) strategies in particular, there are years where all strategies perform well in a particular market (Hong Kong in 1997, for example) and corresponding years where each of the short-term strategies tends to perform poorly (the Netherlands in 2000, for example). A tendency for good and poor returns to alternate from one year to the next can be observed in the charts, particularly for the short-term strategies.

7.4 Long-Only and Short-Only Returns

The cumulative returns presented in Section 7.2 and the returns by calendar year discussed in Section 7.3 indicate that the returns to individual momentum strategies are not consistent over time. The returns presented in the previous sections are based on both long and short market positions, with each strategy buying the market index following periods of high returns and selling the market index following periods of low returns.

As discussed in Section 6.4, some investors may not have full or cost-effective access to short positions in stock markets. As a result, some researchers have noted that empirically observed anomalies in returns may persist due to the difficulties associated with undertaking arbitrage which requires a short market position to be initiated (Shleifer and Vishny, 1997). That is to say, persistent profit opportunities which can be exploited by taking long market positions will be arbitraged away, but it may not be cost-effective or practicable for market participants to undertake arbitrage activity where this requires a short market position to be initiated[67]. If this is the case, one would expect positive returns to individual momentum strategies to be driven largely by returns to short positions. As this section explains, no evidence is found to support this theory.

[67] This hypothesis is supported by Finn et al (1999), for example, who find that large-cap short sale candidates in the US stock market tend to be overpriced by up to four times the amount that purchase candidates are underpriced.

Table 7.3 shows the cumulative returns to long-only strategies. For the 1 trading day long-only strategy, the cumulative return is positive for all 14 markets, and is significantly different to the bootstrap average (based on a two-tailed test) at the 1% level for 5 countries and at the 5% level for a further 3 countries. As discussed in Section 7.1, however, significant excess returns to the 1 trading day strategies may simply be due to nonsynchronous trading. For the 2 through 5 trading day long-only strategies, positive returns are generated for between 6 and 9 of the 14 countries in each case, although each strategy specification generates significant excess returns for a maximum of only 3 of the 14 countries considered. For the 10 through 63 trading day long-only strategies, positive returns are generated for all but one of the countries considered, whilst the 126 and 252 trading day strategies produce positive returns for 10 and 12 countries respectively. Each of the 10 through 252 trading day strategies produces excess returns which are statistically significant for between 4 and 8 of the 14 data sets. The returns to long-only momentum strategies presented in Table 7.3 therefore appear to generate positive returns across the entire range of strategy specifications, in contrast to the returns of the long/short strategies described in Section 7.2.

Table 7.4 repeats the analysis presented in Table 7.2 for the long-only strategies, showing the number of calendar years in the data samples over which each strategy generates a positive return, together with the maximum and minimum annual returns achieved. The long-only strategies tend to produce positive annual returns over a greater number of calendar years in the data than do the long/short strategies. For example, whilst the long/short strategies produce positive returns on average in 3.00 years for the 5 trading day strategy, the equivalent long-only strategies produce an average of 4.64 years of positive returns. Again, no clear patterns emerge in the maximum and minimum annual profits achieved by individual strategies.

Table 7.3 Cumulative Long-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	21.06% *2.38%* SIG 5%	12.67% *4.30%*	-4.89% *4.42%*	-18.70% *2.42%*	-8.11% *3.16%*	1.51% *3.07%*
Belgium	72.06% *2.26%* SIG 1%	40.38% *4.05%* SIG 1%	36.52% *4.73%* SIG 5%	42.06% *4.87%* SIG 5%	24.59% *13.82%*	21.83% *26.14%* SIG 5%
Canada	45.62% *3.06%* SIG 1%	28.62% *5.04%*	21.77% *6.70%*	9.83% *6.97%*	27.31% *9.07%*	40.41% *8.94%* SIG 5%
Denmark	33.54% *2.78%* SIG 5%	20.18% *4.40%*	38.74% *4.53%* SIG 5%	58.07% *4.22%* SIG 1%	68.82% *6.71%* SIG 1%	30.84% *8.55%*
France	19.85% *2.58%*	-22.77% *5.38%*	-0.81% *5.40%*	-5.80% *5.91%*	-19.41% *7.82%*	17.09% *10.32%*
Germany	5.50% *1.03%*	-14.37% *1.77%*	-13.69% *1.57%*	-15.08% *3.44%*	20.05% *2.80%*	-8.40% *4.59%*
Hong Kong	56.17% *-2.47%* SIG 1%	41.65% *-3.91%*	12.76% *-1.27%*	0.17% *-4.90%*	26.43% *-6.73%*	34.92% *-9.69%*
Italy	2.33% *2.99%*	-6.68% *5.88%*	14.06% *13.10%*	59.37% *5.40%* SIG 1%	35.10% *3.01%*	80.05% *2.43%* SIG 1%
Japan	6.74% *-1.75%*	27.87% *-2.38%*	4.87% *-2.55%*	-35.47% *-0.28%*	-17.01% *-4.71%*	2.62% *-4.24%*
Netherlands	34.97% *0.05%* SIG 1%	-28.97% *-0.84%*	-23.72% *7.72%*	-55.24% *9.50%*	-9.82% *10.06%*	57.43% *14.99%* SIG 1%
Spain	20.88% *3.50%*	-25.36% *6.54%*	-11.90% *7.53%*	13.45% *9.64%*	52.72% *9.72%* SIG 5%	61.12% *10.11%* SIG 5%
Switzerland	28.38% *4.65%* SIG 5%	25.97% *8.69%*	-13.92% *8.72%*	8.43% *9.60%*	6.42% *10.77%*	59.90% *15.03%* SIG 1%
UK	16.88% *0.29%*	-19.58% *0.55%*	-17.58% *-0.45%*	-9.65% *0.16%*	-23.40% *0.93%*	23.30% *0.23%*
USA	39.72% *3.25%* SIG 1%	-0.25% *6.09%*	-5.43% *7.66%*	11.62% *9.20%*	10.55% *8.63%*	41.13% *10.39%* SIG 5%

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.3 (continued)

PANEL B: 21-252 Trading Day Strategies	**21**	**42**	**63**	**126**	**252**
Australia	5.30% *7.79%*	-1.29% *8.91%*	5.12% *9.38%*	-5.08% *10.58%*	12.87% *10.57%*
Belgium	29.09% *21.79%* SIG 1%	66.71% *27.59%* SIG 1%	40.65% *11.78%* SIG 5%	88.17% *13.04%* SIG 1%	87.11% *14.01%* SIG 1%
Canada	53.56% *12.63%* SIG 1%	71.36% *14.96%* SIG 1%	36.25% *15.75%*	10.94% *18.11%*	40.33% *19.97%*
Denmark	7.49% *7.88%*	39.57% *9.14%* SIG 1%	79.00% *4.97%* SIG 1%	89.96% *12.57%* SIG 1%	51.12% *13.03%* SIG 5%
France	25.77% *10.16%*	56.90% *11.83%* SIG 5%	88.65% *14.23%* SIG 1%	27.36% *15.06%*	66.34% *18.19%* SIG 1%
Germany	18.72% *3.83%*	58.45% *4.35%*	77.72% *6.74%* SIG 5%	-3.80% *5.77%*	88.49% *6.54%* SIG 1%
Hong Kong	95.05% *-11.27%* SIG 1%	15.31% *-3.52%*	-2.17% *-7.01%*	-24.24% *-7.08%*	-6.48% *-7.10%*
Italy	22.24% *9.30%*	7.65% *-8.93%*	58.50% *-0.32%* SIG 5%	46.90% *3.33%*	51.82% *-10.48%*
Japan	13.81% *-6.34%*	8.36% *-5.97%*	0.01% *-5.27%*	14.71% *-6.06%*	-9.88% *-5.96%*
Netherlands	18.68% *16.22%*	72.56% *17.09%* SIG 5%	101.75% *18.20%* SIG 1%	47.76% *21.45%*	100.90% *25.46%* SIG 1%
Spain	93.40% *7.40%* SIG 1%	86.15% *12.62%* SIG 1%	87.32% *21.03%* SIG 1%	75.64% *22.39%* SIG 1%	12.94% *26.02%* SIG 1%
Switzerland	18.35% *17.47%*	25.12% *19.52%*	103.14% *21.34%* SIG 1%	63.49% *23.21%* SIG 1%	101.02% *27.39%* SIG 1%
UK	-24.39% *0.21%*	9.74% *1.57%*	15.55% *1.06%*	-10.32% *-5.81%*	33.89% *0.24%*
USA	17.98% *11.28%*	27.48% *13.03%*	40.66% *14.47%*	35.57% *16.05%*	104.77% *18.21%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.4 Consistency of Long-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	6 6.87% -0.37%	6 7.35% -3.87%	4 8.50% -8.14%	2 4.03% -10.05%	4 4.25% -6.73%	4 3.07% -2.09%
Belgium	7 21.03% -4.13%	6 15.11% -16.34%	5 23.92% -7.37%	6 14.01% -12.03%	4 20.02% -8.25%	4 24.11% -17.80%
Canada	7 10.81% -1.76%	6 10.46% -5.97%	5 12.43% -7.66%	6 11.05% -24.97%	7 9.42% -1.45%	6 12.68% -4.47%
Denmark	5 20.44% -19.45%	5 15.81% -14.25%	6 16.84% -5.08%	6 30.63% -4.36%	7 28.17% -2.17%	6 16.11% -14.76%
France	6 13.14% -9.19%	3 9.34% -18.88%	5 10.91% -15.57%	5 11.59% -18.02%	5 9.06% -33.42%	6 15.04% -12.94%
Germany	4 9.71% -8.60%	4 8.27% -16.10%	5 5.86% -27.44%	6 8.96% -33.13%	6 6.51% -9.53%	5 11.71% -22.70%
Hong Kong	7 14.39% -1.88%	7 13.85% -2.12%	5 9.24% -3.78%	4 11.89% -10.25%	5 14.11% -11.69%	4 32.88% -14.43%
Italy	3 13.05% -9.35%	5 13.90% -23.86%	6 14.94% -23.82%	6 29.72% -9.41%	4 22.66% -6.16%	7 28.35% -2.36%
Japan	5 12.87% -11.45%	6 9.18% -6.66%	5 11.89% -9.42%	3 12.98% -21.10%	2 10.52% -9.33%	3 10.67% -9.73%
Netherlands	7 17.02% -1.58%	4 14.69% -21.85%	4 13.00% -17.38%	2 13.37% -36.10%	3 12.46% -11.77%	5 32.46% -4.74%
Spain	6 13.10% -16.20%	4 14.74% -26.37%	4 11.00% -17.38%	5 15.56% -26.92%	5 20.06% -4.49%	6 30.91% -19.78%
Switzerland	6 12.85% -2.48%	6 12.67% -4.71%	4 8.10% -15.70%	4 11.42% -15.48%	4 12.19% -10.60%	7 31.79% -10.09%
UK	5 13.33% -7.42%	5 5.54% -18.92%	4 10.24% -20.50%	4 3.73% -9.72%	3 4.42% -16.25%	7 11.97% -1.15%
USA	6 12.17% -3.57%	4 10.58% -6.09%	4 13.02% -11.01%	4 11.19% -10.19%	6 9.18% -11.57%	6 14.72% -4.61%

Table shows the number of calendar years over the period 1995 to 2002 inclusive over which each strategy produced a return greater than or equal to zero, together with the maximum and minimum annual return achieved.

Table 7.4 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	5 5.24% -4.84%	4 7.20% -9.76%	5 7.25% -6.89%	4 8.73% -9.02%	6 6.71% -2.36%
Belgium	5 31.42% -13.11%	5 41.30% -14.43%	4 31.58% -14.96%	5 45.80% -4.60%	6 50.42% -5.40%
Canada	7 18.12% -9.46%	7 18.80% -2.25%	8 16.52% 1.05%	6 16.89% -32.34%	6 23.30% -21.27%
Denmark	5 17.12% -15.37%	4 27.8% -16.38%	7 39.16% -1.18%	8 41.27% 0.00%	5 43.80% -24.02%
France	5 20.22% -16.06%	4 37.03% -11.61%	6 27.05% -2.52%	7 23.67% -35.15	7 46.49% -24.04%
Germany	5 13.40% -11.20%	5 37.88% -9.52%	7 34.37% -0.36%	4 2500% -37.42%	7 37.76% -1.14%
Hong Kong	7 33.91% -2.02%	5 17.08% -23.38%	3 9.23% -14.01%	4 34.04% -37.45%	6 24.54% -33.79%
Italy	4 23.03% -10.17%	4 37.93% -21.84%	7 35.57% -10.67%	6 35.86% -23.86%	7 43.01% -36.37%
Japan	4 26.81% -9.42%	4 29.78% -10.94%	5 17.62% -15.27%	6 26.24% -21.37%	5 11.67% -8.13%
Netherlands	4 17.60% -18.94%	5 33.22% -8.22%	7 43.25% -1.28%	6 40.84% -33.54%	6 48.31% -25.88%
Spain	8 26.13% 0.10%	4 48.97% -12.33%	6 38.30% -4.03%	5 51.31% -26.61%	7 40.31% -4.05%
Switzerland	4 22.47% -12.33%	4 34.41% -11.44%	8 38.45% 0.24%	5 51.31% -26.61%	8 52.92% 0.00%
UK	3 4.31% -10.82%	5 13.97% -12.07%	6 6.83% -7.28%	5 18.29% -29.30%	7 16.25% -9.10%
USA	6 10.88% -9.72%	4 21.64% -11.49%	5 20.30% -8.49%	6 18.27% -8.97%	7 25.35% -0.36%

Table shows the number of calendar years over the period 1995 to 2002 inclusive over which each strategy produced a return greater than or equal to zero, together with the maximum and minimum annual return achieved.

Table 7.5 shows the cumulative returns to short-only momentum strategies over the 8 year period from January 1995 through December 2002, whilst Table 7.6 shows the number of years in the sample over which each strategy produces a positive return together with the maximum and minimum annual return achieved.

The returns to the short-only strategies are simply the difference between the returns to the corresponding long-short strategies and long-only strategies[68]. The returns to the short-only strategies are generally lower than those to the long/short and long-only strategies, and returns are only significant based on the bootstrap test for one of the 154 strategies considered (the one trading day strategy for Belgium).

The long/short returns discussed in Section 7.2 show positive returns to the 1 trading day strategy, mixed results for the 2 to 5 trading day strategies, and generally positive returns for the 10 through 252 trading day strategies. This section decomposes these returns into the contribution from long and from short positions. The pattern of returns to long positions generally reflects that of the overall returns, although the positive returns over 10 through 252 trading days are typically higher for the long-only strategies than for the long/short strategies, reflecting a negative contribution from short positions over these periods. Over 1 through 5 trading days, the returns to long positions are mixed with some positive and some negative returns although all significant returns based on the bootstrap test are positive. Short positions, however, contribute almost exclusively negative returns to the 2 through 5 trading day strategies.

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[68] The results described in this section therefore reflect the contribution of long and short positions to overall profitability. Alternatively, long-only and short-only strategies could be run in isolation on each data sample; this would be expected to generate a greater number of signals to each individual strategy compared to the long-short strategies which are the basis of this study, the reason being that in the long-short strategies, no new signals are accepted whilst a position is being held.

Table 7.5 Cumulative Short-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	-10.03% *-2.89%*	-34.17% *-4.17%*	-16.86% *-5.09%*	-24.74% *-8.11%*	-21.06% *-9.31%*	-49.99% *-6.82%*
Belgium	56.31% *-2.97%* SIG 1%	40.33% *-3.54%* SIG 5%	-9.28% *-4.89%*	-20.62% *-6.04%*	-44.92% *-8.79%*	-13.24% *-15.16%*
Canada	31.24% *-3.38%* SIG 1%	-7.59% *-5.42%*	-7.35% *-5.91%*	-23.66% *-6.24%*	-17.94% *-6.96%*	6.49% *-7.12%*
Denmark	2.45% *-2.33%*	-16.18% *-4.48%*	-35.32% *-5.82%*	-17.96% *-6.66%*	-19.11% *-7.42%*	2.52% *-7.73%*
France	1.52% *-3.61%*	-45.84% *-4.12%*	-51.83% *-4.46%*	-51.12% *-6.58%*	-65.05% *-5.74%*	-27.70% *-7.47%*
Germany	-16.93% *-2.70%*	-37.04% *-3.63%*	-39.79% *-3.09%*	11.12% *-2.39%*	-3.13% *-2.59%*	-9.01% *-3.48%*
Hong Kong	14.88% *3.11%*	25.21% *4.55%*	28.71% *4.65%*	14.84% *4.42%*	-16.98% *6.56%*	1.98% *5.65%*
Italy	11.73% *-3.05%*	-27.40% *-4.63%*	-35.01% *4.43%*	-6.62% *3.62%*	-39.40% *6.70%*	24.44% *16.81%*
Japan	16.54% *1.58%*	-20.98% *2.67%*	-56.86% *2.37%*	-90.96% *0.74%*	-92.93% *0.25%*	-22.22% *4.42%*
Netherlands	-13.16% *1.78%*	-45.64% *-10.81%*	-49.03% *-7.84%*	-36.96% *-7.90%*	-49.10% *-8.84%*	13.12% *-9.83%*
Spain	11.49% *-5.24%*	-17.17% *-7.44%*	-19.78% *-8.12%*	-31.94% *-8.41%*	-36.30% *-10.93%*	12.53% *-11.94%*
Switzerland	18.15% *-3.51%*	-22.39% *-5.40%*	-27.10% *-7.34%*	-24.26% *-8.15%*	-43.39% *-9.47%*	12.96% *-10.55%*
UK	22.04% *-0.19%*	-32.10% *-1.13%*	-48.03% *1.21%*	-53.48% *-1.23%*	-56.29% *-1.88%*	-19.84% *-0.72%*
USA	-16.18% *-4.28%*	-37.80% *-5.66%*	-59.92% *-5.96%*	-63.30% *-6.48%*	-89.60% *-6.17%*	-53.20% *-6.52%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.5 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-42.09% *-6.29%*	-33.57% *-6.09%*	-49.18% *-5.15%*	-7.45% *-5.33%*	-16.56% *-5.43%*
Belgium	-30.26% *-0.55%*	4.63% *-2.85%*	-15.10% *-7.73%*	-25.35% *-8.24%*	-15.72% *-6.77%*
Canada	-41.76% *-9.36%*	0.05% *-9.87%*	-28.03% *-10.21%*	-7.20% *-8.34%*	13.85% *-6.85%*
Denmark	-9.90% *-7.37%*	-7.13% *-15.01%*	-4.77% *-6.19%*	18.91% *-15.42%*	25.10% *-7.65%*
France	10.18% *-9.13%*	18.20% *-9.11%*	-17.92% *-10.65%*	-51.12% *-9.39%*	25.21% *-8.35%*
Germany	2.06% *-6.63%*	0.46% *-4.67%*	2.94% *-4.24%*	-0.95% *-3.35%*	2.49% *-4.09%*
Hong Kong	-16.84% *6.58%*	21.68% *23.34%*	-24.00% *12.91%*	38.73% *11.36%*	-87.74% *13.46%*
Italy	-24.32% *14.81%*	-6.68% *-3.89%*	-6.68% *3.51%*	4.34% *-16.40%*	13.15% *-3.61%*
Japan	-35.65% *4.06%*	18.39% *7.38%*	32.22% *7.54%*	-12.74% *9.04%*	-4.56% *8.29%*
Netherlands	-5.64% *-13.12%*	39.51% *-14.13%*	4.28% *-11.75%*	-28.57% *-10.15%*	23.38% *-8.30%*
Spain	-10.81% *-3.11%*	-26.56% *-5.19%*	-27.01% *-3.33%*	5.91% *-10.64%*	1.67% *-11.06%*
Switzerland	-0.20% *-10.29%*	-5.47% *-12.09%*	-2.11% *-10.43%*	-27.80% *-12.05%*	-12.55% *-9.73%*
UK	-23.68% *-0.08%*	-27.01% *0.81%*	15.43% *-0.67%*	-21.35% *4.79%*	2.35% *-2.38%*
USA	-11.24% *-9.66%*	-43.19% *-8.32%*	-29.29% *-7.92%*	17.19% *-7.93%*	4.30% *-7.71%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.6 Consistency of Short-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	3 7.75% -7.37%	1 0.83% -16.53%	3 5.98% -14.50%	2 3.88% -13.61%	2 3.19% -7.93%	1 1.06% -12.75%
Belgium	6 20.99% -0.62%	7 12.42% -1.84%	2 15.13% -10.70%	3 12.86% -12.46%	3 3.01% -23.40%	2 5.72% -8.26%
Canada	7 14.33% -3.26%	4 3.49% -13.92%	4 15.69% -14.21%	3 19.46% -24.19%	3 11.52% -14.29%	3 14.52% -8.35%
Denmark	4 8.76% -9.43%	2 15.15% -17.92%	3 9.39% -23.44%	4 7.39% -25.61%	3 2.40% -15.52%	4 9.44% -8.08%
France	3 15.85% -13.07%	2 8.18% -20.33%	1 2.01% -14.87%	3 0.84% -18.99%	2 9.09% -18.42%	1 6.49% -13.44%
Germany	3 12.94% -13.66%	3 5.67% -15.98%	2 7.09% -15.28%	4 12.15% -5.51%	2 13.62% -8.70%	4 11.72% -14.95%
Hong Kong	5 20.05% -10.53%	6 18.46% -7.68%	3 42.25% -12.31%	5 32.21% -17.25%	3 22.13% -23.31%	4 10.54% -10.32%
Italy	4 16.99% -5.45%	4 5.00% -12.12%	3 15.80% -37.00%	2 21.05% -10.36%	2 17.74% -21.03%	4 19.40% -9.01%
Japan	5 8.93% -2.42%	3 4.26% -8.95%	2 10.24% -20.60%	2 8.10% -27.95%	2 3.60% -29.00%	3 8.51% -16.79%
Netherlands	3 20.46% -14.18%	2 6.82% -13.77%	3 4.90% -22.64%	1 11.88% -12.42%	1 19.42% -23.93%	4 12.23% -11.21%
Spain	3 18.57% -5.66%	3 4.97% -16.25%	3 3.74% -10.91%	2 1.45% -9.73%	2 7.95% -13.81%	4 13.07% -7.38%
Switzerland	4 14.96% -5.73%	3 9.12% -12.52%	3 5.46% -13.93%	3 7.65% -12.14%	2 3.60% -16.32%	4 9.27% -4.73%
UK	6 13.30% -1.50%	0 -0.54% -9.51%	1 0.97% -11.27%	1 1.33% -13.29%	1 1.56% -13.67%	3 8.57% -14.79%
USA	3 1.88% -6.35%	1 9.47% -18.65%	1 4.75% -19.08%	1 3.36% -15.67%	0 -4.88% -25.47%	1 3.64% -26.83%

Table shows the number of calendar years over the period 1995 to 2002 inclusive over which each strategy produced a return greater than or equal to zero, together with the maximum and minimum annual return achieved.

Table 7.6 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	1 1.09% -12.69%	2 0.00% -11.09%	2 4.14% -12.66%	6 5.42% -12.32%	6 0.00% -14.24%
Belgium	4 13.94% -32.42%	4 20.09% -11.80%	4 11.36% -8.50%	5 12.25% -19.48%	5 16.45% -14.69%
Canada	2 4.84% -14.29%	4 17.70% -18.34%	4 7.00% -19.36%	5 12.04% -7.82%	7 25.11% -11.27%
Denmark	4 9.22% -20.61%	5 3.29% -7.38%	4 16.71% -8.54%	7 12.57% -17.11%	7 25.80% -0.94%
France	5 16.45% -15.61%	5 25.96% -7.79%	3 17.01% -15.42%	3 0.00% -29.72%	6 36.88% -8.67%
Germany	4 14.44% -12.81%	5 21.03% -13.09%	5 30.14% -16.31%	7 20.53% -25.58%	7 4.87% -2.38%
Hong Kong	3 28.67% -16.61%	4 23.35% -8.09%	6 9.07% -32.33%	8 31.54% 0.00%	4 16.86% -40.56%
Italy	4 10.86% -25.63%	6 11.78% -16.59%	5 11.06% -19.89%	6 13.66% -6.61%	7 30.28% -17.13%
Japan	2 2.07% -17.41%	6 22.98% -8.22%	5 19.85% -10.45%	4 4.12% -6.28%	6 12.73% -17.54%
Netherlands	4 19.72% -21.35%	8 23.49% 0.00%	6 19.22% -13.30%	7 2.71% -33.32%	7 31.47% -8.09%
Spain	3 7.67% -12.95%	5 20.19% -40.66%	5 3.83% -15.59%	7 10.65% -4.75%	5 30.22% -12.99%
Switzerland	5 17.67% -16.62%	6 7.32% -13.55%	6 14.95% -17.38%	4 0.00% -22.70%	7 12.09% -29.30%
UK	4 4.47% -22.28%	3 1.27% -6.76%	8 13.98% 0.00%	5 1.53% -14.18%	6 22.48% -21.08%
USA	4 13.07% -14.29%	3 0.00% -17.32%	5 8.49% -20.82%	8 10.60% 0.00%	7 4.59% -0.29%

Table shows the number of calendar years over the period 1995 to 2002 inclusive over which each strategy produced a return greater than or equal to zero, together with the maximum and minimum annual return achieved.

The results discussed in this section indicate positive returns to long positions over a period of 1 day (indicating continuation among winners) and mixed returns to short positions (losers). Over 2 through 5 trading days, the overall returns and returns to long positions are mixed, with some limited evidence of negative returns to short positions (indicating reversal among losers) although few results are statistically significant. Over 10 through 252 trading days, the returns to long positions are generally positive, indicating continuation, although no clear pattern is observed in the significant results.

These results are not strongly consistent with the results of previous short-term studies reported in Section 4.2. Whilst a number of studies[69] find evidence of one-day continuation for winners, Bremer and Sweeney (1991) find evidence of reversal over the same period. This may reflect the lack of a clear pattern in the contribution of long and short positions to 1 trading day strategies. In some data sets, these returns are driven largely by long-only returns, whilst in others the returns to short positions dominate. The prior empirical evidence over test periods from 2 to 10 days is mixed, with some studies reporting continuation and others reversal for winners[70]. Again, the returns reported in this study are mixed, and no clear pattern of significant results is reported. Over longer periods of up to 252 trading days, previous research tends to find evidence of continuation for both winners and losers[71]. This contrasts with the results of the current study, which indicate limited evidence of continuation for winners over periods from 10 through 252 trading days.

Medium-term continuation in returns may be driven by any number of factors described in Chapters 2 and 3. One of the main aims of this thesis is to assess the possible causes of these effects through an examination of the properties of stock market trends. This analysis is described in Chapters 8 and 9.

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[69] Akhigbe et al (1998) and Lasfer et al (2003), for example.

[70] Lasfer et al (2003), for example, report continuation over test periods of up to 10 days. Otchere and Chan (2000), on the other hand, report reversal for winners over test periods of 2 to 4 days. It is important to note that each of these studies uses a formation period of one day, whereas the results reported in this chapter are analogous to formation and test periods of equal length.

[71] See, for example, Jegadeesh and Titman (1993, 2001) and Rouwenhorst (1998).

7.5 Mean Transaction Profits

This section considers the mean transaction profits to the 154 momentum strategies considered in this part of the research. These provide a measure of the returns to strategies over those days where investors hold a position, and therefore enables an intuitive analysis of whether the positive returns to some strategies are likely to exceed transaction costs for the majority of investors.

Table 7.7 presents the mean transaction profits for the 154 strategies considered. The mean profit of 0.8363% for the 10 day strategy for Switzerland, for example, reflects a mean return of 0.8363% for each transaction entered into by the strategy over the eight years of the data sample, or 0.08363% per day on which the strategy held a market position.

The maximum transaction profits are generated by the longest strategies. The 252 trading day strategy produces a mean transaction profit of 21.2695% for Spain, for example, and 15.5815% for the USA. These figures are based on funded returns, that is to say they take into account dividend income received and also the cost of funding. One would expect that returns of this magnitude would be more than sufficient to cover transactions costs for the majority of investors. Nevertheless, very few values are statistically significant based on the bootstrap test.

Table 7.7 Mean Transaction Profits

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	0.0318% *-0.0014%*	-0.0827% *0.0004%*	-0.1077% *-0.0031%*	-0.2454% *-0.0328%*	-0.2040% *-0.0411%*	-0.5571% *-0.0416%*
Belgium	0.3056% *-0.0023%* SIG 1%	0.2461% *0.0021%* SIG 5%	0.1121% *-0.0008%*	0.1031% *-0.0072%*	-0.1136% *0.0352%*	0.0851% *0.1592%*
Canada	0.2135% *-0.0012%* SIG 1%	0.0678% *-0.0019%*	0.0609% *0.0040%*	-0.0702% *0.0043%*	0.0568% *0.0157%*	0.4643% *0.0213%*
Denmark	0.0825% *0.0013%*	0.0130% *-0.0004%*	0.0139% *-0.0061%*	0.2057% *-0.0145%*	0.3088% *-0.0053%*	0.3550% *0.0091%*
France	0.0505% *-0.0030%*	-0.2144% *0.0051%*	-0.2122% *0.0045%*	-0.2860% *-0.0045%*	-0.4910% *0.0139%*	-0.1179% *0.0341%*
Germany	-0.0275% *-0.0055%*	-0.1749% *-0.0080%*	-0.2219% *-0.0083%*	-0.0206% *0.0059%*	0.1025% *0.0015%*	-0.1872% *0.0122%*
Hong Kong	0.2108% *0.0028%* SIG 5%	0.2591% *0.0033%*	0.2094% *0.0181%*	0.0878% *-0.0032%*	0.0626% *0.0001%*	0.4101% *-0.0505%*
Italy	0.0377% *-0.0001%*	-0.1253% *0.0046%*	-0.1017% *0.0816%*	0.3014% *0.0520%* SIG 5%	-0.0264% *0.0680%*	1.1610% *0.2162%* SIG 1%
Japan	0.0614% *-0.0005%*	0.0246% *0.0008%*	-0.2280% *-0.0008%*	-0.6619% *0.0018%*	-0.6745% *-0.0312%*	-0.2227% *-0.0007%*
Netherlands	0.0498% *0.0058%*	-0.2376% *-0.0494%*	-0.3149% *-0.0011%*	-0.4728% *0.0096%*	-0.3593% *0.0082%*	0.8017% *0.0585%*
Spain	0.0754% *-0.0053%*	-0.1390% *-0.0034%*	-0.1377% *-0.0028%*	-0.1005% *0.0073%*	0.0989% *-0.0081%*	0.7515% *-0.0199%*
Switzerland	0.1193% *0.0041%*	0.0129% *0.0142%*	-0.1873% *0.0072%*	-0.0856% *0.0089%*	-0.2311% *0.0097%*	0.8363% *0.0529%* SIG 5%
UK	0.0918% *0.0003%*	-0.1641% *-0.0033%*	-0.2804% *0.0038%*	-0.3358% *-0.0064%*	-0.4980% *-0.0063%*	0.0403% *-0.0042%*
USA	0.0569% *-0.0031%*	-0.1247% *0.0014%*	-0.2700% *0.0080%*	-0.2561% *0.0162%*	-0.4734% *0.0174%*	-0.1298% *0.0436%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.7 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-0.8175% *0.0338%*	-1.4523 % *0.0338%*	-2.3188% *0.2367%*	-1.2528% *0.5515%*	-0.7379% *0.9708%*
Belgium	-0.0210% *0.4427%*	2.3782% *0.9690%* SIG 1%	1.1612% *0.2114%*	4.4871% *0.4679%*	10.1990% *1.4194%*
Canada	0.2134% *0.0685%*	2.4623% *0.1863%*	0.4111% *0.2958%*	0.3119% *1.0095%*	9.0301% *2.5249%*
Denmark	-0.0423% *0.0111%*	1.0464% *-0.2202%*	3.5346% *-0.1283%* SIG 1%	9.0727% *-0.2876%* SIG 5%	10.8884% *0.9319%*
France	0.7190% *0.0237%*	2.8885% *0.1118%*	3.2152% *0.1751%*	-1.8280% *0.6062%*	13.0786% *1.8034%*
Germany	0.4157% *-0.0616%*	2.1040% *-0.0276%*	4.4813% *0.1339%*	-0.4319% *0.2386%*	18.1966% *0.4196%*
Hong Kong	1.5642% *-0.0998%*	1.4798% *0.7692%*	-1.4538% *0.3314%* SIG 5%	1.3169% *0.4090%*	-15.7036% *1.2225%*
Italy	-0.0378% *0.4481%*	0.0359% *-0.4812%*	3.2388% *0.0977%*	4.6578% *-1.4087%*	12.9944% *-2.6336%*
Japan	-0.4645% *-0.0576%*	1.0291% *0.0523%*	2.0143% *0.1263%*	0.2193% *0.3307%*	-3.6099% *0.5307%*
Netherlands	0.2557% *0.0629%*	4.4826% *0.1170%* SIG 5%	5.5806% *0.3467%* SIG 5%	1.4759% *1.1728%*	17.7541% *3.2653%*
Spain	1.6519% *0.0863%*	2.1316% *0.2729%*	3.0157% *0.9822%*	7.4134% *1.1798%*	21.2695% *2.7575%*
Switzerland	0.3424% *0.1500%*	0.7277% *0.2786%*	5.3175% *0.5957%* SIG 5%	2.7453% *1.1456%*	14.7441% *3.2567%*
UK	-1.0681% *0.0035%*	-0.6644% *0.0912%*	1.8220% *0.0338%*	-3.1671% *-0.0128%*	6.0399% *-0.5498%*
USA	0.1349% *0.0284%*	-0.5610% *0.1927%*	0.5683% *0.3645%*	5.2758% *0.8367%*	15.5815% *1.9556%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.8 shows the mean profit across all 14 data sets per transaction and per day where a position is held for each strategy from 1 to 252 trading days. Interestingly, the strategy lengths which produced mixed results across data sets in terms of cumulative returns correspond to those strategy lengths shown in Table 7.8 where the mean transaction and daily profits are negative. These also reflect the autocorrelation structure of the underlying data sets, shown in Table 5.5.

Table 7.8 Mean Transaction and Daily Profit by Strategy Length

Strategy Length (Trading Days)	Mean Transaction Profit	Mean Daily Profit
1	0.0971%	0.0971%
2	-0.0457%	-0.0228%
3	-0.1190%	-0.0397%
4	-0.1312%	-0.0328%
5	-0.1744%	-0.0349%
10	0.2636%	0.0264%
21	0.2026%	0.0096%
42	1.2920%	0.0308%
63	2.1849%	0.0347%
126	2.1640%	0.0172%
252	9.2661%	0.0368%

Table shows the mean transaction profit across all 14 data sets for each strategy length together with the mean daily profit for days on which each strategy holds a market position.

An examination of the mean daily returns shown in Table 7.8 reveals that these are typically small. Mean daily returns on days where strategies hold a position (that is to say excluding the zero returns on days where no position is held) are below 0.0750% for 135 of the 154 strategies considered and below 0.0500% for 111 strategies. For short-term strategies, these returns are unlikely to exceed transaction costs for any but the largest investors.

The returns to the momentum strategies considered in this chapter therefore tend to indicate that although positive returns are generally found over 1 trading day and over periods ranging from 10 to 252 trading days, very few strategies generate statistically significant excess returns, and only the returns to the longest strategies are likely to generate sufficiently large returns to exceed the cost of trading for most investors. The attractiveness of these strategies may be at least partially offset by the lack of consistency in annual returns highlighted in Section 7.3. Sections 7.6 and 7.7 go on to consider more formally the risk inherent to the strategies considered in this part of the research.

7.6 Standard Deviation of Daily Returns

Table 7.9 shows the standard deviation of daily returns to each of the 154 momentum trading strategies considered in this part of the research. Daily returns in this context are simply the daily percentage profit or loss as calculated in Section 6.3.2 and include the returns to all days in the data sample, regardless of whether or not the strategy in question held a position on that day. The standard deviations reported therefore reflect the overall distribution of returns to an investor following the strategy in question. Each standard deviation is annualised by multiplying by the square root of 252[72].

The main feature of the standard deviations of momentum strategy returns shown in Table 7.9 is that these are significantly higher than the bootstrap values in almost all cases. This reflects a higher variance of daily returns to an investor following the momentum strategies than to an investor following a passive investment strategy. In other words, the momentum strategies considered carry greater risk than do passive investment strategies on the same stock market indices. The 2 through 5 trading day strategies similarly carry more risk than a passive investment in the index, although they do not provide consistently positive excess returns for the data samples considered.

Whilst the 1 trading day and 10 to 252 trading day strategies show some tendency to generate positive excess returns, these returns may be attributable to nonsynchronous trading in the case of the 1 trading day strategy. For the longer strategies, not only are many excess returns not statistically significant at the 5% level, but there is no clear pattern to the significant returns obtained and the standard deviation of returns is generally significantly higher than the bootstrap value. This calls into question whether the momentum strategies considered are able to generate significant risk-adjusted excess returns.

[72] This is based on an average of 252 daily observations per year. The potential issue associated with using the square root of time to annualise standard deviations when the daily returns are not in fact normal is discussed in Section 5.6.

Table 7.9 Standard Deviation of Daily Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	6.63% *5.62%* SIG 1%	7.84% *6.90%* SIG 1%	8.37% *7.54%* SIG 5%	8.77% *7.94%* SIG 5%	8.77% *8.20%*	9.69% *8.94%* SIG 5%
Belgium	10.38% *6.53%* SIG 1%	12.25% *8.11%* SIG 1%	12.71% *8.91%* SIG 1%	12.95% *9.48%* SIG 1%	13.88% *9.84%* SIG 1%	14.55% *10.89%* SIG 1%
Canada	8.47% *6.60%* SIG 1%	10.97% *8.22%* SIG 1%	12.06% *9.12%* SIG 1%	12.68% *9.70%* SIG 1%	11.99% *10.09%* SIG 1%	13.13% *11.15%* SIG 1%
Denmark	10.27% *6.92%* SIG 1%	11.71% *8.49%* SIG 1%	12.04% *9.42%* SIG 1%	12.26% *9.90%* SIG 1%	12.45% *10.25%* SIG 1%	13.23% *11.19%* SIG 1%
France	11.58% *8.59%* SIG 1%	14.95% *10.64%* SIG 1%	15.04% *11.72%* SIG 1%	15.64% *12.40%* SIG 1%	16.38% *12.89%* SIG 1%	16.54% *14.18%* SIG 1%
Germany	13.11% *9.24%* SIG 1%	16.33% *11.49%* SIG 1%	16.83% *12.73%* SIG 1%	17.47% *13.52%* SIG 1%	18.29% *14.11%* SIG 1%	19.23% *15.51%* SIG 1%
Hong Kong	14.78% *11.05%* SIG 1%	16.79% *13.45%* SIG 1%	18.17% *14.76%* SIG 1%	18.40% *15.60%* SIG 1%	19.43% *16.26%* SIG 1%	21.22% *17.99%* SIG 1%
Italy	12.84% *10.25%* SIG 1%	16.15% *12.50%* SIG 1%	16.38% *13.82%* SIG 1%	16.74% *14.30%* SIG 1%	17.73% *14.77%* SIG 1%	18.23% *16.39%* SIG 1%
Japan	10.29% *8.35%* SIG 1%	13.10% *10.16%* SIG 1%	13.86% *11.17%* SIG 1%	14.25% *11.82%* SIG 1%	14.69% *12.21%* SIG 1%	15.75% *13.41%* SIG 1%
Netherlands	13.01% *8.02%* SIG 1%	15.74% *10.42%* SIG 1%	16.17% *11.70%* SIG 1%	17.05% *12.46%* SIG 1%	17.86% *13.02%* SIG 1%	17.74% *14.43%* SIG 1%
Spain	12.69% *9.36%* SIG 1%	15.60% *11.52%* SIG 1%	15.99% *12.67%* SIG 1%	16.16% *13.42%* SIG 1%	17.24% *13.93%* SIG 1%	18.07% *15.24%* SIG 1%
Switzerland	11.63% *7.43%* SIG 1%	13.34% *9.30%* SIG 1%	14.28% *10.28%* SIG 1%	15.55% *10.90%* SIG 1%	15.23% *11.37%* SIG 1%	15.70% *12.59%* SIG 1%
UK	9.41% *6.88%* SIG 1%	11.31% *8.32%* SIG 1%	12.25% *9.41%* SIG 1%	12.44% *9.99%* SIG 1%	12.31% *10.37%* SIG 1%	13.33% *11.37%* SIG 1%
USA	10.01% *7.48%* SIG 1%	12.15% *8.94%* SIG 1%	12.56% *9.83%* SIG 1%	13.42% *10.36%* SIG 1%	13.24% *10.76%* SIG 1%	13.63% *11.85%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.9 (continued)

PANEL B: 21-252 Trading Day Strategies	**21**	**42**	**63**	**126**	**252**
Australia	9.84% *9.47%*	9.92% *9.84%*	10.73% *9.97%*	10.54% *10.26%*	10.55% *10.50%*
Belgium	15.22% *11.72%* SIG 1%	15.57% *12.36%* SIG 1%	15.60% *12.44%* SIG 1%	16.16% *12.79%* SIG 1%	17.15% *13.17%* SIG 5%
Canada	14.25% *11.97%* SIG 1%	13.56% *12.49%*	14.37% *12.78%*	15.99% *13.13%* SIG 5%	17.15% *13.46%* SIG 5%
Denmark	14.23% *11.93%* SIG 1%	14.54% *12.28%* SIG 1%	14.58% *12.67%* SIG 1%	15.71% *13.06%* SIG 5%	16.24% *13.25%*
France	17.74% *15.18%* SIG 1%	17.49% *15.73%*	19.55% *15.95%* SIG 1%	20.87% *16.27%* SIG 1%	21.48% *16.69%* SIG 5%
Germany	19.52% *16.59%* SIG 1%	20.29% *17.23%* SIG 1%	19.85% *17.40%*	21.34% *17.84%*	20.09% *17.90%*
Hong Kong	22.58% *19.45%* SIG 5%	21.23% *20.61%*	22.73% *20.68%*	19.49% *20.88%*	25.59% *20.84%*
Italy	19.78% *17.99%*	20.05% *19.08%*	19.42% *18.98%*	20.79% *19.32%*	22.81% *19.79%* SIG 5%
Japan	15.57% *14.23%*	15.60% *14.62%*	15.65% *14.81%*	15.91% *15.00%*	14.42% *14.93%*
Netherlands	18.92% *15.53%* SIG 1%	18.22% *16.21%*	20.02% *16.47%* SIG 1%	21.14% *17.04%* SIG 5%	20.41% *17.54%*
Spain	18.99% *16.02%* SIG 1%	19.61% *16.74%* SIG 1%	19.51% *16.99%*	21.10% *17.73%*	21.50% *18.24%*
Switzerland	16.39% *13.54%* SIG 1%	16.25% *14.21%*	15.64% *14.44%*	18.32% *15.10%* SIG 5%	17.61% *15.59%*
UK	14.01% *12.09%* SIG 1%	14.39% *12.53%* SIG 5%	14.19% *12.74%*	14.41% *13.30%*	14.44% *13.09%*
USA	14.86% *12.70%* SIG 1%	14.45% *13.22%*	15.33% *13.49%*	14.77% *13.89%*	17.56% *14.30%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

7.7 Sharpe Ratios

The Sharpe ratio, described in Section 6.4, is a measure of the relationship between the return and risk of an investment strategy. Table 7.10 shows the Sharpe ratios calculated for each of the 154 momentum strategies considered in this part of the research.

Each ratio gives the return to the strategy per unit of risk. Strategies with higher Sharpe ratios therefore dominate those with lower ratios. Strategies which produce negative cumulative returns have negative Sharpe ratios, whilst those with positive cumulative returns have positive Sharpe ratios. The Sharpe ratios from the bootstrap are all small compared to those calculated for the original data samples.

Very few of the 154 strategies considered produce statistically significant Sharpe ratios. For the 1 trading day strategies, both Belgium and Canada produce significantly high ratios, as does Belgium over 2 trading days. Three strategies (Belgium, Canada, and the Netherlands) produce significant results over 42 trading days, as do Denmark and Switzerland over 63 trading days, Denmark over 126 trading days, and the Netherlands, Spain, Switzerland and the USA over 252 trading days. There is no clear pattern however in the significant results.

In general, therefore, the Sharpe ratios calculated for the 154 momentum strategies considered are not significantly large. Positive excess returns to momentum strategies may therefore simply provide compensation for the additional risk inherent to such strategies. In addition, the analysis of returns by calendar year presented in Section 7.3 indicates that the returns to those strategies with significantly high Sharpe ratios is not consistent throughout the data samples. That is to say, strategies which appear to generate particularly attractive returns relative to the standard deviation of those returns cannot be expected to do so consistently over time. There remains, therefore, significant risk to returns over common performance evaluation horizons even for those strategies with the highest Sharpe ratios.

Table 7.10 Sharpe Ratios

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	0.18 *-0.01*	-0.30 *0.00*	-0.29 *-0.01*	-0.55 *-0.08*	-0.37 *-0.08*	-0.55 *-0.05*
Belgium	1.37 *-0.01* SIG 1%	0.73 *0.01* SIG 5%	0.24 *0.00*	0.18 *-0.01*	-0.16 *0.05*	0.07 *0.12*
Canada	1.01 *-0.01* SIG 1%	0.21 *-0.01*	0.13 *0.01*	-0.12 *0.01*	0.09 *0.02*	0.40 *0.02*
Denmark	0.39 *0.01*	0.04 *0.00*	0.03 *-0.02*	0.36 *-0.03*	0.44 *-0.01*	0.28 *0.01*
France	0.21 *-0.01*	-0.51 *0.01*	-0.39 *0.01*	-0.41 *-0.01*	-0.57 *0.02*	-0.07 *0.02*
Germany	-0.10 *-0.02*	-0.35 *-0.02*	-0.35 *-0.01*	-0.03 *0.01*	0.10 *0.00*	-0.10 *0.01*
Hong Kong	0.53 *0.01*	0.44 *0.00*	0.25 *0.02*	0.09 *0.00*	0.05 *0.00*	0.19 *-0.02*
Italy	0.12 *0.00*	-0.23 *0.01*	-0.14 *0.14*	0.35 *0.07*	-0.03 *0.07*	0.63 *0.13* SIG 1%
Japan	0.26 *0.00*	0.06 *0.00*	-0.43 *0.00*	-1.01 *0.00*	-0.85 *-0.04*	-0.14 *0.00*
Netherlands	0.18 *0.02*	-0.52 *-0.12*	-0.49 *0.00*	-0.59 *0.01*	-0.36 *0.01*	0.44 *0.04*
Spain	0.28 *-0.02*	-0.30 *-0.01*	-0.22 *-0.01*	-0.13 *0.01*	0.11 *-0.01*	0.45 *-0.01*
Switzerland	0.45 *0.02*	0.03 *0.04*	-0.32 *0.02*	-0.11 *0.01*	-0.27 *0.01*	0.52 *0.04*
UK	0.46 *0.00*	-0.51 *-0.01*	-0.59 *0.01*	-0.56 *-0.01*	-0.72 *-0.01*	0.03 *0.00*
USA	0.26 *-0.02*	-0.35 *0.00*	-0.58 *0.02*	-0.43 *0.03*	-0.66 *0.02*	-0.10 *0.04*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table 7.10 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-0.41 *0.02*	-0.39 *0.03*	-0.45 *0.05*	-0.13 *0.05*	-0.04 *0.05*
Belgium	-0.01 *0.20*	0.51 *0.22* SIG 1%	0.18 *0.03*	0.43 *0.04*	0.46 *0.05*
Canada	0.09 *0.03*	0.59 *0.04* SIG 5%	0.06 *0.05*	0.03 *0.08*	0.35 *0.10*
Denmark	-0.02 *0.00*	0.25 *-0.05*	0.56 *-0.02* SIG 1%	0.77 *-0.02* SIG 1%	0.52 *0.04*
France	0.23 *0.01*	0.48 *0.02*	0.40 *0.02*	-0.13 *0.04*	0.48 *0.05*
Germany	0.12 *-0.02*	0.32 *0.00*	0.45 *0.01*	-0.02 *0.01*	0.50 *0.01*
Hong Kong	0.38 *-0.03*	0.19 *0.10*	-0.13 *0.03*	0.08 *0.02*	-0.40 *0.03*
Italy	-0.01 *0.15*	0.01 *-0.08*	0.29 *0.01*	0.27 *-0.08*	0.31 *-0.08*
Japan	-0.16 *-0.02*	0.19 *0.01*	0.23 *0.02*	0.01 *0.02*	-0.11 *0.02*
Netherlands	0.08 *0.02*	0.67 *0.02* SIG 5%	0.58 *0.04*	0.10 *0.07*	0.67 *0.09* SIG 5%
Spain	0.48 *0.03*	0.34 *0.05*	0.34 *0.11*	0.30 *0.07*	0.66 *0.07* SIG 5%
Switzerland	0.12 *0.06*	0.13 *0.06*	0.72 *0.08* SIG 5%	0.22 *0.08*	0.56 *0.11* SIG 5%
UK	-0.38 *0.00*	-0.13 *0.02*	0.24 *0.00*	-0.24 *0.00*	0.28 *-0.02*
USA	0.05 *0.01*	-0.12 *0.04*	0.08 *0.05*	0.40 *0.06*	0.69 *0.07* SIG 5%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

7.8 Summary

The main aim of this part of the research is to assess the evidence of significant continuation and reversal effects in financial market returns using a methodology which closely reflects the experience of real-world investors. A time-series methodology is implemented based on the profitability of momentum trading strategies which buy the stock market index following a market rise and sell following a market fall.

There is some evidence of a tendency towards positive excess returns to momentum strategies for the 1 trading day strategies although this may be due to spurious positive serial correlation in the index values in the very short term as a result of nonsynchronous trading. Similarly, there is a tendency towards positive excess returns for strategies based on holding periods of between 10 and 252 trading days, although there are few significant results and no clear pattern is observed in these results. The returns to strategies based on holding periods of 2 through 5 trading days are mixed. The cumulative profits to long positions are high for the 1 day and 10 through 252 trading day strategies, with mixed returns to the 2 through 5 trading day strategies. For short positions, mixed results are obtained for the 1 trading day strategies, with generally negative returns thereafter.

These results are interpreted as very limited evidence of continuation effects in the medium-term (10 to 252 trading days) for winners.

An analysis of the profitability of each strategy by calendar year reveals a high degree of inconsistency in returns over time, indicating that risk may be an important consideration for investors embarking on any such strategy. The standard deviation of daily returns is significantly high for almost all of the strategies considered. The Sharpe ratios, which measure strategy returns per unit of risk, are generally insignificant based on the bootstrap test, indicating that strategy profitability is not significantly high once risk is taken into account.

The second part of the research examines the features of stock market trends with the objective of reconciling the results of this part of the research with the behavioural and alternative theories of continuation and reversal effects in financial market returns discussed in Chapters 2 and 3.

Chapter 8

Trend Analysis Methodology

8.1 Introduction

The results of the analysis described in Chapters 6 and 7 show very limited evidence of excess profits to momentum trading strategies with holding periods of one trading day and 10 through 252 trading days driven largely by the returns to long positions. Once risk is taken into account, however, the excess profits achieved by the strategies considered are not statistically significant.

The aim of the research documented in this thesis is to examine short- and medium-term continuation and reversal effects in stock market returns and to consider the extent to which these may be caused by the behavioural and alternative explanations proposed in the literature and discussed in Chapters 2 and 3. The second part of the research, documented in this chapter and the following chapter, considers the issue of continuation effects in stock market returns from a different angle. If such effects are indeed present in stock market returns, what are the implications for the time series properties of stock market returns and in particular for trends in market prices?

Three causes can be identified for empirical findings of continuation effects in stock market returns:

- Continuation effects in the data samples used by previous studies such as those of Jegadeesh and Titman (1993 and 2001) may occur as a result of chance (Fama, 1998). Chance alone is sufficient to ensure that periods of time will exist in which the returns to any given financial market will exhibit continuation effects. Data-snooping bias may therefore explain some of the findings of previous research.

- The distribution of daily stock market returns may in itself generate findings of continuation effects. The distribution of daily returns may be biased as a result of behavioural biases such as a tendency to react more strongly to bad news than good, for example. If the distribution of returns is heavily skewed to the right, empirical studies are likely to find evidence of positive momentum profits, particularly from long positions[73]. The data samples used in this study exhibit positive mean and median returns. Positive returns are therefore likely to be followed by further positive returns. Even if the overall descriptive statistics for a data sample appear normal, periods of highly biased returns may be present within the sample.

- Even if the distribution of daily stock market returns is not in itself biased, patterns in the order in which returns occur in the data sample may generate continuation effects. If, for example, positive returns tend to cluster together, a continuation effect will result. This could occur as a result of market microstructure issues such as nonsynchronous trading or behavioural biases such as representativeness, for example. Once investors see a pattern forming in returns, the expectation that the trend will continue may result in a greater probability of a confirming rather than a conflicting return on the following trading day.

The focus of this second part of the research is on assessing the extent to which biases in the distribution of stock market returns and patterns in the order of returns might generate continuation effects. This in turn may shed some light on the results of the first part of the research, discussed in Chapter 7. Continuation effects imply trending in stock market prices. By examining the properties of stock market trends and considering the factors which might drive such trends, this part of the research considers whether stock market trend behaviour is consistent with medium-term continuation effects driven by the behavioural and alternative theories described in Chapters 2 and 3.

This chapter introduces the analytical framework within which this part of the research is carried out, and describes in detail the methodology employed in an analysis of the statistical properties of stock market trends. Chapter 9 presents the results of this analysis.

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[73] This is the broad pattern of returns to momentum strategies identified by the current study and described in Chapters 6 and 7.

Within this chapter, Section 8.2 discusses the issue of trends in financial market prices in more detail. Section 8.3 provides a brief review of statistical methods used to extract turning points from time series data, whilst Section 8.4 extends this to describe the algorithm used in this study. Section 8.5 discusses the analysis to be performed once the trends in the data have been identified using the algorithm, Section 8.6 reviews the use of the bootstrap methodology to assess significance levels, and Section 8.7 concludes.

8.2 Market Trends

Market trends have traditionally been defined by market commentators as periods of generally increasing and/or decreasing prices, with periods of rising prices typically referred to as bull markets and periods of falling prices as bear markets[74]. More recently, a cumulative market move of a specific size appears to be required for a phase to be termed a bull of bear market. Davis (2003, p178), for example, defines a bear market as

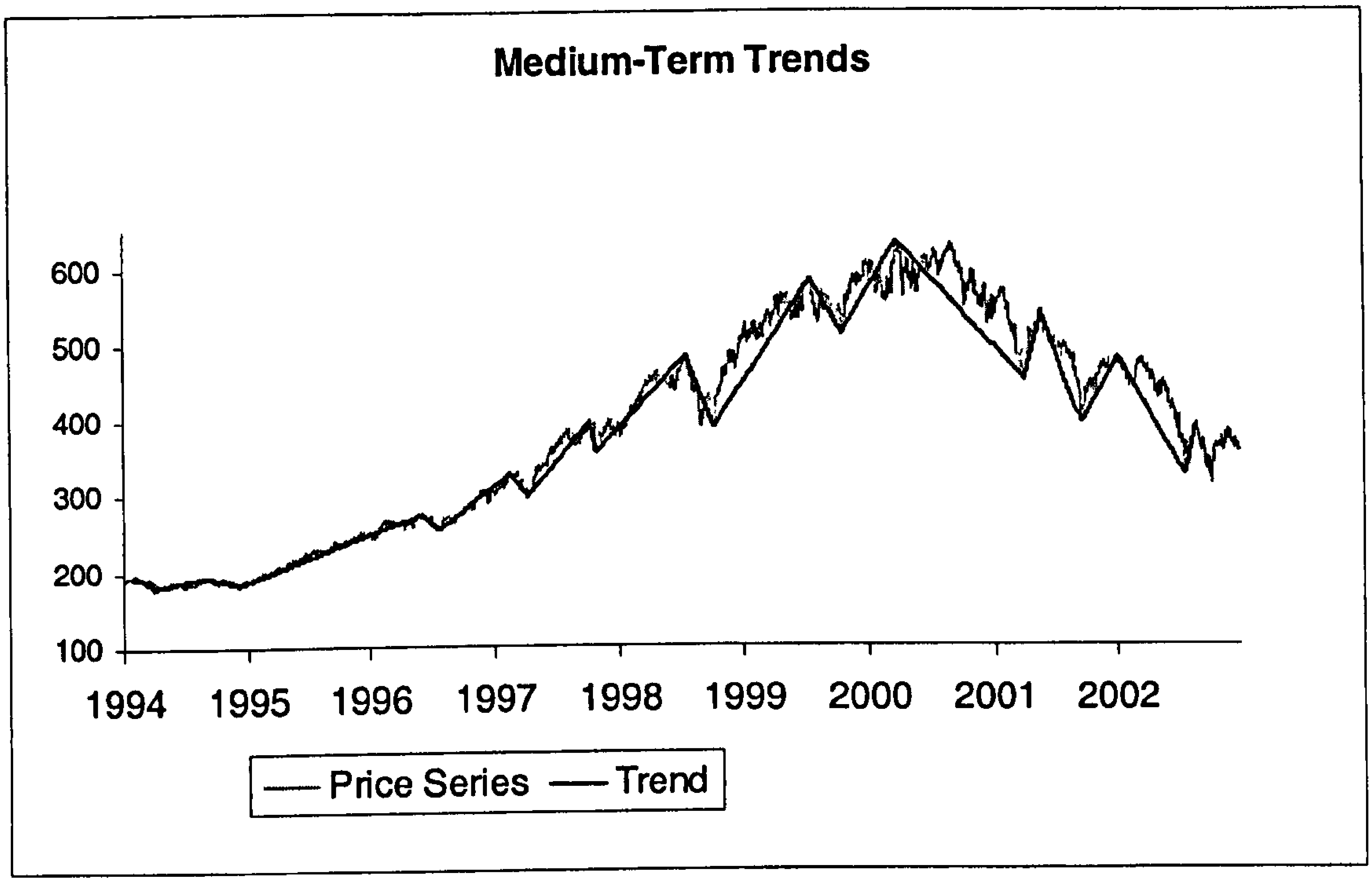
> "a prolonged period of falling equity prices, usually by 20 percent or more over several years"

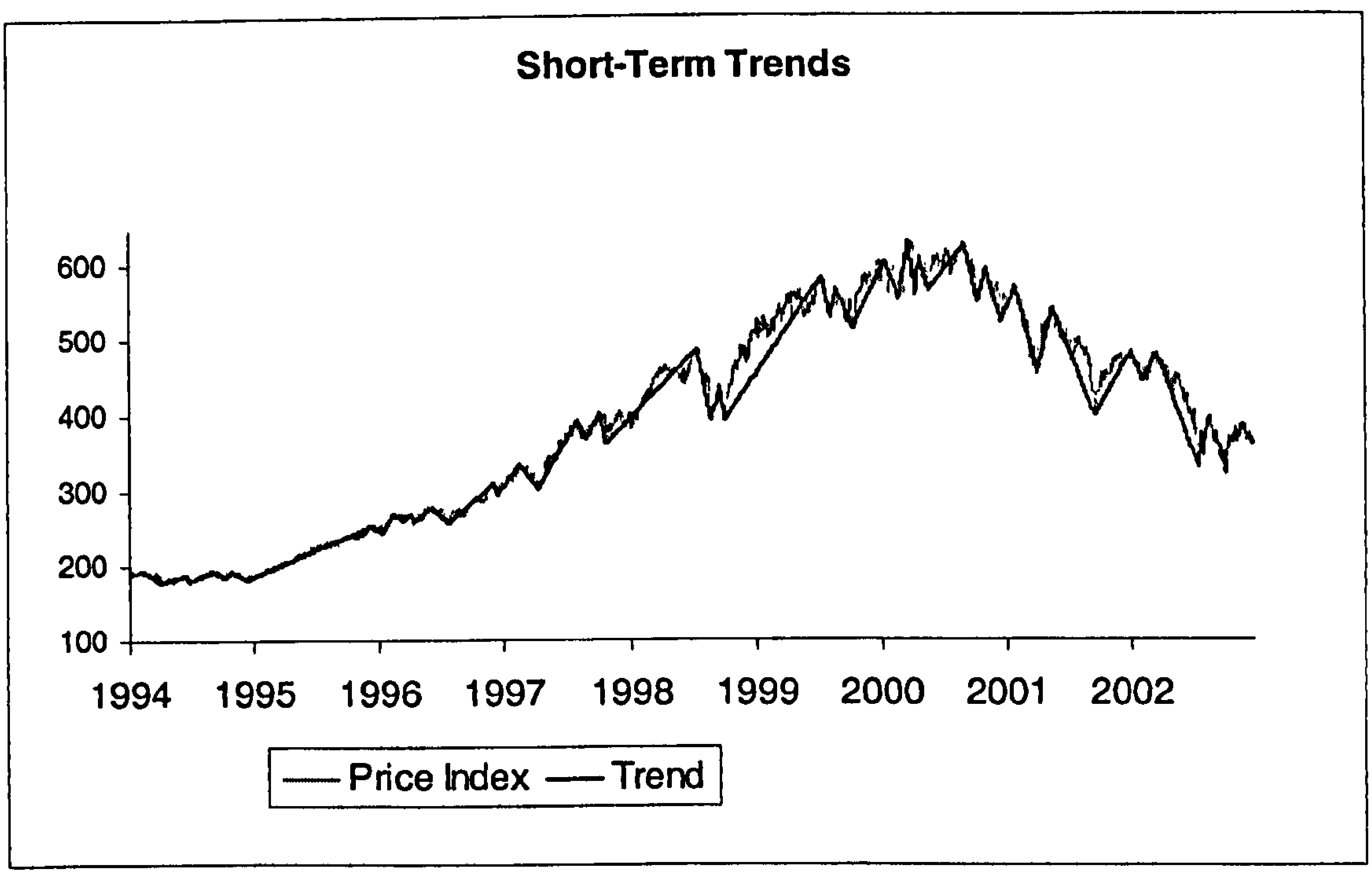
At the same time, market practitioners commonly differentiate between short-term and long-term market trends[75]. Short-term trends relate to trends occurring over periods of days and weeks rather than the months and years associated with long-term trends. A long-term trend, therefore, can be thought of as a combination of shorter-term trends. Figure 8.1 illustrates this by showing both medium-term and short-term trends in the US stock market data employed in this study.

[74] For this reason, the analysis described in this chapter focuses on trends in the price series of each of the 14 stock markets considered, rather than trends in the total return series or in funded returns.

[75] The definition of short-term and long-term used in this context is somewhat arbitrary.

Figure 8.1 Medium-Term and Short-Term Stock Market Trends





NOTE: Trends are depicted as straight lines joining their start and end points. The medium-term trends were generated using the price index series for the USA and the Fink and Pratt algorithm with R=2/3. The short-term trends were generated using the same data and algorithm with R=0.25. The identification of trends using the Fink and Pratt algorithm is discussed later in this chapter.

The concept of trends of differing magnitudes is not new. In a 1902 Wall Street Journal editorial (quoted in Nelson, 1903 and reproduced in Galbi, 2001, p8), Charles Dow says, for example,

> "Nothing is more certain than that the market has three well defined movements which fit into each other. The first is the daily variation due to local causes and the balance of buying or selling at that particular time. The secondary movement covers a period ranging from ten to sixty days, averaging probably between ten and forty days. The third swing is the great move covering from four to six years"

Subsequent authors have questioned the length of Dow's trends. Hamilton (1922, reprinted 1998, p24) notes that according to his analysis, the primary trend is

> "rarely three years and oftener less than two"

The aim of this part of the research is not only to empirically examine the duration and amplitude of trends in the fourteen stock market data sets described in Chapter 5, but by examining their statistical properties to draw some conclusions as to the likely relevance of the behavioural and alternative theories introduced in Chapters 2 and 3 in driving the findings of medium-term continuation effects in stock market returns reported by previous studies and the continuation and reversal effects identified in the first part of the current study and described in Chapters 6 and 7.

In simple terms, trends occur when, in a subsection of a data series, either

- the proportion of positive price changes exceeds the proportion of negative price changes for a bull trend (and vice versa for a bear trend), and/or

- the absolute size of positive price changes exceeds that of negative price changes, for a bull trend (and vice versa for a bear trend)

If, in any given subsection of the data, for example, there are more positive daily price changes than negative changes, and the average absolute size of the positive price changes is larger than that of the negative price changes, then clearly the market price level will tend to increase over that subsection of data. This upward trend in prices represents a bull trend. Similarly, a downward pattern in prices would be identified as a bear trend.

Many market observers seem to believe that financial market trends are "different" in some way from random patterns of price fluctuation. Experiments using both normally distributed and uniformly distributed daily price returns, however, produce price index charts which are intuitively indistinguishable from charts of real-world financial market prices[76].

Most importantly, however, whilst random data and financial market prices both display trend behaviour, random data will not generate systematic continuation effects. At any point, assuming a symmetric distribution of returns, a positive increment is as likely as a negative increment, and momentum strategies will on average produce zero returns. The existence of medium-term momentum profits of the kind identified by studies such as Jegadeesh and Titman (1993) presupposes predictability in financial time series data. That is to say, trends must persist such that at any given point, a trend is more likely to continue than to reverse[77]. The analysis of stock market trends contained in this thesis centres therefore on how the behaviour of stock market trends deviates from that of random trends.

Continuation effects could be produced by extreme stock market trending behaviour in a number of different ways:

- Trends might become longer, either in terms of duration or total amplitude, than random trends based on the same distribution of daily returns. The distribution of daily returns in terms of the proportion of positive and negative daily returns in the trend and the relative size of each may not differ from random trends, but clustering of positive and negative returns within the data sample may result in trends which simply continue for longer before reversing. This could occur, for example, if stock market investors were susceptible to underreaction.

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[76] Sample charts are not reproduced in this thesis in the interests of brevity and to avoid potential biases in the selection of a small number of charts for reproduction.

[77] Aaberge (2002) discusses the definitions of, and approaches to the measurement of, duration dependence in economic data.

Excessively long financial market trends would induce predictability in financial market returns in that, at any point in time, a trend would be more likely to continue than to reverse.

- Alternatively, trends may have the same average duration and total amplitude as random trends but patterns in the steepness of trends may introduce predictability to returns. If trends end more steeply than they begin, for example, this implies that although the probability of continuation may not be significantly greater than the probability of reversal at any point in time, the potential rewards from continuation may exceed the potential losses from reversal. This might in itself be sufficient to drive findings of significant excess returns to momentum trading strategies. Patterns in the steepness of trends can be generated in two main ways, as discussed above. Either

    - the proportion of positive versus negative daily returns differs systematically from that of random trends, or
    - the relative absolute magnitude of positive versus negative daily returns differs systematically from that of random trends.

If financial market trend behaviour can be shown to be systematically different from the behaviour of random trends based on the same distribution of daily returns, then this may provide evidence to support the notion of continuation effects in stock market returns, and may enable some conclusions to be drawn regarding the sources of such effects. From the above analysis, three main potential sources of such differences can be identified and are examined empirically in this part of the research. These are

1. The average duration and amplitude of trends
2. The proportion of positive and negative daily returns within trends
3. The relative magnitude of positive and negative daily returns within trends

This part of the research examines the statistical properties of stock market price trends, beginning with the three key features listed above. A bootstrap approach is used to generate random price series with the same empirical distribution of daily price returns as the original data. An analysis of the properties of trends present in the bootstrap data enables inferences to be made regarding the nature of systematic deviations from randomness in the trend behaviour of the 14 original time series.

8.3 Identifying Trends in Time Series Data

The initial objective of this part of the research is the identification of bull and bear trends in the price series of fourteen stock market indices[78]. The approach used is similar to that proposed in the literature on dating the business cycle, with turning points in trends (local maxima and minima) identified directly from the data using a suitably-specified algorithm.

Section 8.3.1 reviews the use of algorithms in the context of dating the business cycle. Section 8.3.2 discusses previous research using algorithms based on business cycle dating techniques to date financial market cycles. Section 8.3.3 discusses related research in financial markets using Markov switching models to identify turning points. Section 8.4 then goes on to introduce the approach used in this study, which is based on an algorithm proposed in the information technology literature by Fink and Pratt (2004).

8.3.1 Dating the Business Cycle

The main area in which turning point detection algorithms have been used in finance and economics is in dating the business cycle, that is, identifying peaks and troughs in the business cycle from quarterly or monthly historical levels of GDP or other macroeconomic variables such as unemployment.

The business cycle dating methods developed and used by the National Bureau of Economic Research (NBER) on the basis of early work by researchers such as Burns and Mitchell (1946) have gained semi-official status for the US economy, and form the basis of the non-parametric algorithm proposed by Bry & Boschan (1971). This algorithm, and slight variations of it, are used widely in business cycle research. Artis (2002), for example, uses the

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[78] These are the same data samples as those used in the first part of the research and are described in detail in Chapter 5.

Bry and Boschan algorithm to date the UK business cycle between January 1974 and February 2002.

The Bry and Boschan algorithm identifies turning points in the business cycle based on the duration of expansion and contraction phases. The first step is to identify points in monthly data which are the maximum / minimum in a window six months either side of the month in question. The alternation of maxima and minima is then enforced by selecting the highest of multiple peaks and the lowest of multiple troughs (in some studies this rule is amended slightly and the latest-occurring of any multiple peaks or troughs is taken). This gives a series of alternating peaks and troughs, each of which is a local maximum/minimum in a six month window either side.

Further censoring operations are then undertaken to ensure that the peaks and troughs identified comply with generally accepted principles in terms of the characteristics of the business cycle. Cycles (combinations of one expansion and one contraction phase) lasting less than fifteen months are eliminated, as are any phases (individual expansions or contractions) with a duration of less than six months.

Research into dating the business cycle is further complicated in that it commonly uses smoothed data in order to remove outliers. Data may also be detrended using either a low-order polynomial or a filter (Harding and Pagan, 2003). The methodologies employed are not described in detail in this thesis as they are not relevant to the dating of financial market trends. Whilst there may be a desire to remove outliers when working with macroeconomic data, extreme values of stock market prices are of particular interest.

One issue with Bry and Boschan-type algorithms is that the way in which they are set up determines the turning points that are found. Academic studies on dating the business cycle have tended to use very similar parameters (6 month window, 6 month minimum phase length, 15 month minimum cycle) and so have identified similar turning points. Changing these parameters will result in the identification of different turning points. Harding and Pagan (2002), for example, encounter difficulties when dating the UK business cycle using a Bry and Boschan approach, finding it necessary to reduce their initial minimum phase duration from 5 months to 4 for the UK data in order not to miss what they consider to be an important turning point in 1974. Section 8.3.2 provides an overview of the use of Bry and Boschan-type algorithms in financial markets research.

8.3.2 Studies using a Bry and Boschan Approach

A number of studies have used a modified Bry and Boschan approach to examine trends in financial market prices. These studies typically take the standard Bry and Boschan algorithm as described in the previous section and amend the algorithm to allow for the identification of very short steep trends such as the market crash of 1987. Maxima and minima are identified using a short window and the censoring rules amended such that the minimum duration rules are not applied if the amplitude of a trend exceeds a given level over a specified period, say 20 percent in one month. Monthly data is typically used for ease of implementation of the algorithm.

The use of monthly data in previous studies necessarily involves a lack of fineness in the results, since turning points in stock market trends can only be identified in terms of the month in which they occur. The Fink and Pratt (2004) algorithm on which this study is based, on the other hand, enables daily (or even intraday) data to be used without the need to reconfigure the algorithm. This enables a more detailed analysis of the statistical properties of daily price returns in stock market trends to be carried out in this study than has been possible in previous work using the Bry and Boschan approach.

Kaminsky and Schmukler (2001) conduct a descriptive analysis of stock market cycles in 28 emerging and mature economies over the period January 1973 to June 1999 and consider the extent to which financial liberalisation influences stock market trends. A simplified Bry and Boschan-type algorithm is used where trends are required to have a minimum duration of twelve months. No additional amplitude-based rules are applied. After identifying trends in the underlying data, qualitative information regarding periods of financial liberalisation in individual countries is used to compare the duration and total amplitude of stock market trends both before and after liberalisation.

Kaminsky and Schmukler report that bull trends last on average for 26 months and bear trends for 18 months. The boom and bust cycle appears to be more pronounced in developing than in developed markets. In the short run, financial liberalization does tend to trigger more explosive financial cycles, although these become less pronounced within three years. Rather than intensifying stock market cycles, therefore, liberalisation appears to make cycles smoother over the medium to long term.

Pagan and Sossounov (2003) examine trends in the US stock market using monthly data for the equivalent of the S&P500 index over the period January 1835 to May 1997. The algorithm used to identify turning points in the data is based on Bry and Boschan with a window length of eight months used to identify local maxima and minima. Trends have a minimum length of four months, except where the market falls by more than 20 percent in a single month in which case the minimum duration rule is not applied.

Bull trends have an average duration of 25 months, which is significantly longer than the average bear cycle duration of 17 months. Over time, bull trends are seen to grow longer and stronger whilst bear trends become shorter and weaker. In addition to the duration and amplitude of trends, Pagan and Sossounov also consider a measure of the deviation in the shape of trends from a straight line, finding that this deviation becomes stronger over time. That is to say, the asymmetric behaviour of stock market trends has become more pronounced in recent decades. Over the most recent section of the data, from January 1945 to May 1997, bull trends have an average duration of 27 months and amplitude of 46 percent, whilst bear trends have an average duration of just 12 months and amplitude of –23 percent. The average sum of squares deviation from a straight line is 0.03 for bull trends and 0.014 for bear trends.

Pagan and Sossounov go on to generate simulated price series using a range of asset pricing models to see which best replicate the properties of stock market trends identified in the earlier analysis. A random walk without drift fails to replicate the durations, amplitudes or shapes of trends. A random walk with drift and a GARCH (1,1) process, each with parameters set based on the past history of returns, do capture the general characteristics of trends but are unable to fit the asymmetric durations or shape of trends in real data as the distribution of returns is symmetrical for each. An EGARCH (1,1) model fits the shape of the data better than the other models, whilst a Hamilton switching methodology fails to improve on EGARCH. Overall, none of the models is able to closely replicate the characteristics of the trends observed in the original data.

Gonzalez et al (2005, forthcoming) use a modified Bry and Boschan approach where bull and bear markets are defined as the periods between troughs and peaks subject to the requirement that these intervals contain sufficient "persistent gains". A 5 month window is used to identify local maxima and minima. The highest peak and lowest trough are selected as turning points, with further turning points selected according to the criterion that trends must produce a cumulative return of at least 10 percent. Any local maxima and minima not meeting this requirement are discarded.

The data used is monthly US stock price data from January 1800 through December 2001. The profitability of two basic trading rules based on the trends identified by the algorithm is calculated. A conservative strategy buys the market on identification of a market trough, sells on identification of a market peak, and holds short-term treasury bills otherwise. Over the period from January 1968 through December 2001, this strategy produces slightly higher returns than a simple buy-and-hold strategy (1.11 percent compared to 1.01 percent per month) and lower standard deviation of monthly returns (3.03 percent compared to 4.46 percent) leading to a higher Sharpe ratio (0.1783 compared to 0.1001). An aggressive strategy which borrows in order to double up on long positions, holding short-term treasury bills otherwise, earns 1.55 percent per month with a standard deviation of 6.07 percent and a Sharpe ratio of 0.1627.

Gonzalez et al report that over the full data sample, bull markets have an average duration of 20 months with 73.74 percent of monthly returns during a bull trend proving positive. The average monthly return is 1.9427 percent with a standard deviation of 4.0939 percent, skewness of 2.0060 and kurtosis of 15.6247. Bear markets have an average duration of 15 months with 63.02 percent of monthly returns during a bear trend proving negative. The average monthly return is –1.8330 percent with a standard deviation of 4.3430 percent, skewness of -0.4461 percent and kurtosis of 5.9876. The authors note that bull and bear phenomena seem to have become more important as the sample progresses with the spread between bull and bear returns widening sharply.

8.3.3 Regime Switching Models of Financial Market Trends

A number of authors have used parametric regime switching models to identify bull and bear trends in stock market data. These follow the Hamilton (1989) parametric approach in which a non-stationary time series is modelled using a stationary piecewise linear process.

The returns process is constructed with two distinct states of mean returns, one reflecting a bull market state and the other a bear market state. Although the current state of the market cannot be known with certainty at any point in time, it can be inferred based on a hazard function which governs the switching process between states. The hazard function is estimated from the past data, and the identification of market trends carried out on the basis of probability. If at any point in time there is a greater than 50 percent chance of being in a bull state, a bull trend is recorded, otherwise a bear trend is recorded. Turning points occur when the hazard function passes through 50 percent and the most likely state of the market switches from bull to bear or vice versa.

