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Non-linear dependence of returns, volatility and trading volume in currency futures markets

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Non-Linear Dependence of Returns, Volatility and Trading Volume in Currency Futures Markets

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Dedication

This work is dedicated to my late father

***Allahyarham* Wan Mahmood Bin Yusof**

for his love and tolerance.

Semoga dicucuri rahmat keatas Ruhnya dan ditempatkan

di Syurga Jahnah bersama-sama dengan orang yang beriman.

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Abstract

In this study, we formally test for nonlinear dependence in four currency futures contracts traded on the International Monetary Market of the Chicago Mercantile Exchange, since most prior research studies have reported that financial time series exhibit nonlinear behaviour. Four nonlinear testing procedures are used. Our initial findings provide evidence of nonlinear dependence for all currencies; namely the British Pound (BP) the Japanese Yen (JY), the German Mark (DM) and the Swiss Franc (SF), each quoted in US dollars per foreign currency unit. As the BDS test rejects the null hypothesis of i.i.d. while the third moment test fails to reject multiplicative dependence, this suggests that the nonlinearity occurs in the variance of the process.

Since our results show significant ARCH effects; *i.e.*, that large and small changes in returns tend to be systematically clustered over time, the study employs the specifications of conditional heteroscedasticity and finds that Bollerslev's GARCH generalization (1986) of the ARCH process provides a parsimonious model that represents the data satisfactorily. As a result, further related analyses conducted in the study make use of similar GARCH procedures throughout. Perhaps the most important point to emerge from our empirical analysis is the ability of the GARCH (1,1) model to capture nonlinear dependence in all the series.

Following the procedures laid down by Lamoureux and Lastrapes (1990), we test for the 'mixtures of distributions' hypothesis in which the stochastic mixing variable is hypothesized to be the rate of information arrival. Our findings on the contemporaneous relationship between volume and returns are consistent with this hypothesis, indicating that currency futures pricing appears to be efficient. The study also considers the informational role of contemporaneous volume with respect to volatility, and our results in this context show that trading volume contains significant explanatory power over the conditional variance in the GARCH specifications of the returns series.

The important contribution of this analysis to current research literature is the

confirmation that, for currency futures, trading volume can effectively explain the conditional variance. Indeed, the GARCH effects diminish in all cases examined and this finding supports that of Lamoureux and Lastrapes (1990) for the stock market. Moreover, the present study overcomes the problem of the high serial correlation of volume by replacing it with unexpected volume in the conditional variance, following the procedure of Bessembinder and Seguin (1993). Using uncorrelated volume surprises, a similar result of a positive contemporaneous relationship between volume and return volatility is obtained, albeit with a slightly lower level of significance. However, the GARCH effects remain significant; *i.e.*, they do not vanish.

Next, we show that lagged uncorrelated volume has a low explanatory power, which confirms the role of contemporaneous (unexpected) volume, there being none of the problems of simultaneity in the conditional variance equation that were found by Najang and Yung (1991) in treasury bond futures. In addition, we report results for subperiods which are almost identical to those of the full period, indicating structural stability in the entire sample period.

Finally, our results reveal that in the case of the conditional variance equation, ARCH effects exist simultaneously with spillover effects from other currencies for the BP and the DM, but not for the SF or the JY. Also, while the BP and the SF are found to be the main exporters of volatility to other currency futures, there is no clear evidence that any currency futures contract imports volatility on a bilateral basis. However, our results show that the inclusion of a third and fourth contract in the conditional variance equation reduces the volatility spillover between the first and second contracts, leading to the conclusion that a common economic effect is responsible to some extent for volatility interactions.

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Glossary of Terms and Abbreviations

ADF	Augmented Dickey Fuller
ADJR	Adjusted Price Range
AIC	Akaike Information Criterion
AR(1)	Autoregressive (1)
ARCH	Autoregressive Conditional Heteroscedasticity
ARIMA	Autoregressive Intergrated Moving Average
ARMA	Autoregressive Moving Average
BDS	Brock, Dechert and Scheinkman
BIC	(Schwarz) Bayesian Information Criterion
BP	British Pound
CD	Canadian Dollar
CME	Chicago Mercantile Exchange
DF	Dickey Fuller
DM	German Mark
ED	Eurodollar
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
EMH	Efficient Market Hypothesis
FF	French Franc
FTSE	Financial Time-Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GARCH-M	Generalized Autoregressive Conditional Heteroscedasticity- in Mean
GMM	Generalized Method of Moment
IGARCH	Intergrated Generalized Autoregressive Conditional Heteroscedasticity
IID	Independent and Identically Distributed
IMF	International Monetary Fund

IMM	International Monetary Market
IL	Italian Lira
JGB	Japanese Government Bond
JY	Japanese Yen
LB	Ljung Box
LIFFE	London International Financial Futures Exchange
LM	Lagrange Multiplier
LME	London Metal Exchange
MDH	Mixture of Distributions Hypothesis
MP	Mexico Peso
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PCCP	Percentage Change in (Daily) Closing Prices
SEQ	Sequential Information Model
SETAR	Self-Exciting Threshold Autoregression
SF	Swiss Franc
SIM	Simultaneous Information Model
SIMEX	Singapore Monetary Exchange
S&P	Standard and Poors
TMT	Third Moment Test
TSE	Toronto Stock Exchange
VAR	Vector Autoregressive
VOL/OI	Volume Relative to Open Interest

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Chapter One

Introduction

1.1 Background to the Study

Futures markets have received considerable attention over the past few years, particularly given the increase in financial risk in the markets. The development of the market for financial futures stems from the collapse of the Bretton Woods fixed exchange rates system in 1971, following which there was a period of unprecedented volatility in both exchange rates and interest rates. The increase in risk associated with such volatility had the potential effect of reducing both production and consumption of commodities leading to welfare losses. As a result, companies and financial institutions needed better exchange rate and interest rate exposure management techniques in order to compensate for this increase in risk, which in turn created a need for new financial instruments such as futures. The International Monetary Market (IMM), part of the Chicago Mercantile Exchange (CME), introduced currency futures in 1972 in order to allow companies to hedge against risk. Since then, many futures markets have emerged around the world functioning similar to the IMM.

Apart from minimizing the problems arising from default risk, futures markets also provide liquidity in secondary dealing. Risk can be easily shifted from hedger to speculators who willingly assume the risk in exchange for extra profits, and it is this process of shifting the unwanted risk which leads to the increased liquidity of the futures market. In the absence of futures markets, the cost of managing this risk would be higher. However, the market cannot function effectively unless information flows to the market are efficient. Thus, the effectiveness of the futures market in hedging risk depends on its own efficiency. It follows that one of the key issues in assessing futures markets is the extent to which these markets can be considered as efficient. If the markets are not efficient, then their existence will not alone be sufficient to avoid the losses which would occur due to the increased financial risk and volatility. Furthermore, this inefficiency will also bring extra costs.

The market efficiency hypothesis suggests that the current price of an asset in the market should fully reflect all available information. A market is deemed to be efficient with respect to an information set if it suggests that it is not possible to make economic profits using that information set. On the other hand, in an inefficient market, investors can earn abnormally high returns on their investments by using information which is not available to the market as a whole. As noted by Fama (1991), market efficiency *per se* is not testable; it must be tested jointly with some model of pricing assets. In the case of the futures markets, efficiency is commonly tested on the basis of a model which implies that the current futures price should equal the currency spot price expected to prevail at the expiry date. This implies that the futures price is the best predictor of the eventual spot price and that the futures price incorporates all relevant information including the past spot and futures prices. However, if the joint hypothesis is rejected this does not necessarily imply that the market is inefficient or that the asset pricing model used is inappropriate (Antonious, 1996). For example, Beck (1994) argues that the hedging demand by risk-averse agents may in itself cause the existence of the risk premium. Indeed, a further study by Danthin (1978) reports that, even in efficient markets, the existence of a risk premium created by the hedging demand of risk averse investors may violate the simplest hypothesis that the current futures price is an unbiased estimate of the future spot price.

Based on the above assumptions, numerous authors have examined the role of market efficiency for various types of futures contract [e.g. Cornell (1981); Chowdhury (1991); McCurdy and Morgan (1988); Antonious and Holmes (1996)]. Generally, they report mixed results. The reasons for these mixed results are various, among them being the different methodologies employed and the sample periods used. But there are also limitations arising from the assumptions underlying the simple unbiasedness hypothesis. In particular, a better understanding of the process through which futures prices are generated is required, taking into account not only the distribution of their returns but also their time series properties.

With respect to the behaviour of returns in financial time series, it is well known that the empirical distributions of price changes are usually too leptokurtic to be consistent with Gaussian populations. As Locke and Sayer (1993) note, this knowledge dates back to the pioneering works of Mandlebrot (1963) and Fama (1965) on stock returns. Both these authors found that, in the majority of cases, the empirical distributions of daily price changes had more observations located around the mean and in the extreme tails than did a normal distribution. Moreover, this leptokurtosis appeared in spot exchange rates as well as in stock returns [Hsieh (1988); Friedman and Vandersteel (1982)] and elsewhere. In addition, further studies of stock returns [Hinnich and Patterson (1985), Akgiray (1989), Blank (1991), Scheinkman and LeBaron (1989), Hsieh (1991)] and spot exchange rates [Bollerslev (1987); Hsieh (1989a); Krager and Kugler (1993)] revealed behaviour exhibiting significant levels of second-order dependence and, as such, they could not be modelled as linear white-noise procedures. An appropriate explanation for the existence of such behaviour was given in the work on the application of autoregressive conditional heteroscedasticity (ARCH) models (Engle, 1982) and their generalized (GARCH) form (Bollerslev, 1986). Nonlinear models of this type allow for persistence in the variance structure and have been found to provide a good approximation to return series in various financial markets, as they account in particular for the tendency of financial returns to cluster together in chronological time.

Among the authors who have employed time-varying variance models in asset markets are Domowitz and Hakkio (1985); Akgiray (1989); Baldaulf and Santoni (1991). As for futures markets, the search for nonlinear dependence has also been widespread; the empirical work of DeCoster, Labys & Mitchell (1991) was among the first to consider commodity futures, and Blank (1992) provided similar results from a nonlinear dynamical analysis of the S&P 500 index futures contract.

Following the success in modelling univariate time series using a nonlinear model, the present study extends to include trading volume in the analysis. The importance of this factor is widely acknowledged by the fact that trading in asset markets is mainly induced by the arrival of new information leading to subsequent revisions of expectations by investors. The trading volume therefore can be considered to reflect information about changes in the expectations of investors and their agreement on the pricing implications (Harris and Raviv, 1993). Indeed, Blaum, Easley and Hara (1994) argue that the role of volume as a signal of the precision of beliefs means that the volume of statistics provides information to the market that is not conveyed by the price. Besides trading volume, residual terms (*i.e.*, financial disturbances) are also now known to have informational content in that they contribute to explaining the conditional variance (Najang, Rahman and Yung, 1992). Moreover, this effect may spill over from one futures contract to another, and is observable in the transmission of volatility. In the currency futures market, for example, a hedger can take clues from the residuals of the contract in question (*i.e.*, an ARCH effect) and from other currency futures (*i.e.*, a spillover effect). It is these recent developments that are the focus of the modelling approach investigated in this thesis.

1.2 Aims of the Study

The aims of this study are threefold. To begin, we will test for nonlinear dependence in the returns series for four leading currency futures contracts. As noted above, it is now widely acknowledged that the linearity assumptions of financial time series are no longer appropriate. Therefore, as a starting point, this study will adopt several nonlinear testing procedures which can properly account for the second order moment in the return series.

Secondly, as the results show highly significant GARCH effects in the series, we will take one step forward by attempting to uncover the source of these effects. Similar attempts using common stock returns have been made by Lamoureux and Lastrapes (1990) and Sharma, Mougoué and Kamath (1996) and futures returns have been examined by Najang and Yung (1991) and Fujihara and Mougoué (1997a). In this study, we will take a similar approach to that of Lamoureux and Lastrapes (1990) and test the extent to which trading volume explains the GARCH effects found in the currency futures returns. We will also reexamine the relationship between trading volume and price variability using GARCH procedures. Two competing hypotheses will be tested, namely the mixtures distribution hypothesis (MDH) and the sequential information model (SEQ).

Finally, this study will extend the existing research on spillover effects in several important ways. Firstly, we will test both mean and volatility spillover using data which avoids any period when a price limit was imposed as this has affected some prior research. Secondly, our study will provide a more comprehensive analysis of spillover effects. More specifically, we will analyse both pairwise and multi-currency spillover in order to test whether there is a common economic effect in the currency futures return series.

1.3 An Overview of the Thesis

The thesis is presented in eight chapters. Following this introduction, Chapter Two presents a theoretical and empirical review of prior research and its purpose is to survey the body of literature on four major issues related to the thesis: (i) market efficiency; (ii) nonlinearity in financial returns; (iii) the relationship between trading volume and price variability; and (iv) spillover effects. Prior research is discussed not only in the context of the currency futures, but in the wider framework of the equity market, the foreign exchange market and futures market.

Chapter Three presents an in-depth discussion of the currency futures contract in relation to market microstructures and pricing, starting with a brief outline of the basic features of market operations and the important characteristics of futures contracts. We go on to describe the currency futures market, in particular, before reviewing research into the pricing of such contracts.

Chapter Four presents the data for a relationship between volume and volatility and for spillover effects, followed by an introduction to the methodological issues arising when testing for nonlinear dependence, An overview of heteroscedasticity modelling is also provided, focussing on the GARCH specification.

Chapter Five contains a detailed analysis of autocorrelation and nonlinearity in the four currency returns series, as well as in the GARCH residuals. Results on a number of testing procedures for nonlinear dependence are presented.

The empirical results concerning the informational role of trading volume are contained in Chapter Six. Two competing hypotheses are considered: namely, the sequential information model (SEQ) and the mixtures distribution hypothesis (MDH). This is followed by a test of GARCH effects for contemporaneous volume and lagged volume, and the consistency of the new results is demonstrated for subsamples of the data.

Chapter Seven presents the findings concerning mean and volatility spillover effects. In order to demonstrate the presence of common economic effects in currency futures series, the spillover effects are modelled both on a pairwise basis and for all four contracts together.

Chapter Eight gives a summary of the research and the methods employed. In order to place the results in context and to demonstrate the contribution of this thesis with regard to the informational role of volume in pricing volatility and its spillover between futures contracts, the findings of the present study are compared with previously published results. Finally, the implications of the results for futures trading are discussed and possible directions for further research into the currency futures market are suggested.

Chapter Two

Nonlinearity, Volatility and Trading Volume: Theoretical Issues and Empirical Evidence in Finance.

2.1 Introduction

In this chapter, we explore the early theoretical issues and analyse the empirical evidence in the futures markets, as well as in the foreign exchange and equity markets, which influences the work developed in this thesis. Four issues are put forward and critically evaluated. These are: market efficiency and the assumption of linearity in Section 2.2; nonlinear dependence in financial returns in Section 2.3; the relationship between trading volume and price variability in Section 2.4; and spillover effects in Section 2.5. Selected related literature is reviewed for each of the issues under discussion in the three different markets. Studies investigating the same issues as well as other issues related to the currency futures market will, however, be reviewed in Chapter 3. Finally, Section 2.6 gives a summary of previous findings.

2.2 Market Efficiency Tests and the Assumption of Linearity

The research on the intrinsic value of security has resulted in a large volume of literature on modern portfolio theory and capital market theory. The Efficient Market Hypothesis (EMH) suggests that if the market is regarded as price efficient, investors cannot, in general, outperform the market since information regarding price is already impounded in the price itself. Earlier empirical work testing the EMH was based on the random walk model Fama (1970). Many analyses concluded that stock prices follow a random walk. However, new evidence which opposes the EMH has been found in recent studies by Fama and French (1988), Poterba and Summers (1988) and Lo and MacKinlay (1988). This suggests that stock returns contain relatively large predictable components.

In the literature on the futures market, the subject of market efficiency has long been debated. The search for a market efficiency hypothesis for futures markets and foreign exchange has been based on assessing whether forward or futures rates are unbiased predictors of future spot rates. Most of the tests conducted in these markets use unit roots, cointegration and error correction models: for example; Meese and Singleton (1982), Domowitz and Hakkio (1985), and Baillie and Bollerslev (1989) on the foreign exchange market; and Lai and Lai (1991), and Antoniou and Holmes (1996) on the futures market. A market is said to be efficient if the market price fully reflects the available information so that there is no strategy from which traders can profit consistently by speculating on the expected futures spot price.

Testing for Time Varying Risk Premium in Gold Futures

An empirical estimation of the time varying risk premium in the gold futures market and an identification of the factors that may contribute to such a risk premium was the purpose of the study by Melvin and French (1990). Specifically, the authors examined whether South African political unrest or oil price movements could affect gold market participants' perception of the future, thus leading to a change in the premium attached to futures price quotations. According to risk premium theory, the futures price at time *t* for delivery one period forward should be equal to the expected future spot price plus a time varying risk premium.

Melvin and French (1990) use data from COMEX and the *Wall Street Journal* (Febuary 1975 to November 1988) on the futures settlement price of a contract 30 days prior to the last day of trading. The corresponding spot market price on the same day was used for the spot price observation, yielding one observation per month for each variable. Data on the spot price were taken from the Data Resource, Inc; daily data tape. A GARCH parameterization was used to estimate the conditional variance since the evidence indicated that the spot price forecast error follows an ARCH process.

The results of the author's estimation showed that South African political unrest and oil price changes were in fact significant determinants of the conditional variance of spot price forecast errors. Furthermore, there was evidence of a significant time varying risk premium in gold futures prices. Thus, the futures price is a biased estimate of the expected future spot price.

Testing Market Efficiency Using Cointegration for Four Futures Nonferrous Metals

Chowdhury (1991) examined the efficient market hypothesis for four nonferrous metals: copper, lead, tin and zinc, all of which were traded in the London Metal Exchange (LME). Specifically, the efficiency of these markets was tested using the recently developed cointegration theory after accounting for the presence of nonstationarity in the data series. The author noted that, in the presence of nonstationary series, the conventional market efficiency statistical testing procedures are no longer appropriate since they tend to bias toward an incorrect rejection of efficiency.

Futures prices for three-month delivery and the subsequent spot price when the contract matured were used; specifically the monthly average spot and futures (three months) prices from July 1971 to June 1988. Sixty-four observations were used for estimation. The results indicated the presence of nonstationarity in the price for all cases, thus casting into doubt most of the previous studies that had tested for market efficiency using the levels of spot and futures prices of these metals. To account for nonstationary behaviour and to resolve one of the major concerns regarding the previous studies, the author used the cointegration approach. The empirical results indicated the rejection of the efficient market hypothesis for the four nonferrous metals; thus, the futures price appears to be a biased predictor of the subsequent spot price in these markets.

Testing the Market Efficiency and Unbiasedness Hypothesis for the FTSE-100 Stock Index Futures

An investigation into the joint hypothesis of market efficiency and the unbiasedness of futures prices was carried out by Antoniou and Holmes (1996) using UK data. Unlike previous research, their study tested for both the short- and long-run efficiency of the FTSE-100 stock index futures contract traded on the London International Financial Futures Exchange (LIFFE), using cointegration and error correction models. In addition, variance-bounds tests were developed and employed to test for futures market efficiency.

Quarterly spot values of the FTSE-100 stock index and the FTSE-100 futures contract prices were used, covering all the futures contracts which expired in the period from September 1984 to June 1993. The observations related to futures prices were divided into subsets according to the time to expiration. The results show that the market is efficient and thus provides an unbiased estimate of future spot prices for a period of one and two months away from expiration. However, they are not unbiased predictors when considering three or more months prior to maturity. The reasons, as the authors argue, could either be due to a positive risk premium or to inefficiencies caused by the fact that these dates correspond with the dates of the maturity of earlier futures contracts because stock index futures trade on a three-month cycle.

Another study testing the unbiasedness hypothesis and the existence of a risk premium was carried out by Kolb (1992) on 29 commodities with 980,800 daily settlement price observations between 1957 and 1988. In particular, he examined the implications of the

Keynsian theory of normal backwardation which suggests that futures prices should be lower than expected future spot prices due to the presence of a risk premium in futures pricing which arises because hedgers are risk averse.

Kolb's results show that, while some commodities allow for normal backwardation in their pricing, others in fact follow an opposite process, that of contango where futures prices are consistently higher than expected futures spot prices. As a result, Kolb concluded that normal backwardation is not a universal feature of futures contracts. In addition, he inferred that most commodities exhibit no risk premium.

Testing for Unbiasedness Hypothesis in the Foreign Exchange Market

The original work on testing for unit roots in exchange rates was done by Meese and Singleton (1982). Specifically, they tested for the presence of unit roots in the autoregressive representations of the logarithm of the spot and forward exchange rates. The authors argued that the test for unit roots is important because assuming that levels or differences of exchange rates are stationary can lead to substantially different conclusions (e.g., testing whether forward rates are unbiased predictors of futures spot rates). Testing for the presence of unit roots in the autoregressive representation of a time series amounts to testing whether certain coefficients are unity.

Their data consisted of the weekly series of Wednesday twelve o'clock Swiss franc-U.S. dollar, German mark-U.S dollar and Canadian dollar-U.S. dollar spot bid rates and the midpoint of the twelve o'clock bid-ask spread on the three-month forward rates. The sample began on 7 January 1976 for all currencies and ended on July 8, July 2 and June 24, 1981 for Switzerland, Canada and Germany, respectively. Using the unit root test of Dickey and Fuller (1981), the authors found that levels and logarithms of foreign exchange rates do not have stable univariate AR representations (nonstationary). In addition, the series ($\ln s_{t+n} - \ln f_t$) for Canada and Germany have stable univariate AR representations. However, the results suggest the presence of a single unit root in the series for Switzerland.

Testing for Rational Expectations and Market Efficiency in the Foreign Exchange Market

Baillie, Lippens and McMahon (1983) were among the first researchers to test for rational expectations and efficiency in the foreign exchange market. Their hypothesis was that if the foreign exchange market is efficient in the sense that all available information is used rationally by risk-neutral agents in order to determine the spot and forward exchange rates, then the expected rate of return to speculation will be zero. Thus, under the assumption of rational expectations and risk neutrality, a hypothesis can be derived in which the forward rate is an unbiased predictor of the future spot rate. This hypothesis is clearly a joint hypothesis since it includes the assumption of rational expectations and the assumption that the risk premium for the forward rate is zero.

Using weekly data from the New York foreign exchange market from June 1973 to April 1980 for six different currencies: the British pound, the German mark, the Italian lira, the France franc, the Canadian dollar and the Swiss franc, the authors first modelled the forward and spot exchange rates as an unrestricted bivariate autoregressive. Then they tested the null hypothesis that the forward exchange rate is an unbiased estimate of the corresponding futures spot exchange rate, using a nonlinear Wald test. Their result rejected the null hypothesis in all cases. These results cast doubt on the assumption made in many macroeconomic models.

Testing for Time-Varying Risk Premium in the Foreign Exchange Market

The research of Domowitz and Hakkio (1985) relates to the study of Melvin, *et.al.*, (1990) on the gold futures market and also to Lai and Lai's study (1991) on the forward currency market in that they all examine the existence of a risk premium. However, Domowitz and Hakkio (1985) are more comprehensive as they examine the risk premium in the foreign exchange market as a function of the conditional variance of market forecast errors.

Averages of bid-ask rates obtained from the Bank of America for five foreign currencies: the British pound (BP), the France franc (FF), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF), are used, consisting of 108 nonoverlapping observations from June 5, 1973 to August 17, 1982 for three variables: the spot rate, the forward rate and the future spot rate. Since many studies recognize the presence of conditional heteroscedasticity in the forecast errors of foreign exchange, the authors model the series based on the ARCH specification of Engle (1982) using likelihood techniques to obtain efficient estimates. Their results reject the null hypothesis of no risk premium only for the BP and the JY. Nor is there much evidence that the conditional variance of the exchange rate forecast is an important sole determinant of the risk premium.

Testing Market Efficiency Using Cointegration in the Foreign Exchange Market

Baillie and Bollerslev (1989) carried out research on testing for unit roots in exchange rates which is closely related to the study of Meese and Singleton (1982). However, they use different testing procedures and sampling method. Meese and Singleton (1982) employed Dickey and Fuller's unit roots test on weekly data but Baillie and Bollerslev follow Phillips and Perron's (1988) tests for unit roots on daily series, arguing that these tests have been robust for a wide variety of serial correlation and time-dependent heteroscedasticity. Subsequently, the authors tested for cointegration in order to certify whether there was some long-run equilibrium relationship between spot and forward rates.

Baillie and Bollerslev employed daily spot and thirty-day forward exchange rate data from the New York Foreign Exchange Markets for the period between March 1, 1980 and January 28, 1985 constituting a total of 1,245 observations. Their data were the opening bid prices for the British pound (BP), the German mark (DM), France franc (FF), the Italian lira (IL), the Swiss franc (SF), the Japanese yen (JY) and the Canadian dollar (CD). The results reveal strong evidence of the presence of a unit root in the univariate time-series representation for seven daily spot and forward exchange rates series. Furthermore, all seven spot and forward rates appear to be cointegrated, thus supporting the hypothesis that the seven series are in a relationship of equilibrium in the long-run. These findings imply market efficiency where there is no systematic divergence between the futures and spot prices which could profitably be exploited by traders.

Testing for Market Efficiency and Unbiasedness Hypothesis in the Foreign Exchange Market

Lai and Lai (1991) examined the testing of future market efficiency in a study which is closely related to the research by Chowdhury (1991), in that both use cointegration technique. Although both studies accounted for the nonstationarity of data series in their analysis, they focused on different markets: Chowdhury (1991) examined the futures markets of four nonferrous metal while Lai and Lai (1991) were concerned with the forward foreign currency market.

Lai and Lai used the monthly spot and forward rates for five major currencies against the U.S. dollar: the British pound (BP), the German mark (DM), the Swiss franc (SF), the Canadian dollar (CD) and the Japanese yen (JY). Each series consisted of 198 observations, taken over the period from July 1973 to December 1989. These data are nonoverlapping and they are end-of-month observations on the bid spot exchange rate and the bid one-month forward rate from the *International Monetary Market Yearbook* for the 1973-1987 period and from *The Wall Street Journal* for the 1988-1989 period. The research findings do not support the unbiasedness hypothesis, which can be interpreted as a violation of the joint hypothesis of market efficiency and no-risk premium for all major forward currency markets.

Testing for the Random-Walk Hypothesis in the Stock Market

The behaviour of stock-market prices was investigated by Fama (1965). First, he discussed in detail the theory underlying the random-walk model and then he tested the model's empirical validity. He noted that the theory of random-walks in stock prices actually involves two separate hypotheses: first, that successive price changes are independent and second, that the price changes conform to some sort of probability distribution.

Fama uses the daily price data on thirty stocks from the Dow-Jones Industrial Average. The time periods vary from stock to stock but usually run from about the end of 1957 to September 26, 1962 and consist of about 1,200-1,700 observations per sample. The results of the serial correlation model and the run tests, fail to reject the hypothesis of random-walks in stock prices. This indicates that successive price changes are independent and identically distributed random variables which in turn implies that the series of price changes has no memory; *i.e.*, the past cannot be used to predict futures in any meaningful way.

Testing for the Random-Walk Hypothesis Using Variance Test Ratio

Poterba and Summers (1988) investigated transitory components in stock prices. Specifically, they analysed monthly data on real and excess returns from the New York Stock Exchange since 1926 as well as annual returns data for the 1871-1985 period. The authors also analysed 17 other equity markets and studied the mean-reverting behaviour of individual corporate securities in the U.S.

Using variance ratio tests, they found that stock returns showed positive serial correlation over short periods and negative correlation over longer intervals. This empirical evidence suggests that stock returns, contrary to the random walk hypothesis, contain relatively large predictable components. These results are in line with those of Fama and French (1988) and Lo and MacKinley (1989).

Another study testing the random walk hypothesis which was similar to that of Fama (1965) was carried out by Urrutia (1995), using monthly index prices from the Latin American equity market of Argentina, Brazil, Chile and Mexico from December 1975 to March 1991.

On the basis of variance-ratio tests, Urrutia rejected the hypothesis of random walk. However, run tests indicated that Latin American equity markets are weak-form efficient. These empirical findings suggest that investors might not be able to develop trading strategies that would allow them to earn excess returns.

2.3 Nonlinearity in Financial Returns

Research in financial economics has found that the distribution of returns is not normal but leptokurtic. Specifically, the empirical distributions of daily price changes have more observations located around the mean and in the extreme tails than does a normal distribution. This leptokurtosis appears in stock returns [Fama (1965); Akgiray (1989)];

spot exchange rates changes [Hsieh (1988); Friedman and Vandersteel (1982)] and elsewhere. The modelling of financial time series has become important because it has been found that the naive linear stochastic model known as the random walk, which was generally assumed to be an appropriate model for the return series, is not so. Further studies of stock returns [Hinnich and Patterson (1985), Akgiray (1989), Blank (1991), Scheinkman and LeBaron (1989), Hsieh (1991)] and of spot exchange rates [Bollerslev (1987); Hsieh (1989a); Krager and Kugler (1991)] have confirmed that nonlinear models are more appropriate. Various nonlinear models have been proposed, mainly time varying variance models [Domowitz and Hakkio (1985); Bollerslev (1987); Akgiray (1989); Baldaulf and Santoni (1991)]. However, the self-exciting threshold autoregressive (SETAR) model, suitable for data which have a time-varying mean has also been used [Krager and Kugler (1993)].

Over the past few years, the search for nonlinear dependence in financial time series has become widespread and empirical work has extended to the futures markets [DeCoster, Labys & Mitchell (1991); Yang and Brorsen (1993); Fang, Lai & Lai (1994)]. Blank (1992) provides results from a nonlinear dynamical analysis of the S&P 500 index futures and soybeans futures while Fujihara and Mougoué (1997a) find linear and nonlinear dependence in petroleum futures. In addition, Fujihara and Park (1990) have compared various stochastic processes for weekly futures returns and have concluded that they are best represented by a nonlinear model.

Testing for Nonlinear Structure in Futures Pricing

DeCoster, Labys and Mitchell (1991) were among the earliest to investigate the characteristics of futures prices. Specifically, they examined whether there is a nonlinear dynamic structure and, in particular, a chaotic structure in the behaviour of futures prices. Chaotic analysis is capable of evaluating whether the process has a deterministic structure. If this structure can be shown to exist, the implication would be that the empirical validity of the efficient markets hypothesis, which implies a random walk for asset prices, is called into question.

Daily settlement futures price data are used for four major commodities traded on exchanges in New York; *i.e.,* the Coffee 'C' contract, the Sugar No. 11 contract, the Silver .999 Fine contract and the Refined copper contract. The series for silver and copper begin in January 1968; the series for sugar begins in January 1971; and the series for coffee begins in October 1972. All series end in March 1989 with total observations in excess of 4,000. These series adopt prices from the contract nearest to the maturity. The series data are rendered stationary by taking the first difference of the logs of the price data. Then, using the ARCH (10) model, the transformed series is filtered and the residuals are saved. The correlation dimension technique of Grassberger and Procaccia (1983) is estimated for the standardized ARCH residuals. Their results for the ARCH residuals strongly suggest the presence of nonlinear structure in the data, and this implies the possibility that profitable, nonlinearity-based trading rules may exist. However, the test is unable to verify whether the nonlinear structure is chaotic in nature.

Closely related to the work of DeCoster, Labys and Mitchell (1991), is the study of Blank (1992) who attempted to examine the existence of a nonlinear dynamic in commodity futures markets. In particular, he evaluated the commodity futures markets using methodology of a nonlinear nature to detect any signs of a deterministic system underlying prices over time. In doing so, Blank determines (a) whether there is a difference between chaotic analysis results for cash and financial futures markets; (b) whether there is a difference between the results for financial futures markets and agricultural products.

Futures prices for the S&P 500 index and soybeans are used. For each product, daily closing price data for recent individual futures contracts and nearby contracts are evaluated. For soybeans, the November 1986 and November 1987 contracts are used. The data for each contract begins during July of the previous calender year, yielding 337 and 335 observations, respectively. The nearby futures price series is constructed from the closing prices of the futures contract closest to its maturity date at each point in time and covers the period from 1966 through 1988, with 5,823 observations. The December 1986 and December 1987 S&P 500 contracts are used. Each contract has 250 observations covering the previous calender year. The S&P 500 nearby series begins in May 1982 and ends in December 1987, and consists of 1,420 observations.

The GARCH model is first applied to the data series to generate the residuals for the analysis. This serves as a good filter for studies of chaos. The nonlinear model of Brock and Sayers (1988) is then tested on the residuals to obtain the estimated correlation dimension. Blank's results show that both the S&P index and soybeans appear to have chaotic nonlinearities in their underlying generating processes. When the results for the stock index and soybean futures are compared, similarity is revealed. However, the results of the stock index are different than those reported in earlier stock market studies which use cash price data. Both futures markets are shown to have a low correlation dimension. In particular, the correlation dimension for soybeans is slightly lower for the nearby series than for the contract series. The statistical tests indicate the presence of nonlinearities in both markets but estimates of the Lyapunov exponents suggest that these nonlinearities are deterministic rather than stochastic in nature. Therefore, the author argues that there is a possibility that short-term forecasting models may be improved.

Vaidyanathan and Krehbiel (1992) extend the earlier work of DeCoster, Labys and Mitchell (1991), and Blank (1992). The purpose of their investigation is test for the existence of nonlinear dependence in the S&P 500 futures mispricing series. They argue that the presence of nonlinear structure in the mispricing series would be consistent with a deterministic as opposed to a stochastic explanation. In particular, this study identifies some aspects of market microstructures that can generate chaotic dynamics in the mispricing series.

The authors use daily data representing futures mispricing for the S&P futures contract, computed as the difference between the S&P 500 futures price and the theoretical forward price, which is expressed as a percentage of the index value. The data starts with the September 1983 S&P 500 contract and follows the December, March, June, September cycle with the last series relating to the June 1987 S&P 500 contract. Each series has approximately 1,600 observations. The futures contract prices from the nearest contract at any point is used. The daily interest rate on certificates of deposit is used to compute the theoretical forward and the mispricing series.

The methodology used is quite similar to that of DeCoster, *et.al.*, (1991) except for the testing of nonlinearity. Vaidyanathan and Krehbiel employ the BDS procedure of Brock-Dechert-Scheinkman (1986) to test for independent, identical distribution (i.i.d.) in the series. The BDS statistic converges to a normal distribution with unit variance; *i.e.*, N (0,1), which implies that inference based upon the standard normal distribution is possible. Rejection of the null hypothesis can provide evidence of serial dependence in the data. The results of the BDS test for the null hypothesis of an i.i.d on the return series is rejected. To eliminate the possibility of linear dependence, AR is filtered to the return series and the residuals are then tested for the i.i.d. The results reject the null hypothesis even though the values of the BDS statistic are reduced. By applying the ARCH process, the study again tests for the i.i.d. on the standardised residuals. The results reject the null hypothesis in three out of five cases, implying that the ARCH process cannot account for all the nonlinearity in the data series. The authors note that the possibility of a deterministic/chaotic explanation of the data which suggests that market efficiency is violated in the S&P 500 misprising series.

Yang and Brorsen (1993) test both the GARCH and the deterministic chaos process for a large sample of daily futures price changes. Their study is similar to those of Blank (1992) and DeCoster, *et.al.,* (1991) but more comprehensive in that seasonality, day-of-week and maturity effects are considered simultaneously.

Daily closing data on 15 commodity contracts actively traded in the U.S. futures markets are used. Except for wheat (Kansas City) contracts which start trading from February 1979, the other 11 commodity contracts (corn, coffee, oats, soybean, soybean meal, wheat (Chicago), copper, gold (NY), palladium, platinum and silver) are for the 10 years from January 1979 to December 1988. The other three commodity contracts, the NYSE, the S&P 500 and the Value Line start from January 1984 to December 1988. The authors argue that using more than 2,500 observations for each commodity (except for the stock indexes) provides enough degrees of freedom that it seems reasonable to use tests that are only asymptotically valid.

Using the BDS test, the null hypothesis of i.i.d. is rejected for all return series. Such findings are consistent with deterministic chaos. Next, using a similar method to the study of Vaidyanathan, *et.al.*, (1992) in order to eliminate the possibility of linear dependence, the GARCH model is filtered to the return series and the residuals are then tested for the i.i.d. The BDS test statistics for the standardized residuals indicate significant dependence for eight contracts. In two of these cases, the BDS statistic is negative which is consistent with deterministic chaos. If time series data are stochastic, the estimated dimensions should have full dimension; that is, equal or very close to the embedding dimensions. The results show that only silver has an estimated dimension lower than the embedding dimensions. As for market anomaly, the results show that volatility does not differ according to the day of the week. The maturity effect is significant in six cases and a seasonal pattern is revealed for several commodities, especially agricultural commodities. The authors conclude that these findings provide strong support for the existence of conditional heteroscedasticity. However, there is no conclusive support for or against deterministic chaos.

Fujihara and Mougoué (1997a) test for linear and nonlinear dependence in three petroleum futures returns. Specifically, they re-test the analysis of market efficiency for the futures market based on linear and nonlinear tests for the three energy futures. They argue that this analysis is useful since in the presence of any dynamics, linear and nonlinear, conditional densities can provide a better description of short-term price movements than can unconditional densities.

Daily futures prices for crude oil, heating oil and unleaded gasoline traded at the NYMEX from December 3, 1984 to September 30, 1993 and consisting of 2,217 observations are used. A single time series is constructed by using the nearby futures contract until the day prior to its last trading day at which point the data is rolled over to the next deferred contract. Using the linear model of weak-form efficiency test on the return series, they find evidence against market efficiency in two out of three cases. However, the opposite results are found after nonlinear dependence has been accounted for using BDS tests. The nonlinear behaviour arises solely from the variance of the process as shown by the third-order moment tests. Fixing GARCH models to the data can explain both nonlinear dependence and leptokurtosis. A strong GARCH effect is shown for all three oil futures series. In conclusion, the authors note that the testing and accounting for nonlinearities is important since this may help improve short-term price predictability and may also lead to the long-term improvements in investment strategies.

Testing for Nonlinear Dependence in the Foreign Futures Market

Hsieh (1988) examines the statistical properties of the daily rates of exchange for five foreign currencies. His main purpose is to discriminate between two competing explanations of the observed heavy tails of the distribution. One view is that the data are independently drawn from a fat tail distribution that remains fixed over time, while another proposes that the data come from distributions that vary over time.

Daily closing bid prices of foreign currencies from the interbank market are used. Five major currencies are selected which include the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF). The data consist of 2,510 daily observations from January 2, 1974 to December 30, 1983. The author finds that the exchange rate changes are not independent and identically distributed. In addition, the data are independently drawn from a normal distribution in which the mean and variance change over time.

Hsieh (1989a) extends the previous study, Hsieh (1988) by examining whether changes in the five foreign exchange rates exhibit nonlinear dependence. Specifically, the author employs methodology proposed by Brock, Dechert and Scheinkman (1986) to test directly for nonlinear dependence and to distinguish between different types of nonlinearity. As noted by the author, there are two possible explanations of the nonlinear dependence in the exchange rate changes series: first, that they are purely deterministic processes that look "random" and second, that they are nonlinear stochastic functions of their own past.

Daily closing prices of five foreign currencies in terms of the U.S. dollar from the interbank market provided by the University of Chicago Center for Research on Security Prices are used. They include: the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF), and total 2,510 observations from January 2, 1974 to December 30, 1983. The results demonstrate that daily exchange-rate changes are not independent of changes in the past. Although there is little linear dependence in the data, the BDS test and autocorrelations of squared data detect strong nonlinear dependence. Evidence from the third-order moments indicates that nonlinearity enters through variance rather than through means. The findings are consistent with the presence of conditional heteroscedasticity. Further investigation suggests that a generalized (ARCH) model can explain a large part of the nonlinearities for all five exchange rate changes.

Estimating ARCH and GARCH Models in the Foreign Currency Market

Hsieh (1989b) study estimates autoregressive conditionally heteroscedastic (ARCH) and generalized ARCH (GARCH) models for five foreign currencies. He also examines the ARCH and GARCH specifications as well as the number of nonnormal error densities and the comprehensive set of diagnostic checks for each methods. Although the ARCH and GARCH models have been found to be successful in accounting for most of the heteroscedasticity of exchange-rate data in many studies, Hsieh points out that none have conducted a thorough investigation to identify properly the type of heteroscedasticity in the data-generating process.

Hsieh examines daily closing-bid prices of five currencies in terms of the U.S. dollar: the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF), from 1974 to 1983, totalling 2.510 observations. The data are from the University of Chicago Center for Research on Security Prices. Hsieh's results show that the GARCH (1,1) and exponential GARCH (1,1) are extremely successful at removing conditional heteroscedasticity from daily exchange-rate movements. Goodness-of-fit diagnostics indicate that EGARCH with certain non-normal distributions fits the Canadian dollar extremely well and the SF and the DM reasonably well. However, only one model fits the JY reasonably well and none of them fit the BP.

Kräger and Kugler (1993) study the non-linearities in foreign exchange markets over the last ten years and estimates self-exciting threshold autoregression (SETAR) models for five foreign currencies using weekly data. Their study is motivated by the conjecture that the system of managed floating which prevailed in the 1980s, leads to different behaviour of moderate and large exchange rate changes.

Weekly data series are examined for five currencies against US dollar from June 1980 to January 1990, totalling 500 observations. These currencies are the German mark, the French franc, the Italian lira, the Swiss franc and the Japanese yen. The results show that, in all cases, threshold effects are found to be statistically significant. However, when the BDS test is applied to the SETAR residuals, it shows some misspecification of the models. Similar results are obtained when the standard GARCH model is applied to the data. The authors conclude that neither the SETAR nor the GARCH model provide a convincing framework for describing non-linearities of exchange rate data.

Brooks (1996) also tests for non-linear dependence in the sterling exchange rates using a set of 10 daily sterling exchange rates covering the entire post Bretton-Woods era until the present day. He suggests that the evidence of non-linearity in financial time series may improve in the short term by switching from a linear to non-linear modelling strategy. He examines daily mid-spot exchange rate data series, denominated in pound sterling from January 2, 1974 to July 1, 1994, for the Austrian schilling/pound, the Canadian dollar/pound, the Danish krone/pound, the French franc/pound, the German mark/pound, the Hong Kong dollar/pound, the Italian lira/pound, the Japanese yen/pound, the Swiss franc/pound and the US dollar/pound. Using the nonlinear tests of BDS, Tsay, RESET, Engle and White, Brooks finds, on the whole, that the null hypothesis of linearity is rejected by all the tests, in almost all of the series. Moreover, most of this nonlinear dependence can apparently be explained by reference to the GARCH family of models.

Testing the Behaviour of Stock Prices

Akgiray (1989) published new evidence about the time-series behaviour of stock prices. Many previous studies on stock prices assumed dependence and linearity in the return generating process for the series. However, he challenged these common assumptions noting that there seems to be no compelling theoretical reasons for accepting either assumption.

He uses data from the Center for Research in Security Prices, consisting of 6,030 daily returns of value-weighted and equal-weighted indices covering the period from January

1963 to December 1986. The sample is divided into four different periods of 6 years each and each period as well as the entire period is analysed separately. The author discovers that the daily time series exhibit significant levels of second-order dependence and that they cannot be modelled as linear white-noise processes. Moreover, the return generating process is empirically shown to be a first-order autoregressive (AR1) process with conditional heteroscedasticity innovations. In particular, the generalized autoregressive conditional heteroscedasticity GARCH (1,1) processes fit the data well.

Testing for Nonlinearity in the Stock Market

The Scheinkman and LeBaron (1989) study examines the new technique of algorithms used to distinguish between random systems and deterministic systems and specifically uses this technique to detect the detect nonlinearity departures from random-walk behaviour in U. S. stock returns data. In addition, the Brock, Dechert and Scheinkman (BDS) procedures are used to test for nonlinearities.

Daily returns on the value-weighted portfolio from the Center for Research in Security Prices, totalling 5,200 observations are used. The authors also construct the weekly returns series which they argue are less noisy since these are not sensitive to weekend effects. Before applying the BDS test, the return series is first filtered through the linear models to make sure that linear effects have been removed. The resulting residuals are then tested for i.i.d. using BDS procedures. The results indicate the presence of nonlinearities in weekly returns. In addition, the results of the Brock test show a deterministic system in the return series.

Hsieh (1991) carried out a similar study to detect chaotic and nonlinear behaviour in the stock market. His interest in the subject reflects increased interest in both the financial press and academic literature following evidence that the frequency of large moves in stock markets is greater than would be expected under a normal distribution.

The author applies the BDS test of i.i.d to weekly stock returns data from 1963 to 1987, obtained from the Center for Research in Security Prices. His results strongly reject the hypothesis that stock returns are i.i.d. The cause does not appear to be chaotic dynamics but, rather, conditional heteroscedasticity. Another observation is that the ARCH-type models do not fully capture the nonlinearity of stock returns and this contradicts the findings of Hsieh, (1989a) on foreign exchange rates.

Exploring the Nature of Nonlinear Dynamics in Stock Market

Booth, Martikainen, Sarkar, Virtanen and Yli-Olli (1994) extend the work of previous studies on nonlinear dependence by exploring the nature of the nonlinear dynamics (e.g.. Hsieh, 1991). In particular, they use Grassberger-Procaccia correlation dimensions to test whether returns in the Finnish stock market, during the 1970s and 1980s, were generated by a chaotic process.

The authors use daily data from the Finnish Stock Index (HSI), a value-weighted index consisting of 134 stocks, beginning on the first trading day in January 1970 and ending on the last trading day in December 1989. The sample is split into two consecutive 10 year periods. The results exhibit significant nonlinear dependence of non chaotic form in both periods. A simple GARCH model removes most of the nonlinearity which contradicts the findings of Scheinkman and LeBaron (1989) for US stock returns but supports Hsieh's (1991) contention that US stock returns are not chaotic and that the observed nonlinearities are effectively removed by GARCH processes

Testing Nonlinearity Using High Frequency Data in the Stock Market

Abhyankar, Copeland and Wong (1995) use high frequency data to test for the presence of nonlinear dependence and chaos in real-time returns on the U.K. FTSE-100 Index. The authors employ a larger size sample in order to have a greater potential for observing the microstructures effect as well as an increase likelihood that the underlying process has remained stationary over the sample period.

The data consist 60,000 minute-by-minute real time returns on the UK FTSE-100 Index of stocks quoted on the London International Stock Exchange over the period from January 4, 1993 to June 30, 1993. Using the BDS test for i.i.d. and the Lyapunov Exponent test for chaos, the results show clear evidence of nonlinear dependence in the series. There is little evidence to support the view that the process is chaotic. The authors also test the residuals from a GARCH process fitted to the data, to ascertain whether the nonlinearity can be explained by this type of model. Their results suggest that GARCH can explain some but not all of the observed nonlinear dependence.

2.4 The Relationship Between Trading Volume and Price Variability.

It has been widely accepted and well documented in the literature that GARCH models provide a good fit for exchange rates and currency futures.[1] In the present study, we will also examine whether ARCH effects disappear when volume is included as an exogenous variable in the conditional variance equation. It has been suggested that time-series dependencies in information flows induce the documented ARCH effect. Indeed, Lamoureux and Lastrepes (1990) have shown that ARCH effects tend to disappear when volume is included in the variance (other early empirical studies include Epps and Epps, 1976; Smirlock and Starks, 1985; Karpoff, 1987). As for the futures market, there is a growing body of literature which examines this relationship, including studies by Clark (1973), Tauchen and Pitts (1983), Cornell (1981), Foster (1995) and others.

There are two leading models which can provide explanations of the above finding concerning information arrival for the observed correlation between price variability and volume. The first model which is referred to as the Mixture of Distribution Hypothesis (MDH), was proposed by Clark (1973) and later extended by Harris (1986). It suggests that there is a positive contemporaneous relationship between these variables. In the framework of MDH, when new information arrives, trading increases as the investors revise their expectations. This implies that trading volume and prices change synchronously in respond to new information.

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1 Studies include Hsieh (1989a) and Laux and Ng (1993) among others.

The second model, referred to as the sequential information arrival hypothesis (SEQ), was provided by Copeland (1976) and followed by Smirlock and Starks (1988). In this model, the new information is not transmitted to all traders in a single day. Instead, the new information reaches one trader at a time. Consequently, each individual trader's transaction in response to a given signal represents one of a series of incomplete or intermediate equilibria prior to the final complete information equilibrium, unlike the MDH where the final equilibrium is obtained immediately. In other words, trading occurs in sequence only after information is received by each trader. The primary implication of SEQ suggests that price variability is potentially forecastable given knowledge of past trading volume and vice versa.

Examining Contemporaneous Volume-Price Relationship in the Futures Market

Clark (1973) was among the first to investigate the volume-price variability relationship in the futures markets. He developed a model which argued that the daily price change was the sum of a random number of within-day price changes. Thus, the variance of the daily price change is a random variable with a mean which is proportional to the mean number of daily transactions. Clark argues that the trading volume is related positively to the number of within-day transactions and so the trading volume is related positively to the variability of the price change. If trading volume is not related to the speed of evolution, there should be no correlation between these variables. In other words, his hypothesis implies that trading volume and prices change synchronously in response to new information.

Clark uses daily data on price and volume for cotton futures from 1945 to 1958, excluding the Korean War period (January 26, 1951 to March 23, 1951). The series are divided into periods of 1,000 observations each. Sample 1 is from January 17, 1947 to August 31, 1950, while Sample 2 is from March 24, 1951 to Febuary 10, 1955. Simple linear regression results in a positive relationship between the aggregate volume and the square of the price change, suggesting that trading volume as an appropriate proxy for speed of evolution.

Cornell (1981) also investigated the relationship between the volume of trading and price variability for futures contracts daily data from the Center for the Study of Futures Markets at Columbia University. His sample began on January 1, 1968 and ended on May 1, 1979 except for gold which began on January 1975 for the COMEX and on March 1 for the International Monetary Market of the Chicago Mercantile Exchange. Altogether he selected 18 commodities from those that were actively traded on the major U.S exchanges during that period. The data consisted of daily observations on the settlement prices for all outstanding contracts on each commodity and also aggregate figures, across the contracts, on volume and open interest.

Using simple linear regression, Cornell found a significant positive contemporaneous correlation between the changes in average daily volume and the changes in the standard deviation of daily log price relatives for 14 of the 18 commodities in the sample. For the other four commodities, the correlation was also positive though insignificant. In addition, a pooled time series and cross-sectional regression showed that the contemporaneous correlation between the two variables was significant at the 1 percent level. Conversely, the correlations between changes in price variability and lagged changes in volume were insignificant.

A study by Tauchen and Pitts (1983) is very similar to the earlier studies of Clark (1973) and Cornell (1981). Their research focuses on the relationship between the variability of the daily price changes and the daily volume of trading on the speculative markets. They extend the previous work on the theory of speculative markets in two ways. First, they derive from economic theory the joint probability distribution of the price change and the trading volume over any interval of time within the trading day. Secondly, they determine how this joint distribution changes as more traders enter (or exit from) the market. According to the model, if the number of traders is fixed, then the model predicts that the distribution of the daily price change is leptukurtic and that the square of the daily price change is positively related to the daily trading volume. If the number of traders is growing, then the model predicts that the mean trading increases linearly with the number of traders. Also, the variance of the price change decreases with more traders.

The authors employ daily data on price change and trading volume for the 90-day T-Bill futures contracts traded at the Chicago Mercantile Exchange (CME), a total of 876 observations beginning from January 6, 1976 and ending on June 30, 1979. The price data are aggregate for different delivery dates and are expressed in thousands of dollars. The trading volume is the total for all contracts and is expressed in thousands of contracts.

Using maximum likelihood to estimate the parameter, for a fixed number of traders, the daily volume and the square of the price change are positively related. However, as number of traders increases, the mean daily volume increases while the variance of the price change decreases. In conclusion, the author's results seem to reconcile conflicting findings between the price variability-volume relationship for this market and the relationship obtained by previous researchers for other speculative markets.

Price-Volume Relationship and Cointegration

Malliaris and Urrutia (1998) extend previous research on the relationships between price and trading volume, and the determinants of trading volume. In doing so, they postulate several hypotheses and test them using agricultural commodity futures contracts. Augmented Dickey and Fuller tests of stationarity, tests of cointegration, and error correction methodology are used to test four hypotheses. They are time-series properties of price and volume of trade; short-term and long-term relationships between price and trading volume; the changes in trading volume over time depend on three factors: time, price and volatility of price; the volatility of trading volume as a function of price volatility. They use corresponding daily prices and trading volume from January 2, 1981 through to September 29, 1995, for six agricultural commodity futures contracts: corn, wheat, oats, soya beans, soyabean meal and soybean oil.

For the first hypothesis, the time series of price and trading volume are found to be non-stationary in levels but stationary in growth; that is, they are integrated in order 1, I(1). Because in the second hypothesis the two variables are cointegrated, there is causality in the Granger sense between price and volume of trade in at least one direction. Thus, price and trading volume are interrelated in the long run as well as in the short run. The third hypothesis is confirmed only for price variability; *i.e.*, trading volume is a function of price variability. For the fourth hypothesis, the authors find that price volatility is a determinant of both trading volume and the volatility of trading volume, confirming previous results of Cornell (1981) and Garcia, Leuthold and Zapata (1986).

Malliaris and Urrutia conclude that the strong relationship between price and trading volume highlights the relevance of trading volume and offers support to technical analysis. Furthermore, the evidence of long-run relationship between the variables should help hedgers, who hold positions in the futures markets much longer than speculators.

Examining the Lead-Lag Volume-Price Relationships Between Trading Volume and Price Variability in Commodity Futures Market

Garcia, Leuthold and Zapata (1986) examined the lead-lag relationships between trading volume and price variability for selected contracts of corn, wheat, soybeans, soybean oil and soybean meal during 1979 and the early 1980s. These five agricultural commodities are traded on the Chicago Board of Trade. The daily data used are for each contract and are differenced and subdivided into three periods of approximately four-months' length with roughly an equal number of data points in each group.

The methodology used to examine lead-lag relationships follows the approach suggested by Granger (1969). This linear causality model assumes that the series are generated by a stationary stochastic process with a constant variance. In addition, the authors use two different methods to measure price variability: first, the percentage change in daily closing prices (PCCP) and second, the adjusted price range (ADJR), which is constructed by adjusting the range if today's low price exceeds yesterday's close when prices are increasing or if today's high price is less than yesterday's close when prices are decreasing. As for volume, the daily volume relative to the level of open interest (VOL/OI), was used.

The authors find eighteen lead-lag and two feedback relationships using PCCP , and seventeen lead-lag and three feedback relationships using ADJR. In addition, with PCCP, price variability leads volume more frequently than volume leads price variability. However, with ADJR, the results are reversed; *i.e.*, volume leads price variability more frequently that price variability leads volume. As for the composition of lead-lag relationships by commodities, both show a higher proportion of leads and lags in the soybeans, soybean oil and soybean meal than in the other two commodities. This may reflect the more volatile nature of soybeans.

In conclusion, the authors argue that in general there is no clear pattern in the relationship or in lead-lags and price trends, a finding consistent with that of Cornell (1981) and with the assumption made by Tauchen and Pitts (1983). This suggests that predicting price movements from past changes in price and volume is not very reliable.

Size and Maturity as a Function of Price-Volume Relationship in the Oil Futures Market

Foster (1995) was among the first to investigate the dynamic relationship between trading volume and price variability in the oil futures markets. He extends the previous study of this relationship by raising two more related issues: first, whether the level of trading differs with the direction of price movements and, secondly, whether the size or maturity of a futures market affects its volume-volatility relationship.

His data are daily closing prices for a roll-over of nearby futures contracts written on Brent crude and WTI crude from the IPE and NYMEX, respectively, together with their corresponding daily trading volumes over a period from the January 1990 contract to the June 1994 contract for both Brent and WTI contracts. A third sample of WTI futures covers the period from the January 1984 contract to the June 1988 contract. He makes comparisons of the volume-volatility relationship with respect to market maturity.

Two conflicting theories on testing for the price-volume relationship are discussed. These are the sequential information model (SEQ) and the mixture of distribution hypothesis (MDH). The SEQ model hypothesizes that traders in a market receive new information in a sequential, random fashion. On the other hand, the MDH provides a model which implies a positive relationship between volume and price variability with the relationship being a function of the directing (or mixing) variable, defined as the rate of information arrival.

Using the GARCH model and the generalized method of moments (GMM) model, the author finds that volume and volatility are largely contemporaneously related and both driven by the same factors, assumed to be information. In addition, volume variables are significant in the GARCH models but are numerically small and have a negligible impact on the GARCH coefficients, suggesting that the volume is not an adequate proxy for the rate of information flow. The study also finds that trading volume and the dispersion of price changes are symmetric. Therefore, it is not expected that the level of trading volume is affected by the direction of price changes. The implication of these findings is that oil futures do not react directly to the sign of a price change. Finally, using the GMM model, Foster finds evidence from the NYMEX- WTI contract that as markets become larger and more liquid; *i.e.*, mature markets, their informational efficiency and volatility increases.

Testing Macro and Microeconomic Variables-Volume Relationship in the Metal Futures Market

Martell and Wolf (1987) investigate the relationship between the level of activity (trading volume) and macro- and microeconomic variables instead of the volume-price relationship. Specifically, they expand the variables and empirically examine the determinants of volume in metal futures markets. Daily and monthly data for the active nearby contract month from January 1, 1976 to December 1, 1982, are used.

The daily settlement prices are taken from most recent twenty trading days and the monthly settlement prices are from the average per day. Macro- and microeconomic variables are taken from several sources. The S &P Stock Index is used as a proxy for market performance and the Treasury Bill rate represents risk free interest while the rate of unemployment and the Consumer Price Index measure the level of activity in the real market and the price levels, respectively. Using a linear regression, the authors find that all the variables used explain the trading volume satisfactorily for both daily and monthly data sets. In contrast to previous research, they show that volume is a function of more than one variable.

Testing for Intradaily Price Variability and Volume Relationship in the Bond Futures Contracts

Watanebe (1996) was among the earliest to examine the relationship between price volatility and trading volume using high frequency data. His data set consists of a 5-minute return and trading volume for Japanese Government Bond (JGB) Futures contracts that expire in March and June 1995. The sample period is from March 3, 1995 to May 3, 1995 and the trading volume is the sum of the contracts that expire in March 1995 and June 1995. After omitting data when trading is zero, the observations total 3,234.

Based on the mixture-of-distribution hypothesis, the author first sets up a model in which price volatility and log volume are jointly determined by a single latent common factor. Using a quasi-maximum likelihood procedure via the Kalman filter, the model is then fitted to data. He finds that the common factor is not persistence and that there are highly persistent noises, providing evidence for the misspecification of the mixture-of-distribution hypothesis. In addition, using the VAR model as a comparison, the author finds evidence of bi-directional causality as well as simultaneous causality between volatility and volume. He concludes that the presence of significant causality from volume to volatility suggests that high-frequency trading volume data may provide useful information for financial risk management.

Testing for Volume-Price Variability and the GARCH effect in Treasury Bond Futures Markets

Najang and Yung (1991) investigate two main issues. First, they reexamine the distributional properties of futures price movements. Secondly, they investigate the relationship between volume and price variability, and the GARCH effect in Treasury Bond futures markets. They employ the GARCH specification which is more appropriate than the standard statistical model because it is consistent with the return distribution which exhibits leptokurtosis.

Daily closing prices and the volume data for Treasury Bonds between January 1984 and August 1989 from the Chicago Board of Trade (CBOT), are used. The analysis is performed on the entire period and on each calendar year. The authors find that the returns process of Treasury Bond futures can best be described by a GARCH (1,1) model. Subsequently, when contemporaneous volume is included in the GARCH specification, they find a positive price variability-volume correlation for only 1986 and 1988. However, the GARCH coefficients are statistically significant for the overall period as well as for each calender year. When, instead of contemporaneous volume, lagged volume is included in the GARCH specification to account for simultaneity problems, there is evidence of a positive price variability-volume correlation for the overall period and for most of the subperiods. The authors conclude that in the presence of simultaneity problems, lagged volume is a good instrument for contemporaneous volume in the GARCH specification. Furthermore using volume may help to explain the volatility of Treasury Bond futures despite the persistence of past volatility.

Testing the Returns-Volume Relationship Using Linear and Nonlinear Granger Causality in Petroleum Futures Contracts

Fujihara and Mougoué (1997a) have been the first to study the relationship between returns and trading volume in the futures market employing the nonlinear Granger causality test. They examine the relationship between returns and trading volume for three petroleum futures contracts. Using daily data for futures prices and trading volume for crude oil, heating oil and unleaded gasoline traded on the NYMEX from December 3, 1984 to September 30, 1993, they first employ the VAR model to test for linear causality between returns and volume. Their results show that returns and volume have no predictive power for one another. As substantiated by Baek and Brock (1992), linear causality tests generally have low power against nonlinear relationships and, therefore, fail to detect useful nonlinear relationships between price variability and trading volume.

However, since the distribution of the returns and volume series show some evidence of nonlinear dependence, Fujihara and Mougoué employ a nonlinear causality model. In doing this, they first filter for linear dependence through the use of the VAR process.

Next, a nonparametric test statistic based on the correlation integral is employed. The nonlinear causality test results reveal a significant bidirectional nonlinear causal relationship between the filtered returns and the volume series. Then, since the third moment test on the returns and volume series shows that nonlinear dependence arises solely from the variance, the authors filter the series using GARCH specification. The results still show strong evidence of bidirectional nonlinear Granger causality which suggests that the nonlinear process may influence both the mean and variance of futures returns and volume. The authors conclude that the strong nonlinear causal relationships found between petroleum futures and trading volume imply that knowledge of current trading volume improves the ability to forecast futures prices.

Examining Exchange Rates-Unexpected Change Relationship in the Foreign Exchange Market

A study by Frenkel (1981) analyses the key issues and the lesson taken from the experience with flexible exchange rates during 1970s. Specifically, he analyses the efficiency of the foreign-exchange market and the volatility of exchange rates as well as the relationship between exchange rates and unexpected changes in interest rates, a proxy for "news." As is widely known, the foreign-exchange market is efficient if current prices reflect all currently available information.

Data on the British pound (BP) and the German mark (DM) obtained from the International Monetary Fund (IMF) are used; namely, spot exchange rates (for end-of-month rates) and forward exchange rates (end-of-month bid prices for 1-month maturity) for the period from June 1973 to June 1978. The interest rates are 1-month Eurocurrency rates obtained from the *Weekly Review*, corresponding to the last Friday of each month. Using linear OLS, the author finds that, in general, the behaviour of the foreign-exchange market during the 1970s is consistent with the efficient market hypothesis. In addition, the "news" is found to be a major factor influencing changes in exchange rates, suggesting that exchange-rate changes are dependent on unexpected changes in the rates of interest.

Mussa (1982) examines the exchange rate as an asset price that depends on expectations concerning exogenous real and monetary factors that will affect relative prices and absolute price levels. He develops an integrated model of exchange rate changes by taking the exogenous factors of expected and unexpected changes as a proxy for new information. The author explains that the expected change is the systematic and predictable component of change which contradicts prior beliefs concerning real and monetary changes affecting the exchange rate. Unexpected change, on the other hand, is random and unpredictable and reflects new information concerning real and monetary factors that determine the exchange rate.

In general, the results of theoretical analysis of the effect of economic policy on the exchange rate show that the rate responds not only to the current policy action of the government (the expected) but also to the effect which a given action has on expectations concerning future policy (the unexpected).

Examining the Bid-Ask Spread-Volume Relationship in the Foreign Exchange Market

Bassembinder (1994) examines the relationship between the bid-ask spread and the trading volume in the wholesale foreign exchange markets. He is interested in assessing this relationship because it has been shown that volume is highly correlated and can be forecast to a substantial degree.

A set of daily spot and six-month forward currency quotations at the close of London trading from January 1979 to December 1992, is used. These are ask and bid quotes obtained from Reuters for the British pound (BP), the Swiss franc (SF), the German mark (DM) and the Japanese yen (JY). Because of the lack of a comprehensive database on trading volume in the wholesale foreign exchange market, Bassembinder follows the procedure of Glassman (1987), using currency futures trading volumes as instrumental variables for spot volumes. First, the author applies an ARIMA(10,1,0) specification to decompose futures trading volume into forecastable and unexpected components. Then, using the generalized method of moments (GMM), the coefficients are estimated. His results show that both the forecastable and the unexpected trading volume have heterogeneous effects on the bid-ask spread. For each of the four currencies, the estimated coefficient of unexpected trading volume exceeds the forecastable volume.

Examining the News Events-Exchange Rates Relationship Using High Frquency Data in the Foreign Exchange Market

Goodhart, Hall and Pesaran (1993) investigate the response of short-term movements of exchange rates to news events using an extremely high frequency data set. In particular, they examine the effects of news events within a GARCH-M framework where news may potentially affect either the level or the variance of the sterling-dollar rate. In allowing for the effects of news, they focus on two specific news events: the announcement on Wednesday 17 May of the US trade figures, and the one percent rise in UK base interest rates on Wednesday 24 May.

A continuous time-series of ask/bid prices quoted on the Reuters FXFX page for the sterling-dollar rate over the period Sunday 9 April to Monday 3 July 1989, totalling 130,000 observations over an 8-week period is used. The results show that news can affects the level of the exchange rates, suggesting that the level of the exchange rate is a stable as opposed to a random walk process (since the lagged t-1 is significant). When the effects of news is allowed to enter the conditional variance, similar results are obtained. In addition, the parameter of the GARCH process changes dramatically from one very close to integration to one which is clearly stable.

Testing for Incoming Quote-Price Variability Relationship Using Intradaily Data in the Foreign Exchange Market

A study by Takezawa (1995) is closely related to that of Goodhart, *et.al.*, (1993); both use high frequency data of intradaily foreign exchange rates to investigate the impact of information or news on volatility. However, each uses a different proxy for information. While Goodhart, *et.al.*, (1993) use a news announcement on US trade and UK interest rates, Takezawa employs an incoming quote as the regressor in the conditional variance (GARCH) equation. As he notes that, since volume data are not available for FOREX, the number of incoming quotes can be used a proxy for potential trading and thus for information flow.

Hourly data for the period from January to August 1993 for five foreign exchange currencies: the British pound (BP), the German mark (DM), the Canadian dollar (CD), the Japanese yen (JY) and the Swiss franc (SF) are used to test whether lagged information has an effect on volatility; *i.e.*, whether information is long-lived. The results show that the lagged number of quotes is positively and significantly related to volatility for all currencies, thus providing evidence of a time-consuming or information decay process.

Volume as a Proxy of News Information in the Stock Market

Copeland (1976) focuses on the new techniques of information arrival developed under the key assumption that individuals shift their demand curves sequentially as new information is revealed to them. An individual will react to news of information by shifting his demand curve and his reaction will be followed by others. Finally, when all the individuals have received the news, a new equilibrium is established.

Using volume as a proxy of news information, Copeland finds a positive correlation between the absolute values of price changes and the expected value of trading volume with high values which occurs when traders are unanimous about new information and the low values which occurs when they disagree. Trading volume also seems to increase as a function of the strength of new information.