In later studies, the hazard function is commonly adapted to reflect duration dependence in market trends. In this way, the probability of a switch increases (or decreases) with the period of time the market has spent in its current state.

Maheu & McCurdy (2000) use a regime-switching model in which the mean and variance of returns within bull and bear states is influenced by duration. Monthly total return data for the US stock market is used covering the period 1802 though 1995. Returns are sorted into two states using the switching model: a high return, stable bull market state and a low return, volatile bear market state. An analysis of the results shows that bull and bear markets account for 90 percent and 10 percent of the data sample respectively. The highest returns are achieved at the start of bull markets, and returns decline with the duration of the bull market. The volatility of returns increases with duration in bear markets. Both bull and bear market states display duration dependence, with the probability of a switch declining the longer the market has spent in its current state. The authors conclude that duration is an important conditioning variable for both the mean and variance of returns. One possible reason given for the patterns identified is positive feedback trading into bull markets as optimism grows.

Anas and Ferrara (2002, p30) demonstrate some of the limitations of regime-switching models. A regime-switching model

> "only separates regimes in accordance to the specification of the model"

Using examples, the authors demonstrate how changes in the model specification in terms of number of regimes (typically two or three) and properties of regimes can lead to the identification of very different turning points.

8.4 The Fink and Pratt Algorithm

The Bry and Boschan algorithm, developed for use in dating the business cycle, has a number of limitations when used to date stock market trends.

Firstly, the Bry and Boschan approach is a duration-based approach to identifying trends. Whilst this may be suitable for dating the business cycle, no rationale is proposed in the literature for the identification of stock market trends based on duration. Rather, as discussed in Section 8.2, most observers of stock market prices identify amplitude as the defining factor of a bull or bear trend.

As described in Section 8.3.2, a number of studies using stock market data have attempted to get round this limitation by imposing additional rules to the algorithm such that the minimum duration rule is ignored if a trend has sufficient amplitude. Pagan and Sossounov (2003), for example, ignore the minimum duration imposed on their trends if the market falls by more than 20 percent in any one month. The choice of 20 percent as a trigger level and one month as the relevant time horizon is arbitrary, and different choices of these variables may lead to the identification of different turning points.

Secondly, the Bry and Boschan approach requires a sliding window of fixed length in order to identify local maxima and minima. Gonzalez et al (2005, forthcoming), for example, require a 5 month window either side of a data point before it can be classified as a maximum or minimum. Whilst the Bry and Boschan algorithm will never generate a signal until five months after the relevant turning point, an amplitude-based algorithm may generate a signal much more quickly. An important distinction can be made between dating and detecting turning points. Anas and Ferrara (2002) liken the difference to that between estimating and predicting. Although Bry and Boschan-type algorithms may be useful for dating turning points in historical data, they are unlikely to identify turning points quickly enough in recent data to be useful for predictive purposes.

For these reasons, an amplitude-based algorithm is preferred over the Bry and Boschan approach. To the author's knowledge, no previous study has employed an amplitude-based algorithm of the type used in this study to identify and analyse the statistical properties of trends in financial market prices[79].

The algorithm used in this study to identify market trends based on their amplitude is taken from the data compression literature in information technology. Data compression involves the representation of a time series by a smaller number of points whilst retaining the key features of the time series. Algorithms have been developed to address the problem of storing and manipulating large complex data sets in a range of fields, including computer science, cartography, and image processing. More recently, data compression has been applied to time series data mining problems[80].

Fink and Pratt (2004) propose an algorithm for the generation of a piecewise linear approximation of time series data based on the identification of "important points". An important point in this context is a local maximum /

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[79] Fink and Pratt (2004) employ time series data from a range of fields, including the S&P 100 index, to demonstrate the broad applicability of their algorithm. The aim of their paper, however, is not to examine the properties of trends in time series data.

[80] Keogh et al (2004) provide an overview of the various approaches proposed in this literature for the piecewise linear representation of financial time series.

minimum which is at least x percent higher/lower than the surrounding minima / maxima respectively. The applicability of the algorithm to identifying turning points in time series data is demonstrated for a range of data sets including stock prices (S&P100 stocks from January 1998 to April 2000), air and sea temperatures, wind speeds, and electroencephalograms.

The Fink and Pratt algorithm has four important advantages over Bry and Boschan:

1. it identifies trends based on amplitude rather than duration. This provides a much closer fit with the generally accepted definition of a stock market trend.

2. it can compress a time series as it arrives, resulting in a potentially much faster identification of turning points than under Bry and Boschan where the size of the window used to determine the initial local maxima and minima to be considered places a lower bound on the time taken to identify turning points.

3. changing the frequency of the data used does not require the specification of the algorithm to be amended as would be the case for Bry and Boschan-type algorithms. The algorithm is relatively simple to implement using daily data, enabling a much finer analysis of the statistical properties of daily returns within financial market trends than has been possible in previous studies.

4. it uses a parameter R to control the rate of compression and thus, in terms of the identification of stock market trends, the size of the trends identified. The higher the level of R selected, the more extreme the turning points found. In the context of stock market trends, a high R will identify a small number of long-term trends, whilst a smaller R will result in the identification of a greater number of short-term trends. The Bry and Boschan algorithm cannot be easily adjusted in this way to consider trends of differing magnitudes.

Figure 8.2 reproduces the definition of turning points (important minima and important maxima) within the Fink and Pratt algorithm.

Figure 8.2 Definition of Turning Points in the Fink and Pratt Algorithm

In the Fink and Pratt algorithm,

a point a_m of a series a_1, ..., a_n is an important minimum if there are indices i and j, where $i < m < j$, such that

- a_m is a minimum among $a_i,...,a_j$, and
- $a_i/a_m >= R$ and $a_j/a_m >= R$

a point a_m of a series a_1, ..., a_n is an important maximum if there are indices i and j, where $i < m < j$, such that

- a_m is a maximum among $a_i,...,a_j$, and
- $a_m/a_i >= R$ and $a_m/a_j >= R$

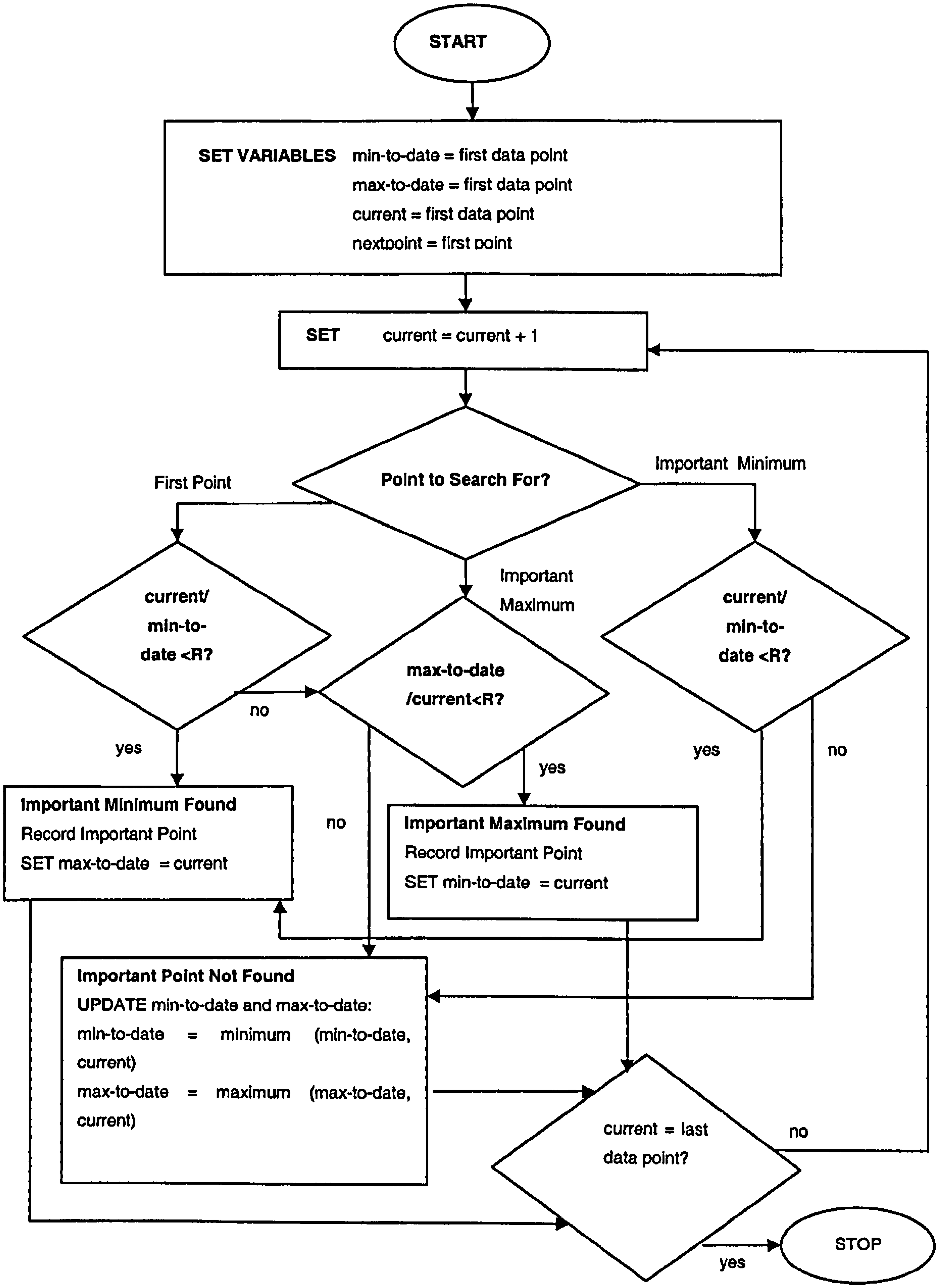
Source: Fink and Pratt (2004)

In simple terms, the Fink and Pratt algorithm searches for points which are the maximum values within a given segment and where the endpoints of the segment are much smaller. These are classified as important maxima. Similarly, important minima are local minima within segments where the endpoints are much larger. Segments do not have fixed length. The algorithm ensures that important maxima and minima alternate, and that all trends have a given minimum amplitude as measured by R.

The Fink and Pratt algorithm is implemented in Microsoft Excel™ for each of the 14 stock market price index series described in Chapter 5. In each case, the first data point is 31 December 1993 and the final data point is 31 December 2002.

Figure 8.3 reproduces the steps involved in the algorithm in the form of a flowchart. Whilst the process is more complex in terms of implementation than the Bry and Boschan approach, the underlying concepts are straightforward.

Figure 8.3 Flowchart: Fink and Pratt Algorithm



The algorithm scrolls through the data day by day, starting with the first data point in the sample. Three main processes are involved: the identification of the first turning point (which can be a peak or a trough), the identification of an important maximum, and the identification of an important minimum.

8.4.1 Identification of the First Turning Point

Until the first turning point in the data sample is found, the algorithm does not know whether that point will be an important maximum or an important minimum. Since the previous point is unknown, the criteria that the first important point in the data sample be higher / lower than the previous point by a factor of R cannot be enforced.

To identify the first turning point, the algorithm therefore scrolls through the data, searching for a local maximum or minimum that is above / below the next local minimum / maximum by at least a factor of R. To do this, variables min-to-date and max-to-date are defined. Initially, both max-to-date and min-to-date are set to equal the first data point. As the algorithm scrolls through the data, these variables are updated at each step as appropriate.

If, at any step, the current value is higher than the minimum-to-date by a factor of at least R then the data point corresponding to min-to-date is identified as the first turning point (an important minimum) and the algorithm looks for a local maximum as the next turning point. Similarly, if at any step, the current value is lower than the variable max-to-date by a factor of at least R then the point represented by max-to-date is identified as the first turning point (an important maximum) and the algorithm looks for a local minimum as the next turning point.

8.4.2 Identification of Remaining Turning Points

Once the first turning point has been found and classified as a maximum or a minimum, the algorithm knows that the next point to be found is a minimum or maximum respectively.

The algorithm specifies that each turning point must be higher / lower than both the preceding point and the next point by a factor of R. Consider the example where R is 1.2 and the first turning point is a maximum. The first and third points must be at least 1.2 times the second point. In identifying the first point, however, the algorithm has already ensured that the first point will be at least 1.2 times the second. To identify the second point, therefore, it is only necessary to ensure that a third point will be found that is at least 1.2 times the level of the second point.

If the algorithm is searching for an important maximum, it updates the variable max-to-date (as appropriate) as it scrolls through the data and considers at each point whether max-to-date exceeds the current market level by a factor of at least R. If it does, then the data point corresponding to max-to-date is classified as an important maximum. The next point to be found is a minimum, and min-to-date is reset to the current price[81].

If the algorithm is searching for an important minimum, it updates the variable min-to-date (as appropriate) as it scrolls through the data and considers at

[81] At the time the important maximum is found, the market is in a down trend (since by definition the maximum cannot be identified until after it occurs). The current level is by definition the minimum price recorded in that bear trend to date, since if a lower price had been recorded, the previous turning point would already have been identified. The next turning point, an important minimum, will be identified after its occurrence by finding a point that is greater than min-to-date by a factor of R. In this context, the minimum recorded in this trend is the relevant variable, not the minimum recorded since the start of the data set. For this reason, when an important maximum is found, min-to-date is reset to the current level at the time the maximum is identified.
A similar argument applies for important minima; when an important minimum is identified, max-to-date is reset to the current price.
Min-to-date or max-to-date is similarly reset to the current market level on identification of the first turning point in the data.

each point whether the current market level exceeds min-to-date by a factor of at least R. If it does, then the data point corresponding to min-to-date is classified as an important minimum. The next point to be found is a maximum, and the variable max-to-date is reset to the current price.

8.4.3 Choice of Compression Rate R

R is constant in the Fink & Pratt algorithm. One reason for this is that their paper is concerned with data compression in a variety of settings and does not specifically relate to financial data.

The choice of R determines the number of turning points found. A high value of R will identify a small number of typically long-term trends, whilst a small R identifies a larger number of typically short-term trends.

One important aim of this study is to carry out a comparative analysis of trend behaviour in the stock markets of fourteen developed countries. The volatility of daily price returns is likely to vary across the fourteen time series and also over time for any individual time series. This is illustrated in Table 8.1, which shows the standard deviation of daily price returns for each of the fourteen stock markets over each calendar year from 1987 to 2002 inclusive[82]. A turning point which might be considered significant in a low volatility series may not be as significant in a high volatility series.

For this reason the Fink and Pratt algorithm is amended in this study such that R is time-varying based on the past volatility of returns. A higher R is therefore

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[82] Table 8.1 shows the annualised standard deviations of daily price changes for each data series for the calendar years 1987 to 2002 inclusive (1st January 1987 is the base date for each index). Although the price index series are available from January 1987, the analysis described in this chapter is restricted to the period 1993 to 2002 inclusive to ensure comparability of the results with those of the first section of the research. Consistent with the analysis of momentum strategy profitability described in Chapters 6 and 7, the data for 1993 is used as an estimation period with results reported for the period 1994 to 2002 inclusive.

Table 8.1

Annualised Standard Deviation of Daily Percentage Price Changes

	Australia	Belgium	Canada	Denmark	France	Germany	HK	Italy	Japan	Neth.	Spain	Switz.	UK	USA
1987	32.96%	22.36%	24.70%	15.79%	26.79%	28.06%	43.08%	21.95%	28.71%	30.64%	26.42%	29.08%	25.90%	30.94%
1988	16.30%	14.23%	10.05%	11.41%	16.62%	17.17%	16.79%	17.60%	13.73%	16.15%	11.53%	17.43%	11.87%	16.09%
1989	14.77%	7.93%	8.11%	13.60%	13.18%	19.63%	35.20%	14.03%	9.40%	12.85%	10.05%	15.93%	12.49%	12.43%
1990	13.86%	14.95%	8.49%	11.96%	17.32%	22.29%	18.71%	17.96%	28.44%	13.79%	20.38%	19.12%	14.43%	15.48%
1991	14.92%	11.93%	8.25%	12.02%	16.67%	18.13%	17.45%	18.98%	17.57%	11.36%	18.15%	15.65%	12.43%	13.76%
1992	12.05%	10.96%	7.70%	15.58%	16.37%	13.01%	21.81%	23.80%	25.22%	10.11%	17.55%	11.76%	15.38%	9.31%
1993	12.05%	8.96%	8.39%	13.05%	13.19%	12.54%	21.96%	21.38%	18.98%	9.42%	14.44%	10.64%	9.38%	8.43%
1994	14.51%	8.97%	10.90%	11.99%	15.22%	14.82%	29.34%	25.42%	14.28%	12.30%	17.97%	14.81%	12.56%	9.55%
1995	11.02%	7.50%	8.92%	9.30%	14.70%	11.56%	19.95%	18.89%	18.87%	8.89%	12.99%	9.96%	9.08%	7.63%
1996	12.32%	9.53%	9.04%	9.22%	10.88%	11.79%	16.03%	18.38%	12.03%	11.54%	12.54%	11.76%	8.64%	11.49%
1997	15.92%	14.72%	13.88%	14.68%	19.85%	22.41%	36.73%	22.68%	22.32%	23.56%	20.89%	18.24%	14.00%	17.33%
1998	15.31%	19.82%	20.39%	21.30%	24.01%	27.43%	43.64%	32.83%	22.36%	26.82%	29.45%	25.90%	19.38%	19.81%
1999	12.34%	17.30%	16.08%	13.69%	17.51%	20.72%	25.53%	20.33%	18.65%	19.04%	20.17%	19.61%	16.59%	17.64%
2000	12.23%	19.00%	26.82%	20.97%	20.38%	21.21%	27.86%	22.49%	20.37%	17.25%	22.48%	14.21%	17.39%	21.97%
2001	13.42%	16.82%	19.49%	18.98%	24.28%	27.75%	24.95%	26.06%	23.53%	26.27%	26.97%	22.72%	20.92%	21.51%
2002	12.05%	27.21%	17.72%	23.57%	34.23%	38.91%	19.00%	26.56%	22.21%	37.01%	32.05%	28.16%	26.63%	25.51%
Mean 87-02	**14.75%**	**14.51%**	**13.68%**	**14.82%**	**18.83%**	**20.46%**	**26.13%**	**21.83%**	**19.79%**	**17.94%**	**19.63%**	**17.81%**	**15.44%**	**16.18%**
Mean 93-02	**13.12%**	**14.98%**	**15.16%**	**15.67%**	**19.43%**	**20.91%**	**26.50%**	**23.50%**	**19.36%**	**19.21%**	**20.99%**	**17.60%**	**15.46%**	**16.09%**

used for more volatile markets and more volatile periods of time within each time series, and a lower R for less volatile markets and periods of time. This provides a "level playing field" for each stock market considered and would also enable the same methodology to be easily applied without adjustment to different types of financial time series such as foreign exchange rates and interest rates. For each trading day, the value of R to be used by the algorithm is defined as two-thirds of the annualised standard deviation of percentage price returns over the previous 252 trading days[83]. As discussed in Section 5.6, the use of the square root of time as a scaling rule when returns are not normal may be a limitation, although it is not considered material in this instance since the aim of the time-varying R is simply to enable the definition of a trend to vary based on some measure of the volatility of the underlying time series.

The choice of 252 trading days as the calculation period for R is somewhat arbitrary. The time period should not be too long, in order that the changing volatility of the data sets over time is captured. On the other hand, the time period chosen should not be too short or the nature of the algorithm may artificially influence the results. If the length over which R is calculated is too short relative to the average length of the trends identified, then the volatility of price changes within a trend may have undue influence on the level of R used to identify the end of the trend. Volatile trends may be prolonged (by inducing a higher R) and less volatile trends shortened. The definition of R used in this study reflects the medium-term nature of the continuation effects identified in previous research. The average length of the trends identified by the algorithm is less than the 252 day period over which the standard deviation of returns is calculated.

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[83] By experimentation, a level of R equal to two thirds of the standard deviation of price returns over the previous 252 trading days was seen to identify trends with a mean duration of between 6 and 12 months. This was considered desirable in order to ensure the potential relevance of the results to the (limited) findings of positive medium-term excess returns to momentum strategies in the first part of the research. A similar analysis with R defined as one third of the standard deviation of price returns over the previous 252 trading days yields a very similar pattern of results. These are reproduced in Appendix G.

The data set is the same as that used in Chapters 6 and 7 to investigate the issue of momentum strategy profitability. In this case, trends are identified in the price return series rather than the funded returns series used previously, as discussed in Section 8.2.

For 1994, the first year of data to be considered, the appropriate level of R is calculated using price index data for the 1993 calendar year. That is to say, the level of R remains constant for each time series for the first 252 trading days considered. After the first 252 trading days, R is calculated for each trading day based on the standard deviation of daily price changes over the previous 252 trading days.

The algorithm is run through the data with R = 2/3 to create a list of turning points for each market. Appendix F shows the turning points identified for each market together with the date on which these are identified by the algorithm.

8.4.4 Identification of Trends and Phases within Trends

Once implemented, the algorithm generates a series of turning points for each data set based on the raw price index data. The first trend starts with the first turning point found in the data, and the last trend ends with the last point found.

Once the turning points have been identified in the raw price series, the next step is to isolate the series of daily price returns occurring within each trend. Again, this is carried out using Microsoft Excel™.

Since the data used to generate these turning points comprises closing price data, each turning point is deemed to have occurred at the close on the date identified by the algorithm. When sorting the daily price returns into trends, therefore, the price return occurring on a day identified as a turning point is the final daily price return in the preceding trend, and the next trend begins with the following day's return. So for turning points identified on 2nd February 1994, 24th June 1994, and 20th July 1995, for example, the daily price returns would be sorted into two trends running from the 3rd February 1994 to the 24th June 1994 inclusive and from the 25th June 1994 to the 20th July 1995 inclusive.

Once the daily price return data has been sorted into trends, each trend is further segmented into quarters based on the total number of observations (trading days) within each trend. This enables a descriptive analysis of the features of stock market trends as they develop.

A simple rule is used to ensure that each trend is segmented in a consistent manner. The number of daily returns in the trend is first divided into two, with the extra day (if the total is not divisible by two) allocated to the second half of the trend. The daily returns allocated to the first half of the trend are split into two, with the extra day (if applicable) allocated to quarter 2. The daily returns allocated to the second half of the trend are split into two, with the extra day (if applicable) allocated to quarter 3. Table 8.2 illustrates this process, showing the number of daily returns allocated to each quarter for trends of differing lengths.

Table 8.2 Allocation of Trading Days to Trends

Trend Length (Trading Days)	Days Allocated to Quarter 1	Days Allocated to Quarter 2	Days Allocated to Quarter 3	Days Allocated to Quarter 4
96	24	24	24	24
97	24	24	25	24
98	24	25	25	24
99	24	25	25	25
100	25	25	25	25
101	25	25	26	25
102	25	26	26	25
and so on				

The segmentation of the price return series for each of the 14 stock markets into trends and quarters of trends forms the basis for the analysis described in the following sections.

8.5 Analysis of Trends

The objective of this part of the research is to examine the statistical properties of stock market returns in bull and bear trends and to consider the ways in which stock market trends differ from random trends based on the same empirical distribution of daily returns. As discussed in Section 8.1, the concept of continuation in medium-term stock market returns as a result of investor underreaction implies that stock market trends are more extreme in some way than random trends.

Most previous studies of bull and bear stock market trends have restricted themselves to considering the mean duration and total amplitude of stock market trends. As discussed in Section 8.4, one advantage of the methodology used in this study is that it can be used with daily data without the need for modification. Whereas previous studies have identified turning points in market trends in terms of the month in which they occur, the daily data used in this study enables turning points to be identified to the day. This permits a finer analysis to be carried out of the statistical properties of returns within bull and bear trends. The statistics reported are in themselves simple; the main methodological difficulties lie in the implementation of the algorithm to identify turning points and the manipulation of the data to identify the daily returns to be included in each calculation.

The average duration of trends is measured in terms of trading days. This enables a consideration of the first potential source of excessive trend behaviour highlighted in Section 8.2, that stock market trends simply continue for longer than random trends. The average total amplitude of trends (measured in percent of the trend's starting value) answers the question of whether trends continue "further" (amplitude) and well as going for "longer" (duration) than random trends.

The daily average price return in bull and in bear trends is calculated for bull and bear trends as a whole and also in terms of the four quarters of each trend considered in Section 8.4.4. This addresses the issue of whether stock market trends are steeper in overall terms than random trends, and whether patterns occur in the steepness of bull and bear trends as they develop.

From here, the analysis moves on to consider the possible sources of patterns in the steepness of trends: patterns in the proportion of positive and negative daily returns and patterns in the relative absolute magnitude of positive and negative daily returns. In each case, statistics are reported for bull and bear trends both as a whole and individually for the four quarters of each.

This analysis of the average duration and total amplitude of bull and bear trends, together with patterns in the steepness, clustering of positive and negative daily returns and relative size of positive and negative returns within trends, enables the three potential sources of excessive stock market trend behaviour identified in Section 8.2 to be specifically addressed.

In addition, further statistics relating to the distributions of daily price returns in bull and bear trends are reported. The mean daily price return calculated earlier in the analysis is supplemented by the standard deviation, skewness and kurtosis of daily price returns both within bull and bear trends and also within the quarters of each trend. This enables a consideration of the way in which the distribution of daily price returns changes as stock markets move through bull and bear cycles.

8.6 Statistical Inference

The objective of this part of the research is to consider the extent to which trends in stock market data differ from random trends based on the same distribution of daily returns.

To achieve this, a bootstrap methodology is employed in much the same way as described in Chapter 7. Trends in the original data sets are identified using the Fink and Pratt algorithm and the statistics described in Section 8.5 are calculated. For each data set, 4999 bootstrap price return series are generated by sampling with replacement from the original data, and these price return series are used to calculate 4999 simulated price index series for each of the 14 stock markets which are the focus of this study. By applying the Fink and Pratt algorithm to each simulated price series and calculating the statistics of interest in exactly the same way as for the original data, an empirical sampling distribution is built up for each statistic. Bootstrap P-values are taken from these empirical sampling distributions using the percentile method as described in Chapter 7[84] and used to test for significant deviations between the properties of trends in the original data and the mean of the empirical sampling distribution estimated from the bootstrap simulations.

8.7 Summary

Very little research has been published to date which specifically examines the properties of trends in financial market prices. Of the work that has been conducted, the use of a duration-based algorithm with monthly data has typically restricted the analysis to a simple examination of the most basic features of trends in stock market prices, namely their duration and total amplitude.

This chapter describes the methodology employed in the current study to carry out a more detailed analysis of the statistical properties of returns in stock market trends. An amplitude-based algorithm from the information technology literature for identifying turning points in time series data is introduced and refined for use in identifying turning points in stock market data. This enables a finer analysis of the properties of stock market trends to be carried out than has been possible for previous research using monthly data, and also enables the calculation of the relevant test statistics for each of the phases of bull and bear trends. In addition, this study extends previous work on identifying the properties of stock market trends, introducing a bootstrap technique to consider the extent to which trends in stock market data are different from random trends. Trends are not specific to stock market prices and indeed can be observed in purely random data. As this chapter explains, it is the differences between stock market trends and random trends which are likely to shed light on the potential sources of predictability in stock market returns rather than the overall properties of stock market trends.

Chapter 9 presents the results of the analysis conducted using the methodology described in this chapter.

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[84] The relevant P-values for a two-tailed test at the 1% significance level are simply the 25th and 4974th ranked values from the bootstrap simulations. For a two-tailed test at the 5% significance level, the 125th and 4874th values are taken. MacKinnon (2002) provides an in-depth discussion of this approach.

Chapter 9

Trend Analysis Results

9.1 Introduction

This chapter presents the results of the analysis of the statistical properties of stock market trends described in Chapter 8.

Section 8.2 discusses three ways in which stock market trends may differ from random trends. These can be summarised as follows:

- stock market trends may have longer duration and / or greater total amplitude than random trends

- patterns in the steepness of stock market trends may occur as a result of bull and bear trends having, either overall or in particular stages of their development, different proportions of positive and negative daily price returns than random trends with the same empirical distribution of daily returns

- patterns in the steepness of stock market trends may occur as a result of bull and bear trends having, either overall or in particular stages of their development, positive and negative daily price changes of higher or lower average magnitude than random trends with the same empirical distribution of daily returns

The results discussed in Sections 9.2 through 9.8 investigate these issues in further depth. Section 9.2 discusses the duration and total amplitude of stock market trends. Section 9.3 considers the steepness of stock market trends. Sections 9.4 and 9.5 develop the analysis in Section 9.3 to consider the two individual sources of excessive steepness described above; Section 9.4 examines the proportion of positive and negative daily price returns in bull and bear trends, whilst Section 9.5 compares the relative magnitude of positive and negative daily price returns in each. Sections 9.6 and 9.7 investigate further the distribution of daily price changes through the different phases of bull and bear trends, building on the analysis in the earlier sections to consider the standard deviation and coefficients of skewness and kurtosis of daily price returns. Section 9.8 summarises.

9.2 Duration and Total Amplitude of Stock Market Trends

This section considers the mean duration (length) and amplitude (height) of trends identified in the price index series of each of the fourteen stock markets considered in this study.

Table 9.1 shows the number of bull and bear trends found for each market, the average duration of these trends in trading days and their average amplitude expressed in percent of their starting level.

The algorithm forces bull and bear trends to alternate, with the result that it is impossible to obtain a difference of more than one in the number of bull and bear trends in the original data or in any individual bootstrap run.

The number of trends in the original data is similar to the number found on average in the bootstrap runs, with a slightly higher number of trends in the original data than the bootstrap in some countries (for example Canada and Switzerland) and slightly less in others (for example France and Spain). Only one observation, that for bear trends in the Hong Kong stock market, is significantly different from the bootstrap at the 5% significance level.

Table 9.1 also shows the average duration of each trend, measured in terms of trading days. The original data shows a longer duration for bull trends than bear trends in all countries except Japan. A similar pattern emerges in the bootstrap, with bull trends longer than bear trends in all countries except Hong Kong and

Table 9.1 Duration and Amplitude of Stock Market Trends

	Number of Trends		Duration (trading days)		Total Amplitude (%)	
	Bull	Bear	Bull	Bear	Bull	Bear
Australia	8.00 *8.39*	7.00 *8.42*	189.00 *152.25*	78.43 *107.30*	20.25% *21.35%*	-14.34% *-15.57%*
Belgium	13.00 *9.93*	14.00 *9.96*	103.54 *123.25*	60.93 *96.55*	22.53% *22.71%*	-18.64% *-17.95%*
Canada	12.00 *10.11*	12.00 *10.15*	112.67 *128.72*	71.50 *86.49*	22.44% *24.15%*	-17.82% *-17.15%*
Denmark	11.00 *8.89*	10.00 *8.91*	115.45 *143.47*	69.80 *102.35*	24.81% *25.77%*	-18.03% *-19.10%*
France	8.00 *9.85*	9.00 *9.87*	164.63 *121.13*	95.89 *99.90*	34.55% *29.41%*	-26.19% *-23.70%*
Germany	9.00 *10.52*	10.00 *10.52*	151.67 *108.13*	84.80 *99.58*	32.79% *29.29%*	-26.98% *-25.94%*
Hong Kong	13.00 *9.15*	14.00 *9.15* SIG 5%	85.23 *105.59*	80.64 *136.29*	31.56% *34.65%*	-31.93% *-37.82%*
Italy	11.00 *9.15*	11.00 *9.15*	102.00 *136.91*	100.18 *104.27*	33.75% *36.53%*	-27.22% *-27.37%*
Japan	7.00 *8.42*	6.00 *8.44*	133.14 *109.13*	190.00 *144.27*	27.19% *25.26%*	-31.85% *-28.69%*
Netherlands	9.00 *11.36*	9.00 *11.40*	172.78 *109.13*	58.44 *84.59*	31.24% *27.79%*	-19.02% *-21.61%*
Spain	8.00 *9.60*	8.00 *9.63*	158.88 *131.01*	117.25 *96.22*	37.02% *33.26%*	-27.89% *-24.60%*
Switzerland	12.00 *9.85*	11.00 *9.87*	125.83 *126.46*	59.91 *93.99*	25.58% *27.21%*	-20.35% *-20.68%*
UK	10.00 *10.18*	10.00 *10.17*	136.00 *111.53*	80.20 *103.10*	22.06% *21.88%*	-18.67% *-19.60%*
USA	10.00 *10.48*	11.00 *10.53*	136.00 *120.42*	75.36 *86.52*	25.93% *24.68%*	-17.90% *-17.98%*

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Japan, reflecting the generally rising markets which are a characteristic of the time period in question.

Previous studies have found a similar pattern in the relative length of bull and bear trends in stock market data. Kaminsky and Schmukler (2001) obtain an average duration for bull trends of 26 months and for bear trends of 18 months using data from 28 emerging and mature economies. Pagan and Sossounov (2003) find average durations for bull and bear trends of 25 and 17 months respectively using US stock market data. The actual durations found by these studies are very different to those reported here as a result of the different methodologies employed. The use of an unmodified Bry and Boschan algorithm identifies much longer-term trends than are the focus of this study. Nevertheless, the ratio of the lengths of bull and bear trends are comparable. The relative duration of bull to bear trends found by Kaminsky and Schmukler is 1.44, with a similar ratio of 1.47 found by Pagan and Sossounov. In this study, the average ratio is 1.68, with values ranging from 0.70 (Japan) to 2.96 (the Netherlands).

Whilst the difference between the average duration of trends in the original data and the bootstrap may appear large, none of the values from the original data is significantly different from the bootstrap average at the 5% significance level. This simply reflects a high degree of variance in the bootstrap runs. Given the lack of statistical significance of the trend duration statistics reported in Table 9.1, the difference between the average duration of bull and bear trends in the original data is interpreted as being a simple function of generally rising stock market prices over the period covered by the data samples.

The final two columns of Table 9.1 show the average total trough-to-peak amplitude of bull trends and peak-to-trough amplitude of bear trends, expressed as a percentage of the starting value. The values from the original data are very similar to the bootstrap average in all cases, with no significant differences at the 5% level. The average total amplitude of bull trends is greater than that of bear trends in absolute terms for most countries; again, this reflects the period of generally rising stock markets over the first five years of the data samples.

The stock market trends identified using the Fink and Pratt algorithm show no significant deviations from random trends in terms of their average duration or total amplitude. This suggests that stock market trends are not systematically longer or higher than random trends.

The first possible source of predictability in stock market returns, that trends in stock market data continue for longer than implied by randomness (as a result of underreaction or betting on trends, for example) is therefore not supported by the data. Trends in the 14 stock market data sets considered in this study have mean durations and amplitudes which are consistent with random trends based on the same distribution of daily returns. Nevertheless, important patterns in the steepness of returns may exist within stock market trends in such a way as to produce continuation effects. Section 9.3 considers the existence of such patterns in the steepness of stock market trends.

9.3 Steepness of Stock Market Trends

The previous section shows that, on average, stock market trends do not appear to be longer or higher than random trends. This section goes on to consider the extent to which patterns may occur in the steepness of stock market trends.

Table 9.2 shows the average price return for each trading day in bull and bear trends, together with the average for each phase within the trends. As discussed in Section 8.4.4, this simply involves splitting each trend identified into four quarters with equal duration.

As one would expect, the overall average daily returns presented in the first two columns of the table are all positive for bull trends and all negative for bear trends. This is the case by definition as the algorithm is picking out periods of rising and falling prices respectively.

For bull trends, the average daily return is lower than the bootstrap average for 9 of 14 countries and significantly so at the 5% level in the case of the Netherlands. For bear trends, the average daily price return is more negative than the bootstrap average for all counties except Japan and Spain, and

Table 9.2 Mean Daily Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	0.11% *0.14%*	-0.18% *-0.15%*	0.19% *0.19%*	0.09% *0.10%*	0.05% *0.10%*	0.11% *0.19%* SIG 5%	-0.25% *-0.21%*	-0.02% *-0.09%*	-0.04% *-0.09%*	-0.43% *-0.21%* SIG 1%
Belgium	0.22% *0.19%*	-0.31% *-0.19%* SIG 1%	0.34% *0.25%*	0.10% *0.13%*	0.13% *0.13%*	0.29% *0.25%*	-0.27% *-0.27%*	-0.17% *-0.12%*	-0.15% *-0.12%*	-0.64% *-0.27%* SIG 1%
Canada	0.20% *0.19%*	-0.25% *-0.21%*	0.30% *0.25%*	0.18% *0.14%*	0.09% *0.14%*	0.23% *0.25%*	-0.29% *-0.29%*	-0.19% *-0.13%*	-0.17% *-0.13%*	-0.34% *-0.29%*
Denmark	0.21% *0.19%*	-0.26% *-0.20%*	0.27% *0.24%*	0.14% *0.13%*	0.15% *0.13%*	0.30% *0.24%*	-0.25% *-0.28%*	-0.19% *-0.12%*	-0.22% *-0.12%*	-0.38% *-0.27%*
France	0.21% *0.25%*	-0.27% *-0.25%*	0.32% *0.33%*	0.18% *0.18%*	0.17% *0.17%*	0.18% *0.33%* SIG 1%	-0.29% *-0.34%*	-0.13% *-0.15%*	-0.08% *-0.15%*	-0.60% *-0.34%* SIG 1%
Germany	0.22% *0.28%*	-0.32% *-0.27%*	0.33% *0.37%*	0.13% *0.19%*	0.12% *0.20%*	0.29% *0.37%*	-0.27% *-0.37%*	-0.19% *-0.18%*	-0.17% *-0.17%*	-0.65% *-0.37%* SIG 1%
Hong Kong	0.37% *0.34%*	-0.40% *-0.29%*	0.63% *0.47%*	0.21% *0.22%*	0.22% *0.22%*	0.43% *0.46%*	-0.39% *-0.39%*	-0.18% *-0.19%*	-0.20% *-0.19%*	-0.82% *-0.38%* SIG 1%
Italy	0.33% *0.28%*	-0.27% *-0.27%*	0.51% *0.36%*	0.18% *0.19%*	0.10% *0.19%*	0.54% *0.36%* SIG 5%	-0.32% *-0.38%*	-0.07% *-0.16%*	-0.17% *-0.18%*	-0.52% *-0.38%*
Japan	0.20% *0.24%*	-0.17% *-0.21%*	0.36% *0.33%*	0.17% *0.15%*	0.11% *0.16%*	0.19% *0.33%* SIG 5%	-0.16% *-0.27%* SIG 5%	-0.14% *-0.14%*	-0.11% *-0.14%*	-0.26% *-0.28%*
Netherlands	0.18% *0.26%* SIG 5%	-0.33% *-0.26%*	0.27% *0.34%*	0.12% *0.18%*	0.14% *0.19%*	0.20% *0.34%* SIG 5%	-0.33% *-0.37%*	-0.15% *-0.16%*	-0.13% *-0.17%*	-0.71% *-0.37%* SIG 1%
Spain	0.23% *0.26%*	-0.24% *-0.27%*	0.36% *0.34%*	0.12% *0.18%*	0.15% *0.19%*	0.29% *0.34%*	-0.24% *-0.37%*	-0.08% *-0.16%*	-0.22% *-0.17%*	-0.41% *-0.37%*
Switzerland	0.20% *0.22%*	-0.34% *-0.23%* SIG 5%	0.36% *0.29%*	0.08% *0.16%*	0.14% *0.15%*	0.23% *0.29%*	-0.35% *-0.32%*	-0.13% *-0.14%*	-0.07% *-0.14%*	-0.83% *-0.31%* SIG 1%
UK	0.16% *0.20%*	-0.23% *-0.20%*	0.29% *0.27%*	0.13% *0.14%*	0.11% *0.14%*	0.12% *0.27%* SIG 1%	-0.28% *-0.27%*	-0.05% *-0.13%*	-0.10% *-0.13%*	-0.51% *-0.27%* SIG 1%
USA	0.19% *0.21%*	-0.24% *-0.22%*	0.33% *0.27%*	0.14% *0.15%*	0.11% *0.15%*	0.18% *0.27%*	-0.27% *-0.30%*	-0.02% *-0.13%*	-0.16% *-0.14%*	-0.50% *-0.30%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

significantly so for Switzerland at the 5% level and Belgium at the 1% level. Whilst these features suggest that overall, bull trends may be slightly more shallow than implied by randomness and bear trends slightly steeper, very few results are statistically significant based on the bootstrap test.

An analysis of the mean daily price returns across the four quarters of bull and bear trends shows that for bull trends, there are few significant differences between the original data and the bootstrap values. If anything, the trends identified in the original data appear to be steeper than the bootstrap at the start of a bull trend but generally less steep over the third and fourth quarters of the trend. In the fourth quarter of bull trends, significant differences between the steepness of trends in the original and the bootstrap data are noted for 6 countries. Of these, 5 have significantly shallower trends than the bootstrap (2 at the 1% significance level and 3 at the 5% significance level). For Italy, conversely, the steepness in the original data is significantly higher than the bootstrap at the 5% level.

Bear trends, on the other hand, do display significant deviations from randomness. In the fourth quarter, bear trends are significantly steeper than the bootstrap at the 1% level for 9 of the 14 countries considered. No clear differences between the original data and the bootstrap are apparent over the first three quarters of bear trends.

Similar features have been identified by research into the properties of the business cycle. Lupi and Ordine (2001) note that economists have long recognised that economic variables display asymmetric behaviour over the cycle. Both Sichel (1994) and Harding and Pagan (2002) document rapid recovery in the early stages of business cycle expansions. Artis et al (1997) find that contractions are steeper than expansions. Such insights are not new. Indeed, Mitchell (1927, p290) states

> "Business contractions appear to be a briefer and more violent process than business expansions"

An important feature of the mean daily returns in Table 9.2 is the symmetry in the bootstrap averages across the four quarters of bull and bear trends. The values for quarters 1 and 4 appear to converge to the same value, with the values for quarters 2 and 3 converging to a different (less extreme) value.

Further investigation reveals this to be a result of the algorithm used to identify turning points in the data.

Consider the example of a turning point identified by the algorithm as an important minimum. In order for that particular point to have been identified as a turning point, the market must fall to that level without having reached a lower level, and then rise afterwards, again without reaching a lower level. This is most likely to occur immediately following sections in the data of steeply falling prices and/or immediately before sections of steeply rising prices. This likelihood is reflected in the bootstrap values, with trends slightly steeper around turning points than in their second and third quarters.

The bootstrap values are consistent, with similar values for quarter 1 and quarter 4 in both bull and bear trends. This is as one would expect given that in random trends, although it is likely that turning points will occur at the beginning or end of steep sections of data, there is no reason why one should occur more frequently than the other. Similarly, there is no reason for any one source of steepness to outweigh another in the bootstrap data. This is reflected in Tables 9.3 through 9.5, where similar patterns are seen in the proportion of positive daily price returns, the magnitude of positive daily price returns, and the magnitude of negative daily price returns.

Bull and bear stock market trends do appear to differ significantly from random trends in terms of their steepness. This is particularly true of the final quarter of bear trends, which are significantly steeper than the trends found in a bootstrap analysis based on the same data sample. There is also some evidence to suggest that bull trends are significantly shallower than random trends in their final quarter.

The following two sections go on to examine the potential sources of these differences in the steepness of stock market trends and random trends based on the same empirical distribution of daily price returns. Section 9.4 considers the proportion of positive and negative daily price returns within trends, whilst Section 9.5 compares the relative magnitudes of positive and negative daily price returns within trends.

9.4 Proportion of Positive and Negative Daily Price Returns

One possible cause of the patterns in the steepness of stock market trends identified in the previous section is a greater degree of clustering of positive and negative daily changes than would be implied by randomness. For example, the very steep final quarter of bear market trends could be a result of a much higher proportion of negative daily returns (relative to positive daily returns) than is present in random trends based on the same empirical distribution of returns. This section explores that possibility, with Section 9.5 going on to consider the second possibility that patterns in the steepness of stock market trends are caused instead by differences in the relative magnitudes of positive and negative daily price returns within trends.

Table 9.2 shows the percentage of trading days within bull and bear trends, and within the four quarters of each, on which a positive price return is recorded.

The percentage of negative daily price returns very closely reflects 100 per cent minus the percentage of positive daily returns (with the difference simply reflecting a very small number of zero daily returns[85]), and the proportion of negative daily price returns is therefore not separately reproduced for reasons of brevity. In all cases, where the percentage of positive changes is significant based on the bootstrap test, the percentage of negative changes is significant at the same level (1% or 5%).

The first two columns in Table 9.3 show the overall percentage of positive and negative daily price returns in bull and bear trends respectively. The proportion of positive price returns is always greater than 50 per cent for bull trends and less than 50 per cent or bear trends for both the original data and the bootstrap – this is as one would expect given that the algorithm identifies periods of generally rising prices as bull trends and periods of generally falling prices as bear trends. By definition, either the proportion of positive moves is above 50 per cent in bull trends or the absolute magnitude of positive returns is greater

[85] The number of zero observations ranges from 0.0435% (Hong Kong) to 0.0500% (Japan) of the total number of observations for each data sample.

Table 9.3 Proportion of Positive Daily Price Returns

	Overall		Bull				Bear			
	Bull	**Bear**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Australia	55.36% *57.19%*	43.17% *43.21%*	54.79% *59.31%*	55.15% *54.94%*	55.12% *55.05%*	56.38% *59.55%*	38.52% *40.21%*	48.91% *46.19%*	46.81% *46.20%*	38.24% *40.13%*
Belgium	59.88% *57.76%*	38.92% *44.03%* SIG 5%	62.46% *60.14%*	56.51% *55.47%*	55.75% *55.39%*	64.88% *60.15%*	38.16% *41.29%*	40.74% *46.80%*	45.66% *46.82%*	30.81% *41.08%* SIG 1%
Canada	60.36% *58.84%*	41.49% *44.61%*	62.76% *61.27%*	59.29% *56.48%*	54.81% *56.56%*	64.69% *61.12%*	40.48% *41.39%*	37.67% *47.67%* SIG 1%	46.36% *47.82%*	41.31% *41.40%*
Denmark	58.98% *56.91%*	40.40% *43.09%*	60.38% *59.18%*	56.43% *54.75%*	57.14% *54.64%*	62.03% *59.16%*	34.12% *40.08%*	39.77% *45.94%*	46.37% *46.03%*	41.04% *40.18%*
France	57.40% *57.92%*	42.41% *43.61%*	59.51% *60.54%*	55.59% *55.39%*	57.10% *55.39%*	57.45% *60.46%*	41.04% *40.58%*	46.54% *46.65%*	47.49% *46.49%*	34.42% *40.58%*
Germany	59.19% *59.10%*	40.92% *44.78%* SIG 5%	59.76% *61.59%*	56.27% *56.36%*	55.65% *56.72%*	65.19% *61.84%*	35.10% *41.93%* SIG 5%	41.59% *47.67%* SIG 5%	48.61% *47.66%*	38.10% *41.73%*
Hong Kong	57.04% *56.40%*	41.10% *43.21%*	58.24% *59.09%*	50.90% *53.60%*	55.16% *53.70%*	64.00% *59.34%*	39.71% *40.96%*	44.56% *45.58%*	44.10% *45.37%*	35.84% *40.88%*
Italy	58.11% *56.19%*	41.74% *41.89%*	58.91% *58.64%*	53.19% *53.72%*	54.04% *53.79%*	66.43% *58.69%* SIG 5%	38.01% *38.82%*	46.76% *45.03%*	44.09% *44.62%*	37.96% *38.93%*
Japan	54.29% *55.00%*	41.84% *41.32%*	53.68% *58.05%*	55.36% *52.08%*	50.21% *52.12%*	58.01% *57.87%*	41.34% *39.07%*	41.61% *43.67%*	41.61% *43.48%*	42.81% *38.98%*
Netherlands	57.11% *58.23%*	40.87% *43.96%*	60.36% *60.77%*	55.27% *55.75%*	54.71% *55.81%*	58.14% *60.73%*	36.43% *40.93%*	49.25% *47.00%*	44.78% *46.83%*	32.56% *40.95%* SIG 5%
Spain	58.38% *57.87%*	43.07% *43.61%*	64.24% *60.26%*	56.74% *55.32%*	50.94% *55.66%*	61.71% *60.32%*	38.53% *40.64%*	49.36% *46.43%*	47.48% *46.56%*	36.75% *40.67%*
Switzerland	58.74% *58.71%*	40.82% *44.77%* SIG 5%	61.23% *61.05%*	53.58% *56.44%*	57.70% *56.43%*	62.50% *61.03%*	34.38% *42.02%* SIG 5%	46.67% *47.65%*	48.54% *47.57%*	33.13% *41.70%* SIG 5%
UK	57.79% *59.03%*	43.64% *44.54%*	58.63% *61.64%*	57.18% *56.60%*	56.40% *56.49%*	59.00% *61.49%*	40.10% *41.67%*	50.99% *47.25%*	46.08% *47.39%*	37.19% *41.75%*
USA	58.90% *58.26%*	41.38% *43.78%*	60.65% *60.56%*	59.24% *55.99%*	56.14% *55.99%*	59.59% *60.59%*	35.96% *40.72%*	47.85% *46.93%*	45.07% *46.74%*	36.27% *40.59%*

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

than that of negative returns, or (more likely) both. A similar argument applies for bear trends.

There are no significant differences between the proportion of positive daily price returns in the original data and the bootstrap for bull trends. For bear trends, the original data has a significantly lower proportion of positive returns (that is to say a higher proportion of negative returns) than the bootstrap for only three countries at the 5% level (Belgium, Germany, and Switzerland).

The results for the individual quarters of bull and bear trends show no clear patterns. Very few significant results are reported, and no clear pattern is observed in the significant results obtained.

Differences in the proportion of positive and negative daily price returns between stock market and random trends are not, therefore, able to explain the patterns in the steepness of trends identified in Section 9.3, most notably the extreme steepness of the fourth quarter of stock market bear trends relative to random trends.

9.5 Magnitude of Positive and Negative Daily Price Returns

The second possible source of patterns in the steepness of stock market trends relative to random trends relates to the relative absolute magnitudes of positive and negative daily price returns. If bull trends are characterised by positive daily returns that are larger than implied those in random trends based on the same empirical distribution of daily returns and/or negative daily price returns that are smaller (more negative), for example, then the resulting trends will tend to be steeper than random trends. This will be the case even if the duration of the trend and the proportion of positive and negative daily returns are not significantly different to those of random trends.

Tables 9.4 and 9.5 show the average positive and negative daily price returns respectively for bull and bear trends and the four quarters of each.

Table 9.4 Mean Positive Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	0.66% *0.68%*	0.61% *0.57%*	0.84% *0.70%* SIG 1%	0.63% *0.67%*	0.55% *0.67%* SIG 1%	0.61% *0.70%* SIG 5%	0.48% *0.55%*	0.66% *0.59%*	0.65% *0.59%*	0.62% *0.56%*
Belgium	0.74% *0.80%* SIG 5%	0.69% *0.64%*	1.02% *0.83%* SIG 1%	0.60% *0.78%* SIG 1%	0.61% *0.78%* SIG 1%	0.70% *0.83%* SIG 5%	0.67% *0.61%*	0.67% *0.66%*	0.71% *0.66%*	0.69% *0.61%*
Canada	0.73% *0.81%* SIG 1%	0.77% *0.66%* SIG 1%	0.87% *0.83%*	0.68% *0.79%* SIG 5%	0.68% *0.78%* SIG 5%	0.70% *0.83%* SIG 5%	0.78% *0.63%* SIG 5%	0.79% *0.68%*	0.77% *0.67%*	0.73% *0.63%*
Denmark	0.78% *0.84%* SIG 5%	0.67% *0.70%*	0.87% *0.86%*	0.68% *0.82%* SIG 1%	0.68% *0.82%* SIG 1%	0.88% *0.86%*	0.75% *0.67%*	0.66% *0.73%*	0.61% *0.71%*	0.69% *0.67%*
France	0.97% *1.07%* SIG 1%	0.97% *0.88%* SIG 5%	1.13% *1.10%*	0.89% *1.05%* SIG 5%	0.96% *1.04%*	0.91% *1.10%* SIG 1%	0.68% *0.85%* SIG 5%	0.96% *0.90%*	1.09% *0.90%* SIG 5%	1.14% *0.85%* SIG 1%
Germany	0.96% *1.13%* SIG 1%	1.13% *0.93%* SIG 1%	1.19% *1.17%*	0.86% *1.10%* SIG 1%	0.85% *1.10%* SIG 1%	0.92% *1.16%* SIG 1%	0.99% *0.89%*	1.01% *0.95%*	1.26% *0.96%* SIG 1%	1.23% *0.89%* SIG 1%
Hong Kong	1.33% *1.40%*	1.11% *1.07%*	1.72% *1.46%*	1.31% *1.33%*	1.14% *1.33%*	1.15% *1.45%* SIG 1%	0.97% *1.04%*	1.16% *1.11%*	1.28% *1.11%*	0.99% *1.03%*
Italy	1.29% *1.28%*	1.05% *1.06%*	1.60% *1.31%* SIG 1%	1.13% *1.25%*	1.19% *1.24%*	1.22% *1.31%*	1.04% *1.03%*	1.12% *1.09%*	1.03% *1.10%*	1.00% *1.03%*
Japan	1.01% *1.09%*	0.94% *0.89%*	1.37% *1.13%* SIG 5%	0.97% *1.05%*	0.92% *1.05%*	0.80% *1.12%* SIG 1%	0.85% *0.86%*	0.77% *0.91%* SIG 5%	1.12% *0.91%* SIG 1%	1.03% *0.86%* SIG 5%
Netherlands	0.90% *1.06%* SIG 1%	0.84% *0.83%*	1.09% *1.10%*	0.80% *1.02%* SIG 1%	0.90% *1.02%*	0.79% *1.09%* SIG 1%	0.73% *0.80%*	0.78% *0.86%*	0.85% *0.85%*	1.05% *0.79%* SIG 1%
Spain	1.00% *1.15%* SIG 1%	1.18% *0.94%* SIG 1%	1.13% *1.18%*	0.79% *1.12%* SIG 1%	1.05% *1.12%*	1.01% *1.17%* SIG 5%	1.04% *0.91%*	1.04% *0.97%*	1.21% *0.97%* SIG 1%	1.46% *0.91%* SIG 1%
Switzerland	0.81% *0.92%* SIG 1%	0.88% *0.73%* SIG 1%	1.04% *0.95%*	0.71% *0.90%* SIG 1%	0.74% *0.89%* SIG 5%	0.73% *0.94%* SIG 1%	0.65% *0.70%*	0.90% *0.76%*	0.98% *0.75%* SIG 1%	0.95% *0.71%* SIG 1%
UK	0.75% *0.84%* SIG 1%	0.74% *0.68%* SIG 5%	0.95% *0.87%*	0.73% *0.82%*	0.67% *0.81%* SIG 5%	0.65% *0.86%* SIG 1%	0.61% *0.66%*	0.74% *0.71%*	0.72% *0.71%*	0.92% *0.66%* SIG 1%
USA	0.76% *0.88%* SIG 1%	0.91% *0.70%* SIG 1%	0.90% *0.91%*	0.68% *0.85%* SIG 1%	0.71% *0.85%* SIG 1%	0.75% *0.90%* SIG 1%	0.94% *0.67%* SIG 1%	0.74% *0.72%*	0.99% *0.72%* SIG 1%	1.01% *0.67%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Table 9.5 Mean Negative Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	-0.58% *-0.58%*	-0.79% *-0.71%* SIG 5%	-0.60% *-0.57%*	-0.59% *-0.60%*	-0.58% *-0.60%*	-0.55% *-0.57%*	-0.71% *-0.73%*	-0.66% *-0.68%*	-0.65% *-0.68%*	-1.08% *-0.73%* SIG 1%
Belgium	-0.58% *-0.66%* SIG 1%	-0.95% *-0.86%* SIG 5%	-0.81% *-0.64%* SIG 5%	-0.58% *-0.69%*	-0.48% *-0.69%* SIG 1%	-0.46% *-0.63%* SIG 1%	-0.88% *-0.90%*	-0.76% *-0.82%*	-0.89% *-0.82%*	-1.24% *-0.90%* SIG 1%
Canada	-0.62% *-0.69%* SIG 5%	-0.98% *-0.91%*	-0.66% *-0.67%*	-0.54% *-0.71%* SIG 1%	-0.63% *-0.71%*	-0.65% *-0.67%*	-1.03% *-0.95%*	-0.79% *-0.87%*	-0.98% *-0.86%*	-1.11% *-0.94%*
Denmark	-0.62% *-0.70%* SIG 1%	-0.89% *-0.89%*	-0.68% *-0.68%*	-0.57% *-0.72%* SIG 1%	-0.56% *-0.72%* SIG 1%	-0.67% *-0.67%*	-0.77% *-0.93%* SIG 5%	-0.75% *-0.85%*	-0.93% *-0.85%*	-1.13% *-0.92%* SIG 5%
France	-0.82% *-0.88%*	-1.19% *-1.11%*	-0.88% *-0.85%*	-0.72% *-0.91%* SIG 5%	-0.88% *-0.91%*	-0.80% *-0.85%*	-0.96% *-1.15%* SIG 5%	-1.09% *-1.07%*	-1.15% *-1.07%*	-1.51% *-1.15%* SIG 1%
Germany	-0.87% *-0.96%* SIG 5%	-1.33% *-1.25%*	-0.95% *-0.93%*	-0.82% *-1.00%* SIG 5%	-0.80% *-0.99%* SIG 5%	-0.91% *-0.93%*	-0.96% *-1.29%* SIG 1%	-1.05% *-1.21%*	-1.52% *-1.19%* SIG 1%	-1.83% *-1.29%* SIG 1%
Hong Kong	-0.91% *-1.03%* SIG 5%	-1.45% *-1.33%* SIG 5%	-0.89% *-0.98%*	-0.94% *-1.07%*	-0.92% *-1.08%*	-0.86% *-0.97%*	-1.29% *-1.38%*	-1.26% *-1.28%*	-1.38% *-1.28%*	-1.84% *-1.37%* SIG 1%
Italy	-1.02% *-1.03%*	-1.23% *-1.26%*	-1.07% *-1.01%*	-0.94% *-1.06%*	-1.18% *-1.06%*	-0.85% *-1.00%* SIG 5%	-1.17% *-1.30%*	-1.12% *-1.21%*	-1.15% *-1.22%*	-1.46% *-1.29%*
Japan	-0.77% *-0.81%*	-0.98% *-0.99%*	-0.83% *-0.78%*	-0.83% *-0.84%*	-0.72% *-0.84%*	-0.68% *-0.78%*	-0.87% *-1.02%* SIG 5%	-0.81% *-0.96%* SIG 5%	-1.00% *-0.96%*	-1.27% *-1.01%* SIG 1%
Netherlands	-0.79% *-0.87%*	-1.14% *-1.14%*	-0.99% *-0.84%*	-0.76% *-0.90%* SIG 5%	-0.80% *-0.89%*	-0.63% *-0.83%* SIG 1%	-0.95% *-1.19%* SIG 1%	-1.07% *-1.08%*	-0.93% *-1.09%*	-1.56% *-1.19%* SIG 1%
Spain	-0.85% *-0.97%* SIG 1%	-1.32% *-1.22%* SIG 5%	-1.02% *-0.94%*	-0.75% *-1.01%* SIG 1%	-0.79% *-1.00%* SIG 1%	-0.87% *-0.94%*	-1.06% *-1.26%* SIG 5%	-1.18% *-1.17%*	-1.52% *-1.17%* SIG 1%	-1.52% *-1.26%* SIG 5%
Switzerland	-0.66% *-0.78%* SIG 1%	-1.19% *-1.01%* SIG 1%	-0.72% *-0.75%*	-0.65% *-0.80%* SIG 5%	-0.69% *-0.81%*	-0.59% *-0.75%* SIG 5%	-0.88% *-1.06%* SIG 5%	-1.06% *-0.97%*	-1.07% *-0.96%*	-1.70% *-1.05%* SIG 1%
UK	-0.64% *-0.72%* SIG 5%	-0.99% *-0.91%* SIG 5%	-0.66% *-0.69%*	-0.68% *-0.75%*	-0.61% *-0.74%* SIG 5%	-0.63% *-0.69%*	-0.87% *-0.94%*	-0.88% *-0.88%*	-0.80% *-0.88%*	-1.36% *-0.94%* SIG 1%
USA	-0.63% *-0.72%* SIG 1%	-1.05% *-0.93%* SIG 5%	-0.55% *-0.70%* SIG 5%	-0.64% *-0.75%*	-0.66% *-0.75%*	-0.66% *-0.70%*	-0.95% *-0.97%*	-0.73% *-0.89%* SIG 5%	-1.11% *-0.89%* SIG 1%	-1.37% *-0.96%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

The first two columns of Table 9.4 show the average positive daily price return in bull and bear trends overall. For bull trends, the average positive return is significantly lower than the bootstrap at the 1% level for 8 countries (Canada, France, Germany, the Netherlands, Spain, Switzerland, the UK, and the USA) and the 5% level for 2 countries (Belgium and Denmark). For bear trends, the average positive daily price return is significantly higher than the bootstrap at the 1% level for 5 countries (Canada, Germany, Spain, Switzerland, and the USA) and at the 5% level for 2 countries (France and the UK).

Table 9.4 also shows the average positive daily price return for each of the quarters of bull and bear trends.

For bull trends, there is limited evidence to suggest that in the first quarter of the trend, the average positive daily return is high, with the values obtained significantly in excess of the bootstrap values for 3 countries at the 1% level (Australia, Belgium and Italy) and one at the 5% level (Japan). The average positive return is smaller than the bootstrap throughout the remainder of the trend for all countries with the single exception of Denmark in the fourth quarter, with the difference significant for 9 countries in the second quarter (7 at the 1% level and 2 at the 5% level), 8 countries in the third quarter (5 at the 1% level and 3 at the 5% level) and 12 countries in the fourth quarter (8 at the 1% level and 4 at the 5% level).

For bear trends, the pattern is less clear. A consideration of the significant deviations from the bootstrap reveals that whilst the pattern is mixed for quarter 1 (2 countries significantly larger than the bootstrap, one at the 1% level and one at the 5% level, and one significantly smaller than the bootstrap at the 5% level) and quarter 2 (one country significantly smaller than the bootstrap at the 5% level), the results are consistent for quarters 3 and 4. For the third quarter of bear trends, the average positive daily price return is significantly high for 6 countries (5 at the 1% level and 1 at the 5% level). For the fourth quarter, the average positive daily price return is significantly high for 8 countries (7 at the 1% level and 1 at the 5% level).

Patterns in the magnitude of positive price returns in bull trends do appear to contribute to the differences in the steepness of stock market trends relative to random trends identified in Section 9.4. Large positive daily returns in the second half of bear trends, however, run contrary to the evidence in Section 9.4, where bear trends are seen to become excessively steep in the fourth quarter. In order to reconcile these two results, negative price returns in the fourth quarter of bear trends must exceed the bootstrap by a sufficient amount to more than offset the impact of large positive daily returns.

Table 9.5 shows the average daily negative price returns in bull and bear trends.

For bull trends, the pattern in the first quarter is again somewhat different from that observed in the remainder of the trend. In the first quarter, no clear picture emerges. In the second, third, and fourth quarters, the average daily negative daily price return is less extreme than the bootstrap with the sole exceptions of Italy in the third quarter and Denmark in the fourth. The difference between the original data and the bootstrap is significant for 7 countries in the second quarter (3 at the 1% level and 4 at the 5% level), 5 countries in the third quarter (3 at the 1% level and 2 at the 5% level) and 4 countries in the fourth quarter (2 at the 1% level and 2 at the 5% level).

For bear trends, a clear pattern emerges. Overall, the average negative daily price return is larger than the bootstrap for most countries. An analysis of the pattern across the four quarters of bear trends reveals that negative returns are typically less extreme than the bootstrap in quarters 1 and 2 (with significant differences for 2 countries at the 1% level and 5 countries at the 5% level in quarter 1, and 2 countries at the 5% level in quarter 2), and more extreme in quarters 3 and 4. Significant differences between the average negative daily price return and the bootstrap value are found for only 3 countries in quarter 3 (all at the 1% level), but for 12 of the 14 stock markets considered in quarter 4 (10 at the 1% level and 2 at the 5% level).

Section 8.2 introduced three possible explanations for the profitability of momentum strategies based on the characteristics of stock market trends. Sections 9.2 and 9.3 identified that extreme trend behaviour is based on patterns in the steepness of trends rather than their overall duration or amplitude. Section 9.4 ruled out patterns in the proportions of positive and negative daily price returns as the source of these patterns in trend steepness.

This section has identified the relative magnitude of positive and negative daily price returns in bull and bear trends as a potential source of the patterns identified in Section 9.3 in the overall steepness of the trends, particularly as regards the extreme steepness observed in the fourth quarter of bear trends.

9.6 Standard Deviation of Daily Price Returns

Table 9.6 shows the mean standard deviation of daily price returns in bull and bear trends and the four quarters of each.

The average values from the bootstrap runs are consistent across the four quarters of each trend for all countries. This is as one would expect given that trends in the bootstrap data are generated by random sampling from the original data. For most countries, the bootstrapped standard deviation of daily price returns is slightly higher for bear trends than bull, reflecting the positive mean and median daily returns present in most of the data samples and presented in Table 5.1. For countries such as Japan, with negative mean and median returns, a slightly higher standard deviation of daily returns is observed in bull trends than in bear trends.

For bull trends, the overall standard deviation of daily price returns is lower than the average value from the bootstrap runs for all fourteen stock markets, with the difference significant at the 1% level for ten countries.

In quarter 1 of bull trends, the standard deviation of daily price returns is higher than the bootstrap average for all countries except Denmark and the USA, with the difference significant at the 5% level for 4 countries.

For quarters 2 through 4, the standard deviation of daily price returns from the original data is lower than the bootstrap average in all cases except Australia in quarter 2 and Italy in quarter 3. The differences are significant for ten countries in quarter 2 (9 at the 1% level and one at the 5% level), eleven countries in quarter 3 (8 at the 1% level and 3 at the 5% level), and ten countries in quarter 4 (8 at the 1% level and 2 at the 5% level).

Table 9.6 Standard Deviation of Daily Price Returns

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	0.81% *0.83%*	0.93% *0.86%*	0.95% *0.82%* SIG 5%	0.83% *0.83%*	0.72% *0.82%* SIG 5%	0.74% *0.82%*	0.76% *0.87%*	0.83% *0.85%*	0.81% *0.84%*	1.21% *0.86%* SIG 1%
Belgium	0.93% *1.05%* SIG 1%	1.16% *1.05%* SIG 5%	1.29% *1.06%* SIG 5%	0.77% *1.04%* SIG 1%	0.76% *1.04%* SIG 1%	0.77% *1.05%* SIG 1%	0.99% *1.07%*	1.01% *1.04%*	1.18% *1.04%*	1.35% *1.06%* SIG 1%
Canada	0.91% *1.03%* SIG 1%	1.25% *1.12%* SIG 5%	1.04% *1.03%*	0.81% *1.03%* SIG 1%	0.83% *1.02%* SIG 1%	0.92% *1.02%*	1.33% *1.14%*	1.13% *1.09%*	1.26% *1.07%*	1.27% *1.13%*
Denmark	0.92% *1.03%* SIG 1%	1.07% *1.09%*	1.01% *1.03%*	0.84% *1.03%* SIG 1%	0.81% *1.03%* SIG 1%	1.01% *1.03%*	0.92% *1.10%* SIG 5%	0.96% *1.07%*	1.03% *1.07%*	1.31% *1.09%* SIG 5%
France	1.18% *1.32%* SIG 1%	1.48% *1.36%* SIG 1%	1.38% *1.32%*	1.04% *1.32%* SIG 1%	1.17% *1.32%*	1.10% *1.31%* SIG 5%	0.99% *1.36%* SIG 1%	1.36% *1.34%*	1.65% *1.34%* SIG 1%	1.76% *1.36%* SIG 1%
Germany	1.21% *1.44%* SIG 1%	1.69% *1.51%* SIG 1%	1.46% *1.44%*	1.13% *1.44%* SIG 1%	1.06% *1.43%* SIG 1%	1.16% *1.43%* SIG 1%	1.18% *1.52%* SIG 1%	1.35% *1.50%*	1.95% *1.48%* SIG 1%	2.06% *1.52%* SIG 1%
Hong Kong	1.72% *1.82%*	1.82% *1.74%*	2.12% *1.86%*	1.74% *1.77%*	1.55% *1.77%*	1.36% *1.83%* SIG 1%	1.53% *1.76%*	1.72% *1.72%*	1.80% *1.71%*	2.10% *1.74%* SIG 5%
Italy	1.49% *1.51%*	1.51% *1.52%*	1.73% *1.51%* SIG 5%	1.26% *1.51%* SIG 1%	1.54% *1.50%*	1.37% *1.50%*	1.39% *1.52%*	1.41% *1.51%*	1.47% *1.52%*	1.73% *1.52%* SIG 5%
Japan	1.20% *1.28%*	1.29% *1.24%*	1.52% *1.29%* SIG 5%	1.16% *1.27%*	1.08% *1.27%* SIG 5%	0.98% *1.28%* SIG 1%	1.14% *1.24%*	1.07% *1.24%* SIG 5%	1.44% *1.24%* SIG 1%	1.46% *1.23%* SIG 1%
Netherlands	1.14% *1.36%* SIG 1%	1.40% *1.40%*	1.46% *1.37%*	1.00% *1.36%* SIG 1%	1.13% *1.35%* SIG 5%	0.91% *1.36%* SIG 1%	1.15% *1.42%* SIG 1%	1.23% *1.37%*	1.19% *1.37%*	1.85% *1.41%* SIG 1%
Spain	1.23% *1.42%* SIG 1%	1.64% *1.45%* SIG 1%	1.52% *1.42%*	1.00% *1.42%* SIG 1%	1.19% *1.41%* SIG 1%	1.15% *1.41%* SIG 1%	1.25% *1.46%* SIG 5%	1.42% *1.43%*	1.82% *1.43%* SIG 1%	1.97% *1.45%* SIG 1%
Switzerland	1.04% *1.20%* SIG 1%	1.44% *1.24%* SIG 1%	1.30% *1.21%*	0.93% *1.20%* SIG 1%	0.91% *1.19%* SIG 1%	0.94% *1.20%* SIG 1%	1.06% *1.26%* SIG 5%	1.28% *1.22%*	1.37% *1.20%*	1.81% *1.26%* SIG 1%
UK	0.95% *1.05%* SIG 1%	1.15% *1.09%*	1.10% *1.05%*	0.99% *1.05%*	0.84% *1.05%* SIG 1%	0.83% *1.05%* SIG 1%	0.91% *1.10%* SIG 1%	1.02% *1.08%*	1.00% *1.08%*	1.53% *1.09%* SIG 1%
USA	0.97% *1.11%* SIG 1%	1.33% *1.14%* SIG 1%	1.06% *1.12%*	0.94% *1.11%* SIG 5%	0.92% *1.11%* SIG 1%	0.94% *1.11%* SIG 5%	1.24% *1.15%*	0.94% *1.12%* SIG 5%	1.45% *1.12%* SIG 1%	1.58% *1.14%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Overall, therefore, bull trends are characterised by a significantly high standard deviation of returns in the initial stages of the trend, followed by a significantly low standard deviation of returns through the remainder of the trend.

For bear trends, the overall standard deviation of daily price returns is higher than the bootstrap average for all countries except Denmark, Italy, and the Netherlands, with the difference significant at the 1% level for 5 countries and at the 5% level for a further 2 countries.

In quarter 1 of bear trends, the standard deviation of daily price returns from the original data is lower than the bootstrap average for all countries except Canada and the USA, with the difference significant at the 1% level for 4 countries and the 5% level for a further 3 countries. In quarter 2, the standard deviation of daily price returns is lower than the bootstrap average for all countries with the exception of Canada, France, and Switzerland, although the difference is only significant for 2 countries at the 5% significance level.

In quarter 3 of bear trends, the standard deviation of daily price returns from the original data is higher than the bootstrap average in 9 of the 14 stock markets considered, with the difference significant at the 1% level in 5 cases.

The most salient feature of the standard deviation of daily price returns in bear trends occurs in quarter 4, where the standard deviation from the original data exceeds the bootstrap value for all fourteen countries considered, and the differences are significant for 10 countries at the 1% level and a further 3 at the 5% level.

Overall, therefore, bear trends are characterised by a generally low standard deviation of returns in the initial stages of the trend, increasing in the third quarter with a particularly high standard deviation of daily price returns observed in quarter 4.

The results presented in Table 9.6 demonstrate an asymmetric pattern of volatility present in different stages of bull and bear trends. Previous research has identified a relationship between volatility and market returns, although the empirical results are somewhat conflicting[86]. In general, studies tend to find that lower volatility is associated with high market returns rather than low market returns. Wu (2001), for example, notes that the phenomenon of asymmetric volatility is most apparent during market crashes when significant increases in volatility tend to occur. The results presented in this section indicate that increases in market volatility may not be confined to market crashes but may be a general feature of the latter stages of market downturns.

Two main explanations have been put forward in the literature for asymmetric volatility in stock market returns:

- Leverage Effects (Christie, 1982)
  If the price of a stock drops, its financial leverage increases. This increases the risk associated with the stock, hence its price volatility also increases. In other words, negative return shocks increase volatility.

  A related argument is that of time-varying risk premia. If the risk premium of a stock increases (this might occur as a result of an expected increase in volatility), prices must fall to increase the expected return to investors in line with the increased risk premium. In other words, positive shocks to volatility result in negative shocks to returns.

- Volatility Feedback Effects (French et al, 1987)
  News entering the market in relation to a given stock, whether good or bad, increases uncertainty in relation to that stock and thus its price volatility. Volatility is persistent, hence news has an impact on both current and future expected volatility. The rate of return required by investors increases as a result of higher volatility (risk), and prices therefore fall.

  In the case of good news, the effect of the news is to raise prices, and the effect of volatility feedback is to lower them. Volatility feedback dampens the positive impact of news on prices and lowers volatility.

[86] Bekaert and Wu (2000) provide a review of this literature.

In the case of bad news, the effect of volatility feedback is to accentuate the fall in price caused by the bad news, thus increasing volatility.

The analysis presented in this section indicates that the volatility of daily returns follows a clear pattern through the bull and bear trend cycle. Volatility is high in the initial stages of bull trends, and low throughout the rest of the trend. In the initial stages of bear trends, volatility is low but increases dramatically in the final stages of the trend.

These results are not consistent with the leverage theory of asymmetry in stock market volatility. Volatility does not fall steadily as bull markets progress and rise steadily in bear markets as might be expected if leverage effects alone were the driving force behind asymmetries.

The results presented in this section may, however, be considered to be broadly supportive of volatility feedback theories of asymmetric volatility. Low volatility in bull markets and correspondingly high volatility in bear markets is observed. In addition, volatility feedback may explain the apparent spill-over of low volatility into the first quarter of bear trends and high volatility into the first quarter of bull trends. Volatility feedback alone, however, may not be sufficient to explain the large increases in volatility observed during the final stages of bear trends.

9.7 Skewness and Kurtosis

Table 9.7 shows the coefficient of skewness for daily price returns in bull and bear trends and the four quarters of each. The calculation of these coefficients is described in Chapter 5.

The first two columns in Table 9.7 show the average coefficient of skewness for bull and bear trends overall. Not surprisingly given that bull trends are periods of rising prices and bear trends periods of falling prices, returns are positively skewed in bull trends and negatively skewed in bear trends (with the exception of Spain where very slightly positive overall skewness is reported for bear markets).