Closely related to the work of Copeland (1976) is the study of Epps and Epps (1976) who provide a theoretical model for the distribution of stock prices and empirically explain the stochastic dependence between transaction volume and changes in the logarithm of security prices. The authors examine 20 common stocks selected from the New York Stock Exchange (NYSE), and derive a model in which the variance of the price change on a single transaction is conditional upon the volume of that transaction, thus supporting the work of Clark (1973). A change in the logarithm of price can therefore be viewed as following a mixture of distributions, with transaction volumes as the mixing variable.

Number of Transactions-Price Relationship in the Stock Market

Harris's (1987) study is related to the work of Clark (1973) and Tauchen and Pitts (1982). He examines the flow of information (the mixture of distributions hypothesis) for the distributions of daily price changes and volume. While the previous researchers use daily intervals, Harris uses transaction data to test for the mixture of distribution hypothesis, which assumes that the variance per transaction is related to the volume of that transaction.

The prices and volume of fifty common stocks traded continuously on the New York Stock Exchange between December 1, 1981 to January 31, 1983 are used. For each security, price changes and volume are computed over fixed intervals of 1, 10, 50 and 100 transactions and over daily time intervals. The prices and volume are then adjusted for the effects of dividend, stock splits and stock dividends. The results, generally support the mixture of distribution hypothesis and the author points out that the daily number of transactions may be a good estimate of a time-varying information.

Review of Previous Studies on Price Change-Volume Relationship in the Financial Market

Karpoff (1987) reviews the previous and current research on the contemporaneous relation between price changes and trading volume in the financial market. He draws four conclusions.

First, the empirical relations are established; *i.e.,* volume is positively related to the magnitude of the price change and, in equity markets, to the price change *per se*. This can help discriminate between different hypotheses of market structure. Secondly, the price-volume relation is important for event studies that draw inferences from a combination of price and volume data. If price changes and volume are jointly determined, incorporating them will increase the power of these tests. Thirdly, he finds that price-volume tests generally support the mixture of distribution hypothesis and that price data are generated by a conditional stochastic process with a changing variance parameter that can be proxied by volume. Fourthly, price-volume relations have significant implications for research into futures markets because the time to delivery of a futures contract affects the volume of trading and therefore possibly the price.

Modelling ARCH Using Conditional t-Distribution in the Stock Market

Bollerslev (1987) develops a simple time series model designed to capture the dependence of speculative price changes. Specifically, the author extends the ARCH model to allow for conditional t-distribution errors. This permits a distinction between conditional heteroscedasticity and conditional leptokurtic distribution, either of which could account for the observed unconditional kurtosis in the data.

Five different monthly stock price indices for the U.S. economy including Standard and Poor's 500 Composite, Industrial, Capital Goods, Consumer Goods and Public Utilities, are used. The indices are monthly averages of daily prices and consist of 453 observations. He finds that speculative price changes are approximately uncorrelated (but dependent) over time. The standard t-distribution fails to take account of this temporal dependence, and ARCH and GARCH models with conditionally normal errors do not seem to fully capture the leptokurtosis. However, the GARCH (1,1)-t model fits the data adequately.

Testing for Price Change-Volume Relationship in the Stock Market

Smirlock and Starks (1988) investigate the empirical relationship between absolute stock changes and trading volume in the stock market. Specifically, they test whether the proxy for information arrival by trading volume follows a sequential (SEQ) or a simultaneous (SIM) process. According to SEQ there are intermediate equilibria prior to the final complete information equilibrium, while in the SIM there is only the final equilibrium.

Daily stock prices and volume data for the 49 consecutive trading days from June 15 through August 21, 1981 obtained from a sample of New York Stock Exchange firms are used. Granger causality tests reveal a significant causal relationship between absolute price changes and volume at the firm level. The results show some evidence in support of the SEQ as a more accurate description of dominant market behaviour than the SIM. The SEQ implies that knowledge of the behaviour of volume can improve conditional price change forecasts based on past price changes.

Examining for Volume-Returns Relationship Using Intradaily Data in the Stock Market

A study by Jain and Joh (1988) is closely related to work by Clark (1973) on the contemporaneous relationship between trading volume and returns. They extend the study to include the lead and lagged relationship between these variables using a long time series of hourly data. The authors note that high frequency data enable them to obtain precise estimates of correlations.

Hourly data for trading volume and the returns of common stocks on the New York Stock Exchange (NYSE) for the years 1979 to 1983, comprising 1,263 trading days from are used. The data consist of 7,578 hourly observations for the six hours per day trading time. The hourly trading volume data for the NYSE are taken from The Wall Street Journal and the market returns are from Standard and Poor's (S&P) 500. Using linear causality models, a strong positive correlation emerges between contemporaneous trading volume and absolute value of returns which is consistent with the mixture of distributions hypothesis as developed by Clark (1973) and others. Trading volume is positively correlated with returns lagged up to four hours.

Testing for Linear and Nonlinear Causality Between Returns and Volume in the Stock Market

Hiemstra and Jones (1994) are among the few who use both linear and nonlinear causality tests to examine the dynamic relation between daily Dow Jones stock returns and percentage changes in New York Stock Exchange trading volume. They examine whether the nonlinear causality from volume to returns can be explained by volume serving as a proxy for information flow.

Daily closing prices of stocks are obtained from the Dow Jone Price Index. They are calculated as a returns and are obtained from Dow Jones Industrial Average for the period 1915 to 1940 and from the Dow Jones 65 Composite Index for the period 1941 to 1990. The trading volume series is the total daily trading volume on the NYSE. The test using linear VAR models, indicates unidirectional causality from stock returns to percentage volume changes for both sample periods. The modified Baek and Brock (1992) test results show significant bidirectional nonlinear Granger causality between stock returns and trading volume for both sample periods. In addition, there is evidence of nonlinear causality from trading volume to the exponential GARCH filtered stock returns for both periods.

Testing for Price Variablity-Volume Relationship and the GARCH Effects in Stock Market

Lamoureux and Lastrapes (1990) examine the validity of the implication of the mixture model that the variance of daily price increments is heteroscedastic in order to ascertain whether they are positively related to the rate of daily information arrival proxy by volume.

Daily closing prices and volume for 20 actively traded stocks during the period from July 1981 to June 1985 were obtained from the Standard and Poor's Daily Stock Price Records. When the GARCH (1,1) model is applied to the sample together with volume as an exogenous variable in the conditional variance equation, the ARCH effects vanish in 16 out of 20 cases. The results suggest that lagged squared residuals contribute little if any additional information about the variance of the stock return process after accounting for the rate of information flow, as measured by the contemporaneous volume.

Sharma, Mougoué and Kamath (1996) extended the work of Lomoureux and Lastrapes (1996) by examining whether trading volume explains the GARCH effects for the macro structure of the market. Their data comprises 1,008 observations of daily returns and corresponding volume taken from the NYSE index over a four-year period beginning in 1986 and ending in 1989, obtained from the *Wall Street Journal*.

The GARCH model is estimated using two assumptions: conditional normality and conditional *t*-distribution. When volume is introduced as a proxy for information arrival in the conditional variance, the GARCH effects remain, contrary to the findings of Lamoureux, *et.al.,* (1990). Sharma, Mougoué and Kamath conclude that there is a possibility that other variables besides volume contribute to the heteroscedasticity.

2.5 Spillover Effects

The increased globalization of financial markets brought about by the relatively free flow of goods and capital as well as the recent revolution in information technology has resulted in a voluminous flow of information from one market to another and, consequently, in the publication of many studies related to price and volatility transmission. One study by Hamao *et.al.*, (1990) finds that the spillover effect from the Japanese stock market to the US stock market has increased steadily. Another by Lin *et.al.*, (1994) finds that price and volatility spillovers between the US and the Japanese markets are generally reciprocal; *i.e.*, the two markets influence each other. Other studies show similar results, [Eun and Shim (1989);King and Wadhwani (1990); Cheung and Kwan (1992); Susmel and Engle (1994); Liu, Pan and Fung (1996)].

Similar evidence of spillovers is reported in the foreign exchange market. For example, Engle, Ito and Lin (1990) developed their famous hypotheses of heat waves and meteor shower and tested them on the daily exchange rate in the New York and Japanese markets. Their findings support the meteor shower, suggesting spillovers from one market to another market. Similar findings are also reported in Ito *et.al.*, (1992). As for the futures market, studies on transmission are relatively few. Abhayankar (1995), investigates the Eurodollar futures markets spillover while Puttonen (1995) examines the international transmission of volatility between the stock and stock index futures markets. Tse and Booth (1996) test for spillovers between U.S. and Eurodollar interest rates using U.S. Treasury Bill and Eurodollar futures.

Examining for Inter-Market Transmission of Volatility and Volume in the Futures Market

Studies of volatility spillover in the futures market are rare compared to those in the equity market. The Abhyankar (1995) study is one of a few which attempt to assess spillover in the futures market. He investigates the inter-market transmission of returns, volatility and trading volume between the Eurodollar (ED) futures markets of the Chicago Mercantile Exchange (CME) and the Singapore Monetary Exchange (SIMEX). The author points out that his study provides an unbiased test of inter-market transmission effects because his two samples are from non-overlapping time zones.

Intra-daily data on opening and closing prices as well as volume and open interest were obtained from DATASTREAM (CMD ED futures contract) and from SIMEX. They cover the period from December 14, 1987 to September 16, 1991. The price of the near contract is used and the series is rolled over into the next near contract on the expiration day. The results of the GARCH (1,1) model, indicate lagged spillover effects in the mean return only from the CME to the SIMEX. However, there is some evidence of a symmetric effect in the lagged spillovers in volatility from one market to another, and this finding is similar to the meteor shower effect observed by Engle, Ito and Lin (1990). Abhyankar also finds that the volume in the market that has traded earlier has a significant impact on the conditional volatility of the market that follows.

Testing for Heat Wave and Meteor Shower Using Intradaily Data in the Foreign Exchange Market

Engle, Ito and Lin (1990) investigate the causes of volatility clustering in exchange rates by developing two types of volatility process; namely, the heat wave and the meteor shower, and by testing them on the intra-daily data for yen/dollar exchange rate. The heat wave hypothesis is that volatility has only a country-specific autocorrelation. The meteor shower is a phenomenon of intra-daily volatility spillovers from one market to the next.

The intra-daily yen/dollar exchange rates from October 3, 1985 to September 26, 1986 are used. The data in Tokyo are collected daily from transaction rates reported in the *Nihon Keizai Shibun* while the New York rates are the simple average of ask and bid rates in the Federal Reserves Bank of New York. The hourly rates for the second moment (conditional variance equation) of the GARCH model reject the heat wave hypothesis and this is consistent either with market dynamics which exhibit persistence volatility (possibly due to private information or heterogeneous beliefs) or with stochastic policy coordination.

Testing for Heat Wave and Meteor Shower Over Difference Regime in the Foreign Exchange Market

Ito, Engle and Lin (1992) extend the work of Engle, Ito and Lin (1990) by examining the intra-day volatility of the foreign exchange rate. Their sample is divided according to potential changes in policy coordination and Japanese deregulation of capital control and is analysed over several different periods from 1979 to 1988 as well as for the entire time span according to potential changes in policy. In each regime, the authors test for heat shower and meteor shower effects. They hypothesize that the heat wave allows volatility to produce only country-specific autocorrelations while the meteor shower assumes volatility spillovers across markets.

The intra-daily yen/dollar exchange rates from February 1, 1979 to December 23, 1988, are used. The series are decomposed into four non-overlapping segments using closing and opening quotes in the New York and the Tokyo markets. The Tokyo quotes are collected from *Nihon Keizai Shinbun* and the New York quotes are the simple average of bid and ask rates given by the Federal Reserve Bank of New York. The first sample begins on December 1, 1980 and corresponds to the enactment of the Foreign Exchange and Foreign Trade Control Law (capital control period); the second sample starts on September 22, 1985, corresponding to the Plaza Agreement. The heat wave hypothesis is rejected for all the periods examined although the model is accepted in the Tokyo market during the capital control period which implies that capital controls did prevent meteor showers in Tokyo.

Testing for Spillover Across International Stock Markets Using Daily and Intradaily Data

Hamao, Masulis and Ng (1990) study the short-run interdependence of prices and price volatility across three major international stock markets: Tokyo, London and New York by examining the extent to which price changes in one market influence the opening prices in the next market to trade. In addition, they investigate whether changes in price volatility in one market are positively related to changes in price volatility observed in the subsequent trading market.

Daily and intraday stock price activity over a three-year period, from April 1, 1985 to March 31, 1988 from the Tokyo, London and New York markets is examined. The daily open and close data are obtained from the Nikkei 225 Stock Index for Tokyo, from the Financial Time-Stock Exchange 100 Share (FTSE) Index for London and from the Standard & Poors 500 Composite Index for New York. The ARCH family statistical models provide evidence of spillover effects from the U.S. and the U.K stock markets to the Japanese market, suggesting asymmetry. In addition, there are spillover effects from U.S. to U.K stock markets.

Testing for Spillover Across International Stock Markets Using Weekly Data

Theodossiou and Lee (1993) investigate the transmission mechanism of stock market returns and volatility shocks across the U.S., Japan, the U.K., Canada and Germany by investigating the extent to which conditional volatility in these markets affects expected returns, using the multivariate GARCH-M model.

Weekly data on stock returns for the U.S, Japan, the U.K., Canada and Germany for the period January 11, 1980 to December 27, 1991 are used, obtained from Barron's National Business and Financial Weekly which publishes data based on Friday's closing prices of major international stock market indices. The indices used are the S&P 500 for the U.S., the Nikkei for Japan, the Financial Times 100 for the U.K., the Toronto Stock Exchange for Canada and the Commerzbank for Germany. The authors report a significant mean spillover from the U.S to the U.K., the Canada and the Germany, and a spillover with low explanatory power from Japan to Germany. There is evidence of volatility spillover from the U.S. to all four stock markets, suggesting that the U.S market is the exporter of volatility.

Testing for Returns and Volatility Transmission Without Overlapping Trading Hours in the Stock Market

Lin, Engle and Ito (1994) investigate the returns and volatilities transmission of stock indices between the New York and Tokyo markets. Since these markets do not have any overlapping trading hours, it is appropriate to decompose the daily price changes (returns and volatility) into daytime (open-to-close) and overnight (close-to-close). According to the authors, such decomposition, is crucial for clean tests of how information is transmitted from one market to the other.

Stock price indices from the Nikkei 225 (NK225) for Tokyo market and the Standard and Poor's 500 (S&P 500) for New York market are used. The GARCH-M model, with similar methodology to that of Hamao *et.al.*,(1990), provides evidence that Tokyo daytime returns are correlated with New York overnight returns and vice versa. The authors interpret this result as evidence that information revealed during the trading hours of one market has a global impact on the returns of the other market.

Examining for Spillover Between Stock Markets with Two Hours Simultaneous Trading Using High Frequency Data

Susmel and Engle's (1994) study on mean and volatility spillover in international equity markets uses a similar approach to that of Engle *et.al.*, (1990) and Hamao *et.al.*, (1990). However, the data sets are different. While the earlier studies use daily data, Susmel and Engle (1994) employ 533 very high frequency hourly observations from the Dow Jones 30 Industrial Average for the New York and Financial 30 Share Index, covering the period between January 2, 1987 and Febuary 29, 1989. These markets are selected because they share two and a half hours of simultaneous trading so that the authors can examine the impact of news revealed in one market on the returns and return volatility in the other market hours later.

The results of the GARCH model show no strong evidence of volatility spillover between these markets, which contradicts the findings of Hamao *et.al.*, (1990). The only significant effects are very small and surround the movement of share prices around the New York opening. In addition, there seems to be no evidence of mean spillovers when non-overlapping trading periods are used.

Examining for Spillover Between Stock Markets with Perfectly Synchronous Trading Hours

Karolyi (1995) examines the short-run dependence in price movements for stocks traded on the Toronto Stock Exchange (TSE) and the New York Stock Exchange (NYSE). He focuses on the dynamic relationship between the daily stock price returns and stock-return volatility for the two largest national markets, the Standard and Poor (S&P) 500 and the TSE 300 stock indexes, specifically in terms of equity capitalization when there are perfectly synchronous trading hours.

Time series of daily stock-market indexes for both markets at the close of trading are used. These data are from Reuters Datalink and from the Index Section of the Toronto Stock Exchange for the period from April 1981 through December 1989, generating a total of 2,133 observations. The use of a bivariate GARCH model results in of cross-market patterns in the S&P 500 and the TSE 300 returns and volatility. However, when the sample is divided into subperiods, cross-market dynamics in returns and volatility are much weaker during later subperiods.

2.6 A Summary of Previous Findings

This chapter has reviewed the empirical evidence on the main theoretical issues which influence the work developed in this thesis. These are: market efficiency and the assumption of linearity; nonlinear dependence in financial returns; the relationship between trading volume and price variability; and spillover effects which are discussed within the framework of specific markets: futures, foreign exchange and equity.

In examining efficiency, two hypotheses are tested in different markets. The first is the unbiasedness hypothesis, which is relevant to the futures and foreign exchange (forward) markets and tests whether futures prices are unbiased predictors of futures spot rates. The second is the efficient market hypothesis (EMH) in the equity market which suggests that a market is efficient if its share prices reflect all available information and which also implies that futures stock returns cannot be predicted using past stock returns. The results of the test hypotheses are mixed, depending on the sample data used and the methodology employed.

In testing for nonlinear dependence using the BDS and other tests, it was noticed that, in the majority of cases, the financial and currency time series reject the null hypothesis of independent, identical distribution (i.i.d). Nonlinearity generally occurs through variance of the data generating process. When modelling these time series the problem of heteroscedasticity should be taken into account . Our results show that the ARCH family model captures most of the heteroscedasticity and fits the data satisfactorily.

We have reviewed most of the literature concerning the arrival of information to the markets which is hypothesized by the sequential information model (SEQ) and the mixture of distribution hypothesis (MDH). The SEQ model hypothesises that traders in a market receive new information in a sequential, random fashion. On the other hand, the MDH model implies a positive relationship between volume and price variability, the relationship being a function of the directing (or mixing) variable, defined as the rate of information arrival. In most cases, volume is used as a proxy for news, while in some cases other determinants are used, such as the number of quote arrivals, public announcements, the number of transactions etc. The results are mixed: the SEQ or the MDH is accepted in some cases and rejected in others. Of the different models employed, the ARCH family models resulted in the most appropriate procedure for computing the model parameters because they accounted for heteroscedasticity.

Finally, in analysing the mean and volatility spillover, it was observed that, in most cases, the use of GARCH models enabled the capturing of the first and second order moments. The results of those studies indicate that the New York stock market is the main exporter of volatility to other markets. Regarding the foreign exchange market, the meteor shower hypothesis, which allows volatility spillover acrossmarkets, appears to be widely accepted in most cases.

Chapter Three

Currency Futures: Market Microstructures and Pricing

3.1 Introduction

The preceding chapter focused on theoretical issues and the empirical evidence on four topics: market efficiency and the assumption of linearity, nonlinearity in financial returns, the relationship between trading volume and price variability; and spillover effects. The literature pertaining to the futures market, the foreign exchange market and the equity market was discussed.

The aim of this chapter is to present a general overview of the currency futures markets. We will also look at some studies which relate to the issues discussed in Chapter 2 or which fit within the framework of currency futures markets, noting their research methodology.

This chapter is divided into six sections. Section 3.2 gives an overview of currency futures contracts and Section 3.3 focuses on the basic structure of the futures markets. In Section 3.4, we review previous studies in the context of the currency futures markets. Section 3.5 is an in depth discussion of the research issues as well as the hypothesis to be tested in this study. Finally, Section 3.6 presents the summary.

3.2 An Overview of Currency Futures Contracts

In May 1972, the Chicago Mercantile Exchange (CME) established the International Monetary Market (IMM) for the trading of futures contracts in foreign currencies following the breakdown of the Bretton Woods system of fixed exchange rates. The IMM holds approximately 90 percent of the U.S. market share of these contracts. Besides the IMM, the only other major exchange which successfully trades currency futures contracts is the Singapore Mercantile Exchange (SIMEX), a partner of the IMM. Together they clear currency futures. SIMEX trades mainly when the IMM is closed at night and its transactions are limited to two currency futures: the German mark (DM) and the Japanese yen (JY).

The four most actively traded contracts on the IMM, are the German mark (DM), the Japanese yen (JY), the Swiss franc (SF) and the British pound (BP). The exchange rates are quoted in U.S dollars per unit of foreign currency. Trading at the IMM starts at about 7:30 a.m. Central Time (CT) for all currencies. The closing times of the contracts are however, staggered. The SF closes at 1:16 P.M. and is followed by the DM at 1:20 P.M. The JY is the next to close at 1:22 P.M. The BP closes at 1:24 P.M. On the last trading day of the contract which is the second business day before the third Wednesday of the delivery month, the currency futures close between 9:16 A.M. and 9:21 A.M.

The contracts traded on the IMM are quite similar for all currency futures. The major difference is the quantity of the currency represented by a particular futures contract or standardized contract. The limits are £62,500 for the BP, 125,000 for the DM,12.5 million for the JY and 125,000 for the SF. This standardization of contracts in the futures market itself facilitates the emergence of the liquid market over the forward market.

3.3 The Basic Structure of Futures Markets

3.3.1 Futures Contract

A simple definition of a futures contract can be stated as "an agreement between two parties to make a particular exchange at a particular future date." (Duffie, 1989). However, as the market becomes more complex, a more developed and precise definition is required:

> *"A futures contract is an agreement for a seller to deliver a specified quantity of a particular grade of a certain commodity to a predetermined location on a certain date at an agreed price. The obligation of the buyer is the opposite, i.e. to take delivery."(Winstone, 1995).*

This contract is legally binding between the respective parties. The above definitions refer specifically to the commodity contract, since this was the first futures market to exist. However, in recent years, with the introduction of the financial futures contract, the need for a more specific related definition has arisen, as follows:

"A futures contract is a binding agreement between two parties to make or take delivery of commitment at a stated price at a specified future date." (Winstone, 1995)

Falkena,, Kok, Luus and Raine (1991) describe a futures contract as an agreement or legal obligation to purchase or to sell a futures exchange; *i.e.*, a standard quantity and quality of a specified asset, on a specific date at a price that is determined at the time of trading the contract. Thus, a futures contract is a financial instrument regardless of whether the underlying asset happens to be cotton, gold, an index, a currency or a financial asset. Such obligations of the purchaser or the seller can only be eliminated if the futures position is 'offset'. This term refers to an equal but opposite transaction that eliminates the original obligation in the futures market.

3.3.2 The Futures Exchange

The futures exchanges are incorporated as membership associations and operated as nonprofit organizations for the benefit of their members. The main objective of the futures exchange is to provide an organised marketplace, with uniform rules and standardised contracts. Like any other organization, the futures exchange consists of a board of directors, managers and the owner (shareholders). Daily business operations are managed by the managers with the help of officers and other staff, and by various committees. The power to decide important issues usually resides with the committees, which are typically extensive and active. In addition to futures trading, the exchange may also actively operate in other markets such as spot commodities, options and other financial securities, and may provide other goods and services (such as price information) to the public. Operating expenses come from the membership dues and from the fees for services provided; for example, the transaction fees per contract traded. (Duffie, 1989).

3.3.3 Exchange Members and Customers

The exchange member sometimes, also referred to as membership or *seat*, are individuals who act on behalf of firms such as brokerage houses, investment banks or commodity dealers. The *seats* are quite limited in number and can be sold to others on the floor of an exchange; however, substantial and risky investment is often required. The advantage of a *seat* is mainly the privilege it offers to trade contracts directly on the floor of the exchange with the advantage of immediacy and low transaction fees (Edwards and Ma, 1992).

Members or individual members who act on behalf of those who actually own the *seats* and who use the privilege for trading are known in futures markets as *traders*. These traders can be categorised into several classifications according to their reasons for trading. Floor brokers, for example, sometimes trade on their own as well as providing a chain of transaction services to allow the public at large to buy or sell contracts. Their incomes come mainly from fees for their services. Other traders, such as scalpers and day traders, trade mainly on their own accounts and may either gain or lose from price movements (Winstone, 1995).

In contrast to the stock exchange markets, futures trading activity is conducted on the floor of an exchange mainly in the form of an open outcry auction.

As for the customers, they can be divided into two categories; large and ordinary. Large customers, such as commodity merchants, exporter investment banks and producers normally become customers by purchasing exchange membership or *seat* which allow them to trade directly at the futures exchange, taking advantage of the immediacy and lower transaction costs. Ordinary customers may establish futures accounts with the Futures Commission Merchant (FCM) before they can trade at the futures exchange (Duffie, 1989).

3.3.4 A Clearinghouse

A clearinghouse is typically a nonprofit incorporated membership association. Its members mainly come from associated exchange corporations. However, in some countries, the clearinghouse is established independently of any particular exchange in order to serve one or more exchanges. In England, for example, the International Commodities Clearing House (ICCH) clears for most of the futures exchanges (Edwards and Ma, 1992).

The basic function of the clearinghouse is to clear futures contracts. It assumes the role of intermediary to each futures transaction by guaranteeing an obligation among the clearing members, mainly the seller and the buyer. For example, if there is any default by a member of a clearinghouse (seller or buyer), the loss will fall on the clearinghouse and not with the members (Sutcliffe, 1993). As a consequence, futures traders are not concerned about the credit risk of the party with whom they deal. As Bernstein (1989) notes, if one party to a contract defaults for any reason, the fulfilment of the contract is guaranteed by the clearinghouse. In carrying this important responsibility, the clearinghouse requires that its members maintain a margin account with the clearinghouse which can be used to fulfill the contractual or financial obligations of members who default. Finally, the clearinghouse also monitors the financial integrity of its members.

3.3.5 Margin Requirements and Marking to Market

A margin can be defined as good faith money from both parties trading a futures contract to guarantee that each will abide by the terms of the contract. Margin requirements on other hand refer to the minimum level of money deposited and this is set by the exchange for each contract. There are several types of margin used by the exchange. First, is the initial margin, also known as the original margin, which is the amount a trader must initially deposit into his or her trading account when establishing a position. The idea of the margin is to cover at least the maximum allowable price fluctuation per day of a net futures position and therefore to cover all likely customer losses.

Second, the original margin call refers to the demand by futures commission merchants when the customer's losses have exceeded the initial margin requirement deposited. Third, the variation margin refers to the money deposited daily in order to meet the required margin call by the exchange and which must be made before the market opens on the next trading day. Fourth, the maintenance margin refers to adjustments made by the FCM (Futures Commission Merchants) to customer accounts in response to changes in the value of customer positions (Dubofsky, 1992).

Marking to market refers to daily entries made across the equity account the holder of the futures position has with an exchange member. Using the daily settlement price, a committee composed of clearinghouse members will determine the difference between today's settlement price and the previous day's settlement price. This difference is then credited or debited to the holder's account. For example, if the difference is positive; *i.e.*, the settlement price is increased, the amount is credited to the margin accounts of those holding long positions and debited to the account to the holders of short positions. On the other hand, if the difference is negative; *i.e.*, the settlement is decreased, the amount is credited to the holders of short positions and charged to those holding long positions. (Sercu and Uppal, 1995) This process is sometimes referred to as daily settlement and is an important feature of futures markets as well as a major difference between the futures and forward markets.

3.4 Previous Research into Currency Futures Pricing

Research on the currency futures market started in the late 1970's and early 1980's. The early studies mainly focused on tests of market efficiency on the basis of contracts using forecast bias [Panton and Joy (1978); Hill and Schneeweis (1981)]; and on risk and returns [Naidu and Shin (1980)]. The issue of market efficiency continued to be the main research of the topic late 1980's and 1990's. However, these studies use long continuous series as opposed to contract by contract series. For example, numerous papers [e.g., McCurdy and Morgan (1987); Cavanaugh (1987); McCurdy and Morgan (1988); Pan, Chan and Fok (1997)] have tested for the martingale hypothesis, and others [Hodrick and Srivastava (1987); Kodres (1988); Kodres (1993); Tse and Booth (1996)] have examined the unbiasedness hypothesis.

Studies which model heteroscedasticity [Fujihara and Park (1990); Venkateswaran, Brorsen and Hall (1993)] nonlinear dependence [Hsieh (1993a); Hsieh (1993b)] and information arrival [Harvey and Huang (1991); Laux and Ng (1993); Bessembinder and Seguin (1993); Leng (1996); Chatrath, Ramchander and Song (1996)] have also become widespread.

Below, we shall briefly review the main literature related to the currency futures market, grouping it under five separate issues: the unbiasedness hypothesis; the random walk hypothesis, non-stationarity and cointegration, nonlinear dependence and heteroscedasticity, and the relationship between information arrival and volatility.

3.4.1 The Unbiasedness Hypothesis

Testing for the Unbiasedness Hypothesis and the Nature of Time Variation in Risk Premia

Hodrick and Srivastava (1987) examine the unbiasedness hypothesis and the nature of time variation in risk premia in the currency futures market. In particular, they seek further evidence of whether the rejection of the unbiasedness hypothesis and the nature of these variation in risk premia which are found in the forward market also occurs in the futures market.

Their data comprise daily currency futures prices from June 1, 1973 to December 8, 1983 for the British pound, the Japanese yen, the German mark, the Canadian dollar and the Swiss franc traded on the International Monetary Market (IMM). Employing the Generalized Method of Moments model, the hypothesis that daily currency futures are unbiased predictors of the following day's futures prices is rejected for all currency futures and this is consistent with the findings of other studies on the forward exchange market.

Testing for Unbiasedness Hypothesis with Daily Price Limit

Previous tests on the unbiasedness hypothesis using daily futures data have failed to take proper account of daily price limits [e.g., Hodrick and Srivastava (1987)]. Kodres (1988), explicitly incorporated price limit structure into the econometric model in order to test for unbiasedness. A price limit restricts the amount by which the price can fluctuate and thus the "marked to market" gains (losses), that are received (paid) by market participants at the end of a trading session.

Five actively traded foreign currency futures contracts on the International Monetary Market (IMM) are used. These are the British pound (BP), the German mark (DM), the Japanese yen (JY), the Swiss franc (SF) and the Canadian dollar (CD).The settlement prices represent the prices at the close of trading for the nearby contract. The number of limited futures prices in the data are as follows: SF 67; JY 31; DM 27; BP 16; and CD 13. Kodres employs the econometrics model of maximum likelihood estimation for the limit model and without limit structures. The null hypothesis that β_1 through β_5 should be zero is tested. The results show that with the inclusion of the daily price limit the null hypothesis of unbiasedness is rejected for all currencies except for the BP.

Testing for Uncorrelatedness of Returns and Risk Premium

Liu and He (1992) test the uncorrelatedness of returns on daily foreign currency futures prices and derive implications of risk premia. Their study is quite different from previous works on same area in that they use a broader sample set and adopt a relatively new testing methodology. In particular, they apply the heteroscedasticity-consistent variance ratio test developed by Lo and MacKinley.

The authors use daily currency futures prices for the British pound (BP), the Canadian dollar (CD), the German mark (DM), Japanese yen (JY) and Swiss franc (SF) during the periods from June 1977 to June 1980 and from March 1984 to December 1989. The variance ratio test, indicates that there is statistically significant evidence of serial correlations in daily currency futures prices. This implies that the futures price is not an unbiased predictor of the spot price on its corresponding contract maturity date. The existence of a time-varying risk premium, is also implied, thus violating the efficient market hypothesis. In addition, the authors find more rejections of zero risk premium during the 1970s than in the 1980s.

Testing for Unbiasedness and Heteroscedasticity

A further study by Kodres (1993) extends his previous work on testing for unbiasedness in currency futures. Here he focuses not only on daily price limits but also on observed conditional heteroscedasticity in the data. The data are the daily settlement prices of five actively traded foreign currency futures contracts, for the British pound (BP), the German mark (DM), the Canadian dollar (CD), the Japanese yen (JY) and the Swiss franc (SF) traded on the International Monetary Market (IMM) of Chicago Mercantile Exchange, (CME). The sample period is from July 1, 1973 to March 17, 1987.

The unbiasedness hypothesis states that today's futures price is the best predictor for tomorrow's futures price, given the information available at time t, as follows:

$$F_t = E(F_{t+1}|I_t)$$

where F_t is the futures price at time t and F_{t+1} is the futures price at $t + 1$. The $E(\cdot|\ I_t)$ is the mathematical expectation conditioned on the information in the time t information set, I_t. Using the maximum likelihood estimations and the GARCH model, Kodres finds that the rejection of the unbiasedness hypothesis is detected only in the DM and the CD, not in of all five currency futures as found in his 1988 study.

Predicting the Futures Spot Prices from the Currency Futures Prices

Jabbour (1994) assesses how accurately futures spot exchange rates can be predicted from currency futures prices. He poses three relevant questions: Do current futures prices convey some information about future spot exchange rates not captured by current exchange rates? How well can the current implied spot exchange rates derived from current currency futures prices predict future spot rates? How sensitive is the result to the time to maturity of the futures contract?

His data are the daily settlement prices of the German mark (DM) and the Japanese yen (JY) obtained from the Chicago Mercantile Exchange (CME). Other data employed include the simultaneous currency spot rates, the date and time of the transaction, the delivery dates of the futures contract and the interest rates for both currencies. The futures market model is employed to predict the futures spot rates. The ordinary least squares regression is then applied to estimate the coefficients. The performance of the model is measured by the value of the relative, the absolute and the squared error between the model price and the market price. The results show that the currency futures prices convey little information not captured by spot exchange rates. The continuous compounding cost-of-carry model which is used to predict future spot rates appears to hold strongly for contracts with less than 60 days to maturity.

Testing for Autocorrelation

Tse and Booth (1996) reexamine the significant autocorrelation results of foreign currency futures reported by Liu and He (1992) using Lo and MacKinlay's variance ratio test, Diebold's Q-statistics test and the Box-Pierce-Ljung Q-statistic test.

They use daily settlement prices obtained from the IMM for of five foreign currency futures: the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF), from January 3, 1986 to December 31, 1993. The nearest contract to the first trading day of the delivery month (March, June, September and December) is used. The results show that none of the five futures contracts provides significant autocorrelation, a finding consistent with Hsieh (1993) but contradicting that of Liu and He (1992) which the authors explain is because of thin trading and imprecise interpretation of the tests. The joint hypothesis of market efficiency and risk neutrality is, however, maintained.

3.4.2 The Random Walk Hypothesis

Testing Futures Exchange Rates from Predicted Futures Exchange Rates

Panton and Joy (1978) were among the first to do research on currency futures. Their study has three aims: to compare the currency futures prices traded on International Monetary Market (IMM) with prices predicted by the interest rate parity theorem; to investigate the characteristic bias; and to present the realized rate of return.

The data used are daily spot prices, interest rates and settlement prices of eight currency futures: the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Dutch guilder (DG), the French franc (FF), the Japanese yen (JY), the Mexican peso (MP) and the Swiss franc (SF) from Chicago Mercantile Exchange (CME) during the period from June 18, 1972 to December 15, 1976. Panton and Joy apply the interest rate parity theorem in order to model the deviations of observed futures exchange rates from predicted futures exchange rates. Their results show that for the BP, the observed futures prices are less than futures prices predicted through the interest rate parity theorem. In addition, the three- month contracts on the MP exhibit a significant difference between futures and spot prices at contract maturity which can be explained by the bias to expectation of devaluation. Finally, the mean returns for the CD, the DG and the FF are mixed. None are significantly different from zero.

Testing for Futures Currency Exchange Market as a Source of Information on Futures Spot Rates

Hill and Schneeweis (1981) were among the earliest researchers to conduct a study on the value of the future currency exchange market as a source of information on futures spot rates. They analyse the effectiveness of the futures market as a means of forecasting futures spot currency rates using the methodologies applied in previous tests on the forward foreign currency market. Previous studies by Isard (1978), Levish (1979) and Kolhogen 1978), focused on the ability of the forward foreign exchange markets to forecast future spot rates; they concluded that the forward rate is an unbiased forecast of future spot rates.

Hill and Schneeweis use daily futures contract prices for five currencies: the British pound, the German mark, the Swiss franc, the Canadian dollar and the Japanese yen, traded on the International Monetary Market, IMM, for a sample period of September 1972 through December 1978. When the model of the futures price as an unbiased estimator of the futures spot price is applied, the currency futures market, on average, provides unbiased forecasts of spot rates and this is consistent with the results obtained for the forward market. However, the longer the forecast horizon the lower the degree of forecast efficiency.

Testing for Market Efficiency in Relation to Time Varying Risk, Central Bank Intervention and Trading Volume

Glassman's (1987) empirical work on the efficiency of the futures markets is an extension of previous research by Panton and Joy (1987), and by Hill and Schneeweis (1981). However, she broadens her scope and relates efficiency to time varying risk, central bank intervention and futures trading volumes. The hypothesis of an efficient market holds that market prices reflect all available information which implies that the correlation between the successive price changes is zero. Glassman's data consist of daily settlement futures prices changes for four actively-traded currency futures: the British pound, the Canadian dollar, the German mark and the Swiss franc, beginning in May 1972. Her sample includes prices for 38 Chicago Mercantile Exchange futures contracts with quarterly delivery dates for the period from September 1972 to December 1981.

Using a regression equation, Glassman finds evidence of multimarket and joint multimarket inefficiency in the foreign futures markets during the period under study, which appears to be short term in duration. The results of the regression analysis between the serially correlated price changes and time-varying risk, central bank intervention and futures trading volume, suggest that periods of inefficiency do not systematically correspond to periods of market turbulence.

Testing for Martingale Hypothesis

McCurdy and Morgan (1987) examine the martingale hypothesis for the daily and weekly rates of change of futures prices for five currency futures with time-varying volatility from the Chicago Mercantile Exchange (CME). Daily data for the British pound (BP), the German mark (DM) and the Swiss franc (SF) are from 1974 while the first observations for the Japanese yen (JY) and the Canadian dollar (CD) start in 1977. The ending date for all the currency futures is 1983. Weekly data, for the BP, the DM and the SF is taken from the first week in 1974 to the last week of 1983 while data for the JY and the CD data are collected from the second week of 1977 to the last week of 1983.

The GARCH model of conditional heteroscedasticity is employed in the study. A comprehensive series of diagnostic tests are carried out, including checks on model specification, residual properties and tests for omitted variables. The results show that the martingale hypothesis for daily data is rejected for each of the currency futures tested. As for weekly data, the null hypothesis is rejected only for the DM, suggesting the existence of a time-varying risk premium.

Testing for Serial Dependence

Cavanaugh (1987) claims to have been among the earliest to conduct a study of serial dependence in daily foreign currency futures prices using daily settlement prices. His study focuses on whether currency futures prices follow a submantingale or a martingale stochastic process as implied by Paul Samuelson's influential model of the competitive, informationally efficient futures market. The model assumes the expected return to be constant or uncorrelated over the life of each contract although it may differ across currencies or contracts. Eight British pound (BP) and seven Canadian dollar (CD) futures contracts traded on the International Monetary Market (IMM) for the period 1975 through 1980 are used.

Five tests for serial correlation are employed, including the Ljung-Box, the cumulative periodogram, the F-test, the Wilcoxon signed-rank test and Fisher's test. The results show evidence of significant serial correlation in daily changes of log prices for four foreign exchange futures contracts. These are March 1978 and December 1977 contracts for the CD, and December 1980 and 1979 contracts for the BP. Some evidence of negative serial correlation following large price changes is also found.

Testing for Martingale Hypothesis

McCurdy and Morgan (1988) examine the form of heteroscedasticity in German mark (DM) futures price data and compare different specifications of the particular way that the variance changes over time. In doing so, they test for the martingale hypothesis using daily and weekly rates of change for DM futures prices from 1981 to 1985. According to the martingale hypothesis, changes in futures prices from period t-1 to period t are innovations or forecast errors orthogonal to the information available at t-1.

Daily and weekly data for the outstanding DM contract with the shortest time to maturity of the contracts maturing in March, June, September and December are obtained from the Chicago Mercantile Exchange. Using the time-varying variance of GARCH under the martingale hypothesis and GARCH-M under the hypothesis of time-varying risk premium, the authors find that the models exhibit a good fit for daily as well as weekly data. The martingale hypothesis is rejected for daily data and the authors suggest this is due to trading day effects as well as the resulting day-of-week patterns of the futures prices.

Testing the Random Walk for Long-Time Series and Individual Contracts

Pan, Chan and Fok (1997) examine the random walk process for four currency futures prices using both long time-series prices and individual contract prices for the period 1977-1987. The random walk hypothesis is tested through asymptotic standard statistics as well as by computing the significance level based on the bootstrap method.

The data consist of daily settlement prices for four currency futures: the British pound (BP), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF) for the period from January 2, 1977 to December 31, 1987 from the International Monetary Market (IMM) of the Chicago Mercantile Exchange. To avoid the possibility of noise created by options of redemption during the delivery month, the price data within the delivery month are excluded. The results of the variance ratio test provide little evidence against the random walk except in the case of the JY futures. Similar results are obtained from a contract by contract basis examination, suggesting that, overall, the currency futures markets are efficient.

3.4.3 Non-Stationarity and Cointegration

Testing for Stationarity

Doukas and Rahman (1987) assess whether foreign exchange currency futures follow a stationary process. They use daily settlement prices for the five most actively traded currency futures on International Monetary Market (IMM): the German mark (DM), the Canadian dollar (CD), the British pound (BP), the Swiss franc (SF) and the Japanese yen (JY). These data span the period from June 1, 1977 to June 30, 1983. The authors note that the period selected is characterized by relatively high daily volume, thus avoiding the well-known problems of thin market literature.

The unit root testing procedure developed by Fuller, Dickey and Fuller, and Hasza and Fuller are used in the study. Monte Carlo experiments are also conducted to investigate sensitivity in both the presence of heteroscedasticity and in roots near the unit root circle. The results suggest that foreign currency futures rates have autoregressive representations with a single unit root since the β estimates fall within 0.95 and 1; exhibiting borderline non-stationarity. Therefore, it appears that the process generating the log of currency futures rates is well approximated by random walks.

Testing for Market Efficiency Using Unit Root and Cointegration

Chan, Gup and Pan (1992) examine the efficiency of the currency futures markets on both an individual and a collective basis. They apply unit root and cointegration tests of the pairwise and the higher order, Augmented Dickey Fuller (ADF) test on four foreign currency futures traded on International Monetary Market (IMM): the British pound (BP), the German marks (DM), the Japanese yen (JY) and the Swiss franc (SF). Daily settlement prices nearest to the contract maturity dates between June 1, 1977 and December 31, 1987 are obtained from the *International Monetary Market Yearbook.*

The results show that foreign currency futures prices of the BP, the DM, the JY and the SF have one unit root (nonstationary), suggesting that the individual markets are weak form efficient. Pairwise cointegrations are found only between the DM and the SF. The higher order cointegration tests support the existence of cointegration among all the currency futures, implying multi-market inefficiency.

Testing for Long-Equilibrium Relationship

Naka and Wei (1996) examine the existence of a long-equilibrium relationship in the currency futures market. Prices are cointegrated if a long-run equilibrium relationship exists among these prices. A set of prices is said to be cointegrated if each individual price series is non-stationary and a linear combination of these prices is stationary. If prices are closely related over time or cointegrated, then past price information will be helpful in predicting futures price changes.

Daily settlement prices of the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF) for the period from January 2, 1981 to June 29, 1990, consisting a total of 2,401 observations, are used. They are obtained through the International Monetary Market Yearbook. This study uses a rollover approach by combining data from various contracts in such a way that the resulting data reflect the prices of the most active contracts. Using the cointegration test developed by Johansen (1991), they find no evidence of a long-equilibrium relationship among five currency futures, suggesting the unpredictability of futures price changes. When the same procedure is applied for the subperiod beginning on Febuary 22, 1985, when the price limit on foreign exchange was removed, the results are similar.

3.4.4 Non-Linear Dependence and Heteroscedasticity

Determining the nature of Dependence

Fujihara and Park (1990) compare various stochastic processes to determine which process best describes the changes in currency futures prices. In particular, they address the issues of independence, nonnormality and time varying parameters. However, they consider only the hypothesis involving mixtures of distributions with finite variance and time varying parameters. The three processes considered are: the ARCH process; the compound normal distribution; the mixed diffusion-jump process; and the student t-distribution.

The data are weekly spot and futures prices recorded in the Wall Street Journal from November 1977 to December 1987 for five currencies: the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen and the Swiss franc (SF), are used. The results show dependence for futures as well as for spot prices but the dependence model represented by the ARCH process is not the best fitting stochastic process for two of the currencies examined. Using the nonlinear test developed by Hsieh (1989), the authors find that the nature of this dependence is of the variance stochastic process, typical of the ARCH process.

Examining the Time-Series Property of Currency Futures Returns

Kao and Ma examine the time series properties of four actively traded currency futures on the International Monetary Market (IMM): the British pound (BP), the Canadian dollar (CD), the German mark (DM) and the Swiss franc (SF). They use daily closing prices for near-term contracts gathered from Commodity Perspective Inc. from November 1, 1979 to December 31, 1987. In order to account for the daily price limit which was in effect until Febuary 22, 1985, the authors divide the time series into one period when price limits were in place (November 1, 1979 to Febuary 22, 1985) and another period with no price limits (Febuary 25, 1985 to December 31, 1987). By dividing the entire sample period into intervals of various lengths, the modified rescale range (R/S) model which is proposed by Philips (1987) and Lo (1989) and employed in the analysis may identify the presence of short, medium and long nonperiodic cycles that are not visible through the autocorrelation coefficient function. The R/S model mentioned by the authors assumes the return series has constant mean, nonconstant variance and is serially correlated at lower orders.

The results show that for the mixed period, the null hypothesis that the return series exhibits short-term price dependence is rejected for three out of the four currency futures. When examined separately, however, the null hypothesis cannot be rejected for all currency futures. This suggests that the long-term dependence found in the mixed period can be induced by nonconstant means in the return series. The authors conclude that the four currencies which exhibit short-term price dependence are consistent with the hypothesis of heterogeneous traders.

Correcting for Heteroscedasticity

Closely related to the Fujihara and Park (1990) paper is a study of Venkateswaran, Brorsen and Hall (1993) on correcting for heteroscedasticity in daily futures returns. They follow the procedures of Taylor (1986), who suggests that the rescaled daily returns are more likely to be independently and identically distributed (i.i.d) than the actual daily returns and thus have a reasonably homogeneous variance. The raw data are corrected for heteroscedasticity by dividing each observation by its forecast conditional standard deviation generated by an exponentially weighted moving average (EWMA) model. The raw and rescaled data are then tested for convergence to normality using the stability under addition test of the stable distributions.

Daily returns data for 31 commodities including agriculture commodities, livestock, metal and financial instruments from 1960 to 1988[2] are used. To maintain continuity in the data and to minimize differences in maturity, the log changes in closing prices are used from the contract with the nearest delivery month are used. We report the results pertaining only to the six currency futures returns. For the rescaled data the null hypothesis of no skewness is rejected at the 5 percent level. Similarly, using the K-S test of normality, the null hypothesis an i.i.d. normal distribution is also rejected. However, when using the McLeod-Li chi- square test on the same data, the i.i.d. is only rejected for the Japanese yen at the 5 percent level. This indicates that rescaling the returns reduces nonlinear dependence. The authors note that the EWMA model seems to work as well as the GARCH models considered in previous research.

Testing for Rational Expectations and Time-Varying Risk Premium Using Linear and Nonlinear Methods.

A study by Hsieh (1993a) differs from the previous study. He tests the joint null hypotheses of rational expectations and the absence of time-varying risk premium of currency futures prices. While the other researchers use linear methodology, he employs both linear and non-linear methods. His data are daily currency futures prices of the British pound (BP), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF) traded on the International Monetary Market (IMM) between February 22, 1985 and March 9, 1990, totalling 1,275 observations.

[2]The number of years of data available vary with the commodity.

A linear regression model is used to test for the autocorrelation of the forecast error under the join hypotheses. For estimation purposes, the ordinary least squares (OLS) with heteroscedasticity-consistent standard errors and GARCH(1,1) are employed. The results show no linear or nonlinear predictability in the log price changes, either using its own past or past interest differentials. Thus, the author concludes that if a time-varying premium exists in the currency futures markets, it is neither linearly nor additively non-linearly dependent on its own past or past interest rate differentials.

Testing for Independence and Identically Distribution (i.i.d)

Hsieh (1993b) examines the independence and identical distribution (i.i.d.) for four currency futures. He argues that when log price changes are not i.i.d, their conditional density may be more accurate than their unconditional density in describing short-term behaviour.

Daily settlement prices for four currency futures contracts traded on the Chicago Mercantile Exchange (CME): the British pound (BP) the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF) from Febuary 22, 1985 to March 9, 1990, totalling 1,275 observations are used. In order to obtain a continuous time series, the contracts are rolled over to the next expiration cycle one week prior to expiration. Using the BDS test for i.i.d, it is shown that daily log price changes in the four currency futures contracts are not i.i.d. Moreover, it appears that the conditional variance is predictable and can be described by an autoregressive volatility model. Indeed, the exponential GARCH employed captures all the departures from i.i.d.

Testing for Long-Term Dependence

Fang, Lai and Lai (1994) examine the relevance of fractal dynamics in currency futures markets. Fractal dynamics are an interesting form of dynamics which are characterized by irregular cyclical fluctuations and long-term dependence, and the appeal of this fractional model is its ability to capture a wide range of long-term dependence with a single parameter. The authors employ a semi-nonparametric procedure devised by Geweke and Porter-Hudak (1983) in order to estimate the fractional parameter since it is not sensitive to short-term dependence, nonnormal innovations or variance nonstationary.

Daily data are from January 4, 1982 to December 31, 1991 for five currency futures prices: the British pound (BP), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF), are used. The 2,527 observations for each currency are settlement prices of futures contracts closest to maturity, and are drawn from various issues of the *International Money Market Yearbook.* The results of the ARCH test statistics show the presence of substantial ARCH effects in all the four return series. Applying the Geweke-Porter-Hudak procedure provides statistically significant evidence that all currency futures return series are well described by a long-memory fractional process, except for the BP. The authors conclude that, on the whole, currency futures price dynamics contain fractal structure with long-term dependence.

3.4.5 The Relationship Between Information Arrival and Volatility.

Examining for Contemporaneous Relationship Between Volume and Price Variability

Grammatikos and Saunders (1986) examine the contemporaneous relation between asset price variability and volume traded, using contract disaggregate data on five currency futures prices. Underlying this empirical research is a theoretical framework which suggests price variability and volume traded should be positively correlated. Furthermore, according to this theoretical framework, the so-called mixture of distribution hypothesis (MDH), the correlation between price variability and volume should be positive because of joint dependence on a common directing variable or event.

Daily data for five currency futures traded on the International Monetary Market (IMM), the British pound (BP), the German mark (DM), the Canadian dollar (CD), the Japanese yen (JY) and the Swiss franc (SF), are used. The observations are for high, low, opening and closing prices; volume traded; and open interest from March 1978 to March 1983. Employing both the classical, and the Garman and Klass (1980) tests, the authors find strong positive contemporaneous correlations between the trading volume and price volatility and this is consistent with the MDH. Similarly, using the Geweke, Meese and Dent (1983) causality test, price variability and trading volume show a contemporaneous correlation in the majority of cases.

Examining Volatility As a Function of Public News Announcements

Harvey and Huang (1991) examine volatility patterns in the market for foreign exchange and the role of public news announcements in determining these patterns. They test for the volatility implications of around-the-clock foreign exchange trading using transaction data on futures contracts from the Chicago Mercantile Exchange (CME) and the London International Financial Futures Exchange (LIFFE). The public information hypothesis tested implies that the effect of public economy-wide information on one currency is transmitted across national borders.

The data consist of foreign currency futures transactions on the International Monetary Market of CME from July 21, 1980 to May 10, 1988 for nearby futures contracts. Opening and closing prices are obtained by taking the first transaction price during the first 20 minutes of trading and the last transaction price during the last 20 minutes. The hourly returns are from the 8:30 a.m opening to the 12:30 p.m. close. The analysis of the LIFFE futures contracts are confined to the years 1986 and 1987 when transactions were more frequent. Using the variances of the hourly returns to compute the variance rate, they find evidence of higher U.S.-European and U.S.-Japanese exchange-rate volatilities during U.S. trading hours and higher European cross-rate volatilities during European trading hours. Moreover, they find that the disclosure of private information through trading and the macroeconomic news announcements explain most of these volatility patterns. Their analysis of inter- and intraday data also reveals that volatility increases at times that coincide with the release of U.S. macroeconomic news.

Estimating the Transmission of Volatility

Najang, Rahman and Yung (1992) carry out an empirical examination of the transmission of volatility among currency futures in order to expand the knowledge of price dynamics in currency futures markets. Daily currency futures prices of the five most active currency futures in the Chicago Mercantile Exchange are used. These are; the British pound (BP), the Canadian dollar (CD), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF). A continuous sequence of 2,631 observations of price data gathered over the ten-year period from January 1980 to December 1989 are examined.

Using the GARCH (1,1) model, the authors test whether the rate of information arrival is a function of the residual terms of other currency futures. The results show a strong GARCH effect in the returns-generating process of each currency futures during the periods 1985-1989 and 1980-1989. As for spillover effect, only the stronger currency futures such as the DM and the SF are involved in the transmission process. The authors also find that generally the ARCH effect and spillover effect do not exist simultaneously. These results hold for both the pre-price and post-price limit periods. Finally, the DM tends to exert more influence than the other four currencies in the futures markets.

Testing for Mixture Distribution Hypothesis

Laux and Ng (1993) investigate the mixture of distribution hypothesis which assumes that an increase in volatility is due to an increased rate of information arrival. This can be shown by a positive autocorrelation of either the information arrival rate or of time-consuming information processing. The authors propose a GARCH model with the decomposition of volatility into systematic and unique sources. In addition, the number of price changes per period is employed in the conditional variance equation as a measure of the rate of information arrival.

The data are intradaily data for five actively traded currency futures on the CME; namely, the British pound, the German mark, the Swiss franc, the Japanese yen and the Canadian dollar, during the period from December 14, 1982 through December 15, 1986. The time of the first transaction at each new price is reported to the nearest second. Intraday returns for the currencies underlying these futures are measured at approximately half-hour intervals as the first difference of the natural log of the final timed price in each half-hour of the trading day. The data set of half-hourly and overnight returns includes 13,169 observations per currency.

Using both univariate and multivariate GARCH models, the authors find that the estimates of parameters for the lagged volatility univariate GARCH model are uniformly very small and insignificant, while those for the number of price changes are positive and significant. On the other hand, the multivariate GARCH estimates of the coefficient on lagged systematic volatility and the past squared innovation are both highly significant. They conclude that the univariate GARCH models are misspecified due to their failure to account for the fact that systematic and unsystematic volatilities evolve at different rates and with different persistence.

Testing for Expected/Unexpected Volume- Price Relationship and the Analysis of Market Depth

Bessembinder and Seguin (1993) extend the previous research on the relations between trading activity and volatility in two ways. First, they investigate whether the effect of volume on volatility is homogeneous by separating volume into its expected and unexpected components and allowing each component to have a separable effect on observed price volatility. Second, they examine the contribution of market depth, which Kyle (1985) defines as the order flow required to move prices by one unit.

Data from the Columbia Business School Futures Centre consisting of daily settlement prices, trading volume and open interests for all outstanding maturities on eight futures markets, including two currency futures; *i.e.*, the German mark and the Japanese yen are used, beginning May 1982 and ending March 1990. The return series are the percentage change in the settlement price of the contract closest to expiration. To obtain an aggregate measure of activity in each market, volumes and open interests are summed across all outstanding maturities.

Initially, univariate Box-Jenkins methods are employed to partition volume and open interest into expected and unexpected components. Next, a conditional mean and a conditional volatility equation following Schwert and Seguin (1990) is employed. Bessembinder and Seguin find a positive relationship between futures price volatility and both the expected and unexpected components of volume. However, an unexpected shock will have, on average, seven times the effect on price volatility as changes in expected volume. When market depth which is proxied by open interest is analysed, the results show that volatility is negatively related to the expected level of open interest in all eight markets. Moreover, the authors find that a change in open interest during the day has explanatory power, even when the volume series are included in the specification.

Testing Price Variability-Volume Relationship Using State Space Model

McCarthy and Najand (1993) assess the relationship between trading volume and price change *per se* as well as between trading volume and the absolute price change. They use state space modelling because it is best able to test for the relationship among the above variables. Their data are daily near-month contract currency futures prices and volume from the Chicago Mercantile Exchange (CME), for the British pound (BP), the Swiss franc (SF), the German mark (DM) and the Japanese yen (JY) from January 1979 to May 1990. The natural logarithm of the price relative to all 2,884 observations is used to calculate the price change.

In order to overcome model identification, the authors suggest the use of the Akaike Information Criterion (AIC), developed in 1976.The AIC is able to determine which k-lag structure of the initial Yule-Walker equations gives the best AIC value, and will minimise the prediction error which is subject to the number of parameters used. Once the model is selected, it will be put in a state space form to which the Kalman filter will be applied for predicting and smoothing.

The authors' results exhibit no relationship between trading volume and price change *per se*. As for volume and absolute price change, they find that there is a positive relationship for all the currency futures except for the JY. It thus appears that absolute price change is positively dependent upon the trading volume of the previous day which is consistent with the sequential models of Copeland (1976). In addition, the authors find that the state space model is very effective in detecting the direction of causality in the data. This can be seen from the results which indicate that there is a significant relationship between the lagged absolute return (up to two lags) and volume. Moreover, there is evidence that causality between returns and volume is bidirectional for the BP, the SF and the DM.

Testing the Macroeconomic Announcements-Price Variability Relationship

Leng (1996) investigates the reaction of the market to anticipated U.S. monthly macroeconomic announcements during U.S. trading hours. He pays attention to the intraday patterns of four price variables: the transaction price movements, the transaction costs, the maximal possible gross profits per contract and the information flows.

His data comprise of time and sales data on the DM and the JY futures from the Chicago Mercantile Exchange (CME) and announcement dates from the Money Market Services (MMS) International for the period from November 1988 to December 1993. The announcements made at 7:30 Central Standard Time include the consumer price index (CPI), the durable goods order, employment, the gross national product (GNP), the housing starts (HS), the lending indicators (LI), the merchandise trade deficit, the producer price index (PPI) and retail sales. The announcements for 8:15 include industrial production and capacity utilization; those for 9:00 include business inventories, construction spending, factory orders, the NAPM survey, new home sales and personal income; and the 13:00 announcement is on the federal budget.

Using a partial price adjustment model, the author's first finding is that for seven major announcements (all 7:30 announcements excluding HS and LI) the impact on the price statistic of absolute value price changes (AAC) , the number of prices (NP), the price fluctuation range (PR) and first-order autocorrelation of log price changes (FAC) lasts for at least an hour. On the other hand, the impact of the other 11 minor announcements is rather short lived, indicating that higher information flows are more likely to be accompanied by price adjustments. Secondly, while minor announcements do not have much effect on the price path, they do have a more lasting impact on transaction costs for the DM., suggesting that information usually affects both the movement of transaction prices and the magnitude of successive price changes. Finally, the evidence shows that major announcements attract more information trading than do minor announcements.

Examining the Relationship Between Volume in Currency Futures Market and Price Variability in Foreign Exchange Market

The study of Chatrath, Ramchander and Song (1996) differs from previous studies, most of which investigate the relationship between volume and volatility in the same market. The authors examine the relationship between the above two variables in two separate markets and focus their research on the relationship between the level of trading in currency futures markets and price variability in underlying foreign exchange markets. The authors observe that growth in the popularity of currency futures occurs during an interval that has also witnessed increased volatility in the major currencies. These coinciding trends raise an important question as to a possible relationship between futures trading activity and the behaviour of exchange rates.

Their data are daily spot rates for the British pound, the German mark (DM), the Swiss franc (SF), the Canadian dollar (CD) and the Japanese yen (JY) along with the corresponding Chicago Mercantile Exchange's currency futures volume and open interest. Daily observations are taken from December 1975 to March 1993 for the BP, the DM and the SF; from December 1977 to March 1993 for the CD; and from June 1982 to March 1993 for the JY. Daily levels of trading volume and open interest from the nearby-contract until the trading day prior to the expiration month at which point the data switches to the next contract are obtained. The proxy for the level of trading activity is futures volume, standardized by the futures open interest.

The conditional variance from Bollerslev's (1986) GARCH (1,1) model is used as a proxy for volatility of the exchange rates series since this measure captures extreme volatility. The results of the Vector Autoregressive (VAR) system of the Granger causality test indicate a positive relationship between the level of futures trading activity and the volatility of exchange rates changes. The evidence also suggests that futures activity has a positive impact on the conditional volatility of exchange rate changes, with a weaker feedback from exchange rate volatility to futures activity.

3.5 Research Issues Arising

Having reviewed prior research concerning currency futures pricing in its broadest sense, we shall now focus on the particular research issues arising from past work which are to be emphasised in this study. Firstly, this thesis begins with the formal testing for nonlinear dependence in currency futures returns. Therefore, a summary of relevant methodological issues is given below in 3.5.1. In addition, as we find that currency futures returns exhibit time-varying variance, we consider whether this can be explained by employing the hypothesis that price changes are generated by a mixture of distributions in which the rate of information arrival is proxied by trading volume. A review of previous research testing the mixture of distributions hypothesis (MDH) is provided in 3.5.2. Finally, as the thesis attempts to contribute to the understanding of price dynamics by investigating how information is transmitted between currency futures contracts, the issue of spillovers is considered in 3.5.3.

3.5.1 Modelling Nonlinear Dependence

Studies by Brock, Hsieh and LeBaron (1991), and Blank (1992), for example, find deterministic nonlinear dynamics in the data generating process which they argue can provide a useful description of movements in asset prices. Moreover, these nonlinearities imply that price changes are predictable, though not predictable using linear specifications. On the basis of this argument and noting recent developments in the study of nonlinearity, the present study intends to provide an important contribution to the understanding of financial price data behaviour in that nonlinear procedures are used in testing the behaviour of currency futures returns. In examining nonlinearity, we employ several testing procedures which include the McLeod-Li Portmanteau test, the Engle ARCH test, and the Brock, Dechert and Scheinkman (BDS) test.

Regarding the modelling of heteroscedasticity, the present study is influenced by the methodology used by McCurdy and Morgan (1987) and McCurdy and Morgan (1988) who find evidence of conditional heteroscedasticity in the currency futures returns traded on the International Monetary Market. The above studies on the statistical properties of currency futures show that these data exhibit significant volatility clustering; *i.e.,* large changes tend to be followed by large changes and small changes tend to be followed by small changes of either sign. This clustering could represent the arrival of information in clusters to the market. As Engle, *et.al.* (1990) argue, if information arrives to the market in clusters, such a time series may exhibit ARCH (Autoregressive Conditional Heteroscedasticity) behaviour. In addition, the distribution of currency futures returns exhibits a leptokurtic distribution, as shown by Cavanaugh (1987).

Hsieh (1989b), and Baillie and Bollerslev (1989) show that the two statistical properties of conditional heteroscedasticity and leptokurtic distribution are appropriately modelled by the ARCH and GARCH. These procedures allow the variance of returns to change over time. Thus, in our present study on the daily rate of change for four currency futures, we evaluate the empirical performance of various types of conditional heteroscedasticity and find that the GARCH generalization of the ARCH process of Bollerslev (1986) fits the data satisfactorily.

In the next section, we will attempt to uncover the source of the GARCH effects as our earlier section demonstrates that the generating process exhibits high conditional heteroscedasticity. First, however, we must reexamine the relationship between the trading volume and price variability for four currency futures returns and so we will investigate the explanatory role of information proxied by trading volume on variance persistence and, in particular, we will evaluate the effectiveness of volume in explaining the structure of price change variance; *i.e.,* whether the GARCH effect remains significant when volume is included in the variance equation. Najang and Yung (1991), who have carried out similar studies on Treasure Bond futures market, argue that the time varying variance in Treasure Bond futures returns is a function of the information arrival to the market.

3.5.2 Modelling the Relationship Between Volatility and Trading Volume

This section will reexamine the general relation between trading volume and price variability using GARCH specifications, which can be achieved by exploring both the predicted contemporaneous volume-volatility relationship as well as the lagged volume volatility; in other words, by assessing whether the former holds over the latter or vice versa in explaining the volume-price variability relationship. If the former is true, the notion of informational efficiency in the currency futures markets holds. This means that traders are not able to make abnormal returns using news information proxied by trading volume. If trading volume is found to play an important information providing role in explaining price variability, the findings of this study will be relevant to technical analysis.

Two leading models provide theoretical explanations for the observed correlation between price variability and trading volume: the sequential arrival of information model (SEQ) developed and extended by Copeland (1976, 1977), Jenning and Barry (1983), Jennings, Starks and Fellingham (1981) and Smirlock and Stark (1985), and the mixture of distribution hypothesis (MDH) developed by Clark (1973), Epps and Epps (1976) and Harris (1987). The difference between these two competing hypotheses centres around the speed with which the new equilibrium is attained following the arrival of information. In the framework of SEQ, new information is not transmitted to all traders in a single day while the MDH assumes that new information is received simultaneously by all investors in a single trading day and that they act upon it after revising their expectations. A more detailed explanation of the two models follows.

The Sequential Information Model (SEQ)

The Sequential Information Model (SEQ) was first discussed by Copeland (1976) and subsequently developed by Smirlock and Starks (1988). The key assumption of the SEQ is that traders in a market receive new information in a sequential fashion. In other words, each individual trader trades in response to a signal representing one of a series of incomplete equilibria. Once all the traders have received the information signal, a final market equilibrium is established in which all traders observe the same information set. The main implication of the SEQ model is that asset price volatility is potentially forecastable given the knowledge of past information on trading volume.

The Mixture of Distributions Hypothesis (MDH)

The mixture-of-distribution hypothesis was first proposed by Clark (1973) an. subsequently used by many authors, including Lamoureux and Lastrapes (1990) and Foster (1995). The basic premise of the mixture-of-distributions hypothesis is that the amount of information that arrives into the market during a certain time interval changes randomly over time.

Following Lamoureux and Lastrapes (1990), let R_t denote the total equilibrium of logarithm asset price increment in day *t*, which implies

$$R_t = \sum_{i=1}^{I_t} \epsilon_{i,t} \tag{3.1}$$

where $\epsilon_{i,t}$ denotes the *i*th intraday equilibrium price increment that flows into the market during day *t*. The random variable I_t is the mixing or directing variable representing the stochastic rate of information arrival to the market. Equation 3.2 implies that daily price changes are generated by a subordinate stochastic process in which R_t is subordinate to $\epsilon_{i,t}$ and I_t is the directing process. Suppose $\epsilon_{i,t}$ is i.i.d. with mean zero and finite variance, σ^2. If I_t is sufficiently large, applying the Central Limit Theorem to equation 3.2 yields

$$R_t|I_t \sim N\ (0,\sigma^2 I_t) \tag{3.2}$$

where the logarithm of daily price changes is conditional on the number of information arrivals , I_t, to the market, and is normally distributed with mean zero and variance proportional to I_t. It is well known that volatility shocks persist over time, as shown in GARCH. If we assume that I_t is serially correlated, the resulting model can give rise to this persistence. For example, suppose that the logarithm of I_t follows an AR(p) process which can be expressed as follows:

$$\ln I_t = a_0 + \sum_{i=1}^{p} a_i \ln I_{t-i} + \nu_t \tag{3.3}$$

where a_0 is a constant, I_{t-i} is a lag polynomial of order p, and v_t is white noise. Innovations or shocks to the mixing variable persist according to the autoregressive structure of Equation 3.4. By defining a variance term

$$\sigma_t^2 = E(\sigma^2 | I_t) \tag{3.4}$$

and if the mixture model is valid, then $\sigma_t^2 = \sigma^2 | I_t$. Combining Equations 3.3 and 3.4 will yield:

$$\sigma_t^2 = \sigma^2 a_0 + \sum_{i=1}^{p} a_i \sigma_{t-i}^2 + \sigma^2 \nu_t \tag{3.5}$$

The amount of information I_t may also influence the trading volume. The reason, as noted by Watanebe (1996), is that the larger the amount of information that flows into the market, the more do the traders' expectation spread and hence the larger the trading volume. If so, he further noted, then the mixture of distribution hypothesis is also consistent with the well known phenomenon of a comovement between volatility and trading volume.