Table 9.7 Skewness of Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	0.12 *0.14*	-0.86 *-0.68*	0.60 *0.10*	-0.30 *0.04*	-0.25 *0.08*	-0.31 *0.09*	0.35 *-0.53*	0.24 *-0.47*	0.27 *-0.49*	-0.68 *-0.45*
Belgium	0.86 *0.64*	-0.41 *-0.60*	0.85 *0.66*	-0.04 *0.42*	0.23 *0.42*	0.20 *0.65*	0.05 *-0.53*	-0.18 *-0.46*	-0.12 *-0.45*	0.45 *-0.54* SIG 5%
Canada	0.27 *0.22*	-0.63 *-1.10*	0.45 *0.22*	-0.08 *0.09*	-0.15 *0.11*	0.08 *0.22*	-0.90 *-0.93*	-0.43 *-0.84*	-0.47 *-0.83*	-0.28 *-0.90*
Denmark	0.01 *0.10*	-0.47 *-0.63*	-0.04 *0.08*	0.02 *-0.01*	-0.21 *-0.02*	-0.28 *0.08*	0.12 *-0.51*	0.04 *-0.48*	-0.18 *-0.53*	-0.47 *-0.49*
France	0.04 *0.31*	-0.09 *-0.49* SIG 5%	0.22 *0.26*	0.14 *0.18*	-0.37 *0.18*	-0.27 *0.26*	0.22 *-0.40*	-0.02 *-0.39*	-0.07 *-0.38*	0.33 *-0.40*
Germany	0.18 *0.31*	-0.32 *-0.65*	0.26 *0.28*	0.43 *0.17*	-0.25 *0.16*	-0.32 *0.23*	0.41 *-0.60* SIG 5%	-0.21 *-0.55*	0.29 *-0.50*	-0.48 *-0.58*
Hong Kong	1.78 *1.50*	-0.67 *-0.69*	1.78 *1.43*	2.08 *0.95*	1.25 *0.92*	0.16 *1.33*	0.02 *-0.73*	-0.49 *-0.49*	0.32 *-0.48*	-1.04 *-0.71*
Italy	0.31 *0.24*	-0.33 *-0.26*	0.31 *0.19*	0.09 *0.18*	0.15 *0.14*	-0.18 *0.16*	0.06 *-0.11*	-0.01 *-0.17*	-0.17 *-0.17*	-0.44 *-0.13*
Japan	0.59 *0.58*	0.06 *-0.10*	0.94 *0.46*	-0.10 *0.43*	0.03 *0.44*	0.02 *0.43*	-0.23 *-0.09*	-0.54 *-0.01*	0.30 *-0.01*	0.29 *-0.08*
Netherlands	0.08 *0.47*	-0.35 *-0.73*	0.09 *0.47*	0.17 *0.31*	-0.32 *0.33*	0.16 *0.46*	-0.04 *-0.63*	0.47 *-0.57* SIG 1%	-0.52 *-0.58*	0.75 *-0.65* SIG 1%
Spain	0.10 *0.26*	0.02 *-0.43* SIG 5%	0.02 *0.22*	0.00 *0.15*	0.16 *0.19*	-0.35 *0.20*	0.29 *-0.29*	-0.10 *-0.30*	-0.06 *-0.34*	0.27 *-0.30*
Switzerland	1.04 *0.59*	-0.77 *-0.85*	1.17 *0.61*	0.19 *0.39*	-0.11 *0.37*	1.65 *0.58*	-1.21 *-0.79*	-0.40 *-0.67*	0.05 *-0.65*	0.45 *-0.73* SIG 5%
UK	0.21 *0.21*	-0.39 *-0.53*	0.54 *0.17*	-0.29 *0.11*	0.08 *0.08*	-0.12 *0.15*	0.20 *-0.44*	-0.23 *-0.40*	0.10 *-0.43*	0.06 *-0.45*
USA	0.46 *0.40*	-0.15 *-0.59*	1.18 *0.38* SIG 1%	-0.27 *0.28*	0.02 *0.28*	0.16 *0.34*	-0.13 *-0.45*	-0.29 *-0.43*	0.14 *-0.41*	0.28 *-0.45*

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

The coefficients of skewness reported reflect the properties of returns within trends identified throughout this chapter. In bull trends, for example, Sections 9.2 and 9.4 identify a higher proportion of positive price returns than negative price returns, and that the average absolute size of positive returns is greater than that of negative returns. This is reflected in a positive coefficient of skewness in Table 9.7.

For bull trends, a number of countries show levels of skewness which, although positive, are much lower than the bootstrap values (Australia, France and Germany for example). The differences, however, are not statistically significant. For bear trends, daily price returns for most countries are less negatively skewed than the bootstrap, but are significant in only two cases, both at the 5% level (France and Spain).

Lower absolute levels of skewness than the bootstrap values may indicate that extreme events in the direction of the underlying trend play a less important role in the formation of stock market trends than is the case for random trends. This might be the case, for example, if market participants underreact to news which confirms the current trend, for example.

Table 9.7 also shows the coefficients of skewness calculated for each of the four quarters of bull and bear trends respectively.

For bull trends, the only significant difference between the skewness of trends in the original data and the bootstrap lies in the first phase of bull trends for the US stock market, where the skewness coefficient from the original data is significantly in excess of the bootstrap average at the 1% level. It is interesting to note that daily price returns in each market display negative skewness for at least one of the four quarters. Of the fourteen markets considered, 1 has negative skewness in the first quarter, 6 in the second, 7 in the third, and 7 in the fourth.

For bear trends, the coefficient of skewness is significantly higher (less negative) than the bootstrap average (and is in fact positive) for Germany in the first quarter (at the 5% level), the Netherlands in the second (at the 1% level), and Belgium and Switzerland (at the 5% level) together with the Netherlands (at the 1% level) in the fourth quarter. The daily price returns in each market display positive skewness for at least one of the four quarters. Of the fourteen markets considered, 9 have positive skewness in the first quarter, 3 in the second, 7 in the third, and 8 in the fourth.

Table 9.8 shows the coefficient of kurtosis for daily price returns in bull and bear trends and the four quarters of each. The calculation of these coefficients is described in Chapter 5. The coefficients of kurtosis calculated from the original data are typically smaller than the bootstrap values, although few of the differences are statistically significant. Few significant results are reported other than for the first quarter of bear trends, where the kurtosis of daily price returns is significant for 7 of the 14 countries considered.

Bai and Ng (2001) consider the sampling distributions for the coefficients of skewness and kurtosis in serially correlated data. Using Monte Carlo analysis, they demonstrate that the test statistic for skewness is accurate for large sample sizes (where 200 observations is considered to be large). The test statistic for kurtosis, on the other hand, is heavily biased for finite sample sizes. The true value of kurtosis is generally underestimated and very large sample sizes are required to generate reasonable results. On the basis of the Monte Carlo analysis, the authors conclude that even with 5000 observations, kurtosis cannot be accurately estimated from serially correlated data.

This study uses between 2222 and 2296 observations for each data sample. On the basis of Bai and Ng's research, one would expect the coefficients of skewness calculated using the bootstrap methodology to have acceptable power, although the bootstrapped kurtosis values should be treated with caution.

Table 9.8 Kurtosis of Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	5.42 *5.25*	7.94 *7.18*	5.82 *5.17*	5.25 *4.95*	3.59 *4.99*	4.11 *4.85*	3.16 *7.11*	2.85 *6.06* SIG 5%	2.55 *6.14* SIG 1%	8.57 *6.59*
Belgium	9.19 *7.98*	5.19 *5.93*	7.62 *8.01*	4.71 *7.37*	6.27 *7.35*	5.40 *7.95*	4.12 *5.57*	5.43 *5.98*	5.64 *6.11*	4.73 *5.65*
Canada	5.79 *6.26*	7.64 *8.63*	5.85 *6.15*	5.42 *6.28*	3.77 *6.08* SIG 5%	6.36 *5.96*	9.81 *8.27*	9.26 *7.77*	6.55 *7.74*	5.26 *8.06*
Denmark	4.40 *5.35*	5.56 *5.62*	4.05 *5.30*	4.89 *5.21*	4.12 *5.26*	4.35 *5.25*	3.70 *5.65*	5.26 *5.34*	3.99 *5.56*	5.85 *5.39*
France	4.53 *5.65*	5.88 *5.29*	5.11 *5.64*	3.70 *5.50*	3.74 *5.50*	3.46 *5.61* SIG 5%	2.60 *5.16* SIG 1%	3.95 *5.33*	6.27 *5.21*	5.37 *5.22*
Germany	5.30 *6.28*	5.75 *5.90*	5.41 *6.32*	5.24 *6.10*	3.79 *6.05* SIG 5%	4.58 *6.18*	3.07 *5.70* SIG 1%	4.33 *5.85*	5.47 *5.85*	4.31 *5.82*
Hong Kong	17.28 *14.24*	7.45 *8.55*	16.12 *13.30*	22.13 *10.89*	10.73 *10.65*	4.82 *12.65*	4.13 *8.07* SIG 5%	6.63 *7.96*	4.32 *7.84*	9.11 *8.05*
Italy	4.59 *4.51*	4.57 *4.66*	4.51 *4.59*	2.70 *4.49* SIG 1%	4.13 *4.38*	5.72 *4.39*	3.00 *4.68* SIG 5%	3.14 *4.50*	4.74 *4.53*	5.29 *4.71*
Japan	6.09 *5.62*	5.53 *5.01*	5.85 *5.66*	3.88 *5.29*	4.41 *5.30*	5.72 *5.56*	4.85 *4.91*	6.59 *5.00*	6.24 *4.93*	4.03 *4.88*
Netherlands	5.98 *6.71*	6.47 *6.53*	5.58 *6.68*	3.85 *6.61* SIG 1%	5.75 *6.60*	3.96 *6.56* SIG 1%	6.02 *6.42*	5.31 *6.50*	5.35 *6.49*	5.84 *6.32*
Spain	5.74 *5.10*	4.75 *5.21*	6.97 *5.07* SIG 5%	3.94 *5.08*	3.48 *5.02* SIG 5%	3.14 *5.04* SIG 1%	2.69 *5.15* SIG 1%	4.01 *5.12*	4.55 *5.09*	4.53 *5.15*
Switzerland	10.08 *8.25*	5.87 *7.11*	8.41 *8.21*	7.65 *7.70*	4.15 *7.61*	16.30 *8.17* SIG 1%	14.22 *6.92* SIG 1%	4.17 *6.88*	4.19 *6.78*	4.67 *6.76*
UK	5.53 *5.31*	4.86 *5.48*	5.38 *5.33*	5.62 *5.21*	4.32 *5.22*	4.40 *5.19*	3.20 *5.43* SIG 1%	3.31 *5.40* SIG 5%	3.94 *5.45*	4.27 *5.36*
USA	6.40 *5.84*	5.58 *6.43*	7.75 *5.70*	5.72 *5.77*	4.64 *5.81*	5.36 *5.72*	5.55 *6.30*	4.01 *6.12*	5.55 *6.06*	4.86 *6.18*

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5^{th} and 99.5^{th} percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5^{th} and 97.5^{th} percentile values of the bootstrap distribution.

9.8 Summary

The analysis described in this chapter reveals a number of features which clearly differentiate trends in stock market data from trends in random data with the same distribution of daily returns. A clear understanding of the ways in which stock market trends differ from random trends may shed some light on which, if any, of the theories of stock market continuation and reversal effects proposed in the literature are important factors in the predictability of stock market returns

Stock market trends are not significantly different from random trends in terms of their duration or total amplitude. Overall, bull trends appear to be slightly shallower and bear trends slightly steeper than random trends, although the differences are typically not statistically significant.

Clear patterns are, however, observed in the steepness of different phases of bull and bear trends. The fourth quarter of bull trends is somewhat shallow, whilst the fourth quarter of bear trends is particularly steep relative to random trends based on the same distribution of daily returns. These patterns are not accounted for by the proportion of positive and negative daily price returns present in bull and bear trends and the four quarters of each. Rather, patterns in the absolute size of positive and negative daily returns through the bull-bear stock market cycle appear to drive the observed differences in the steepness of trends.

Positive daily price returns are relatively high in the first quarter of bull trends but low throughout the remainder of the trend, whilst negative daily price returns are significantly smaller in quarters 2 through 4 than is the case for random trends. The resulting standard deviation of daily price returns is high, relative to that found in random trends, in quarter 1 but low in quarters 2 through 4.

Positive daily price returns are relatively large in the second half of bear trends, whilst negative daily price returns are relatively small in the first half but large (more negative) in the second half of bear trends. The standard deviation of daily price returns is low in the first half but high in the second half, and particularly so in the final quarter, of bear trends.

Overall, therefore, bull trends are steep and volatile in their initial phase largely as a result of large positive daily price returns. Later, both positive and negative daily returns become smaller (that is to say, negative returns become less negative) than is the case for random trends, and volatility falls. The first half of bear trends is characterised by small negative daily changes resulting in low steepness and volatility. As the trend progresses, both positive and negative daily price returns increase in size (that is to say, negative returns become more negative) and volatility increases markedly.

Patterns in the steepness of bull and bear trends may help to explain some of the excess returns to short-term momentum trading strategies documented by previous research. Bull trends are steepest in their first quarter for 12 of the 14 stock markets considered in this study. It is therefore possible that cross-sectional studies using standard methodologies similar to that of Jegadeesh and Titman (1993) identify winner portfolios that are biased towards stocks at the beginning of a bull trend. Bear trends, on the other hand, are generally steepest in their final quarter, hence it may be the case that studies identify loser portfolios which are biased towards identifying stocks at the end of a bear trend. The length of formation and test periods used, together with the trend behaviour of the underlying market, may influence the observed returns to winner and loser portfolios.

Chapter 10 builds on this analysis by considering which, if any, of the behavioural biases and alternative theories proposed in the literature and examined in Chapters 2 and 3 is capable of explaining the patterns in the profitability of momentum trading strategies documented in Chapter 7 and the particular features of stock market trends described in this chapter.

Chapter 10

Main Findings and Interpretation

10.1 Introduction

The research documented in this thesis has two main objectives. Firstly, a time series approach is implemented to consider the empirical evidence of continuation and reversal effects in the returns of 14 major stock markets. This first part of the research examines to what extent anomalies, in the words of Fama (1998, p283), "tend to disappear with reasonable changes in technique".

The second main objective of the research documented in this thesis is to examine the potential causes of continuation and reversal effects in financial market returns. One of the main limitations of the existing literature is that, although an extensive menu of possible behavioural and non-behavioural causes of continuation and reversal effects has been identified, the empirical methodologies used to identify such effects in returns often do not allow the researcher to differentiate clearly between these possible causes. As Chapter 8 discusses, findings of continuation and reversal effects in stock market returns imply that stock market trends have properties which differ systematically from those of random trends based on the same empirical distribution of daily returns. The current study therefore aims to draw some broad conclusions regarding the possible causes of continuation and reversal effects in stock market returns by examining the statistical properties of stock market trends.

This chapter revisits the empirical results presented in Chapters 7 and 9, and considers the implications of these results in the light of the possible behavioural and alternative explanations proposed in the literature and discussed in Chapters 2 and 3.

Section 10.2 discusses the findings of the study of momentum strategy profitability described in Chapters 7 and 8. A review is provided of the main findings of this part of the research, and the consistency of these findings with those of previous research is considered. Finally, the implications of the results of this part of the research for market efficiency are discussed.

Section 10.3 goes on to consider the results of the study of the properties of stock market trends documented in Chapters 8 and 9. Again, the main findings are summarised and their consistency with the results of previous research is discussed.

Section 10.4 brings together the results of the two parts of the research and discusses ways in which empirical findings of continuation and reversal effects in stock market returns may be linked to the properties of stock market trends.

Sections 10.5 and 10.6 consider, in turn, the possible contribution to the empirical results of the current study of the behavioural and alternative explanations proposed in the literature and reviewed in Chapters 2 and 3. Section 10.7 then considers in more detail the possible role of loss aversion in driving the observed patterns in stock market trends. Section 10.8 discusses suggestions for further research, and Section 10.9 summarises.

10.2 Study of Momentum Strategy Profitability

10.2.1 Main Findings

The research documented in Chapters 6 and 7 examines the extent to which continuation and reversal effects are present in the 14 stock market indices which are the focus of the current study. Momentum trading strategies are constructed which buy the relevant stock market index following a market rise and sell following a market fall. For each momentum strategy, a corresponding contrarian strategy can be defined which buys the index following a market fall and sells following a rise in the market. Significant momentum profits are therefore evidence of continuation effects in returns, whilst significant momentum losses (significant profits to the corresponding contrarian strategy) are interpreted as evidence of reversal effects in returns. This section summarises the main results of this part of the research.

Evidence of continuation effects in returns is found over periods of one trading day, with positive cumulative returns generated by the one day momentum trading strategies for thirteen of the fourteen countries considered (the exception being Germany). In many cases, these returns are economically substantive (the one trading day strategy for Belgium, for example, generates a cumulative return of 128.36% over the eight year data sample), and returns are statistically significant based on the bootstrap test in four cases (Belgium and Canada at the 1% level, and Hong Kong and Switzerland at the 5% level).

Although at first sight, the returns to the one trading day strategies may appear attractive, an examination of returns by calendar year reveals that returns are not consistent over time. On average, the one trading day strategies generate positive returns for between 3 and 8 of the 8 years in the data sample, with a mean of 5.71 years of positive returns and a median of 6 years.

One important feature of the returns to the one day momentum strategies examined in the current study is that the returns to long positions appear to make a greater contribution to overall returns than do the returns to short positions. Long positions generate a positive contribution to overall cumulative returns for all 14 countries and the long-only returns are significant in 8 cases (5 at the 1% level and 3 at the 5% level). Short positions generate positive cumulative returns for 10 of the 14 countries considered, although these returns are significant in only two cases.

The standard deviation of daily returns to the one trading day strategies is significantly high based on the bootstrap test for all 14 countries considered, and the Sharpe ratio is significant in only two cases (Belgium and Canada). Overall, therefore, the one trading day strategies tend to produce high returns, although the standard deviation of returns is high and returns may therefore simply reflect compensation for the increased risk of the momentum strategy over a passive investment in the relevant index.

Over 2 through 5 trading days, no clear patterns emerge in the returns to momentum strategies and strategies appear to be profitable as often as they are unprofitable. For the 2 trading day strategy, for example, positive returns are achieved for 6 of the 14 countries considered, with cumulative returns ranging from -74.61% (the Netherlands) to 80.72% (Belgium). Only 2 strategies of the 56 considered (2, 3, 4, and 5 trading day strategies for each of the 14 countries) produce significant cumulative returns based on the bootstrap test (1 at the 1% level and 1 at the 5% level). This is approximately the number of significant results one would expect to occur by chance alone from 56 observations.

An examination of returns by calendar year shows that returns to the 2 through 5 trading day strategies vary considerably from year to year in much the same way as for the one trading day strategies. Long-only returns are generally positive and short-only returns negative, although as in the case of the overall cumulative returns for these strategies, few of these returns are statistically significant.

The standard deviations of daily returns to the 2 through 5 trading day strategies are significantly high in the same way as for the one trading day strategies, and the Sharpe ratio is significant for only one of the 56 strategies (the 2 day strategy for Belgium, whose Sharpe Ratio of 0.73 is significantly greater than the bootstrap value of 0.01 at the 5% significance level).

In summary, therefore, the 2 through 5 trading day strategies do not appear to generate significant cumulative returns over the period covered by the data samples and no particular features of the returns stand out for further analysis.

Over 10 through 252 trading days, the momentum strategies considered tend to produce positive cumulative returns, although these are not generally statistically significant based on the bootstrap test. Of the 84 strategies considered in this section (6 strategies for 14 countries), 64 produce positive cumulative returns. The principal exception to the rule is Australia, where the cumulative return to each of the 10, 21, 42, 63, 126 and 252 trading day strategies is negative. Fifteen strategies generate significant cumulative returns (6 at the 1% level and 9 at the 5% level).

In common with the shorter strategies, the returns to the 10 through 252 trading day strategies are inconsistent from year to year, and the positive overall returns tend to be driven exclusively by high long-only returns, with the short-only returns often negative. Nevertheless, although the standard deviations of returns to the 10 through 252 trading day strategies tend to be significantly high and only 10 of the 84 strategies have Sharpe ratios which are significantly in excess of the bootstrap values (3 at the 1% level and 7 at the 5% level).

The main features of the results of this part of the research which are revisited later in this chapter can be summarised as follows:

- Evidence of continuation over one trading day, possibly as a result of nonsynchronous trading
- no significant continuation or reversal effects over 2 through 5 trading days
- limited evidence of continuation over periods ranging from 10 through 252 trading days driven by returns to long positions.

Section 10.2.2 considers the extent to which these findings are consistent with the results of previous research into continuation and reversal effects in stock market returns.

10.2.2 Consistency with the Results of Prior Research

Chapter 4 provides a review of studies of continuation and reversal effects in stock market returns.

In the short-term, the current study finds evidence of continuation over periods of one trading day, with a lack of any significant effects over periods ranging from 2 through 5 trading days.

For single stock data, most studies of short-term continuation and reversal effects in stock market returns have tended to find evidence of reversal for losers (see, for example, Bremer and Sweeney, 1991 and Akhigbe et al, 1998). For winners, the picture is less clear. Howe (1986), for example, reports evidence of continuation for winners over periods of one week. Atkins and Dyl (1990), on the other hand, find that winners generate small negative returns over 1 though 7 days following the initial price event.

The evidence from studies which consider stock market index data is mixed. Lasfer et al (2003), for example, find evidence of continuation for both winners and losers, with returns to winners increasing (and returns to losers correspondingly decreasing) monotonically over 1 through 10 days following the initial price event. Schnusenberg and Madura (1998) find similar evidence of continuation for winners, but mixed results for losers. Ratner and Leal (1999) report no significant findings for winners whilst for losers, continuation is reported for some indices and reversal for others.

The lack of consistency in the results of previous studies of short-term continuation and reversal effects makes a direct comparison with the results of the current study difficult. The pattern of results reported in this study is not fully consistent with any of the previous studies in isolation, although it should be noted that neither are the results of any of the previous studies fully consistent with one another.

In the medium-term, the current study finds very limited evidence of significant continuation effects over periods of 10 through 252 trading days. Positive overall returns are driven by very high returns to long positions, with negative positions typically contributing negative returns. This could be considered analogous to findings of continuation for winners and reversal for losers within a traditional cross-sectional research approach.

Most previous studies of medium-term effects in stock market returns use a standard cross-sectional methodology together with stock-level data, and find evidence of significant continuation effects (see, for example, Jegadeesh and Titman, 1993, and Rouwenhorst, 1998). Findings of medium-term continuation effects in the current study appear at first sight to be consistent with the results of prior research, although a question mark remains over the role of long and short positions in generating these returns. Whilst previous research has tended to suggest that both long (winner) and short (loser) positions make a positive contribution to overall returns, the results of the current study suggest that overall returns are driven by the returns to long positions, with short positions contributing negative (although non-significant) returns.

In the long-term, studies tend to find evidence of significant reversals in returns over periods ranging from 2 years to 5 years (see, for example, De Bondt and Thaler, 1985). The results of these studies are generally consistent, although some authors find that reversal effects disappear when risk is controlled for. Allen and Prince (1995), for example, find evidence of reversals in returns in line with those identified by previous studies, but note that continuation effects are instead identified when time varying risk is accounted for by re-estimating market model betas using the approach suggested by Chan (1988). Similarly, Forner and Marhuenda (2000) find that reversals disappear when risk is controlled for. The issue of time-varying risk is revisited later in this chapter.

Section 10.2.3 goes on to consider the implications for market efficiency and market rationality of the results of the current study in terms of momentum strategy profitability.

10.2.3 Implications for Market Efficiency and Market Rationality

The returns to momentum trading strategies described in Chapter 7 and summarised in Sections 10.2.1 through 10.2.3 do not appear to contradict the concepts of weak-form market efficiency and market rationality for the 14 stock market indices considered.

Weak-form market efficiency requires that investors cannot make money by trading on past prices alone. Whilst a number of the trading strategies considered generate returns which appear to be economically substantive (the 1 trading day strategy for Belgium, for example, generates a return of 128.36% over the 8 year data sample), not all of the strategies produce such attractive returns (the 2 trading day strategy for France, for example, produces a cumulative loss of 68.61%).

For momentum strategies of this type to be appealing to investors, they must offer the expectation of consistent profit. This might be the case if a range of momentum strategies were shown to work particularly well on a particular market, for example. Alternatively, a particular strategy specification might work well across a range of stock markets. This does not appear to be the case for the strategies considered in the current study.

Figure 10.1 shows the number of strategies, of a total of eleven, which generate significant positive cumulative returns for each country. For four countries, no strategy produces significant returns based on the bootstrap test.

For a further three countries, only one strategy produces statistically positive returns. Four countries enjoy statistically positive returns for 2 strategies, two for 3 strategies, and one for 4 strategies. No data set generates positive returns for more than 4 of the 11 momentum trading strategies considered.

Figure 10.2 examines the returns to momentum trading strategies of specific length across stock markets. The most consistently profitable strategies are the 1 trading day strategy, which generates significant positive cumulative returns based on the bootstrap test for 4 of the 14 countries considered, and the 252 trading day strategy, which produces a significantly positive cumulative return for 5 countries. For the remaining strategy specifications, no more than 3 of the 14 data sets produce significant cumulative returns based on the bootstrap test. In particular, an analysis of the risk-return characteristics of the momentum strategies considered reveals that very few have Sharpe ratios significantly in excess of the bootstrap values. That is to say, even those strategies which do generate significant excess returns may not do so on a risk-adjusted basis. In addition, as shown in Appendix C, the returns to individual strategies vary considerably from year to year and even strategies which appear attractive based on the cumulative returns or Sharpe ratios over the 8-year data sample may not prove attractive when considered over shorter investment horizons.

These initial results suggest that investors are not leaving a free lunch on the table. That is to say, they are not failing to exploit significant and consistent excess returns. Although individual anomalies may occur, such as a tendency towards momentum profits over horizons between 10 and 252 trading days, these effects are not sufficiently consistent to imply that the market behaves irrationally in failing to exploit them.

Figure 10.1 Momentum Strategy Results by Country

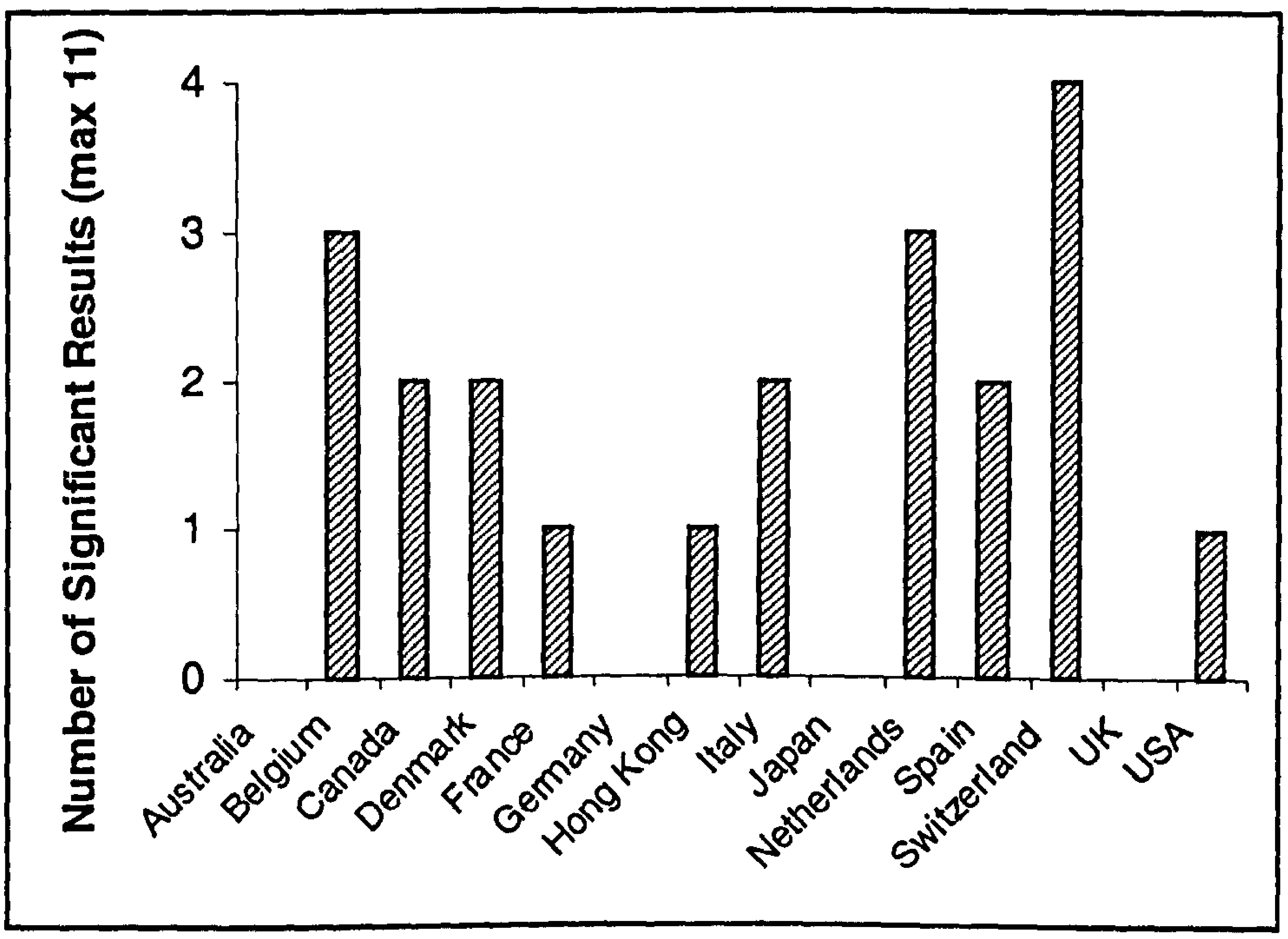
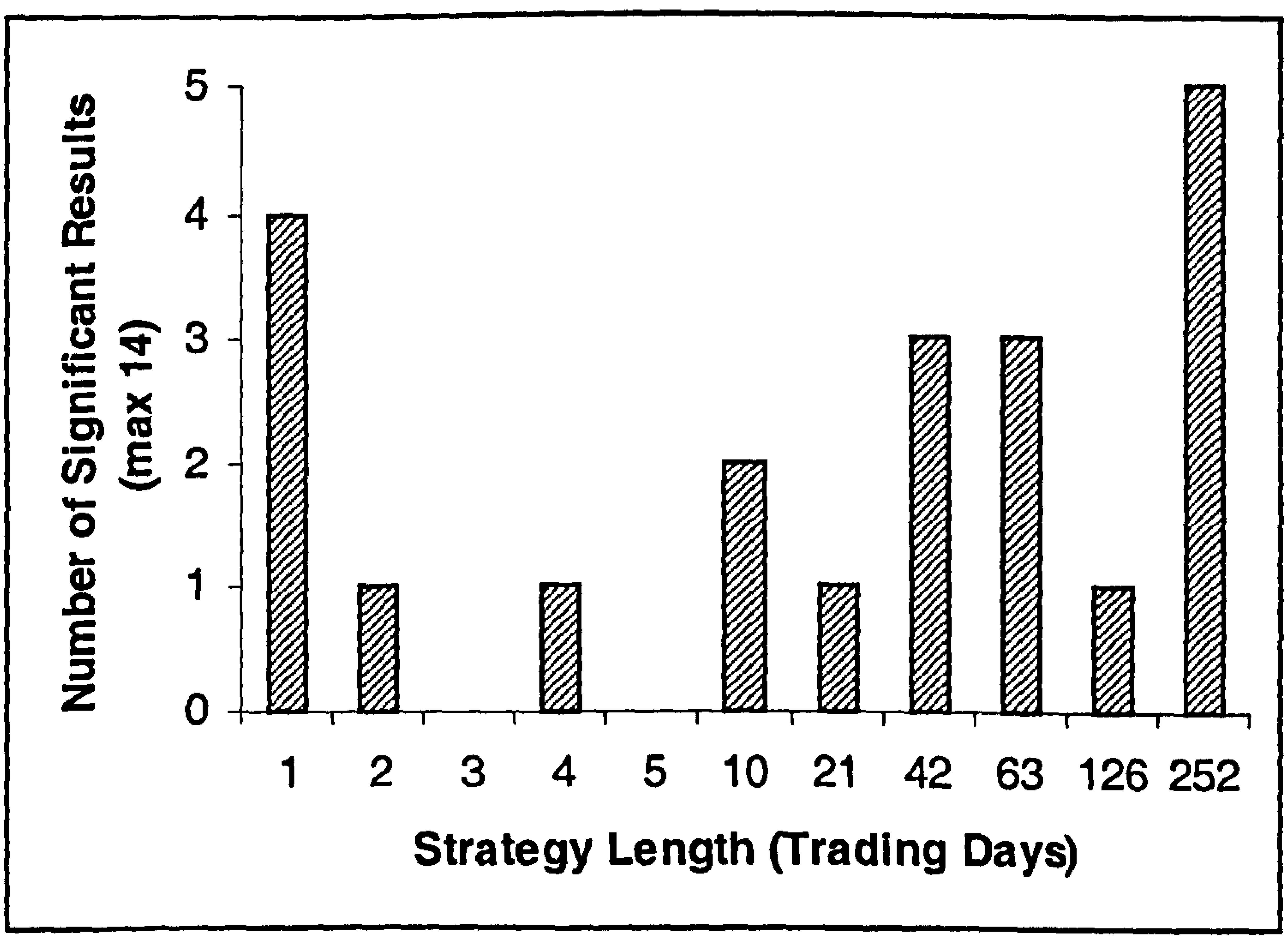


Figure 10.2 Momentum Strategy Results by Strategy Length



10.3 Analysis of the Properties of Price Trends

10.3.1 Main Findings

The second part of the research documented in this thesis uses an algorithm from the information technology literature (Fink and Pratt, 2004) to date turning points in price trends in the 14 stock market index data sets which form the basis of this study. The statistical properties of returns within bull and bear trends and four phases of each are then considered. A number of features are identified which clearly differentiate trends in stock market data from trends in random data based on the same distribution of daily returns.

Whilst stock market trends are not significantly different from random trends in terms of their duration or total amplitude, patterns are observed in the steepness of different phases of bull and bear trends, in the magnitude of positive and negative price returns through bull and bear trends, and in the standard deviation of those price returns. Table 10.1 provides a summary of these patterns.

As discussed in detail in Chapter 9, although trends in the 14 stock market indices which are the focus of the current study do not appear to have longer duration or total amplitude that random trends based on the same empirical distribution of daily returns, patterns are observed in both the steepness of trends as they develop and also in the standard deviation of daily price changes within trends.

Bull trends tend to be shallow in their final quarter. The steepness of bear trends does not differ significantly from the bootstrap over the first three quarters of the trend. The final quarter of bear trends, however, is steeper than the bootstrap value for all countries except Japan, and significantly so for 9 countries at the 1% level.

Table 10.1 Summary of Patterns Identified in Stock Market Trends

	Bull				Bear			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Steepness				Low				High
Standard Deviation of Returns	High?	Low	Low	Low	Low		High?	High
Positive Returns	High?	Low	Low	Low			High?	High
Negative Returns		Low	Low?	Low?	Low			High

Note: The table shows the main pattern of results identified across the 14 stock market indices which are considered in this study, identified by a significant result at the 5% level for more than 6 of the 14 countries considered. A question mark denotes that only between 4 and 6 significant results were recorded. Blank cells in the table indicate that no clear pattern is identified in the results (three or less significant results).

Patterns are also observed in the standard deviation of daily price returns through the bull-bear cycle, with a significantly high standard deviation of returns in the second half of bear trends and first quarter of bull trends. Again, the fourth quarter of bear trends appears to be particularly extreme, with the standard deviation of daily price returns significantly high based on the bootstrap test for 9 of the 14 countries considered at the 1% level and a further 4 countries at the 5% level.

Patterns in the magnitude of positive and negative price changes through the bull-bear cycle appear to drive these observed patterns in the steepness of trends and in the volatility of price returns. This can be observed with reference to the examples provided in Table 10.2 for the UK data sample[87].

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[87] No one data sample fully reflects all of the general features identified across the 14 data sets and summarised in Table 10.1. The UK results, for example, do not exhibit

Table 10.2 Summary Results for the UK Data Sample

	Bull				Bear			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Steepness (mean daily price return)	0.29% *0.27%*	0.13% *0.14%*	0.11% *0.14%*	0.12% *0.27%* SIG 1%	-0.28% *-0.27%*	-0.05% *-0.13%*	-0.10% *-0.13%*	-0.51% *-0.27%* SIG 1%
Standard Deviation of Returns	1.10% *1.05%*	0.99% *1.05%*	0.84% *1.05%* SIG 1%	0.83% *1.05%* SIG 1%	0.91% *1.10%* SIG 1%	1.02% *1.08%*	1.00% *1.08%*	1.53% *1.09%* SIG 1%
Positive Returns	0.95% *0.87%*	0.73% *0.82%*	0.67% *0.81%* SIG 5%	0.65% *0.86%* SIG 1%	0.61% *0.66%*	0.74% *0.71%*	0.72% *0.71%*	0.92% *0.66%* SIG 1%
Negative Returns	-0.66% *-0.69%*	-0.68% *-0.74%*	-0.61% *-0.74%* SIG 5%	-0.63% *-0.69%*	-0.87% *-0.94%*	-0.88% *-0.88%*	-0.80% *-0.88%*	-1.36% *-0.94%* SIG 1%

Note: Figures in italics are the mean values from 4999 bootstrap runs. "SIG 1%" and "SIG 5%" denote significance at the 1% level and 5% levels respectively based on the bootstrap test.

There is some evidence to suggest that in the first quarter of bull trends, positive price returns are significantly higher than those found in random trends with the same empirical distribution of daily returns. Throughout the remainder of the bull trend, positive price returns tend to be significantly lower than the bootstrap values. Negative price changes tend to be significantly low through quarters 2, 3, and 4 of the bull trend. The combination of these patterns in the magnitude of positive and negative price returns results in bull trends may be responsible for the observation that bull trends tend to be significantly shallow in their fourth quarter.

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the same steepness in quarter 1 of bull trends seen for other countries such as Hong Kong or Italy. In addition, quarter 3 of bear trends is not as steep for the UK data as, for example, Denmark or Spain.

For bear trends, no clear patterns in the magnitude of positive daily returns are observed in the first half of the trend, although positive returns are significantly larger than the bootstrap in quarter 4 for most countries. Negative daily returns are typically less extreme than the bootstrap in quarter 1 and more extreme in quarter 4. These patterns result in bear trends which are significantly steeper than the bootstrap average in their fourth quarter. Whilst the standard deviations of daily returns is low in the first quarter of bear trends, it is significantly high in quarter 4.

The main features of the results of this part of the research which are revisited later in this chapter can be summarised as follows:

- Stock market trends are not significantly long (duration) or high (amplitude)

- Patterns occur in the steepness of trends through the bull-bear cycle.
    - Bull trends are steepest at the beginning, becoming more shallow thereafter
    - Bear trends become extremely steep in their final stages

- Patterns occur in the volatility of price returns within trends
    - High volatility of returns in steep sections of trends, combined with low volatility of returns in shallow sections

- These effects appear to be driven by the changing distribution of daily price returns, reflected in the mean positive and negative daily returns, through the bull-bear cycle.

One of the major challenges for the different explanations of continuation and reversal effects proposed in the literature and described in Chapters 2 and 3 is therefore to explain the ways in which stock market trends appear to differ significantly from random trends based on the same distribution of daily returns. In particular, any successful explanation of continuation and reversal effects in financial market returns should be consistent with the observed patterns in the magnitude of positive and negative price returns through the bull-bear cycle.

Section 10.3.2 considers the extent to which the findings of the current study, summarised in this section, are consistent with the findings of previous research.

10.3.2 Consistency with the Results of Prior Research

Previous studies have examined the features of stock market trends using algorithms based on the approach of Bry and Boschan (1971) and regime-switching models based on the work of Hamilton (1989).

As Chapter 8 discusses, only a very limited amount of work has been published in this field, and the use of monthly data by most of these studies means that they have been unable to carry out an analysis of the basic properties of stock market trends to the same level of detail as that reported in the current study.

One feature of the results of most previous studies is that bull trends last for longer than bear trends. Kaminsky and Schmukler (2001), for example, report that bull trends last for 26 months on average whilst bear trends last for only 18 months. Similarly, Pagan and Sossounov (2003) report average durations of 25 months for bull trends and 17 months for bear trends respectively.

One of the main findings of the current study is that, although bull trends do last for longer than bear trends, this does not appear to be one of the features that differentiates stock market trends from random trends. Bull trends are also longer than bear trends on average across 4999 bootstrap runs generated by sampling with replacement from the original daily price returns of the 14 data sets which are the focus of the current study.

The current study concludes that the excess duration of bull trends over bear trends observed in most prior research is simply a result of data samples characterised by rising stock prices. When considering the possible causes of continuation and reversal effects in returns, however, the important features are likely to be those which systematically differentiate trends in actual stock market data from trends in random data with the same overall distribution of daily returns.

The current study considers data samples covering the years 1993 to 2002. This is in contrast to many of the previous studies, which use much longer data samples. Gonzalez et al (2005, forthcoming), for example, consider trends in the US stock market over the period 1800 through 2001.

Although the results of previous studies may not provide the same depth of analysis as the current study as a result of their use of monthly rather than daily data, potentially important observations can be drawn by considering subsections of the long periods of data on which they are commonly based. Pagan and Sossounov (2003) consider a data sample covering the US market from 1835 to 1997. Over time, Pagan and Sossounov observe that bull trends become longer and stronger whilst bear trends become shorter and weaker. In addition, the deviation of trends from a straight line increases through the data sample. These results tend to indicate that the specific features of stock market trends may have been increasing, rather than decreasing, over the very long-term.

This provides an immediate contrast to many of the market microstructure theories of continuation and reversal effects in stock market returns, such as bid-ask bounce and non-synchronous trading, whose effects are postulated to reduce over time as market liquidity increases. In addition, the findings of Pagan and Sossounov may relate in some way to those of studies of momentum strategy profitability using very long data samples. Chen and Sauer (1997), for example, report patterns in the long-term profitability of the 5-year contrarian strategy of buying past losers and selling past winners with the strategy generating negative returns in the mid to late 1930s, very high returns in the late 1930s and early 1940s, and very low returns from the mid 1940s to the mid 1950s.

An important challenge for any successful theory of stock market continuation and reversal effects is therefore to explain not only how patterns in the magnitude of positive and negative daily returns occur through the bull-bear cycle, but also to explain how it could be, as suggested by previous research, that such effects appear to be non-stationary over time.
Sections 10.2 and 10.3 have summarised the findings of each of the main sections of the research documented in this thesis, and discussed the consistency of these findings with those of the existing literature. Section 10.4

considers how the results of the two parts of the research may be related, that is to say, how the properties of stock market trends may contribute to the profitability of momentum trading strategies.

10.4 Stock Market Trends and Momentum Strategy Profitability

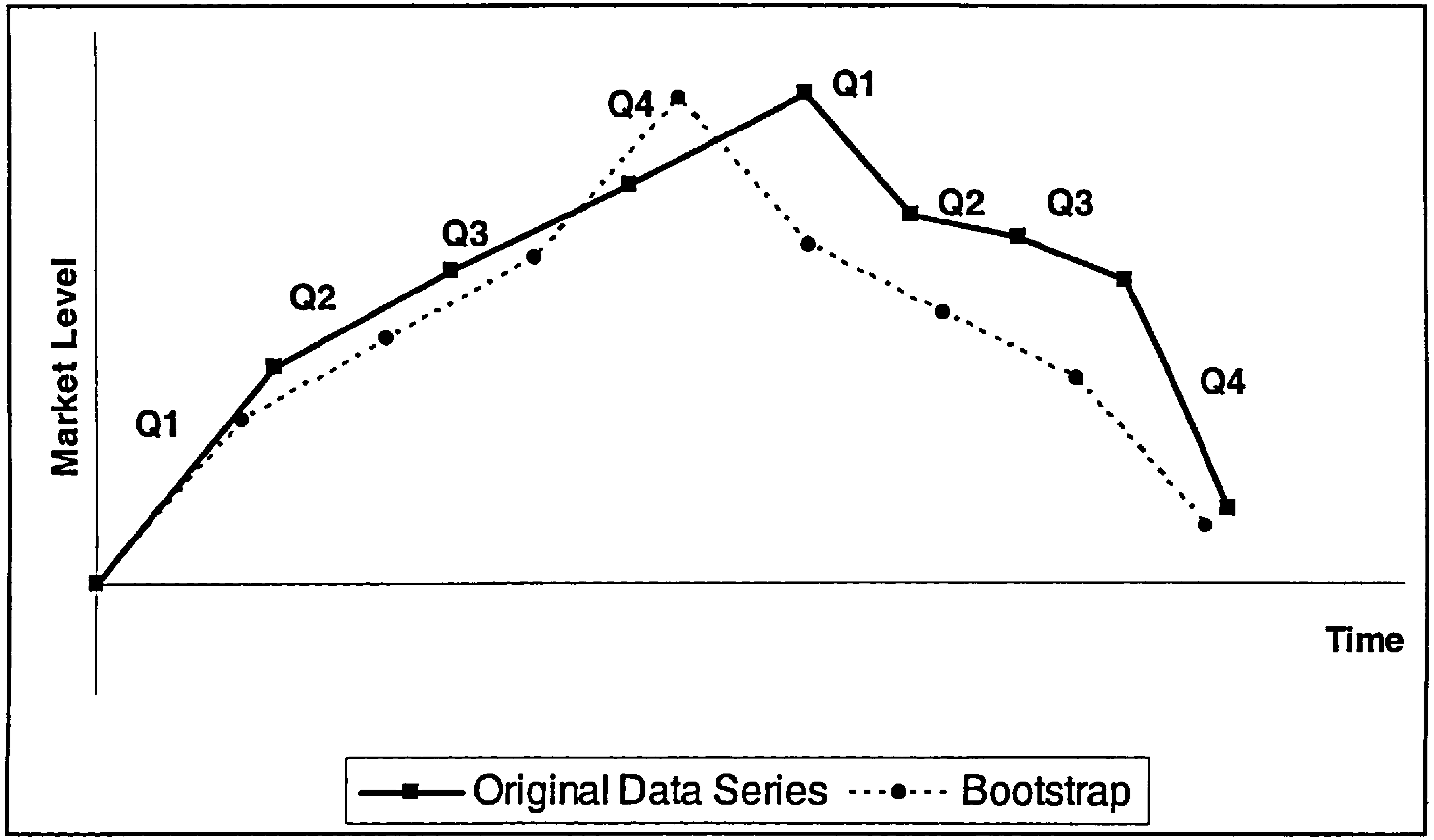
Chapter 8 describes how the existence of continuation and reversal effects in stock market returns implies that stock market trend behaviour is systematically different from that of random time series based on the same distribution of daily returns.

This section considers the relationship between stock market trends and continuation and reversal effects in returns in the light of the results presented in Chapter 9. It is possible that stock market trend behaviour may be at least partly responsible for findings of continuation and reversal effects in the existing literature.

Patterns in stock market trend behaviour may influence both the results of the existing literature and also the results of the study of momentum strategy profitability described in Chapters 6 and 7. That is not to say that the results of any of these studies are necessarily invalid. Rather, this section attempts to reconcile, in simple terms, the properties of returns that such studies may in fact be measuring. Figure 10.3 illustrates the typical pattern of the stock market bull-bear cycle.

As illustrated in Figure 10.3, the part of the bull/bear cycle with the highest mean returns is the first phase of the bull trend, whilst that with the lowest mean returns is the final phase of the bear trend. Studies based on a cross-sectional methodology and single stock data typically form winner portfolios based on the best-performing decile of stocks over a specified formation period. Given the stock market trend behaviour shown in Figure 10.3, it is likely that these studies will be biased towards identifying winner stocks that are in

Figure 10.3 The Stock Market Bull/Bear Cycle



The figure shows the typical bull / bear cycle identified by the current study. The chart is based on the UK data.

the initial phases of a bull trend. If this is the case, then these stocks will continue to perform well over the test period, and studies are likely, therefore, to find evidence of continuation for winners. Similarly, loser portfolios are likely to be biased towards identifying stocks that are in the final stages of a bear trend, and studies might therefore be expected to find evidence of reversal among losers.

Previous cross-sectional studies of medium-term continuation and reversal effects have tended to find evidence of continuation for both winners and losers (Jegadeesh and Titman, 1993, and Rouwenhorst, 1998, for example). Whilst the above analysis may help to explain findings of continuation for winners, therefore, it is not at first sight able to explain similar findings of continuation for losers.

The analysis does, however, provide a close fit to the results of the study of momentum strategy profitability described in Chapters 6 and 7. The methodology adopted in the current study identifies periods of high and low returns in time series data rather than portfolios of winning and losing stocks in a cross-sectional approach. As previously discussed, the properties of stock market trends may bias the results of the first part of the research towards findings of continuation for winners (long positions) and reversal for losers (short positions) in the medium-term. This is indeed the pattern identified in the first part of the research for the 10 through 252 trading day strategies.

The properties of medium-term stock market trends considered in the current study do not explain the findings of continuation over one trading day or the lack of significant continuation or reversal effects over 2 through 5 trading days, however. It is possible that very short term effects are driven by separate factors to those driving stock market trend behaviour. Market microstructure arguments, for example, could explain findings of momentum returns (or lack of returns) in the very short-term which do not appear to be reflected in the properties of medium-term stock market trends. Alternatively, very short-term trends (which combine to make up medium-term trends) might have different properties to the medium-term trends considered in the current study.

The next two sections go on to consider which, if any, of the possible behavioural and non-behavioural alternative arguments proposed in the literature and discussed in Chapters 2 and 3 might be responsible for the empirical findings of the current study.

10.5 Consistency with Behavioural Explanations

The main features of the empirical results of the current study can be summarised as follows:

- Very limited evidence of one-day and 10 through 252 day continuation effects is identified by the study of momentum strategy profitability, and

- There is evidence of patterns in the steepness and volatility of stock market trends. As discussed in the previous section, these are hypothesised to be responsible for the findings of medium-term momentum strategy profitability in the current study.

This section considers the extent to which these empirical findings are consistent with the principal behavioural explanations proposed in the literature and reviewed in Chapter 2. Specifically, this section discusses the potential impact of mental accounting, representativeness, availability, anchoring, overconfidence, aversion to loss, and aversion to ambiguity on market returns and considers the extent to which the results of this study are consistent with each.

10.5.1 Mental Accounting

Mental accounting describes the way in which investors view different portions of wealth independently. A portfolio of stocks designed as an investment for retirement provision is likely to be treated very differently to a day trading account held for the purposes of entertainment and short-term gain, for example.

Mental accounting does not in itself provide an explanation for empirical findings of continuation and reversal effects in stock market returns. It does, however, help to explain why such effects might differ across markets. For example, a blue-chip stock which is widely held by large institutions such as pension funds can be expected to behave differently to a small stock traded speculatively. Differences in the trend behaviour of individual stocks may therefore shed further light on the factors driving patterns in stock market trends. Mental accounting is revisited in Section 10.8 where suggestions are given for further research based on the findings of the current study.

10.5.2 Representativeness, Availability and Anchoring

The representativeness, availability, and anchoring heuristics are rules of thumb used by individuals to simplify decision-making situations. As described in this section, all three heuristics can be expected to have the same effect on stock market trend behaviour, and as such they are considered together.

Under representativeness, investors simplify decision-making or prediction scenarios by considering the extent to which they are stereotypical of known situations. A period of rising prices, for example, might be considered to be representative of a bull (rising) trend, in which case investors will expect similar price changes in the future. The use of the representativeness heuristic can be expected to result in a tendency to "chase the trend" with expectations of future price changes formed on the basis of past returns.

The availability heuristic describes how individuals may estimate the probability of events according to their salience, that is to say, the ease with which similar events can be brought to mind. In an investment scenario, recent price changes and extreme price changes are particularly salient and may lead investors to overestimate both the probability of a continuation of the recent trend and the probability of extreme price changes. If investors overestimate the probability of reoccurrence of recent price changes, then this will result in trend-chasing behaviour in the same way as one would expect from the use of the representativeness heuristic.

When forming expectations of future price changes, investors may also use the anchoring heuristic. Under the anchoring heuristic, an anchor is chosen as a starting point and adjusted up or down to reach a predicted value. The choice of anchor is likely to depend on the investment situation. When forming long-term investment views, for example, an investor may choose the long-run average price level as the anchor, whilst recent returns may be considered a more appropriate anchor for short-term investments (De Bondt, 1998). The use of the anchoring heuristic can therefore be expected to result in a tendency to chase trends in much the same way as for the representativeness and availability heuristics.

The findings of the study of momentum strategy profitability contained in Chapters 6 and 7 indicate evidence of continuation effects over 1 trading day, although no clear effects are evident over 2 through 5 trading day horizons. This does not appear to be consistent with the use of the representativeness, availability or anchoring heuristics by investors. Whilst arguments might be constructed that decision-making heuristics might lead investors to extrapolate trends occurring over a period of just one day, there is no reason to expect this not to continue over 2 through 5 days.

Specific patterns in stock market price behaviour would be expected as a result of investors making decisions based on the representativeness, availability, and/or anchoring heuristics. Bull and bear trends should accelerate as the market rises / falls respectively, becoming steeper over time as more and more investors "recognise" the trend and make investment decisions accordingly. When fundamental information dictates a reversal in trend, this will not be immediately recognised by investors using the representativeness, availability and anchoring heuristics, resulting in a continuation of the trend and prices overshooting fundamental values.

If investors made decisions in this way, therefore, stock market trends would be expected to have higher amplitude than random trends based on the same distribution of daily returns, and trends should become steeper as they develop. Trends need not necessarily have longer duration than random trends (with trends both starting and finishing later than the turning points suggested by fundamental values). The representativeness, availability and anchoring heuristics do not in themselves suggest any asymmetry in the characteristics of bull and bear trends. That is to say, the properties of bull and bear trends would be expected to be mirror images of one another if trends in stock market returns were driven solely by decision-making heuristics such as representativeness, availability and anchoring.

The features of stock market trends which would be associated with the representativeness, availability and anchoring heuristics are not reflected in the results of the current study. Trends in the 14 stock market indices considered do not have significantly greater amplitude than random trends based on the same distribution of daily returns. The steepness of trends does not generally increase through the four quarters of the trend (although the market decline in the fourth quarter of bear trends is significantly steep). Finally, the results of this study exhibit clear asymmetry in the characteristics of bull and bear trends. The fourth quarter of bear trends is significantly steep and volatile, whilst no similar patterns are observed at the end of bull trends, for example.

Overall, therefore, the representativeness, availability and anchoring heuristics do not seem to provide, in isolation, an adequate explanation of the results of either part of the current study. Although prior research (see Barberis and Thaler, 2002, for a review) shows that these heuristics are used by individuals in investment scenarios, they do not appear to be the sole driving force behind the momentum strategy profits or properties of stock market trends which are documented in this thesis.

10.5.3 Overconfidence

Overconfidence causes individuals to overestimate the expected returns to the investment strategies they select (De Bondt, 1998), and may therefore exaggerate the impact of other factors (such as the representativeness, availability and anchoring heuristics) on investment behaviour. If the recent path of prices is upwards, for example, then representativeness, availability and anchoring will all tend to lead investors to expect further short-term price increases. An overconfident investor would exaggerate the expected size of these increases.

Overconfidence among investors cannot on its own, therefore, be expected to generate continuation effects in stock market returns or patterns in the steepness and volatility of stock market trends of the type evidenced in this study. If other behavioural factors cause these patterns, however, then overconfidence may have a role to play in exaggerating their impact on market prices.

10.5.4 Aversion to Loss

Investors have been shown to be highly averse to realising losses (see Odean, 1998, for example). The degree of loss aversion is lower following gains than it is following losses (Thaler and Johnson, 1990). The frequency with which outcomes are evaluated is also important (Benartzi and Thaler, 1985), with investors generally displaying a higher degree of loss aversion when outcomes are evaluated more frequently.

In the stock market, investors gain on aggregate when the market rises and lose when the market falls. The degree of market loss aversion can therefore be expected to fall through bull trends and rise through bear trends. Importantly, therefore, loss aversion may be capable of generating asymmetry in the properties of stock market returns between bull markets and bear markets. In particular, loss aversion may help to explain the asymmetric pattern of returns through the bull/bear stock market cycle shown in Figure 10.3. The possible relationship between loss aversion and the properties of stock market trends is discussed more fully later in this chapter.

10.5.5 Aversion to Ambiguity

Aversion to ambiguity describes the tendency among individuals to prefer gambles where the probability of outcomes is known. Aversion to ambiguity is inversely linked to overconfidence (Heath and Tversky, 1991). Increasing ambiguity has the same effect as reducing confidence. As discussed above, overconfidence cannot in itself generate the observed pattern of returns through the bull/bear cycle but may be responsible for exaggerating the impact of other factors. Similarly, aversion to ambiguity cannot in itself generate patterns in returns of the type observed, but may be responsible for reducing the impact of whichever factors do drive these returns.

This section has considered the main behavioural factors discussed in Chapter 2. None of these factors appears able to explain findings of momentum strategy profits over one trading day combined with a lack of significant returns over 2 through 5 trading days. Loss aversion is the only one of the behavioural theories considered which would produce asymmetries across bull and bear markets and therefore may have a role to play in generating the patterns observed in stock market returns through the bull/bear cycle. Section 10.6 goes on to consider the alternative theories of continuation and reversal effects in stock market returns discussed in Chapter 3.

10.6 Consistency with Alternative Explanations

Chapter 3 describes a range of non-behavioural alternative explanations proposed in the literature for continuation and reversal effects in financial market returns.

This section considers the extent to which the empirical findings of the current study are consistent with the explanations reviewed in Chapter 3. Specifically, this section discusses the impact of market microstructure issues such as bid-ask bounce and nonsynchronous trading, methodological issues, and risk on market returns and considers the extent to which the results of this study are consistent with each.

10.6.1 Bid-Ask Bounce

Bid-ask bounce implies negative autocorrelation in stock returns in the very short-term. The results of the study of momentum strategy profitability described in Chapters 6 and 7, on the other hand, are consistent with positive short-term autocorrelation in returns leading to positive returns to one-day momentum trading strategies. The results of the current study do not, therefore, appear to be consistent with bid-ask bounce affecting returns.

10.6.2 Nonsynchronous Trading

Nonsynchronous trading implies negative autocorrelation in individual stock returns in the very short-term but positive autocorrelation in stock index returns over the same horizon.

The current study finds evidence of positive momentum strategy returns for 13 of the 14 stock market indices considered (the exception being Germany). No significant effects are found over horizons of 2 to 5 trading days, on the other hand. This does appear to be consistent with nonsynchronous trading, the effects of which can be expected to dissipate over very short horizons such as 1 trading day.

Nonsynchronous trading may also explain why many previous studies of short-term continuation and reversal effects in the returns of individual stocks using a cross-sectional methodology find evidence of reversal over periods of one trading day, in contrast to the results of the current study.

Nonsynchronous trading does, therefore, appear to provide a plausible explanation for findings of the continuation effects in the 14 stock market indices considered over periods of one trading day. In addition, this explanation is consistent with the lack of significant effects over periods of 2 through 5 trading days, and is also consistent with the results of the existing literature.

10.6.3 Methodological Issues

A range of methodological issues have been identified in the literature as being capable of introducing bias to the results of previous studies of continuation and reversal effects in stock market returns. In particular, the choice of an appropriate measure of expected returns and the method used to cumulate returns can have an important influence on the results of individual studies. Furthermore, simplistic comparisons of formation and test period returns may result in unwarranted findings of asymmetries between the winner and loser portfolios. The study of momentum strategy profitability described in Chapters 6 and 7 aims to mitigate any methodological bias by ensuring as far as possible that the returns measured match those which would have been available to a real-world data (without taking into account transaction costs or taxation issues).

In the study of the properties of stock market trends, described in Chapters 8 and 9 the same methodology is used to identify turning points in the original and bootstrapped time series, with the same analysis then applied to the resulting trends. Any methodological issues would therefore be expected to have an impact on the bootstrap results as well as the results from the original data sets. As such, it is highly unlikely that methodological issues cause the observed differences between the properties of trends in the 14 stock market data sets and those in random data generated from the same empirical distribution of daily returns. Nevertheless, the choice of algorithm used to identify the trends to be examined (The amplitude-based Fink and Pratt algorithm rather than the duration-based approach used by previous research) may influence the results obtained.

10.6.4 Cross-Sectional Dispersion in Risk and Expected Returns

Conrad and Kaul (1998) suggest that positive returns to momentum strategies may occur simply as a result of buying high return high risk stocks (past winners) and selling low return low risk stocks (past losers). This might explain the positive returns to both long (winner) and short (loser) positions in cross-sectional momentum strategies of the type considered by Jegadeesh and Titman (1993) and Rouwenhorst (1998), among others.

In isolation, Conrad and Kaul's argument does not appear to explain the results of the current study. The momentum strategies considered in the current study are based on stock market indices. Although the FTSE All-World Indices considered in this study are not tradeable in their own right (the only way to trade them being to transact in the underlying constituents of the indices), other well-known indices (such as the FTSE 100 index in the UK) can be traded as an asset in their own right. If the results of the current study were shown to extend to traded indices[88], then cross-sectional dispersion in risk would not

[88] Indices which have liquid futures contracts, for example.

explain the medium-term returns to momentum strategies based on those indices.

10.6.5 Time-Varying Risk and Expected Returns

Time-varying risk may have a role to play in driving continuation and reversal effects in stock market returns. Chan (1988) argues that leverage effects may be responsible for changing risk levels over time. As the price of a stock falls, its financial leverage increases and the risk of the stock increases. Investors will therefore increase the discount rate used to value the stock, and its price will fall further. The converse argument can be applied to stocks whose price rises, and findings of continuation for winners and losers will result.

Time-varying risk of the type described by Chan (1988) does not explain the asymmetries observed by the current study in the properties of stock market trends. If increases in leverage cause stock prices to fall so quickly in the final stages of a bear trend, for example, then why is the initial stage of the bull trend not correspondingly steep as leverage falls again?

This section has discussed the possible non-behavioural causes of continuation and reversal effects in stock market returns proposed in the literature and reviewed in Chapter 3. Nonsynchronous trading appears to provide a highly plausible explanation for the findings reported in the current study of positive returns to one-day momentum trading strategies.

Whilst risk does clearly vary across stocks and over time, it is difficult to see how changing risk levels alone might explain the asymmetric features of stock market trends identified in the current study. Loss aversion therefore stands out as the only one of the potential causes of continuation and reversal effects put forward in the literature and briefly reviewed earlier in this chapter which is clearly capable of generating asymmetric returns in bull and bear markets. The following section goes on to consider how this might occur.

10.7 Loss Aversion and the Properties of Stock Market Trends

This section proposes one way in which loss aversion among investors might result in the patterns in the steepness of stock market trends and the volatility of returns within trends identified in the current study.

Prospect theory describes decision-making under loss aversion. Under prospect theory, investors will value stocks by multiplying the subjective values of all possible outcomes (measured relative to a reference point reflecting current wealth) by decision weights which overestimate the probability of very unlikely events and correspondingly underestimate the probability of all other events. The value function is concave for gains and convex for losses, reflecting a reducing marginal pleasure from higher gains and an increasing marginal discomfort to higher losses.

It is unlikely that the value function used by investors will be stationary over time. Under the house money effect of Thaler and Johnson (1990), for example, loss aversion increases following losses and falls following gains. The shape of the value function to be used at any point in time will therefore depend on returns in the recent past.

During a market downturn, investors are losing money on a net basis, and the degree of loss aversion will therefore be increasing. As the value function steepens in the region of losses, investors' valuations will be reduced and stock prices will fall. As prices fall, the house money effect will tend to further steepen the value curve, resulting in accelerating bear trends of the type observed in the current study.

Once a turning point is reached and the market begins to rise again, the initial steepness of the value curve means that prices will tend to rise quickly. The house money effect will result in a tendency for the value curve to begin to flatten, resulting in decelerating bull trends of the type observed in the current study.

Changes in the steepness of the value function may also help to explain patterns in the volatility of returns through the bull/bear stock market cycle.

During phases where the value function is steep, investors' valuations will react in an extreme manner to any new information entering the market. This implies a positive relationship between the steepness of the value curve, the steepness of trends, and the volatility of returns within trends.

The analysis in this section provides one possible explanation for the pattern. As discussed in previous sections, the analysis of patterns within stock market trends presented in the current study is, to the author's knowledge, new to the literature and as a result, no studies have explicitly addressed the possible contribution of the behavioural and alternative explanations of continuation and reversal effects in stock market returns proposed in the literature to the formation of these patterns.

The following section offers a number of suggestions for further research.

10.8 Suggestions for Further Research

The analysis presented in this chapter offers a number of avenues for further research. These are considered in turn in this section.

10.8.1 Trends within Trends

As discussed in Chapter 8, the medium-term stock market trends which are considered in the current study are themselves made up of shorter trends. The statistical properties of medium-term trends, identified in the current study, are not able to explain the empirical findings of the current study of positive cumulative returns to one-day momentum trading strategies but no significant returns to the equivalent 2 through 5 day strategies.

One plausible explanation for the short-term returns to momentum trading strategies identified in the current study is nonsynchronous trading. It is, however, possible that very short-term stock market trends may have different properties to those of medium-term trends and that an analysis of the properties of very short-term trends in the 14 data sets may shed further light on the sources of returns to the short-term momentum trading strategies considered.

The first suggestion for further research based on the findings of the current study is therefore to examine the properties of stock market trends of different magnitudes. This can be easily achieved by changing the parameter R used to identify trends and running the same analysis used in the current study[89]. An R of 1.00 will identify runs in stock market data[90]. As R is increased, the degree of allowable movement in the opposite direction to the trend is increased, and longer trends will therefore be identified[91].

An analysis of the properties of trends over a range of different levels of R would therefore address the question of whether very short-term trends in returns may be able to explain the findings of the current study of one-day continuation but no significant continuation or reversal effects over periods ranging from 2 through 5 trading days.

10.8.2 Cross-Sectional Dispersion in the Trend Behaviour of Stocks

One important avenue for further research is to consider whether the trend behaviour of individual stocks differs. The current study examines the properties of trends in stock market indices. Section 10.5.1 discusses mental accounting and hypothesises that if the features of stock market trends identified in the current study are caused by behavioural factors, then mental

[89] In the Fink and Pratt (2004) algorithm, R controls the minimum amplitude of the trends identified. With an R of 1.20, for example, the algorithm will identify bull/bear trends with a minimum amplitude of 20 percent from trough-to-peak / peak-to-trough respectively. In the current study, R is variable and is calculated as 2/3 of the standard deviation of price returns over the previous 252 trading days.

[90] A run is a series of exclusively positive or negative price returns in stock market data.

[91] Previous research has considered runs in stock market returns. Yao et al (2003), for example, use a proportional hazards model to examine duration dependence in runs in Australian stock market returns. One disadvantage of the use of runs is that they can be misleading in certain circumstances. A series of 10 days of positive returns followed by one very small negative return and then 10 further days of positive returns would be segmented into three individual runs. The use of the Fink and Pratt (2004) methodology with R slightly in excess of one enables such patterns to be treated for the purposes of analysis as a single upwards trend.

accounting should result in different trend behaviour for different types of stocks.

If patterns in the steepness and volatility of stock market trends are caused by loss aversion, for example, then stocks which are more actively traded might exhibit more extreme trend behaviour as a result of more frequent reviewing of outcomes[92] than stocks which are less actively traded (forming part of long-term investment portfolios).

The methodology employed in the current study can be easily applied to price data for individual stocks in order to measure cross-sectional dispersion in trend behaviour across stocks. This in turn may enable further conclusions to be drawn regarding the possible role of loss aversion in driving patterns in the steepness of trends in stock market prices and the volatility of returns within trends.

10.8.3 Returns to Momentum Trading Strategies across Markets

Section 10.6.4 notes that cross-sectional dispersion in risk and return across stocks cannot explain excess returns to momentum trading strategies applied to stock market indices which can be separately traded as an asset in their own right. An analysis of the returns to the momentum trading strategies developed in the current study and applied to the returns of traded indices such as the FTSE 100 index in the UK and the S&P 500 index in the USA is therefore of interest in assessing the role of cross-sectional differences in the risk and expected returns of individual stocks in driving the empirical results of studies using a cross-sectional research methodology.

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[92] Benartzi and Thaler (1985) note a negative relationship between loss aversion and the frequency of evaluating outcomes.

10.8.4 Cross-Sectional Momentum Returns and Stock Market Trends

Section 10.4 argues that the medium-term continuation effects identified in the current study are consistent with the observed properties of stock market trends. Winners are likely to be identified in the early stages of bull trends, resulting in findings of continuation, whilst losers are more likely to be identified in the final stages of bear trends, resulting in findings of reversal.

In order to assess the validity of this argument, one important avenue for further research would be to carry out a decomposition of the returns to the momentum trading strategies considered in, for example, Jegadeesh and Titman (1993). An analysis of trends in the winner and loser stocks identified by the strategy would enable the hypothesis to be tested that winner and loser portfolios are biased towards identifying stocks in the initial stages of bull trends and final stages of bear trends respectively.

10.8.5 Loss Aversion and Stock Market Trends

Section 10.7 describes one way in which loss aversion might be responsible for generating the particular features of stock market trends identified in the current study. Whilst outside the scope of the current study, one avenue for further research in this direction would be the construction of a model of loss aversion and the stock price formation process in order to verify whether such a model is capable of generating trends in simulated data sets which are consistent with those observed empirically in the current study.

The list of possible avenues for further research discussed in this section is brief and by no means exhaustive. The research documented in this thesis has identified a wide range of questions which might be addressed by further research. The aim of the suggestions provided in this section is merely to provide a starting point for further investigation into momentum and continuation effects in stock market returns and the properties of stock market trends.

10.9 Summary

The aim of this chapter is to summarise the main research results documented in Chapters 7 and 9 and to compare these results to those of the existing literature. A possible link is identified between the findings of the two parts of the empirical research documented in the current study. Momentum strategies buy following periods of high returns and sell following low returns. The patterns in the steepness of stock market trends in the current study suggests that high returns are likely to be identified near the beginning of bull trends, with low returns tending to occur towards the end of bear trends. Winners will therefore tend to exhibit continuation, whilst losers reverse.

The potential behavioural and alternative explanations proposed in the literature for continuation and reversal effects in stock market returns are then discussed in turn. Of these, nonsynchronous trading appears to be the most plausible explanation of short-term momentum strategy profitability although further research is recommended into the properties of short-term stock market trends in order to ascertain whether these provide a suitable alternative explanation. Similarly, loss aversion among investors is identified as the most likely cause of the observed patterns in the steepness and volatility of stock market trends.

This chapter then goes on to discuss in further depth one way in which loss aversion among investors might generate the features of stock market trends identified in the current study. Finally, a number of suggestions for further research are provided.

Chapter 11

Summary and Conclusions

11.1 Introduction

The research documented in this thesis examines the existence of, and possible causes of, continuation and reversal effects in the returns of 14 major world stock markets. The background to this research was discussed in Chapter 1.

Chapters 2 and 3 introduced the main behavioural and non-behavioural alternative explanations proposed in the literature as possible causes of continuation and reversal effects in returns, whilst Chapter 4 went on to consider the results of previous empirical studies which aim to identify such effects in stock market returns.

The first main part of the research aimed to identify continuation and reversal effects in the 14 data sets using a time-series approach which closely reflects the experiences of real-world investors[93]. The second part of the research then considered the implications of continuation and reversal for stock market trend behaviour before going on to consider the statistical properties of stock market trends using an algorithm from the information technology literature (Fink and Pratt, 2004) to identify the turning points of trends in the 14 data sets. This research is described in detail in Chapters 6 through 9. A summary and interpretation of the main findings of the research was provided in Chapter 10.

This Chapter discusses the motivations of the research and provides a brief summary of its main findings and conclusions. The limitations of the research are considered and a framework for further research is discussed.

[93] The measure of returns used in the current study is the return to investors (from capital gains and dividends) after taking into account the cost of funding at the short term interest rate (in the relevant currency for each stock market).

11.2 Motivation for the Current Study

The motivation for the current study was provided by two fundamental limitations of the existing literature on the existence of, and possible causes of, medium-term continuation and reversal effects in financial market returns.

Firstly, the results of previous empirical work which aims to identify such effects have been inconsistent[94]. A number of widely-quoted studies, such as those of Jegadeesh and Titman (1993 and 2001) and Rouwenhorst (1998) find evidence of significant continuation and reversal effects for both winners and losers using a cross-sectional methodology with formation and test periods ranging from 3 to 12 months in length. Other studies, such as that of Hameed and Kusnadi (2002), find no such evidence of continuation or reversal effects within their data samples. In addition, there is some evidence to suggest that methodological issues may be responsible for some of the results of previous studies. Pan and Hsueh (2001), for example, find that momentum profits within their data sample disappear when non-overlapping time periods are used.

The fist aim of the current study is therefore to consider the issue of the existence of continuation and reversal effects using a different methodology to the cross-sectional approach employed by the majority of previous studies. A time-series approach is used to examine the profitability of momentum and contrarian trading strategies based on fourteen major world stock market indices. This approach aims to match as closely as possible the returns available to real-world investors in order to consider whether significant continuation and/or reversal effects are present within the data samples over the short-term and medium-term[95]. In addition, the extent to which any such effects are consistent across markets and/or across time is considered. Many of the possible explanations proposed in the literature[96] for the existence of continuation and reversal effects in financial market returns would be expected to operate consistently across time and across a range of markets. The extent

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[94] This body of research is reviewed in Chapter 4.

[95] The profitability of short-term strategies is also considered in this part of the research since medium-term effects are likely to represent an amalgamation of shorter-term effects.

[96] These are reviewed in Chapters 2 and 3.

to which continuation and reversal effects are consistent within and across the data samples is therefore an important factor in interpreting which, if any, of the proposed explanations fits the empirical evidence. Finally, the use of a methodology which closely reflects the experiences of real-world investors enables the risk and return inherent to momentum and contrarian trading strategies to be explicitly considered and conclusions drawn as to whether the market acts irrationally in failing to exploit significant profit opportunities.

The second main aim of the current study is to address the question of which, if any, of the possible explanations proposed in the literature might cause continuation and reversal effects in stock market returns. Whilst the existing literature has identified anomalies of continuation and reversal in stock market returns and a range of behavioural and non-behavioural proposed explanations, research has not generally been able to identify a direct link between individual causes and their effects. As Chapter 2 demonstrates, for example, a number of different behavioural biases would all be expected to have the same impact on financial market returns.

The second part of the research documented in this thesis therefore takes a different approach to the issue of continuation and reversal effects in returns in an attempt to differentiate between some of the potential causes identified in the wider literature. More specifically, Chapter 8 discusses how the presence of continuation and reversal effects in stock market returns would imply systematic features of trends in stock market trends which differentiate them from trends found in random data. The manner in which stock market trends differ from random trends may therefore enable some insight to be drawn into the potential causes of such effects.

11.3 Main Results and Conclusions

The first part of the research examines whether continuation and reversal effects are present in the 14 data sets by considering the profitability of momentum trading strategies which buy the stock market index following a market rise and sell following a market fall. Significant profits to momentum strategies are indicative of continuation effects in returns, whilst significant losses to momentum strategies imply profits to the equivalent contrarian strategy and hence reversal effects in returns.

Positive returns to momentum strategies are found for 1 trading day strategies and for longer-term strategies with holding periods from 10 to 252 trading days. Mixed results are obtained for strategies based on 2 through 5 day returns. Overall, however, few results are statistically significant. As discussed in Chapter 7, the positive returns to the longer-term strategies in particular are driven by the returns to long positions, with short positions typically generating negative returns. Chapter 8 argues that evidence of continuation will be found where data sets are significantly skewed, either overall or in subsections of the data, and it may be the case that the momentum profits found in this part of the research are simply a result of generally rising market prices during the period of the data considered.

Certainly, an analysis of the profitability of each strategy by calendar year suggests that returns are highly inconsistent over time. The standard deviation of daily returns is significantly high for almost all of the strategies considered, and the Sharpe ratios are not significantly different from zero. Although a simplistic approach may draw the conclusion that momentum effects are present in the data samples, there is no evidence to suggest that the returns to momentum strategies offer significant risk-adjusted returns.

The second part of the research documented in this thesis uses an algorithm from the information technology literature to date price trends in the 14 stock market index data sets which form the basis of this study. The statistical properties of returns within bull and bear trends and four phases of each are then considered.

A number of features are identified in the research which clearly differentiate trends in stock market data from trends in random data with the same distribution of daily returns. Whilst stock market trends are not significantly different from random trends in terms of their duration or total amplitude, clear patterns are observed in the steepness of different phases of bull and bear trends. The fourth quarter of bull trends is somewhat shallow, whilst the fourth quarter of bear trends is particularly steep. Patterns are also observed in the volatility of daily price changes within stock market trends, with returns particularly volatile in the final stages of bear trends.

An analysis of the relative frequency and size of positive and negative daily returns within price trends reveals the source of these patterns in the steepness of trends. Patterns in the absolute size of positive and negative daily returns through the bull-bear stock market cycle rather than patterns in the proportion of positive and negative daily price returns within trends appear to be the driving force behind systematic patterns in the steepness of trends and the volatility of returns within trends. These patterns, which have not been analysed in depth by the existing literature[97], may have an important role to play in driving previous empirical findings of momentum and reversal effects in stock market returns.