The implication of MDH is that price and volume have similar information values due to their common distribution. All traders respond to a new piece of information simultaneously. Such a case implies that there is no information in volume which can be used in forecasting futures returns and, likewise, there is no information in the futures returns which can be used in forecasting volume.

In the next section, we will focus our empirical investigations on the variance of returns conditional on knowledge of the mixing variable. Since I_t is not observable, we proxy trading volume as a measure of information flow.

Testing the Informational Role of Volume through GARCH Effects

In a famous study, Lamoureux and Lastrapes (1990) investigate actively traded stocks to examine whether the ARCH effects commonly found in daily stock returns are due to time dependence in the process generating information flows. In particular, they empirically test the variance of daily returns which are conditional upon the directing variable of information flow into the market using contemporaneous trading volume. Their results strongly support the mixture-of-distribution hypothesis. Similarly, Locke and Sayers (1993) apply this approach to minute-by-minute data on the S&P 500 Index Futures. In contrast to the results of Lamoureux and Lastrapes (1990), they find that significant variance persists after controlling for volume.

The present study has not only attempted to investigate the relationship between trading price variability in the currency futures markets *per se*, but also to examine the role of trading volume in determining price changes, taking an approach similar to that of Lamoureux and Lastrapes (1990). Specifically, we explore the source of GARCH effects in the context of the mixtures distribution hypothesis (MDH) in which the stochastic mixing variable, proxied by volume, is hypothesised to be the rate of information arrival.

Having examined the relationship between price variability and volume, and discussed the role of volume in the GARCH processes in the context of intra-currency futures, we must now consider both the intra and inter-currency futures returns relationship. In particular, we will analyse the mean and volatility spillover within the currency futures, and between and among the currency futures traded on the IMM.

3.5.3 Modelling Currency Futures Pricing as ARCH Effects and Spillover Effects.

Most previous studies have examined information transmission between and among markets. Among many others, Eun and Shim (1989), Hamao, Masulis and Ng (1990), and Koutmos and Booth (1996) examined information transmission between the U.S., the U.K. and the Japanese stock markets, and Theodossious and Lee (1993) investigated information transmission between the U.S., the U.K, Canada, German and the Japanese stock markets. But, few studies have investigated information transmission between assets in the same market.

In this study, we will take a different approach and examine information transmission within currency futures (the ARCH effects), and between and among currency futures trading in the same market (the spillover effect) using data from the International Monetary Market. A similar approach has been taken by Najang, Rahman and Yung (1992) and, we intend to validate the implication of their observation that the ARCH effects disappear when there are strong spillover effects and become significant when spillover effects are nonexistent or weak. However, our approach differ from theirs in two aspects. First, we consider both the conditional first and second moments between and among currency futures returns and allow for changing conditional variances as well as conditional mean returns. Secondly, this study explores the pairwise spillover effects and the ARCH effects between two currency futures, and the multi-currency spillover effects and the ARCH effects among four currency futures.

Following Hamao, *et.al.*,(1990), we first examine the pairwise mean and volatility spillover. Next, we investigate the multi-currency futures spillover by expanding the exogenous variables in the conditional mean and volatility to include the third and fourth squared residuals from other currency futures in order to test for the common economic effect in all four currency futures. The common economic effect postulates that the currencies are close substitutes and move in the same direction (Tse and Booth, 1996). If this argument holds, expanding the exogenous variable will diminish the mean and volatility spillover effect of the first and second currency futures and also of other currency futures.

3.6 Summary

The purpose of this chapter has been to provide a general view of the currency futures market and its relationship with microstructures and pricing. We began the chapter by looking at the currency futures market contracts and its basic structure. Then we briefly reviewed selected literature on issues related to the currency futures market. The issues related to the present study are: the unbiasedness hypothesis, the random walk hypothesis, non-stationarity and cointegration, nonlinear dependence and heteroscedasticity, and the relationship between information arrival and volatility.

Having reviewed most of the literature on currency futures, we then discussed the issues dealt with in this study in greater detail. First, we tested for nonlinear dependence employing several nonlinear testing procedures: the McLeod-Li Portmanteau test; the Engle ARCH test; and the Brock, Dechert and Scheinkman (BDS) test.

Secondly, we reexamined the general relation between trading volume and price variability using GARCH specifications because this model allows the variance of returns to change over time. We explored both the predicted contemporaneous volume-volatility relationship as well as the lagged volume volatility, which also amounts to a test of informational efficiency in the currency futures markets. The nonlinear specification of GARCH was used since the returns exhibit significant volatility and clustering, and leptokurtic distribution. The test for returns series using the BDS procedure rejected the null hypothesis of i.i.d.

Thirdly, we extended the investigation into this relationship by examining the role of trading volume as a proxy of information in determining price changes. We explored the source of GARCH effects in the context of the mixtures distribution hypothesis (MDH); *i.e.*, whether the ARCH effects remained when volume or uncorrelated volume was included in the conditional variance equation.

Finally, we looked at the information transmission within currency futures (the ARCH effect) and between currency futures trading in the same market (the spillover effect). In addition, we validated the implication of Najang, Rahman and Yung (1992) that ARCH effects disappear when there are strong spillover effects and that ARCH effects become significant when spillover effects are nonexistent or weak. We also explored the multi-currency futures spillover by expanding the exogenous variables in the conditional mean and volatility equations in order to test whether the common economic effect holds when the third and the fourth squared residuals from other currency futures are included in the equations.

Chapter Four

Data and Methodology

4.1 Introduction

Chapters 1 to 3 have provided an overview of the main empirical studies of the equity and the futures markets with a particular focus on the currency futures market as well as a discussion of the research methods used in those studies.

The main aim of this chapter is to discuss the sample data and methodology applied in this study and to elaborate the stages employed. Section 4.2 discusses our sample and source of data. Sections 4.3 and 4.4 test for stationarity and nonlinearity of currency futures data , respectively. Section 4.5 estimates the GARCH modelling of volatility. Section 4.6 describes the test of relationship between volume and price variability. Section 4.7 focuses on the GARCH modelling of mean and volatility spillover. Finally, Section 4.8 offers some conclusions.

4.2 The Data

Our data set was constructed from quotations on the International Monetary Market

(IMM) of the Chicago Mercantile Exchange (CME), United States, via Datastream International, London, quoted in dollars per unit of a foreign currency. To validate the collection process, the data has been cross-checked to FT quotations on a weekly basis. The data consist of the daily settlement foreign currency futures prices for the British pound (BP), the German mark (DM), the Japanese yen (JY) and the Swiss franc (SF) from January 1, 1986 to April 30, 1997 together with their corresponding daily trading volume. The settlement price is in principle equal to the day's closing price but the CME takes the average of the transaction prices in the last half hour of trading as the settlement price in order to avoid manipulation. It may be noted that, although automatic trading after the close of pits means that price changes can occur between official closing and opening transactions, we nevertheless use the official settlement prices in this thesis as these are the quotations which serve to mark outstanding futures positions to market. The delivery months for the currency futures contracts are September, December, March and June.

These four currency futures (BP, DM, JY and SF) are selected over other currency futures for two reasons: firstly, these are the only currency futures which started trading on the first day of the sample period of study and thus make our analysis of spillover effect possible. Secondly, the trading volumes of these currency futures are relatively large compared to other currency futures in the IMM. This is important since a large trading volume minimises the potential biases to the volatility estimator, as shown by Grammatikos and Saunder (1986).

4.2.1 Currency Futures Returns Data

The data for this study are daily futures prices. The settlement prices on day t $\{ P_t \}$ are transformed to daily returns using the formula $R_t = \ln (P_t / P_{t-1})*100$, which produces 2,954 observations on each currency futures contract examined. As mentioned above, the delivery months for currency futures contracts are September, December, March and June. Consequently, each price series is constructed from the settlement price on the nearby futures contract until the day prior to its last trading day; *i.e.*, the maturity date, when the data is rolled over to the next futures contract. It worth noting here that, although it may be suspected that taking futures returns up to the maturity of the nearby contract could create a seasonal volatility effect attributable to the close of contract, we found no such effects in a detailed exploratory analysis. Therefore, we have followed the approach adopted by other researchers in this area and have used nearby prices until the maturity date.

The use of more than 2,500 observations in each return series provides a sufficient degree of freedom for those tests that are only asymptotically valid (Yang and Brorsen, 1993). The return series are multiplied by 100 to avoid possible scaling problems in the estimation. Therefore, all subsequent analysis and reported statistics are also expressed in interpretable percentage terms.

The use of natural logarithmic price changes prevents nonstationarity in the mean and variance of price levels in the data series from affecting futures price variability and these can be interpreted as percentages of continuous time (Brock and Baek, 1991). As noted by Cavanaugh (1983), the choice between using the raw price or the natural logarithms of the futures prices is largely a matter of econometrics convenience. Since sample logarithms of the first difference in futures prices or price change or returns often appear to have a better-behaved distribution than the first difference of the raw series, it will be more convenient to base our hypothesis testing on the first difference of the natural logarithm of prices. Furthermore, the fact that futures prices are quoted in terms of U.S dollars will not significantly affect the analysis.

Our observations include data on non-trading days[4] since eliminating them would result in unequal numbers of observation for each series which in turn could make an analysis of spillover impossible. In other words, since the focus of the present study is on the temporal spillover effect between two or more futures currency returns where simultaneous price observations are necessary, we include the non-trading days in our analysis.

All the currency futures data used have an overlapping trading hours. They have the same opening times but different closing times according to Chicago Central Time. (For detailed discussions on opening and closing times, see Chapter 3, 3.2). For this reason, traders cannot easily take heed of any information revealed by any currency futures. As noted by Lin, Engle and Ito (1994), this is crucial for clean tests on how information is transmitted from one currency future to another. All the traders can do is to intuitively use the available information revealed in yesterday's returns of their own currency

4 Days when no trading occurs, the data day before are used or when two consecutives day of notrading occurs the data two day before are used.

futures as well as other currency futures; in other words, traders in one currency future can draw inferences about the returns and innovations by observing price movements in other currency futures.

To gauge whether the results are robust over the sample period, two almost equal-length subperiods are partitioned. These are from January 1, 1986 to September 18, 1991 (*i.e.*, the contract maturity date closest to the mid-point of the series) for Subperiod I and September 19, 1991 to April 30, 1997 for Subperiod II. The number of observations for the currency futures and trading volume for both Subperiods are reported in Table 4.1.

Table 4.1: Number of Observations in Subperiods: Return Series

Subperiod	BP	DM	JY	SF
I	1490	1490	1490	1490
II	1464	1464	1464	1464
Total	2954	2954	2954	2954

Notes: TheSubperiods are from January 1, 1986 to September 18, 1991 for Subperiod I and September 19, 1991 to April 30, 1997 for Subperiod II.

The price series and returns series are presented in Appendix 1: Figures A-1 and A-2 give the time series plots for the BP; Figures A-3 and A-4 for the DM; Figures A-5 and A-6 for the JY; and Figures A-7 and A-8 for the SF. It is evident from an inspection of these time series plots that the data sets are not characterised by extreme values.

4.2.2 Data on Volume

Earlier statistical models predicting currency futures returns based on past return series and volume data have been found to be successful. However, most of the volume series which have been incorporated in previous studies have used Granger's (1981) specification of linear model causality (see, for example, Grammatikos and Saunders, 1986) or the state space model (see, for example, McCarthy and Najang, 1993). For this reason, one of the objectives of the present study is to offer an interesting arena and to by investigate the dynamic relationships between currency futures returns and volume using a nonlinear model; *i.e.*, trading volumes will be included in the conditional variance equations.

The trading volumes data used in the study are a continuous series made up of the aggregate of all volumes for all existing futures contracts,[5] similar to the data procedure employed by Clark (1973), Cornell (1981) and Tauchen and Pitts (1983). In addition, following Fabozzi, Ma and Briley (1994), we eliminate a daily observation when there is no trading volume for the day. Previous researchers have argued that the inclusion of non-trading in the observation often creates positive serially correlated daily price changes. Similarly, Scholes and William (1977), and Dimson (1979) have noted that nonsynchronous and infrequent trading could induce autocorrelation in computed returns even when the true returns are not autocorrelated. This happens because daily price data are reported everyday including non-trading days where the previous day's price is used.

[5] Trading volumes are expressed in number of contract traded.

After the exclusion of non-trading days and weekends, the daily futures returns and volume series yield a total of 2,863 net days for the British pound, 2,865 for each of the German mark and the Swiss franc and 2,861 for the Japanese yen. Appendix 2 presents the figures for four variables: raw prices, return series, volume and uncorrelated volume. Figures A-9, A-10, A-11 and A-12 give data on the above variables for the BP; Figures A-13, A-14, A-15 and A-16 for the DM; Figures A-17, A-18, A-19 and A-20 for the JY; and Figures A-21, A-22, A-23 and A-24 for the SF. The percentages of non-trading days are quite small: 3.10 percent for the British pound, 3.15 percent for the Japanese yen and 3.01 percent for both the German mark and the Swiss franc. Table 4.2 contains the number of daily observations.

Table 4.2: The Number of Daily Observations

Currency Futures	Total Days	Non-Trading Days	% of Non-Trading days	Net Days
BP	2954	91	3.10	2863
DM	2954	89	3.01	2865
JY	2954	93	3.15	2861
SF	2954	89	3.01	2865

Notes: Total days are calculated from January 1, 1986 to April 31, 1997.

Using similar methodology for spillover analysis to that used in the studies described above, the present study partitions the sample period into two almost equal-length subperiods to test whether the results are robust over the sample period. Subperiod I is from January 1, 1986 to September 18, 1991 and Subperiod II is from September 19, 1991 to April 30, 1997. The number of observations for the currency futures for both subperiods are reported in Table 4.3.

Table 4.3: Number of Observations in Subperiods: Returns Synchronised with Trading Volume

Subperiod	BP	DM	JY	SF
I	1443	1444	1446	1443
II	1420	1421	1415	1422
Total	2863	2865	2861	2865

Notes: The subperiod are from January 1, 1986 to September 18, 1991 for Subperiod I and September 19, 1991 to April 30, 1997 for Subperiod II.

4.3 Tests of Stationarity.

In order to test for stationarity in raw, return and volume series, we apply both the Dickey-Fuller (DF) (1979) and the Augmented Dickey-Fuller (ADF) (1981) unit root test which is based on an ordinary least square (OLS) regression.

A series is said to be nonstationary in levels and stationary in growth rates if the price series is integrated of order one, as discussed by Johansen (1991). Both the Dickey-Fuller and the Augmented Dickey-Fuller unit root test are based on an ordinary least square (OLS) regression.

4.3.1 The Dickey-Fuller (DF)Test for Unit Roots

The Dickey-Fuller test for the presence of one unit root can be made by following one of the three specifications, depending on the choice of an intercept and/or a trend term.

$$\Delta Y_t = \alpha_1 Y_{t-1} + \varepsilon_t \qquad \textbf{(4.1)}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \varepsilon_t \qquad \textbf{(4.2)}$$

$$\Delta Y_t = \alpha_0 + \beta_1 + \alpha_1 Y_{t-1} + \varepsilon_t \qquad \textbf{(4.3)}$$

where the α_0 α_1 and β_1, are the regression coefficients and ε_t is the random error term which is normally distributed with a mean of zero and variance, σ^2. Equations 4.1 and 4.2 are acceptable for a unit root test of time series without drift and with drift, respectively. However, when drift and trend are suspected, Equation 4.3 is the appropriate specification. The null hypothesis $H_0{:}\alpha_1 = 0$ for each equation is tested against the alternative hypothesis $H_1{:}\alpha_1 < 0$. The *t*-statistics value can be checked against the critical values found in the tables given in Fuller (1976, p. 373).

4.3.2 The Augmented Dickey-Fuller (ADF) Test for Serially Independent Errors

Under the Dickey-Fuller test, the assumption of e_t being independent may not be realized because of the existence of serial correlation. Because of this probability, higher order lags may deemed necessary to remove the serial correlation. The DF test regression in Equations 4.1, 4.2 and 4.3 can be augmented accordingly, as follows:

$$\Delta Y_t = \alpha_1 Y_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta Y_{t-i} + \varepsilon_t \quad for\ i = 1,2,\ldots,p \qquad \textbf{(4.4)}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta Y_{t-i} + \varepsilon_t \quad for\ i = 1,2,\ldots.,p \qquad \textbf{(4.5)}$$

$$\Delta Y_t = \alpha_0 + \beta_t + \alpha_1 Y_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta Y_{t-i} + \varepsilon_t \qquad for\ i = 1,2,....,p \qquad \textbf{(4.6)}$$

where Y_t is the variable of interest, t is the time, p the lag order to be chosen from change of ΔY_t; *i.e.*, $(Y_t - Y_{t-1})$, so that the residuals series e_t is uncorrelated or white noise. Similar to the DF test, the null hypothesis $H_0{:}\alpha_1 = 1$ for each equation is once again tested. The specification of the lag structure of Equations 4.4, 4.5 and 4.6 enables the ADF test to account for a more dynamic specification of the regression as compared to the DF test. Once the order of p is determined, the next step is to find the t-statistic of α_1 and compare it with the appropriate critical value provided by Fuller (1976).

4.4 Tests for Nonlinearity

Many studies show that financial and economic data exhibit a nonlinear generating process. In this section, we will verify these studies by employing four nonlinear dependence testing procedures developed by McLeod and Li (1983), Engle (1982), Brock, Dechert and Scheinkman (1986) and Hsieh (1989a).

4.4.1 The McLeod-Li Portmanteau Test

The McLeod and Li Portmanteau test for nonlinear dependence is carried out by examining the Ljung-Box Q- statistic of the squared residuals from an Autoregressive Moving Average (ARMA) representation. Both the return series and the residuals are examined here through the use of the k autocorrelation coefficients ρ for return series

$\{x_t\}$, squares return series $\{ x_t^2 \}$ and absolute return series $\{|x_t|\}$, and residuals $\{R_t\}$, squares residuals $\{R_t^2\}$ and absolute residuals$\{|R_t|\}$. The McLeod and Li Portmanteau test is employed in order to detect the presence of serial correlation as suggested by Granger and Newbold (1986). That is, if

$$\rho_x(k) = [\rho_x(k)]^2 \; for \; all \; k \tag{4.7}$$

then the return series and residuals are linear. Alternatively, if they are not equal, then it implies nonlinearity. The first step in the testing procedure is to estimate the autocorrelation function of returns squared, x_t^2 and residuals squared, R_t^2. The null hypothesis of independence is then set for both x_t^2, $\{|x_t|\}$, and R_t^2,$\{|R_t|\}$.

The Ljung-Box Q-statistics to test the hypothesis are calculated as follows,

$$Q_{xx}(k) = n(n+2)\sum_{k=1}^{m}(n-k)^{-1}\rho_{xx}^2(k) \tag{4.8}$$

where n is the number of observations and $Q_{xx}(k)$ is the autocorrelation coefficient of the squared series. The critical value τ obtained from the chi-square distribution at a given significance level, $\chi^2(k)$ distributed with k degree of freedom, is compared to $Q_{xx}(k)$. The null hypothesis of independence will be rejected if $Q_{xx}(k) > \tau$, suggesting that the returns and residuals time series both exhibit possible conditional heteroscedasticity; *i.e.*, are nonlinearly dependent. One of the drawbacks of the McLeod Li nonlinearity test is that it is sensitive to nonnormality both for the returns series and the residuals.

4.4.2 The Engle ARCH Test

Engle's Lagrange multiplier test leads to the rejection of the null hypothesis of no Autoregressive Conditional Heteroscedasticity (ARCH) based on the estimated TR^2 statistics (having a chi square distribution). The ARCH test determines if large changes in asset returns are followed by a large variance of return and if small changes in returns are followed by small changes in the variance of returns. It is an alternative to the McLeod- Li Portmanteau test of nonlinear dependence discussed earlier

The presence of an ARCH effect indicates that some types of nonlinear dependency exist in the return series. Hsieh (1989a) points out that McLeod and Li Q-statistic is related to Engle's (1982) test for heteroscedasticity since the former uses the autocorrelation coefficients of squared data while the latter employed the partial autocorrelation coefficients. Furthermore, the generalized ARCH model of Bollerslev (1986) is also capable of capturing and analysing the data generating process from the nonlinearity in the variance. The GARCH(1,1) process is given by

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t \qquad \textbf{(4.9)}$$

$$\varepsilon_t | \psi_{t-1} \sim N(0,h_t) \qquad \textbf{(4.10)}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \qquad \textbf{(4.11)}$$

$$\alpha_0>0,\ \alpha_1\geq 0,\ \beta_1\geq 0.$$

where y_t is the log return , ψ_{t-1} is the information set at time t-1, and ε_t is the stochastic error conditional on ψ_{t-1}, which is assumed to be normally distributed with zero mean and conditional (time varying) variance, h_t. As such, GARCH models the conditional variance of the error term as a linear function of the lagged squared residuals and the lagged conditional variance itself. A notable difference between the GARCH (1,1) model and ARCH (1) is the inclusion of the lagged conditional variance term (σ^2_{t-1}) as an explanatory variable in the conditional variance equation. The advantage of a GARCH model is that it captures the tendency in financial data for volatility clustering. Engle and Bollerslev (1986) also introduced the integrated or I-GARCH as an extension of the model. For a process to be considered as I-GARCH, the parameters α_1 and β_1 in Equation 4.11 must together sum to unity which implies the presence of a unit root in the autoregressive polynomial. This non-stationarity in variables also implies that current information remains important for forecasts of the conditional variances for all horizons.

4.4.3 The BDS Test

The procedure known as BDS, proposed by Brock, Dechert and Scheinkman (1987), tests the null hypothesis of independence and identical distribution (i.i.d.) for a univariate time series x_t against an unspecified alternative by utilizing the concept of *spatial correlation.* The test has power in describing not only a simple nonlinear deterministic system but also nonlinear stochastic processes. Rejection of the null hypothesis means that the series is nonlinear.

The time series, x_t, which is embedded in m-space is employed to form the following vectors such that

$$x_t^m = [x_t, .. x_{t+1}, ..., x_{t+m-1}] \quad t = 1,2,....,T - m + 1 \tag{4.12}$$

This concept of embedding can be illustrated for the time series x_t where $t = 1, 2, 3....5$ and $m = 5$ as follows,

$$x_1^5 = x_1, x_2, x_3, x_4, x_5$$

$$x_2^5 = x_2, x_3, x_4, x_5, x_6$$

$$x_3^5 = x_3, x_4, x_5, x_6, x_7$$

$$x_4^5 = x_4, x_5, x_6, x_7, x_8$$

$$x_5^5 = x_5, x_6, x_7, x_8, x_9$$

In this case, the embedding operation creates five-dimension vectors of $x_1^5, x_2^5, x_3^5, x_4^5$ and x_5^5. Since the vectors require equal length, m-1 data points are lost in the above illustration.

The correlation integral, a measure that examines the distances between points, is able to detect the dependency of x_t and in our case a five-dimensional vector. For each embedding dimension, m, and choice of epsilon, ε, the correlation integral is defined by,

$$C(\varepsilon,m,T) = \frac{2}{T_m(T_m-1)}\sum_{t\neq s} I[x_t^{\,m},x_s^{\,m};\varepsilon] \qquad \textbf{(4.13)}$$

where $T_m(T-m+1)$ and, t and s both range from 1 to $T-m+1$ in the summation and are restricted such that $t\neq s$ and the indicator function of $I[x_t^{\,m},x_s^{\,m};\varepsilon]$ is defined as,

$$I[x_t^{\,m},x_s^{\,m};\varepsilon] = 1 \;\; if \;\; \|x_t^{\,m} - x_s^{\,m}\|<\varepsilon] \qquad \textbf{(4.14)}$$

$$= 0, \;\; \text{otherwise}$$

where the metric or maximum-norm is given by $\|x\| = \max_{0\leq i \leq -1}|x_i$. Thus, the correlation integral is a measure of the total number of pairs ($x_t^{\,m}$, $x_s^{\,m}$) that are within ε distance of each other and is a measure of the concentration of m consecutive observations, $x_t^{\,m}$.

Brock and Baek (1991) noted that under the null hypothesis that x_t is i.i.d., $C(\varepsilon, m,T)$ $\rightarrow$ $C(\varepsilon, 1,T)^m$ with probability one, where $T\rightarrow\infty$.

The test statistic for dependence is given by:

$$W(\varepsilon,m,T) = \frac{\sqrt{(T-m+1)}[C(\varepsilon,m,T)-C(\varepsilon,1,T)^m]}{\sigma(\varepsilon,m,T)} \qquad \textbf{(4.15)}$$

Under the null hypothesis of i.i.d., the distribution of the W statistic converges to a standard normal random variable with unit variance; *i.e.*, $N(0,1)$. Rejecting the null hypothesis provides evidence of serial dependence in the data. The alternate hypothesis can imply either linear or nonlinear dependence in the returns series. Fujihara *et.al,* (1997), argues that a rejection of the null hypothesis could result from some type of dependence in the returns: namely, a linear stochastic process, nonstationarity or a nonlinear deterministic system. Linear dependence can be ruled out since the study follows the procedure of Scheinkman and LeBaron (1989) and filters the returns series using a linear autoregression AR(p) process, which can be written as:

$$R_t = \beta_0 + \sum_{i=1}^{p} \beta_i R_{t-i} + v_t$$

where the β_i is the regression coefficients and v_t is the random error term, which is normally distributed with a zero mean and is not serially correlated. The residuals from this fit are then tested for i.i.d. using the BDS statistic. In addition, nonstationarity associated with structural change is not likely to be an important issue since the present study employs daily data and as such the impact is minimal. As a result, a rejection of the null hypothesis of i.i.d. by the BDS test applied to the filtered series appears to be associated with evidence of nonlinearity.

It can be seen from the statistic there are two unknown functions in embedding dimension m and the ε. As there is a relationship between these two functions, their choice becomes an important issue. Hsieh (1989a) explains the interaction with ε. Given m, ε should not be too small because $C(\varepsilon,,T)$ will capture few points, also ε should not be too big because $C(\varepsilon,T)$ will capture too many points. In practice, ε is set in terms of standard deviations of the data. Following Brock and Baek (1991), if the critical values from the standard normal are to be used, the number of observations should be greater than 500; the dimension m should be $m \leq 5$; and ε should be between one half and twice the standard deviation; *i.e.*, $0.5\sigma \leq \varepsilon \leq 2\sigma$ of the data. On the basis of this evidence and given that the present study employs $T = 2{,}954$, m is set from 2 to 10 and ε is set from 0.5 to 1.5.

4.4.4 The Third Moment Test

The BDS test is able to detect nonlinearity in a series. However, it cannot determine the source of nonlinearity; *i.e*, whether the nonlinearity is in the mean of the stochastic process or the variance, or possibly in both.

Hsieh's (1989) third moment test, however, differs from other nonlinear tests in that it is able to discriminate between two types of nonlinearity; namely, additive and multiplicative, after nonlinearity has been found in the series using the BDS test or another nonlinear test. Both additive and multiplicative nonlinearity imply that the squared residual e_t is correlated with its own lags [see, for example, Hsieh (1991) and Najang *et al.* (1992)]. However, additive dependence implies that the conditional expectation of the residuals given past lags of the variable, x_t and the residuals, e_t, is nonzero,

$$E\,[e_t | e_{t-1},\ldots,e_{t-k},\ x_{t-1},\ldots,x_{t-k}] \neq 0 \qquad \textbf{(4.16)}$$

while multiplicative dependence implies that the conditional expectation is zero

$$E[e_t | e_{t-1},\ldots,e_{t-k},\ x_{t-1},\ldots,x_{t-k}] = 0 \qquad \textbf{(4.17)}$$

Under additive dependence e_t is correlated with at least one of the terms e_{t-1} to e_{t-k} so that $E\,[e_t\ e_{t-1}\ e_{t-k}] \neq 0$ while under multiplicative dependence e_t is not correlated with these terms so that $E\,[e_t\ e_{t-1}\ e_{t-k}] = 0$. The Three Moments Test (TMT) is able to distinguish between mean and variance nonlinear dependence from where e_t is the residual obtained from the linear filtered data, AR(1). The TMT can suggest not only the source of the nonlinearity but also provides a general indication of the data generating process. For example, if multiplicative nonlinearity is detected, the ARCH model introduced by Engle (1982) or the generalized ARCH (GARCH) model developed by Bollerslev (1986) are able to fit the data satisfactorily.

Additive dependence occurs when the source of the nonlinearity is in the mean of the process while multiplicative dependence occurs when nonlinearity enters through the variance of the process.

Additive dependence is represented by:

$$e_t = v_t + f\,[e_{t-1}, \ldots\ldots, e_{t-k}, x_{t-1}, \ldots\ldots, x_{t-k}]; \qquad \textbf{(4.18)}$$

and multiplicative dependence by:

$$e_t = v_t\, f\,[e_{t-1}, \ldots\ldots, e_{t-k}, x_{t-1}, \ldots\ldots, x_{t-k}]; \qquad \textbf{(4.19)}$$

where v_t is an i.i.d random variable with zero mean and independent of previous e_t and x_t and the function $f(\ )$ is a nonlinear function of $e_{t-1}, \ldots\ldots, e_{t-k}$, and $x_{t-1}, \ldots, x_{t-k}$ for some finite k. Bilinear and threshold models are examples of additive dependence and the autoregressive conditional heteroscedasticity (ARCH) model developed by Engle (1982) is an example of multiplicative dependence. In order to execute the third moment test, the null hypothesis of multiplicative nonlinearity is constructed to imply that the third-order correlation coefficient, $\rho_{eee}\ (i,j) = 0$ for all $i, j > 0$. This is tested against the alternative hypothesis that $\rho_{eee}\ (i,j) \neq 0$ for some $i, j > 0$, for the residuals from a linear filtered specification of AR(1) model. By fitting a linear model to the data, any nonlinearity which might exist in the return series is removed into the residuals. After the AR(1) model has been fitted, the third-order moment of the residuals e_t can be estimated as follows:

$$\rho_{eee}(i,j) = \frac{(1/T)\sum e_{t-i}^2 e_{t-j}^2}{\left[(1/T)\sum e_t^2\right]^{1.5}} \qquad (4.20)$$

The null hypothesis that a residual possess multiplicative (or variance) nonlinearity is then tested using the following statistic:

$$v(i,j) = \frac{T^{1/2}\rho_{eee}(i,j)}{w(i,j)} \qquad (4.21)$$

where $w(i,j)$ can be consistently estimated by

$$w(i,j) = \frac{(1/T)\sum e_t^2 e_{t-i}^2\, e_{t-j}^2}{\left[(1/T)\sum e_t^2\right]^3} \qquad (4.22)$$

The null hypothesis is tested using the standard normal distribution, $N(0,1)$. It will be rejected if the value of $V(i,j)$ is greater than the selected critical value and accepted if it is smaller than the critical value.

4.5 Estimating GARCH Models of Volatility

In modelling the joint conditional mean and variance of the returns, the widely used Generalized autoregressive conditional heteroscedasticity (GARCH) family of statistical processes, is applied.

4.5.1 Autoregressive Conditional Heteroscedasticity (ARCH)

Engle (1982) introduced the first ARCH model to capture the effects of changing volatility in a series. He also pointed out that even though the ordinary least squares procedures produce unbiased estimators of the model, the ARCH structure using the maximum likelihood is substantially more efficient. Consider the following ARCH (1,1) model:

$$R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t \tag{4.23}$$

$$\varepsilon_t | \psi_{t-1} \sim N\ (0, h_t) \tag{4.24}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{4.25}$$

where R_t is a random variables, R_{t-1} is an exogenous variable with an autoregression of order 1 in the mean of price changes, and ε_t is the residual term which is conditionally normally distributed and serially uncorrelated. The α's are the parameters to be estimated. The ARCH (1,1) model in Equations 4.23 - 4.25 allows the conditional variance of the random disturbance to depend on the behaviour of past squared errors. Similarly, in an ARCH(2) model the conditional variance is a linear function of lagged squared errors from the two most recent prior periods.

4.5.2 Lagged Conditional Variances (GARCH)

The above model was later extended by Bollerslev (1986) to a generalized (ARCH) specification to account for more flexible lag structure. For instance, GARCH models include lagged conditional variance together with lagged squared residuals in the conditional variance equation to achieve a more parsimonious representation of higher order ARCH models. As further noted by Bollerslev, the GARCH process is very much like that of the time series process to a general Autoregressive Moving Average (ARMA) model. Although standard time series could be used to identify the orders of p and q, as noted by Bollerslev, the GARCH (1,1) model has been proven to be an adequate representation for most financial time series. Numerous recent studies on United States (US) data of financial time series suggest that one lagged conditional variance term appears to model conditional variance adequately. (see, for example, Hsieh, 1988; Akgiray, 1989; Baillie and Bollerslev, 1989; and McCurdy and Morgan, 1987).

The conditional variance in the GARCH (1,1) model is defined as follows:

$$R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t \quad \textbf{(4.26)}$$

$$\varepsilon_t | \psi_{t-1} \sim N\,(0, h_t) \quad \textbf{(4.27)}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1.} \quad \mathbf{(4.28)}$$

$$\alpha_0 > 0 \quad \alpha_1 \geq 0 \quad \beta_1 \geq 0$$

where Equation 4.28 represents the extended ARCH models which allow the conditional variance, h_t, to be dependent on the last period's squared errors and conditional variance, h_{t-1}. If the lag of coefficient polynomials $\alpha_1 \varepsilon_{t-1}^2$ and $\beta_1 h_{t-1}$ are positive, then surprise to volatility persists over time. Furthermore, the degree of persistence is determined by the magnitude of these coefficients.

4.6 Test for a Relationship Between Volume and Price Variability

Blume *et.al.*(1994) showed that observing volume and price together provide more information than price alone. He further noted that a trader watching prices only cannot learn as much as a trader watching both prices and volume and thus faces an unnecessary penalty if he ignores the trading volume statistic.[6] For this reason, the present study emphasises empirical tests of the variance of returns which are conditional on the knowledge of the mixing variable. We use trading volume as the mixing variable in order to investigate its informational role in explaining futures price movements. In particular, trading volume may be informative about the process of futures markets return. Lamoureux; *et.al.*, (1990) point out that trading volume as the mixing variable

[6]This complementary role of price and volume is a main characteristic of technical analysis methods.

is consistent with the sequential information models of Copeland (1976) and the mixture of distribution hypothesis (MDH) of Epps and Epps (1976) which states that when no information is available, trading is slow and the price process evolves slowly; and when new information violates old expectations, trading is brisk with the price process evolving much faster.

The present study presents an analysis of trading volume as a mixing variable using both contemporaneous as well as lead and lagged relations.

4.6.1 Contemporaneous Volume

In the first stage of our empirical strategy, we estimate the conditional variance given by h_t by restricting the coefficient δ_1 in Equation 4.31 to zero, using the approximate maximum likelihood algorithm of Berndt, Hall, Hall and Hausman (1974) of the following model,

$$R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t \tag{4.29}$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{4.30}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1.} + \delta_1 V_t \tag{4.31}$$

where V_t is the volume of trade at time t, ψ_{t-1} is the information set at time t - 1 and ε_t is the stochastic error conditional on ψ_{t-1}, and is assumed to be normally distributed with zero mean and conditional (time varying) variance, h_t. The α_0, α_1, β_1 and δ_1 are parameters to be estimated. For this reason, GARCH models the conditional variance of the error term as a linear function of the lagged squared residuals and the lagged residual conditional variance. The advantage of a GARCH model is that it captures the tendency in financial data for volatility clustering.

To investigate the notion of volume as a mixing variable in the conditional variance, following Lamoureux and Lastrapes (1990) and Laux and Ng (1993), we fit the unrestricted model of Equation 4.31; *i.e.*, where $\delta_1 \neq 0$. If a cluster of information, as proxied by contemporaneous trading volume, affects price variability, then we would expect a positive and significant δ_1.

4.6.2 Uncorrelated Contemporaneous Volume

To avoid the possible problem of high serial correlation in the volume series, V_t, which can lead to a high correlation between the explanatory variables used in the unrestricted model of Equation 4.31, we consider the effect of news on the conditional variance for each of the currency futures, by extracting the unexplained component from the autoregressive models (AR) of trading volume proposed by Bessembinder and Seguin (1992) Bessembinder (1994), and Lamoureux and Lastrapes (1990). As empirically noted by Bessembinder (1994), trading volumes are highly autocorrelated, implying that volumes can be forecast to a substantial degree. As such, he employs an ARIMA (10,1,0) specification to decompose futures trading volume into forecastable and unexpected components. He shows that coefficient estimates on the forecastable (expected) and unexpected components of futures trading volume, used as a proxy for trading volume in the interbank foreign exchange market, support the conclusion that the forecastable (expected) and unexpected trading volumes have heterogeneous effects on the bid-ask spread. Similarly, Bessembinder and Seguin (1992) provide evidence consistent with the reasoning that expected and unexpected trading volumes convey different information to market participants.

This study applies the univariate autoregressive models to find the order of lags until the Ljung-Box Q-statistics- LB(.) show no autocorrelation in the residuals. The uncorrelated residuals are then squared and included in the conditional variance of returns in Equation 4.33.

Let $V_{j,t}$ be the volume in currency futures market j during day t and is specified as a linear function from past lagged one day volume of all four currency futures markets, j, where $j = 1, 2, 3, 4$ (1 = BP, 2 = DM, 3 = JY and 4 = SF). The autoregressive pth AR(p) model for volume series can be written as follows[7]:

$$V_{j,t} = \alpha_{0,j} + \sum_{i=1}^{p} \alpha_{i,j} V_{j,\, t-i} + \varepsilon_{j,t} \quad for \quad j = 1,2,3,4. \qquad \textbf{(4.32)}$$

where $\alpha_{0,\,j}$ is the intercept of currency futures j and $\varepsilon_{j,\,t}$ is the error term of currency futures j during time t which is an independent, stationary process and p is the number of lags of the dependent variable.

7 Note: p is conditioned on j; i.e., the number of lags is naturally dependent on the currency futures to be analysed.

In addition, because the GARCH (1,1) could not capture the unexpected volume satisfactorily from the evidence of higher order dependence as reported by the Ljung-Box Q-statistics on the squared standardized residuals, denoted by LB^2, we argue that the GARCH (p,q) family may be more appropriate in modelling the series. As noted by Bollerslev (1987), the above characteristic is a feature of GARCH (p,q) models. In our particular case, there is a need for more GARCH parameters than the mere GARCH (1,1) can provide. Specifically, the variance equation will now take the following form:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_1 h_{t-j} + \delta_1 V_t^* \quad \textbf{(4.33)}$$

where, V_t^* is the uncorrelated innovation of trading volume or volume surprise or unexpected news obtained from Equation 4.32. The orders of p and q can be identified by applying the traditional Box and Jenkins (1970) time-series techniques to the autocorrelations for the squared process of residuals, ε_t.

The Informational Role of Volume and the GARCH Effects

This study also examines the extent to which contemporaneous correlated or uncorrelated trading volume explain the GARCH effects in currency futures. Consequently, if trading volume is serially correlated, then α_1 should be small and statistically insignificant when the coefficient of volume, δ_1, is greater than zero. This phenomenon as explained by Lamoureux and Lastrapes (1990) is due to the fact that volume can explain price volatility. Furthermore, the persistence of variance as measured by the sum of $\alpha_1 + \beta_1$ should become negligible if accounting for an uneven flow of information, which explains the presence of GARCH effects in the series.

4.6.3 Uncorrelated Lagged Volume

Najang and Yung (1991), Lamoureux and Lastrapes (1990) and Harvey (1989) discuss the possible existence of a simultaneity problem in the specification of simultaneous volume. Harvey (1989) points out that trading volume may be *endogenous* to the larger part of the simultaneous equation. Thus, to treat volume as an exogenous variable and to estimate it in the conditional variance based on a likelihood function is inappropriate. Furthermore, Najang and Yung (1991) noted that if volume is correlated with disturbances in the stochastic part of the model, the estimating procedures are likely to yield inconsistent estimators of the parameters in Equation 4.33. Najang and Yung (1991), and Lamoureux and Lastrapes (1990) have attempted to overcome this problem by using lagged volume in the GARCH specification. They report different results. While this variable has little explanatory power in the results of Lamoureux and Lastrapes (1990), the findings of Najang and Yung (1991) show the opposite. In fact, Najang and Yung (1991) find a positive and significant relationship between lagged volume and price variability in four cases as compared to only one case where contemporaneous volume is used. Implicitly Najang and Yung (1991) conclude that the volume-volatility is not contemporaneous but sequential. Moreover, they find that the ARCH effect remains when lagged volume is included in the conditional variance equation.

In the present study, we use uncorrelated innovation, V_t^*, the effect of the problem of correlated volume might be minimal or nonexistent. However, to overcome the problem of simultaneity, following Lamoureux and Lastrapes (1990), and Najang and Yung (1991), an uncorrelated lagged single day volume, t-1, is used as an instrument for the mixing variable and Equation 4.33 is reestimated as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_1 h_{t-j} + \delta_1 V_{t-1}^* \qquad \textbf{(4.34)}$$

where V_{t-1}^* is the uncorrelated volume for day t-1.

There are several implications of the sequential information model (SEQ) hypothesis proxy by V_{t-1}^*. One, as argued by Blaum, *et.al.*(1994), is that if the coefficient δ_1 is significant, then it may suggest some degree of strong form pricing inefficiency in currency futures markets. Second, it indicates that knowledge of past uncorrelated trading volume proxying for information could be used to explain current price variability. In other words, knowledge of the behaviour of volume can marginally improve conditional price change forecasts.

Estimating the Model

The GARCH model is estimated by employing the nonlinear optimization technique of Berndt, *et.al.*, (1974) to compute maximum likelihood estimates. As noted by Chou (1988), maximum-likelihood methods are more efficient in estimation procedures than are ordinary least squares (OLS) procedures. This procedure also takes into account the heteroscedasticity of the data, whereas the OLS estimations assume that the variance remains constant throughout.

Given the return series and initial values of ε_1 and h_1, for 1 = 0,....,r and with r = max (p,q), the log-likelihood function we have maximized for a GARCH (p,q) model with normal distributed conditional errors is the following:

$$L(\phi|p,q) = -\frac{1}{2}T\ \ln(2\pi) + \sum_{t=1}^{T}(\frac{1}{\sqrt{h_t}})\exp(\frac{-\varepsilon_t^2}{2h_t})$$

where T is the number of observations; h_t, the conditional variance, is defined by Equation 4.33 for the GARCH model and ε_t^2 are the residuals obtained from the appropriate model for the currency futures under consideration.

4.6.4 Identification of the Model and the Ljung-Box Statistic

The identification procedures of the estimated models can be tested by employing a variety of diagnostic test statistics. The Ljung-Box Q-statistic

$$Q(m) = n\sum_{j=1}^{m}(n+2)(n-j)^{-1}r_j^2$$

with r_j as the jth sample standardized residual autocorrelation, is a test for the disturbances following an autoregressive or moving average process of order m and is asymptotically equivalent to a Lagrange Multiplier test. Under the null hypothesis of no serial correlation, $Q(m)$ will have an asymptotic chi-squared distribution with m degrees of freedom where n is the number of observations.

The Ljung-Box statistic is also applied to the squared standardized residuals and is denoted by $Q^2(m)$ to test for ARCH (m) disturbances. Under the null hypothesis of no ARCH effects, $Q^2(m)$ will also have an asymptotic chi-squared distribution with m degree of freedom.

Finally, we report the sample of skewness (SK) and kurtosis (KU) statistics. As noted by Hsieh (1989a), in testing the goodness of fit, the skewness and kurtosis of the standardized residuals ought to be smaller (in absolute size) than that of the raw data. Under the null hypothesis of normality $SK \sim N(0,6/n)$ and $KU \sim N(0,24/n)$. These two coefficients are helpful in detecting non-normality. The skewness coefficient measures the asymmetry of the observation, whereas the kurtosis coefficient explains the tendency of the distribution to be flat or too peaked. The skewness coefficient for a normal distribution is zero; positive skewness exists if a distribution is skewed to the right; negative skewness exists if a distribution is skewed to the left.

4.7 Modelling Mean and Volatility Spillover

In this section, we continue our investigation of information flow by analysing whether a given currency futures may have an impact on the return as well as volatility of other currency futures. While the previous section used trading volume within the currency futures itself as a proxy for information arrival in the conditional variance specification, this study hypothesizes that the rate of information arrival is a function of the shocks of other currency futures.

Specifically, our study introduces the univariate GARCH model to account for the spillover in mean and variance for the currency futures returns. In particular, we test for spillovers in the conditional mean and conditional volatility across currency future returns using correlation analysis and the inclusion of lagged returns and estimated squared residuals from the other currency futures returns in the GARCH (1,1) models. As shown in earlier studies, the ARCH family of statistical models has captured the effect of changing volatility in many financial time series. Engle (1982) developed the ARCH model in which the conditional variance is a linear function of past squared residuals as well as possible exogenous variables X_t. For example, ARCH (1) has the form

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t \qquad where \qquad \varepsilon_t | \psi_{t-1} \sim N(0,h_t)$$

and

$$h_t = a + b\varepsilon_{t-1}^2 + dX_t \qquad where \qquad a>0, \quad b,d \geq 0$$

Bollerslev (1986) generalized this model by allowing the past conditional variance to be also included in the conditional variance equation as well as past squared residuals. The GARCH (1,1) model with possible exogenous variables X_t included defines the conditional variance of returns at time t (R_t) to be of the form

$$R_t = \alpha R_{t-1} + \varepsilon_t \qquad where \qquad \varepsilon_t | \psi_{t-1} \sim N(0,h_t)$$

$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} + dX_t$$

where the variable X_t at time t is the squared residuals from the other currency futures returns and d is its estimated coefficient. The advantage of this model is that the parameters of interest can be estimated simultaneously. In particular, the coefficient of the conditional mean, α, is obtained as well as the persistence parameter $b+c$ by a maximum-likelihood technique. For the volatility process to be stable, the coefficients of the lagged residuals squared and the lagged conditional variances must add up to less than one.

In the following subsections, the procedures for modelling the own mean spillovers and the mean spillover effects in the conditional mean as well as the volatility spillovers and the ARCH effects in the conditional variance will be examined in detail.

The first thing to note is that only one exogenous variable at a time is included in each of the conditional mean and variance equations; *i.e.*,pairwise spillover. Six pairs of currency futures are analysed: the British pound and the German mark; the British pound and the Japanese yen; the British pound and the Swiss franc; the German mark and the Japanese yen; the German mark and the Swiss franc; the Japanese yen and the Swiss franc. Second, we expand the exogenous variables by including all currency futures returns and residuals in the conditional mean and conditional variance equation; *i.e.*, multi-currency futures spillover. This procedure is employed in order to test whether the coefficient d is statistically significant or otherwise with and without the expanded exogenous variables. As noted by Hamoa *et.al* (1990), if the spillover effect reflects the influence of a common economic effect on the mean and volatility of all four currency futures returns, introducing the second currency futures returns is unlikely to add much incremental explanatory power to α in the conditional mean, nor to X_t in the conditional variance equations.

4.7.1 Pairwise Spillover

To examine the mean spillover across two currency futures; *i.e.*, pairwise spillover, the lagged returns for currency futures j are introduced in the mean equation of currency futures i during day t, as in Equation 4.35. In other words, the conditional mean $\mu_{i,t}$ is a linear function of the past one day returns from its own currency futures i as well as from currency futures j and of the residuals from currency futures i at time t. That is,

$$\mu_{i\,t} = \beta_0 + \beta_i\, R_{i,\,t-1} + \beta_j\, R_{j,\,t-1} + \varepsilon_{i,\,t} \qquad where \quad i \neq j \tag{4.35}$$

where i, j from 1 to 4, (1 = BP, 2 = DM, 3 = JY and 4 = SF), β_0 is the intercept and ε is the error term which is distributed as conditionally normal with time varying variance. The analysis is then repeated, this time introducing the corresponding lagged returns for currency futures i in the mean specification of currency futures j during day t.

A statistically significant value for β_i suggests that the conditional mean of currency futures returns i is influenced by its own past values; *i.e.*, own mean spillovers. On the other hand, a statistically significant β_j, value for $j \neq i$ indicates that past returns in currency futures j affect the conditional mean in currency futures returns i, which can be interpreted as pairwise mean spillovers from currency futures j to currency futures i.

As for the volatility spillover, the conditional variance of returns in currency futures i is specified as a linear function of its own past conditional variance and lagged residuals squared (past innovations) from currency futures j and can be written as,

$$h_{i,t} = \alpha_0 + \alpha_i \varepsilon^2_{i,t-1} + \alpha_j \varepsilon^2_{j,t-1} + \gamma_i h_{i,t-1} \qquad where \quad i \neq j \qquad \textbf{(4.36)}$$

where i, j are values from 1 to 4, (1 = BP, 2 = DM, 3 = JY and 4 = SF) and α_0 is the intercept. γ_i measures the effect of past volatility on the present volatility in currency futures i. The analysis is then repeated, introducing the corresponding lagged squared errors (past innovations) for currency futures j as exogenous variables in the conditional variance equation in the currency futures i during day t.

Similar to the explanation for the value of β_i in the mean equation, if α_i is statistically significant in the variance equation, past volatility surprise in currency futures i is said to have an influence on the present volatility in market i; namely, to have its own volatility spillover or ARCH effects. Statistically significant α_j values for $j \neq i$ suggest that past volatility surprise in currency futures j affects present volatility in currency futures i, which can be interpreted as pairwise volatility from currency futures j to currency futures i. As noted by Puttonen (1995), comparing the relative magnitudes of α_i and α_j provides evidence concerning whether aggregate (pairwise) shocks have differential effects across currency futures.

4.7.2 Multi-Currency Spillover

In multi-currency futures spillover analysis, the exogenous variables in the conditional mean and variance equation are expanded to include the past returns and past squared innovations from the GARCH (1,1) model across four currency futures returns which yield Equations 4.37 and 4.38.

Let $\mu_{i,t}$ be the conditional mean of returns in currency futures i during day t, specified as a linear function from past lagged one day returns of all four currency futures returns i, j, where $i, j = 1, 2, 3, 4$ (1 = BP, 2 = DM, 3 = JY and 4 = SF). That is,

$$\mu_{i,\,t} = \beta_0 + \sum_{i=1}^{4} \beta_{i,j}\, R_{j,\,t-1} + \varepsilon_{i,\,t} \qquad for \quad i, j = 1, 2, 3, 4 \tag{4.37}$$

where β_0 is the intercept and $\varepsilon_{i,\,t}$ is the error term of currency futures i during time t which is distributed as conditionally normal with time varying variance. If coefficient $\beta_{i,\,i}$ is statistically significant, the results suggest that the conditional mean of currency futures return i is influenced by its own one day lagged value; *i.e.*, its own mean spillovers. On the other hand, a statistically significant coefficient $\beta_{i,j}$ value for $j \neq i$ implies that returns in currency futures j influence the conditional mean of returns in currency futures i, thus exhibiting multi-currency futures mean spillovers or mean spillover effects.

$$h_{i,t} = \alpha_0 + \sum_{i=1}^{4} \alpha_{i,j} \varepsilon_{j,t-1}^2 + \gamma_1 h_{i,t-1} \qquad for \quad i, j = 1, 2, 3, 4 \qquad \textbf{(4.38)}$$

Finally, the volatility surprise across four currency futures returns (multi-currency futures) employing the GARCH models are examined simultaneously in a single conditional variance equation as in Equation 4.38. The past conditional variance i and lagged innovations from currency futures returns j are introduced as an exogenous variable in the conditional variance equation i. That is, where α_0 is the intercept, γ_1 measures the effect of past volatility on current volatility in currency futures returns i and the $\alpha_{i,j}$ value for $j \neq i$ measures the impact of past innovations of other currencies during the day t-1. Volatility spillovers within currency futures returns; *i.e.,*own volatility spillovers or ARCH effects are measured by $\alpha_{i,i}$ while volatility spillovers across currency futures returns; *i.e.*, multi-currency futures returns or spillover effects are measured by $\alpha_{i,j}$ for $i, j = 1, 2, 3, 4$ (1 = BP, 2 = DM, 3 = JY and 4 = SF) and $j \neq i$. A significant $\alpha_{i,i}$. implies that past innovations in currency futures i have an impact on the current volatility in the same currency futures. On the other hand, a significant $\alpha_{i,j}$ indicates that the past innovations in returns on currency futures contract j have an influence on the current volatility of currency futures contract i.

4.8 Conclusion

This chapter has discussed in detail the data and methodologies used in our study. The data from the International Monetary Market (IMM) are structured into two different sets in order to examine two related phenomena. The first set consists of daily time series of four currency futures returns from January 1, 1986 to April 30, 1997, including non-trading days and totalling 2,954 observations. The inclusion of non trading days is crucial since the focus of the study is on the temporal spillover effect between two or more futures currency returns and the use of an equal number of day's price observations is absolutely necessary. The second set of data are daily time series for four currency futures returns together with their trading volume during the same period excluding non-trading days. These data are to be used in the analysis of the relationship between returns and trading volume. Here the exclusion of non trading day is crucial since this can reduce the possibility of serially correlation in the daily price changes. Serially correlated data can possibly produce biased estimations.

GARCH methodology is used to analyse the relationship between returns and trading volume as well as for the subsequent spillover effects. Trading volume is used as the mixing variable in order to investigate its informational role in explaining futures price movements. In particular, trading volume may be informative about the process of futures markets return. Our study first examines raw volume in the GARCH variance equation. Secondly, we use uncorrelated contemporaneous volume since it is possible to eliminate the problem of the high serial correlation of raw volume, by using the univariate autoregressive models to find the order of lags until the Ljung-Box Q-statistics- LB(.) show no autocorrelation in the residuals. The uncorrelated residuals are then squared and included in the conditional variance of returns.

The GARCH (p,q) family is chosen because the GARCH (1,1) cannot capture the unexpected volume satisfactorily, as indicated by the higher order dependence reported by the LB^2.

Taking our argument one step further, in order to anticipate the possible existence of a simultaneity problem in the model, we include the lagged uncorrelated volume to test for the sequential information model (SEQ) hypothesis in the conditional variance equation.

Next, using a similar GARCH model, we test for the hypothesis of information arrival or spillover effects across currency futures in both the conditional mean and variance equations. Two aspects of spillover are analysed: pairwise and multi-currency. In pairwise spillover, one exogenous variable of the residual terms of other currency futures are included in the equations. In multi-currency futures spillover, however, the exogenous variables are expanded to include all the currency futures examined in the equations. This is done to test for the influence of a common economic effect on the mean and volatility of all four currency futures returns.

Finally, in order to test whether the results are robust over the sample period, we conduct similar analyses of the relationship between returns and trading volume on two subperiods of almost equal length.

Chapter Five

Nonlinear Dependence in Daily Currency Futures Pricing

5.1 Introduction

The objectives of this chapter are to report the results of the stationarity test, to provide summary statistics, to analyse the serial correlation of the currency futures returns as well as their residuals and to discuss the results of the test of nonlinear dependence. In addition, we shall also report and analyse the diagnostic test procedure in order to determine the fit of the model to the returns generating process. This process is crucial since our further analysis is conditional on the assumption of the appropriateness of the model.

This chapter proceeds as follows: Section 5.2 reports the stationarity test results. Section 5.3 provides the results of descriptive statistics for the four currency futures returns. Section 5.4 gives the results of serial correlation in the returns as well as the residuals series. The results for various nonlinearity tests are reported in Section 5.5. Section 5.6 describes the estimations of the GARCH (1,1) model and diagnostic test results. Finally, some conclusions are drawn in Section 5.7.

5.2 Stationarity in Futures Prices

Univariate time series data including financial data contain only a single observation or realization at a given point in time t. In estimating the first and the second moments of a time series, a stationary process is required so that its mean and variance do not change through time. In case the original series is non-stationary, a logarithm differencing transformation is performed on the series using the following formulation:

$$Log\ P_t - Log\ P_{t-1}$$

where P_t, P_{t-1} are the prices at day t and lagged one day, respectively.

In this study, the unit roots test for stationarity as proposed by Dickey & Fuller (DF) (1979) and the Augmented Dickey-Fuller (ADF) (1981) are employed to verify that the usual properties of nonstationarity in levels and stationarity in returns are present in the currency futures series used here. A series is said to be nonstationary in levels and stationary in growth rates if the price series is integrated of order one as discussed by Johansen (1991). Both the Dickey-Fuller and the Augmented Dickey-Fuller unit root test are based on an OLS regression, (for the full explanation of this methodology, see Chapter 4, Sections 3.1 and 3.2).

The estimated results of the Dickey Fuller (DF) and the Augmented Dickey Fuller (ADF) test with one lag, which include tests for both the raw levels and the natural logarithmic returns, are shown in Tables 5.1A and B, respectively. The null hypothesis of a unit root (nonstationary) is accepted both with and without trend for the levels in each currency at the 5 percent significant level. However, after first-differencing, the null hypothesis of a unit root is rejected, confirming that the returns series are integrated of the order one. The critical values for the DF and ADF tests at the 5 percent significance level are -2.90 (without trend) and -3.46 (with trend). These findings are consistent with the results of Naka and Wei (1996) and Doukas and Rahman (1987), who find that foreign currency futures prices are nonstationary in levels and stationary in growth (change).

Table 5.1: Stationarity Test Results:

A. Raw Series

Currency Futures	Sample size (N)	Dickey-Fuller Test, DF(1)		Augmented Dickey-Fuller Test, ADF(1)	
		without trend	with trend	without trend	with trend
British Pound	2955	-2.5860	-2.6865	-2.5524	-2.6491
German Mark	2955	-2.8825	-2.7035	-2.8535	-2.7021
Japanese Yen	2955	-2.1987	-1.2846	-2.1695	1.2195
Swiss Franc	2955	-2.6957	-2.5080	-2.6868	-2.5265

Notes: The null hypothesis of nonstationary cannot be rejected at significant levels of 5%

B. Returns Series

Currency Futures	Sample size (N)	Dickey-Fuller Test, DF(1)		Augmented Dickey-Fuller Test, ADF(1)	
		without trend	with trend	without trend	with trend
British Pound	2954	-55.125	-55.120	-38.604	-38.607
German Mark	2954	-54.209	-54.252	-39.400	-39.457
Japanese Yen	2954	-55.033	-55.109	-39.384	-39.480
Swiss Franc	2954	-53.884	-53.914	-39.522	-39.563

Notes: The test examines the null hypothesis of a unit roots in the series against the stationary alternative of a unit root. The null hypothesis will be rejected in favour of the stationary alternative when the test statistics is too small. For returns series, the null hypothesis of a unit root is rejected at 5% level of significant for all currency futures.

5.3 Summary Statistics for Currency Futures Returns

Table 5.2 provides summary statistics for the return series $\{R_t\}$, $t = 1, \ldots, T$, for the entire period. These include the distribution parameters of mean, median, minimum, maximum, variance, skewness and kurtosis (see Appendix 3 for more details on the computation of mean, variance, skewness and excess kurtosis). None of the means are statistically different from zero and the sample moments show that zero skewness cannot be rejected for the German mark and the Swiss franc. However, the British pound and the Japanese yen show negative skewness and positive skewness, respectively. The excess kurtosis of each currency futures returns series confirms that the distributions are leptokurtic in nature with thick tails and sharp peaks at the centre compared to the normal distribution.. Both skewness and excess kurtosis measures should be equal to zero. Thus, all the four series have strong departures from normality. This finding is consistent with numerous tests applied to distributions of stock returns, and spot rates in foreign currencies (Hsieh, 1988) and foreign currency futures (Najang, Rahman and Yung, 1992).

Significant deviations from normality can be a symptom of nonlinear dependence. Before applying models to time series data, however, the underlying assumption that the returns be independent, random and identically distributed variables should be fulfilled.

Table 5.2: Summary Statistics on Daily Currency Futures Returns on Near-Month Contracts, 1986- 1997.

Log Futures Changes: $R_t = \log (S_t / S_{t-1})* 100$

Statistics	BP	DM	JY	SF
Sample size (N)	2954	2954	2954	2954
Mean	0.0042	0.0117	0.0156	0.0113
Variance	0.5065	0.5158	0.4983	0.6424
Skewness	-0.3290	-0.0347	0.2316	0.0466
Kurtosis	3.5737	2.2295	4.0605	1.8750
Maximum	3.4748	3.6013	4.7533	3.9271
Minimum	-4.8424	-3.3125	-4.2073	-3.9881
Jarque-Bera	1622*	612*	2082*	429*

Notes: Kurtosis refers to excess kurtosis where 0 denotes normality. The critical values of Jarque-Bera to test for normality are from the chi-square distribution with 2 degree of freedom, χ^2 (2): 4.61 , 5.99 and 9.21 for significance levels of 10%, 5% and 1%, respectively. * Indicates statistically significant at 5% significance level.

5.4 Autocorrelation in the Returns Series

In order to test the null hypothesis of independence, the autocorrelation coefficients for four currency futures returns and the portmanteau tests of Ljung-Box Q-statistics (1978), are used. The asymptotic distribution of the Ljung-Box statistics, LB(.), is a chi square (χ^2) distribution under the null hypothesis of no serial correlation in the series. The results of the test statistic for autocorrelation coefficient of lag 1 to 6 and Ljung-Box Q-statistics of lags 6, 12, 18 and 24 are reported in Table 5.3A. The results for all four series show that no coefficients are significantly different from zero at the 5 percent level and the only statistically significant Q-statistic is for the Japanese yen for higher lags, which was reported by Hsieh (1989a) using the spot foreign exchange rates. These results seem to support the notion that past returns do not have information content on the current returns using linear model, supporting the findings of Naka and Wei (996) but contradicting those of McCurdy, *et.al.*(1987), Cavanaugh (1987) and Hodrick and Srivastava (1987) who find strong autocorrelation in the currency futures returns using the data series which includes and is affected by the daily price limits.

Since the empirical evidence shows that current returns in these four currency futures contain possible significant conditional heteroscedasticity, the notion that past returns do not have information content on the current returns should also be tested using a nonlinear model. As noted by Booth and Koutmos (1998), there is still a possibility that the returns series are nonlinearly related to their own past history. Our results using nonlinear specification of the autocorrelation coefficients of the absolute returns are statistically different from zero, in more than half of the cases. Furthermore, when the joint test using the Ljung-Box statistic is performed on lags 6, 12, 18 and 24, the series are found to be highly correlated, as reported in Table 5.3B. This indicates that the four daily returns time series exhibit possible strong conditional heteroscedasticity, as described by Hsieh (1993b).

In the case of the residuals, after applying the Autoregressive, AR(1), the autocorrelation coefficients reported in Table 5.3C show that the residuals are not statistically different from zero. Also, the joint test using Ljung-Box Q-statistics reports no serial correlation among the residuals (with the exception of the Japanese Yen at higher levels). However, when the test is applied to absolute and squared residuals, their Q-statistics, reported in Table 5.3D and E, respectively, are highly significant. Thus, the null hypothesis of strict white noise is rejected in all cases, even at significance levels lower than one percent. As mentioned by Taylor (1986), if the residuals exhibit strict white noise, then so do their absolute values and squares. Thus, we can conclude that the currency futures daily return series and their residuals are linear independent (*i.e.*, there is no evidence of serial correlation) but nonlinear dependent. The presence of nonlinear dependence implies that linear (e.g., Box-Jenkins) methods cannot be used to model the return series.

It may be inferred that the Autoregressive Conditional Heteroscedasticity (ARCH) models which assume that the conditional error is serially uncorrelated and that the conditional variance is time varying are appropriate for the series and well specified. Furthermore, the general absence of significant higher order serial correlation leads to the conclusion that specifying an AR(1) process in conjunction with a Generalized

Autoregressive Conditional Heteroscedasticity (GARCH) model would result in the most parsimonious model for the data [see Bollerslev (1986)].

Table 5.4 reports the summary statistics from the univariate autoregressive models, AR(p) using Schwarz Bayesian Information Criterion, BIC = $-2L(\phi) + (\ln T)K$, where K is the number of coefficients in the model. The selected criterion is based on minimization of the value of test ratio. As such, AR(1) is selected for all currency futures returns since it has the minimum value for the test ratio.

Table 5.3: Autocorrelations Coefficients and the Ljung-Box Q-Statistics Test Results

A. Returns

Autocorrelations Coefficients	BP	DM	JY	SF
Lag (1)	-0.0145 (0.0184)	0.0022 (0.0184)	0.0127 (0.0184)	-0.0081 (0.0184)
Lag (2)	0.0020 (0.0184)	-0.0267 (0.0184)	-0.0182 (0.0184)	-0.0327 (0.0184)
Lag (3)	-0.0033 (0.0184)	-0.0013 (0.0184)	-0.0109 (0.0184)	-0.0081 (0.0184)
Lag (4)	0.0098 (0.0184)	0.0140 (0.0184)	0.0112 (0.0184)	0.0079 (0.0184)
Lag (5)	0.0347 (-0.0184)	0.0077 (0.0184)	-0.0112 (0.0184)	0.0029 (0.0184)
Lag (6)	-0.0445 (0.0185)	-0.0165 (0.0185)	-0.0507 (0.0184)	-0.0369 (0.0184)
Ljung-Box Q-Statistics	**BP**	**DM**	**JY**	**SF**
Lag (6)	10.393	8.0420	10.179	7.8026
Lag (12)	13.582	11.981	35.437*	11.374
Lag (18)	24.571	15.788	48.757*	15.997
Lag (24)	27.918	20.256	52.569*	23.4

Notes: * Indicates statistically significant at 5% level, for two tail test.

B. Absolute Returns

Autocorrelations Coefficients	BP	DM	JY	SF
Lag (1)	0.0845*	0.0711*	0.1095*	0.0613*
Lag (2)	0.0803*	0.0337	0.0453*	-0.0011
Lag (3)	0.0872*	0.0800*	0.0824*	0.0592*
Lag (4)	0.1047*	0.0644*	0.0394	0.0629*
Lag (5)	0.0635*	0.0455*	0.0817*	0.0228
Ljung-Box Q-Statistics	**BP**	**DM**	**JY**	**SF**
Lag (6)	145.19*	82.094*	102.073*	59.246*
Lag (12)	274.73*	156.103*	147.145*	116.823*
Lag (18)	400.92*	243.805*	196.569*	189.498*
Lag (24)	494.80*	283.721*	222.728*	208.625*

Notes: *Indicates statistically significant at 5% level.