Chapter 10 analyses the results of the two parts of the current study with reference to the potential causes of continuation and reversal effects proposed in the literature and discussed in Chapters 2 and 3. The consistency of the results of each part of the research with those of the existing literature is also considered. Nonsynchronous trading appears to provide the best explanation of the returns to the short-term momentum trading strategies considered in the first part of the research, whilst the properties of stock market trends are consistent with explanations of continuation and reversal effects based on loss aversion among investors. The proposals for further research presented in Section 10.8 focus on exploring further the properties of stock market trends and the possible relationship between investor loss aversion and continuation and reversal effects in returns. Section 11.4 provides a summary of the limitations of the current study and the suggested framework for further research.

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[97] Partly as a result of the use of monthly rather than daily returns in most studies.

11.4 Limitations and Framework for Further Research

The main limitation of the current study is its exclusive use of index-level data. Whilst this was necessary as a result of the broad scope of the research documented in this thesis, the use of individual stock data in addition to index-level data may enable further insight to be drawn into the relationship between the behavioural and non-behavioural factors discussed in Chapters 2 and 3 and the existence of continuation and reversal effects in returns.

The proposals for further research contained in Section 10.8 therefore aim to address this limitation by proposing firstly that the current study be extended to consider the statistical properties of trends in the prices of individual stocks. A decomposition of the results of one of the most commonly quoted studies of medium-term continuation and reversal effects (Jegadeesh and Titman, 1993, for example) is then proposed to address the hypothesis raised in Chapter 10 that systematic trend behaviour in stock prices may be an important driving factor behind the results of previous empirical studies based on a cross-sectional methodology.

A further limitation of the current study is that, whilst the properties of medium-term trends are considered, no analysis is presented of the way in which short-term trends in stock market prices (positive and negative runs in prices being the extreme example) combine to form the medium-term trends which are the focus of the current study. Again, Section 10.8 proposes to address this deficiency by considering initially the way in which short-term trends combine to form longer-term trends in the 14 data sets which are the focus of the current study.

The final major limitation of the current study is that, whilst it raises important questions regarding the role of loss aversion in driving the observed patterns in stock market trend behaviour, a further analysis of this mechanism falls outside the scope of the current work. Modelling the price formation process in a market characterised by loss-averse investors is the next logical step in answering some of the questions raised by the study. In particular, do trends in the simulated price series generated by such a model share the empirical characteristics of trends in the real-world data which is the focus of this study?

Similarly, are simulated time series characterised by significant momentum or contrarian profits similar to those identified in the current study?

11.5 Summary

The current study aims to make a significant contribution to knowledge by examining from a new angle the issue of continuation and reversal effects in stock market returns.

The existence of such effects in the fourteen stock market indices which are the focus of the study is first analysed using a time series approach which closely reflects the returns available to real-life investors. Continuation effects are observed over periods of 1 trading day and 10 through 252 trading days, with no significant continuation or reversal effects identified over periods of 2 through 5 trading days.

Continuation and reversal effects in returns imply that stock market trends are systematically different to trends in random data. The second part of the current study therefore adapts an algorithm from the information technology literature to examine in detail the statistical properties of trends in each of the fourteen data sets. Important patterns are identified in the steepness of trends as they develop as well as in the volatility of returns within trends.

The possible causes of continuation and reversal effects proposed in the literature are considered in the light of the continuation effects identified in the first part of the research and the patterns in stock market trends identified in the second part. Whilst nonsynchronous trading stands out as the most probable cause of short-term effects in the data samples, loss aversion among investors most closely fits the empirical features of stock market trends.

As in any study of this nature, the research documented in this thesis raises as many questions as it answers. The scope of the current study does not permit each of these questions to be addressed in full; instead, the most important outstanding issues are highlighted in the suggestions for further research.

Appendix A: Datastream Codes

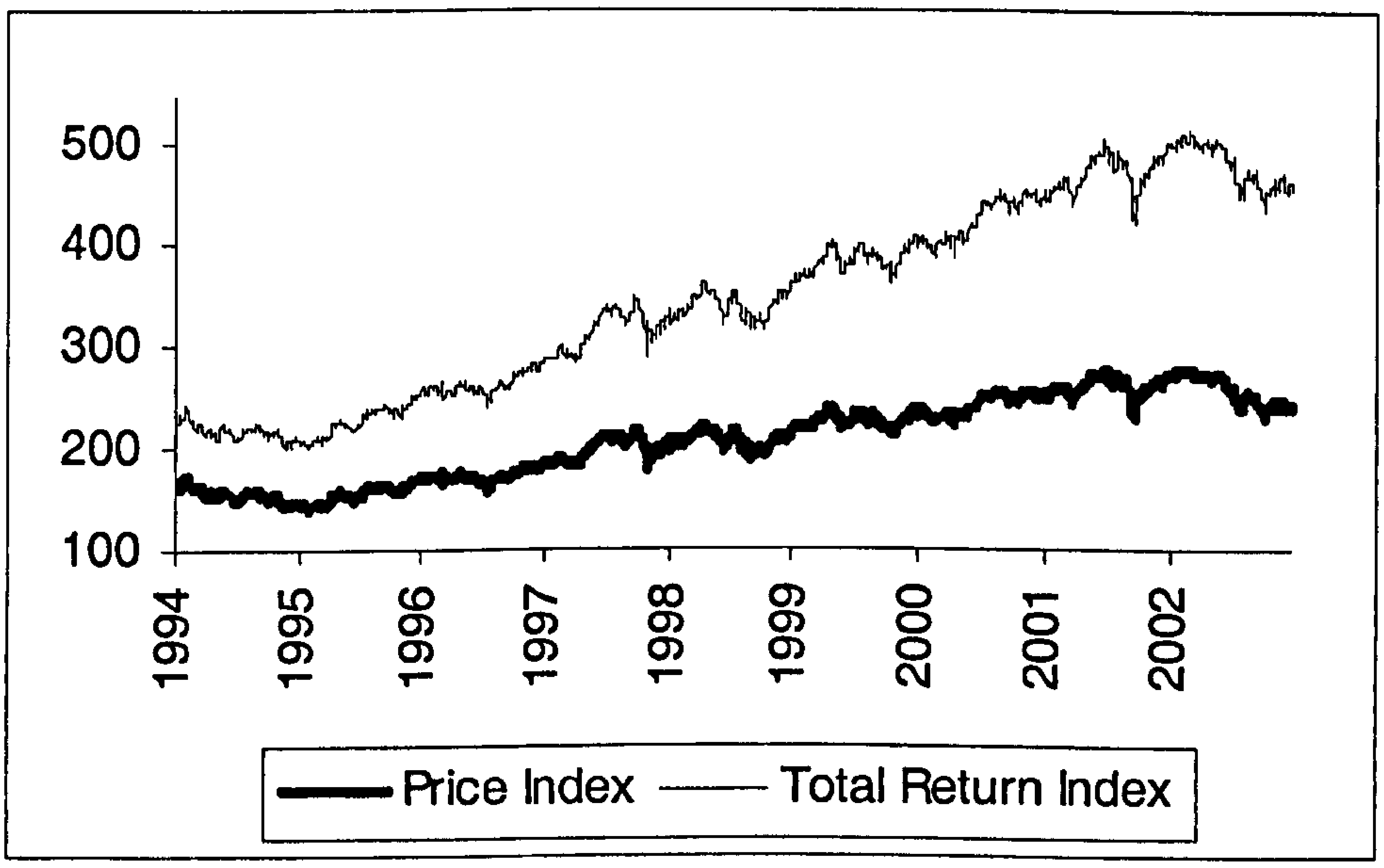
The table shows, for each country, the Datastream codes for each data item used. For the FTSE all-world index series, the data type (PI or TR) determines the price index / total return index for stock market data.

	Stock Market	Currency	Interest Rate
Australia	WIAUSTL	A$	AUSIBCL
Belgium	WIBELGL	E	ECBFRST
Canada	WICNDAL	C$	ECCD$ST
Denmark	WIDNMKL	DK	ECDKNST
France	WIFRNCL	E	ECFFRST
Germany	WIWGRML	E	ECWGMST
Hong Kong	WIHGKGL	K$	HKDEPCL
Italy	WIITALL	E	ECITLST
Japan	WIJPANL	Y	ECJAPST
Netherlands	WINETHL	E	ECNLGST
Spain	WISPANL	E	ESMIBON
Switzerland	WISWITL	SF	ECSWFST
UK	WIUTDKL	£	ECUK£ST
USA	WIUSAML	U$	ECUS$ST

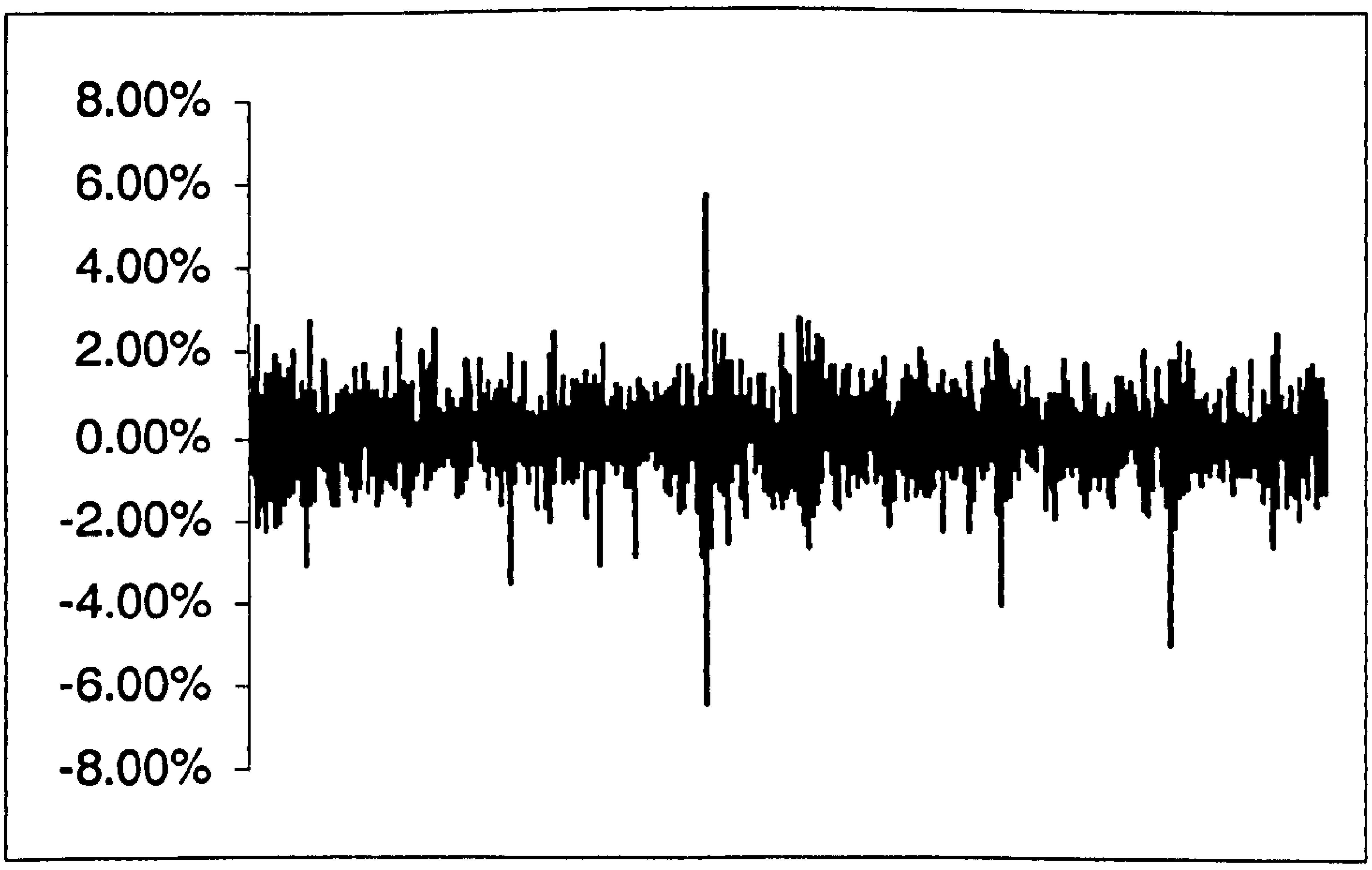
Appendix B: Data Samples

Australia

Price Index and Total Return Index Data

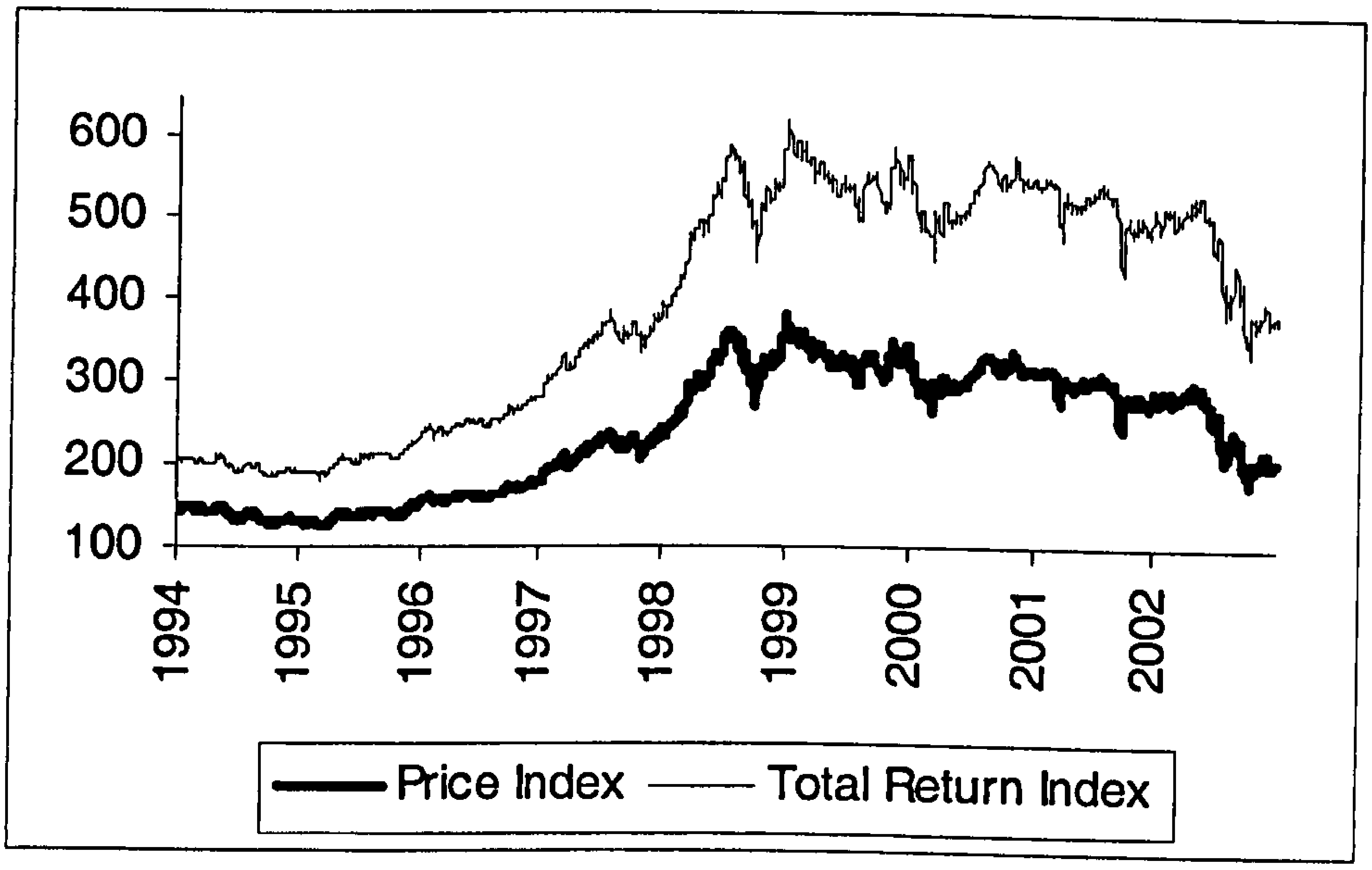


Funded Returns



Belgium

Price Index and Total Return Index Data



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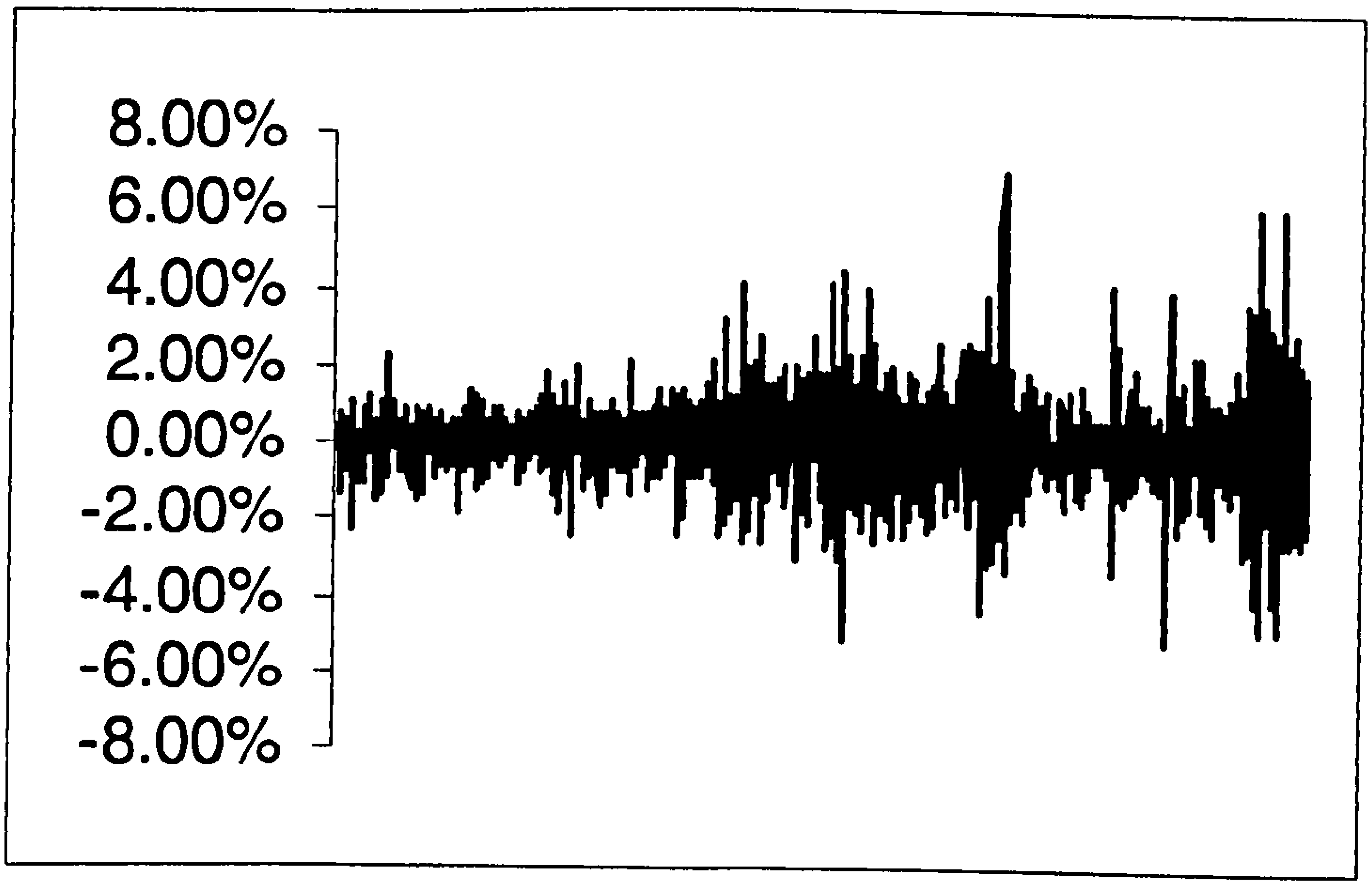
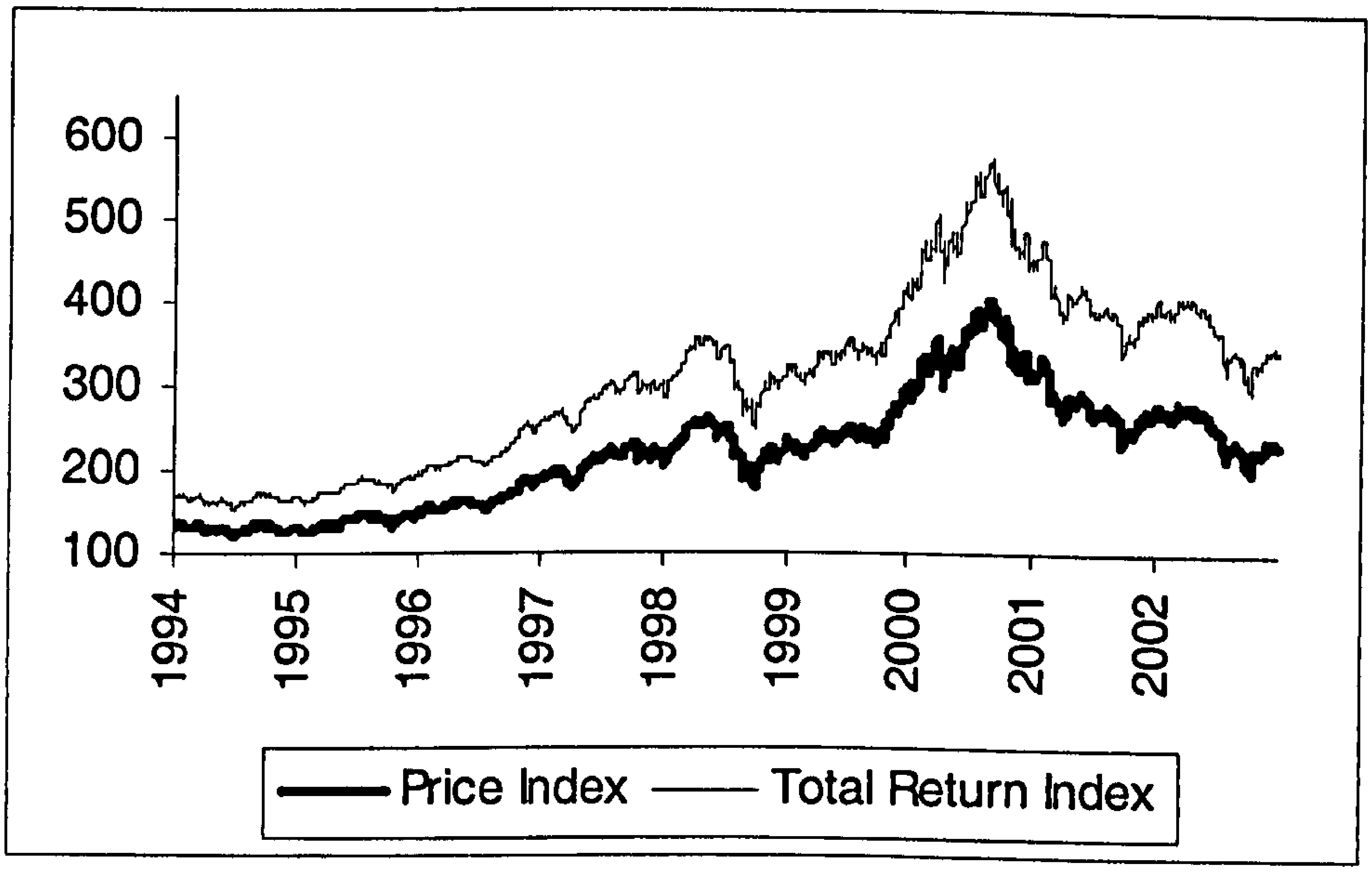


Canada

Price Index and Total Return Index Data



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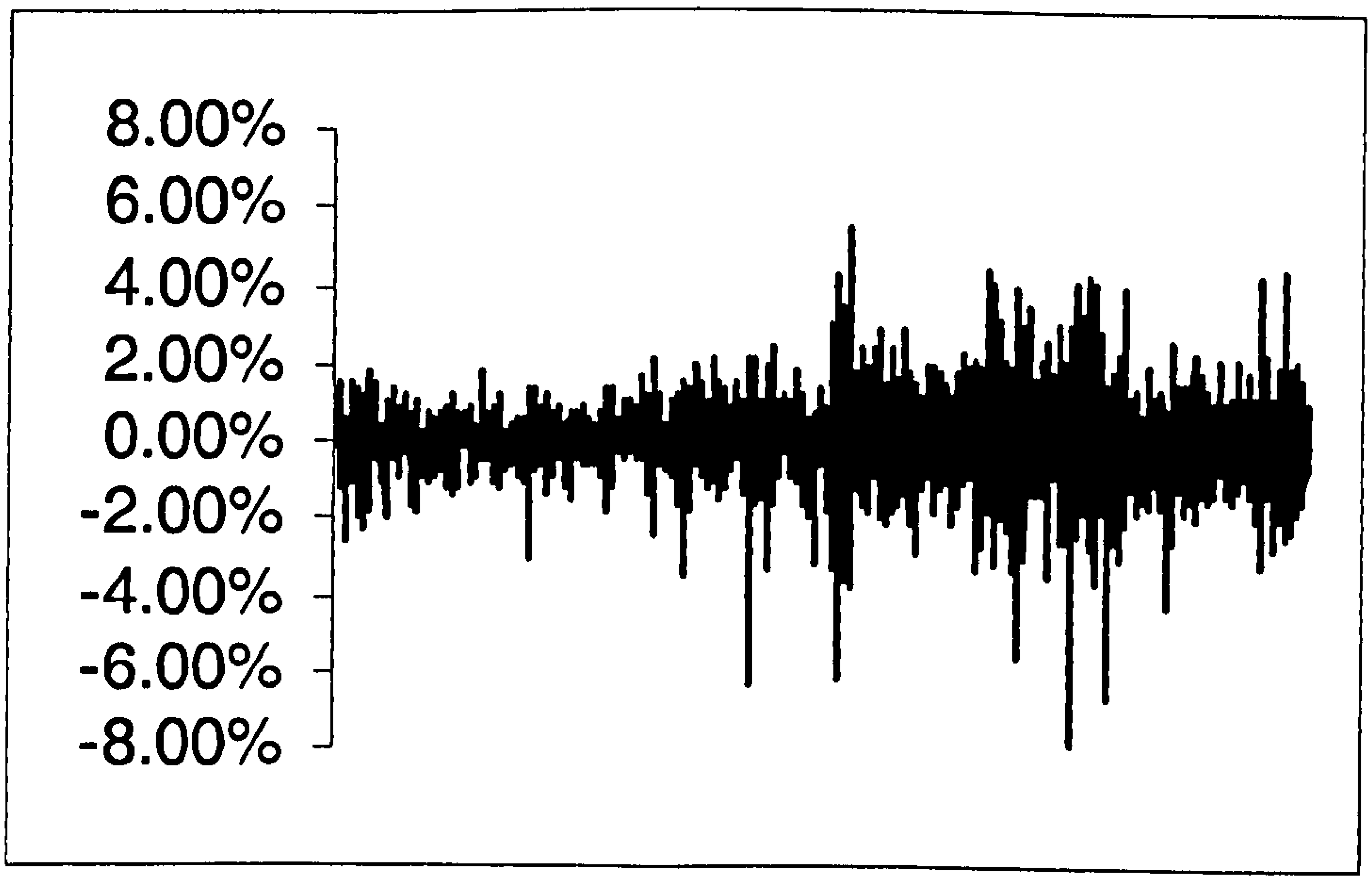
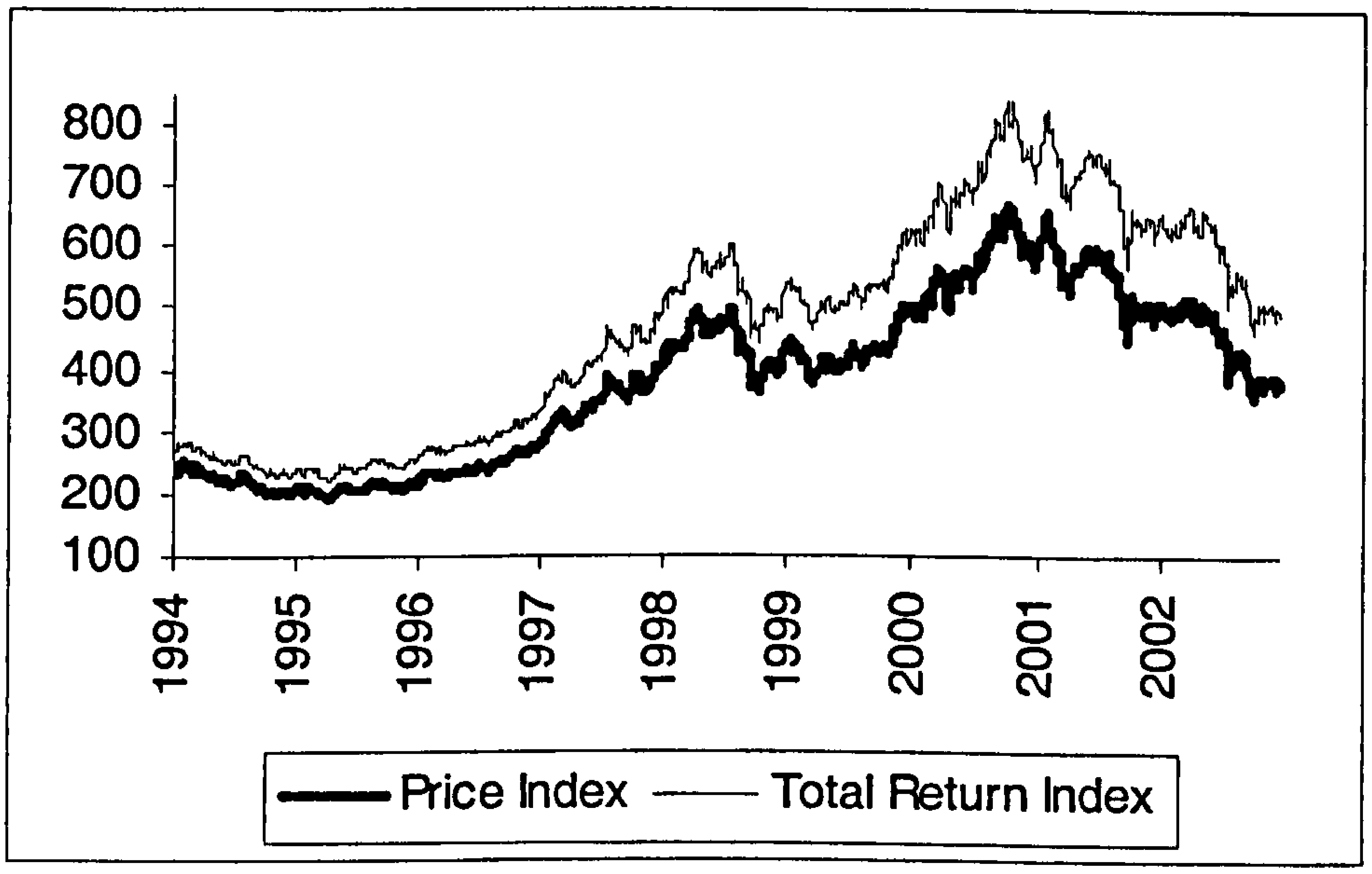


Denmark

Price Index and Total Return Index Data



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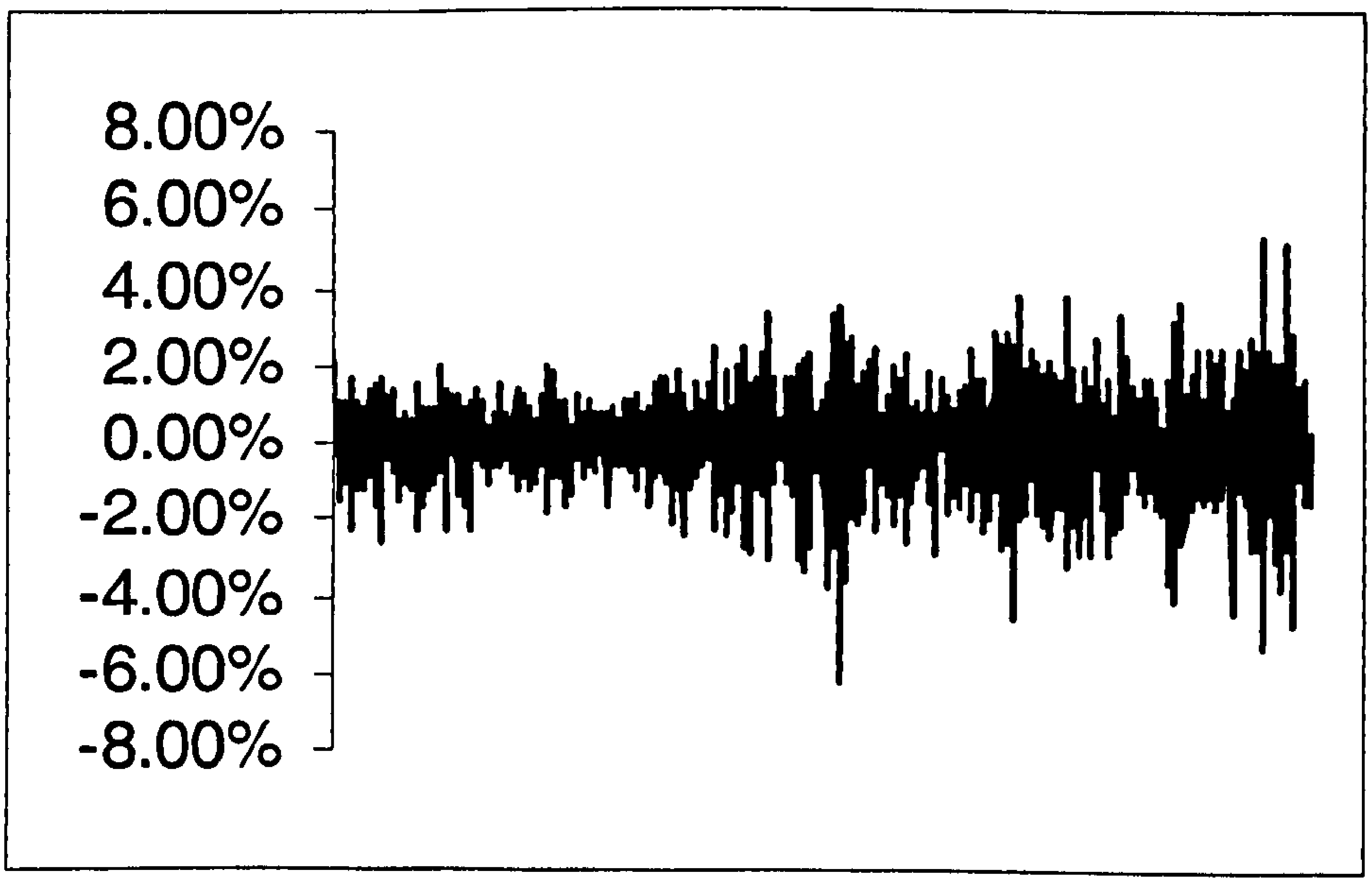
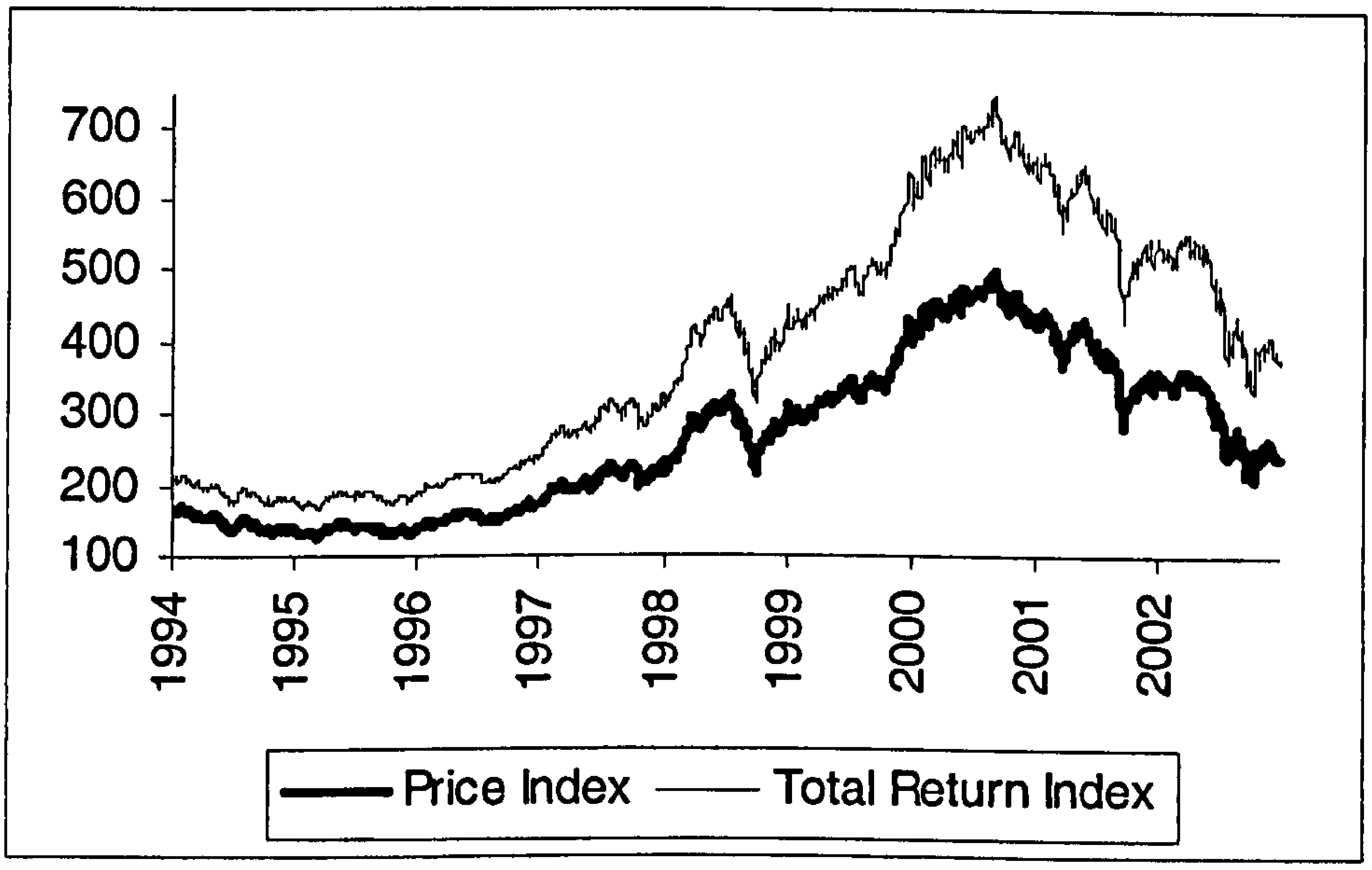
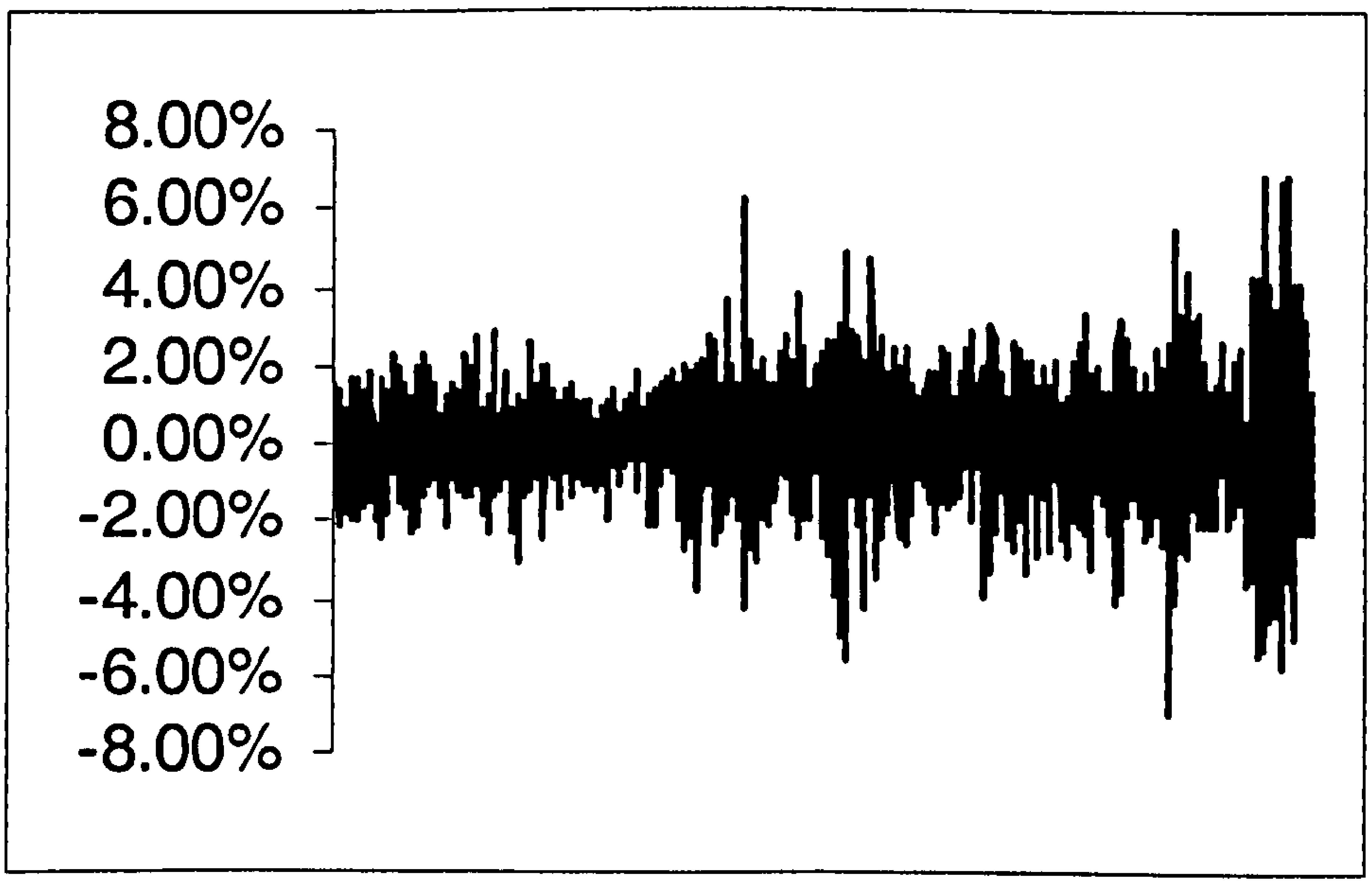