C. Residuals

Autocorrelations Coefficients	BP	DM	JY	SF
Lag (1)	0.0008	0.0009	0.0012	0.0007
Lag (2)	0.0019	-0.0270	-0.0189	-0.0327
Lag (3)	-0.0034	0.0012	-0.0110	-0.0079
Lag (4)	0.0102	0.0145	0.0115	0.0083
Lag (5)	0.0334	0.0072	0.0105	-0.0030
Ljung-Box Q-Statistics	**BP**	**DM**	**JY**	**SF**
Lag (6)	9.2684	7.9466	9.5940	7.5431
Lag (12)	12.461	11.915	34.982*	11.165
Lag (18)	23.698	15.681	48.469*	15.689
Lag (24)	27.214	20.300	52.208*	23.309

Notes: *Indicates statistically significant at 5% level.

D. Absolute Residuals

Autocorrelations Coefficients	BP	DM	JY	SF
Lag (1)	0.0854*	0.0701*	0.1067*	0.0604*
Lag (2)	0.0821*	0.0333	0.0455*	-0.0014
Lag (3)	0.0873*	0.0806*	0.0830*	0.0598*
Lag (4)	0.1050*	0.0642*	0.0379	0.0625*
Lag (5)	0.0634*	0.0447*	0.0804*	0.0225*
Ljung-Box Q-Statistics	BP	DM	JY	SF
Lag (6)	146.35*	82.008*	100.62*	59.343*
Lag (12)	276.30*	156.06*	145.74*	117.52*
Lag (18)	401.96*	242.52*	195.36*	189.33*
Lag (24)	496.23*	282.44*	221.04*	208.27*

Notes: *Indicates statistically significant at 5% level.

E. Squared Residuals

Autocorrelations Coefficients	BP	DM	JY	SF
Lag (1)	0.0949*	0.0685*	0.0781*	0.0854*
Lag (2)	0.0857*	0.0539*	0.0284	0.0064
Lag (3)	0.0686*	0.0620*	0.0586*	0.0469*
Lag (4)	0.0553*	0.0344	0.0207	0.0456*
Lag (5)	0.0329	0.0200	0.0446*	0.0093
Ljung-Box Q^2-Statistics	BP	DM	JY	SF
Lag (6)	90.837*	65.162*	47.759*	65.477*
Lag (12)	155.12*	107.52*	73.217*	125.37*
Lag (18)	206.01*	160.19*	101.65*	188.33*
Lag (24)	254.95*	179.93*	113.07*	197.76*

Notes: The asymptotic distribution of the Ljung-Box statistics, LB(p), is χ^2 under the null hypothesis of no serial correlation in the returns, absolute returns, residuals, absolute residuals and squared residuals. and have an asymptotic chi-squared distribution with p degree of freedom. *Indicates statistically significant at 5% level.

Table 5.4 Autoregressive Models for Currency Futures Returns

AR(p)	Schwarz Bayesian Information Crit[illegible]			
	BP	DM	JY	SF
1	-0.6755	-0.6570	-0.6913	-0.4374
2	-0.6739	-0.6565	-0.6892	-0.4356
3	-0.6710	-0.6538	-0.6900	-0.4337
4	-0.6681	-0.6510	-0.6875	-0.4308

Notes: the univariate autoregressive models is given by AR(p) using Schwarz Bayesian Information Criterion, BIC = $-2L(\phi) + (\ln T)K$, where K is the number of coefficients in the model. The criterion select is based on minimization of the value of test ratio.

5.5 Test Results for Nonlinearity

The McLeod-Li Portmanteau Test

The results from the McLeod and Li (1983) method are reported in Table 5.5. More than half of the autocorrelation coefficients in the squared returns are significantly different from zero at the 5 percent level for each of the lags tested. Furthermore, their Q^2-statistics are highly significant for all lags. This indicates that the returns series of all the daily currency futures exhibit the presence of strong conditional heteroscedasticity, evidence of nonlinearity in the series. Indeed, when the estimated autocorrelations for the return series $\{x_t\}$ (see Table 5.3A) and absolute return series $\{|x_t|\}$ (see Table 5.3B) are analysed, the results show that autocorrelations of the absolute return series are much higher than those in the returns series which suggests that large price changes are followed by large changes and small price changes are followed by small changes. Similar results are found in the residual series. This is consistent with the finding of

Mandelbrot (1963) on speculative prices. In general, the distribution of today's squared and absolute returns depends not only on yesterday's return but also on several previous days' returns. Thus, we can confidently conclude that the return series are not made up of strictly white noise processes. The most that can be inferred from the results is that the series are just white noise or linear independent (uncorrelated).

Table 5.5: McLeod-Li Test (Autocorrelation of Squared Returns)

Autocorrelations Coefficients	BP	DM	JY	SF
Lag (1)	0.9441*	0.0686*	0.0800*	0.0869*
Lag (2)	0.0834*	0.0539*	0.0277	0.0065
Lag (3)	0.0679*	0.0618*	0.0590*	0.0465*
Lag (4)	0.0548*	0.0342	0.0208	0.0452*
Lag (5)	0.0321	0.0202	0.0456*	0.0095
Lag (6)	0.0740*	0.0946*	0.0571*	0.1015*
Lag (7)	0.0246	0.0408*	0.0049	0.0695*
Lag (8)	0.0286	0.0277	0.0406*	0.0335
Lag (9)	0.0827*	0.0298	0.0620*	-0.0006
Lag (10)	0.0848*	0.0763*	0.0304	0.0882*
Ljung-Box Q^2-Statistics	BP	DM	JY	SF
Lag (6)	88.764*	65.049*	48.606*	65.728*
Lag (12)	151.881*	107.631*	73.829*	125.680*
Lag (18)	202.865*	161.002*	102.569*	189.052*
Lag (24)	250.767*	180.292*	114.088*	198.424*
Lag (36)	348.491*	209.173*	175.861*	221.859*
Lag (60)	510.634*	281.630*	208.823*	299.803*

Notes: This test for nonlinear independence is attributed to McLeod and Li (1983). The test is asymptotically equivalent to a Lagrange Multiplier under the null hypothesis of the squared residuals being uncorrelated. *Indicates statistically significant at 5% level.

The Engle ARCH Test

The Engle ARCH test is conducted by first filtering a linear AR(1) model to the return series. The resulting squared residual series is then tested for the autoregressive conditional heteroscedasticity (ARCH) effects employing the standard TR^2 test, where T is the number of effective observations and R^2 is the coefficient of determination from regressing the squared residual on a constant and its lagged values at r lags. It is distributed asymptotically as $\chi^2(r)$ under the null hypothesis of no ARCH effects.

Table 5.6 reports the ARCH (r) statistic, which strongly rejects the null hypothesis of no ARCH effect at a 1 percent level. This result indicates the presence of ARCH effects in all four currency futures return series. The estimate suggests that price variations in the current period are related to price variations that occurred over one, six and twelve previous periods.

Table 5.6: Lagrange Multiplier Test for the Presence of ARCH Effects

No.of Lags	BP	DM	JY	SF
ARCH(1)	26.598*	13.885*	18.098*	21.531*
ARCH(6)	68.725*	54.481*	40.823*	61.379*
ARCH(12)	100.946*	77.272*	55.270*	98.090*

Notes: The test for presence of ARCH is given by Engle (1982). The ARCH (p) statistics, obtained as TR^2 from regressing the squared residual on a constant and its lagged value at p lags, is distributed asymptotically as χ^2 (p) under the null hypothesis of no ARCH effects. The results indicate that ARCH effects are present in daily percentage changes in all currency futures prices. *Indicates statistically significant at 5% level.

The BDS Test

Table A-1 in Appendix 4 reports the results of the BDS test statistics applied to the return series of the British pound, the German mark, the Japanese yen and the Swiss franc. The ε ranges used are from 0.5σ to 2.0σ while the embedded dimensions m are integers from 2 to 10. The value of the test statistics are all positive and are highly significantly, rejecting the null hypothesis of i.i.d. at the 1 percent level for all the return series. The BDS test is also applied to the residuals series from an AR(1) model. This model is used to filter the series in order to remove serial dependence. This autoregressive process with the lag truncation length is chosen according to the Schwarz Bayesian information Criterion (see Table 5.4). The BDS test results shown in Table 5.7 suggest that the null of i.i.d. behaviour for the residuals should be rejected at the one percent level, a finding which does not differ substantially from that for the return series. This is consistent with the results of Hsieh (1993b) for currency futures and Fujihara, *et.al.*, (1997a) for petroleum futures. Moreover, the rejection of i.i.d. (random) behaviour suggests that there is indeed some dependence in the daily currency futures returns and residuals series that the AR(1) filter is unable to detect. This should not come as a suprise since the filter used is not designed to remove nonlinear dependencies.

Table 5.7: BDS Statistics for the Residuals from AR(1) Model (Linear Filtered Series)

Length in Standard Deviation (ε)	Embedding Dimension (m)	W Statistic (BDS/SD)			
		BP	DM	JY	SF
2.0	2	4.4040*	3.4053*	4.8665*	3.6569*
2.0	3	5.6945*	3.2361*	4.7144*	3.5892*
2.0	4	7.5412*	2.6167*	5.8256*	4.0402*
2.0	5	11.429*	0.2222	4.9180*	3.8343*
2.0	6	13.496*	1.4606	2.8841*	-0.6344
2.0	7	22.694*	-7.5568*	2.9808*	-8.2379*
2.0	8	21.591*	-5.8117*	15.813*	-6.3591*
2.0	9	-3.9945*	-4.5839*	-4.6448*	-5.0356*
2.0	10	-3.1930*	-3.6856*	-3.7389*	-4.0657*
1.5	2	4.1255*	3.1111*	4.6401*	3.2140*
1.5	3	5.0255*	2.8694*	4.0371*	3.4974*
1.5	4	6.4394*	3.5160*	4.0742*	5.3557*
1.5	5	8.6009*	1.9449	1.1969	5.1488*
1.5	6	5.4297*	-9.5913*	-3.7309*	-10.310*
1.5	7	22.030*	-7.1029*	-7.2334*	-7.6604*
1.5	8	-4.7831*	-5.4437*	-5.5532*	-5.8918*
1.5	9	-3.7391*	-4.2783*	-4.3719*	-4.6479*
1.5	10	-2.9776*	-3.4268*	-3.5080*	-3.7377*
1.0	2	4.0111*	3.1255*	4.2397*	2.6555*
1.0	3	5.3471*	3.8978*	3.7825*	1.7770
1.0	4	9.7280*	2.9446*	6.5561*	1.5852
1.0	5	7.6314*	13.025*	-7.3091*	10.352*
1.0	6	-8.0307*	-8.5794*	-8.9466*	-9.5055*
1.0	7	-5.8969*	-6.3118*	-6.6038*	-7.0284*
1.0	8	-4.4784*	-4.8041*	-5.0435*	-5.3782*

1.0	9	**-3.4854***	**-3.7482***	**-3.9489***	**-4.2202***
1.0	10	**-2.7628***	**-2.9795***	**-3.1504***	**-3.3750***
0.5	2	**2.9958***	**3.3031***	**4.2302***	**1.8409**
0.5	3	**7.1623***	**8.0649***	**7.0844***	**1.4650**
0.5	4	**6.7659***	**6.2852***	**20.782***	**7.9674***
0.5	5	**63.315***	**-9.5883***	**-10.833***	**202.62***
0.5	6	**-6.3366***	**-6.6051***	**-7.5292***	**-8.1922***
0.5	7	**-4.5786***	**-4.7734***	**-5.4926***	**-5.9900***
0.5	8	**-3.4184***	**-3.5655***	**4.1436***	**-4.5310***
0.5	9	**-2.6129***	**-2.7274***	**3.2029***	**-3.5131***
0.5	10	**-2.0322***	**-2.1236***	**-2.5212***	**-2.7751***

Notes: The BDS statistic has a standard normal limiting distribution. The null hypothesis of a random iid process is rejected if the probability of any two M-histories being close together exceeds Mth power of the probability of any two points being close together, where M is the vector dimension. *Indicates statistically significant at 5% level for two-tail tests. The critical value for 5% is 1.960

Lee *et.al.*(1993) suggest that the possibility of nonlinearity in financial time series could be due to factors such as neglected nonlinear structure either in the mean of the process or the ARCH effects. As such, this study further explores the possibility that conditional heteroscedasticity is responsible for the rejection of i.i.d. behaviour by applying the BDS test to the residuals from the GARCH model.

Following Abhyankar *et.al* (1995), this study applied the BDS test to the standardized residuals from a GARCH(1,1) model,

$$\hat{\varepsilon}_t = (x_t - \hat{\mu})/\hat{h}_t^{1/2},$$

where $(x_t - \hat{\mu})$ is the residual of the mean equation and $\hat{h}_t$ its estimated variance.

The GARCH(1,1) is selected since it shows the best fit and is reported to be a parsimonious representation of conditional variance (see Akgiray, 1989; Bollerslev, *et.al.*, 1992). The diagnostic tests results are given in Tables 5.10, 5.11 and 5.12. The tests for nonlinear dependence in squared standardized residuals (GARCH filtered residuals) for $\varepsilon = 1$ and $m = 2$ to 10 are reported in Table 5.9. The null hypothesis of i.i.d. is not rejected for the values of m from 2 to 5 for the British pound and the Japanese yen and for m from 2 to 4 for the German mark and the Swiss franc. However, the null hypothesis is rejected for an m value of more than 5 in all cases. The findings for the standardized residuals suggest that the GARCH(1,1) model is able to capture nearly half of the cases of the nonlinear dependence in the series.

The Third Moment Test

While the BDS test statistics show some nonlinearity in the series, they do not indicate whether it is mean or variance nonlinearity. The third-moment test statistic proposed by Hsieh (1989a) is able to differentiate between such nonlinearities. Tables 5.8A, B, C and D show the results of the test statistics for $i, j = 1, 2, 3, 4, 5$ on filtered residual series (using AR(1) model, see methodology section on page 132), for the British pound, the German mark, the Japanese yen and the Swiss franc, respectively. None of them are statistically significant except the Swiss franc for $i, j = 2, 5$, indicating that the null hypothesis of multiplicative dependence is not rejected at the 5 percent level. The evidence supports the view that the rejection of i.i.d. in the series is attributable solely to the variance of the process. Thus, a GARCH process is the most appropriate and will be used to model the conditional heteroscedasticity as shown below.

Table 5.8: Third Moments Test for the Residuals from AR(1) Model (Linear Filtered Series)

A. British Pound

No. of Lag				
i	j	ρeee	w	V
1	1	-0.12701	11.9191	-0.54813
2	1	-0.00483	2.6613	-0.09335
2	2	-0.13111	10.7754	-0.62588
1	3	-0.00853	2.8633	-0.15319
1	4	0.008602	1.6339	0.270804
1	5	-0.01541	1.5505	-0.51138
2	3	-0.00664	2.43	-0.14053
2	4	-0.021	2.1228	-0.50876
2	5	-0.02142	2.4139	-0.45643
3	3	-0.07208	7.7904	-0.47592
3	4	-0.02042	1.7808	-0.58992
3	5	-0.04536	2.3714	-0.98385
4	4	-0.04391	7.0967	-0.31831
4	5	-0.00772	1.3727	-0.28922
5	5	-0.05541	6.693	-0.42586

Notes: * Significant at 5% levels (two-tail test). The critical value for 5% is 1.960. The i and j are number of lags.

B. German Mark

No. of Lag				
i	*j*	ρeee	*w*	*V*
1	1	0.014831	6.4569	0.11815
2	1	-0.04692	1.43116	-1.68645
2	2	0.002863	6.62204	0.02224
1	3	0.005146	1.46794	0.18033
1	4	0.012226	1.538	0.40892
1	5	-0.00389	1.13265	-0.17674
2	3	0.001048	1.55283	0.03471
2	4	0.006402	1.15318	0.28556
2	5	-0.03692	0.99723	-1.90416
3	3	-0.05058	5.79385	-0.44903
3	4	0.026811	1.53879	0.89624
3	5	0.011239	1.22245	0.4729
4	4	-0.04299	5.17482	-0.42736
4	5	-0.02198	1.18773	-0.95212
5	5	0.043666	4.30416	0.52185

Notes: * Significant at 5% levels (two-tail test). The critical value for 5% is 1.960. The *i* and *j* are number of lags.

C. Japanese Yen

No. of Lag				
i	*j*	ρeee	*w*	*V*
1	1	0.011557	10.946	0.054313
2	1	-0.00953	2.0402	-0.24023
2	2	-0.00476	6.6568	-0.03681
1	3	0.019453	1.8158	0.551061
1	4	0.000364	2.1618	0.008663
1	5	0.002553	1.545	0.084988
2	3	0.010458	1.5342	0.350655
2	4	0.013492	1.4645	0.473888
2	5	-0.01988	1.9702	-0.51904
3	3	-0.00289	7.293	-0.02039
3	4	0.008906	1.9487	0.235098
3	5	-0.02415	1.4382	-0.8639
4	4	-0.03202	5.9813	-0.27536
4	5	-0.00388	1.5501	-0.12875
5	5	0.11232	7.8173	0.7391

Notes: * Significant at 5% levels (two-tail test). The critical value for 5% is 1.960. The *i* and *j* are number of lags.

D. Swiss Franc

No. of Lag				
i	*j*	*peee*	*w*	
1	1	0.015249	7.18807	0.10913
2	1	-0.03518	1.42845	-1.26681
2	2	0.000919	3.52252	0.01342
1	3	-0.01403	1.28624	-0.56117
1	4	0.021858	1.51616	0.74159
1	5	0.010712	1.23003	0.44796
2	3	-0.00707	1.3217	-0.27534
2	4	0.005703	0.91379	0.32102
2	5	-0.04812	0.82023	-3.01768*
3	3	-0.04634	4.54005	-0.52504
3	4	-0.0095	1.64431	-0.29725
3	5	0.000807	0.99415	0.04177
4	4	-0.00501	5.40148	-0.04771
4	5	0.001903	1.16547	0.08399
5	5	0.05657	3.70292	0.78584

Notes: * Significant at 5% levels (two-tail test). The critical value for 5% is 1.960. The *i* and *j* are number of lags.

5.6 GARCH Modelling of Heteroscedasticity

While the third-moment test can give clues as to the source of the nonlinearity, it does not give the researcher a specific model with which to test the data generating process. This section provides the framework for analysing nonlinearities suggested by the third-moment test. For example, the GARCH specification is able to capture any multiplicative nonlinearity, while the GARCH-in-mean is able to detect additive nonlinearity. Since our results show multiplicative nonlinearity, we modelled the data generating process using the GARCH (1,1) model.

The Estimations of GARCH (1,1)

Within the class of GARCH processes, GARCH (1,1) shows the best fit. Other models such as GARCH (*p, q*) for p = 1,....3 and q = 1,......, 3 were also used, but they did not improve the goodness-of-fit based on likelihood-ratio tests. Table 5.10 shows the results for all four currency futures return series with *t*-statistics reported in parentheses. The coefficient estimates of α_1 and β_1 are all statistically significant. For all four futures contracts, the sum ($\alpha_1 + \beta_1$) is fairly close to one and this indicates that a larger part of the current currency futures price volatility is explained by past volatility, which tends to persist over time. These results also provide strong evidence that daily currency futures prices volatility can be characterized by a GARCH(1,1) specification and that none of the return series can be appropriately modelled as an integrated GARCH since the sum ($\alpha_1 + \beta_1$) is less than 1.

Test of Goodness-of-Fit

The fit of the GARCH(1,1) model is further evaluated by investigating the standardized residuals and the squared standardized residuals. The test statistics for the standardized residuals and the squared standardized residuals are reported in Table 5.11A and B, respectively. The Ljung-Box Q- statistics for the British pound, the German mark and the Swiss franc are not statistically significant at the usual 5 percent level. However, Q-statistics results for the Japanese yen at lags 12, 18, 24, 36 and 60 are statistically significant, indicating that some degree of serial correlation still remains in the residuals. Higher order lags did not eliminate the serial correlation. In addition, the McLeod-Li Q-statistics for second-order serial dependence are not statistically significant at the 5 percent level for all the series, suggesting that squared standardized residuals are serially uncorrelated. Thus, the hypothesis that there is any nonlinear dependence in the standardized residuals is rejected. It is interesting to note how a GARCH (1,1) process can eliminate the long autocorrelations in the squared residuals for all currency futures series. The GARCH (1,1) models appear to be successful in terms of describing nonlinear dependencies in the returns.

The test for the null hypothesis of a normal distribution of standardized residuals from the GARCH (1,1) model is rejected. Table 5.12 reports their estimated skewness and excess kurtosis. The GARCH (1,1) models fail to remove or reduce the skewness except in the case of the British pound and the German mark. In contrast, the model reduces leptokurtosis considerably for all the series. For example, the excess kurtosis is reduced from 3.5737 to 2.9410 for the British pound; from 2.2295 to 1.7736 for the German mark; from 4.0605 to 2.5436 for the Japanese yen and 1.8750 to 1.4516 for the Swiss franc.

Overall, these results provide evidence that the four currency futures returns may be adequately described by GARCH (1,1). The results show that the GARCH (1,1) model reduced the leptokurtosis in the series. Furthermore, the standardized residuals remove most of the nonlinear dependence. They provide strong support for the existence of conditional heteroscedasticity.

Lastly, the results for Ljung-Box autocorrelation for standardized residuals in Table 5.11A are quite similar to those in Table 5.3A. On the basis of the Ljung-Box Q-statistics, the results of GARCH filtered series are uncorrelated up to 60 lags in all cases except for the Japanese yen which is correlated for lags 12 or more. However, the standardized residuals squared of the Ljung-Box Q^2-statistics are clear of any ARCH effects for all cases as shown in Table 5.11B. Moreover, using BDS procedures our study is able to account for second-order dependence in the standardized residuals for conditional normal distribution, in nearly half of the cases as shown in Table 5.9.

Table 5.9: BDS Statistics for GARCH(1,1)-Filtered Residuals

Length in Std. Dev. (ε)	Embedding Dimension (m)	W Statistic (BDS/SD)			
		BP	DM	JY	SF
1.0	2	0.7544	0.6903	1.9975*	0.2597
1.0	3	1.2508	1.8295	0.1017	0.3287
1.0	4	0.3520	1.5710	-1.1467	-0.1147
1.0	5	-1.8297	3.1698*	-1.9300	-7.2524*
1.0	6	-9.6216*	-9.3491*	-5.9557*	-9.8915*
1.0	7	-7.1300*	-6.9132*	-7.5767*	-7.3315*
1.0	8	-5.4681*	-5.2901*	-5.8274*	-5.6245*
1.0	9	-4.3002*	-4.1507*	-4.5967*	-4.4251*
1.0	10	-3.4466*	-3.3190*	-3.6962*	-3.54878*

*Indicates statistically significant at 5% level for two-tail tests. The critical value for 5% is 1.960

Table 5.10: GARCH(1,1) Model Estimates

Coefficient	BP	DM	JY	SF
ϕ_0	0.0139 (1.2730)	0.0061 (0.5023)	0.0095 (0.7816)	0.0031 (0.2271)
ϕ_1	-0.0270 (-1.4190)	-0.0039 (-0.2106)	-0.0144 (-0.7504)	0.0090 (0.4761)
α_0	0.0025* (4.9066)	0.0070* (4.9752)	0.0114* (6.7573)	0.0093* (4.3825)
α_1	0.0303* (12.864)	0.0383* (8.6633)	0.0394* (10.462)	0.0310* (7.4985)
β	0.9647* (345.47)	0.9485* (153.10)	0.9375* (160.22)	0.9545* (149.10)
$\alpha_1 + \beta$	0.9950	0.9868	0.9769	0.9855

Notes: Numbers in parentheses are t-statistics. * Indicates statistically significant at 5% level

Table 5.11: Ljung-Box Q Test Results of The GARCH(1,1) Process

A. Autocorrelation of Standardized Residuals

Q-Statistics	BP	DM	JY	SF
Lag (6)	6.7015	5.9473	7.7162	5.8981
Lag (12)	8.7326	11.142	37.489*	12.578
Lag (18)	18.674	15.075	49.469*	18.068
Lag (24)	21.841	18.927	53.120*	25.425
Lag (36)	35.473	36.367	75.560*	42.425
Lag (60)	72.648	49.528	93.665*	65.550

Notes: * Indicates statistically significant at 5% level

B. Autocorrelation of Squared Standardized Residuals.

Q^2-Statistics	BP	DM	JY	SF
Lag (6)	8.0513	6.1491	6.225	10.106
Lag (12)	11.660	8.5351	10.831	17.530
Lag (18)	12.996	10.104	15.986	24.601
Lag (24)	15.043	18.675	20.571	31.706
Lag (36)	28.107	28.473	31.574	37.119
Lag (60)	55.933	61.267	44.856	74.173

Notes: This test for nonlinear independence is attributed to McLeod and Li (1983). The test is asymptotically equivalent to a Lagrange Multiplier under the null hypothesis of the squared standardized residuals being uncorrelated. * Indicates statistically significant at 5% level

Table 5.12: Test for Normality on Standardised GARCH(1, 1) Residuals

	BP	DM	JY	SF
Skewness	-0.2607	0.0065	0.3177	0.0858
Kurtosis	2.9410	1.7736	3.5436	1.4516

Notes: The null hypothesis of a normal distribution is rejected

5.7 Conclusion

This chapter has reported the BDS test and autocorrelations of the squared data which show strong nonlinear dependence; *i.e.*, they are correlated through their second moment. The rejection of i.i.d (evidence of nonlinearity) in the returns and filtered returns series most likely arises from the variance of the process rather than through the mean, as suggested by the third moment test. This is consistent with the presence of conditional heteroscedasticity. But after accounting for the presence of nonlinear dependence using GARCH (1,1) models, the results fail to reject the null hypothesis of uncorrelated squared standardized residuals using the McLeod-Li portmanteau test. As for test statistics using BDS on the squared standardized residuals from the GARCH (1,1) model, our results capture nonlinearity in nearly half of the cases. This results is consistent with Hsieh (1989a) and Hsieh (1993b) findings on spot exchange for the British pound and the German mark and on currency futures for the Swiss franc and the German mark. In addition, the GARCH (1,1) model fails to remove the skewness. although it reduces kurtosis considerably for all series.

Regardless of the fit of the model, the diagnostics test shows that on the whole the GARCH (1,1) model provides a great improvement in that the nonlinear dependence in the return series is mostly accounted for.

Chapter Six

Informational Role of TradingVolume

6.1. Introduction

This chapter presents research findings based on the data described in Section 4.2 and the methodology described in Section 4.6; that is, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) with contemporaneous and lagged trading volume acting as proxies of information flow in the conditional variance equation.

The present study differs from previous work on the relationship between returns and trading volume in several ways. First, as in the previous chapter, the analysis accounts for the strong conditional heteroscedasticity in the series by employing a nonlinear GARCH model to capture the time varying variance. Secondly, the present study not only examines the volume-volatility relationship *per se* but also investigates the role of trading volume as a proxy for information flow in the conditional variance equation. Thirdly, following Bessembinder and Seguin (1993), the volume is partitioned into expected and unexpected components, and the impact on returns of the volume surprise is assessed.

Section 6.2 will discuss the stationarity test results for the raw data, futures returns and volume. Section 6.3 reports the statistical properties of currency futures returns and trading volume. Section 6.4 discusses the initial test results of the relationship between return volatility and trading volume. Section 6.5 presents the results of the GARCH (1,1) with contemporaneous and lagged volume included in the equation. Section 6.6 reports the consistency of results across subsamples. Finally, Section 6.7 presents the conclusion.

6.2 Stationarity in the Return Series with Synchronised Volume Data

The Dickey-Fuller (DF) (1979) and the Augmented Dickey-Fuller (ADF) (1981) statistical tests for the stationarity of raw data, return series and volume series are carried out (see Chapter 4.3.1 and 4.3.2 for the regressions). Tables 6.1, 6.2 and 6.3 show the results for the raw data, return series and volume series, respectively. It may be noted that the series now differ in length, due to the deletion of non-trading days in the case of each futures contract. Both the DF and the ADF statistics for raw data fail to rejects the null hypothesis of non-stationary at the 1 percent level. However, the return series statistics significantly reject the null hypothesis of non-stationarity at the 1 percent level. As for volume, the null hypothesis of non-stationarity is also rejected for the level series and this contradicts the findings of Malliaris, *et.al.*,(1998) of non-stationarity in levels for six agricultural commodity futures contracts. Thus, the differenced price series; *i.e.*, returns, and undifferenced volume series will be used for analysis.

Table 6.1: Stationarity Test Results: Raw Data.

Currency Futures	Sample size (N)	Dickey-Fuller Test, DF(1)		Augmented Dickey-Fuller Test, ADF(1)	
		without trend	with trend	without trend	with trend
British Pound	2863	-2.5621	-2.6620	-2.6194	-2.7291
German Mark	2865	-2.8371	-2.6397	-2.9323	-2.7504
Japanese Yen	2861	-2.1696	-1.2634	-2.2516	-1.2764
Swiss Franc	2865	-2.6707	-2.4785	-2.7491	-2.5692

Notes: The null hypothesis of nonstationary cannot be rejected at significant levels of 5%

Table 6.2: Stationarity Test Results: Returns Series.

Currency Futures	Sample size (N)	Dickey-Fuller Test, DF(1)		Augmented Dickey-Fuller Test, ADF(1)	
		without trend	with trend	without trend	with trend
British Pound	2863	-53.832	-51.829	-38.293	-38.241
German Mark	2865	-53.150	-53.198	-39.234	-39.268
Japanese Yen	2861	-53.990	-54.076	-39.216	-39.227
Swiss Franc	2865	-52.813	-52.847	-39.869	-39.375

Notes: The null hypothesis of nonstationary is rejected at significant levels of 5%

Table 6.3: Stationarity Test Results: Volume Series.

Currency Futures	Sample size (N)	Dickey-Fuller Test, DF(1)		Augmented Dickey-Fuller Test, ADF(1)	
		without trend	with trend	without trend	with trend
British Pound	**2863**	**-36.577**	**-36.814**	**-26.782**	**-27.080**
German Mark	**2865**	**-25.886**	**-26.450**	**-25.856**	**-19.212**
Japanese Yen	**2861**	**-29.494**	**-29.498**	**-22.286**	**-22.290**
Swiss Franc	**2865**	**-30.869**	**-31.447**	**-23.721**	**-24.265**

Notes: The test examines the null hypothesis of a unit roots in the series against the stationary alternative of a unit root. The null hypothesis will be rejected in favour of the stationary alternative when the test statistics is too small. For volume series, the null hypothesis of a unit root is rejected at 5% level of significant for all currency futures.

6.3 Summary Statistics for Currency Futures Returns and Synchronised Trading Volume

Descriptive statistics for the distributional properties of the daily currency futures returns, R and synchronised trading volumes, V, for the British pound, the German mark, the Japanese yen and the Swiss franc, are reported in Table 6.4, including the number of observations, mean, standard deviation, skewness, kurtosis, Jarque-Bera (J-B) statistic and other statistics. (see Appendix 3 for more details on the computation of mean, standard deviation, variance, skewness and excess kurtosis). A number of observations can be drawn from this table.

First, the returns and volume for all four series show strong departures from normality, just as the coefficients of skewness and kurtosis are statistically different from those of a normal distribution although the magnitude is smaller in volume than returns except for the Japanese yen. The non-normality is due to leptokurtosis as shown by high kurtosis. Hence, a GARCH model is more appropriate to capture the return generating process than normal statistical methods.

Secondly, in contrast to the finding by Grammatikos, *et.al.*, (1986) the magnitude of price variability measured by standard deviation does not depend on the average daily trading volume. For instance, the German mark, the currency futures with the largest average daily trading volume, has only the third largest price variability, while the Swiss franc, which has the second smallest trading volume, has the highest price variability.

Thirdly, unlike returns, trading volume exhibits high significant serial correlation for all series in the first moment. However, in the Ljung-Box Q-statistic, proposed by McLeod and Li (1983) on returns and volume squared for testing second-order dependence and denoted by $LB^2(6)$, the presence of strong serial correlation (the ARCH effects) is detected, thus suggesting nonlinear dependence in both series. The test statistics have an asymptotic chi square (χ^2) distribution under the null hypothesis of no serial correlation in the series with 6 degrees of freedom.

Table 6.5 reports the autocorrelation coefficients and standard errors for returns, R and volume series, V. The results for returns indicate insignificant autocorrelation in all the series. They are not predictable using their own preceding day's returns. However, for the volume series, all four currency futures are highly correlated at the one percent level. Their first-order autocorrelation coefficients of 0.3630, 0.6211, 0.5332 and 0.5003 for the British pound, the German mark, the Japanese yen and the Swiss franc, respectively, indicate that about 13 percent, 38 percent, 28 percent and 25 percent of the volume in each currency futures contract may be predicted using yesterday's trading volume. Although the autocorrelations reduce as the number of lags increases, they remain significant, particularly for the German mark, a finding similar to that reported by Bessembinder and Seguin (1993).

Similar to the Q-statistic test, the Lagrange multiplier test used by Engle (1982) on returns and volume also rejects the null hypothesis of no ARCH effect as shown in Table 6.6A and B, based on the estimated TR^2 statistics where T = number of observations and R^2 represents the coefficient of determination from regressing the squared residual on a constant and its lagged values at r lags have a chi square distribution. The results indicate that the ARCH effects are present in both the daily percentage changes and the trading volume of all currency futures prices. The estimate suggests that price variations in the current period are related to price variations that have occurred over one, six and twelve previous periods. The evidence of nonlinear dependencies in the returns of currency futures series is similar to Hsieh's finding (1993) for four currency futures: the British pound, the German mark, the Japanese yen and the Swiss franc as well as to the finding of Chatrath, *et.al,* (1996) for five currency futures: the British pound, the German mark, the Canadian dollar, the Japanese yen and the Swiss franc.

Table 6.4: Descriptive Statistics of Currency Futures Returns and Synchronised Volume Series.