France

Price Index and Total Return Index Data

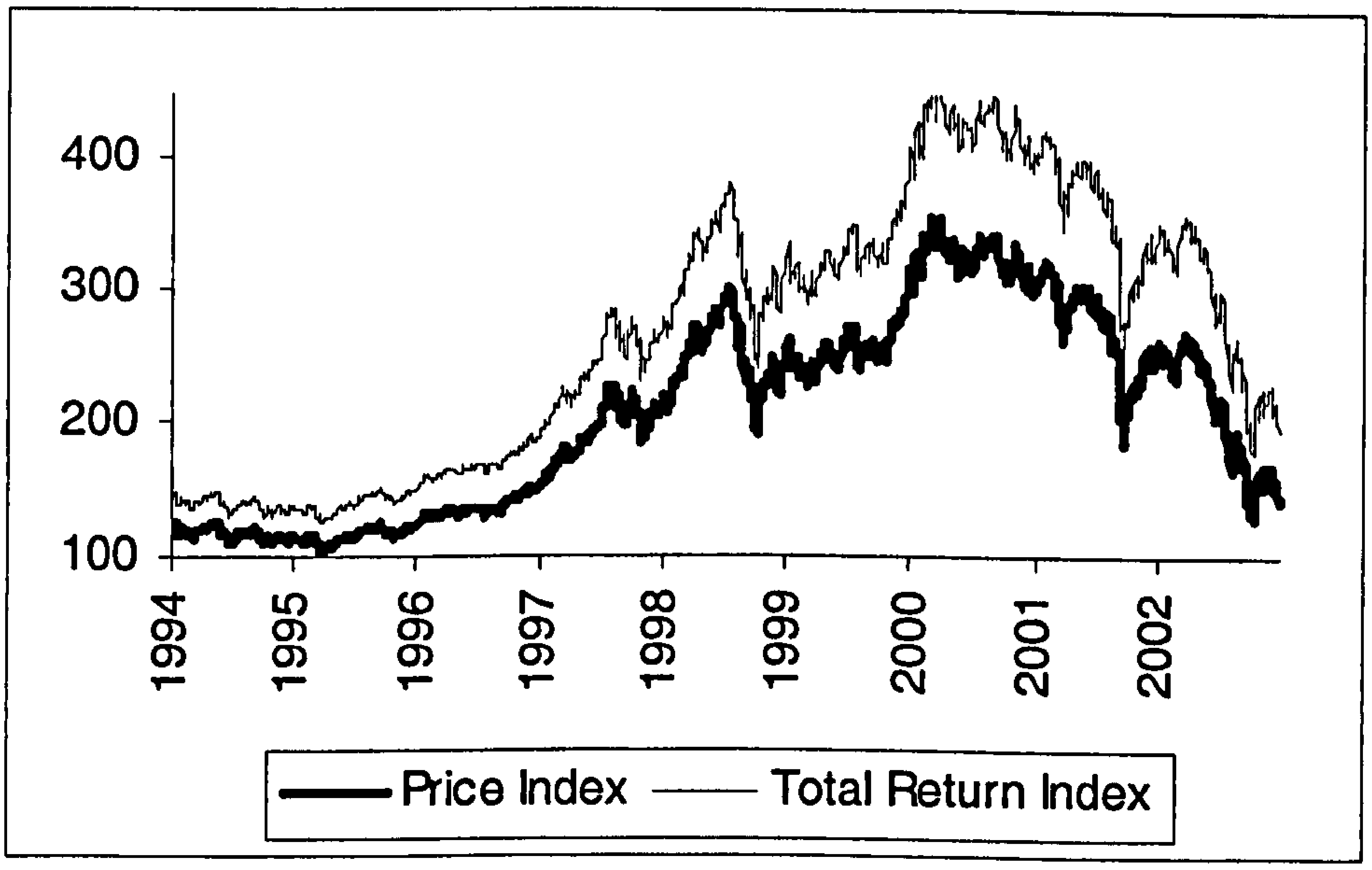


Funded Returns

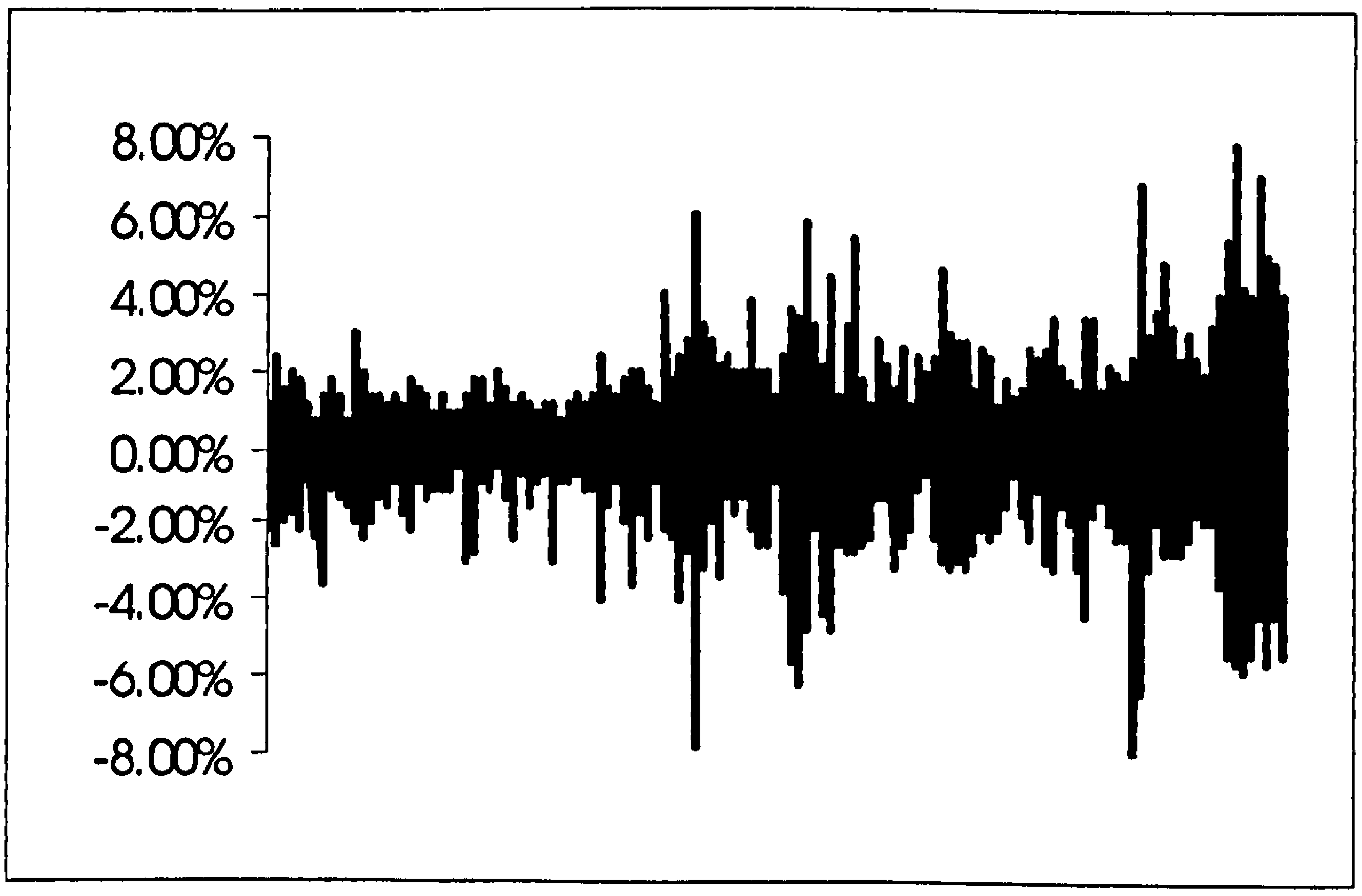


Germany

Price Index and Total Return Index Data

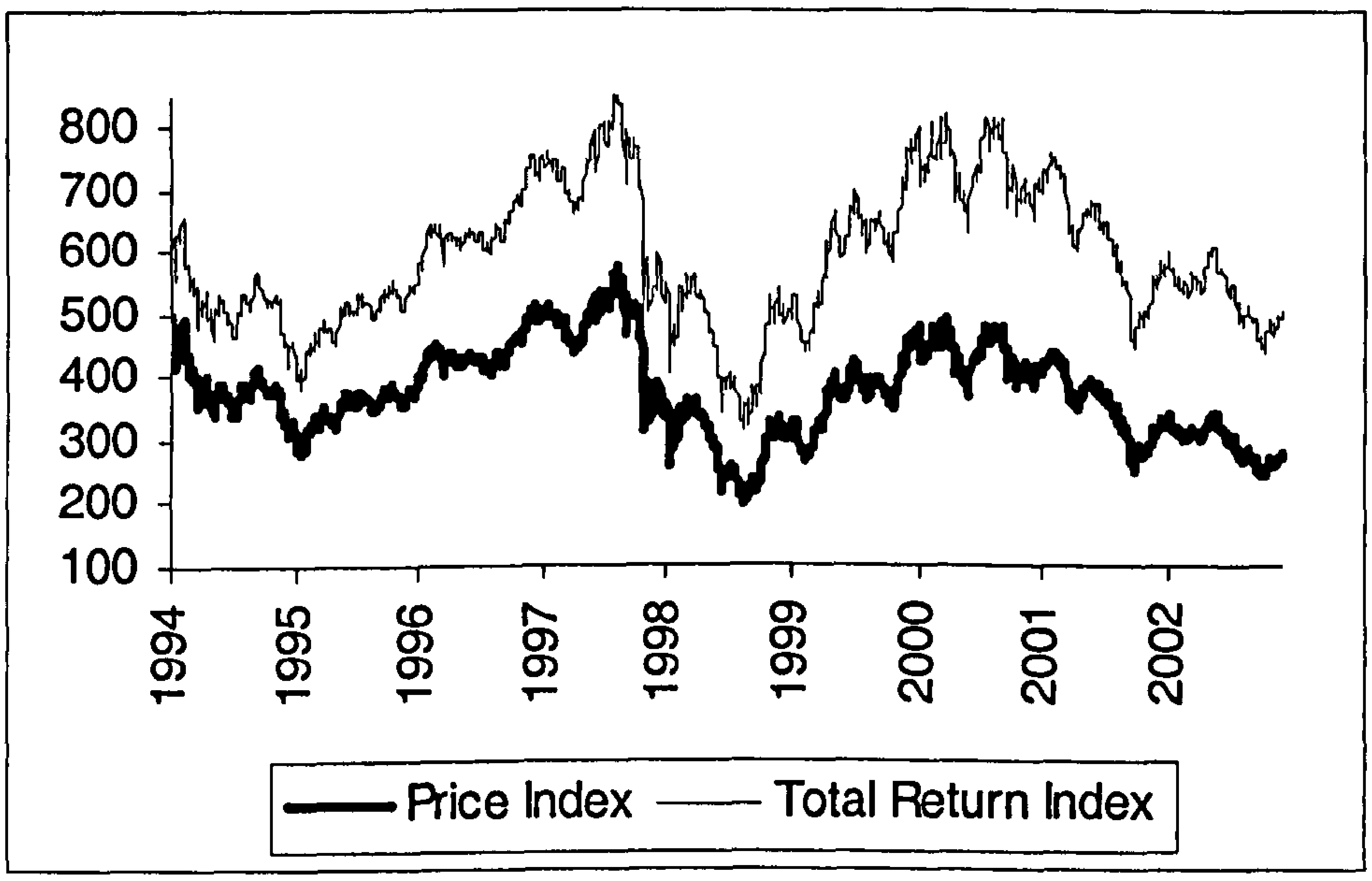


Funded Returns

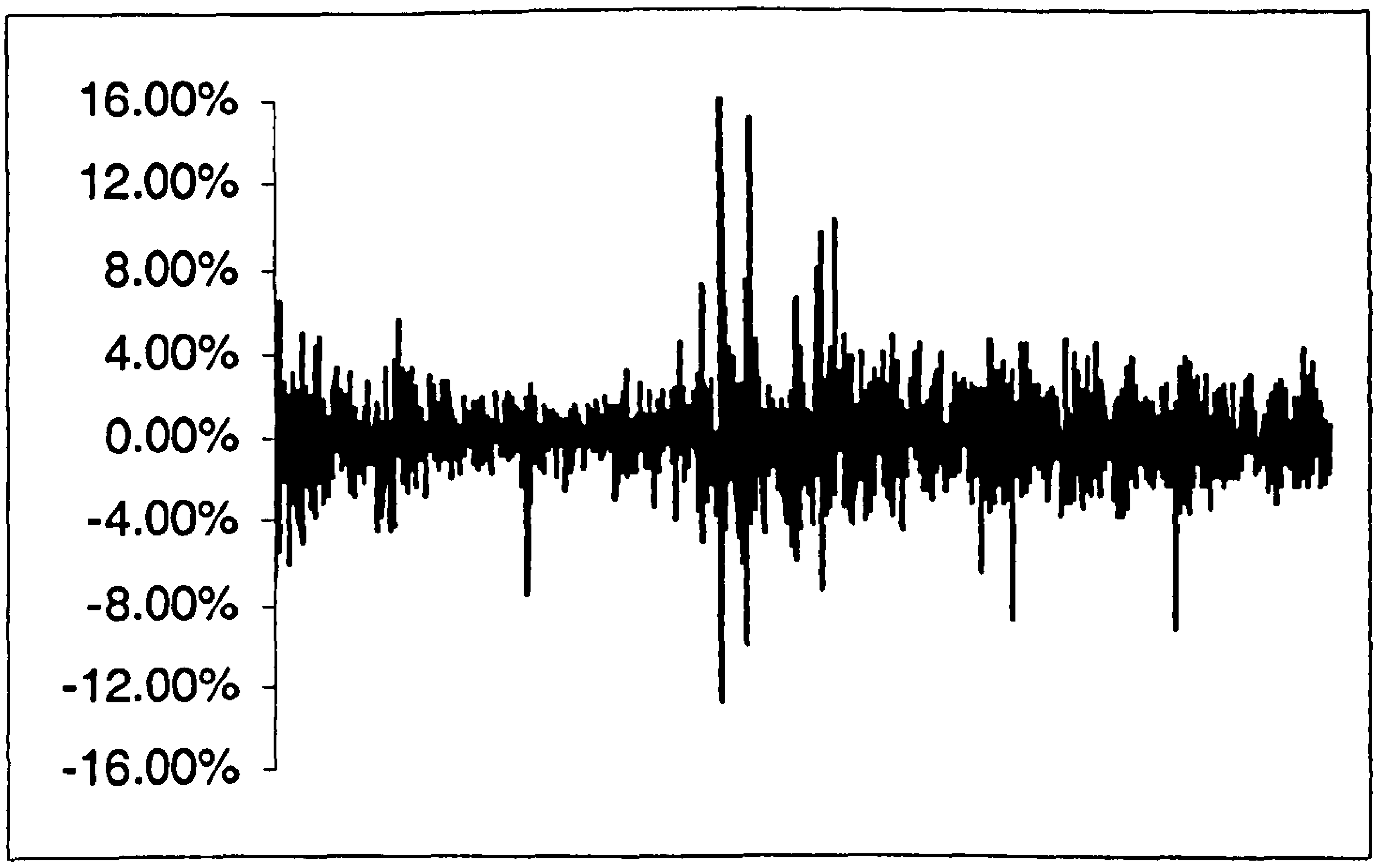


Hong Kong

Price Index and Total Return Index Data

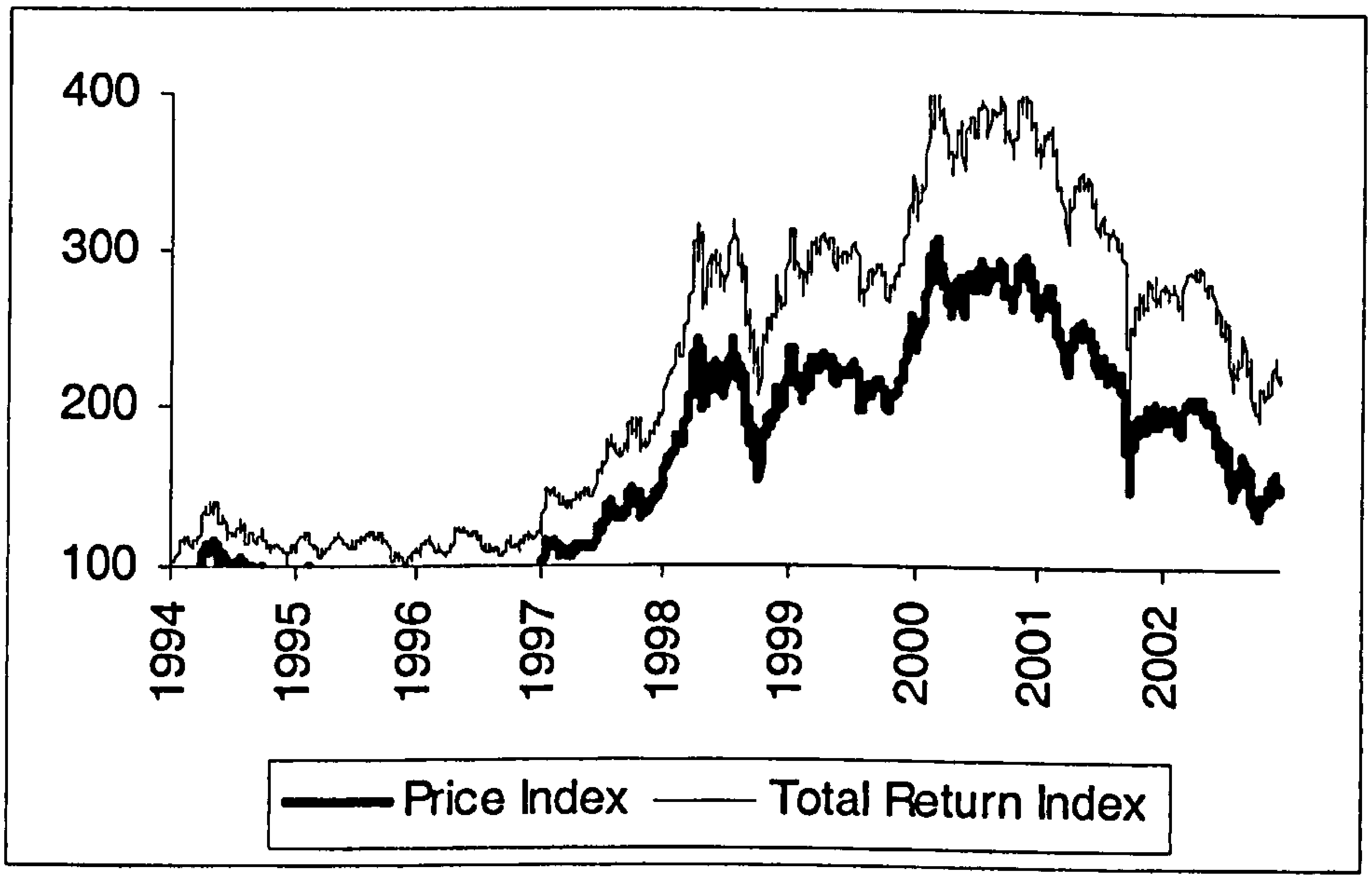


Funded Returns

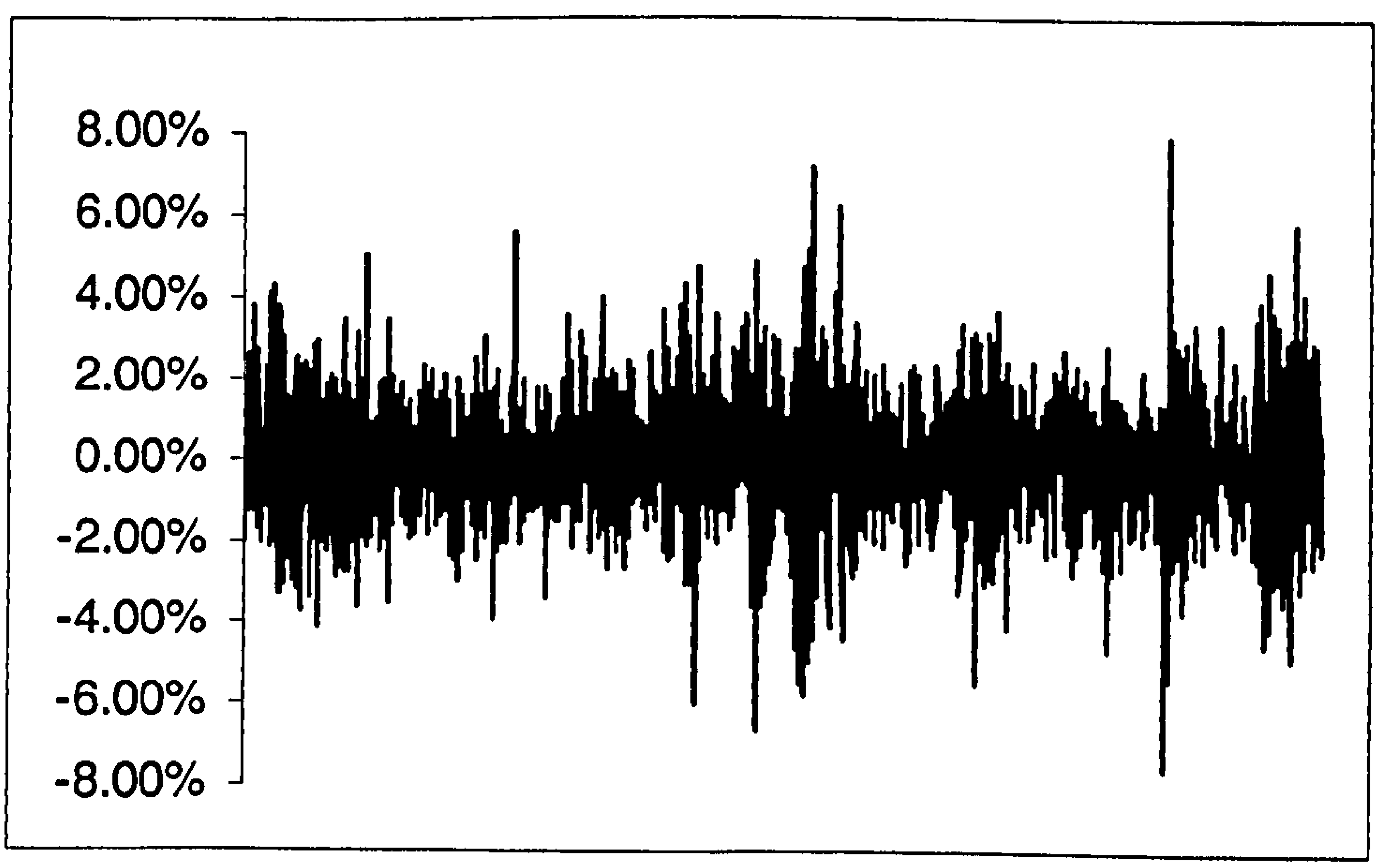


Italy

Price Index and Total Return Index Data

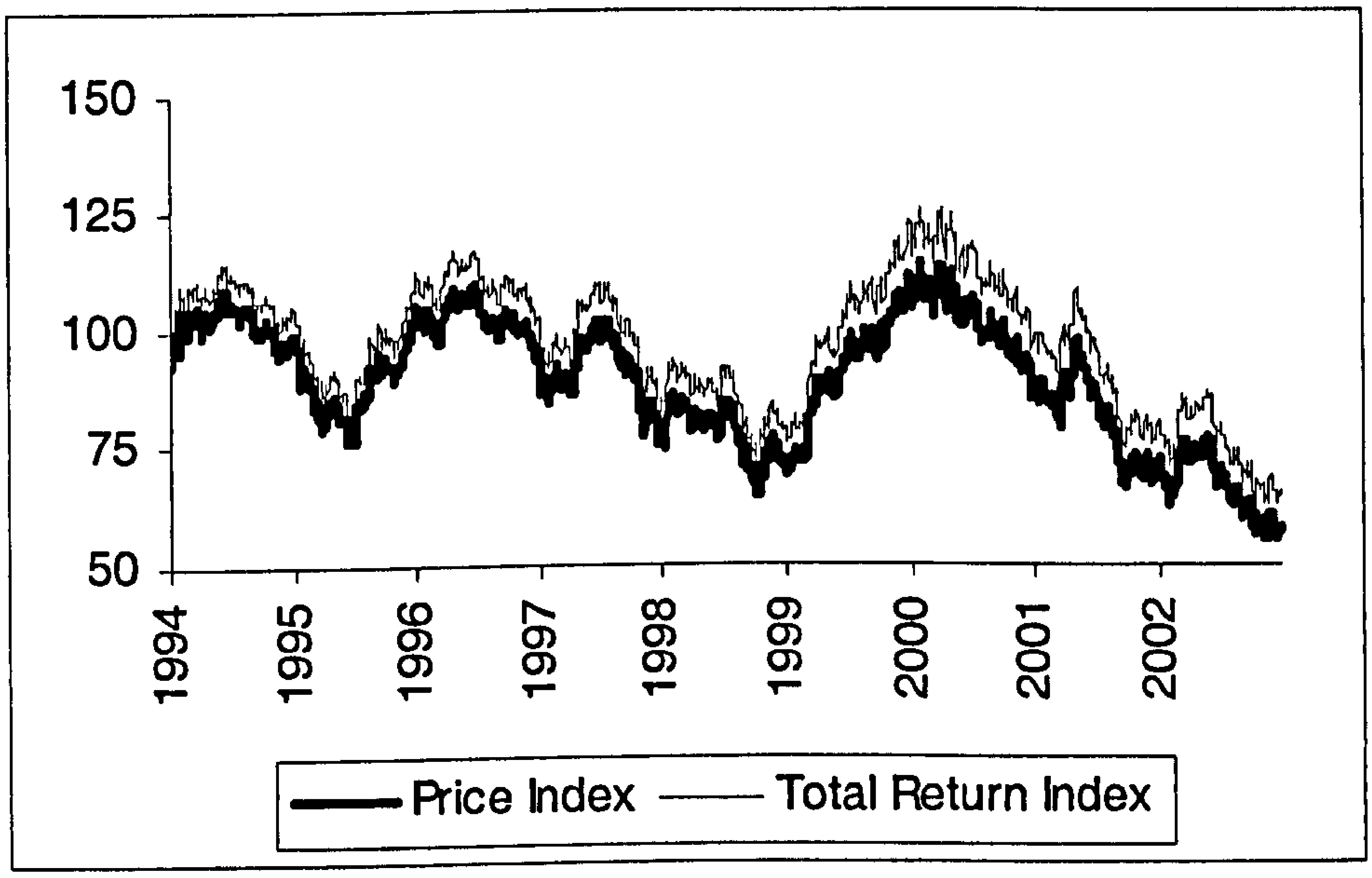


Funded Returns

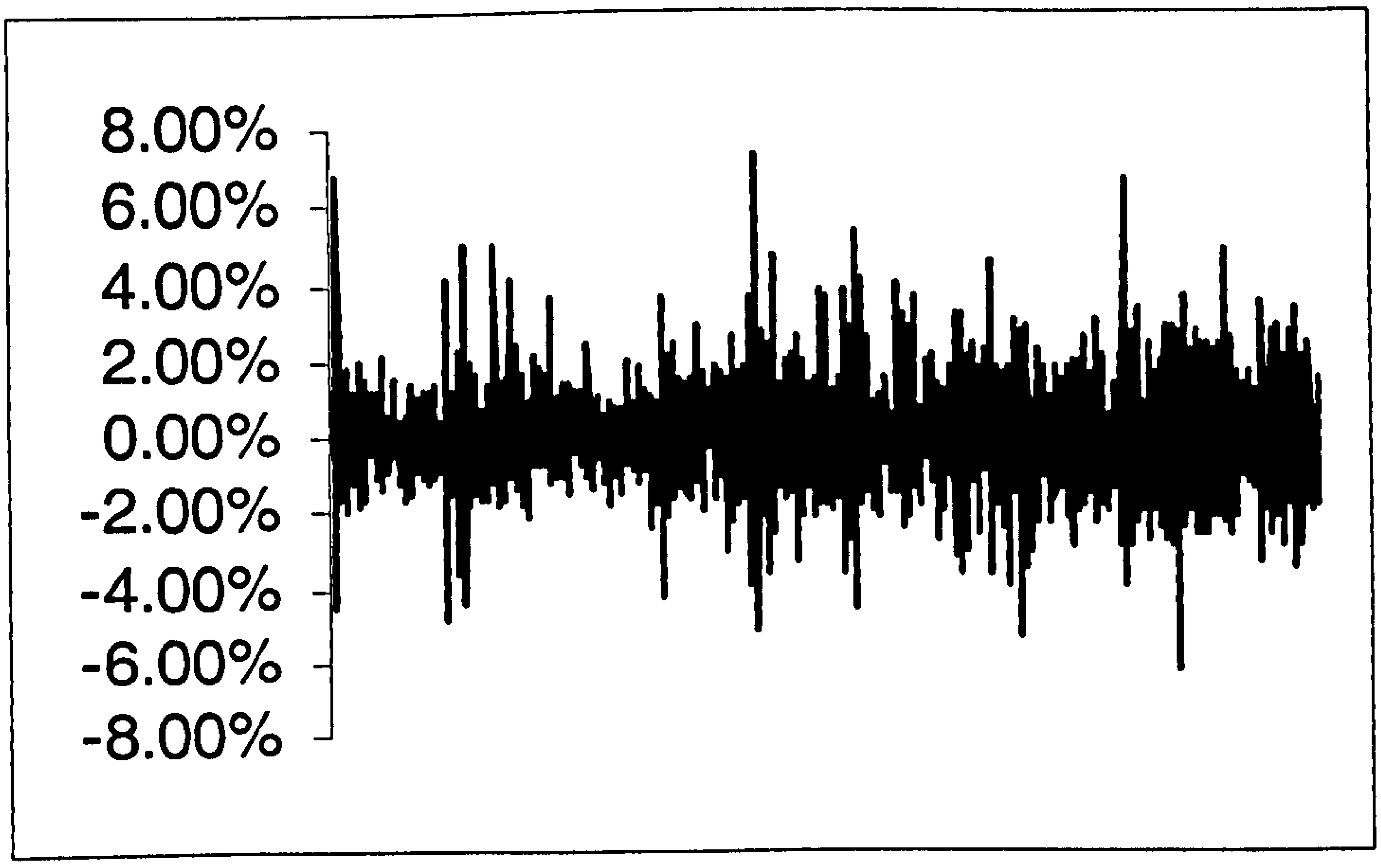


Japan

Price Index and Total Return Index Data

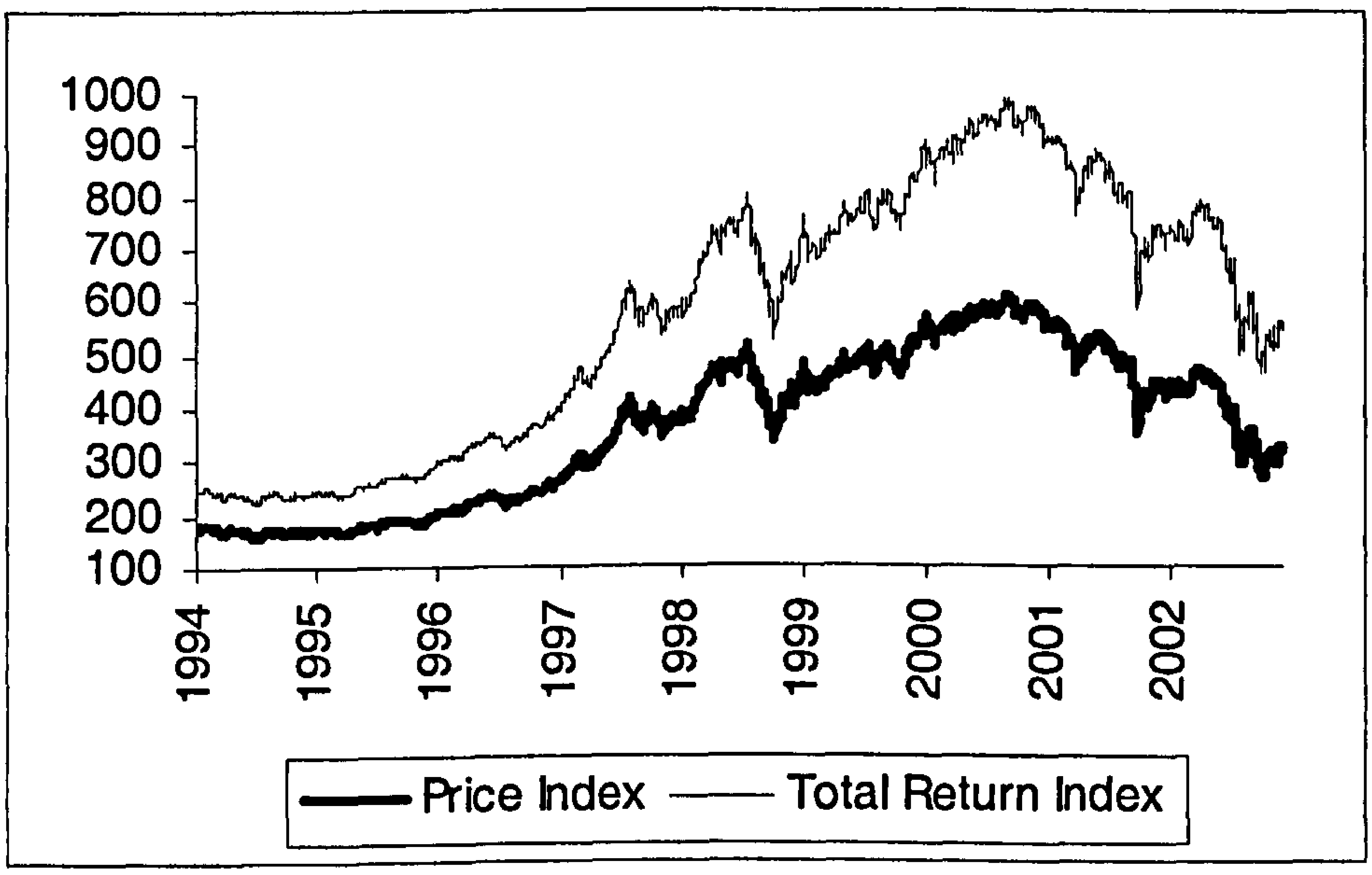


Funded Returns

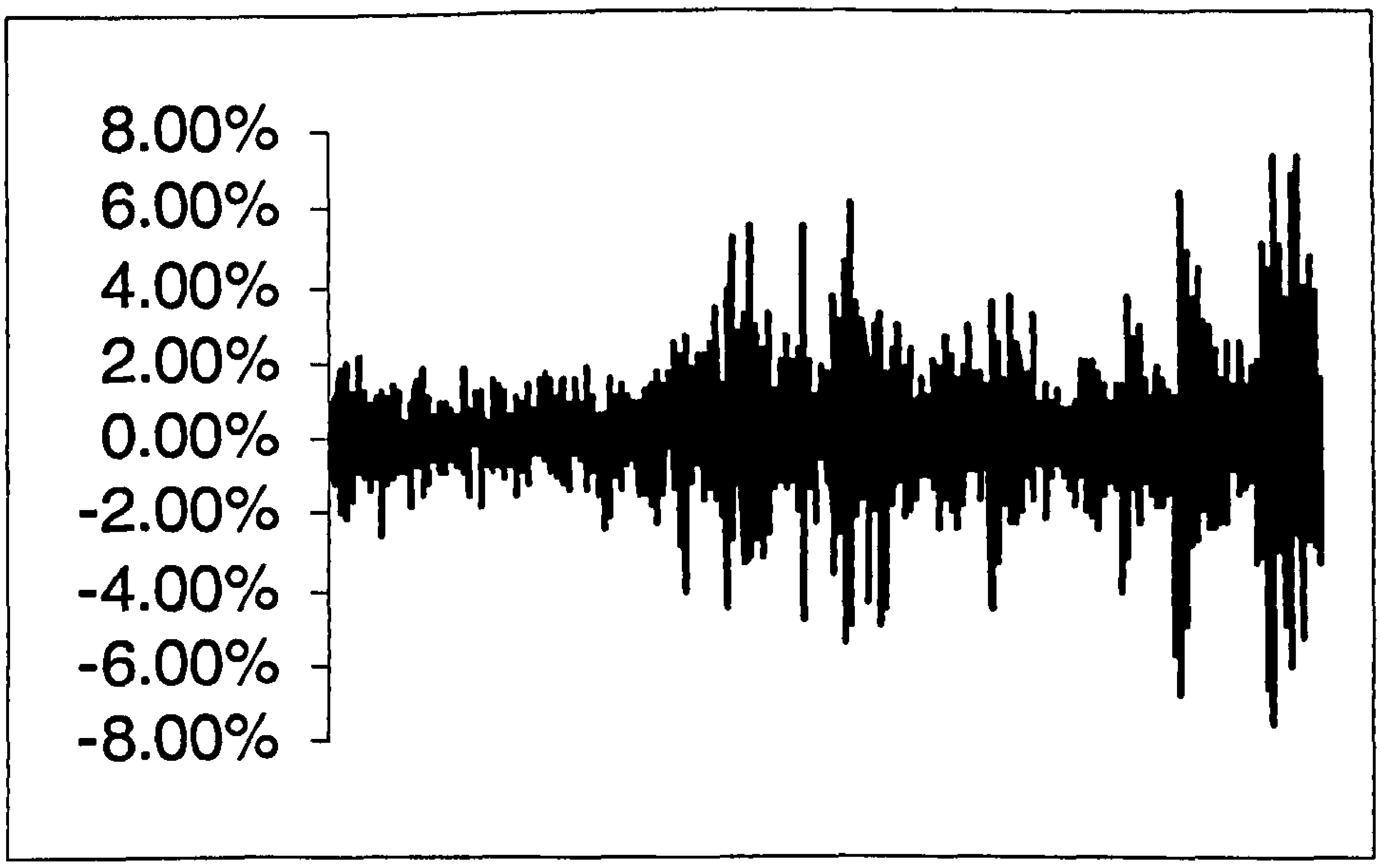


Netherlands

Price Index and Total Return Index Data

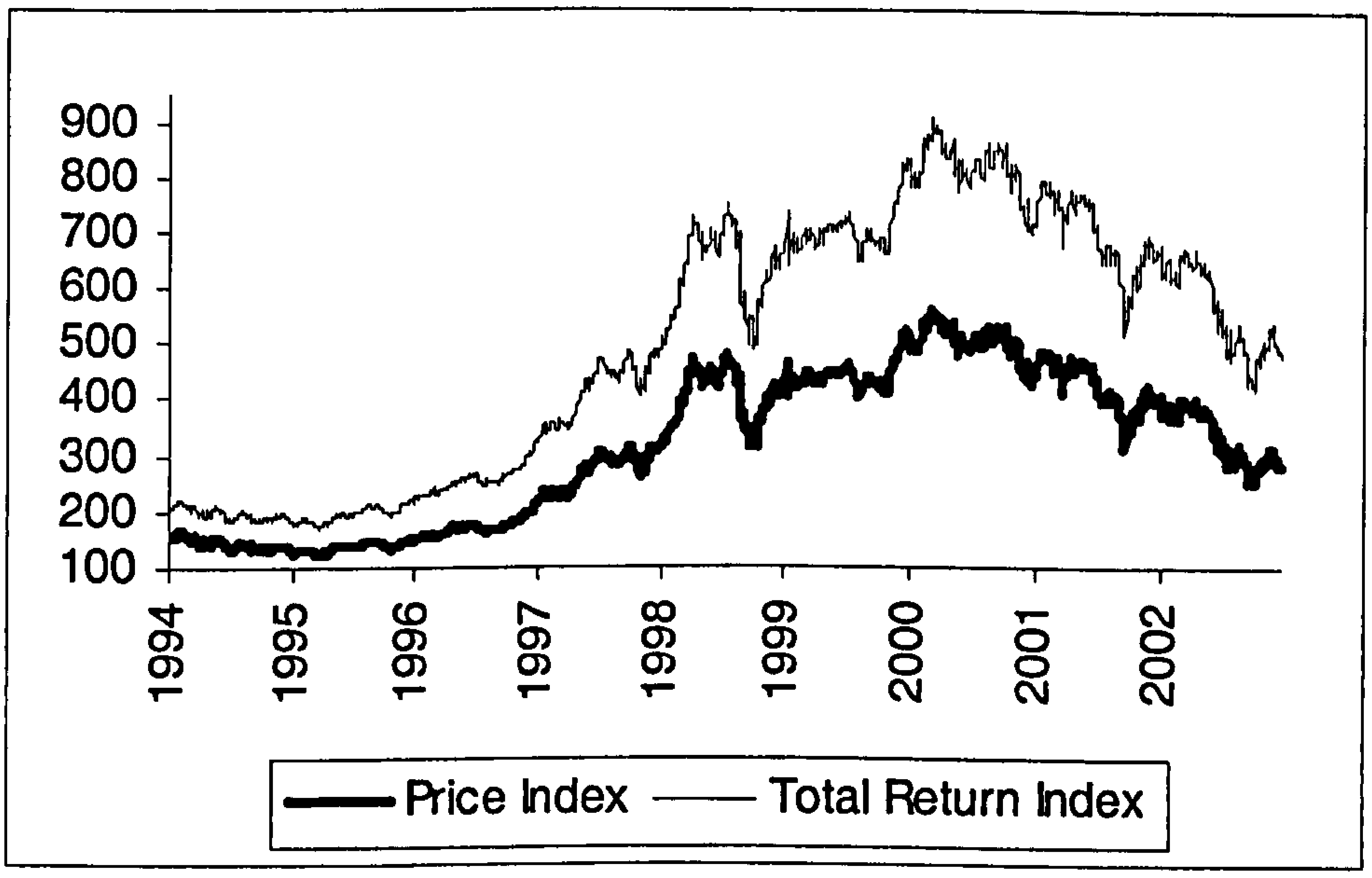


Funded Returns

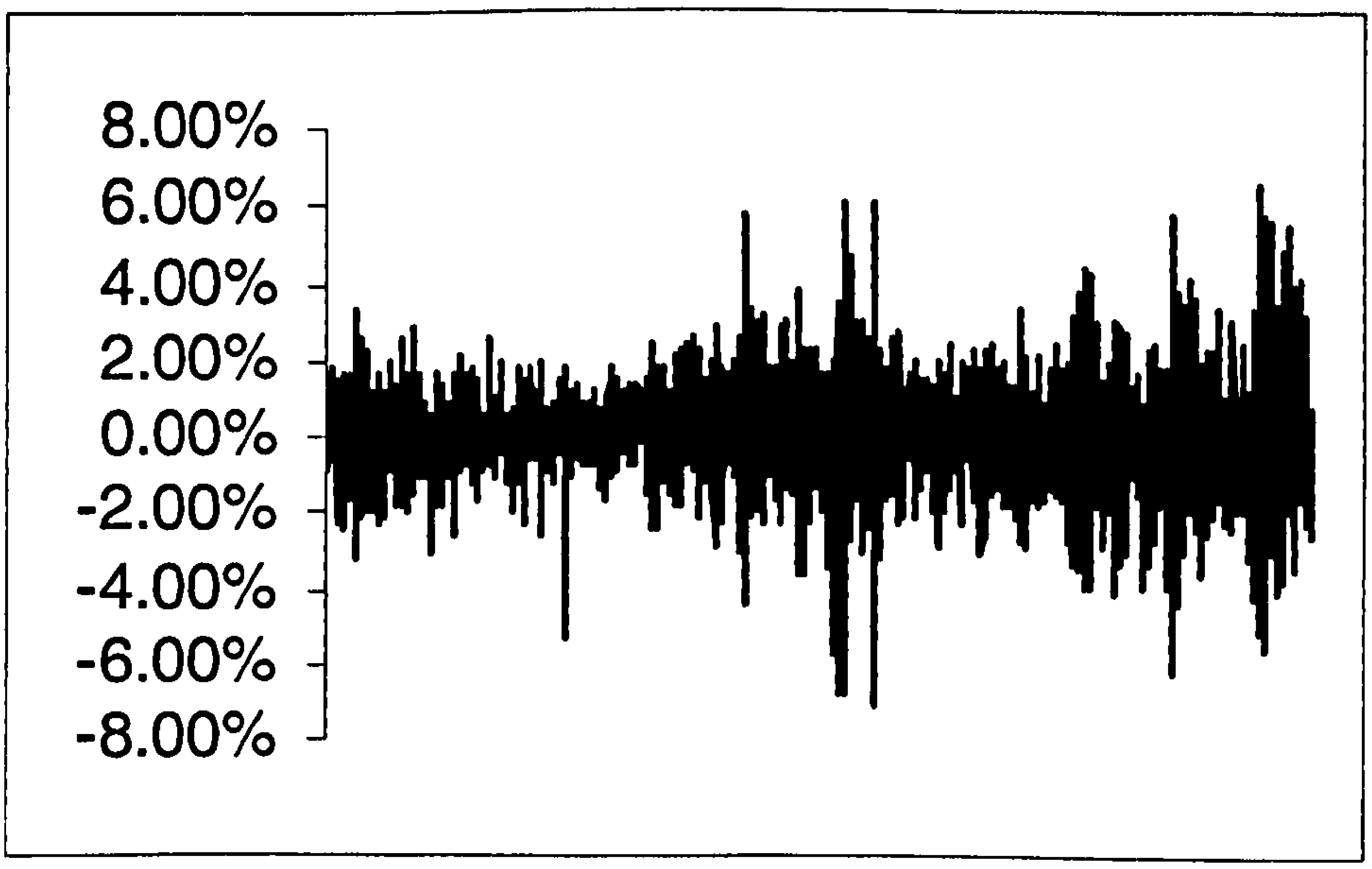


Spain

Price Index and Total Return Index Data

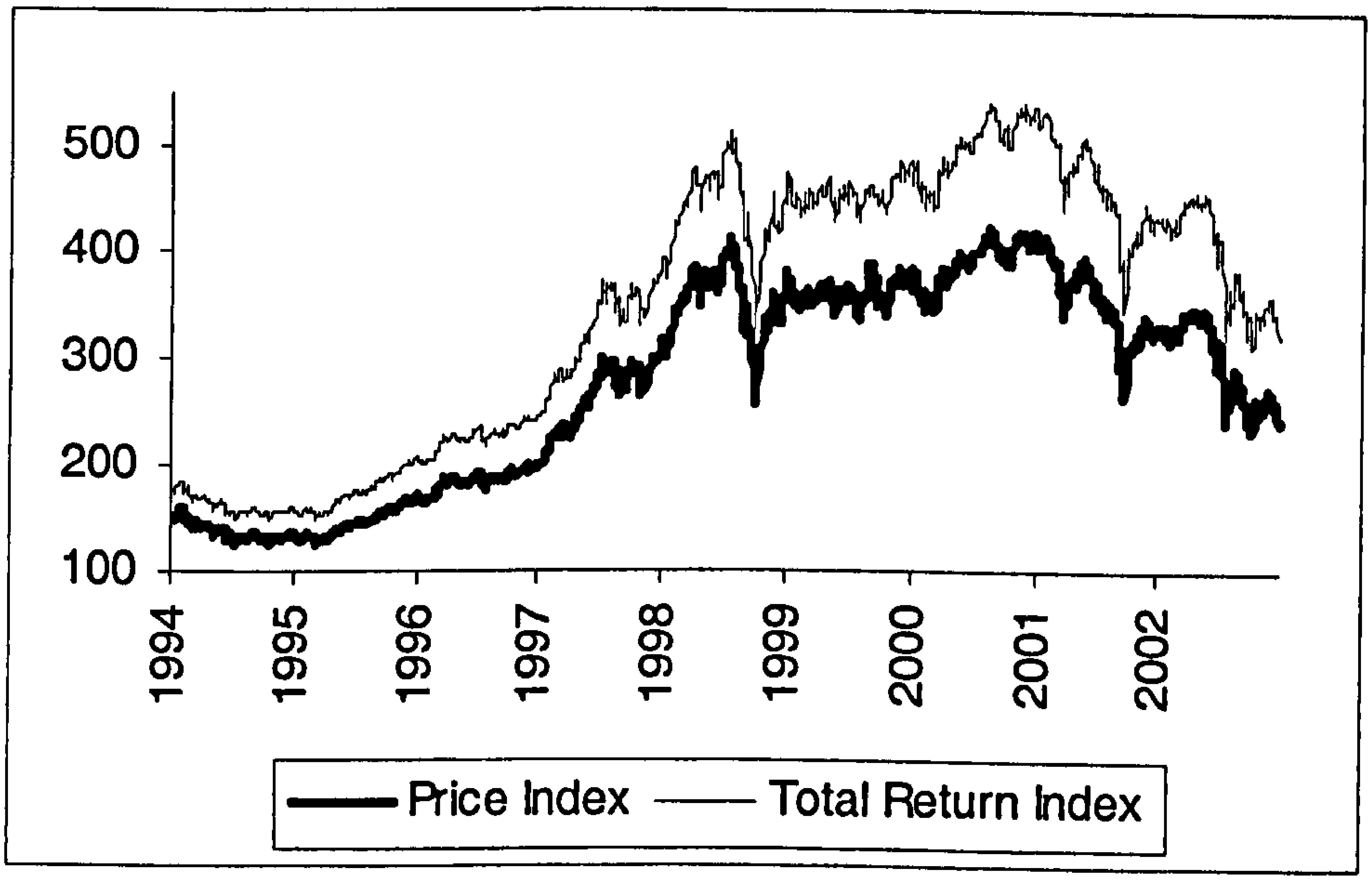


Funded Returns

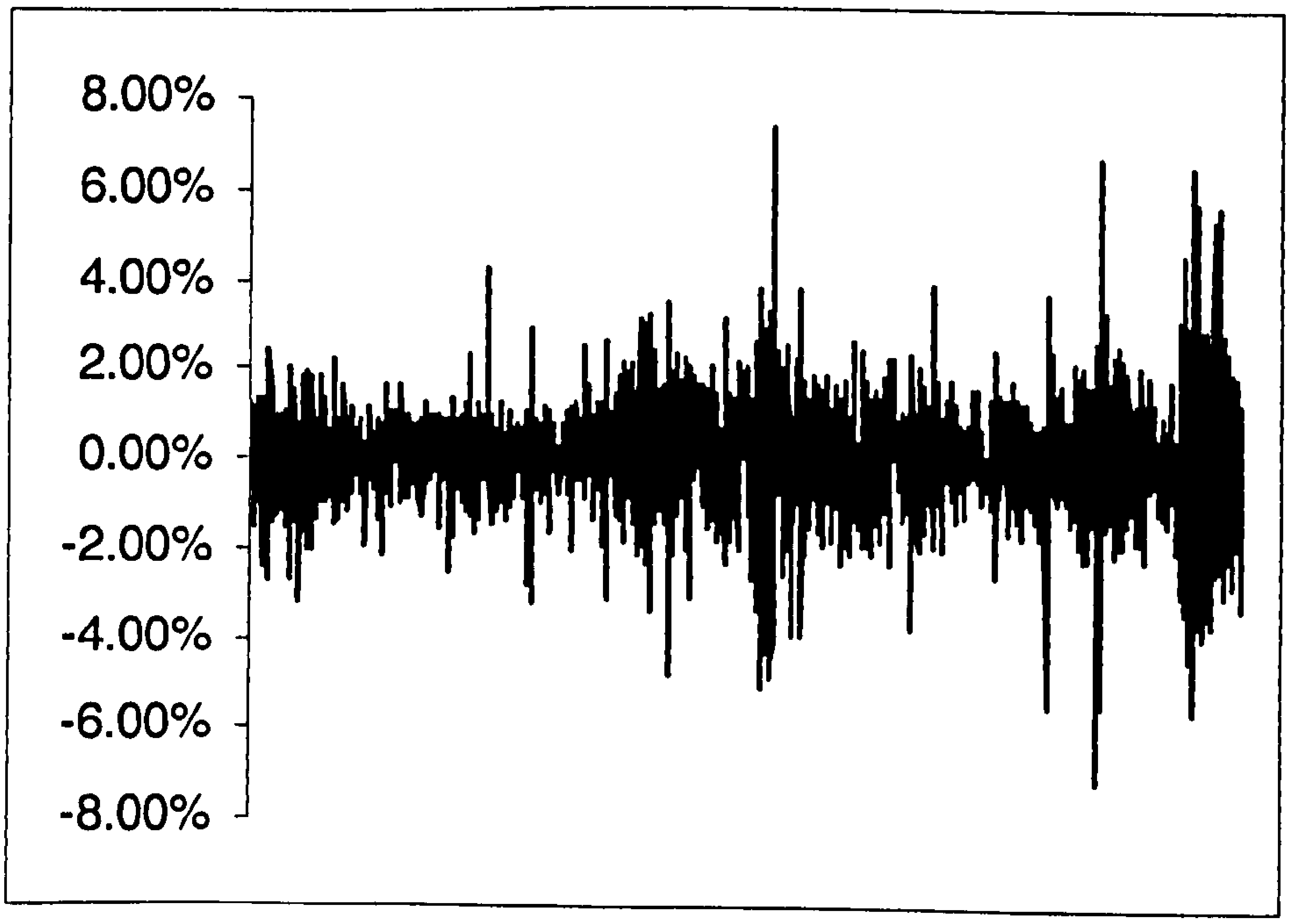


Switzerland

Price Index and Total Return Index Data

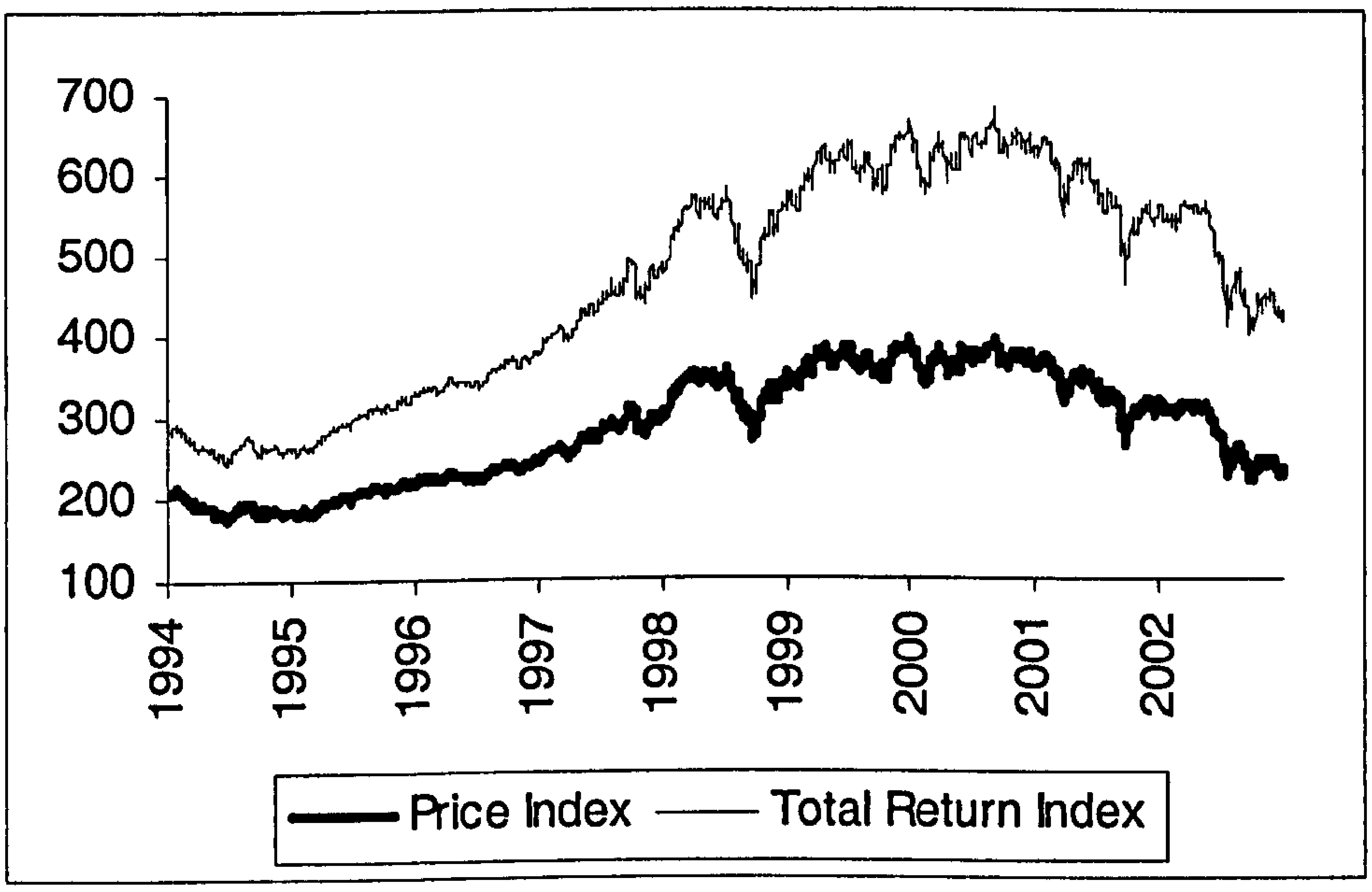


Funded Returns

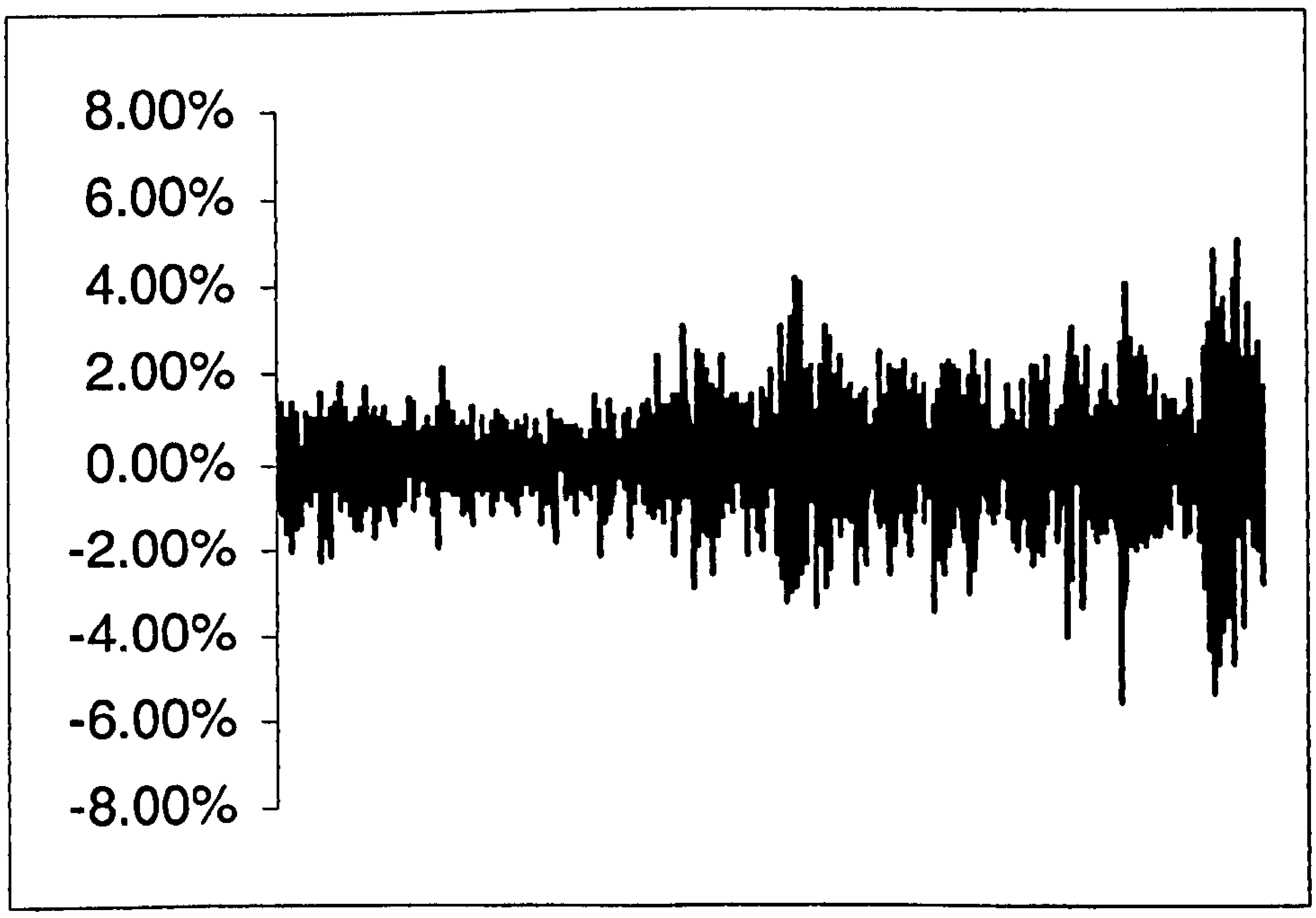


UK

Price Index and Total Return Index Data

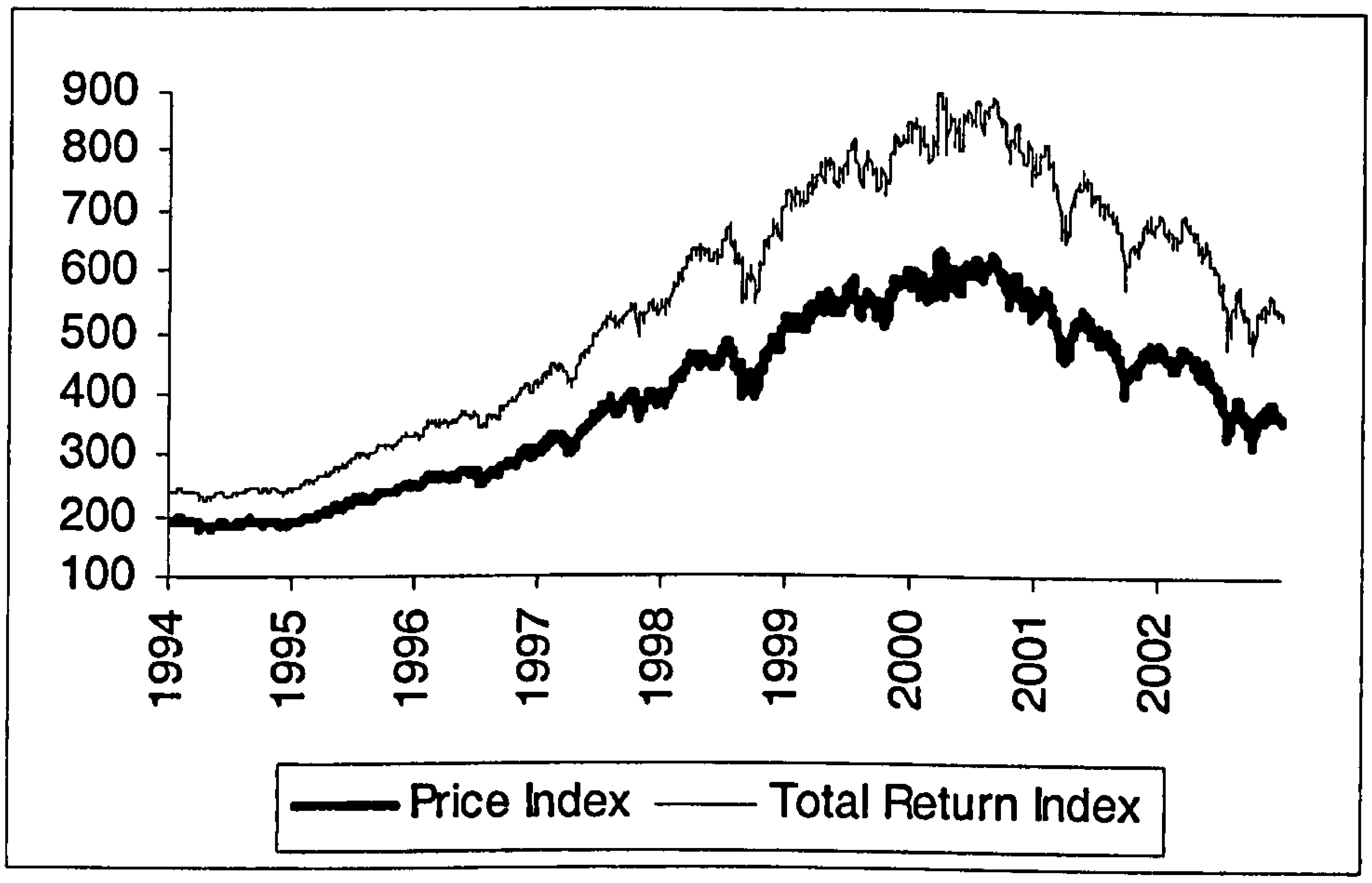


Funded Returns

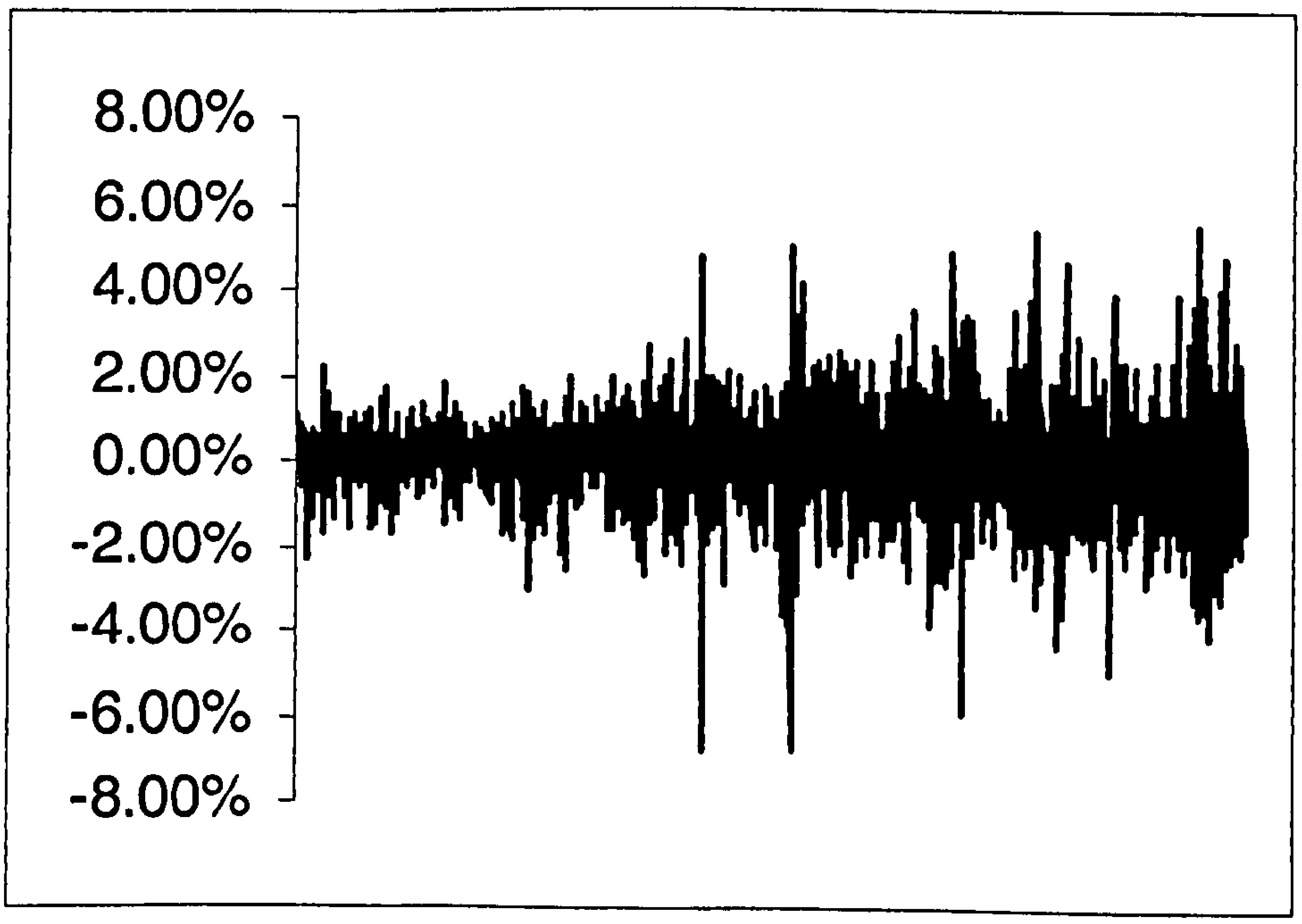


USA

Price Index and Total Return Index Data



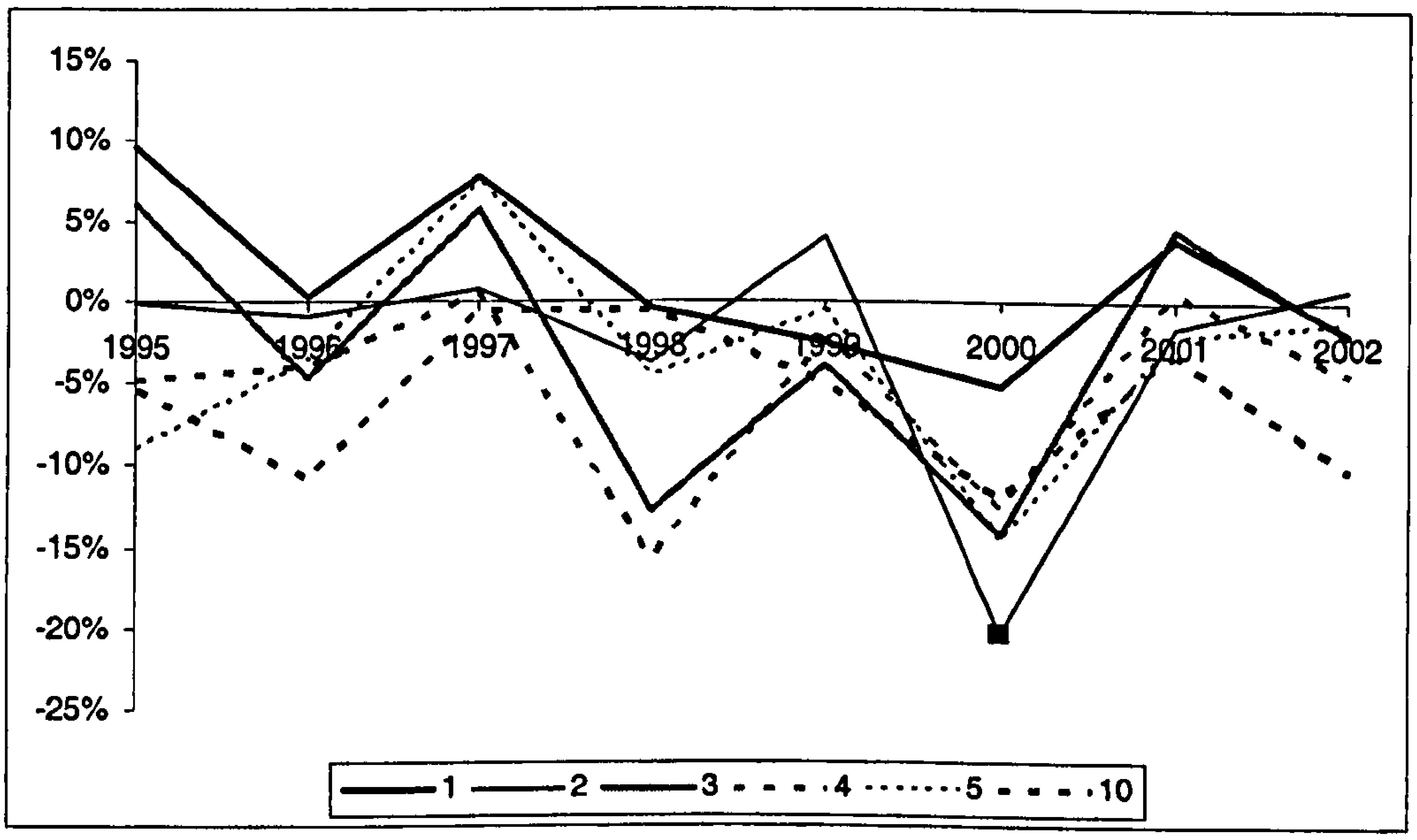
Funded Returns



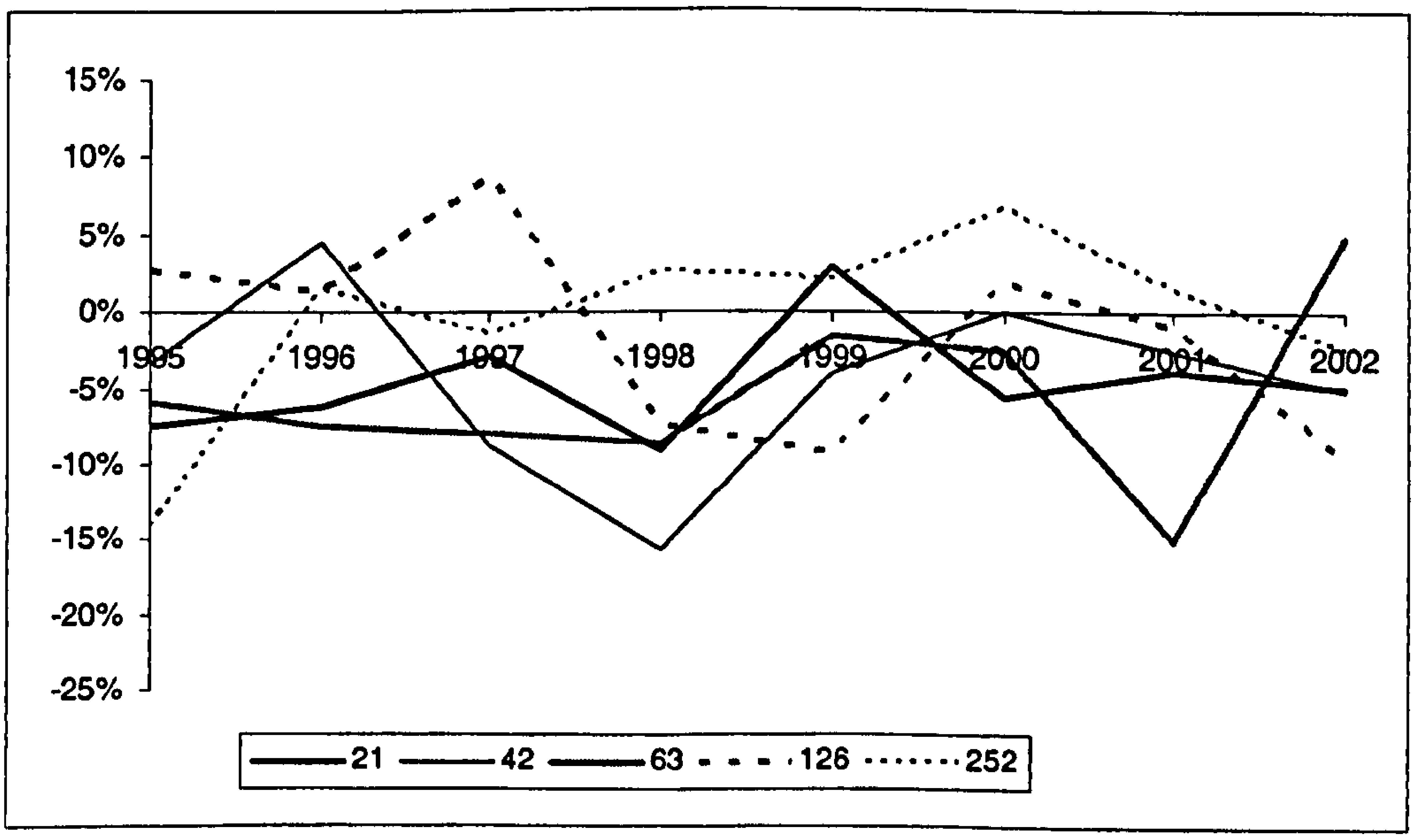
Appendix C: Momentum Strategy Returns by Year

Australia

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

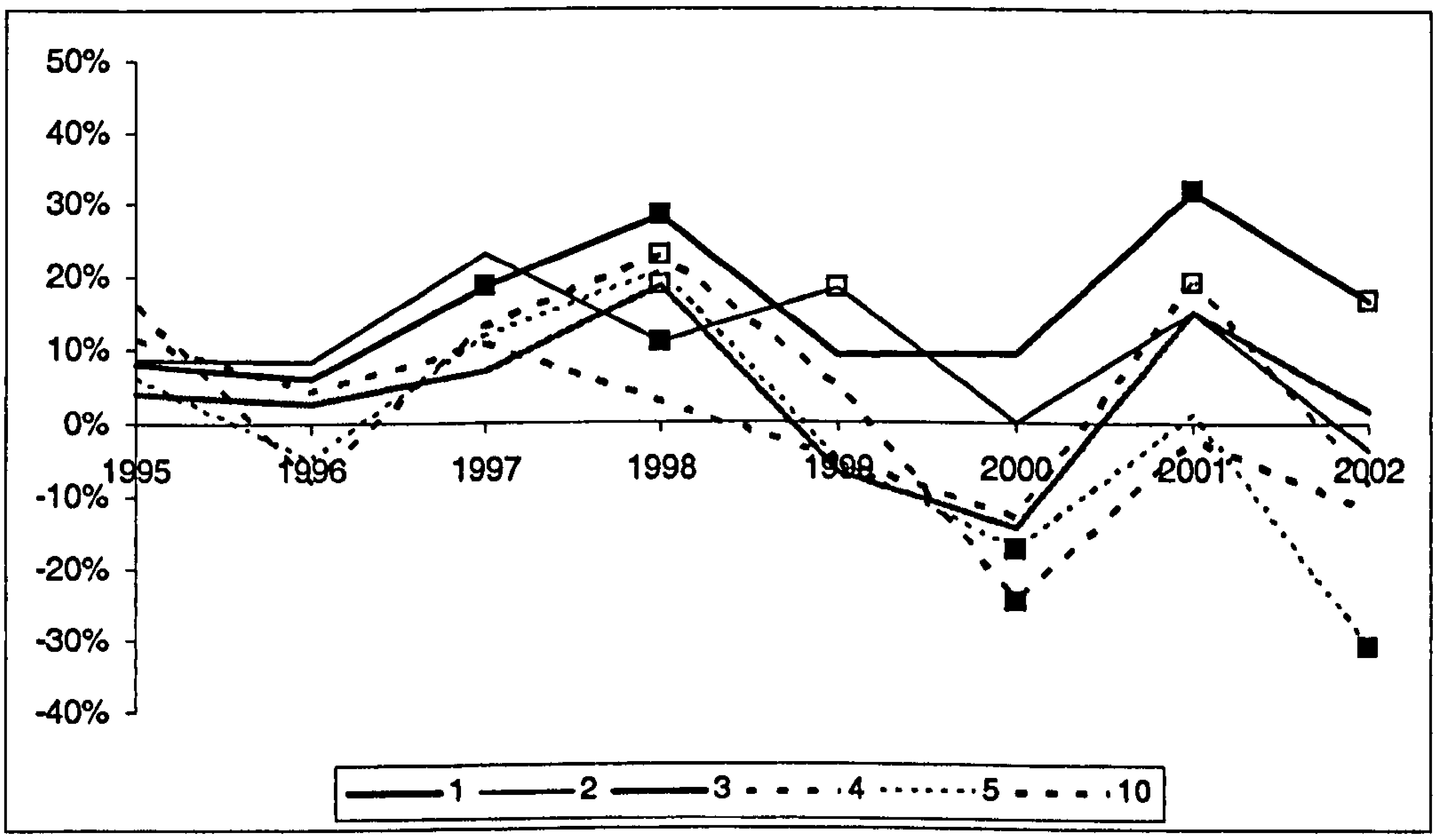


■ denotes bootstrap significance at the 1% level

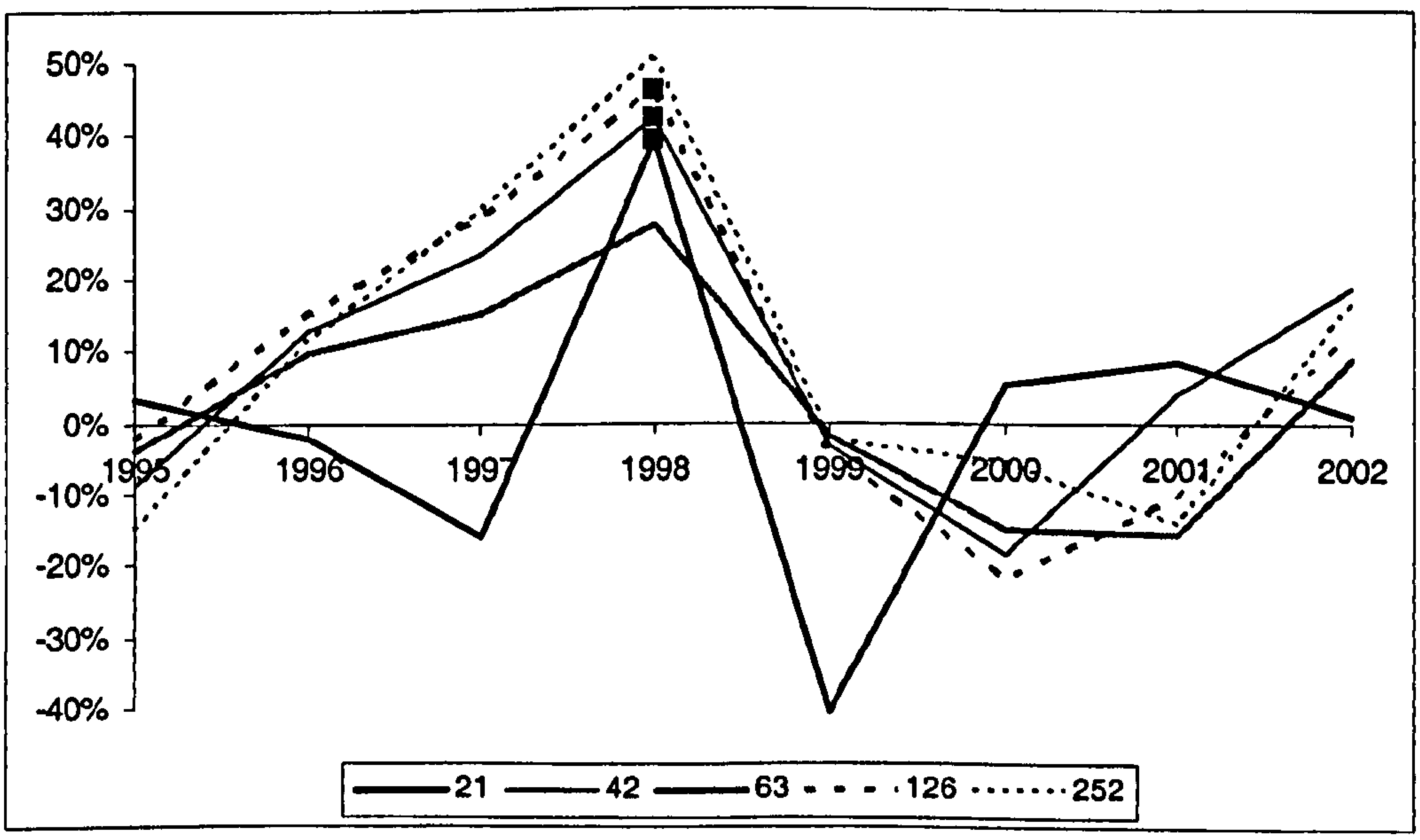
□ denotes bootstrap significance at the 5% level

Belgium

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

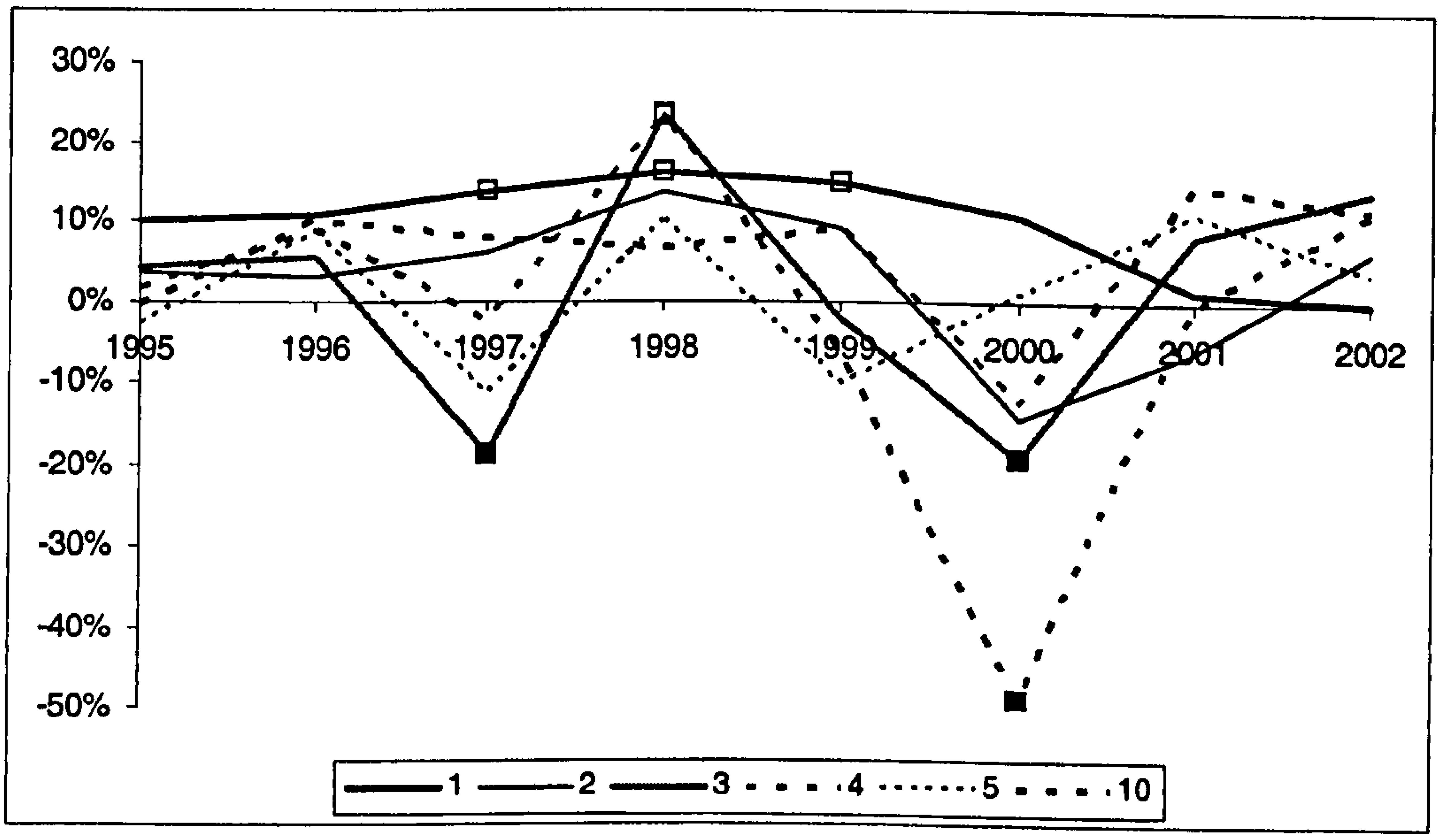


■ denotes bootstrap significance at the 1% level

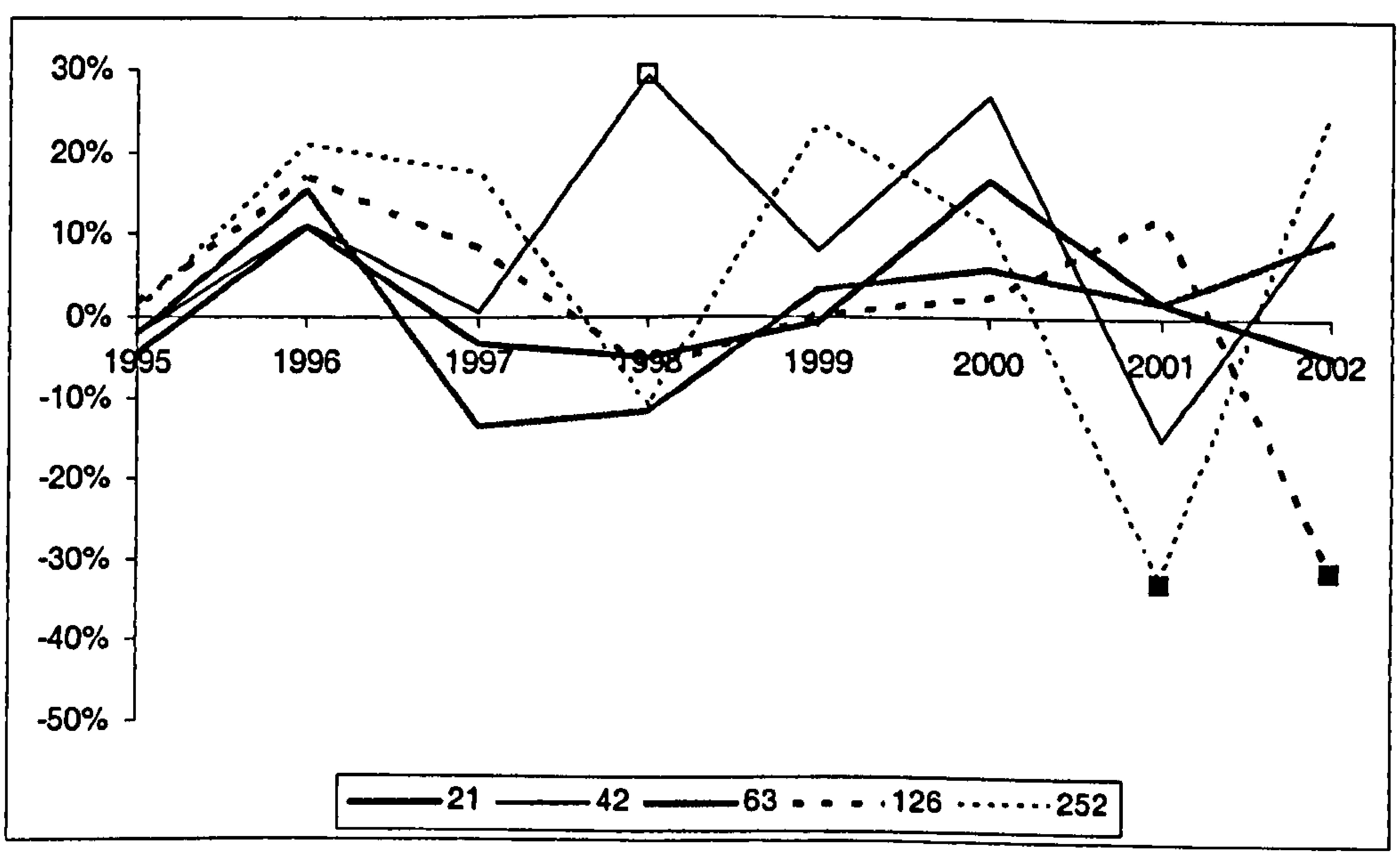
□ denotes bootstrap significance at the 5% level

Canada

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

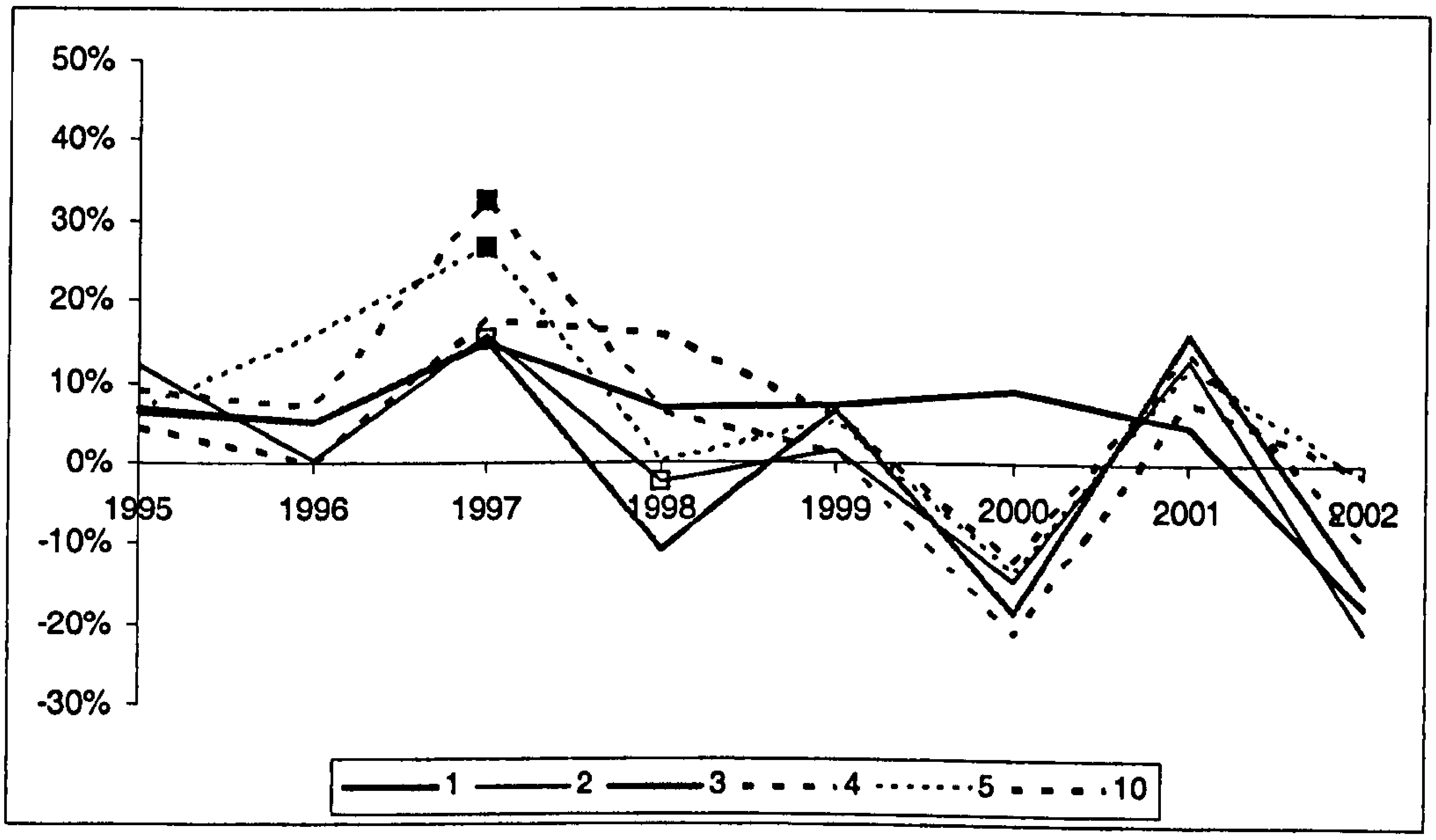


■ denotes bootstrap significance at the 1% level

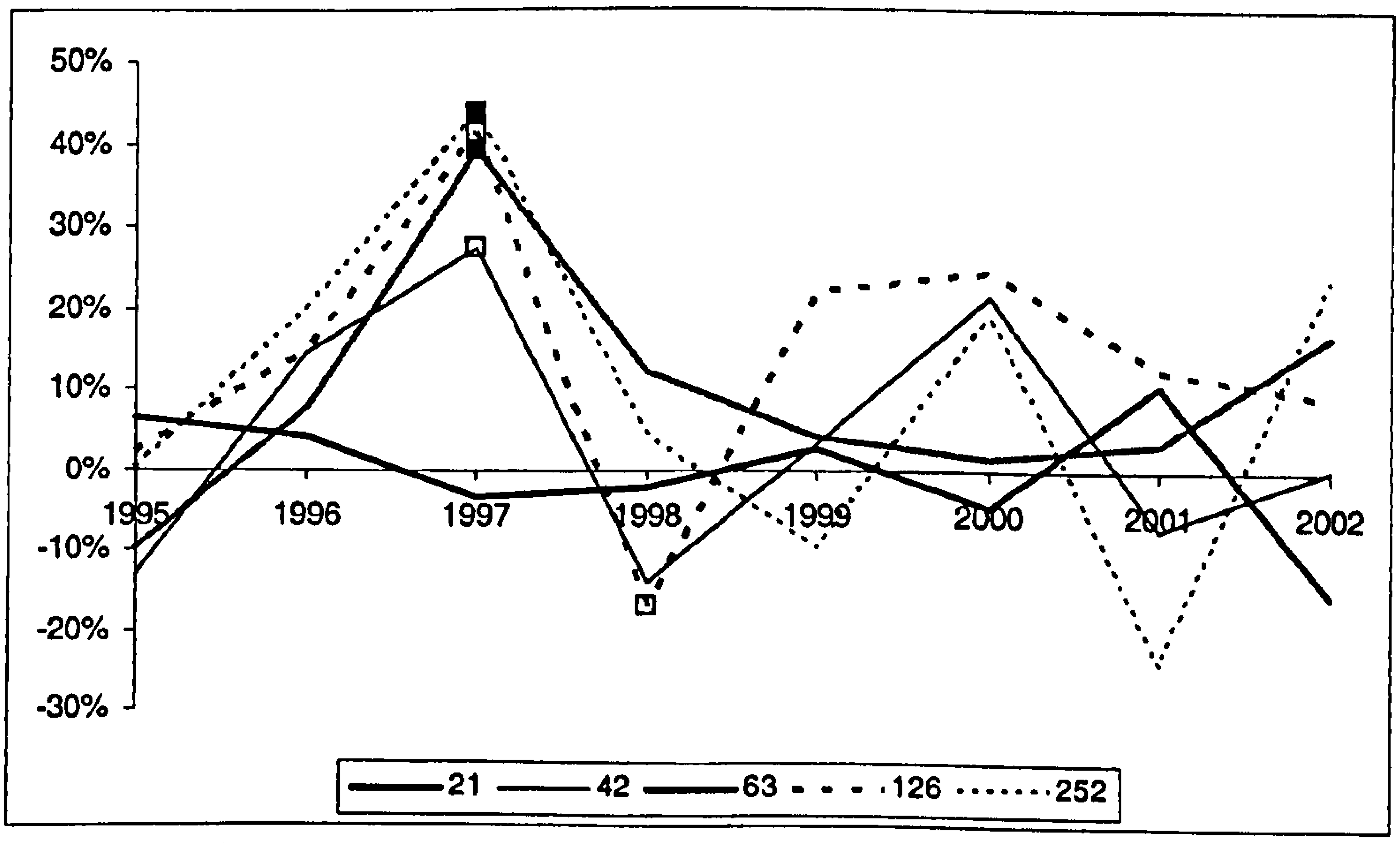
□ denotes bootstrap significance at the 5% level

Denmark

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

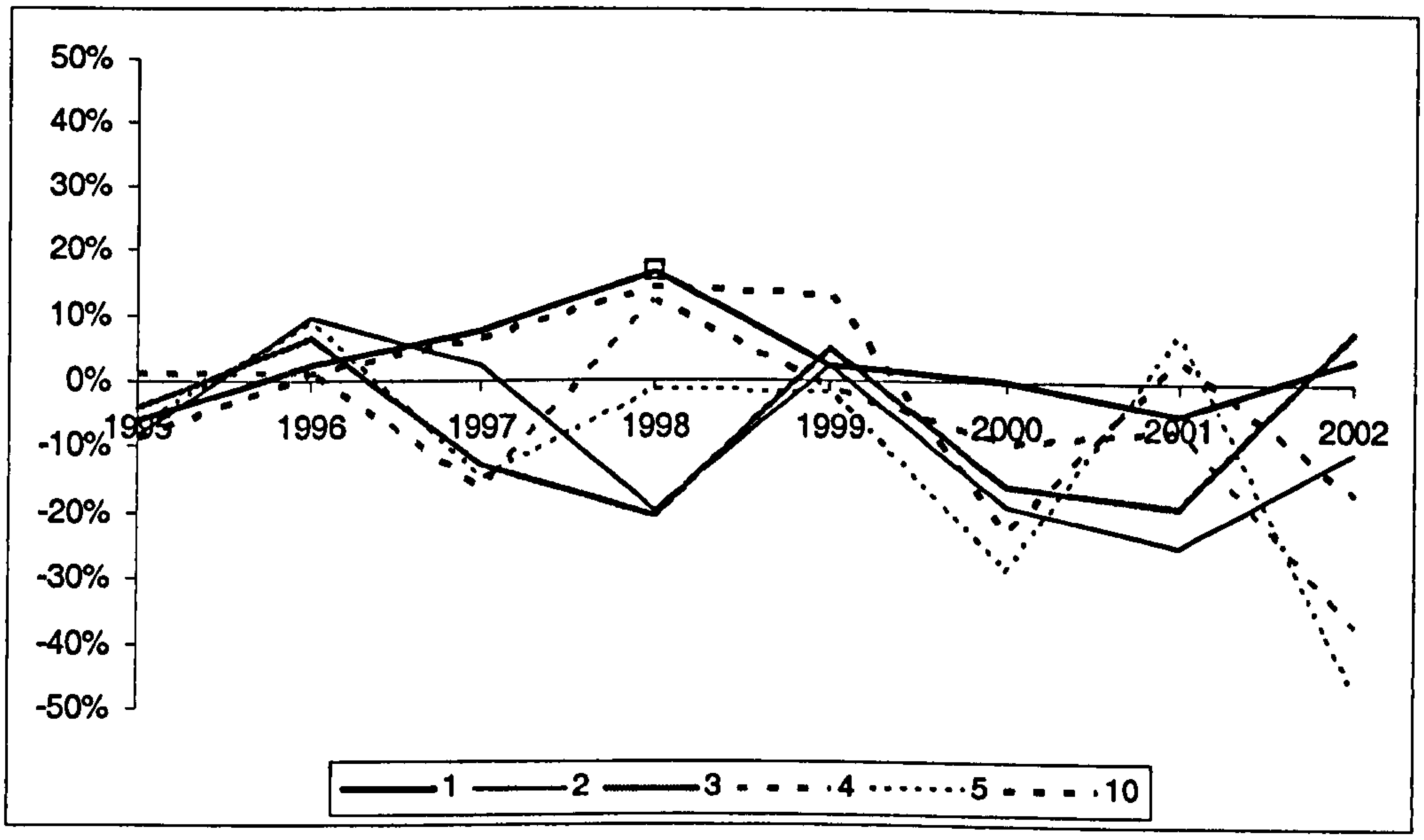


■ denotes bootstrap significance at the 1% level

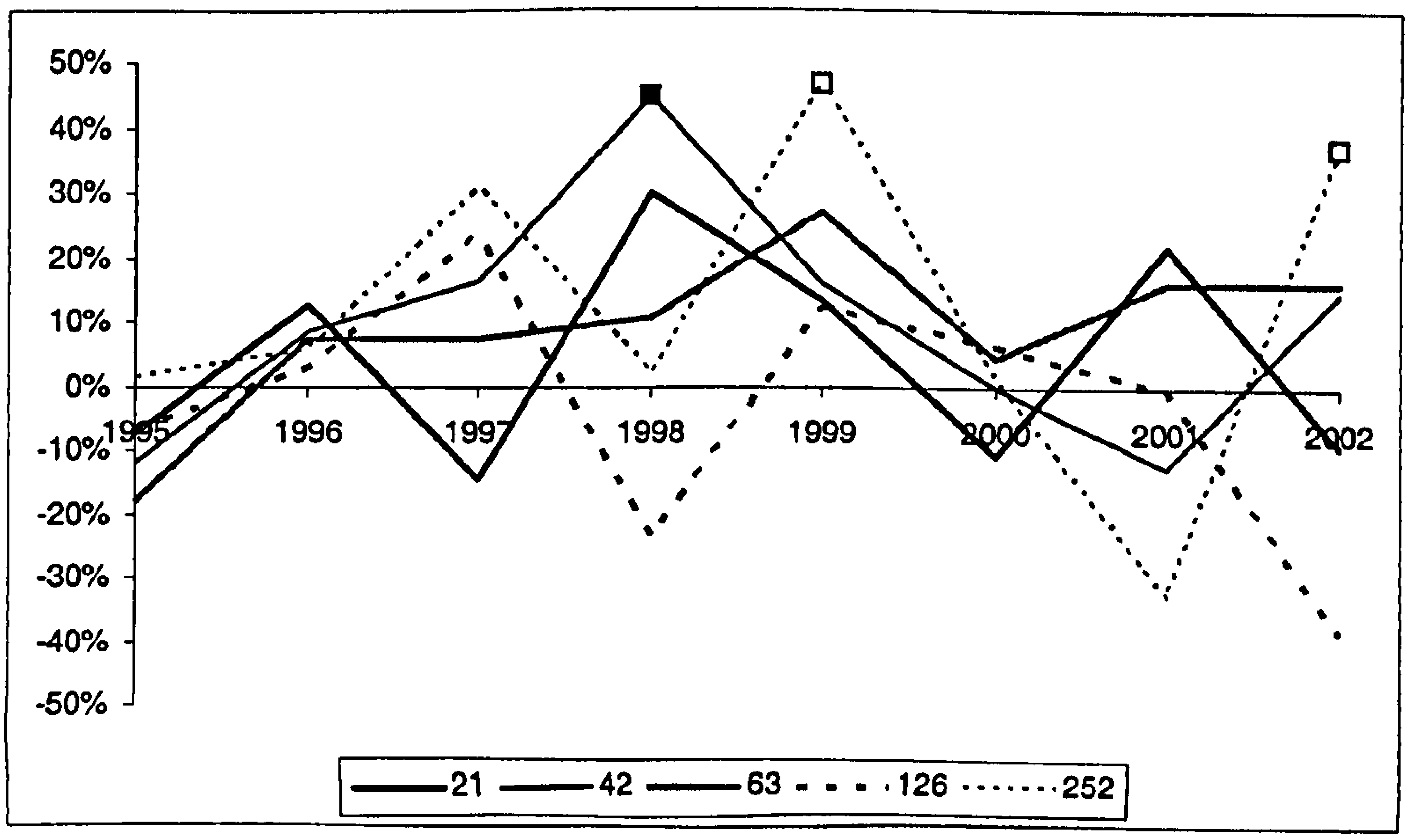
□ denotes bootstrap significance at the 5% level

France

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

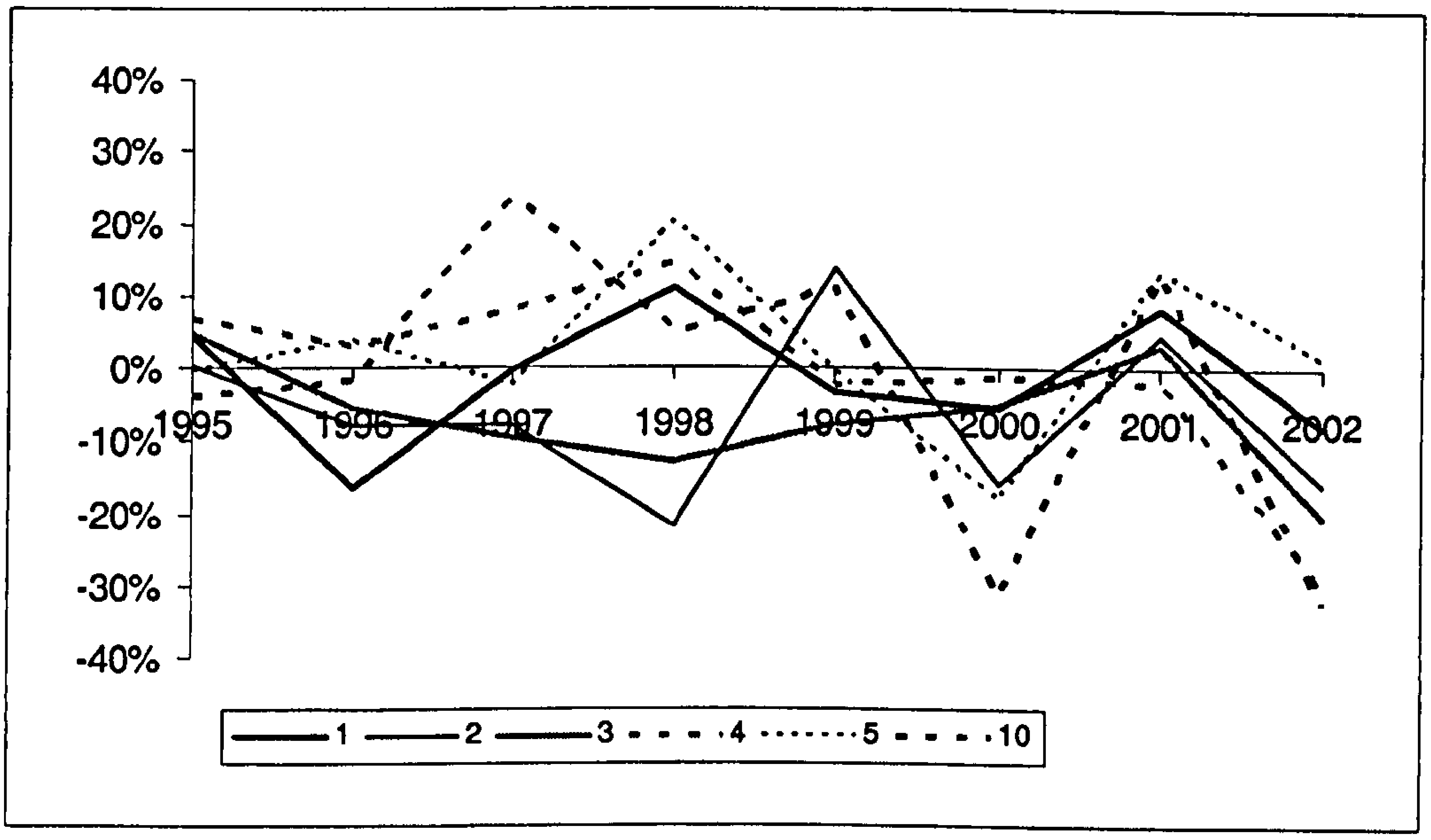


■ denotes bootstrap significance at the 1% level

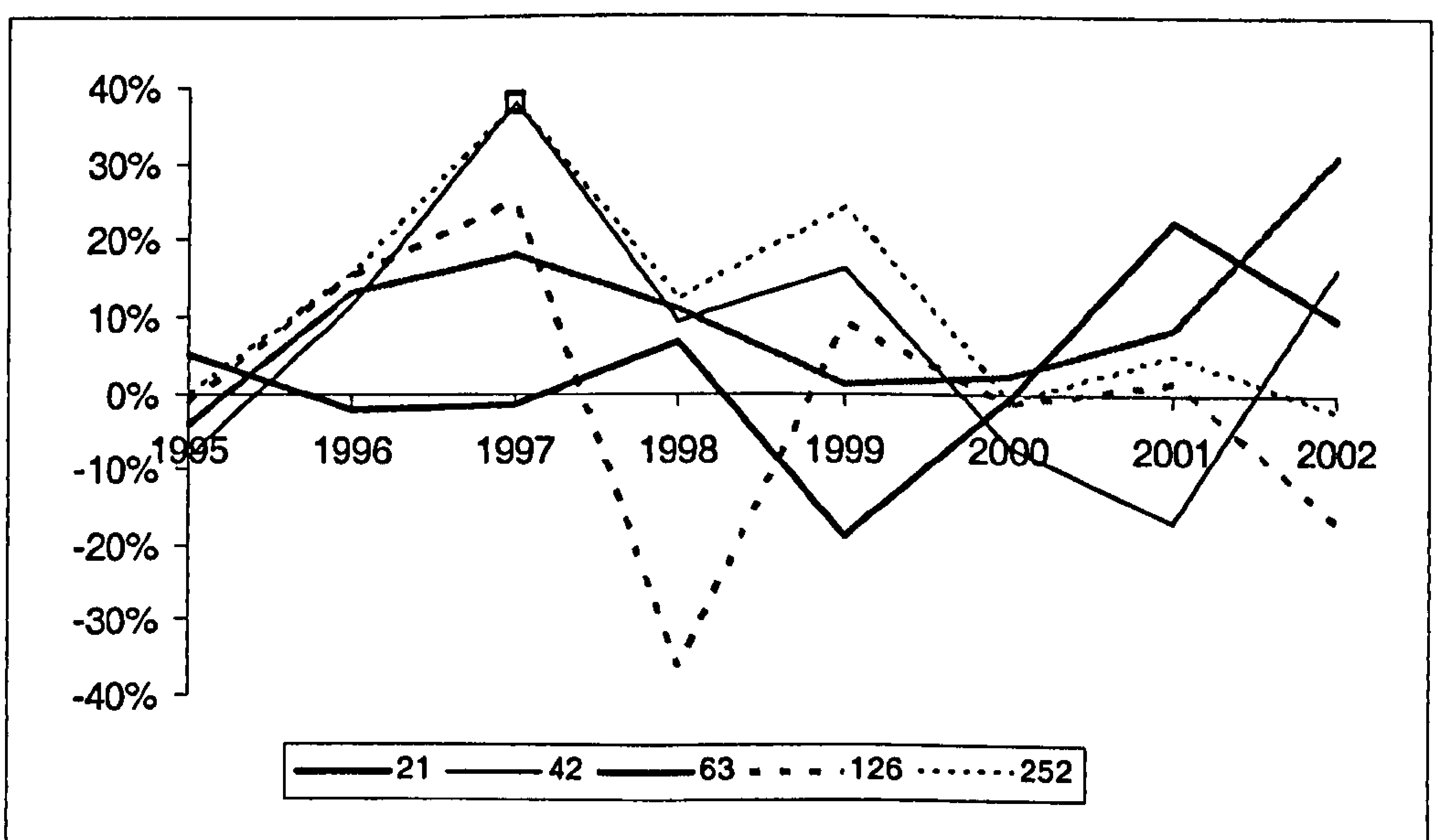
□ denotes bootstrap significance at the 5% level

Germany

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

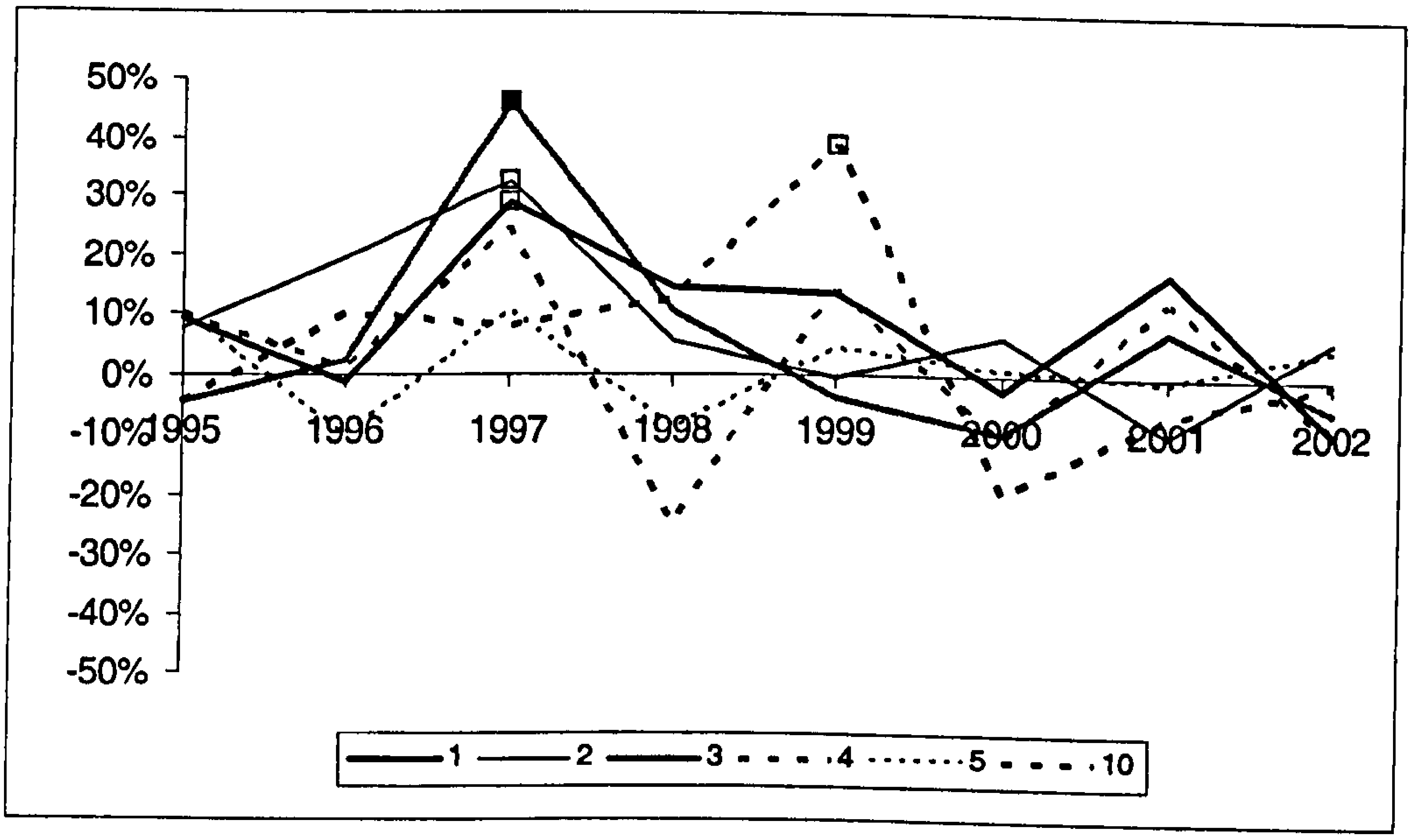


■ denotes bootstrap significance at the 1% level

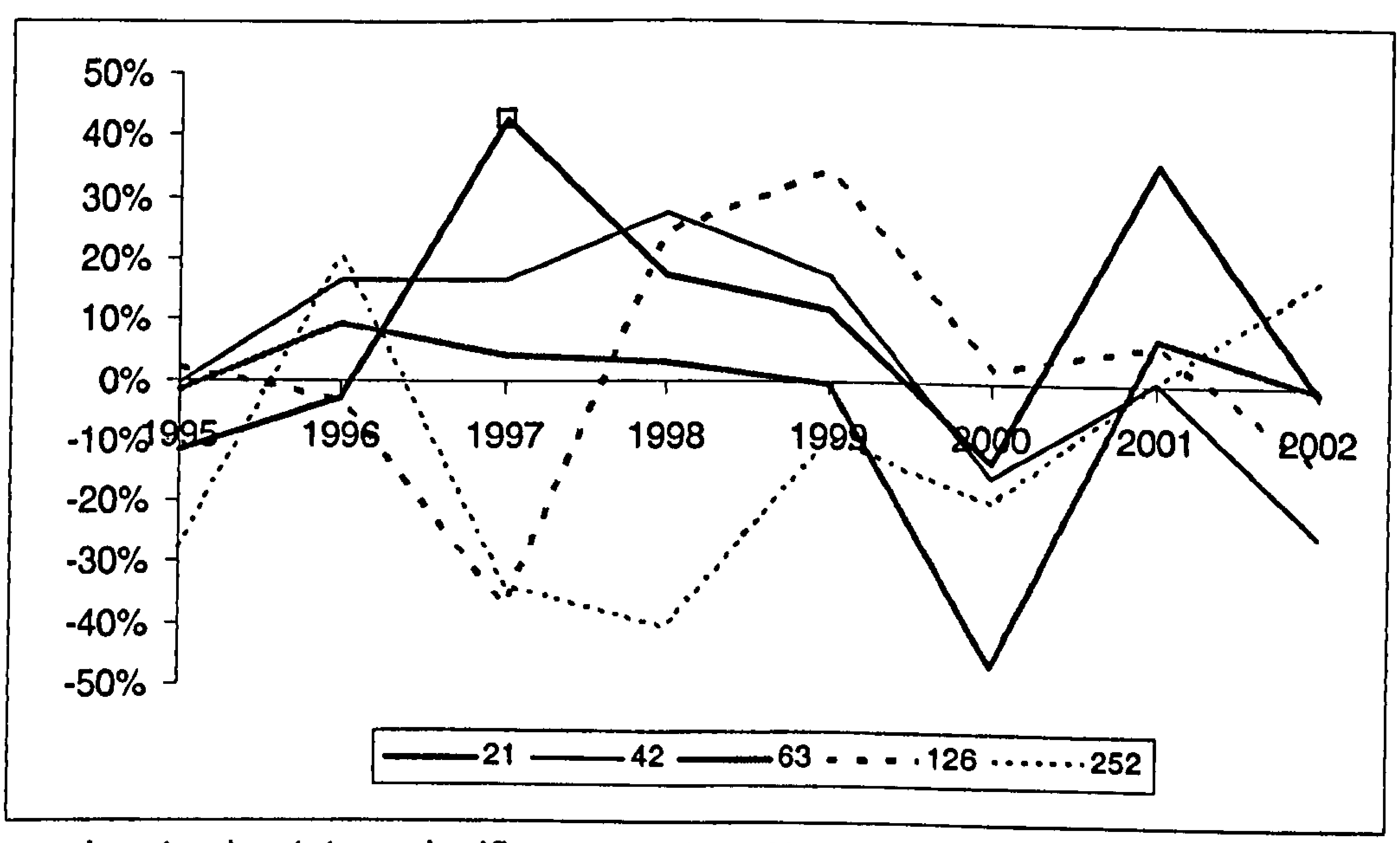
□ denotes bootstrap significance at the 5% level

Hong Kong

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

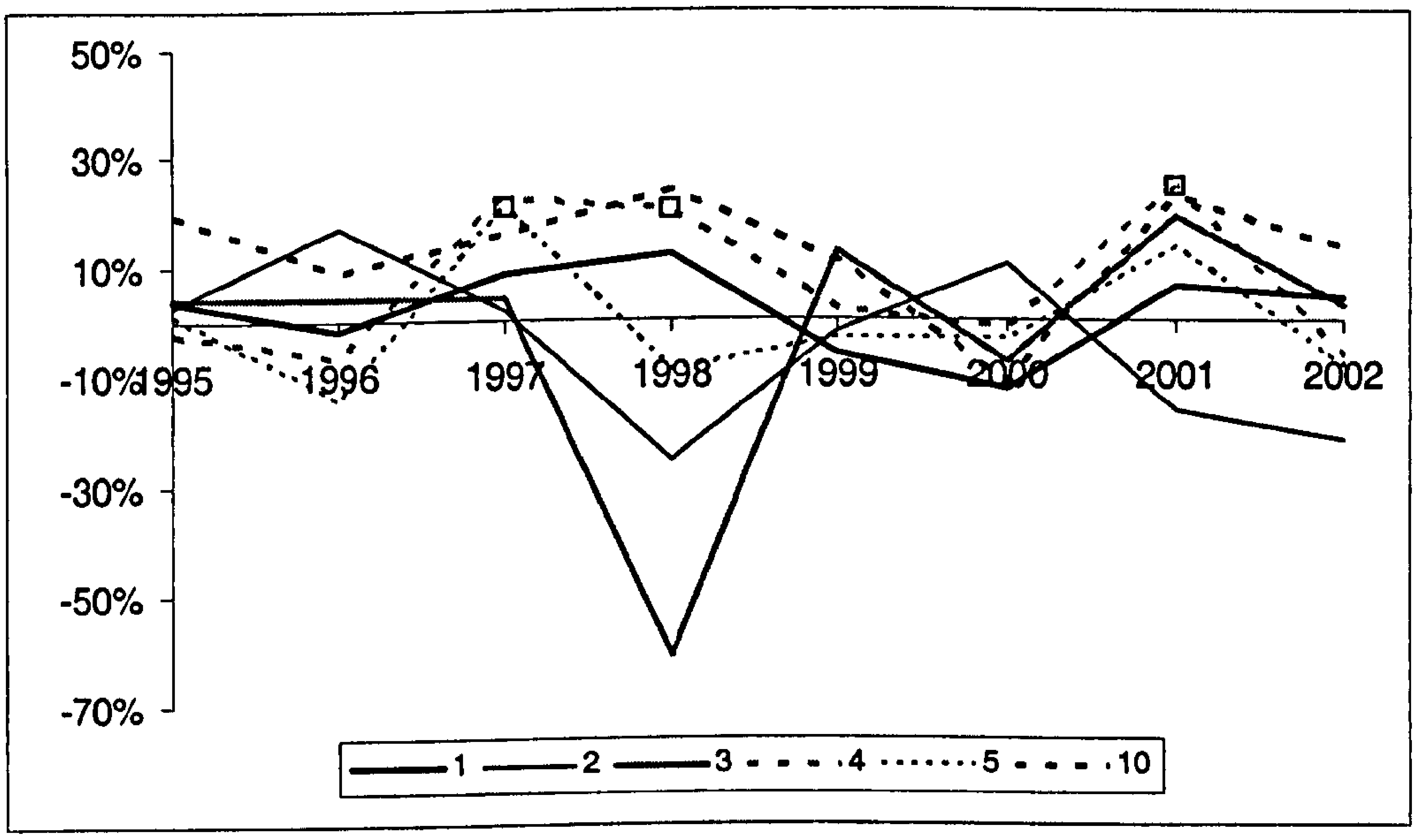


■ denotes bootstrap significance at the 1% level

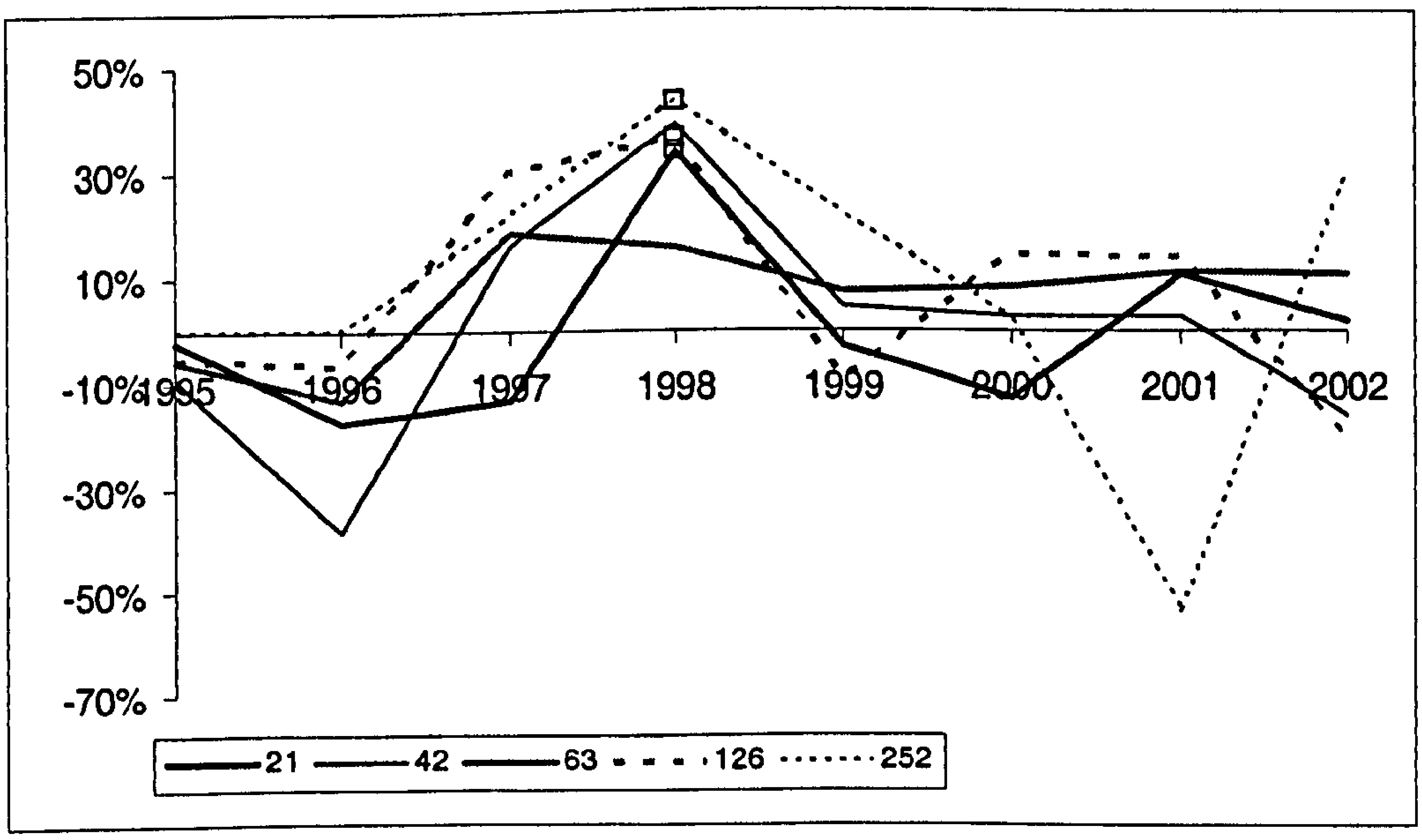
□ denotes bootstrap significance at the 5% level

Italy

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

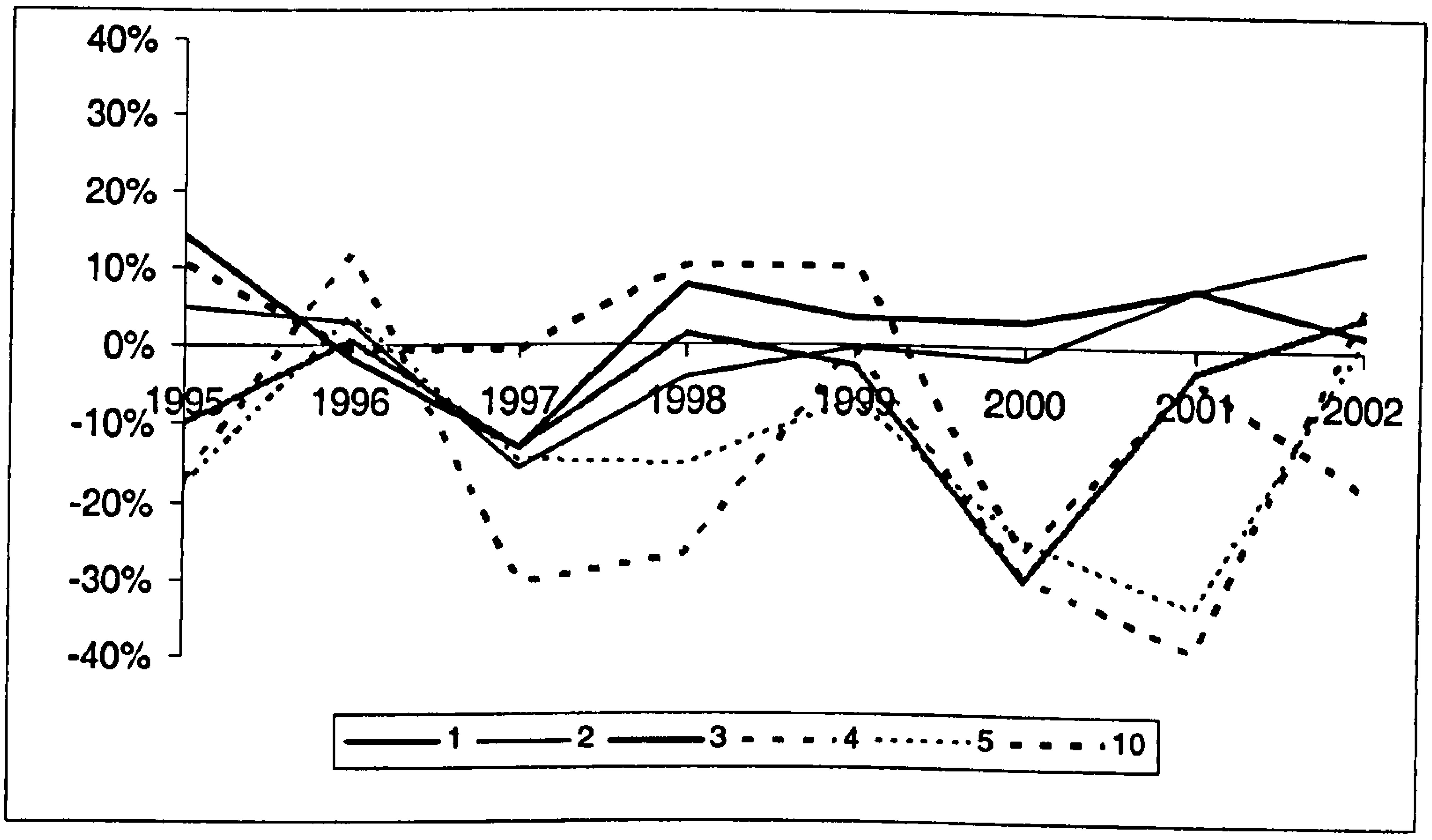


■ denotes bootstrap significance at the 1% level

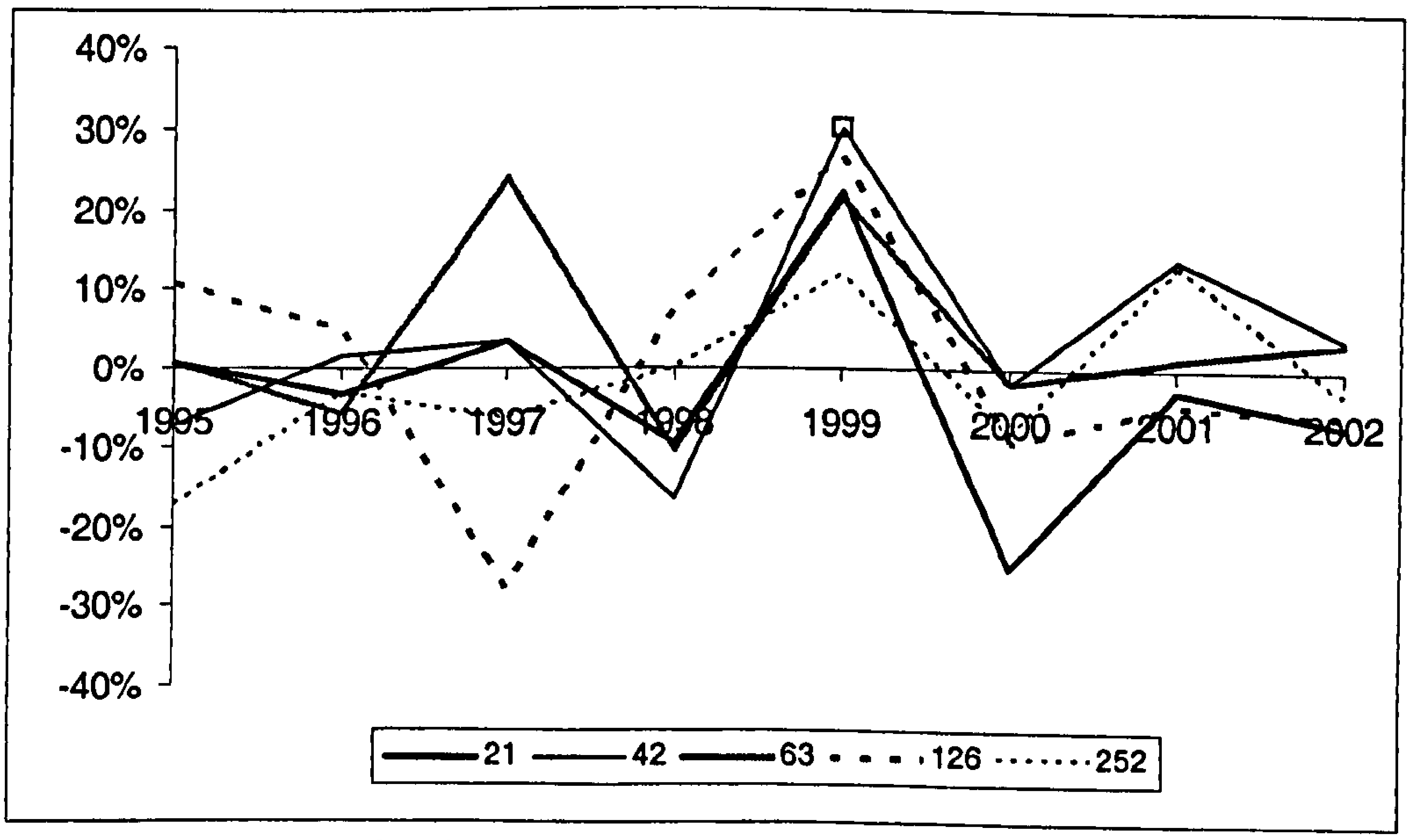
□ denotes bootstrap significance at the 5% level

Japan

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

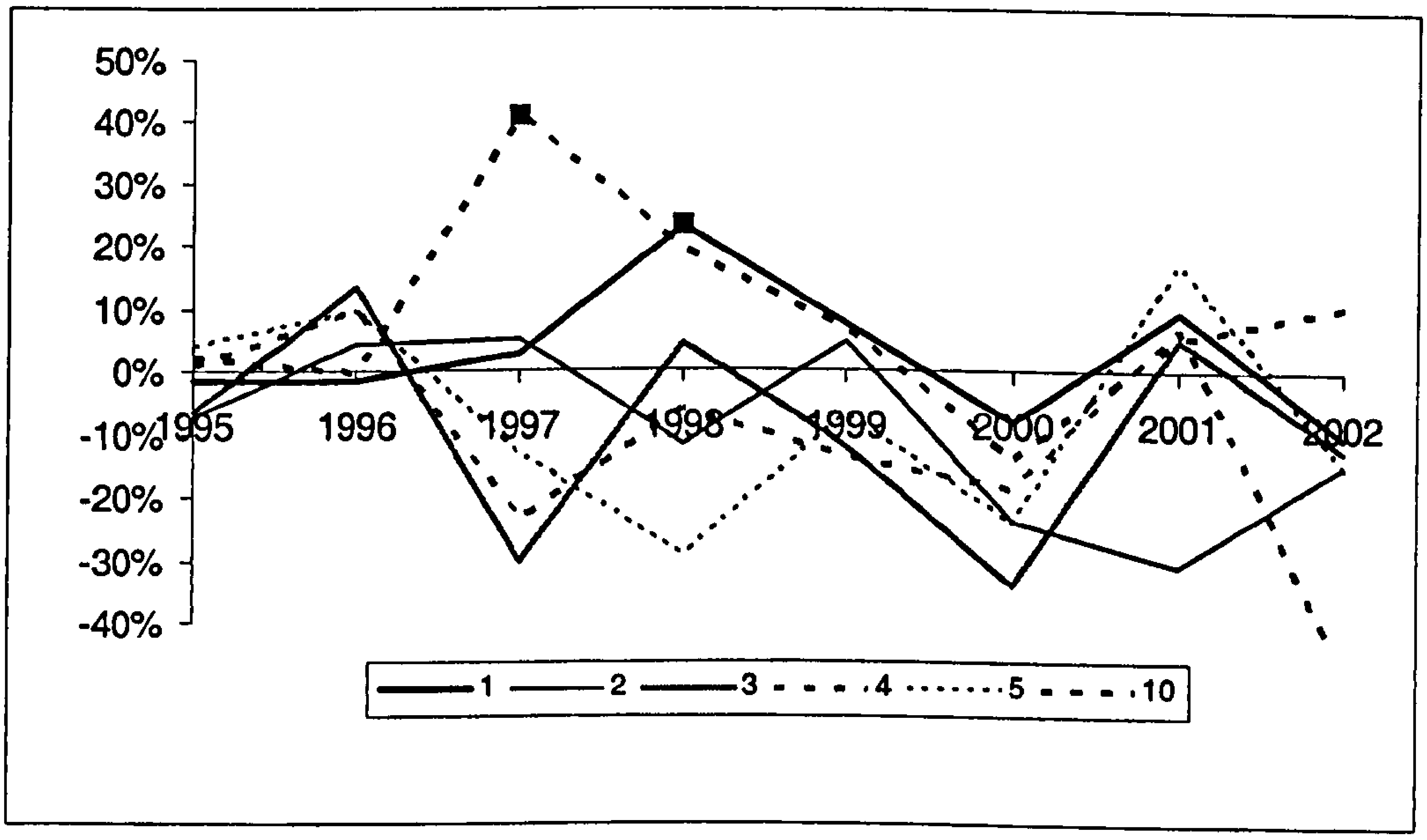


■ denotes bootstrap significance at the 1% level

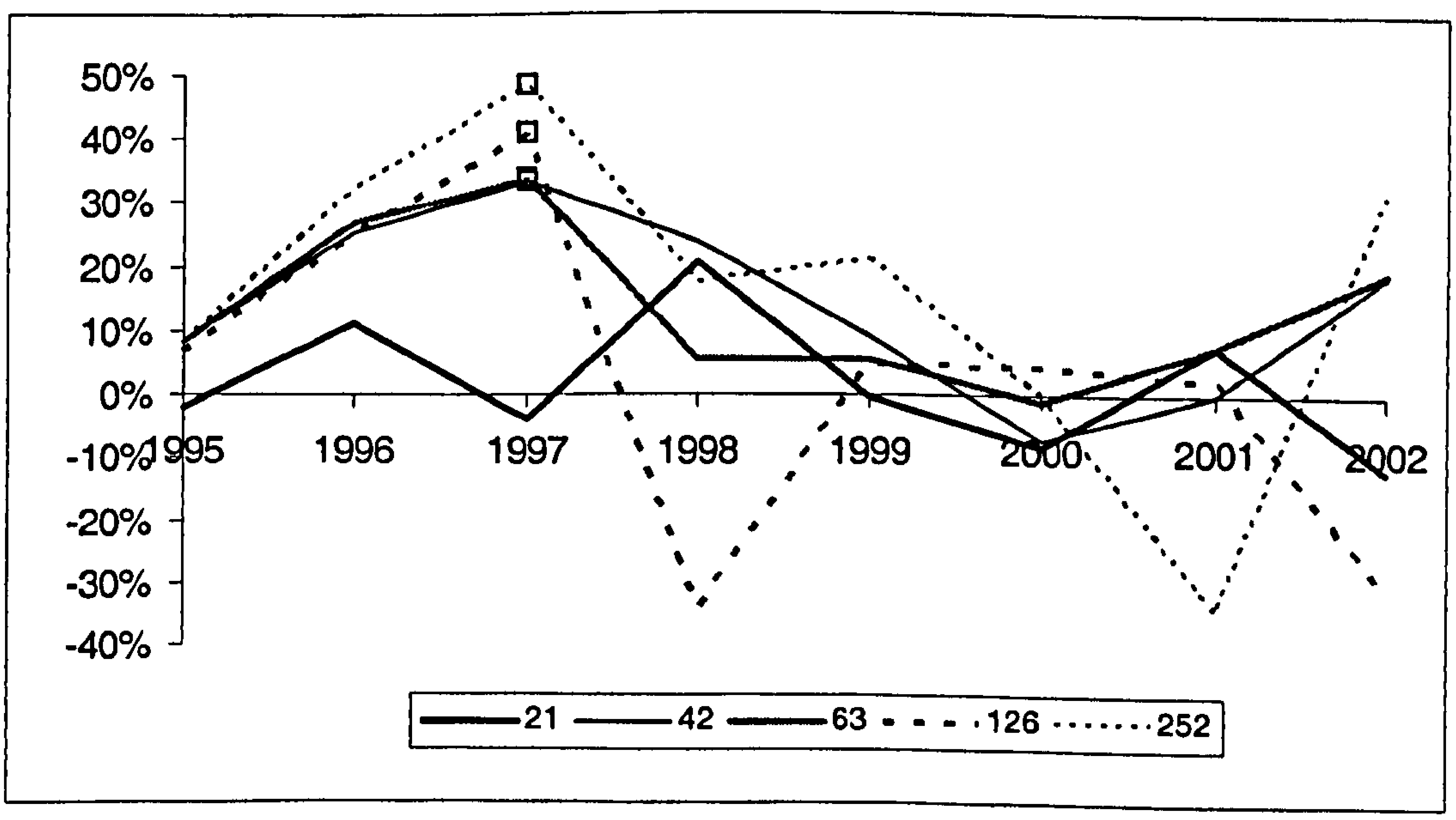
□ denotes bootstrap significance at the 5% level

Netherlands

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

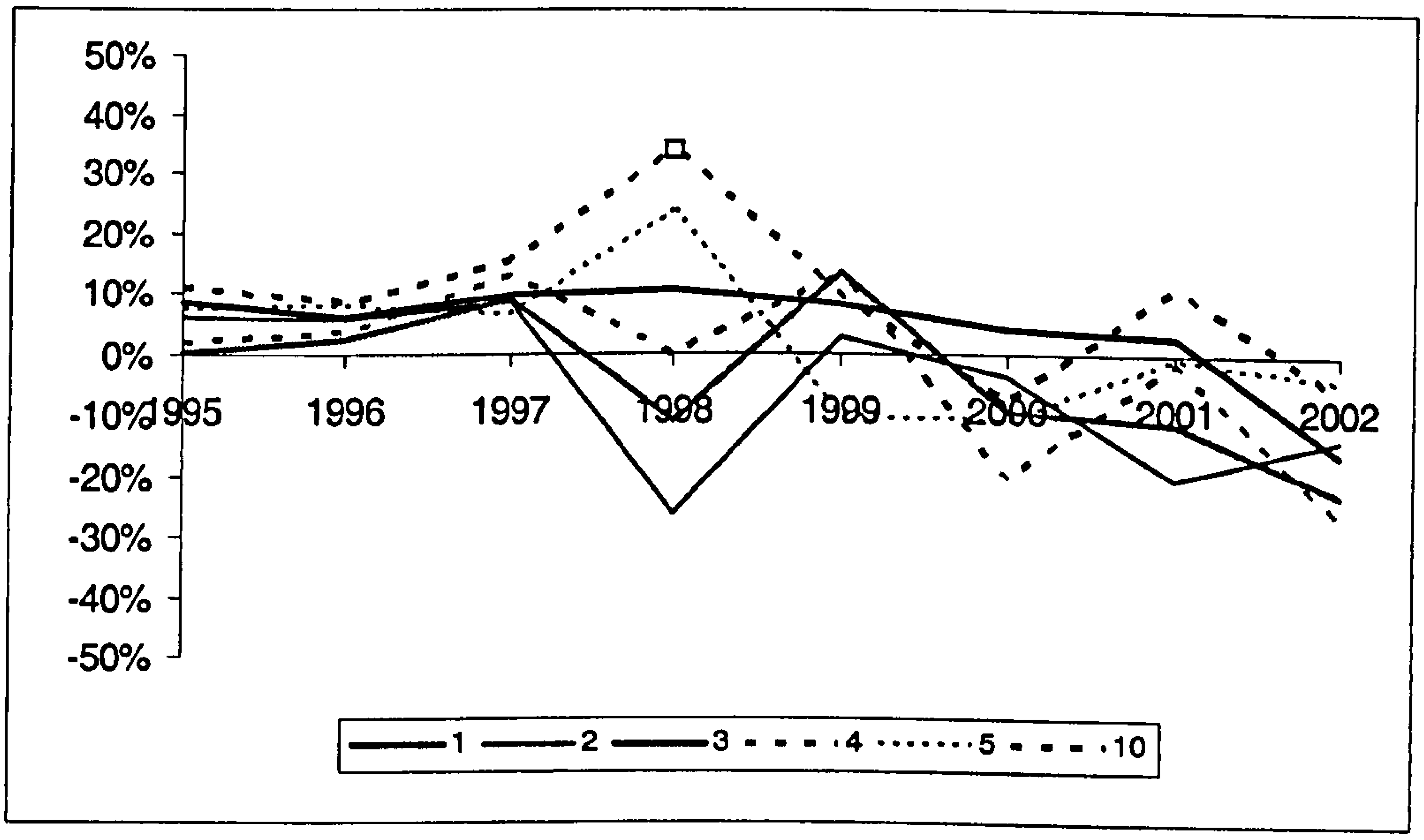


■ denotes bootstrap significance at the 1% level

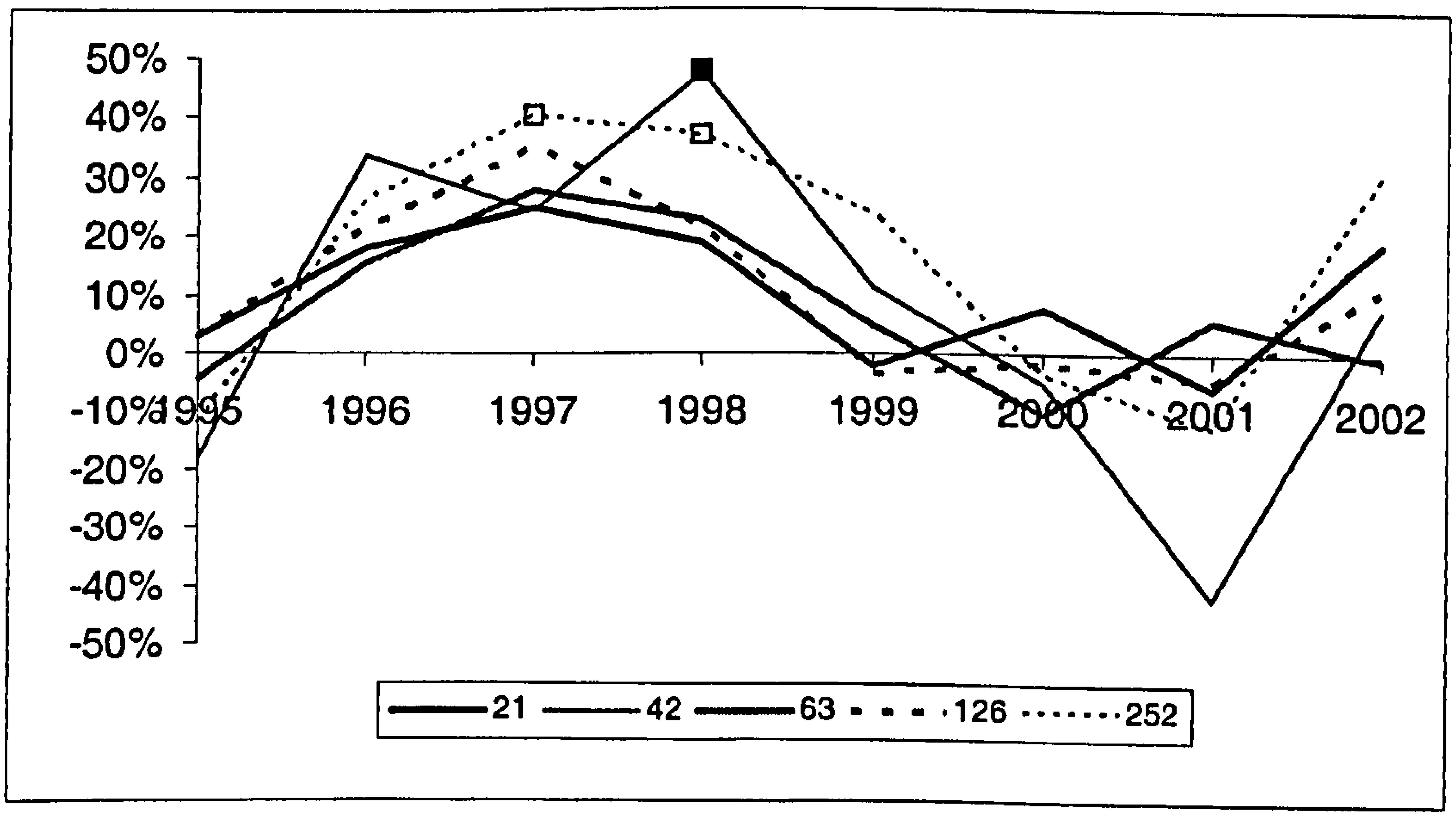
□ denotes bootstrap significance at the 5% level

Spain

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

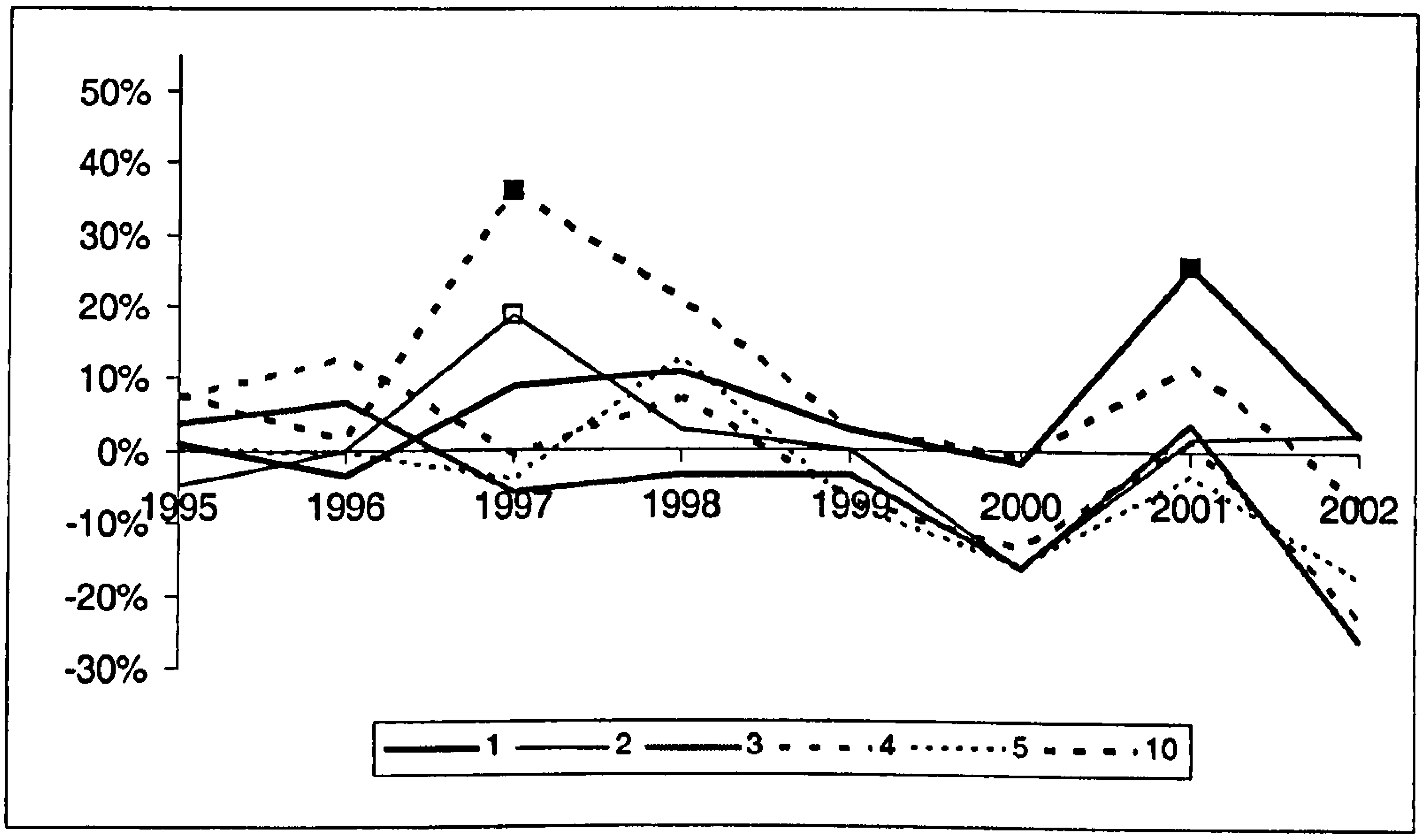


■ denotes bootstrap significance at the 1% level

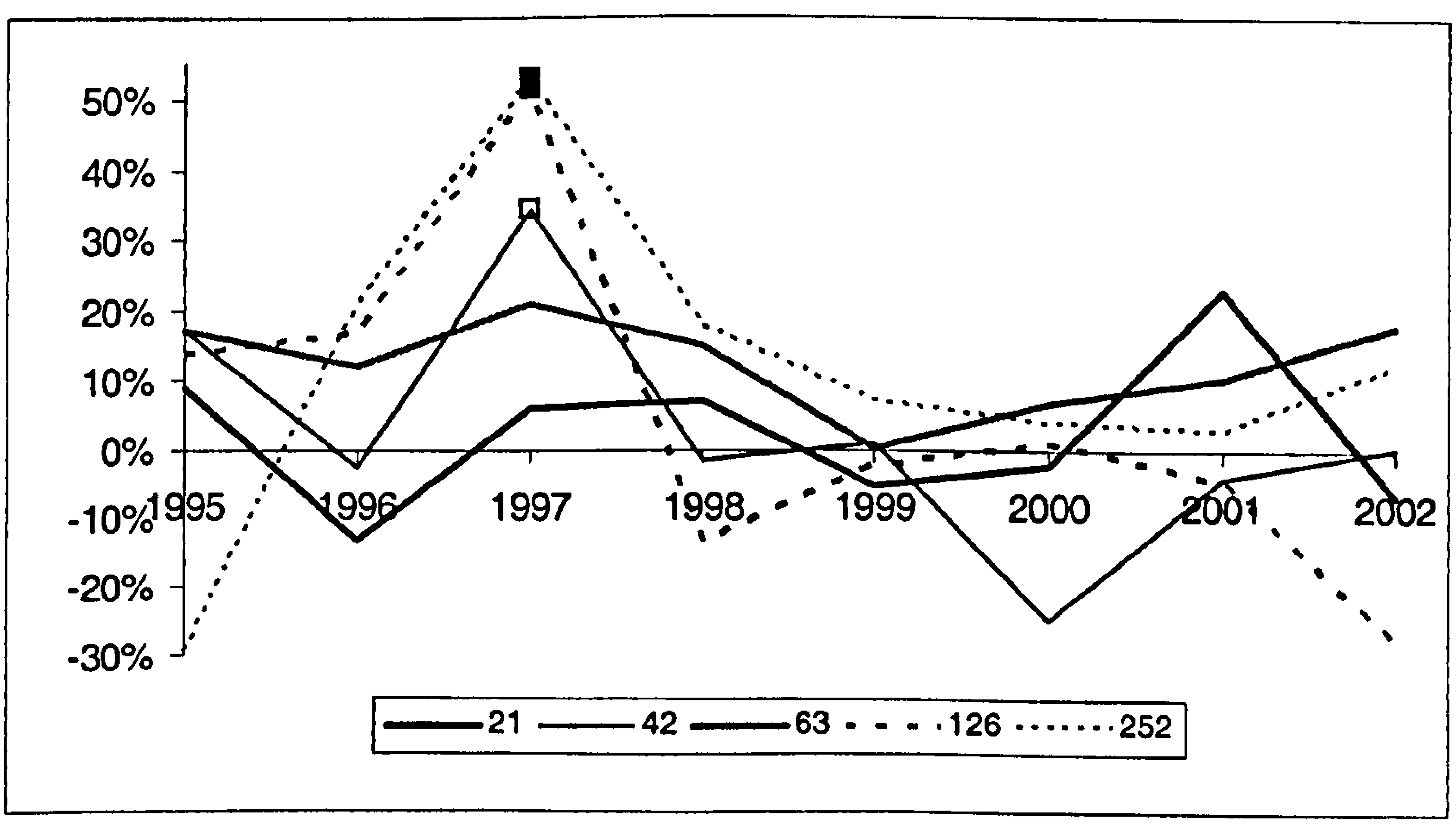
□ denotes bootstrap significance at the 5% level

Switzerland

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

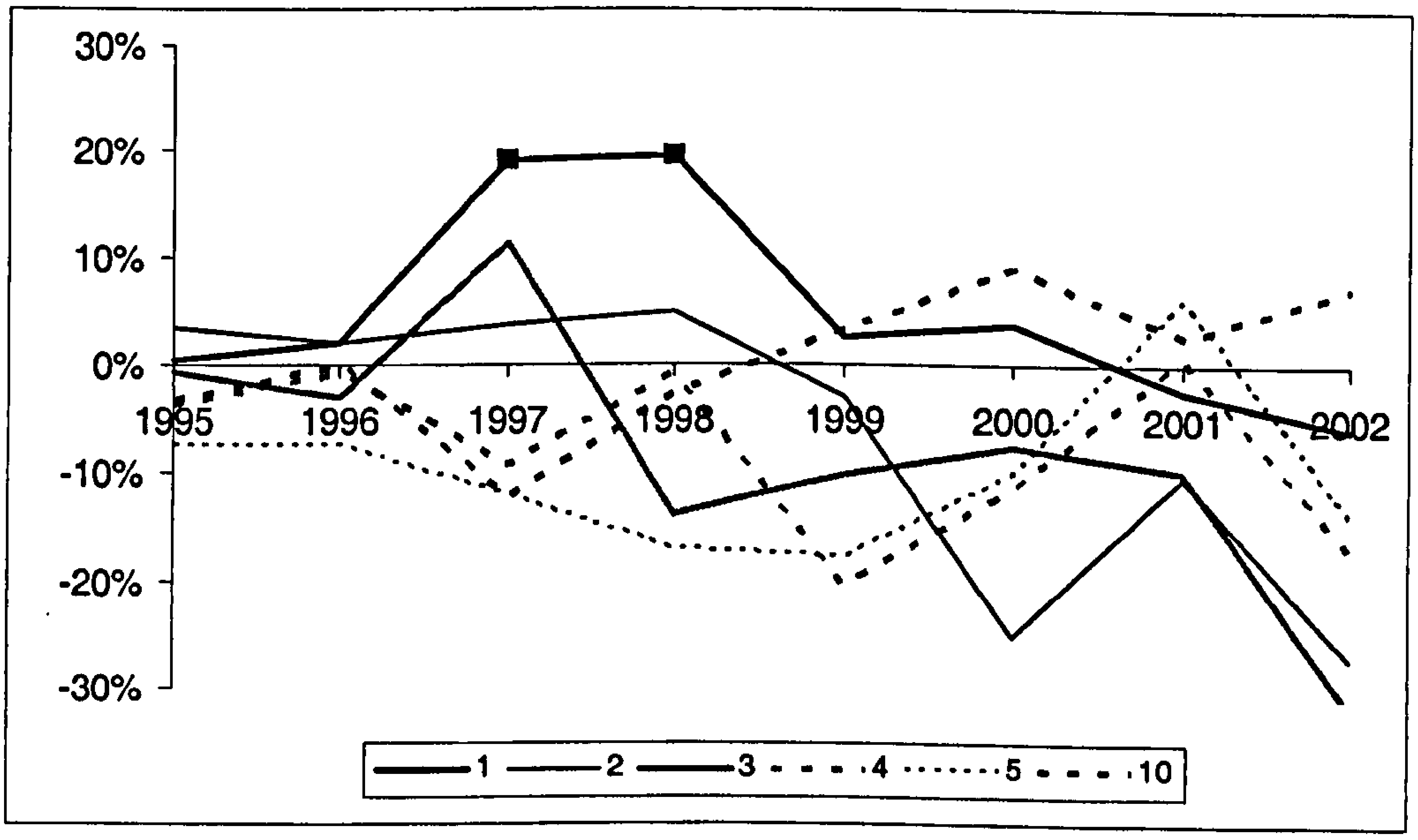


■ denotes bootstrap significance at the 1% level

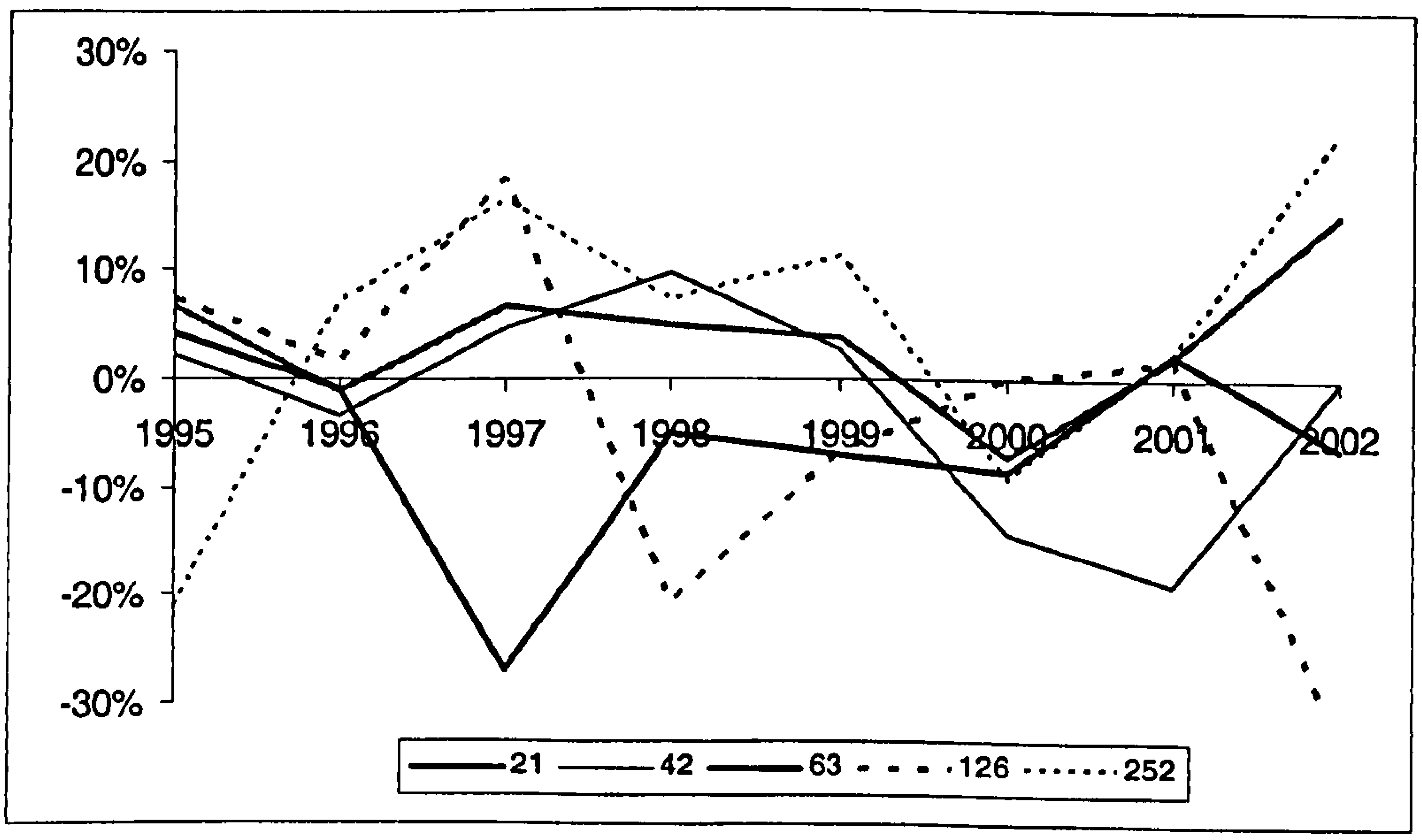
□ denotes bootstrap significance at the 5% level

UK

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies

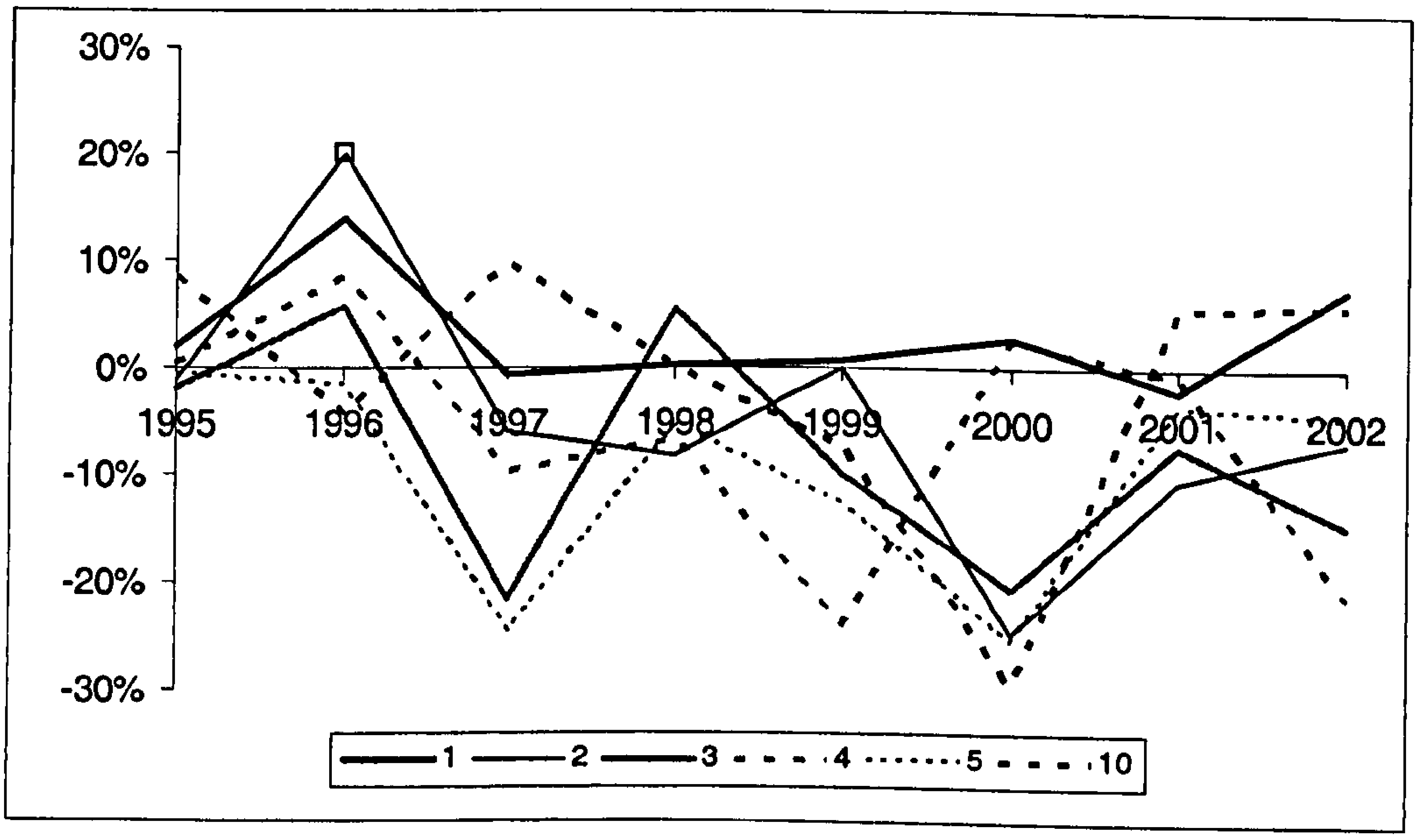


■ denotes bootstrap significance at the 1% level

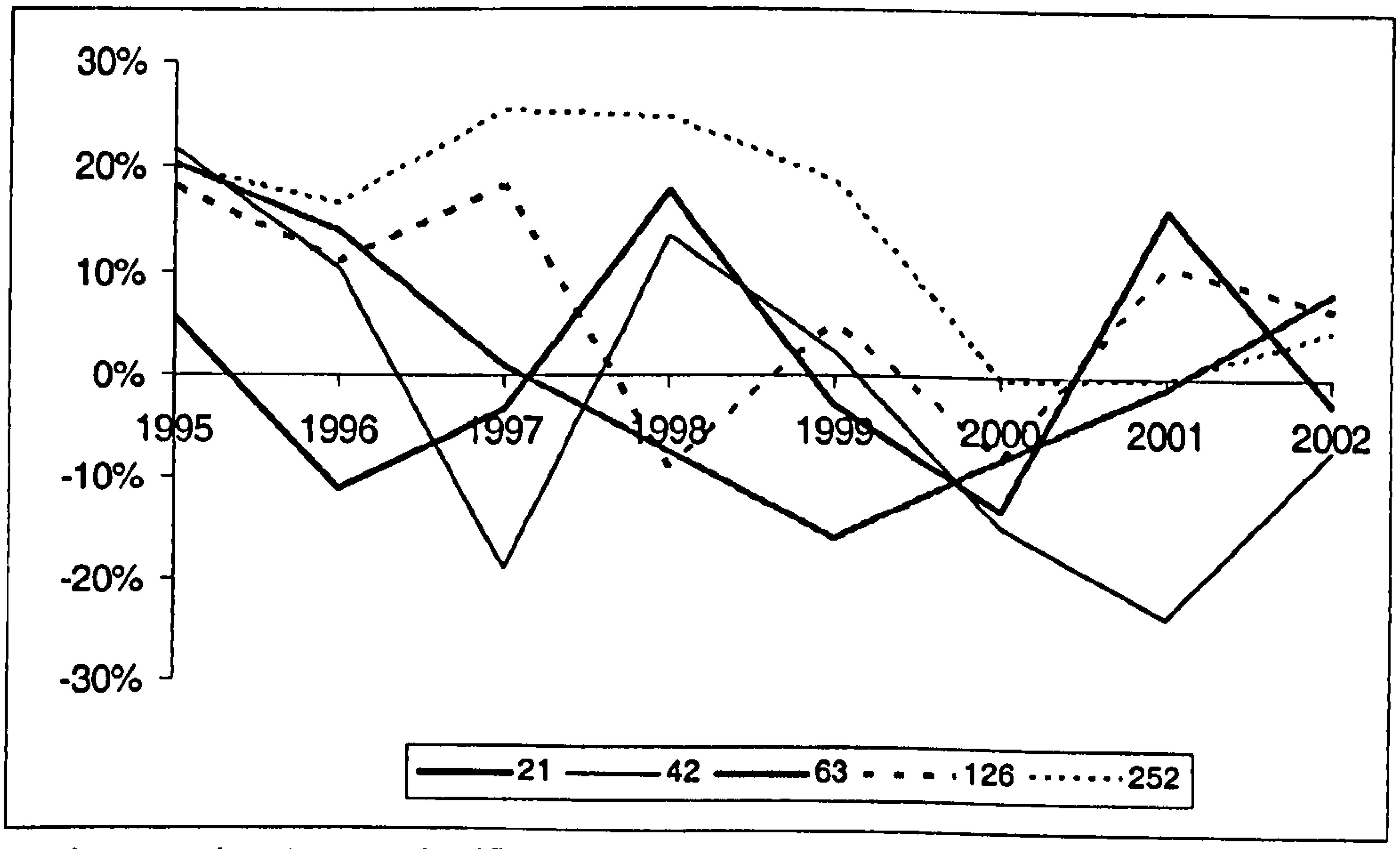
□ denotes bootstrap significance at the 5% level

USA

1 to 10 Trading Day Strategies



21 to 252 Trading Day Strategies



■ denotes bootstrap significance at the 1% level

□ denotes bootstrap significance at the 5% level

Appendix D: Returns to Momentum Strategies (Signals based on Price Returns)

This Appendix presents the returns to momentum strategies where trading signals are generated based on past price returns (rather than on past funded returns as in the original analysis).

The calculation of the returns to each strategy is then carried out based on funded returns as described in detail in Chapter 6.

Table D-1 Cumulative Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	9.66% *0.93%*	-15.91% *0.22%*	-19.81% *1.61%*	-42.17% *0.74%*	-28.44% *1.76%*	-41.99% *1.43%*
Belgium	123.98% *-0.33%* SIG 1%	80.65% *0.58%* SIG 1%	32.31% *1.16%*	6.50% *-0.79%*	-13.75% *-1.32%*	18.02% *-2.97%*
Canada	75.64% *-0.42%* SIG 1%	18.02% *-0.59%*	13.35% *-0.10%*	-9.49% *-1.11%*	18.22% *-0.99%*	38.57% *1.77%*
Denmark	38.78% *-0.11%* SIG 5%	1.23% *0.01%*	5.44% *0.30%*	34.15% *1.44%*	38.13% *-0.02%*	36.12% *-0.02%*
France	20.48% *-1.36%*	-71.12% *-1.27%*	-47.72% *0.48%*	-56.25% *-0.44%*	-75.17% *1.87%*	-0.02% *2.02%*
Germany	-5.73% *15.20%*	-50.18% *-2.18%*	-68.26% *-1.06%*	0.99% *-1.33%*	-4.96% *-4.68%*	-16.84% *0.31%*
Hong Kong	71.43% *-1.78%* SIG 5%	66.59% *-1.34%*	47.43% *-4.09%*	9.18% *-2.30%*	15.18% *-2.01%*	35.92% *-1.70%*
Italy	14.05% *0.68%*	-26.60% *2.17%*	-20.17% *0.81%*	65.22% *1.29%*	-5.69% *1.31%*	95.52% *4.83%* SIG 5%
Japan	22.45% *-0.54%*	8.17% *-2.00%*	-51.33% *-3.25%*	-124.53% *-2.72%*	-107.59% *-3.24%*	-21.99% *-2.49%*
Netherlands	23.39% *0.06%*	-75.67% *0.79%*	-70.83% *-1.16%*	-95.06% *-1.26%*	-57.05% *1.11%*	65.18% *2.46%*
Spain	38.78% *-1.38%*	-31.48% *2.85%*	-32.01% *-1.39%*	-11.58% *1.41%*	25.23% *-0.40%*	75.23% *2.77%*
Switzerland	41.93% *0.97%* SIG 5%	3.90% *0.57%*	-27.45% *0.99%*	-10.29% *0.98%*	-28.18% *1.94%*	72.31% *3.80%* SIG 5%
UK	36.70% *0.76%*	-52.88% *0.17%*	-79.16% *0.10%*	-56.63% *-0.55%*	-73.52% *0.26%*	-7.07% *0.33%*
USA	20.40% *-1.05%*	-38.94% *-0.48%*	-79.52% *2.08%*	-48.22% *1.80%*	-76.48% *2.28%*	-6.77% *3.43%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-1 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-27.37% *2.98%*	-38.68% *2.91%*	-18.44% *5.16%*	-1.17% *6.95%*	1.05% *10.18%*
Belgium	8.45% *0.08%*	65.76% *1.65%*	42.28% *2.83%*	33.20% *5.10%*	64.96% *8.18%*
Canada	34.14% *4.29%*	57.48% *6.07%*	16.13% *7.89%*	-7.07% *12.05%*	79.52% *16.80%* SIG 5%
Denmark	8.30% *1.30%*	10.92% *-0.99%*	85.50% *4.93%* SIG 1%	100.17% *8.11%* SIG 1%	83.29% *10.82%* SIG 5%
France	54.49% *2.67%*	80.23% *3.13%*	75.08% *4.65%*	-13.07% *6.03%*	65.53% *28.33%*
Germany	41.42% *-0.45%*	64.68% *-2.44%*	68.03% *1.28%*	-19.83% *1.90%*	57.58% *3.60%*
Hong Kong	86.63% *-3.89%*	40.74% *-4.61%*	-46.86% *0.35%*	32.72% *-4.00%*	-79.55% *0.15%*
Italy	11.25% *5.38%*	-15.14% *8.01%*	30.22% *5.84%*	50.03% *6.06%*	114.19% *9.49%* SIG 5%
Japan	-34.89% *1.38%*	21.60% *5.66%*	35.77% *1.44%*	4.79% *2.22%*	-15.60% *1.26%*
Netherlands	6.32% *1.91%*	115.28% *4.30%* SIG 5%	111.82% *8.48%* SIG 5%	18.22% *10.44%*	132.80% *16.54%* SIG 1%
Spain	95.57% *2.20%* SIG 5%	43.45% *7.79%*	64.34% *9.80%*	68.37% *14.93%*	125.78% *18.31%* SIG 5%
Switzerland	36.87% *4.72%*	44.66% *5.87%*	92.13% *9.47%* SIG 5%	36.33% *11.56%*	96.32% *16.58%* SIG 5%
UK	-32.43% *1.51%*	-13.45% *2.39%*	29.04% *1.24%*	-41.27% *-0.26%*	72.63% *-2.38%*
USA	6.64% *3.63%*	-17.14% *8.75%*	32.83% *9.93%*	64.44% *10.42%*	113.55% *10.49%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-2 Cumulative Long-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	20.72% *3.07%* SIG 5%	14.23% *4.91%*	-4.03% *5.12%*	-18.07% *5.01%*	-5.34% *6.48%*	1.50% *7.41%*
Belgium	71.88% *2.42%* SIG 1%	39.58% *5.00%* SIG 1%	37.51% *6.91%* SIG 5%	28.76% *5.61%*	24.68% *5.32%*	30.50% *5.96%*
Canada	47.35% *3.31%* SIG 1%	28.13% *3.83%*	19.48% *5.87%*	12.47% *6.62%*	32.41% *6.99%*	40.61% *10.41%* SIG 5%
Denmark	35.30% *3.37%* SIG 1%	21.02% *4.20%*	41.84% *5.80%* SIG 5%	56.71% *6.71%* SIG 1%	65.13% *6.44%* SIG 1%	38.07% *7.23%* SIG 5%
France	19.48% *2.25%*	-22.94% *3.36%*	4.10% *5.50%*	-5.16% *6.44%*	-14.66% *8.79%*	22.94% *10.00%*
Germany	5.46% *5.28%*	-15.28% *-0.31%*	-24.25% *1.39%*	-8.07% *1.64%*	11.46% *1.02%*	-6.09% *4.18%*
Hong Kong	56.54% *-2.68%* SIG 5%	41.69% *-4.99%*	14.79% *-5.37%*	-6.05% *-6.11%*	31.01% *-6.79%*	33.08% *-6.61%*
Italy	3.54% *3.85%*	-9.30% *6.85%*	14.06% *7.45%*	65.90% *7.89%* SIG 5%	39.36% *7.99%*	87.44% *9.78%* SIG 1%
Japan	5.91% *-2.39%*	27.87% *-4.81%*	5.53% *-5.17%*	-36.35% *-5.55%*	-17.01% *-7.28%*	0.88% *-7.03%*
Netherlands	35.32% *4.26%* SIG 5%	-29.90% *5.73%*	-29.33% *6.65%*	-58.09% *7.50%*	-8.30% *11.01%*	51.09% *13.54%* SIG 5%
Spain	20.02% *3.45%*	-24.94% *8.10%*	-16.56% *7.74%*	17.98% *10.40%*	54.34% *10.87%* SIG 5%	62.73% *14.70%* SIG 5%
Switzerland	27.58% *3.93%* SIG 5%	28.58% *5.79%*	-6.67% *8.10%*	13.66% *9.43%*	14.54% *10.68%*	58.93% *13.19%* SIG 1%
UK	16.53% *0.95%*	-18.99% *0.74%*	-24.28% *0.83%*	-9.06% *0.32%*	-26.01% *0.53%*	19.07% *0.99%*
USA	40.42% *3.23%* SIG 1%	-1.07% *4.17%*	-14.06% *7.19%*	15.38% *6.98%*	12.63% *8.23%*	46.74% *10.05%* SIG 5%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-2 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	2.54% *8.40%*	0.89% *8.93%*	9.60% *10.26%*	-0.63% *12.14%*	18.82% *14.55%*
Belgium	43.46% *9.56%* SIG 5%	67.76% *10.96%* SIG 1%	51.24% *10.78%* SIG 5%	66.47% *13.30%* SIG 1%	83.31% *14.51%* SIG 1%
Canada	57.37% *12.26%* SIG 1%	75.01% *14.16%* SIG 1%	31.81% *16.64%*	5.82% *19.72%*	66.46% *22.53%* SIG 1%
Denmark	15.95% *7.34%*	19.13% *6.34%*	78.24% *11.30%* SIG 1%	89.22% *13.35%* SIG 1%	74.36% *16.44%* SIG 1%
France	36.91% *12.26%*	58.55% *12.76%* SIG 5%	88.98% *13.65%* SIG 1%	29.96% *14.63%*	69.41% *25.47%* SIG 1%
Germany	34.01% *4.84%*	61.42% *3.79%*	75.92% *6.29%* SIG 5%	-3.09% *6.87%*	57.58% *8.32%*
Hong Kong	94.56% *-10.17%* SIG 1%	19.75% *-10.38%*	-19.04% *-8.77%*	-7.65% *-11.00%*	11.21% *-9.36%*
Italy	34.43% *12.66%*	-0.90% *12.84%*	41.73% *11.68%*	41.44% *12.59%*	92.68% *16.50%* SIG 1%
Japan	9.92% *-5.52%*	8.18% *-3.85%*	0.01% *-5.76%*	14.71% *-6.00%*	-10.44% *-6.04%*
Netherlands	15.27% *14.19%*	69.23% *17.11%* SIG 5%	108.22% *19.47%* SIG 1%	47.76% *22.02%* SIG 5%	107.07% *23.92%* SIG 1%
Spain	102.06% *14.12%* SIG 1%	57.78% *17.35%* SIG 5%	91.35% *20.21%* SIG 1%	78.95% *23.51%* SIG 1%	111.62% *25.46%* SIG 1%
Switzerland	34.66% *15.47%*	36.58% *17.57%*	102.33% *19.41%* SIG 1%	64.14% *21.01%* SIG 1%	96.32% *25.35%* SIG 1%
UK	-10.36% *1.89%*	9.00% *1.60%*	25.25% *1.43%*	-4.64% *0.82%*	60.47% *-0.48%* SIG 5%
USA	21.69% *11.58%*	26.16% *15.60%*	57.64% *16.75%* SIG 1%	48.79% *17.30%* SIG 5%	97.07% *18.29%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-3 Cumulative Short-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	-11.06% *-2.14%*	-30.14% *-4.69%*	-15.79% *-3.50%*	-24.09% *-4.27%*	-23.10% *-4.73%*	-43.50% *-5.98%*
Belgium	52.10% *-2.76%* SIG 1%	41.06% *-4.42%* SIG 1%	-5.20% *-5.75%*	-22.26% *-6.40%*	-38.42% *-6.63%*	-12.48% *-8.93%*
Canada	28.29% *-3.73%* SIG 5%	-10.11% *-4.42%*	-6.14% *-5.96%*	-21.96% *-7.74%*	-14.19% *-7.98%*	-2.04% *-8.64%*
Denmark	3.48% *-3.48%*	-19.79% *-4.19%*	-36.41% *-5.49%*	-22.56% *-5.27%*	-27.00% *-6.46%*	-1.95% *-7.25%*
France	1.01% *-3.61%*	-48.18% *-4.62%*	-51.83% *-5.02%*	-51.09% *-6.88%*	-60.51% *-6.91%*	-22.97% *-7.98%*
Germany	-11.19% *9.92%*	-34.90% *-1.86%*	-44.01% *-2.45%*	9.05% *-2.98%*	-16.42% *-5.70%*	-10.75% *-3.88%*
Hong Kong	14.88% *0.90%*	24.90% *3.65%*	32.64% *1.28%*	15.23% *3.81%*	-15.82% *4.78%*	2.84% *4.92%*
Italy	10.51% *-3.17%*	-17.30% *-4.68%*	-34.23% *-6.64%*	-0.68% *-6.59%*	-45.05% *-6.68%*	8.08% *-4.95%*
Japan	16.54% *1.85%*	-19.69% *2.81%*	-56.86% *1.92%*	-88.18% *2.82%*	-90.58% *4.05%*	-22.88% *4.54%*
Netherlands	-11.93% *-4.20%*	-45.78% *-4.94%*	-41.50% *-7.81%*	-36.96% *-8.76%*	-48.74% *-9.90%*	14.09% *-11.08%*
Spain	18.75% *-4.84%*	-6.54% *-5.25%*	-15.44% *-9.13%*	-29.55% *-9.00%*	-29.10% *-11.27%*	12.50% *-11.93%*
Switzerland	14.36% *-2.96%*	-24.68% *-5.21%*	-20.78% *-7.12%*	-23.95% *-8.45%*	-42.72% *-8.74%*	13.38% *-9.40%*
UK	20.17% *-0.19%*	-33.89% *-0.57%*	-54.88% *-0.73%*	-47.58% *-0.86%*	-47.50% *-0.27%*	-26.13% *-0.66%*
USA	-20.02% *-4.29%*	-37.87% *-4.65%*	-65.46% *-5.11%*	-63.60% *-5.18%*	-89.11% *-5.95%*	-53.51% *-6.62%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-3 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-29.91% *-5.42%*	-39.57% *-6.03%*	-28.04% *-5.11%*	-0.54% *-5.19%*	-17.77% *-4.37%*
Belgium	-35.01% *-9.49%*	-2.00% *-9.31%*	-8.96% *-7.96%*	-33.27% *-8.20%*	-18.35% *-6.33%*
Canada	-23.23% *-7.97%*	-17.53% *-8.09%*	-15.67% *-8.75%*	-12.90% *-7.67%*	13.06% *-5.73%*
Denmark	-7.65% *-6.04%*	-8.20% *-7.33%*	7.26% *-6.37%*	10.94% *-5.24%*	8.93% *-5.62%*
France	17.58% *-9.60%*	21.68% *-9.63%*	-13.90% *-9.00%*	-43.03% *-8.61%*	-3.88% *2.86%*
Germany	7.41% *-5.29%*	3.26% *-6.23%*	-7.89% *-5.01%*	-16.74% *-4.97%*	0.00% *-4.72%*
Hong Kong	-7.94% *6.27%*	20.99% *5.78%*	-27.82% *9.13%*	40.37% *7.00%*	-90.76% *9.51%*
Italy	-23.17% *-7.28%*	-14.24% *-4.84%*	-11.51% *-5.84%*	8.59% *-6.54%*	21.51% *-7.01%*
Japan	-44.80% *6.90%*	13.42% *9.51%*	35.77% *7.20%*	-9.92% *8.21%*	-5.16% *7.30%*
Netherlands	-8.95% *-12.28%*	46.04% *-12.81%* SIG 5%	3.60% *-10.99%*	-29.54% *-11.58%*	25.72% *-7.38%*
Spain	-6.50% *-11.92%*	-14.33% *-9.56%*	-27.01% *-10.40%*	-10.58% *-8.58%*	14.16% *-7.15%*
Switzerland	2.21% *-10.74%*	8.08% *-11.70%*	-10.20% *-9.94%*	-27.80% *-9.45%*	0.00% *-8.77%*
UK	-22.07% *-0.39%*	-22.45% *0.79%*	3.79% *-0.19%*	-36.63% *-1.08%*	12.16% *-1.90%*
USA	-15.05% *-7.95%*	-43.30% *-6.85%*	-24.82% *-6.82%*	15.65% *-6.88%*	16.48% *-7.80%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-4 Mean Transaction Profits

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	0.0276% *0.0027%*	-0.0621% *0.0010%*	-0.0976% *0.0077%*	-0.2396% *0.0044%*	-0.1961% *0.0118%*	-0.4772% *0.0154%*
Belgium	0.2938% *-0.0010%* SIG 1%	0.2466% *0.0026%* SIG 5%	0.1330% *0.0064%*	0.0312% *-0.0048%*	-0.0768% *-0.0092%*	0.1749% *-0.0350%*
Canada	0.2107% *-0.0015%* SIG 1%	0.0583% *-0.0027%*	0.0556% *-0.0007%*	-0.0479% *-0.0069%*	0.1091% *-0.0073%*	0.3745% *0.0204%*
Denmark	0.0887% *-0.0003%*	0.0040% *0.0000%*	0.0222% *0.0012%*	0.1751% *0.0079%*	0.2297% *-0.0004%*	0.3762% *-0.0018%*
France	0.0481% *-0.0042%*	-0.2244% *-0.0053%*	-0.1917% *0.0024%*	-0.2827% *-0.0029%*	-0.4396% *0.0121%*	-0.0003% *0.0231%*
Germany	-0.0139% *0.0477%*	-0.1701% *-0.0090%*	-0.2821% *-0.0054%*	0.0051% *-0.0087%*	-0.0299% *-0.0329%*	-0.1792% *0.0046%*
Hong Kong	0.2113% *-0.0060%* SIG 5%	0.2581% *-0.0056%*	0.2445% *-0.0215%*	0.0540% *-0.0142%*	0.0999% *-0.0132%*	0.3991% *-0.0212%*
Italy	0.0372% *0.0018%*	-0.0967% *0.0080%*	-0.0994% *0.0041%*	0.3706% *0.0078%*	-0.0360% *0.0095%*	1.0497% *0.0520%* SIG 5%
Japan	0.0592% *-0.0015%*	0.0292% *-0.0079%*	-0.2261% *-0.0163%*	-0.6520% *-0.0159%*	-0.6601% *-0.0220%*	-0.2499% *-0.0307%*
Netherlands	0.0538% *0.0002%*	-0.2402% *0.0039%*	-0.3093% *-0.0059%*	-0.4850% *-0.0080%*	-0.3500% *0.0080%*	0.7492% *0.0288%*
Spain	0.0912% *-0.0039%*	-0.1029% *0.0111%*	-0.1404% *-0.0070%*	-0.0636% *0.0084%*	0.1529% *-0.0028%*	0.7448% *0.0314%*
Switzerland	0.1095% *0.0032%*	0.0143% *0.0023%*	-0.1283% *0.0056%*	-0.0562% *0.0065%*	-0.1830% *0.0146%*	0.8311% *0.0440%* SIG 5%
UK	0.0866% *0.0024%*	-0.1663% *0.0007%*	-0.3298% *0.0000%*	-0.3029% *-0.0033%*	-0.4595% *0.0020%*	-0.0803% *0.0048%*
USA	0.0492% *-0.0032%*	-0.1281% *-0.0025%*	-0.3259% *0.0104%*	-0.2399% *0.0109%*	-0.4446% *0.0158%*	-0.0728% *0.0387%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-4 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-0.6083% *0.0607%*	-1.6118% *0.1090%*	-1.0846% *0.2842%*	-0.1169% *0.6949%*	0.2107% *1.8724%*
Belgium	0.1537% *-0.0006%*	2.1211% *0.0740%*	1.9218% *0.1528%*	2.2134% *0.5524%*	9.2798% *1.5498%*
Canada	0.6566% *0.0883%*	1.9820% *0.2349%*	0.7683% *0.4205%*	-0.5442% *1.2097%*	11.3594% *3.0124%*
Denmark	0.1482% *0.0294%*	0.3310% *-0.0337%*	4.0716% *0.2765%* SIG 5%	7.1548% *0.8150%* SIG 5%	10.4114% *1.9330%*
France	1.0898% *0.0598%*	3.2093% *0.1252%*	3.5752% *0.2591%*	-1.0892% *0.6120%*	10.9221% *4.9140%*
Germany	0.7966% *-0.0097%*	2.3101% *-0.1041%*	3.5808% *0.0438%*	-1.8025% *0.1243%*	11.5156% *0.7120%*
Hong Kong	1.7679% *-0.0899%*	1.6297% *-0.1689%*	-2.4662% *0.0391%*	3.2721% *-0.4146%*	-13.2583% *-0.0822%*
Italy	0.2084% *0.1112%*	-0.5607% *0.3037%*	1.6790% *0.3229%*	4.5480% *0.6539%*	22.8378% *1.7148%* SIG 5%
Japan	-0.7423% *0.0330%*	0.8308% *0.2282%*	2.1044% *0.0747%*	0.5324% *0.2481%*	-3.9002% *0.3921%*
Netherlands	0.1239% *0.0391%*	4.6110% *0.1708%* SIG 5%	5.8855% *0.4500%* SIG 5%	1.4014% *1.0601%*	18.9708% *3.0704%* SIG 5%
Spain	1.8378% *0.0461%* SIG 5%	1.4981% *0.3025%*	3.0640% *0.5420%*	6.8368% *1.5284%*	20.9638% *3.2657%* SIG 5%
Switzerland	0.6827% *0.1001%*	1.8610% *0.2357%*	4.8490% *0.5418%* SIG 5%	2.7949% *1.2058%*	16.0529% *3.2176%*
UK	-0.7049% *0.0342%*	-0.5605% *0.0810%*	1.6136% *0.0795%*	-3.7521% *-0.0018%*	12.1049% *-0.5383%*
USA	0.1328% *0.0698%*	-0.5910% *0.3290%*	1.7277% *0.5498%*	5.8578% *1.0673%*	18.9245% *1.6824%* SIG 5%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-5 Mean Transaction and Daily Profit by Strategy Length

Strategy Length (Trading Days)	Mean Transaction Profit	Mean Daily Profit
1	0.0966%	0.0966%
2	-0.0414%	-0.0207%
3	-0.1197%	-0.0399%
4	-0.1238%	-0.0310%
5	-0.1631%	-0.0326%
10	0.2600%	0.0260%
21	0.3959%	0.0189%
42	1.2186%	0.0290%
63	2.2350%	0.0355%
126	1.9505%	0.0155%
252	10.4568%	0.0415%

Table shows the mean transaction profit across all 14 data sets for each strategy length together with the mean daily profit for days on which each strategy holds a market position.

Table D-6 Standard Deviation of Daily Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	6.62% *5.62%* SIG 1%	7.79% *6.91%* SIG 5%	8.37% *7.56%* SIG 5%	8.75% *7.96%*	8.79% *8.21%*	9.63% *8.94%*
Belgium	10.47% *6.57%* SIG 1%	12.25% *8.09%* SIG 1%	12.72% *8.94%* SIG 1%	13.08% *9.53%* SIG 1%	13.94% *9.91%* SIG 1%	14.59% *10.99%* SIG 1%
Canada	8.46% *6.59%* SIG 1%	10.88% *8.23%* SIG 1%	12.10% *9.13%* SIG 1%	12.71% *9.69%* SIG 1%	12.18% *10.10%* SIG 1%	13.14% *11.19%* SIG 1%
Denmark	10.27% *6.93%* SIG 1%	11.70% *8.49%* SIG 1%	12.03% *9.34%* SIG 1%	12.29% *9.85%* SIG 1%	12.52% *10.25%* SIG 1%	13.29% *11.22%* SIG 1%
France	11.59% *8.61%* SIG 1%	14.88% *10.63%* SIG 1%	15.11% *11.76%* SIG 1%	15.62% *12.46%* SIG 1%	16.35% *12.93%* SIG 1%	16.51% *14.22%* SIG 1%
Germany	13.05% *9.21%* SIG 1%	16.31% *11.51%* SIG 1%	16.94% *12.72%* SIG 1%	17.45% *13.53%* SIG 1%	18.08% *14.10%* SIG 1%	19.29% *16.27%* SIG 1%
Hong Kong	14.78% *10.89%* SIG 1%	16.79% *13.32%* SIG 1%	17.71% *14.76%* SIG 1%	18.57% *15.58%* SIG 1%	19.46% *16.27%* SIG 1%	21.22% *18.07%* SIG 1%
Italy	12.83% *10.30%* SIG 1%	16.05% *12.55%* SIG 1%	16.36% *13.70%* SIG 1%	16.72% *14.45%* SIG 1%	17.69% *14.96%* SIG 1%	18.44% *16.27%* SIG 1%
Japan	10.29% *8.38%* SIG 1%	13.10% *10.17%* SIG 1%	13.86% *11.15%* SIG 1%	14.24% *11.82%* SIG 1%	14.68% *12.21%* SIG 1%	15.71% *13.32%* SIG 1%
Netherlands	12.97% *8.22%* SIG 1%	15.74% *10.49%* SIG 1%	15.96% *11.67%* SIG 1%	17.07% *12.46%* SIG 1%	17.84% *13.02%* SIG 1%	17.76% *14.48%* SIG 1%
Spain	12.63% *9.33%* SIG 1%	15.43% *11.53%* SIG 1%	15.84% *12.68%* SIG 1%	16.10% *13.45%* SIG 1%	17.20% *13.93%* SIG 1%	18.10% *15.27%* SIG 1%
Switzerland	11.65% *7.35%* SIG 1%	13.36% *9.18%* SIG 1%	14.23% *10.17%* SIG 1%	15.54% *10.80%* SIG 1%	15.08% *11.27%* SIG 1%	15.73% *12.50%* SIG 1%
UK	9.46% *6.85%* SIG 1%	11.30% *8.54%* SIG 1%	12.34% *9.43%* SIG 1%	12.41% *9.98%* SIG 1%	12.18% *10.39%* SIG 1%	13.38% *11.40%* SIG 1%
USA	10.00% *7.47%* SIG 1%	12.11% *8.92%* SIG 1%	12.55% *9.80%* SIG 1%	13.38% *10.37%* SIG 1%	13.24% *10.76%* SIG 1%	13.76% *11.88%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-6 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	9.78% *9.52%*	9.89% *9.88%*	10.05% *10.02%*	10.31% *10.38%*	10.79% *10.65%*
Belgium	15.07% *11.76%* SIG 1%	15.61% *12.25%* SIG 1%	15.70% *12.46%* SIG 1%	16.55% *13.01%* SIG 1%	17.06% *13.29%* SIG 5%
Canada	13.26% *11.97%* SIG 5%	13.72% *12.58%*	14.49% *12.88%*	16.46% *13.28%* SIG 5%	17.33% *13.78%*
Denmark	14.23% *11.87%* SIG 1%	14.68% *12.48%* SIG 1%	14.66% *12.69%* SIG 5%	16.35% *13.09%* SIG 1%	17.79% *13.42%* SIG 1%
France	17.66% *15.15%* SIG 1%	17.39% *15.79%*	19.37% *16.04%* SIG 1%	20.48% *16.47%* SIG 1%	19.04% *17.43%*
Germany	19.45% *16.61%* SIG 1%	20.25% *17.26%* SIG 1%	19.92% *17.45%*	21.45% *17.90%* SIG 5%	19.62% *18.07%*
Hong Kong	22.63% *19.38%* SIG 5%	21.30% *20.28%*	22.86% *20.60%*	18.96% *20.81%*	25.54% *20.60%*
Italy	19.63% *17.29%* SIG 1%	19.95% *17.97%*	20.25% *18.27%*	20.65% *18.78%*	21.20% *19.30%*
Japan	15.56% *14.10%* SIG 5%	15.58% *14.58%*	15.78% *14.87%*	15.91% *15.01%*	14.50% *14.97%*
Netherlands	18.89% *15.56%* SIG 1%	18.14% *16.25%*	19.84% *16.49%* SIG 1%	21.15% *17.07%* SIG 5%	19.82% *17.52%*
Spain	19.11% *16.25%* SIG 1%	19.82% *16.97%* SIG 1%	19.60% *17.21%*	20.10% *17.73%*	22.48% *18.56%*
Switzerland	16.42% *13.50%* SIG 1%	15.72% *14.17%*	16.47% *14.47%*	18.32% *15.00%* SIG 5%	15.70% *15.55%*
UK	14.12% *12.16%* SIG 1%	13.75% *12.56%*	14.42% *12.78%*	14.87% *12.97%*	15.03% *13.12%*
USA	14.69% *12.75%* SIG 5%	14.70% *13.27%*	14.74% *13.60%*	15.14% *14.10%*	16.12% *14.69%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-7 Sharpe Ratios

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	0.16 *0.02*	-0.23 *0.00*	-0.26 *0.02*	-0.53 *0.01*	-0.36 *0.00*	-0.48 *0.02*
Belgium	1.31 *-0.01* SIG 1%	0.73 *0.01* SIG 5%	0.28 *0.01*	0.05 *-0.01*	-0.11 *-0.02*	0.14 *-0.03*
Canada	0.99 *-0.01* SIG 1%	0.18 *-0.01*	0.12 *0.00*	-0.08 *-0.01*	0.17 *-0.01*	0.33 *0.02*
Denmark	0.42 *0.00*	0.01 *0.00*	0.05 *0.00*	0.31 *0.02*	0.34 *0.00*	0.30 *0.00*
France	0.20 *-0.02*	-0.53 *-0.01*	-0.35 *0.01*	-0.40 *0.00*	-0.51 *0.02*	0.00 *0.02*
Germany	-0.05 *0.18*	-0.34 *-0.02*	-0.45 *-0.01*	0.01 *-0.01*	-0.03 *-0.03*	-0.10 *0.00*
Hong Kong	0.53 *-0.02*	0.44 *-0.01*	0.29 *-0.03*	0.05 *-0.02*	0.09 *0.00*	0.19 *-0.01*
Italy	0.12 *0.01*	-0.18 *0.02*	-0.14 *0.01*	0.43 *0.01*	-0.04 *0.01*	0.57 *0.03* SIG 5%
Japan	0.25 *-0.01*	0.07 *-0.02*	-0.42 *-0.03*	-0.99 *-0.03*	-0.83 *-0.03*	-0.16 *-0.02*
Netherlands	0.20 *0.00*	-0.53 *0.01*	-0.49 *-0.01*	-0.61 *-0.01*	-0.35 *0.01*	0.40 *0.02*
Spain	0.34 *-0.02*	-0.23 *0.03*	-0.22 *-0.01*	-0.08 *0.01*	0.16 *0.00*	0.46 *0.02*
Switzerland	0.40 *0.01*	0.03 *0.01*	-0.22 *0.01*	-0.07 *0.01*	-0.21 *0.02*	0.51 *0.03*
UK	0.43 *0.01*	-0.52 *0.00*	-0.71 *0.00*	-0.51 *-0.01*	-0.67 *0.00*	-0.06 *0.00*
USA	0.23 *-0.02*	-0.36 *-0.01*	-0.70 *0.02*	-0.40 *0.02*	-0.64 *0.02*	-0.05 *0.03*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table D-7 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-0.31 *0.01*	-0.43 *0.03*	-0.20 *0.06*	-0.01 *0.07*	0.01 *0.07*
Belgium	0.06 *0.00*	0.47 *0.01*	0.30 *0.02*	0.22 *0.04*	0.42 *0.06*
Canada	0.29 *0.04*	0.47 *0.05*	0.12 *0.07*	-0.05 *0.09*	0.51 *0.12*
Denmark	0.06 *0.01*	0.08 *-0.01*	0.64 *0.04* SIG 5%	0.68 *0.06* SIG 5%	0.52 *0.08*
France	0.34 *0.02*	0.51 *0.02*	0.43 *0.03*	-0.07 *0.04*	0.38 *0.16*
Germany	0.24 *0.00*	0.35 *-0.02*	0.38 *0.01*	-0.10 *0.01*	0.33 *0.02*
Hong Kong	0.42 *-0.02*	0.21 *-0.03*	-0.23 *0.00*	0.19 *-0.02*	-0.34 *0.00*
Italy	0.06 *0.03*	-0.08 *0.05*	0.16 *0.03*	0.27 *0.03*	0.59 *0.04* SIG 5%
Japan	-0.25 *0.01*	0.16 *0.04*	0.26 *0.01*	0.03 *0.02*	-0.12 *0.01*
Netherlands	0.04 *0.01*	0.70 *0.03* SIG 5%	0.62 *0.05* SIG 5%	0.09 *0.06*	0.74 *0.09* SIG 1%
Spain	0.56 *0.01*	0.24 *0.05*	0.37 *0.06*	0.38 *0.09*	0.62 *0.09* SIG 5%
Switzerland	0.25 *0.04*	0.32 *0.05*	0.62 *0.07* SIG 5%	0.22 *0.08*	0.68 *0.11* SIG 5%
UK	-0.25 *0.01*	-0.11 *0.02*	0.22 *0.01*	-0.31 *0.00*	0.54 *-0.02*
USA	0.05 *0.03*	-0.13 *0.07*	0.25 *0.08*	0.47 *0.08*	0.78 *0.06* SIG 5%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Appendix E: Returns to Momentum Strategies (Signals based on Total Returns)

This Appendix presents the returns to momentum strategies where trading signals are generated based on past total returns (rather than on past funded returns as in the original analysis).

The calculation of the returns to each strategy is then carried out based on funded returns as described in detail in Chapter 6.

Table E-1 Cumulative Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	8.49% *-0.23%*	-12.35% *0.55%*	-16.19% *0.62%*	-38.42% *1.67%*	-28.95% *2.01%*	-34.52% *--1.28%*
Belgium	131.44% *-0.41%* SIG 1%	84.16% *0.84%* SIG 1%	40.47% *-0.97%*	22.94% *-0.91%*	-16.07% *-1.63%*	22.98% *-1.86%*
Canada	73.97% *1.36%* SIG 1%	23.17% *-0.33%*	9.86% *0.06%*	-11.47% *-0.50%*	29.73% *0.39%*	32.40% *2.07%*
Denmark	37.14% *-0.67%*	-1.79% *1.65%*	4.15% *1.65%*	35.11% *1.93%*	46.30% *0.83%*	34.70% *0.41%*
France	22.80% *0.99%*	-67.72% *-0.18%*	-48.13% *-1.09%*	-52.06% *0.88%*	-76.72% *0.70%*	-3.34% *-0.55%*
Germany	-2.54% *-1.58%*	-49.62% *-1.77%*	-63.95% *-1.05%*	-3.37% *-0.67%*	-22.51% *-4.11%*	-25.05% *-0.65%*
Hong Kong	71.20% *0.47%* SIG 5%	70.56% *3.33%*	51.26% *1.96%*	2.16% *-1.28%*	26.81% *-1.79%*	32.91% *-2.55%*
Italy	15.84% *1.26%*	-21.64% *2.30%*	-16.56% *0.91%*	69.81% *1.52%*	-5.40% *1.71%*	94.74% *5.58%* SIG 5%
Japan	23.29% *-0.89%*	4.53% *-1.94%*	-47.56% *-0.98%*	-126.79% *0.03%*	-110.63% *-2.27%*	-19.67% *-2.83%*
Netherlands	24.52% *1.47%*	-74.16% *-1.32%*	-69.10% *-1.94%*	-90.95% *0.19%*	-58.88% *2.78%*	80.37% *2.10%* SIG 5%
Spain	42.62% *-0.93%*	-48.13% *2.62%*	-22.15% *-1.30%*	-1.26% *1.90%*	29.88% *0.81%*	79.84% *2.75%*
Switzerland	47.26% *1.17%* SIG 5%	4.89% *0.88%*	-39.84% *1.21%*	-20.90% *1.84%*	-31.41% *2.38%*	75.60% *4.43%* SIG 5%
UK	36.81% *0.36%*	-50.25% *0.33%*	-63.75% *0.03%*	-53.72% *-0.66%*	-72.07% *0.36%*	37.93% *-0.16%*
USA	21.71% *-1.00%*	-38.53% *-0.18%*	-81.44% *2.07%*	-50.66% *2.41%*	-68.85% *2.31%*	-15.88% *-1.27%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-1 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-21.90% *2.67%*	-36.52% *5.05%*	-30.19% *7.08%*	-14.38% *10.15%*	25.36% *14.22%*
Belgium	-3.99% *1.36%*	61.68% *3.73%*	40.41% *4.17%*	1.87% *8.67%*	90.83% *11.47* SIG 5%
Canada	35.36% *4.05%*	58.90% *7.13%*	44.97% *9.62%*	4.01% *15.68%*	86.89% *21.12%* SIG 5%
Denmark	-5.54% *2.61%*	11.41% *4.73%*	63.13% *5.55%*	93.45% *10.34%* SIG 1%	84.41% *12.13%* SIG 5%
France	54.37% *4.38%*	87.54% *4.95%* SIG 5%	79.06% *6.29%*	-17.94% *8.22%*	114.44% *11.16%* SIG 5%
Germany	48.68% *-2.10%*	72.12% *-2.21%*	83.00% *0.88%*	-12.94% *2.90%*	77.52% *2.66%*
Hong Kong	84.17% *-4.58%*	22.42% *-6.51%*	-29.57% *-0.76%*	12.16% *-6.06%*	-106.84% *-1.71%*
Italy	25.47% *4.87%*	-18.04% *8.68%*	24.28% *7.06%*	56.92% *6.55%*	115.84% *11.62%* SIG 5%
Japan	-21.66% *0.70%*	26.79% *4.56%*	28.29% *1.14%*	-0.68% *2.07%*	-13.65% *1.15%*
Netherlands	36.54% *2.81%*	99.07% *7.02%* SIG 5%	120.99% *10.17%* SIG 1%	28.44% *14.05%*	136.32% *20.81%* SIG 1%
Spain	87.17% *3.22%*	7.32% *9.94%*	76.39% *11.72%*	49.26% *17.65%*	135.41% *21.44%* SIG 1%
Switzerland	38.87% *4.50%*	22.09% *6.33%*	94.34% *11.06%* SIG 5%	35.87% *13.59%*	97.68% *19.10%* SIG 5%
UK	-4.57% *1.52%*	-16.15% *1.05%*	31.63% *-6.94%*	-36.55% *-0.49%*	69.90% *-37.66%* SIG 1%
USA	10.09% *5.71%*	-1.61% *9.60%*	33.33% *11.01%*	65.81% *14.47%*	108.54% *19.59%* SIG 1%

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-2 Cumulative Long-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	21.29% *2.53%* SIG 5%	15.60% *3.68%*	0.37% *4.70%*	-12.54% *5.51%*	-6.11% *6.39%*	4.87% *4.07%*
Belgium	74.47% *2.19%* SIG 1%	43.38% *5.16%* SIG 1%	46.23% *4.17%* SIG 1%	42.04% *5.14%* SIG 5%	26.95% *5.14%*	29.45% *6.52%*
Canada	46.53% *4.12%* SIG 1%	32.28% *4.16%* SIG 5%	19.74% *5.99%*	12.90% *6.85%*	40.43% *7.50%* SIG 5%	42.22% *10.68%* SIG 5%
Denmark	33.70% *2.45%* SIG 5%	19.37% *5.08%*	40.56% *5.44%* SIG 1%	58.33% *5.79%* SIG 1%	69.01% *5.59%* SIG 1%	41.68% *7.66%* SIG 5%
France	19.46% *3.27%*	-19.87% *5.38%*	4.61% *5.70%*	-4.42% *7.32%*	-16.49% *7.19%*	17.36% *8.54%*
Germany	8.65% *1.02%*	-15.28% *0.31%*	-19.49% *1.37%*	-8.00% *2.18%*	4.06% *1.17%*	-10.34% *3.18%*
Hong Kong	56.31% *-2.63%* SIG 5%	43.59% *-1.90%*	18.62% *-2.53%*	-13.07% *-5.70%*	33.86% *-7.19%*	45.83% *-7.41%*
Italy	3.54% *3.98%*	-6.91% *6.87%*	19.39% *7.12%*	68.34% *7.75%* SIG 5%	45.13% *8.05%*	87.44% *10.65%* SIG 1%
Japan	6.74% *-2.73%*	26.50% *-3.53%*	9.30% *-3.95%*	-35.86% *-3.66%*	-17.69% *-6.03%*	2.62% *-7.21%*
Netherlands	35.64% *4.75%* SIG 5%	-29.22% *7.32%*	-26.79% *8.57%*	-54.31% *12.04%*	-9.27% *11.95%*	54.37% *13.69%* SIG 5%
Spain	23.57% *3.40%*	-30.54% *7.95%*	-8.10% *7.94%*	26.43% *10.37%*	58.99% *11.37%* SIG 5%	62.50% *14.33%* SIG 5%
Switzerland	30.02% *4.48%* SIG 5%	25.90% *6.07%*	-11.31% *8.44%*	4.31% *9.75%*	11.48% *11.13%*	63.46% *13.91%* SIG 1%
UK	16.20% *0.20%*	-19.36% *0.74%*	-15.45% *0.77%*	-5.90% *0.03%*	-25.49% *0.91%*	17.44% *0.50%*
USA	40.68% *3.33%* SIG 1%	-0.47% *4.28%*	-16.41% *7.44%*	15.07% *7.70%*	15.98% *8.50%*	37.34% *5.80%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-2 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	8.50% *7.29%*	9.85% *10.05%*	2.78% *11.42%*	-11.82% *14.03%*	25.36% *16.73%*
Belgium	36.19% *10.13%*	63.22% *11.79%* SIG 1%	55.51% *11.39%* SIG 5%	49.61% *16.07%* SIG 5%	88.59% *17.45%* SIG 1%
Canada	54.53% *14.27%* SIG 1%	76.18% *15.62%* SIG 1%	44.51% *17.57%* SIG 5%	12.36% *21.75%*	71.65% *25.30%* SIG 1%
Denmark	2.32% *10.21%*	24.88% *11.41%*	69.12% *11.40%* SIG 1%	89.08% *14.88%* SIG 1%	75.75% *16.95%* SIG 1%
France	37.24% *12.37%*	68.08% *13.29%* SIG 5%	86.55% *14.96%* SIG 1%	32.86% *16.35%*	86.96% *16.85%* SIG 1%
Germany	37.81% *2.73%*	58.17% *4.17%*	75.92% *6.14%* SIG 5%	6.85% *7.51%*	49.89% *7.70%*
Hong Kong	90.82% *-10.42%* SIG 5%	-1.76% *-11.84%*	-2.73% *-10.00%*	-22.83% *-13.80%*	-6.11% *-10.92%*
Italy	38.28% *11.91%*	-0.90% *13.22%*	41.73% *11.85%*	51.59% *13.19%*	92.68% *17.38%* SIG 1%
Japan	13.81% *-5.88%*	6.99% *-4.33%*	0.01% *-5.97%*	13.41% *-6.31%*	-8.50% *-5.90%*
Netherlands	30.28% *14.65%*	64.97% *18.26%* SIG 5%	108.42% *20.76%* SIG 1%	52.56% *23.39%* SIG 5%	110.59% *27.42%* SIG 1%
Spain	91.48% *15.00%* SIG 1%	55.07% *19.00%*	98.20% *21.19%* SIG 1%	73.63% *25.32%* SIG 5%	121.61% *28.29%* SIG 1%
Switzerland	32.14% *15.66%*	28.82% *17.96%*	99.76% *21.03%* SIG 1%	63.67% *22.63%* SIG 1%	97.68% *26.99%* SIG 1%
UK	-9.09% *2.25%*	1.98% *1.15%*	29.89% *-3.29%*	4.31% *1.24%*	57.74% *-25.78%* SIG 1%
USA	31.34% *13.44%*	38.47% *15.97%*	61.58% *18.40%* SIG 1%	49.69% *21.78%* SIG 5%	9.07% *25.89%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-3 Cumulative Short-Only Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	-12.80% *-2.75%*	-27.95% *-4.23%*	-16.56% *-4.07%*	-25.87% *-3.84%*	-22.83% *-4.37%*	-39.39% *-5.35%*
Belgium	56.97% *-2.61%* SIG 1%	40.78% *-4.32%* SIG 1%	-5.76% *-5.14%*	-19.10% *-6.05%*	-43.01% *-6.77%*	-6.47% *-8.38%*
Canada	27.44% *-2.75%* SIG 5%	-9.12% *-4.49%*	-9.88% *-5.94%*	-24.38% *-7.36%*	-10.70% *-7.89%*	-9.82% *-8.61%*
Denmark	3.44% *-3.12%*	-21.16% *-3.42%*	-36.41% *-3.79%*	-23.33% *-3.86%*	-22.71% *-4.76%*	-6.98% *-7.25%*
France	3.34% *-2.28%*	-47.85% *-5.56%*	-52.74% *-6.79%*	-47.64% *-6.44%*	-60.24% *-6.49%*	-20.70% *-9.09%*
Germany	-11.19% *-2.60%*	-34.35% *-2.08%*	-44.45% *-2.42%*	4.63% *-2.85%*	-26.57% *-5.28%*	-14.71% *-3.83%*
Hong Kong	14.88% *3.10%*	26.97% *5.23%*	32.64% *4.49%*	15.23% *4.42%*	-7.04% *5.40%*	-12.92% *4.86%*
Italy	12.30% *-2.72%*	-14.73% *-4.57%*	-35.95% *-6.21%*	1.47% *-6.23%*	-50.54% *-6.34%*	7.30% *-5.07%*
Japan	16.54% *1.85%*	-21.96% *1.59%*	-56.86% *2.97%*	-90.93% *3.69%*	-92.93% *3.76%*	-22.29% *4.37%*
Netherlands	-11.12% *-3.28%*	-44.94% *-8.64%*	-42.31% *-10.51%*	-36.64% *-11.85%*	-49.60% *-9.17%*	26.00% *-11.59%*
Spain	19.05% *-4.33%*	-17.60% *-5.32%*	-14.05% *-9.24%*	-27.69% *-8.47%*	-29.10% *-10.56%*	17.34% *-11.58%*
Switzerland	17.24% *-3.31%*	-21.01% *-5.18%*	-28.53% *-7.24%*	-25.21% *-7.92%*	-42.89% *-8.74%*	12.14% *-9.48%*
UK	20.61% *0.16%*	-30.89% *-0.41%*	-48.30% *-0.75%*	-47.31% *-0.69%*	-46.57% *-0.55%*	-9.51% *-0.66%*
USA	-18.97% *-4.33%*	-38.07% *-4.45%*	-65.03% *-5.38%*	-65.73% *-5.30%*	-84.83% *-6.20%*	-53.22% *-7.07%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-3 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-30.39% *-4.62%*	-46.37% *-4.99%*	-32.97% *-4.34%*	-2.55% *-3.87%*	0.00% *-2.51%*
Belgium	-40.17% *-8.77%*	-1.54% *-8.06%*	-15.10% *-7.22%*	-47.74% *-7.41%*	2.24% *-5.98%*
Canada	-19.17% *-10.22%*	-17.28% *-8.50%*	0.46% *-7.95%*	-8.35% *-6.07%*	15.24% *-4.18%*
Denmark	-7.87% *-7.60%*	-13.47% *-6.68%*	-6.00% *-5.85%*	4.37% *-4.55%*	8.6% *-4.82%*
France	17.12% *-7.99%*	19.46% *-8.34%*	-7.49% *-8.67%*	-50.80% *-8.13%*	27.47% *-5.69%*
Germany	10.87% *-4.83%*	13.95% *-6.38%*	7.08% *-5.26%*	-19.79% *-4.61%*	27.63% *-5.04%*
Hong Kong	-6.65% *5.84%*	24.19% *5.33%*	-26.84% *9.23%*	35.00% *7.74%*	-112.95% *9.21%*
Italy	-12.81% *-7.04%*	-17.14% *-4.54%*	-17.45% *-4.79%*	5.33% *-6.64%*	23.15% *-5.76%*
Japan	-35.47% *6.58%*	19.80% *8.88%*	28.29% *7.11%*	-14.09% *8.38%*	-5.16% *7.05%*
Netherlands	6.26% *-11.84%*	34.10% *-11.24%*	12.57% *-10.59%*	-24.12% *-9.34%*	25.72% *-6.61%*
Spain	-4.30% *-11.78%*	-47.74% *-9.06%*	-21.81% *-9.46%*	-24.36% *-7.67%*	13.80% *-6.85%*
Switzerland	6.72% *-11.16%*	-6.73% *-11.63%*	-5.42% *-9.97%*	-27.80% *-9.04%*	-0.00% *-7.89%*
UK	4.53% *-0.73%*	-18.13% *-0.09%*	1.73% *-3.66%*	-40.86% *-1.73%*	12.16% *-11.88%*
USA	-21.26% *-7.73%*	-40.09% *-6.37%*	-28.25% *-7.39%*	16.12% *-7.31%*	16.48% *-6.30%*

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-4 Mean Transaction Profits

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	0.0246% *-0.0006%*	-0.0482% *-0.0022%*	-0.0774% *0.0028%*	-0.2123% *0.0094%*	-0.1969% *0.0132%*	-0.3923% *-0.0150%*
Belgium	0.3078% *-0.0014%* SIG 1%	0.2543% *0.0035%* SIG 1%	0.1619% *-0.0052%*	0.1087% *-0.0055%*	-0.0893% *-0.0114%*	0.2231% *-0.0221%*
Canada	0.2038% *0.0045%* SIG 1%	0.0743% *-0.0015%*	0.0411% *0.0000%*	-0.0577% *-0.0033%*	0.1780% *-0.0030%*	0.3208% *0.0217%*
Denmark	0.0856% *-0.0020%*	-0.0058% *0.0064%*	0.0166% *0.0078%*	0.1800% *0.0108%*	0.2806% *0.0055%*	0.3614% *0.0031%*
France	0.0534% *0.0032%*	-0.2123% *-0.0006%*	-0.1895% *-0.0054%*	-0.2629% *0.0054%*	-0.4540% *0.0051%*	-0.0372% *-0.0089%*
Germany	-0.0061% *-0.0053%*	-0.1694% *-0.0073%*	-0.2653% *-0.0057%*	-0.0172% *-0.0046%*	-0.1340% *-0.0289%*	-0.2637% *-0.0087%*
Hong Kong	0.2100% *0.0023%* SIG 5%	0.2756% *0.0148%*	0.2589% *0.0108%*	0.0125% *-0.0078%*	0.1788% *-0.0117%*	0.3698% *-0.0319%*
Italy	0.0422% *0.0035%*	-0.0790% *0.0084%*	-0.0812% *0.0046%*	0.3944% *0.0089%*	-0.0340% *0.0117%*	1.0645% *0.0605%* SIG 5%
Japan	0.0614% *-0.0024%*	0.0162% *-0.0078%*	-0.2077% *-0.0051%*	-0.6638% *-0.0002%*	-0.6746% *-0.0156%*	-0.2236% *-0.0339%*
Netherlands	0.0561% *0.0055%*	-0.2339% *-0.0057%*	-0.2966% *-0.0097%*	-0.4664% *0.0021%*	-0.3547% *0.0198%*	0.8930% *0.0238%* SIG 5%
Spain	0.1000% *-0.0028%*	-0.1583% *0.0102%*	-0.0959% *-0.0065%*	-0.0069% *0.0109%*	0.1789% *0.0056%*	0.7905% *0.0309%*
Switzerland	0.1212% *0.0041%*	0.0176% *0.0033%*	-0.1828% *0.0064%*	-0.1111% *0.0113%*	-0.1915% *0.0172%*	0.8494% *0.0516%* SIG 5%
UK	0.0868% *0.0012%*	-0.1585% *0.0013%*	-0.2645% *-0.0002%*	-0.2812% *-0.0039%*	-0.4476% *0.0026%*	0.0911% *-0.0006%*
USA	0.0523% *-0.0030%*	-0.1272% *-0.0013%*	-0.3324% *0.0102%*	-0.2520% *0.0146%*	-0.4026% *0.0161%*	-0.1690% *-0.0145%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-4 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-0.4866% *-0.0126%*	-1.4609% *-0.0252%*	-1.6771% *-0.0378%*	-1.4376% *-0.0756%*	5.0716% *-0.1512%*
Belgium	-0.0725% *0.0254%*	1.9897% *0.1430%*	1.7571% *0.2221%*	0.1440% *0.8367%*	15.1383% *1.9808%* SIG 5%
Canada	0.6672% *0.0823%*	1.9634% *0.2610%*	2.1414% *0.5070%*	0.3087% *1.5301%*	12.4129% *3.6907%*
Denmark	-0.0973% *0.0530%*	0.3458% *0.1781%*	2.8694% *0.3019%*	6.6749% *0.9992%*	12.0589% *2.0908%*
France	1.0455% *0.0926%*	3.2422% *0.1909%*	4.1611% *0.3367%*	-1.4948% *0.8318%*	19.0728% *1.9055%* SIG 5%
Germany	0.9545% *-0.0471%*	2.6712% *-0.0977%*	4.3683% *0.0241%*	-1.1764% *0.2385%*	12.9195% *0.3884%*
Hong Kong	1.6835% *-0.1014%*	0.8008% *-0.2448%*	-1.4079% *-0.0241%*	1.1058% *-0.6786%*	-17.8062% *-0.5133%*
Italy	0.4899% *0.0974%*	-0.6682% *0.3155%*	1.3488% *0.3802%*	5.1746% *0.6719%*	23.1671% *1.9244%* SIG 5%
Japan	-0.4608% *0.0176%*	1.0304% *0.1836%*	1.7683% *0.0565%*	-0.0680% *0.2259%*	-3.4137% *0.3793%*
Netherlands	0.7165% *0.0571%*	3.5380% *0.2707%* SIG 5%	6.3681% *0.5296%* SIG 5%	2.1875% *1.3623%*	19.4736% *3.7214%* SIG 5%
Spain	1.6143% *0.0663%*	0.2525% *0.3886%*	3.8195% *0.6312%*	4.1053% *1.7681%*	22.5684% *3.6231%* SIG 5%
Switzerland	0.7475% *0.0942%*	0.8181% *0.2477%*	4.9652% *0.6238%* SIG 5%	2.7592% *1.4133%*	16.2801% *3.6175%* SIG 5%
UK	-0.0952% *0.0328%*	-0.5569% *0.0322%*	1.7570% *-0.4123%*	-3.3227% *-0.0821%*	11.6500% *-7.5886%* SIG 1%
USA	0.1940% *0.1151%*	-0.0557% *0.3612%*	1.5871% *0.5725%*	5.9830% *1.3720%*	18.0908% *3.3643%* SIG 5%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-5 Mean Transaction and Daily Profit by Strategy Length

Strategy Length (Trading Days)	Mean Transaction Profit	Mean Daily Profit
1	0.0999%	0.0999%
2	-0.0396%	-0.0198%
3	-0.1082%	-0.0361%
4	-0.1169%	-0.0292%
5	-0.1545%	-0.0309%
10	0.2770%	0.0277%
21	0.4929%	0.0235%
42	0.9936%	0.0237%
63	2.4162%	0.0384%
126	1.4960%	0.0119%
252	11.9060%	0.0472%

Table shows the mean transaction profit across all 14 data sets for each strategy length together with the mean daily profit for days on which each strategy holds a market position.

Table E-6 Standard Deviation of Daily Returns

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	6.60% *5.63%* SIG 1%	7.87% *6.92%* SIG 5%	8.47% *7.58%* SIG 5%	8.75% *7.98%*	8.76% *8.24%*	9.68% *8.96%*
Belgium	10.38% *6.53%* SIG 1%	12.27% *8.12%* SIG 1%	12.75% *8.94%* SIG 1%	13.01% *9.51%* SIG 1%	13.97% *9.93%* SIG 1%	14.71% *11.01%* SIG 1%
Canada	8.48% *6.57%* SIG 1%	10.91% *8.24%* SIG 1%	12.12% *9.13%* SIG 1%	12.71% *9.70%* SIG 1%	12.24% *10.12%* SIG 1%	12.93% *11.19%* SIG 1%
Denmark	10.28% *6.95%* SIG 1%	11.70% *8.50%* SIG 1%	12.05% *9.33%* SIG 1%	12.27% *9.86%* SIG 1%	12.47% *10.28%* SIG 1%	13.26% *11.24%* SIG 1%
France	11.57% *8.56%* SIG 1%	14.90% *10.67%* SIG 1%	15.12% *11.75%* SIG 1%	15.57% *12.45%* SIG 1%	16.33% *12.97%* SIG 1%	16.49% *14.27%* SIG 1%
Germany	13.07% *9.25%* SIG 1%	16.30% *11.51%* SIG 1%	16.95% *12.72%* SIG 1%	17.48% *13.53%* SIG 1%	18.05% *14.10%* SIG 1%	19.38% *15.51%* SIG 1%
Hong Kong	14.78% *11.07%* SIG 1%	16.59% *13.46%* SIG 1%	17.83% *14.77%* SIG 1%	18.62% *15.58%* SIG 1%	19.27% *16.28%* SIG 1%	21.75% *18.03%* SIG 1%
Italy	12.82% *10.28%* SIG 1%	16.02% *12.55%* SIG 1%	16.42% *13.70%* SIG 1%	16.76% *14.45%* SIG 1%	17.71% *14.97%* SIG 1%	18.29% *16.29%* SIG 1%
Japan	10.29% *8.38%* SIG 1%	13.08% *10.18%* SIG 1%	13.89% *11.19%* SIG 1%	14.25% *11.79%* SIG 1%	14.69% *12.22%* SIG 1%	15.75% *13.32%* SIG 1%
Netherlands	12.98% *8.27%* SIG 1%	15.74% *10.54%* SIG 1%	16.01% *11.70%* SIG 1%	17.07% *12.49%* SIG 1%	17.86% *13.03%* SIG 1%	17.94% *14.50%* SIG 1%
Spain	12.65% *9.34%* SIG 1%	15.60% *11.53%* SIG 1%	15.93% *12.69%* SIG 1%	16.17% *13.45%* SIG 1%	17.24% *13.95%* SIG 1%	18.10% *15.27%* SIG 1%
Switzerland	11.64% *7.45%* SIG 1%	13.40% *9.30%* SIG 1%	14.28% *10.29%* SIG 1%	15.59% *10.93%* SIG 1%	15.25% *11.39%* SIG 1%	15.84% *12.59%* SIG 1%
UK	9.34% *6.88%* SIG 1%	11.25% *8.55%* SIG 1%	12.41% *9.45%* SIG 1%	12.43% *10.00%* SIG 1%	12.19% *10.40%* SIG 1%	13.25% *11.42%* SIG 1%
USA	9.99% *7.49%* SIG 1%	12.10% *8.93%* SIG 1%	12.55% *9.81%* SIG 1%	13.39% *10.39%* SIG 1%	13.21% *10.81%* SIG 1%	13.81% *11.94%* SIG 1%

Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-6 (continued)

PANEL B: **21-252 Trading Day Strategies**	**21**	**42**	**63**	**126**	**252**
Australia	9.85% *9.58%*	9.92% *9.97%*	10.27% *10.20%*	10.33% *10.61%*	10.78% *11.14%*
Belgium	15.18% *11.79%* SIG 1%	15.52% *12.34%* SIG 1%	15.63% *12.61%* SIG 1%	15.10% *13.08%*	14.57% *13.64%*
Canada	13.37% *12.04%* SIG 5%	13.88% *12.63%*	14.71% *12.93%*	16.62% *13.40%* SIG 1%	17.08% *13.98%*
Denmark	14.32% *11.98%* SIG 1%	14.74% *12.49%* SIG 1%	14.88% *12.73%* SIG 5%	16.37% *13.19%* SIG 1%	17.22% *13.59%* *SIG 5%*
France	17.94% *15.13%* SIG 1%	17.92% *15.83%* *SIG 5%*	18.85% *16.10%* SIG 5%	20.62% *16.58%* SIG 1%	19.03% *17.11%*
Germany	19.44% *16.53%* SIG 1%	20.20% *17.31%* SIG 1%	19.93% *17.51%*	21.52% *17.97%*	23.63% *18.18%*
Hong Kong	22.27% *19.42%* SIG 5%	21.54% *20.31%*	23.02% *20.50%*	19.64% *20.78%*	26.82% *20.52%*
Italy	19.32% *17.32%* SIG 5%	19.96% *18.01%*	20.08% *18.37%*	21.16% *18.88%*	21.43% *19.46%*
Japan	15.57% *14.10%* SIG 5%	15.58% *14.59%*	15.69% *14.87%*	16.29% *14.99%*	14.47% *14.90%*
Netherlands	18.59% *15.60%* SIG 1%	18.78% *16.28%* SIG 5%	19.51% *16.64%* SIG 5%	21.30% *17.22%* SIG 5%	20.25% *17.89%*
Spain	19.58% *16.26%* SIG 1%	19.69% *17.01%* SIG 1%	19.37% *17.32%*	20.24% *17.91%*	23.38% *18.96%*
Switzerland	16.24% *13.57%* SIG 1%	16.28% *14.27%* SIG 5%	15.66% *14.50%*	18.35% *15.10%* SIG 5%	15.69% *15.70%*
UK	13.96% *12.18%* SIG 1%	13.53% *12.64%*	14.52% *12.84%*	14.72% *13.21%*	14.58% *13.12%*
USA	14.91% *12.75%* SIG 5%	14.72% *13.32%*	15.05% *13.71%*	15.03% *14.21%*	15.91% *14.94%*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-7 Sharpe Ratios

PANEL A: 1-10 Trading Day Strategies	1	2	3	4	5	10
Australia	0.14 *0.00*	-0.17 *-0.01*	-0.21 *0.01*	-0.49 *0.02*	-0.37 *0.03*	-0.39 *-0.02*
Belgium	1.40 *-0.01* SIG 1%	0.76 *0.01* SIG 5%	0.35 *-0.01*	0.20 *-0.01*	-0.13 *-0.02*	0.17 *-0.02*
Canada	0.97 *0.02* SIG 1%	0.24 *0.00*	0.09 *0.00*	-0.10 *-0.01*	0.27 *0.00*	0.28 *0.02*
Denmark	0.40 *-0.01*	-0.02 *0.02*	0.04 *0.02*	0.32 *0.02*	0.41 *0.01*	0.29 *0.00*
France	0.22 *0.01*	-0.51 *0.00*	-0.35 *-0.01*	-0.37 *0.01*	-0.52 *0.01*	-0.02 *0.00*
Germany	-0.02 *-0.02*	-0.34 *-0.02*	-0.42 *-0.01*	-0.02 *-0.01*	-0.14 *-0.03*	-0.14 *-0.01*
Hong Kong	0.53 *0.00*	0.47 *0.03*	0.32 *0.01*	0.01 *-0.01*	0.15 *-0.01*	0.17 *-0.02*
Italy	0.14 *0.01*	-0.15 *0.02*	-0.11 *0.01*	0.46 *0.01*	-0.03 *0.01*	0.57 *0.04* SIG 5%
Japan	0.26 *-0.01*	0.04 *-0.02*	-0.39 *-0.01*	-1.01 *0.00*	-0.85 *-0.02*	-0.14 *-0.02*
Netherlands	0.21 *0.02*	-0.52 *-0.01*	-0.47 *-0.02*	-0.58 *0.00*	-0.36 *0.02*	0.49 *0.02*
Spain	0.37 *-0.01*	-0.34 *0.02*	-0.15 *-0.01*	-0.01 *0.02*	0.19 *0.01*	0.49 *0.02*
Switzerland	0.45 *0.02*	0.04 *0.01*	-0.31 *0.01*	-0.15 *0.02*	-0.23 *0.02*	0.53 *0.04*
UK	0.44 *0.01*	-0.50 *0.00*	-0.57 *0.00*	-0.48 *-0.01*	-0.68 *0.00*	0.07 *0.00*
USA	0.24 *-0.01*	-0.35 *0.00*	-0.72 *0.02*	-0.42 *0.03*	-0.58 *0.02*	-0.13 *-0.01*

Figures in italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Table E-7 (continued)

PANEL B: 21-252 Trading Day Strategies	21	42	63	126	252
Australia	-0.25 *0.03*	-0.41 *0.05*	-0.33 *0.07*	-0.15 *0.10*	0.26 *0.12*
Belgium	-0.03 *0.01*	0.44 *0.03*	0.29 *0.03*	0.01 *0.07*	0.69 *0.06* SIG 5%
Canada	0.29 *0.02*	0.47 *0.06*	0.34 *0.08*	0.03 *0.12*	0.57 *0.15* SIG 5%
Denmark	-0.04 *0.02*	0.09 *0.04*	0.47 *0.05*	0.63 *0.08* SIG 5%	0.54 *0.08*
France	0.34 *0.03*	0.54 *0.03*	0.47 *0.04*	-0.10 *0.05*	0.67 *0.06* SIG 5%
Germany	0.28 *-0.01*	0.40 *-0.01*	0.46 *0.00*	-0.07 *0.01*	0.36 *0.01*
Hong Kong	0.41 *-0.03*	0.11 *-0.04*	-0.14 *0.00*	0.07 *-0.03*	-0.44 *-0.01*
Italy	0.15 *0.03*	-0.10 *0.05*	0.13 *0.04*	0.30 *0.03*	0.60 *0.05* SIG 5%
Japan	-0.16 *0.01*	0.20 *0.04*	0.20 *0.01*	0.00 *0.02*	-0.11 *0.01*
Netherlands	0.22 *0.02*	0.58 *0.05*	0.68 *0.06* *SIG 5%*	0.15 *0.08*	0.74 *0.11* SIG 5%
Spain	0.50 *0.02*	0.04 *0.06*	0.44 *0.07*	0.27 *0.10*	0.64 *0.10* SIG 5%
Switzerland	0.27 *0.04*	0.15 *0.05*	0.67 *0.08* SIG 5%	0.22 *0.10*	0.69 *0.12* *SIG 5%*
UK	-0.04 *0.01*	-0.13 *0.01*	0.24 *-0.06*	-0.28 *0.00*	0.53 *-0.31* *SIG 1%*
USA	0.08 *0.05*	-0.01 *0.08*	0.25 *0.09*	0.49 *0.10*	0.76 *0.13* SIG 1%

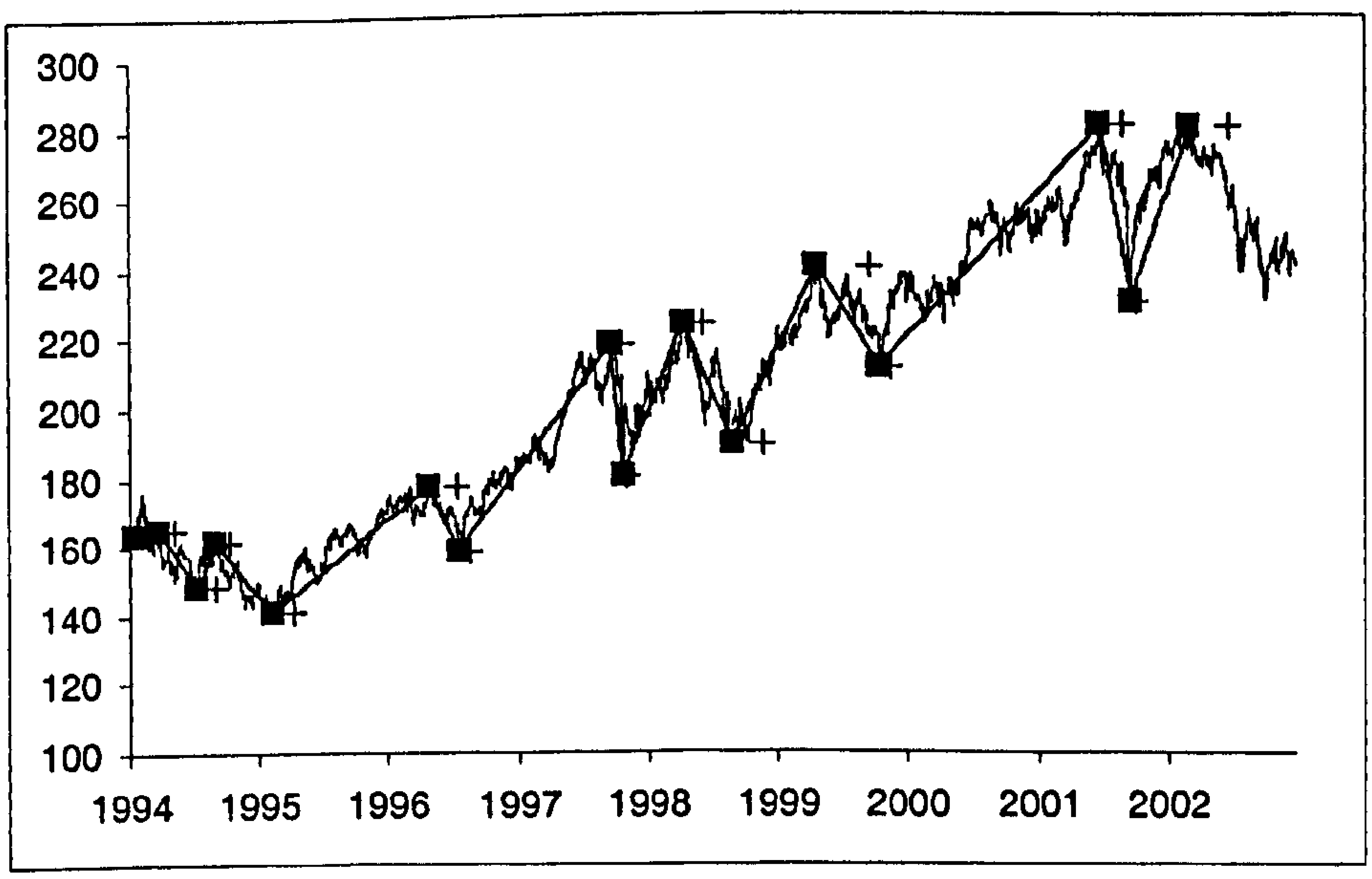
Figures in Italics are mean values from 4999 bootstrap runs
SIG 1% indicates bootstrap significance at the 1% level
SIG 5% indicates bootstrap significance at the 5% level

Appendix F: Trends in Stock Market Prices

Australia

Date	Price	Date Found
13Jan94	163.14	25Feb94
23Mar94	164.38	05May94
11Jul94	148.40	29Aug94
31Aug94	161.54	07Oct94
08Feb95	141.08	11Apr95
26Apr96	177.56	11Jul96
17Jul96	158.87	19Aug96
23Sep97	218.27	24Oct97

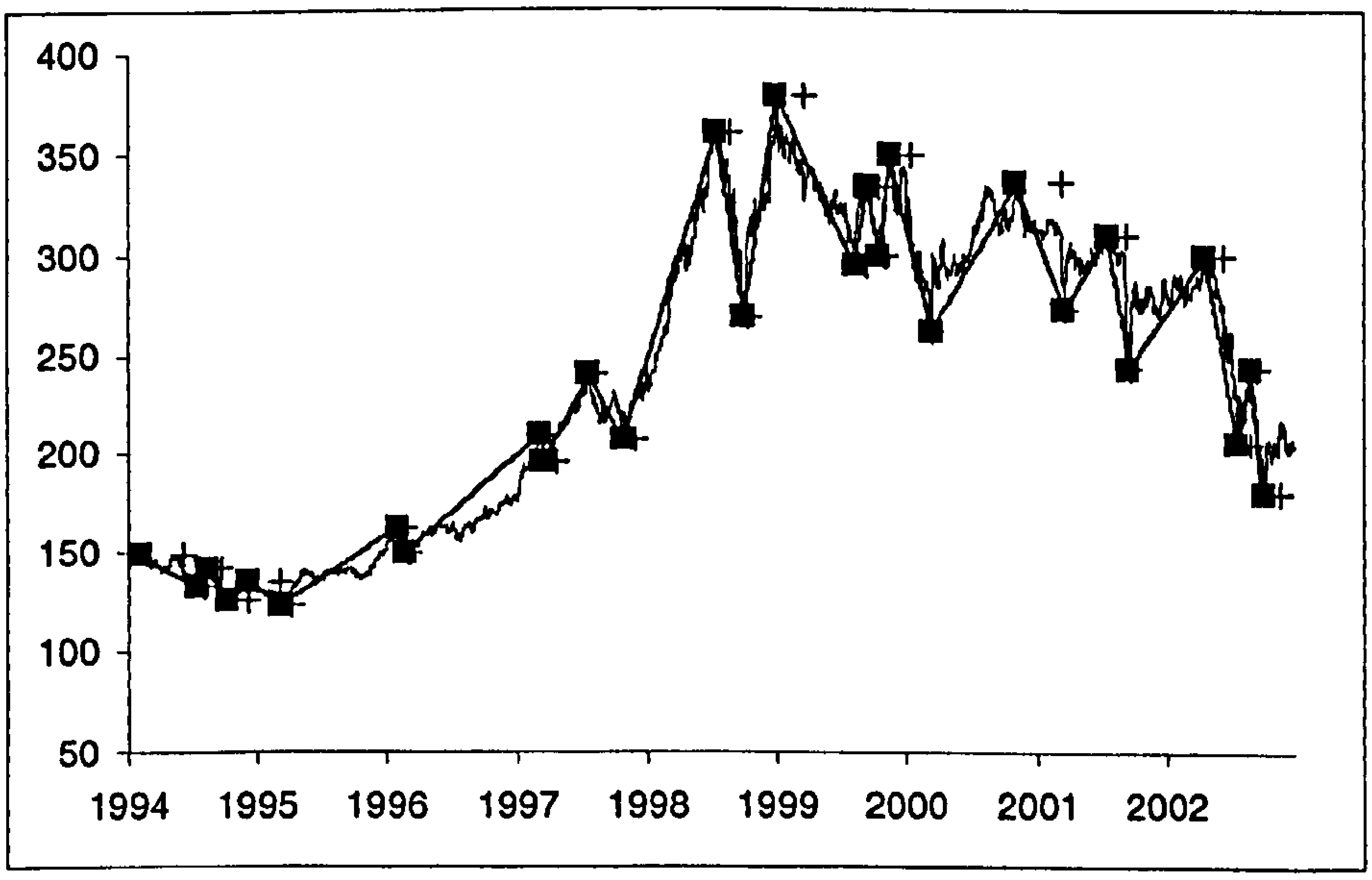
Date	Price	Date Found
28Oct97	180.69	04Nov97
16Apr98	224.16	11Jun98
01Sep98	189.48	23Nov98
27Apr99	240.44	21Sep99
19Oct99	211.84	18Nov99
29Jun01	281.05	31Aug01
24Sep01	230.97	05Oct01
07Mar02	280.19	26Jun02



Belgium

Date	Price	Date Found
31Jan94	148.66	03Jun94
13Jul94	132.77	02Aug94
08Aug94	141.93	19Sep94
07Oct94	126.66	05Dec94
05Dec94	134.98	06Mar95
09Mar95	124.16	11Apr95
01Feb96	163.34	19Feb96
20Feb96	150.44	07Mar96
11Mar97	209.61	20Mar97
20Mar97	196.17	23Apr97
28Jul97	239.98	13Aug97
28Oct97	206.89	01Dec97
20Jul98	360.48	28Aug98
05Oct98	268.42	15Oct98

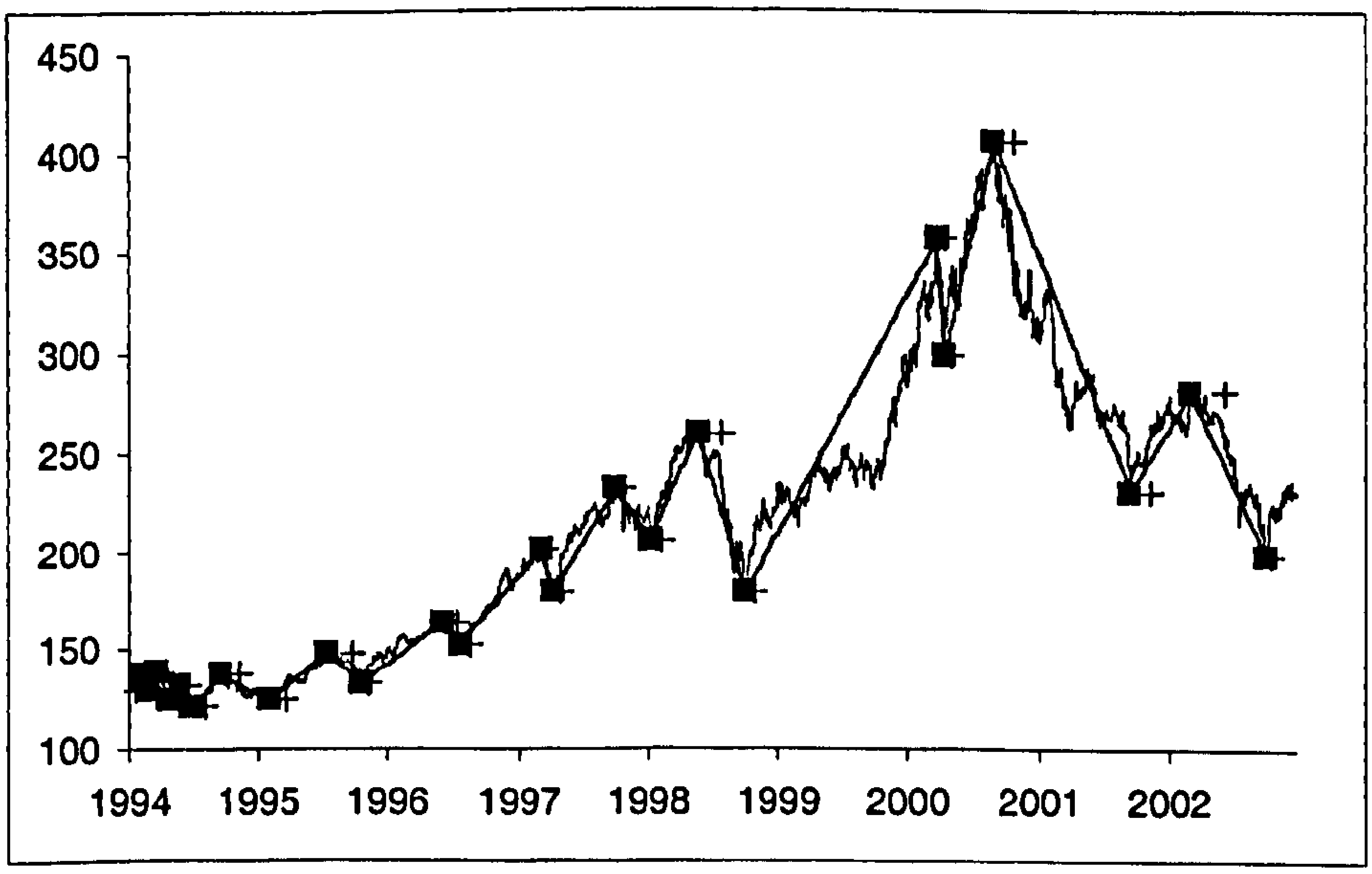
Date	Price	Date Found
06Jan99	377.88	24Mar99
10Aug99	295.04	17Sep99
17Sep99	334.30	18Oct99
18Oct99	299.50	05Nov99
16Nov99	350.30	18Jan00
13Mar00	262.37	16Mar00
06Nov00	335.71	13Mar01
22Mar01	273.25	30Mar01
19Jul01	310.31	10Sep01
21Sep01	243.89	28Sep01
23Apr02	299.40	12Jun02
24Jul02	205.64	27Aug02
27Aug02	244.38	18Sep02
09Oct02	181.03	21Nov02



Canada

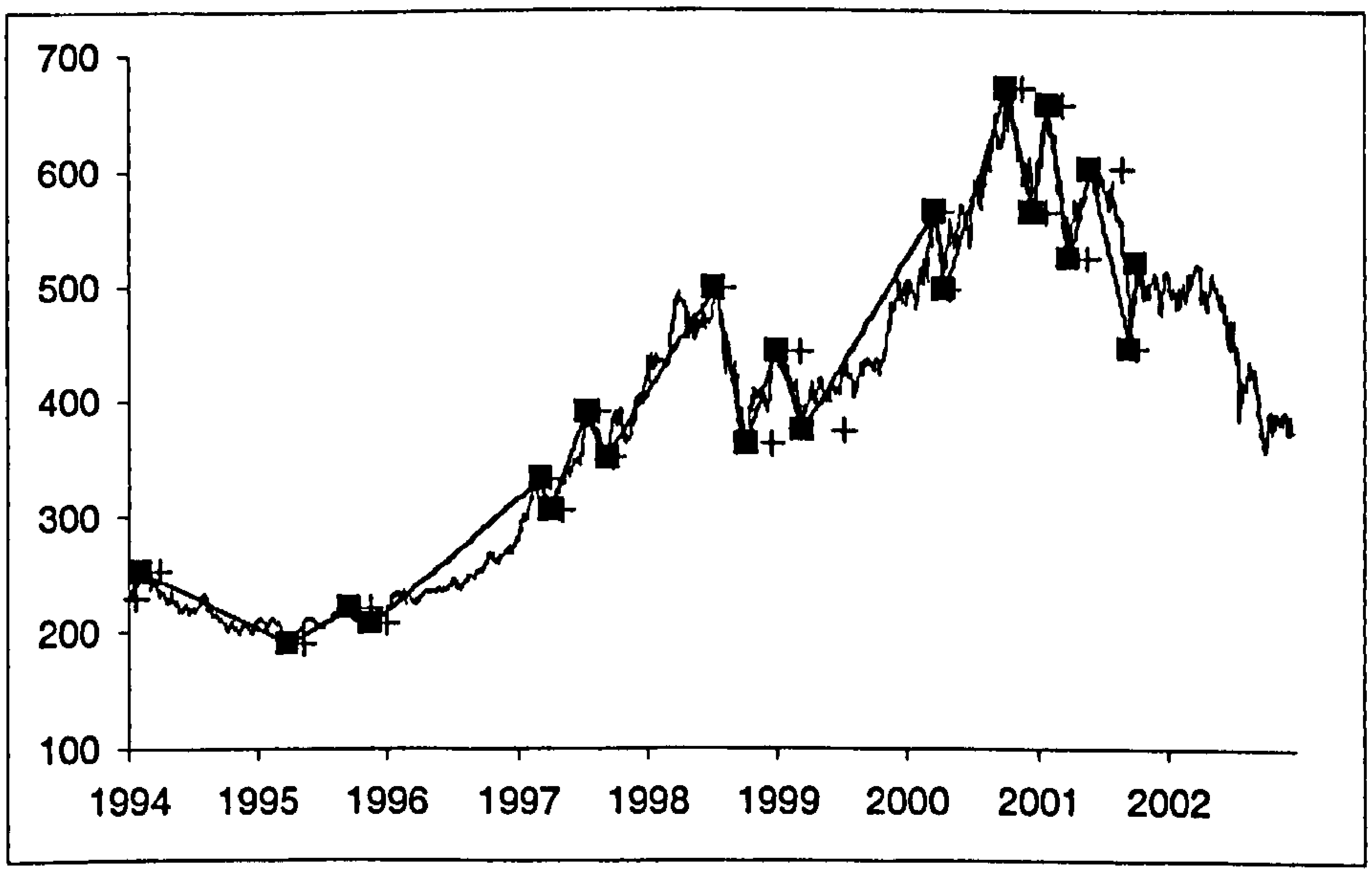
Date	Price	Date Found
31Dec93	130.19	19Jan94
01Feb94	138.14	21Feb94
24Feb94	129.74	18Mar94
23Mar94	139.16	30Mar94
19Apr94	124.66	26May94
26May94	131.70	21Jun94
24Jun94	121.22	02Aug94
19Sep94	137.24	09Nov94
30Jan95	125.01	20Mar95
17Jul95	147.89	27Sep95
23Oct95	132.91	06Nov95
03Jun96	163.72	16Jul96
24Jul96	153.11	22Aug96

Date	Price	Date Found
10Mar97	201.82	27Mar97
11Apr97	180.31	02May97
07Oct97	232.31	27Oct97
12Jan98	206.71	11Feb98
25May98	260.54	29Jul98
05Oct98	179.63	28Oct98
27Mar00	358.39	14Apr00
14Apr00	300.19	05May00
01Sep00	406.26	25Oct00
21Sep01	232.06	19Nov01
07Mar02	282.15	13Jun02
09Oct02	199.35	18Oct02



Denmark

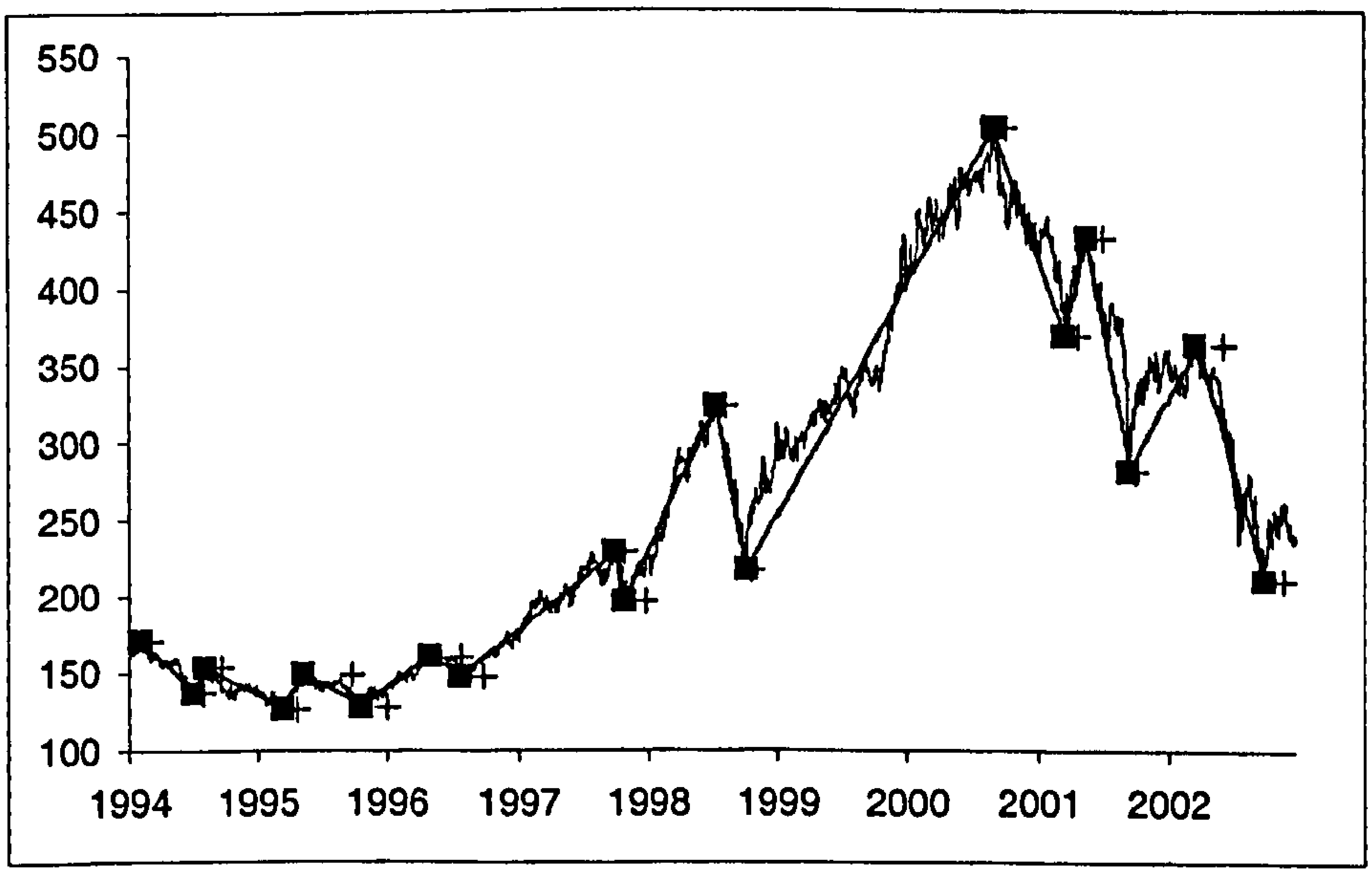
Date	Price	Date Found	Date	Price	Date Found
31Dec93	228.45	19Jan94	06Jan99	444.10	09Mar99
02Feb94	252.63	25Mar94	15Mar99	375.36	09Jul99
29Mar95	189.75	09May95	21Mar00	564.86	11Apr00
15Sep95	220.90	15Nov95	17Apr00	498.06	02May00
15Nov95	207.15	03Jan96	06Oct00	671.16	22Nov00
11Mar97	333.45	03Apr97	21Dec00	564.47	24Jan01
03Apr97	306.63	06May97	31Jan01	655.93	13Mar01
17Jul97	391.13	18Aug97	04Apr01	526.08	22May01
15Sep97	350.78	29Sep97	31May01	601.93	30Aug01
15Jul98	498.97	05Aug98	21Sep01	447.94	11Oct01
08Oct98	362.77	21Dec98	11Oct01	522.34	19Jun02



France

Date	Price	Date Found
02Feb94	171.21	02Mar94
04Jul94	136.74	25Jul94
02Aug94	153.21	20Sep94
13Mar95	127.20	21Apr95
12May95	147.99	22Sep95
23Oct95	128.58	03Jan96
30Apr96	160.85	24Jul96
24Jul96	147.76	30Sep96
03Octl97	228.77	28Oct97

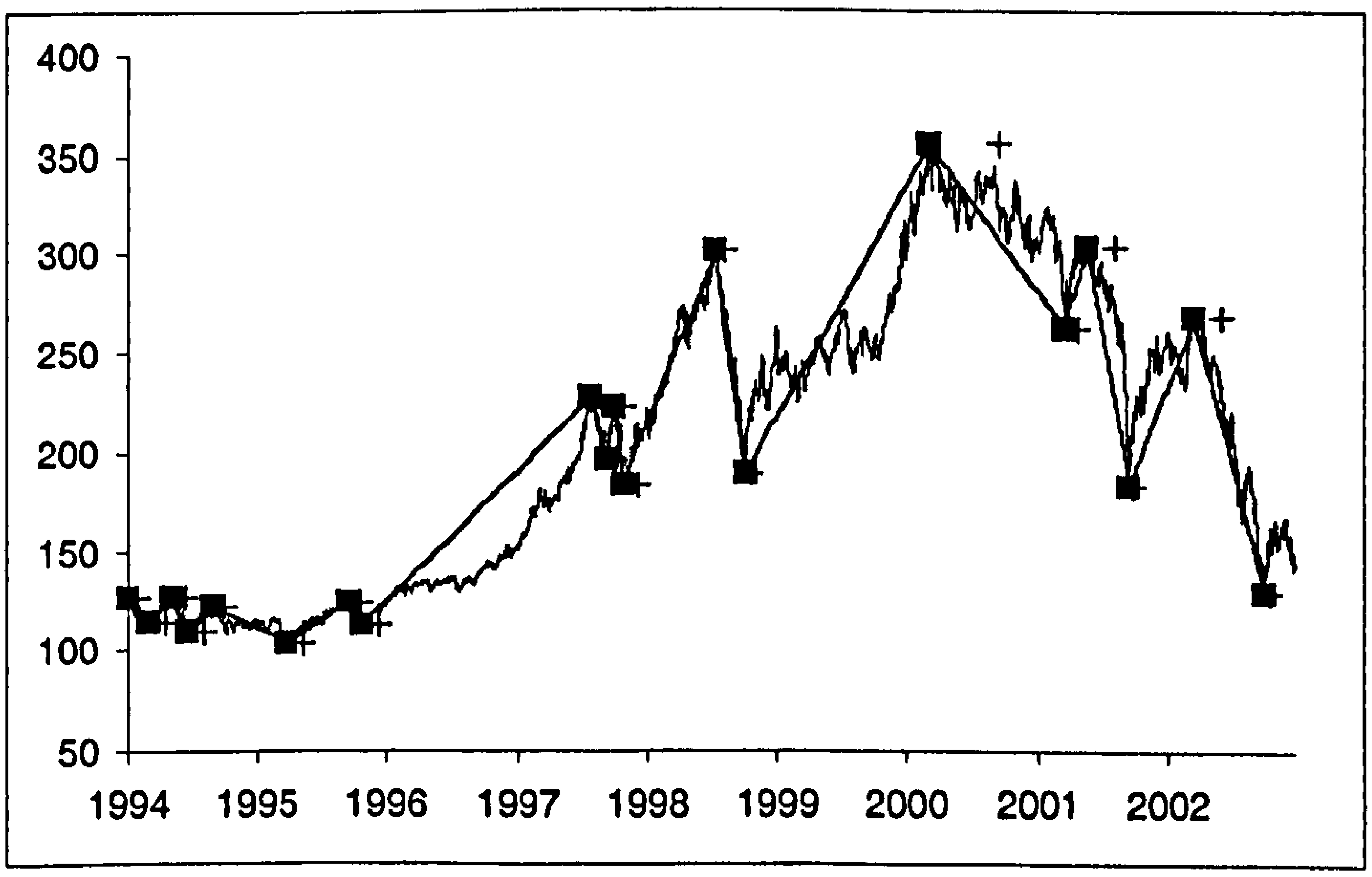
Date	Price	Date Found
28Oct97	197.29	30Dec97
17Jul98	323.25	11Aug98
08Oct98	217.19	27Oct98
04Sep00	505.52	11Oct00
22Mar01	368.91	27Apr01
22May01	433.03	10Jul01
21Sep01	282.95	10Oct01
28Mar02	363.79	13Jun02
09Oct02	212.07	28Nov02



Germany

Date	Price	Date Found
03Jan94	126.93	24Jan94
02Mar94	114.20	18Apr94
02May94	126.17	14Jun94
20Jun94	109.77	02Aug94
31Aug94	121.61	30Sep94
28Mar95	103.95	12May95
15Sep95	124.58	23Oct95
27Oct95	113.35	12Dec95
31Jul97	227.67	26Aug97
15Sep97	196.63	07Oct97

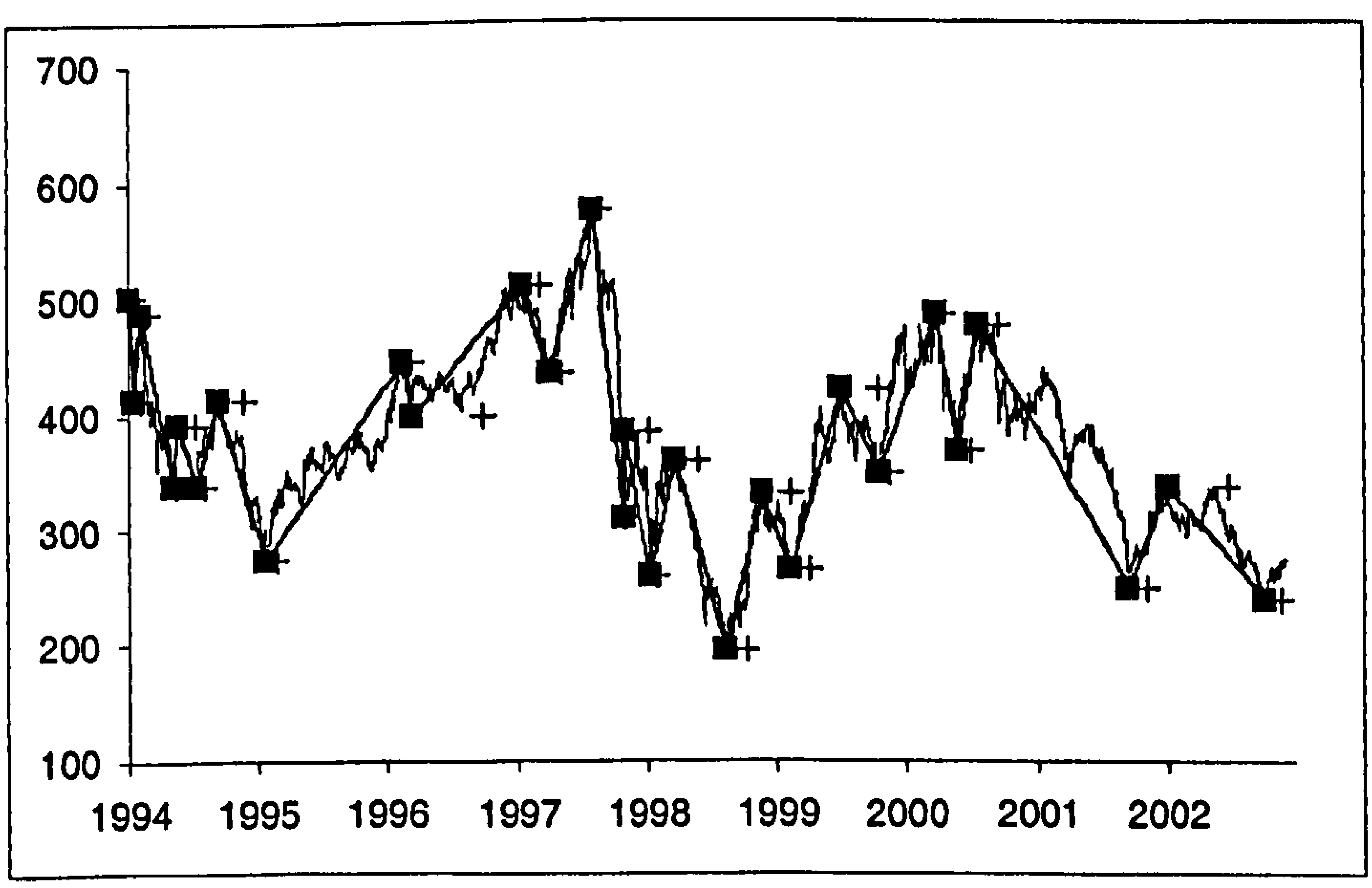
Date	Price	Date Found
08Oct97	222.38	28Oct97
28Oct97	183.73	08Dec97
20Jul98	301.07	11Aug98
08Oct98	189.27	27Oct98
07Mar00	355.04	21Sep00
22Mar01	262.88	30Apr01
24May01	304.24	10Aug01
21Sep01	184.20	04Oct01
19Mar02	268.08	07Jun02
09Oct02	129.93	21Oct02



Hong Kong

Date	Price	Date Found
04Jan94	502.33	12Jan94
13Jan94	413.38	01Feb94
04Feb94	488.89	21Feb94
04May94	338.55	20May94
09Sep94	413.12	22Nov94
23Jan95	275.47	24Feb95
16Feb96	447.97	13Mar96
13Mar96	399.61	27Sep96
16Jan97	511.18	13Mar97
03Apr97	437.59	06May97
07Aug97	576.49	29Aug97
28Oct97	312.46	03Nov97
03Nov97	387.04	08Jan98

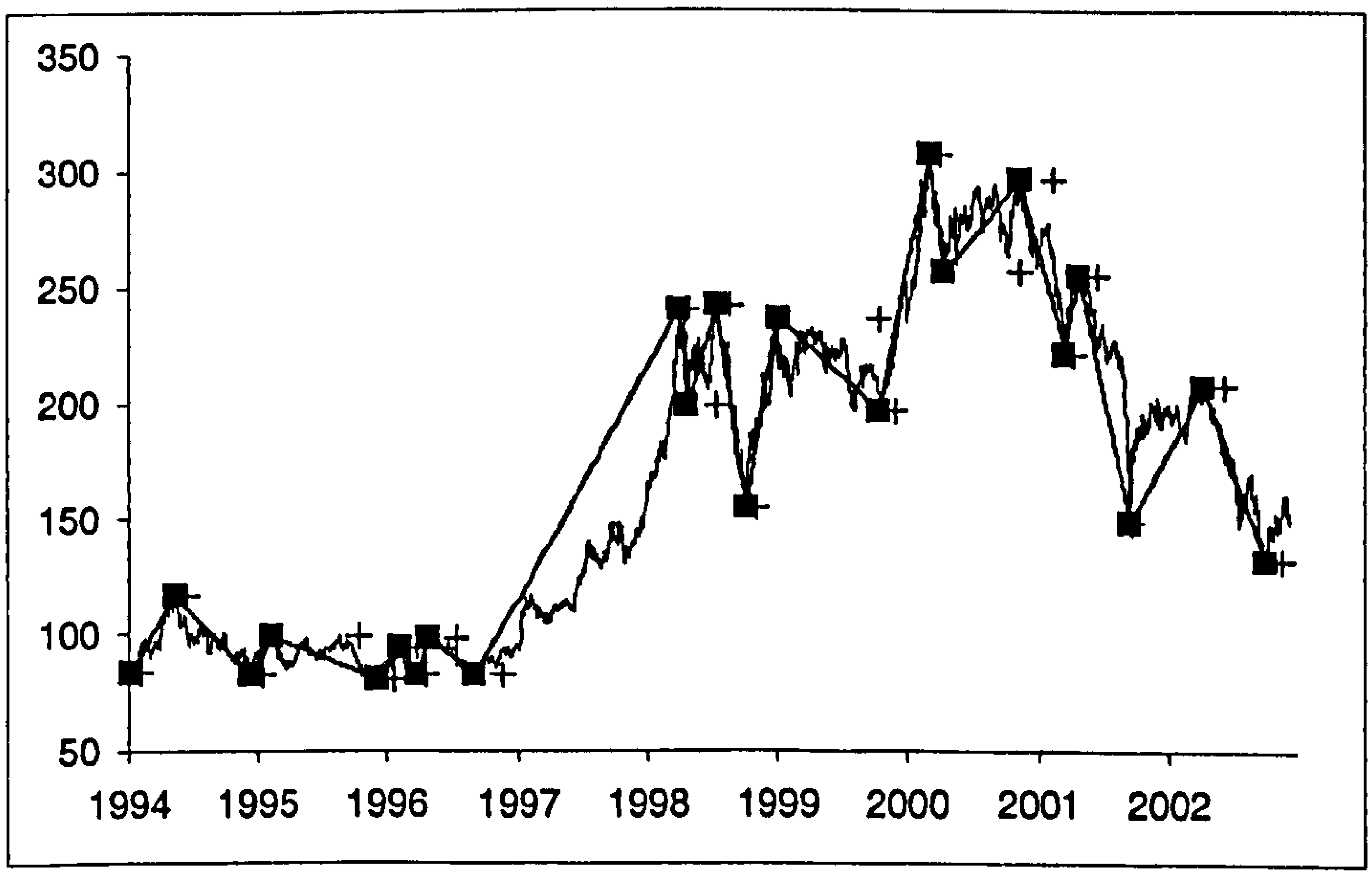
Date	Price	Date Found
12Jan98	261.53	02Feb98
25Mar98	360.58	27May98
13Aug98	195.65	12Oct98
24Nov98	333.76	10Feb99
10Feb99	266.65	07Apr99
05Jul99	422.96	15Oct99
19Oct99	350.66	16Nov99
28Mar00	488.94	17Apr00
26May00	370.45	05Jul00
21Jul00	478.78	22Sep00
21Sep01	251.61	09Nov01
07Jan02	338.79	26Jun02
10Oct02	241.21	25Nov02



Italy

Date	Price	Date Found
10Jan94	83.73	31Jan94
10May94	116.44	15Jun94
12Dec94	82.10	16Jan95
09Feb95	98.94	16Oct95
05Dec95	80.18	19Jan96
08Feb96	94.02	26Mar96
26Mar96	82.75	22Apr96
26Apr96	97.95	16Jul96
05Sep96	82.67	19Nov96
06Apr98	240.65	27Apr98
27Apr98	198.58	16Jul98
20Jul98	241.67	28Aug98

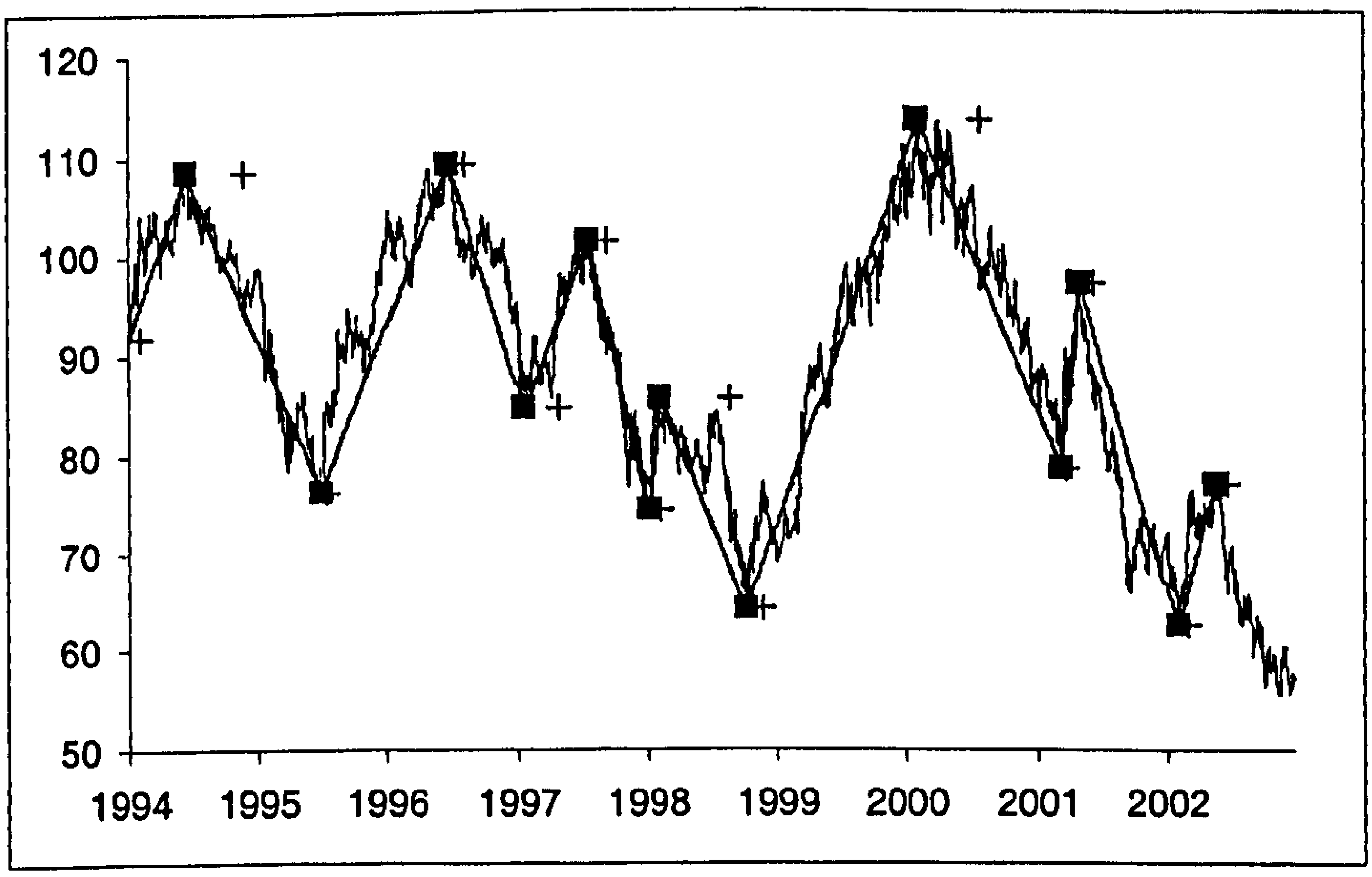
Date	Price	Date Found
09Oct98	155.36	04Nov98
07Jan99	236.46	14Oct99
18Oct99	197.35	01Dec99
06Mar00	306.48	03Apr00
17Apr00	256.92	15Nov00
15Nov00	295.76	16Feb01
22Mar01	221.39	18Apr01
30Apr01	255.22	18Jun01
21Sep01	149.01	27Sep01
16Apr02	207.40	14Jun02
09Oct02	132.30	21Nov02



Japan

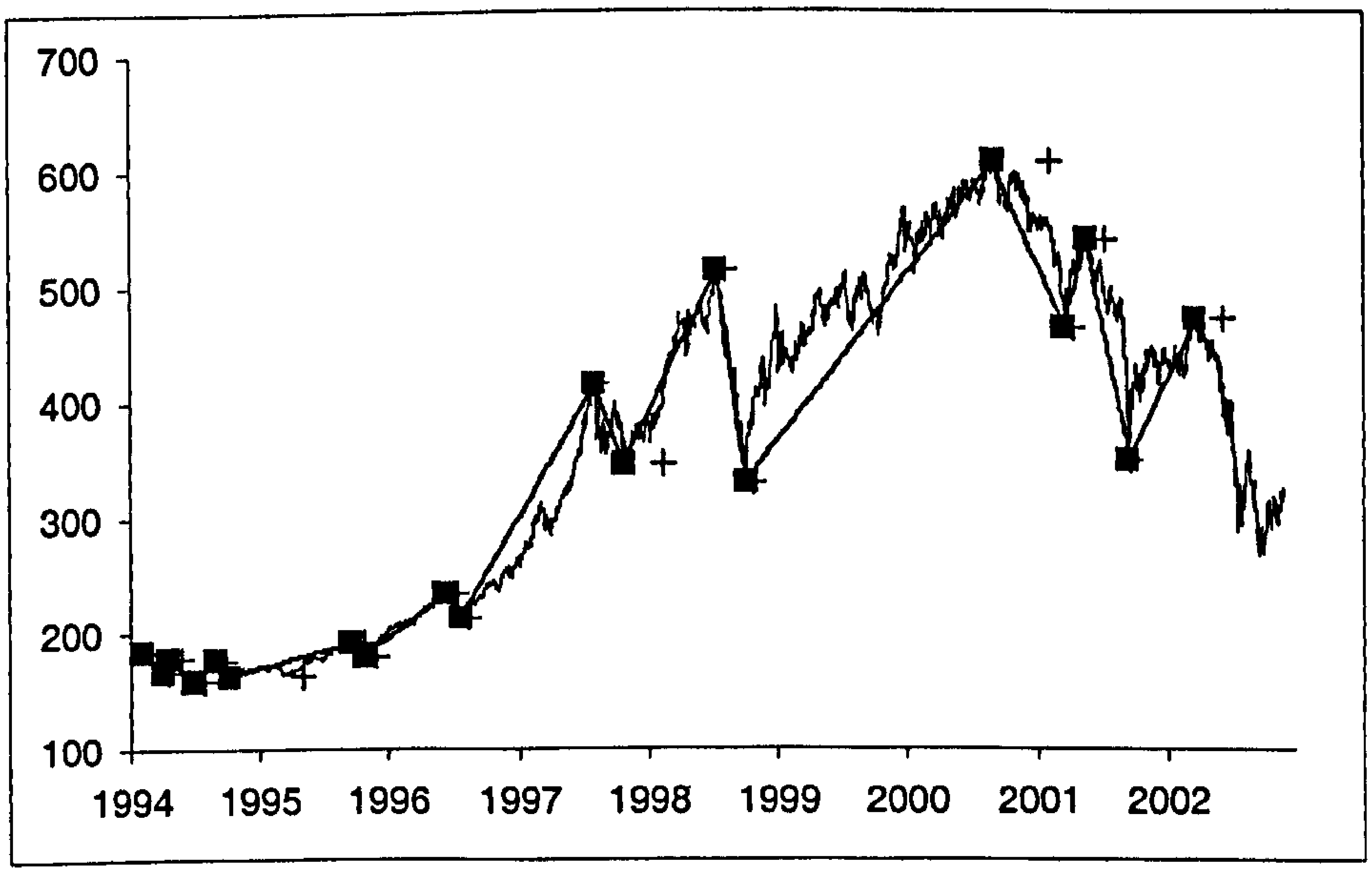
Date	Price	Date Found
31Dec93	91.80	31Jan94
13Jun94	108.46	21Nov94
29Jun95	76.33	17Jul95
26Jun96	109.29	07Aug96
27Jan97	84.66	30Apr97
28Jul97	101.50	17Sep97
12Jan98	74.47	10Feb98

Date	Price	Date Found
10Feb98	85.61	27Aug98
09Oct98	64.31	24Nov98
07Feb00	113.55	27Jul00
14Mar01	78.79	26Mar01
07May01	97.38	15Jun01
06Feb02	62.74	04Mar02
24May02	77.25	26Jun02



Netherlands

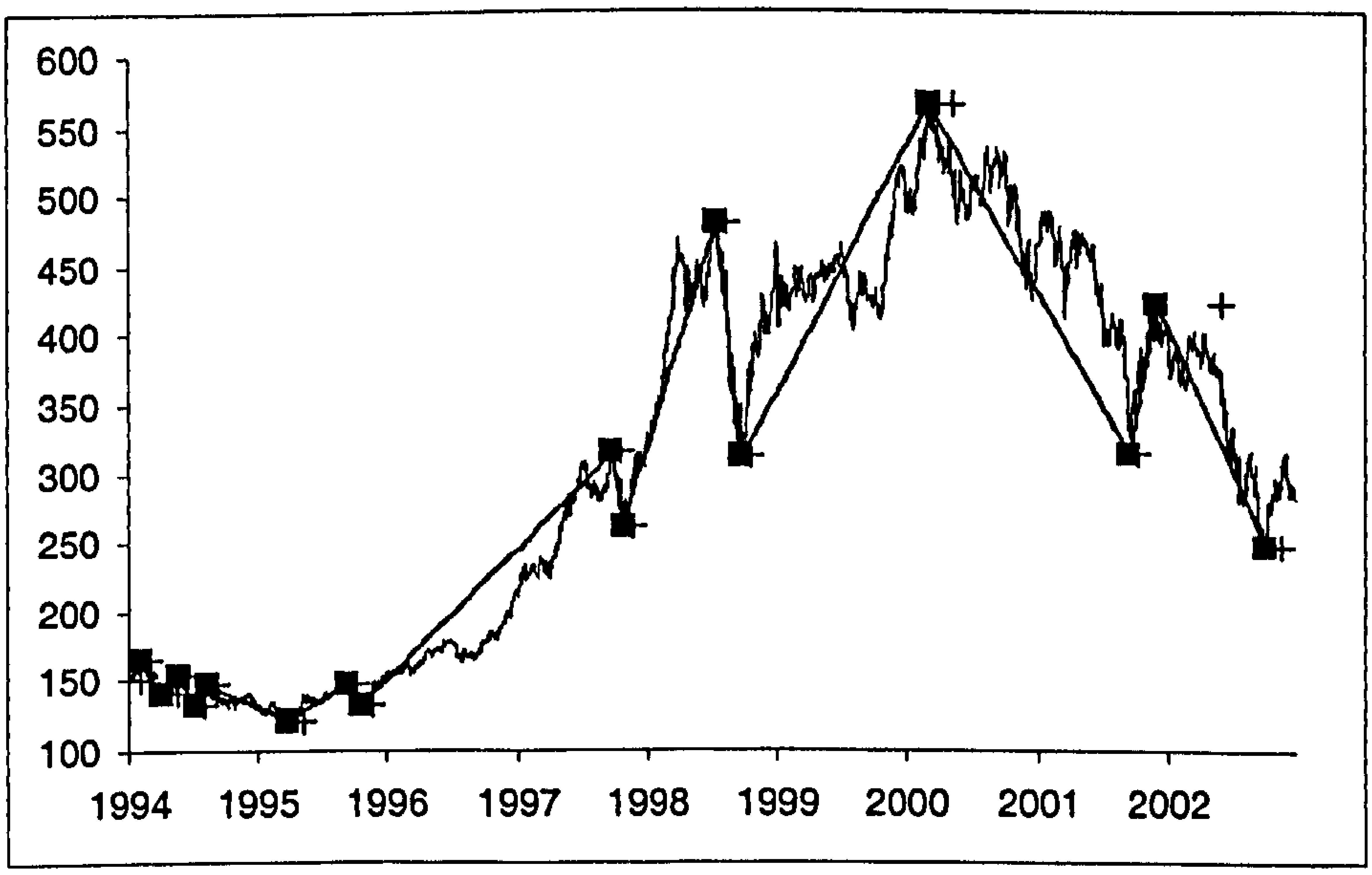
Date	Price	Date Found
31Jan94	184.54	02Mar94
05Apr94	167.17	15Apr94
15Apr94	177.77	27May94
27Jun94	159.18	29Jul94
29Aug94	175.68	22Sep94
06Oct94	162.51	01May95
15Sep95	192.04	27Oct95
27Oct95	180.34	27Nov95
12Jun96	235.15	16Jul96
24Jul96	213.36	16Aug96
07Aug97	415.86	15Aug97
28Oct97	346.26	17Feb98
20Jul98	514.59	11Aug98
08Oct98	331.98	02Nov98
04Sep00	607.11	07Feb01
22Mar01	465.45	18Apr01
22May01	541.02	18Jul01
21Sep01	351.35	28Sep01
28Mar02	473.16	13Jun02



Spain

Date	Price	Date Found
31Dec93	150.88	31Jan94
31Jan94	166.15	02Mar94
04Apr94	140.19	18May94
20May94	154.56	17Jun94
06Jul94	132.01	01Aug94
08Aug94	147.59	06Sep94
23Mar95	121.45	08May95
13Sep95	147.46	09Oct95
23Oct95	133.17	23Nov95

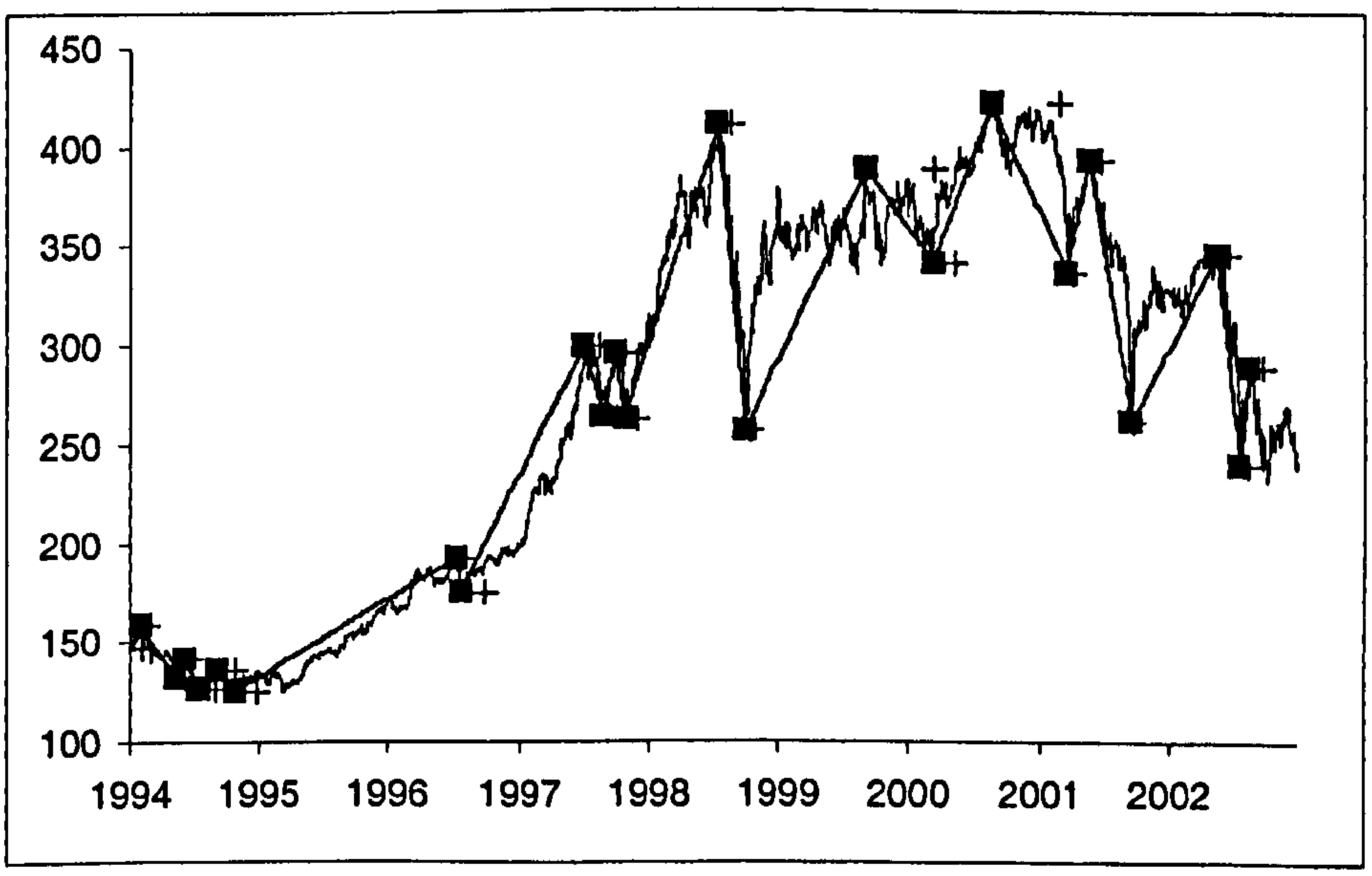
Date	Price	Date Found
01Oct97	315.16	27Oct97
28Oct97	261.23	27Nov97
17Jul98	480.17	21Aug98
01Oct98	311.93	27Oct98
06Mar00	566.27	10May00
21Sep01	314.93	17Oct01
05Dec01	423.57	06Jun02
09Oct02	249.04	21Nov02



Switzerland

Date	Price	Date Found
31Dec93	147.44	31Jan94
31Jan94	158.77	14Feb94
09May94	131.48	08Jun94
08Jun94	141.54	20Jun94
13Jul94	125.75	02Sep94
05Sep94	135.37	26Oct94
27Oct94	125.09	22Dec94
11Jul96	192.96	24Jul96
24Jul96	175.82	02Oct96
08Jul97	299.31	18Aug97
29Aug97	263.01	02Oct97
03Oct97	295.48	28Oct97

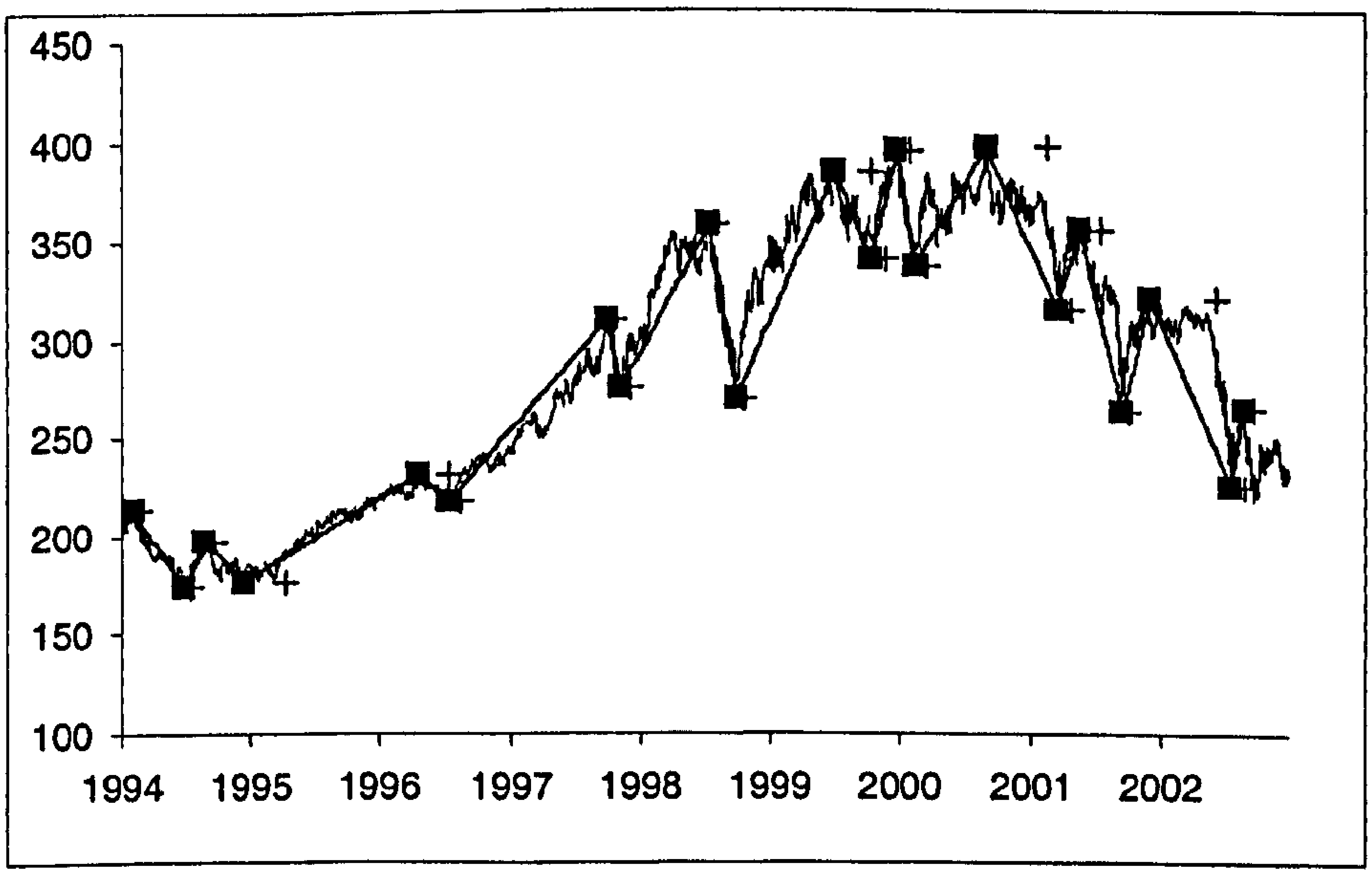
Date	Price	Date Found
28Oct97	262.56	05Dec97
21Jul98	409.67	24Aug98
05Oct98	256.62	20Oct98
07Sep99	388.04	13Mar00
13Mar00	341.83	11May00
23Aug00	421.22	02Mar01
22Mar01	336.95	12Apr01
22May01	392.71	27Jun01
21Sep01	262.11	28Sep01
16May02	345.78	20Jun02
24Jul02	240.56	19Aug02
19Aug02	289.47	23Sep02



UK

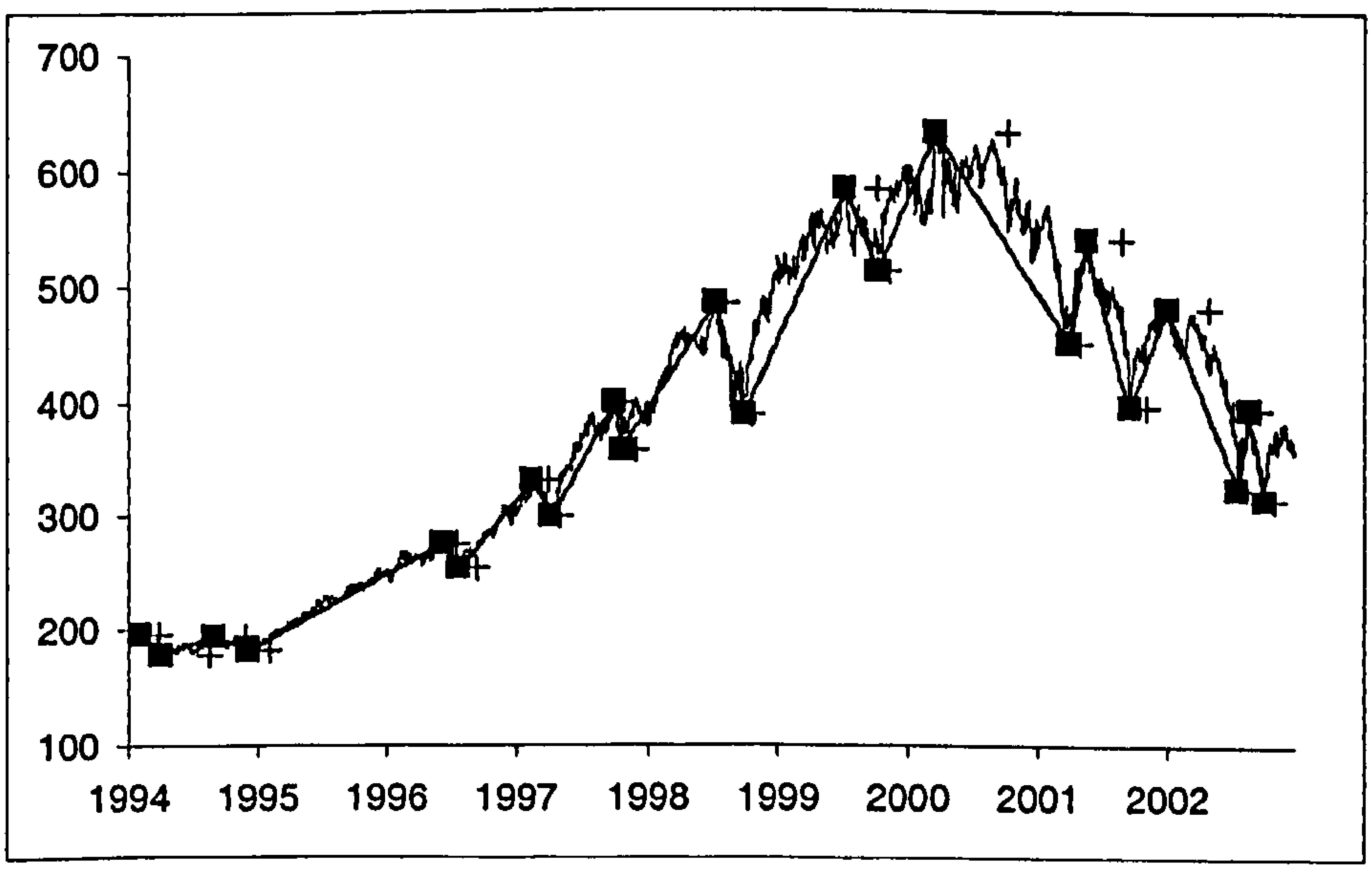
Date	Price	Date Found
02Feb94	213.18	24Feb94
24Jun94	174.10	15Jul94
26Aug94	197.29	16Sep94
12Dec94	177.39	06Apr95
19Apr96	231.93	16Jul96
16Jul96	218.56	16Aug96
03Oct97	310.10	27Oct97
13Nov97	275.18	08Dec97
20Jul98	358.17	06Aug98
05Oct98	270.11	27Oct98
06Jul99	384.65	15Oct99

Date	Price	Date Found
18Oct99	340.57	25Nov99
30Dec99	394.65	04Feb00
15Feb00	337.78	21Mar00
04Sep00	396.84	20Feb01
22Mar01	315.93	27Apr01
22May01	355.56	24Jul01
21Sep01	263.97	10Oct01
06Dec01	321.24	14Jun02
24Jul02	226.34	27Aug02
27Aug02	265.70	23Sep02



USA

Date	Price	Date Found	Date	Price	Date Found
02Feb94	196.04	29Mar94	08Oct98	390.12	29Oct98
04Apr94	178.95	16Aug94	16Jul99	584.07	15Oct99
30Aug94	194.32	01Dec94	15Oct99	512.82	16Nov99
08Dec94	182.33	03Feb95	24Mar00	632.32	12Oct00
05Jun96	276.47	15Jul96	04Apr01	452.23	01May01
24Jul96	254.79	13Sep96	21May01	540.78	29Aug01
18Feb97	331.54	02Apr97	21Sep01	396.41	06Nov01
11Apr97	299.79	02May97	04Jan02	480.93	07May02
07Oct97	399.82	27Oct97	23Jul02	326.98	15Aug02
27Oct97	358.31	05Dec97	22Aug02	394.31	24Sep02
17Jul98	485.88	14Aug98	09Oct02	317.20	04Nov02



Appendix G: Results of Trend Analysis with Adjusted R

This Appendix presents the results of the analysis of the properties of trends in stock market prices described in Chapters 8 and 9 where R is set to 1/3 of the standard deviation of price returns over the previous 252 trading days (rather than 2/3 the standard deviation as in the original analysis). This means that the algorithm will identify more, but shorter, trends for each market.

Table G-1 Duration and Amplitude of Stock Market Trends

	Number of Trends		Duration (trading days)		Total Amplitude (%)	
	Bull	**Bear**	**Bull**	**Bear**	**Bull**	**Bear**
Australia	32.00 *27.09*	31.00 *27.10*	42.38 *46.12*	28.81 *36.77*	9.78% *10.78%*	-8.45% *-8.95%*
Belgium	28.00 *29.94*	29.00 *29.96*	43.00 *40.72*	34.31 *34.30*	13.50% *12.12%*	-11.93% *-10.48%*
Canada	30.00 *30.80*	30.00 *30.81*	42.37 *41.51*	31.30 *31.06*	12.69% *12.49%*	-10.84% *-10.11%*
Denmark	32.00 *28.02*	32.00 *28.05*	39.81 *44.63*	29.66 *35.58*	12.55% *13.22%*	-10.77% *-11.02%*
France	29.00 *29.95*	29.00 *29.95*	44.72 *40.21*	31.14 *34.35*	14.82% *15.62%*	-13.23% *-13.66%*
Germany	28.00 *31.15*	28.00 *31.16*	51.96 *37.50* SIG 5%	28.43 *34.37*	16.77% *16.12%*	-14.89% *-14.98%*
Hong Kong	34.00 *27.62* SIG 5%	34.00 *27.61* SIG 5%	35.59 *38.07*	31.32 *43.93* SIG 5%	18.85% *19.44%*	-19.52% *-20.49%*
Italy	32.00 *28.47*	31.00 *28.46*	37.59 *42.24*	34.13 *37.09*	18.47% *18.77%*	-16.09% *-16.14%*
Japan	23.00 *26.48*	22.00 *26.46*	39.83 *37.66*	58.50 *45.09*	13.99% *14.09%*	-15.69% *-15.22%*
Netherlands	29.00 *32.68*	28.00 *32.68*	52.55 *37.70* SIG 5%	26.86 *31.60*	16.00% *15.19%*	-13.57% *-12.99%*
Spain	35.00 *29.96*	35.00 *29.97*	35.80 *40.88*	27.31 *33.72*	15.20% *17.15%*	-13.11% *-14.30%*
Switzerland	31.00 *29.59*	30.00 *29.61*	43.32 *41.44*	29.93 *33.87*	14.22% *14.34%*	-12.10% *-12.12%*
UK	28.00 *30.73*	27.00 *30.73*	48.36 *37.88*	32.93 *35.09*	11.57% *11.91%*	-10.74% *-11.14%*
USA	27.00 *31.56*	27.00 *31.56*	54.33 *39.42* SIG 5%	27.56 *31.54*	13.89% *12.95%*	-11.45% *-10.64%*

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Table G-2 Mean Daily Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	0.23% *0.24%*	-0.29% *-0.25%*	0.37% *0.31%*	0.16% *0.17%*	0.14% *0.17%*	0.26% *0.30%*	-0.34% *-0.33%*	-0.13% *-0.17%*	-0.17% *-0.17%*	-0.55% *-0.33%* SIG 1%
Belgium	0.31% *0.30%*	-0.35% *-0.31%*	0.45% *0.39%*	0.19% *0.21%*	0.24% *0.22%*	0.38% *0.39%*	-0.36% *-0.42%*	-0.22% *-0.21%*	-0.16% *-0.21%*	-0.67% *-0.41%* SIG 1%
Canada	0.30% *0.30%*	-0.35% *-0.33%*	0.43% *0.39%*	0.23% *0.22%*	0.20% *0.23%*	0.34% *0.38%*	-0.45% *-0.46%*	-0.14% *-0.21%*	-0.12% *-0.22%*	-0.70% *-0.44%* SIG 1%
Denmark	0.32% *0.30%*	-0.36% *-0.31%*	0.45% *0.39%*	0.16% *0.22%*	0.24% *0.22%*	0.43% *0.38%*	-0.30% *-0.43%* SIG 5%	-0.34% *-0.21%* SIG 5%	-0.22% *-0.20%*	-0.59% *-0.42%* SIG 1%
France	0.33% *0.39%*	-0.43% *-0.40%*	0.54% *0.51%*	0.19% *0.28%*	0.21% *0.28%*	0.40% *0.50%*	-0.43% *-0.54%*	-0.20% *-0.27%*	-0.35% *-0.27%*	-0.73% *-0.54%* SIG 5%
Germany	0.32% *0.43%* SIG 1%	-0.52% *-0.44%* SIG 5%	0.52% *0.57%*	0.23% *0.30%*	0.21% *0.31%*	0.35% *0.56%* SIG 1%	-0.47% *-0.60%*	-0.39% *-0.30%*	-0.30% *-0.30%*	-0.95% *-0.58%* SIG 1%
Hong Kong	0.53% *0.52%*	-0.62% *-0.47%* SIG 1%	0.91% *0.69%* SIG 5%	0.28% *0.34%*	0.42% *0.36%*	0.53% *0.68%*	-0.60% *-0.63%*	-0.37% *-0.33%*	-0.30% *-0.33%*	-1.25% *-0.61%* SIG 1%
Italy	0.49% *0.45%*	-0.47% *-0.44%*	0.73% *0.59%*	0.32% *0.31%*	0.35% *0.32%*	0.58% *0.58%*	-0.56% *-0.59%*	-0.25% *-0.30%*	-0.20% *-0.30%*	-0.89% *-0.58%* SIG 1%
Japan	0.35% *0.38%*	-0.27% *-0.34%* SIG 5%	0.70% *0.51%* SIG 5%	0.16% *0.26%*	0.20% *0.25%*	0.36% *0.50%* SIG 5%	-0.30% *-0.45%* SIG 1%	-0.13% *-0.24%* SIG 5%	-0.24% *-0.24%*	-0.41% *-0.45%*
Netherlands	0.30% *0.41%* SIG 1%	-0.51% *-0.42%* SIG 5%	0.46% *0.53%*	0.19% *0.29%*	0.21% *0.29%*	0.36% *0.52%* SIG 1%	-0.49% *-0.56%*	-0.28% *-0.27%*	-0.30% *-0.29%*	-0.97% *-0.55%* SIG 1%
Spain	0.42% *0.42%*	-0.48% *-0.43%*	0.65% *0.55%*	0.25% *0.30%*	0.32% *0.31%*	0.50% *0.54%*	-0.43% *-0.59%* SIG 5%	-0.34% *-0.28%*	-0.41% *-0.29%*	-0.75% *-0.58%* SIG 5%
Switzerland	0.33% *0.35%*	-0.40% *-0.36%*	0.53% *0.45%*	0.17% *0.26%*	0.20% *0.25%*	0.42% *0.45%*	-0.37% *-0.49%* SIG 5%	-0.25% *-0.24%*	-0.21% *-0.24%*	-0.81% *-0.48%* SIG 1%
UK	0.24% *0.32%* SIG 1%	-0.33% *-0.32%*	0.38% *0.42%*	0.20% *0.22%*	0.17% *0.23%*	0.21% *0.41%* SIG 1%	-0.36% *-0.43%*	-0.20% *-0.22%*	-0.19% *-0.22%*	-0.58% *-0.43%* SIG 5%
USA	0.26% *0.33%* SIG 1%	-0.42% *-0.34%* SIG 5%	0.41% *0.43%*	0.17% *0.24%*	0.21% *0.24%*	0.23% *0.42%* SIG 1%	-0.44% *-0.46%*	-0.17% *-0.23%*	-0.23% *-0.23%*	-0.86% *-0.46%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Table G-3 Proportion of Positive Daily Price Returns

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	61.28% *61.89%*	36.51% *38.24%*	64.92% *65.85%*	58.26% *58.12%*	56.13% *58.21%*	66.27% *65.80%*	28.04% *33.47%*	43.11% *42.68%*	42.98% *42.69%*	31.05% *33.70%*
Belgium	64.70% *62.23%*	36.08% *39.30%*	68.73% *66.33%*	58.88% *58.56%*	60.58% *58.49%*	71.04% *66.37%*	32.35% *34.56%*	40.32% *43.75%*	44.62% *43.71%*	26.23% *34.90%* SIG 1%
Canada	66.01% *63.38%*	35.46% *39.40%* SIG 5%	68.93% *67.32%*	62.07% *59.93%*	64.02% *59.77%*	69.84% *67.34%*	28.57% *34.14%*	42.19% *44.42%*	40.89% *44.09%*	29.44% *34.82%*
Denmark	63.42% *61.50%*	35.19% *38.23%*	68.30% *65.36%*	58.20% *57.80%*	59.02% *57.79%*	68.55% *65.50%*	32.44% *33.38%*	33.61% *42.75%* SIG 1%	41.77% *42.80%*	32.48% *33.55%*
France	61.68% *62.54%*	37.21% *38.46%*	67.83% *66.95%*	59.69% *58.68%*	56.80% *58.61%*	62.81% *66.58%*	35.02% *33.53%*	42.98% *43.09%*	40.08% *42.94%*	30.32% *33.87%*
Germany	61.37% *63.65%*	35.80% *39.73%* SIG 5%	64.59% *67.81%*	59.67% *59.78%*	57.18% *59.88%*	64.35% *67.99%*	31.05% *35.06%*	39.11% *44.32%*	44.98% *43.97%*	29.23% *35.37%* SIG 5%
Hong Kong	61.98% *60.84%*	34.55% *38.74%* SIG 1%	66.90% *65.24%*	56.35% *56.50%*	58.73% *56.86%*	66.44% *65.52%*	30.71% *34.84%*	41.79% *42.47%*	37.37% *42.50%*	27.86% *34.85%* SIG 5%
Italy	62.43% *61.04%*	36.11% *37.19%*	67.35% *65.40%*	58.22% *57.10%*	58.52% *57.14%*	66.67% *64.98%*	29.08% *32.67%*	42.75% *41.47%*	43.64% *41.46%*	28.14% *32.68%*
Japan	59.61% *59.65%*	38.54% *36.74%*	63.64% *64.46%*	56.65% *55.56%*	52.94% *55.05%*	67.11% *64.20%*	33.54% *32.73%*	43.83% *40.57%*	40.85% *40.51%*	35.74% *32.80%*
Netherlands	60.24% *62.83%* SIG 5%	35.64% *39.11%* SIG 5%	63.98% *67.01%*	57.85% *59.56%*	56.23% *58.97%*	64.19% *67.02%*	29.61% *34.22%*	41.88% *43.97%*	43.94% *43.60%*	26.09% *34.66%* SIG 1%
Spain	64.49% *62.72%*	35.36% *38.59%*	69.21% *66.79%*	60.63% *58.97%*	62.08% *58.84%*	67.31% *66.84%*	34.35% *33.69%*	36.25% *43.41%* SIG 5%	41.27% *43.06%*	29.91% *33.77%*
Switzerland	63.66% *63.20%*	37.08% *39.94%*	66.56% *67.25%*	57.57% *59.68%*	63.04% *59.27%*	69.79% *67.35%*	31.02% *35.28%*	42.67% *44.46%*	44.12% *44.35%*	29.68% *35.42%*
UK	61.15% *63.63%*	38.92% *39.58%*	64.94% *68.01%*	58.19% *59.83%*	60.63% *59.65%*	61.61% *67.86%* SIG 5%	36.15% *34.94%*	43.95% *43.95%*	42.13% *43.97%*	33.03% *35.17%*
USA	60.40% *62.91%* SIG 5%	36.42% *38.84%*	62.25% *66.89%*	56.84% *59.55%*	58.24% *59.26%*	64.46% *66.98%*	30.51% *33.85%*	42.86% *43.79%*	46.43% *43.31%*	24.73% *34.26%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5^{th} and 99.5^{th} percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5^{th} and 97.5^{th} percentile values of the bootstrap distribution.

Table G-4 Mean Positive Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	**Bear**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Australia	0.69% *0.71%*	0.53% *0.53%*	0.84% *0.73%* SIG 1%	0.67% *0.68%*	0.64% *0.68%*	0.62% *0.73%* SIG 1%	0.51% *0.50%*	0.57% *0.55%*	0.52% *0.54%*	0.50% *0.50%*
Belgium	0.77% *0.83%* SIG 5%	0.62% *0.57%*	0.98% *0.86%*	0.69% *0.79%*	0.70% *0.79%*	0.71% *0.86%* SIG 1%	0.64% *0.55%*	0.60% *0.59%*	0.61% *0.59%*	0.62% *0.55%*
Canada	0.74% *0.83%* SIG 1%	0.75% *0.60%* SIG 1%	0.90% *0.87%*	0.71% *0.80%*	0.64% *0.80%* SIG 1%	0.72% *0.86%* SIG 1%	0.73% *0.57%* SIG 5%	0.77% *0.62%* SIG 1%	0.82% *0.61%* SIG 1%	0.62% *0.57%*
Denmark	0.81% *0.87%* SIG 5%	0.70% *0.64%* SIG 5%	0.89% *0.90%*	0.75% *0.84%*	0.77% *0.84%*	0.82% *0.89%*	0.73% *0.61%* SIG 5%	0.64% *0.66%*	0.74% *0.66%*	0.68% *0.61%*
France	1.01% *1.10%* SIG 1%	0.88% *0.80%* SIG 5%	1.19% *1.14%*	0.93% *1.07%*	0.91% *1.06%* SIG 5%	0.97% *1.14%* SIG 5%	0.72% *0.77%*	0.84% *0.82%*	0.89% *0.82%*	1.10% *0.77%* SIG 1%
Germany	1.03% *1.17%* SIG 1%	1.10% *0.84%* SIG 1%	1.28% *1.22%*	0.96% *1.11%* SIG 5%	0.90% *1.12%* SIG 1%	0.95% *1.21%* SIG 1%	0.88% *0.81%*	1.01% *0.87%* SIG 5%	1.06% *0.87%* SIG 1%	1.51% *0.81%* SIG 1%
Hong Kong	1.40% *1.44%*	0.90% *0.96%*	1.79% *1.52%*	1.27% *1.35%*	1.32% *1.36%*	1.22% *1.50%* SIG 1%	0.69% *0.92%* SIG 1%	0.88% *1.00%*	1.08% *1.00%*	0.89% *0.91%*
Italy	1.32% *1.32%*	0.96% *0.97%*	1.51% *1.37%*	1.25% *1.27%*	1.28% *1.27%*	1.25% *1.37%*	0.78% *0.93%*	1.04% *1.01%*	1.01% *1.00%*	0.94% *0.92%*
Japan	1.10% *1.12%*	0.87% *0.80%*	1.45% *1.17%* SIG 1%	1.02% *1.07%*	1.06% *1.07%*	0.89% *1.17%* SIG 1%	0.77% *0.77%*	0.86% *0.83%*	0.85% *0.83%*	0.97% *0.76%* SIG 1%
Netherlands	1.00% *1.09%* SIG 1%	0.89% *0.75%* SIG 1%	1.27% *1.15%*	0.92% *1.04%*	0.90% *1.04%* SIG 5%	0.88% *1.13%* SIG 1%	0.81% *0.72%*	0.75% *0.77%*	0.84% *0.77%*	1.29% *0.72%* SIG 1%
Spain	1.06% *1.19%* SIG 1%	1.07% *0.86%* SIG 1%	1.33% *1.23%*	0.96% *1.15%* SIG 5%	0.90% *1.14%* SIG 1%	1.03% *1.22%* SIG 1%	0.83% *0.82%*	0.99% *0.89%*	1.10% *0.88%* SIG 1%	1.39% *0.82%* SIG 1%
Switzerland	0.85% *0.95%* SIG 1%	0.85% *0.66%* SIG 1%	1.11% *0.99%*	0.78% *0.92%* SIG 5%	0.69% *0.91%* SIG 1%	0.83% *0.98%* SIG 5%	0.78% *0.64%* SIG 5%	0.87% *0.69%* SIG 1%	0.86% *0.68%* SIG 1%	0.85% *0.64%* SIG 1%
UK	0.80% *0.87%* SIG 1%	0.71% *0.62%* SIG 1%	0.98% *0.90%*	0.84% *0.83%*	0.70% *0.83%* SIG 1%	0.67% *0.90%* SIG 1%	0.63% *0.60%*	0.71% *0.64%*	0.67% *0.64%*	0.85% *0.59%* SIG 1%
USA	0.81% *0.91%* SIG 1%	0.77% *0.63%* SIG 1%	1.00% *0.95%*	0.82% *0.87%*	0.77% *0.87%*	0.66% *0.94%* SIG 1%	0.59% *0.60%*	0.80% *0.65%* SIG 1%	0.79% *0.65%* SIG 5%	0.91% *0.60%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5^{th} and 99.5^{th} percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5^{th} and 97.5^{th} percentile values of the bootstrap distribution.

Table G-5 Mean Negative Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	-0.51% *-0.53%*	-0.77% *-0.73%*	-0.50% *-0.51%*	-0.55% *-0.55%*	-0.50% *-0.55%*	-0.46% *-0.51%*	-0.68% *-0.76%*	-0.66% *-0.70%*	-0.70% *-0.70%*	-1.02% *-0.75%* SIG 1%
Belgium	-0.54% *-0.59%*	-0.91% *-0.90%*	-0.72% *-0.56%* SIG 5%	-0.54% *-0.61%*	-0.50% *-0.61%* SIG 5%	-0.44% *-0.55%* SIG 5%	-0.85% *-0.95%*	-0.78% *-0.85%*	-0.80% *-0.85%*	-1.14% *-0.94%* SIG 1%
Canada	-0.57% *-0.62%*	-0.95% *-0.93%*	-0.61% *-0.59%*	-0.54% *-0.64%* SIG 5%	-0.60% *-0.64%*	-0.52% *-0.59%*	-0.93% *-0.99%*	-0.82% *-0.88%*	-0.76% *-0.88%*	-1.25% *-0.98%* SIG 1%
Denmark	-0.56% *-0.63%* SIG 5%	-0.95% *-0.92%*	-0.54% *-0.60%*	-0.66% *-0.65%*	-0.55% *-0.65%* SIG 5%	-0.47% *-0.59%* SIG 1%	-0.82% *-0.97%* SIG 5%	-0.85% *-0.87%*	-0.91% *-0.87%*	-1.21% *-0.96%* SIG 1%
France	-0.75% *-0.79%*	-1.20% *-1.15%*	-0.83% *-0.76%*	-0.92% *-0.82%*	-0.70% *-0.82%* SIG 5%	-0.58% *-0.76%* SIG 1%	-1.05% *-1.21%* SIG 5%	-0.99% *-1.10%*	-1.19% *-1.10%*	-1.53% *-1.20%* SIG 1%
Germany	-0.80% *-0.86%*	-1.44% *-1.29%* SIG 1%	-0.88% *-0.81%*	-0.86% *-0.89%*	-0.73% *-0.89%* SIG 5%	-0.74% *-0.81%*	-1.11% *-1.37%* SIG 1%	-1.26% *-1.22%*	-1.39% *-1.22%*	-1.94% *-1.35%* SIG 1%
Hong Kong	-0.90% *-0.92%*	-1.43% *-1.38%*	-0.88% *-0.87%*	-0.99% *-0.96%*	-0.86% *-0.96%*	-0.84% *-0.87%*	-1.17% *-1.46%* SIG 1%	-1.28% *-1.31%*	-1.13% *-1.32%* SIG 5%	-2.08% *-1.43%* SIG 1%
Italy	-0.91% *-0.94%*	-1.30% *-1.29%*	-0.90% *-0.90%*	-0.97% *-0.98%*	-0.96% *-0.97%*	-0.78% *-0.91%*	-1.14% *-1.35%* SIG 1%	-1.22% *-1.24%*	-1.16% *-1.24%*	-1.61% *-1.33%* SIG 1%
Japan	-0.77% *-0.74%*	-1.00% *-1.02%*	-0.64% *-0.71%*	-0.93% *-0.77%* SIG 5%	-0.77% *-0.77%*	-0.68% *-0.71%*	-0.85% *-1.06%* SIG 1%	-0.90% *-0.98%*	-1.01% *-0.99%*	-1.23% *-1.05%* SIG 1%
Netherlands	-0.76% *-0.77%*	-1.29% *-1.18%* SIG 5%	-1.00% *-0.74%* SIG 1%	-0.78% *-0.80%*	-0.71% *-0.80%*	-0.57% *-0.73%* SIG 5%	-1.04% *-1.25%* SIG 5%	-1.04% *-1.10%*	-1.20% *-1.12%*	-1.77% *-1.23%* SIG 1%
Spain	-0.74% *-0.88%* SIG 1%	-1.34% *-1.25%*	-0.88% *-0.84%*	-0.84% *-0.91%*	-0.63% *-0.91%* SIG 1%	-0.61% *-0.84%* SIG 1%	-1.11% *-1.32%* SIG 1%	-1.10% *-1.18%*	-1.49% *-1.19%* SIG 1%	-1.64% *-1.30%* SIG 1%
Switzerland	-0.60% *-0.69%* SIG 1%	-1.15% *-1.05%* SIG 5%	-0.63% *-0.66%*	-0.61% *-0.72%*	-0.64% *-0.72%*	-0.51% *-0.66%* SIG 1%	-0.89% *-1.12%* SIG 1%	-1.10% *-0.99%*	-1.06% *-0.99%*	-1.51% *-1.10%* SIG 1%
UK	-0.65% *-0.65%*	-0.99% *-0.94%*	-0.72% *-0.62%*	-0.69% *-0.67%*	-0.64% *-0.67%*	-0.53% *-0.61%*	-0.91% *-0.99%*	-0.91% *-0.89%*	-0.82% *-0.90%*	-1.29% *-0.98%* SIG 1%
USA	-0.59% *-0.65%*	-1.10% *-0.96%* SIG 1%	-0.56% *-0.62%*	-0.68% *-0.68%*	-0.57% *-0.67%* SIG 5%	-0.55% *-0.61%*	-0.89% *-1.01%*	-0.89% *-0.91%*	-1.11% *-0.91%* SIG 1%	-1.44% *-1.00%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5^{th} and 99.5^{th} percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5^{th} and 97.5^{th} percentile values of the bootstrap distribution.

Table G-6 Standard Deviation of Daily Price Returns

	Overall		Bull				Bear			
	Bull	**Bear**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Australia	0.77% *0.80%*	0.87% *0.84%*	0.89% *0.80%*	0.77% *0.80%*	0.74% *0.80%*	0.66% *0.79%* SIG 1%	0.72% *0.85%* SIG 5%	0.80% *0.83%*	0.83% *0.83%*	1.04% *0.84%* SIG 5%
Belgium	0.93% *1.02%* SIG 5%	1.08% *1.04%*	1.22% *1.03%* SIG 5%	0.83% *0.99%* SIG 5%	0.84% *1.00%* SIG 5%	0.75% *1.02%* SIG 1%	1.02% *1.06%*	0.95% *1.01%*	1.03% *1.01%*	1.24% *1.05%* SIG 1%
Canada	0.90% *0.99%* SIG 1%	1.18% *1.10%*	1.05% *0.99%*	0.85% *0.98%* SIG 5%	0.83% *0.98%* SIG 1%	0.83% *0.98%* SIG 5%	1.13% *1.14%*	1.05% *1.05%*	1.06% *1.05%*	1.35% *1.12%*
Denmark	0.91% *0.99%* SIG 1%	1.12% *1.07%*	0.97% *1.00%*	0.93% *0.99%*	0.85% *0.99%* SIG 1%	0.84% *0.98%* SIG 5%	0.96% *1.09%*	1.01% *1.04%*	1.15% *1.04%*	1.29% *1.08%* SIG 1%
France	1.18% *1.28%* SIG 5%	1.40% *1.33%*	1.36% *1.28%*	1.22% *1.27%*	1.09% *1.27%* SIG 1%	1.00% *1.27%* SIG 1%	1.10% *1.34%* SIG 5%	1.24% *1.30%*	1.37% *1.30%*	1.74% *1.34%* SIG 1%
Germany	1.26% *1.38%* SIG 1%	1.69% *1.48%* SIG 1%	1.56% *1.39%*	1.21% *1.36%*	1.11% *1.37%* SIG 1%	1.11% *1.38%* SIG 1%	1.30% *1.52%* SIG 5%	1.42% *1.45%*	1.63% *1.44%* SIG 5%	2.20% *1.50%* SIG 1%
Hong Kong	1.74% *1.77%*	1.68% *1.70%*	2.14% *1.82%*	1.75% *1.69%*	1.56% *1.71%*	1.39% *1.80%* SIG 5%	1.28% *1.74%* SIG 1%	1.49% *1.65%*	1.46% *1.66%*	2.18% *1.71%* SIG 1%
Italy	1.45% *1.47%*	1.49% *1.48%*	1.59% *1.47%*	1.39% *1.46%*	1.44% *1.46%*	1.32% *1.47%* SIG 5%	1.21% *1.48%* SIG 1%	1.39% *1.47%*	1.45% *1.47%*	1.74% *1.46%* SIG 1%
Japan	1.29% *1.26%*	1.21% *1.20%*	1.47% *1.28%* SIG 5%	1.33% *1.24%*	1.25% *1.24%*	1.02% *1.27%* SIG 1%	1.02% *1.19%* SIG 5%	1.13% *1.19%*	1.19% *1.20%*	1.45% *1.19%* SIG 1%
Netherlands	1.24% *1.31%*	1.54% *1.38%* SIG 1%	1.57% *1.34%* SIG 5%	1.19% *1.29%*	1.15% *1.29%*	0.96% *1.31%* SIG 1%	1.26% *1.41%*	1.19% *1.33%*	1.41% *1.34%*	2.07% *1.39%* SIG 1%
Spain	1.22% *1.37%* SIG 1%	1.54% *1.41%* SIG 5%	1.48% *1.38%*	1.20% *1.37%* SIG 5%	1.03% *1.36%* SIG 1%	1.10% *1.36%* SIG 1%	1.25% *1.43%* SIG 5%	1.27% *1.38%*	1.63% *1.38%* SIG 1%	1.89% *1.41%* SIG 1%
Switzerland	1.06% *1.16%* SIG 5%	1.36% *1.22%* SIG 1%	1.32% *1.17%*	1.01% *1.14%*	0.86% *1.14%* SIG 1%	0.95% *1.15%* SIG 5%	1.07% *1.26%* SIG 5%	1.31% *1.18%*	1.35% *1.18%*	1.58% *1.24%* SIG 1%
UK	1.00% *1.02%*	1.13% *1.07%*	1.17% *1.02%* SIG 5%	1.07% *1.01%*	0.90% *1.01%*	0.80% *1.01%* SIG 1%	1.00% *1.09%*	1.06% *1.04%*	0.97% *1.05%*	1.41% *1.08%* SIG 1%
USA	0.99% *1.08%* SIG 5%	1.26% *1.11%* SIG 1%	1.12% *1.09%*	1.06% *1.07%*	0.92% *1.07%* SIG 5%	0.81% *1.07%* SIG 1%	0.97% *1.12%*	1.09% *1.08%*	1.25% *1.09%*	1.55% *1.12%* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Table G-7 Skewness of Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	0.40 *0.32*	-0.75 *-0.79*	0.33 *-0.05*	0.05 *0.22*	0.24 *0.21*	-0.34 *-0.08*	1.00 *-0.29*	0.14 *-0.56*	-0.42 *-0.56*	-0.03 *-0.23*
Belgium	1.02 *0.98*	-0.53 *-0.83*	0.75 *0.73*	0.41 *0.70*	0.90 *0.68*	-0.23 *0.72*	-0.25 *-0.31*	0.07 *-0.72* SIG 5%	-0.32 *-0.72*	0.59 *-0.35* SIG 5%
Canada	0.42 *0.56*	-0.69 *-1.26*	0.30 *0.24*	-0.01 *0.38*	-0.15 *0.42*	0.05 *0.25*	-0.26 *-0.72*	0.34 *-0.97* SIG 1%	0.18 *-1.00* SIG 5%	-0.17 *-0.66*
Denmark	0.37 *0.33*	-0.47 *-0.77*	0.38 *0.01*	-0.25 *0.18*	0.06 *0.20*	-0.18 *0.01*	0.27 *-0.28*	0.04 *-0.60* SIG 5%	-0.71 *-0.63*	0.38 *-0.26*
France	0.18 *0.53*	-0.19 *-0.66* SIG 1%	0.14 *0.15*	-0.17 *0.36*	-0.13 *0.36*	-0.24 *0.18*	0.63 *-0.13*	-0.34 *-0.54*	0.50 *-0.55* SIG 1%	0.38 *-0.14*
Germany	0.60 *0.60*	-0.30 *-0.83* SIG 1%	0.93 *0.24*	-0.38 *0.37* SIG 5%	0.32 *0.40*	0.04 *0.22*	-0.21 *-0.37*	0.15 *-0.71* SIG 5%	-0.19 *-0.70*	0.79 *-0.39* SIG 5%
Hong Kong	1.65 *1.78*	-1.13 *-1.05*	1.18 *1.32*	2.15 *1.24*	1.15 *1.31*	-0.12 *1.27*	0.12 *-0.79*	-0.85 *-0.78*	0.01 *-0.82*	0.23 *-0.78* SIG 5%
Italy	0.37 *0.35*	-0.30 *-0.37*	0.05 *-0.06*	0.17 *0.25*	-0.12 *0.25*	-0.03 *-0.08*	0.64 *0.12*	0.10 *-0.26*	-0.26 *-0.26*	0.62 *0.11*
Japan	0.51 *0.71*	-0.11 *-0.30*	0.09 *0.19*	0.19 *0.53*	0.04 *0.58*	-0.14 *0.23*	0.27 *0.02*	0.00 *-0.20*	0.17 *-0.21*	-0.15 *0.01*
Netherlands	0.62 *0.80*	-0.41 *-0.96* SIG 1%	0.24 *0.46*	0.72 *0.61*	0.72 *0.63*	0.30 *0.47*	0.19 *-0.43*	0.19 *-0.81* SIG 5%	-0.32 *-0.83*	1.08 *-0.48* SIG 1%
Spain	0.63 *0.46*	-0.18 *-0.58* SIG 5%	0.12 *0.09*	0.23 *0.31*	0.31 *0.33*	0.23 *0.09*	-0.22 *-0.01*	0.27 *-0.44* SIG 5%	-0.16 *-0.46*	0.59 *-0.02*
Switzerland	1.34 *0.97*	-0.65 *-1.07* SIG 5%	1.23 *0.67*	0.80 *0.69*	-0.12 *0.75*	1.26 *0.66*	0.00 *-0.60*	-0.55 *-0.91*	-0.63 *-0.89*	0.62 *-0.57* SIG 5%
UK	0.25 *0.45*	-0.39 *-0.69* SIG 5%	0.02 *0.03*	0.27 *0.29*	0.10 *0.30*	-0.12 *0.03*	-0.11 *-0.23*	-0.14 *-0.54*	0.01 *-0.59*	0.31 *-0.23*
USA	0.73 *0.64*	-0.41 *-0.78*	0.77 *0.31*	0.53 *0.46*	0.79 *0.49*	-0.13 *0.29*	1.00 *-0.19* SIG 5%	0.07 *-0.62*	-0.12 *-0.60*	1.40 *-0.20* SIG 1%

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

Table G-8 Kurtosis of Price Returns in Stock Market Trends

	Overall		Bull				Bear			
	Bull	Bear	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Australia	2.02 *1.88*	4.41 *4.42*	3.35 *2.05*	0.46 *1.54*	1.38 *1.58*	0.08 *1.82*	1.03 *4.72*	0.20 *3.37*	3.05 *3.38*	6.25 *4.19*
Belgium	6.23 *5.32*	2.53 *2.41*	5.03 *5.53*	2.46 *4.66*	8.20 *4.64*	2.96 *5.41*	2.64 *2.34*	1.71 *2.58*	3.03 *2.60*	2.50 *2.37*
Canada	3.70 *2.70* SIG 5%	4.84 *5.64*	3.24 *2.85*	3.21 *2.58*	3.68 *2.62*	3.96 *2.88*	8.68 *5.69*	2.44 *4.76*	1.98 *4.85*	4.27 *5.21*
Denmark	2.21 *2.11*	2.12 *2.57*	3.95 *2.27*	1.21 *1.99*	0.79 *1.98*	2.11 *2.21*	0.97 *2.82*	1.88 *2.33*	3.34 *2.48*	1.66 *2.57*
France	2.67 *2.64*	2.56 *2.09*	3.22 *2.93*	2.26 *2.41*	2.06 *2.39*	0.38 *2.82* SIG 1%	1.34 *2.24*	1.37 *2.08*	3.10 *2.11*	2.06 *2.19*
Germany	3.85 *3.28*	2.22 *2.64*	3.85 *3.57*	2.36 *3.01*	2.57 *3.03*	1.71 *3.47*	2.18 *2.61*	0.92 *2.66*	0.72 *2.63* SIG 5%	2.12 *2.68*
Hong Kong	11.94 *11.65*	5.56 *5.11*	11.26 *10.38*	16.79 *8.21*	5.78 *8.52*	1.74 *10.19*	2.46 *5.04*	3.95 *4.26*	1.58 *4.53*	5.19 *4.98*
Italy	1.52 *1.40*	1.70 *1.60*	2.51 *1.66*	0.07 *1.29*	1.02 *1.32*	1.92 *1.52*	0.90 *1.85*	-0.14 *1.49* SIG 1%	1.44 *1.48*	2.64 *1.85*
Japan	3.34 *2.66*	1.48 *1.71*	3.25 *2.93*	3.49 *2.39*	2.59 *2.44*	1.60 *2.79*	0.94 *1.87*	0.15 *1.64* SIG 5%	0.40 *1.65*	2.01 *1.84*
Netherlands	4.40 *3.61*	2.96 *3.30*	2.88 *3.75*	4.29 *3.52*	6.31 *3.57*	1.73 *3.61*	3.91 *3.22*	1.53 *3.52*	1.67 *3.39*	2.29 *3.28*
Spain	2.70 *1.98*	1.80 *2.12*	2.14 *2.18*	2.31 *1.90*	1.83 *1.90*	3.40 *2.16*	2.26 *2.37*	0.42 *1.98*	1.12 *2.04*	1.80 *2.30*
Switzerland	7.50 *5.39*	2.81 *3.77*	5.82 *5.54*	4.93 *4.61*	1.54 *4.84*	12.94 *5.47* SIG 1%	1.38 *3.79*	1.24 *3.75*	4.80 *3.53*	2.61 *3.64*
UK	3.24 *2.13* SIG 5%	1.84 *2.39*	2.81 *2.38*	3.17 *2.04*	2.78 *2.01*	1.98 *2.29*	2.24 *2.49*	1.64 *2.34*	1.02 *2.42*	1.35 *2.44*
USA	3.57 *2.71* SIG 5%	2.52 *3.32*	2.65 *2.91*	3.17 *2.58*	4.59 *2.64*	3.02 *2.80*	2.32 *3.41*	0.83 *2.96*	0.50 *3.09*	3.65 *3.29*

Bootstrap average values are shown in italics. Significance at the 1% level, shown in the table as "SIG 1%", is based on a two-tailed test using the 0.5th and 99.5th percentile values of the bootstrap distribution. Significance at the 5% level, shown in the table as "SIG 5%", is based on a two-tailed test using the 2.5th and 97.5th percentile values of the bootstrap distribution.

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