	BP		DM		JY		SF	
No. of observation	2863		2865		2861		2865	
Variables	R	V	R	V	R	V	R	V
Mean	0.0036	12228	0.1161	34335	0.0158	23515	0.0113	20998
Std. Dev.	0.7225	7057	0.7291	16263	0.7171	11363	0.8138	7970
Skewness	-.3350	3.109	-.0348	1.085	0.2267	1.080	0.0456	0.8268
Kurtosis	3.3842	2.356	2.0753	2.117	3.8458	2.046	1.7291	2.1730
J-B	1421	1019	514	1449	1806	2290	353	1816
Maximum	3.4748	100580	3.6013	128764	4.7533	90426	3.9271	77222
LB(6)	5.2671	907.81*	8.3960	4193*	10.066	2293.4*	9.2899	1845.4*
LB(12)	8.2168	1097.5*	13.276	6668.1*	28.247*	3089.5*	13.090	2259.6*
$LB^2(6)$	87.777*	115.14*	112.43*	2769.5*	75.060*	1668.3*	119.97*	1203.1*
$LB^2(12)$	152.99*	141.17*	198.72*	4141.3*	133.47*	2290.7*	194.67*	1429.4*

Notes: R stands for returns and V stands for volume. The critical values of Jarque-Bera (J-B) to test for normality are from the chi-square distribution with 2 degree of freedom, χ^2 (2): 4.61 , 5.99 and 9.21 for significance levels of 10%, 5% and 1%, respectively. LB(p) and LB ^{2} (p) is the Ljung-Box Q and Q^2-statistic, respectively, for the futures returns and squared futures returns for lag p. * Indicates statistically significant at 5% significance level.

Table 6.5: Autocorrelation Coefficient Currency Futures Returns and Volume Series.

	BP		DM		JY		SF	
No. of observation	2863		2865		2861		2865	
No.of Lags	R	V	R	V	R	V	R	V
1	-0.0056 (0.0234)	0.3630* (0.0314)	0.0075 (0.0213)	0.6211* (0.0246)	-0.0082 (0.0228)	0.5332* (0.0224)	0.0133 (0.0215)	0.5003* (0.0224)
2	-0.0093 (0.0225)	0.2338* (0.0230)	-0.0398 (0.0208)	0.5166* (0.0240)	-0.0311 (0.0211)	0.3885* (0.0216)	-0.0458 (0.0192)	0.3393* (0.0221)
3	-0.0064 (0.0219)	0.1848* (0.0209)	0.0045 (0.0207)	0.4807* (0.0222)	-0.0077 (0.0209)	0.3511* (0.0222)	-0.0070 (0.0200)	0.2927* (0.0206)
4	0.0141 (0.0212)	0.2116* (0.0219)	0.0100 (0.0201)	0.4672* (0.0207)	0.0067 (0.0201)	0.3117* (0.0206)	0.0051 (0.0202)	0.2973* (0.0212)
5	0.0245 (0.0212)	0.1788* (0.0190)	0.0038 (0.0199)	0.4407* (0.0208)	0.0181 (0.0217)	0.2858* (0.0195)	-0.0111 (0.0196)	0.2441* (0.0207)

Notes: R stands for returns and V stands for volume. * Indicates significance at 5% levels for two tail test.

Table 6.6: Lagrange Multiplier Test for the Presence of ARCH Effects.

A: Return Series

No.of Lags	BP	DM	JY	SF
ARCH (1)	30.337*	14.170*	19.082*	21.590*
ARCH (6)	65.628*	50.883*	38.824*	55.415*
ARCH (12)	98.730*	78.494*	55.819*	88.747*

B: Volume

No.of Lags	BP	DM	JY	SF
ARCH(1)	19.410*	121.492*	28.189*	34.887*
ARCH(6)	19.607*	132.157*	53.399*	37.550*
ARCH(12)	23.500*	160.425*	58.840*	40.055*

Notes: The test for presence of ARCH is given by Engle (1982). The ARCH (p) statistics, obtained as TR^2 from regressing the squared residual on a constant and its lagged value at p lags, is distributed asymptotically as $\chi^2(p)$ under the null hypothesis of no ARCH effects. The results indicate that ARCH effects are present in daily percentage changes in all currency futures prices. *Indicates statistically significant at 5% level.

6.4 Initial Tests of the Relationship Between Return Volatility and Trading Volume

Table 6.7 presents the estimated AR(1)-GARCH (1,1) model of currency futures returns without volume included in the explanatory variable. The parameters in the conditional variance for all the currency futures are statistically significant at the 5 percent level. The presence of integrated GARCH (IGARCH) found only in the British pound since the sum of ($\alpha_1 + \beta_1$) is fairly close to one. This indicates the persistence of past volatility in explaining current price volatility as discussed by Engle and Bollerslev (1986) while the other three currencies suggest a near-IGARCH since the sum of ($\alpha_1 + \beta_1$) is greater than 0.90 but less than 1.0. The fit of the GARCH(1,1) model is further evaluated by investigating the standardized residuals. The Ljung-Box Q-statistics of standardized residuals squared due to McLeod-Li do not indicate any further second-order serial dependence in any of the series, indicating that the GARCH (1,1) model does a reasonably good job in capturing the return behaviour of volatility. This model also reduces the skewness and kurtosis considerably; for example, the skewness for the German mark is almost completely removed.

Table 6.7: GARCH Model without Volume

Currency futures	GARCH (1,1)						
	α_1	β_1	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.0028* (4.7467)	0.9623* (312.87)	0.9948	-0.2480	2.7395	6.1047	6.1414
DM	0.0078* (4.9225)	0.9440* (138.75)	0.9857	0.0017	1.6026	6.7292	1.6578
JY	0.0118* (6.4550)	0.9374* (152.90)	0.9770	0.3147	3.3540	7.3266	3.6916
SF	0.0106* (4.3190)	0.9501* (133.52)	0.9841	0.0842	1.2827	6.5274	3.2227

Notes: Number in parentheses are t-statistics. LB(6) and $LB^2(6)$ refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags. *Indicates statistically significant at 5% level.

We take a step further by reexamining the general relationship between trading volume and price variability using the GARCH specifications. In the GARCH model, we include contemporaneous and uncorrelated trading volume as an explanatory variable for the conditional variance. The results presented in Table 6.8 and 6.10 using contemporaneous volume and uncorrelated volume, respectively, demonstrate that in all cases, the contemporaneous variables, denoted by δ_1 are highly significant. For example, in Table 6.8, the values of the coefficients and (*t*-statistics) are 0.3610 (39.938) for the British pound, 0.1270 (39.806) for the German mark, 0.1740 (45.895) for the Japanese yen and 0.7480 (36.897) for the Swiss franc. This suggests a strong contemporaneous relationship between volume and volatility, indicating that both variables are endogenous to the system. These findings strongly support the mixtures of distribution hypothesis (MDH) and provide evidence for the findings of Grammatikos, *et.al.*, (1986) and Harris (1987). This can be interpreted as information flow reflected in a volume proxy that is positively related to the futures price conditional variance and thus suggests pricing efficiency in the foreign currency futures markets since it implies that knowledge of current volume could not be used in explaining futures price variability. Therefore, the results are irrelevant to technical analysis since trading volume is found not to play to any significant role in providing information on the quality of the information contained in the return series

To validate the above results, we replace the contemporaneous volume and uncorrelated contemporaneous volume in the conditional variance equation with lagged raw volume and uncorrelated lagged volume, the results of which are reported in Tables 6.11 and 6.12, respectively. In all cases, the lagged variables are insignificant at 5 percent level, rejecting the sequential information model (SEQ) but confirming the above findings of a contemporaneous relationship between variables.

6.5 A Test of GARCH Effects

Since our purpose is to examine the information content of trading volume, we reestimate the GARCH (1,1) model in Equation 4.8 with volume included in the variance equation. Table 6.8 shows that the coefficient on volume, δ_1, is significantly positive for each of the currency futures examined, thus supporting the results of Grammantikos and Saunder (1986) and Lamoureux and Lastrapes (1990) but contradicting those of McCarthy and Najang (1993) and Najang and Yung (1991). The goodness-of-fit for the Ljung-Box Q-statistics shows that the residuals $V_{t.}$ are cleared of any linear dependence for all currency futures at the 5 percent level. However, the statistics for the squared standardized residuals, denoted by $LB^2(6)$, are highly correlated and this indicates that the time series of currency futures prices exhibit significant nonlinear dependence, and thus cannot be modelled as strict white noise processes. Overall, the statistics suggest that volume does not explain much of the nonnormality of the unconditional distribution. The results also show that when the unrestricted model is applied; *i.e.,* δ_1 is unconstrained, the persistence in volatility as measured by $(\alpha_1 + \beta_1)$, is reduced dramatically and becomes negligible when δ_1 is restricted to zero. These results are similar to those of Lamoureux and Lastrapes (1990) but contradict those of Najang and Yung (1991).

A possible explanation of these results lies in the complex structure of Equation 4.31 (see Chapter 4) in which both lag conditional variance, h_{t-1}, and trading volumes, v_t are included as explanatory variables. The problem arises from the fact that conditional variance can be explained not only by past conditional volatilities but also by current trading volumes. Also, the trading volume shows a high serial correlation and can lead to a high correlation between the explanatory variables used in the equation. As a result, the serial dependence in the trading volume and past conditional volatilities can be argued to have similar information content. Either one of these can be included in the conditional variance as a proxy of information content. The results of Lamoureux and Lastrapes (1990) support this argument in that their coefficient estimates and standard errors of past conditional volatility are mostly zero (negligible) when the correlated trading volume is included in the conditional variance of price changes.

Table 6.8: GARCH Model with Contemporaneous Volume

Currency futures	GARCH (1,1) + Volume							
	α_1	β_1	δ_1 (10^{4})	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.0238* (2.8882)	0.00 (0.00)	0.3610* (36.938)	0.0238	-0.4048	2.9848	8.7215	82.662*
DM	0.0221* (2.1270)	0.00 (0.00)	0.1270* (39.806)	0.0221	0.0917	1.6471	8.2998	71.766*
JY	0.1019* (13.716)	0.00 (0.00)	0.1740* (45.895)	0.1019	0.3200	2.0612	14.965 *	53.622*
SF	0.0479* (5.2459)	0.00 (0.00)	0.7480* (36.897)	0.0479	0.0813	1.1821	9.6025	66.095*

Notes: Number in parentheses are t-statistics. LB(6) and $LB^2(6)$ refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags.*Indicates statistically significant at 5% level.

6.5.1 Contemporary Volume

Summary statistics from the univariate autoregressive model of AR(p) are reported in Table 6.9. The Ljung-Box Q-statistics for unstandardized residuals, over 6 and 12 lags, denoted by LB(6) and LB(12) respectively, are insignificant at the 5 percent level, rejecting the null hypothesis of correlated residuals. The lag length required to produce uncorrelated residuals without overfitting the model is 5, 7, 5 and 4 for the British pound, the German mark, the Japanese yen and the Swiss franc, respectively. These results also suggest that important information does exist in the trading volume of recent (from 4-7) past days. However, the information decays after that period.

As noted earlier, if the volume of trade is serially correlated, then volatility persistence should become negligible in the conditional variance equation. Our results support this hypothesis which has been shown earlier. However, since the unexpected volume, V^* is serially uncorrelated by construction, we argue then that a significant coefficient, δ_1, cannot be attributed to V^* and thus capture the serial correlation in the rate of information arrival.

In Table 6.10, we report the values of p and q and the corresponding log-likelihood for each of the models with normally distributed conditional errors when Equation 4.33 (see Chapter 4) is estimated. Their p and q values are, respectively, 2 and 2 for the British pound; 3 and 4 for the German mark; 2 and 4 for the Japanese yen and 3 and 3 for the Swiss franc. Their log-likelihood values are -2949.43 for the British pound; -2979.90 for the German mark; -2856.98 for the Japanese yen and -3337.08 for the Swiss franc. Table 6.10 also presents other estimation results. Similar to the results obtained in Table 6.8 for trading volume, the estimated parameters of unexpected volume, δ_1, are highly significant for all currency futures although marked by a notable reduction in both size and level of significance. These results indicate that there is information hidden in the uncorrelated trading volume which leads to a significant relationship between the uncorrelated component of trading volume and the variance of price changes. Similarly, the α's remain highly significant for all currency futures, suggesting that the lagged squared residuals still contribute significant information content even after including the rate of information flow proxy (unexpected volume) in the conditional variance. However, volatility persistence is less in the results of the model which exclude volume, though it is still more than the results which include correlated volume, where it is negligible. This implies that the conditional variance of currency futures changes is a function of both the unexpected volume of trade and the GARCH effects, which contradicts the findings of Lamoureux *et.al.*(1990) and also our earlier findings using a correlated mixing variable (raw volume).

Table 6.9: Autoregressive Models for Trading Volume

Currency futures	AR(p)	LB(6)	LB(12)	Log-likelihood
BP	5	1.2446	20.321	-29146.6
DM	7	3.8431	12.897	-30917.1
JY	5	4.1024	14.280	-30213.0
SF	4	2.1600	10.590	-29287.7

Notes: LB(6) and LB(12) refer to the Ljung-Box Portmanteau statistic for unstandardized residuals, over 6 and 12 lags, respectively.

Table 6.10: GARCH (p,q) - Unexpected Contemporaneous Volume Model

	GARCH (p,q) + Unexpected Volume			
	BP	DM	JY	SF
(p,q)	(2,2)	(3,4)	(2,4)	(3,3)
C	0.0235* (2.0555)	0.0010 (0.8550)	0.0081 (0.7022)	0.0004 (0.0272)
R(-1)	-0.0235 (-1.1136)	-0.0200 (-0.9993)	-0.0393 (-1.8536)	0.0013 (0.0652)
α_0	0.0328* (4.9724)	0.0501* (3.8697)	0.0375* (3.3686)	0.0715* (3.9049)
α_1	0.1133* (9.8476)	0.1144* (6.2195)	0.1432* (7.5570)	0.1118* (6.3296)
α_2	0.1416* (8.8365)	0.1080* (6.6431)	0.0822* (6.0955)	0.0485* (3.7463)
α_3	-	0.0669* (3.9493)	-	0.0574* (4.0717)
β_1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.0109 (0.2413)
β_2	0.6257* (27.013)	0.00 (0.00)	0.1874* (4.7973)	0.00 (0.00)
β_3	-	0.1450* (2.9346)	0.0003 (0.0339)	0.5150* (12.002)
β_4	-	0.3070* (5.6585)	0.3065* (7.6879)	-
α 's + β 's	0.8806	0.7413	0.7196	0.7436
δ_1 (10^5)	0.1003* (10.105)	0.6223* (10.196)	0.1172* (13.793)	0.2177* (9.8475)
Log Likelihood	-2949.43	-2979.90	-2.856.98	-3337.08
Skewness	-0.1845	-0.0431	0.2346	0.0169
Kurtosis	1.7061	0.9636	1.1795	0.7796
LB(6)	7.7308	6.1923	13.933*	6.8459
LB(12)	13.537	13.254	35.104*	13.497
$LB^2(6)$	4.4433	3.5783	8.9716	5.4638
$LB^2(12)$	14.821	35.415*	39.566*	26.485*

Notes: p and q are the order of the autoregressive and moving average specifications of the GARCH model, respectively. δ_1 is the coefficient of unexpected volume. * Indicates statistically significant at 5% level.

Test for Model Specifications

The fit of the GARCH (p,q) model is further evaluated by investigating the standardized residuals, $z_{i,t}=\varepsilon_{i,t}/\sigma_{i,t}$. The summary statistics of the standardized residuals assuming normal distributions are reported in the last six rows of Table 6.10. The Ljung-Box Q-statistics of lag 6 and 12, denoted by LB(6) and LB(12) respectively, are not statistically significant at the usual 5 percent level except for the Japanese yen. However, McLeod-Li's Ljung-Box Q-statistics of the standardized residual squared for lags 6 and 12, denoted by $LB^2(6)$ and $LB^2(12)$ respectively, are reduced considerably but are still statistically significant in long lags which suggests that second-order serial dependence is not yet removed from the series, except for the British pound. In most cases, the GARCH (p,q) model also reduces the skewness and leptukurtosis considerably more than the GARCH (1,1) model of the return series. For example, the excess kurtosis are all well below 1.8 as compared to the return series which have values from 1.729 to above 3.0. It seems that in most cases there is a need for more GARCH parameters than merely the GARCH (1,1) when the unexpected volume is included in the conditional variance equation of currency futures returns.

6.5.2 Lagged Volume

Table 6.11 presents the coefficient estimation of δ_1 in the GARCH (1,1) model with lagged volume. It is worth noting that, the t-statistics are insignificant for all the currency futures at the 5 percent level. The highest level of t-statistics of this estimation are 1.9218 for the Japanese Yen followed by 1.6801 for the Swiss franc. This shows that the volume proxied by lagged volume has no explanatory power in the return generating process. The present results thus imply that knowledge of the previous day's volume cannot significantly improve forecast of today's price. However, α_1 , the coefficient on the lagged squared residual term (ε_{t-1}^2) and β_1, the coefficient on the lagged conditional variance term (h_{t-1}) both increase dramatically to a highly significant level for all currency futures. These findings suggest that the introduction of lagged volume as an explanatory variable in the conditional variance equation does not eliminate the GARCH effect but rather increases it. Moreover, the persistence in volatility as measured by ($\alpha_1 + \beta_1$) is fairly close to one which is significantly high. These results contradict those of Lamoureux and Lastrapes (1990) and earlier results using contemporaneous volume. Our results also indicate that there is no simultaneity problem in the conditional variance equation discussed by Najang and Yung (1991) and, therefore, that lagged volume may be a poor proxy for contemporaneous volume. These results seem to suggest that information arrival to investors is contemporaneous in nature and thus, does not follow a sequential (SEQ) process.

Table 6.11: GARCH Model with Lagged Volume

Currency futures	GARCH (1,1) + Lagged Volume							
	α_1	β_1	δ (10'')	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.0329* (12.662)	0.9617* (308.15)	0.00 (0.00)	0.9946	-0.2456	2.7266	6.2602	6.0676
DM	0.0409* (8.5675)	0.9443* (137.50)	0.3410 (0.6317)	0.9852	0.0011	1.6123	6.7078	1.6860
JY	0.0369* (9.2892)	0.9397* (154.68)	0.1510 (1.9218)	0.9766	0.3082	3.2863	7.2932	4.0015
SF	0.0285* (6.9833)	0.9568* (153.15)	0.2720 (1.6801)	0.9853	0.0854	1.3592	7.9288	4.0289

Notes: Number in parentheses are t-statistics. LB(6) and LB2(6) refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags. * Indicates statistically significant at 5% level.

Table 6.12 presents the results when a GARCH (p,q) model with unexpected lagged volume is employed. There is no correlation between price variability and the lagged volume measured by estimation coefficient, δ_1, in the GARCH model for any of the currency futures which totally contradicts the results in Table 6.10, using unexpected contemporaneous volume. However, the sums ($\alpha_1 + \beta_1$) increase and are fairly close to one, which indicates that a substantial part of currency futures price volatility can be explained by past volatility, which tends to persist over time. Similarly, the GARCH effects remain high for all currency futures and many of them could be well explained by the lagged squared residual and lagged variance and not by the unexpected lagged volume.

Similar to the results shown in Table 6.11, the estimated coefficient, δ_1. is statistically insignificant, suggesting that information arrival as proxied by unexpected lagged volume does not possess significant explanatory power and cannot replace unexpected contemporaneous volume in explaining the return generating process. These results seem to agree with those of Lamoureux and Lastrapes (1990) who find that lagged volume and fitted value from univariate regression on volume are poor instruments for contemporaneous volume and therefore have little explanatory power in the variance equation.

Overall, our findings seem to indicate a strong positive relationship between contemporary uncorrelated trading volume and price change, which supports Grammatikos, *et.al.,* (1986). These results are consistent with the mixture of distribution hypothesis (MDH), first developed by Clark (1973) and supported by Tauchen, *et.al.* (1983) and Harris (1986). The fact that contemporaneous volume contains information on current price variability may suggest *prima facie* informational efficiency in the currency futures market, and if this is so, no trader can effectively use current trading volume to forecast possible futures price variability.

Table 6.12: GARCH (p,q) - Unexpected Lagged Volume Model

	GARCH (p,q) + Unexpected Lagged Volume			
	BP	DM	JY	SF
(p,q)	(2,2)	(3,4)	(2,4)	(3,3)
C	0.0135 (1.1933)	0.0032 (0.2617)	0.0091 (0.7219)	-0.0002 (-0.0113)
R(-1)	-0.0190 (-0.9927)	-0.0045 (-0.2272)	-0.0099 (-0.4580)	0.0144 (0.7181)
α_0	0.0056* (4.8090)	0.0277* (5.6048)	0.0331* (5.9488)	0.0235* (3.1125)
α_1	0.0306* (9.5793)	0.0561* (6.0769)	0.0909* (7.5023)	0.0467* (5.9599)
α_2	0.0339* (8.0743)	0.0668* (7.2940)	0.0206 (1.2785)	0.0159* (2.7633)
α_3	-	0.0195* (2.9827)	-	0.0313* (4.6432)
β_1	0.00 (0.00)	0.00 (0.00)	0.2045* (2.3380)	0.00 (0.00)
β_2	0.9250* (151.95)	0.00 (0.00)	0.0070 (0.1413)	0.00 (0.00)
β_3	-	0.00 (0.00)	0.00 (0.00)	0.8663* (46.843)
β_4	-	0.8068* (41.543)	0.6121* (13.698)	-
α 's + β 's	0.9895	0.9492	0.9351	0.9602
δ (10^5)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.6388 (1.2636)
Skewness	-0.2519	-0.0118	0.2657	0.0722
Kurtosis	2.7475	1.5304	3.0320	1.2636
LB(6)	6.2886	6.6723	7.5560	6.7838
LB(12)	9.1562	12.939	27.773*	14.786
$LB^2(6)$	6.4906	1.3039	1.6752	3.0452
$LB^2(12)$	10.2517	3.9980	3.6127	7.2732

Notes: p and q are the order of the autoregressive and moving average specifications of the GARCH model, respectively. δ_1 is the coefficient of unexpected volume. * Indicates statistically significant at 5% level.

6.6 Consistency of Results Across Subsample

Lucas (1976) notes that the above econometric technical analysis is probably not structurally stable in the sense that the estimated coefficients may depend on many factors, such as government policies pursued by different countries and changes in the source and type of technology. These may generate real growth and aggregative fluctuations. Thus, the variances of the underlying stochastic process may vary between the two subperiods. An additional reason to investigate whether subperiods provide the same type of inference as a full sample, as mentioned by Hodrick and Srivastava (1987), is because prices in speculative markets such as futures and options possess stochastic properties that correspond to theories of efficient markets only after the markets are mature. This suggests that the results from the full sample could differ from the results of the samples of the first and second subperiods as well as differing between subperiods.

The results for Subsample 1 and 2, using expected and unexpected contemporaneous volume, and the expected and unexpected lagged volume model are discussed below.

Expected and Unexpected Contemporaneous Volume

The results of the subsamples are presented in Tables 6.13 - 6.20. Tables 6.13 and 6.17, report the results for the first and second subsamples of the GARCH model with volume that corresponds to the similar specification used in Table 6.8 for the full sample. Tables 6.14 and 6.18, reports the results for the first and second subsamples of the GARCH model with unexpected volume that corresponds to the specification used in Table 6.10 for the full sample. Tables 6.15 and 6.19, present the results for the first and second subsamples of the GARCH model with lagged volume that corresponds to the similar specification used in Table 6.11 for the full sample, and Tables 6.16 and 6.20, present the results for the first and second subsamples of the GARCH model with unexpected lagged volume that corresponds to the specification used in Table 6.12 for the full sample.

There are several interesting differences between the subsamples, and across the full sample and subsamples. The results displayed in Table 6.13 report that the coefficient on the lagged squared error term is insignificant for Subsample 1 for all currency futures except the Japanese yen but highly significant for Subsample 2, as shown in Table 6.17. However, the coefficient on the lagged conditional variance term is reduced completely to zero for both subsamples, an insignificant result which is similar to those for the full sample. Taken together, the findings of Subsample 1, with the exception of those for the Japanese yen, are similar to those of the full sample as shown above, and also to those of Lamoureux and Lastrapes (1990) who show that the GARCH effects vanish in the presence of volume for all but four of the 20 stocks in their sample.

As for the GARCH model with unexpected volume included in the conditional variance, the δ_1 in both subsamples remains significant. These results are almost the same as those for the full sample although marked by a notable reduction in size. Similarly, the persistence of volatility, as measured by $(\alpha_1 + \beta_1)$, is slightly reduced for the majority of the currency futures in both subsamples with the exception of the

British pound and the Swiss franc in Subsample 1, both of which show a dramatic reduction, to 0.0931 and 0.1051, respectively. These results show that lagged squared residuals have insignificant information content after taking into account additional information of unexpected contemporaneous volume in the conditional variance equation of the currency futures return process.

Test Goodness-of-Fit

To assess the specification of our GARCH (1,1) model, we obtain a time series of standardized residuals and standardized residuals squared from the unexpected contemporaneous volume regression in Equation 4.33, for both subperiods. Summary statistics for these residuals, assuming normal distributions, are reported in the last six rows of Tables 6.14 and 6.18 for Subsamples 1 and 2, respectively. First order and/or second order dependence, denoted by LB(.) and $LB^2(.)$, are found in all currency futures but for different subperiods. As for skewness and kurtosis, there is generally not much difference between the subperiods, or between the superiods and the entire period. Thus, it is possible to conclude that there is no structural problem in the time series of the currency futures.

Expected and Unexpected Lagged Volume

Tables 6.15 and 6.19, present the results for Subsamples 1 and 2, of the model with expected lagged volume included in the conditional variance of GARCH (1,1).These results differ in a quite an interesting manner from those using contemporaneous volume. The estimated coefficient, δ_1 is statistically significant at 5 percent level for all the currency futures except for the German mark, although in different subsamples and while the British pound in Subsample 1 is positive and statistically significant, the relationship between the returns and lagged volume does not continue into Subsample 2. On the other hand, the coefficient estimates for the Japanese yen and the Swiss franc are positive and significant in Subperiod 2 only, and the results for persistence in volatility and the GARCH effect remains high in both subsamples which is similar for the results of the full sample. Taken together, these results suggest that lagged volume is a poor proxy for information flow since it cannot explain the large variance of return in the generating process.

Finally, Tables 6.16 and 6.20 report the results for Subperiod 1 and 2 of the GARCH (p,q) model with unexpected lagged volume included in the conditional variance equation. None of the estimated coefficients δ_1 are statistically significant at the 5 percent level in either subsample, which is similar to the results for the full sample except in the case of the Swiss franc in Subsample 2. The persistence in volatility remains high in both subsamples except for the British pound in Subsample 1. These results are no different from those discussed above for the model with lagged volume; lagged unexpected volume has no additional information content and is a poor proxy for volume.

Test Goodness-of-Fit

Next, we focus the goodness-of-fit tests for the GARCH model of uncorrelated volume for both subsamples. The standardized residuals and standardized residuals squared are obtained from the lagged regression in Equation 4.33 (see Chapter 4). In subsample 1, no first order dependence is detected in any case. However, significant second order dependence is found in the British pound and the Swiss franc. On the other hand, Subsample 2 shows insignificant second order dependence in all cases but exhibits significant first order dependence in two cases. As for skewness and lepkurtosis, the results for both subperiods are almost similar to those for the full period.

The overall results of the subperiods do not differ significantly from the findings for the full sample. Thus, we can safely suggest that the currency futures returns and volume series do not exhibit heterogenous behaviour over the entire 11-year period.

Subsample 1 (Jan. 1, 1986- Sept.18, 1991)

Table 6.13: GARCH Model with Volume

Currency futures	GARCH (1,1) + Volume							
	α_1	β_1	δ (10^4)	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.0105 (1.0179)	0.00 (0.00)	0.4152* (21.912)	0.0105	-0.3827	2.0695	12.644*	5.5149
DM	0.00 (0.00)	0.00 (0.00)	0.1573* (28.058)	0.0000	0.1254	1.3731	7.5010	20.484*
JY	0.0779* (3.2613)	0.00 (0.00)	0.1790* (29.263)	0.0779	0.3698	1.8093	4.7761	31.269*
SF	0.00 (0.00)	0.00 (0.00)	0.2425* (21.631)	0.0000	0.1092	0.8396	7.1368	43.516*

Notes: Number in parentheses are t-statistics. LB(6) and $LB^2(6)$ refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags. *Indicates statistically significant at 5% level.

Table 6.14: GARCH (p,q) - Unexpected Contemporaneous Volume Model

	GARCH (p,q) + Unexpected Volume			
	BP	DM	JY	SF
(p,q)	(2,2)	(3,4)	(2,4)	(3,3)
C	0.0313 (1.6551)	0.0196 (1.0973)	0.0251 (1.3966)	0.0138 (0.6498)
R(-1)	-0.0054 (-.01788)	-0.8803 (-0.3165)	-0.0330 (-1.0681)	-0.0088 (-0.3355)
α_0	0.3971* (21.125)	0.0436* (2.0841)	0.0666* (2.9808)	0.4360* (9.9947)
α_1	0.0899* (5.5727)	0.0621* (2.8357)	0.1651* (4.9159)	0.0135 (0.5902)
α_2	0.0032 (0.2076)	0.0956* (3.7119)	0.0515* (2.6228)	0.0137 (0.8413)
α_3	-	0.0557* (2.3314)	-	0.0252 (0.9828)
β_1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
β_2	0.00 (0.00)	0.0246 (0.2228)	0.2689* (3.4946)	0.00 (0.00)
β_3	-	0.2370 (1.9215)	0.0710 (1.1982)	0.0527 (0.8558)
β_4	-	0.2769* (3.2350)	0.1158 (1.5446)	-
α 's + β 's	0.0931	0.7519	0.6723	0.1051
δ (10^5)	0.5607* (6.6805)	0.1145* (7.0536)	0.1478* (10.089)	0.4664* (6.9646)
Skewness	-0.1926	-0.0207	0.3702	0.0506
Kurtosis	1.3477	0.7628	1.3433	0.6067
LB(6)	12.485*	5.0905	4.7438	6.5846
LB(12)	20.337*	15.887	14.528	11.137
$LB^2(6)$	7.9733	4.2631	10.789	29.388*
$LB^2(12)$	23.327*	20.206	34.399*	65.130*

Notes: p and q are the order of the autoregressive and moving average specifications of the GARCH model, respectively. δ is the coefficient of unexpected volume. * Indicates statistically significant at 5% level.

Table 6.15: GARCH Model with Lagged Volume

Currency futures	GARCH (1,1) + Lagged Volume							
	α_1	β_1	$\delta\ (10^6)$	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.0244* (4.8954)	0.9535* (95.73)	0.7853* (2.1399)	0.9779	-0.3568	1.9546	8.2956	2.3055
DM	0.0572* (5.6097)	0.9061* (49.973)	0.1319 (0.6501)	0.9633	-0.0072	1.3261	5.6959	3.7130
JY	0.0476* (5.9597)	0.9111* (49.405)	0.00 (0.00)	0.9587	0.2414	2.1317	3.0468	5.3743
SF	0.0401* (3.6115)	0.9140* (31.958)	0.00 (0.00)	0.9541	0.0622	0.7906	4.8078	11.978

Notes: Number in parentheses are t-statistics. LB(6) and $LB^2(6)$ refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags. * Indicates statistically significant at 5% level.

Table 6.16: GARCH (p,q) - Unexpected Lagged Volume Model

	GARCH (p,q) + Unexpected Lagged Volume			
	BP	DM	JY	SF
(p,q)	(2, 2)	(3, 4)	(2, 4)	(3, 3)
C	0.0170 (0.8346)	0.0250 (1.3309)	0.0250 (1.2907)	0.0220 (1.0058)
R(-1)	0.0350 (1.3417)	0.0007 (0.0251)	-0.0230 (-0.7932)	0.0063 (0.2190)
α_0	0.5749 (0.0070)	0.0385* (2.0009)	0.0489* (3.4896)	0.0962 (1.1377)
α_1	0.0009 (0.0007)	0.0251 (1.3695)	0.0651* (5.0773)	0.00 (0.00)
α_2	0.00 (0.00)	0.0711* (2.9725)	0.0605* (4.6702)	0.0062 (0.3521)
α_3	-	0.0312 (0.8547)	-	0.0282 (0.9038)
β_1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.4477 (0.4474)
β_2	0.00 (0.00)	0.3822 (0.8357)	0.1547* (2.1487)	0.3725 (0.3698)
β_3	-	0.4055 (1.0677)	0.00 (0.00)	0.0080 (0.0115)
β_4	-	0.00 (0.00)	0.6278* (8.8432)	-
α 's + β 's	0.0077	0.9151	0.9081	0.8626
δ (10^6)	0.00 (0.00)	0.1345 (1.6682)	0.00 (0.00)	0.00 (0.00)
Skewness	-0.2940	-0.0004	0.2068	0.0489
Kurtosis	2.5963	1.2365	1.8845	0.9027
LB(6)	10.394	5.5677	2.7979	5.3108
LB(12)	15.109	13.618	11.035	9.2741
$LB^2(6)$	17.503*	1.9535	6.7369	13.621
$LB^2(12)$	32.268*	8.9124	11.402	22.937*

Notes: p and q are the order of the autoregressive and moving average specifications of the GARCH model, respectively. δ is the coefficient of unexpected volume. * Indicates statistically significant at 5% level.

Subsample 2 (Sept. 19, 1991- April 30, 1997)

Table 6.17: GARCH Model with Volume

Currency futures	GARCH (1,1) + Volume							
	α_1	β_1	$\delta\ (10^{4})$	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.0440* (2.6486)	0.00 (0.00)	0.2793* (31.568)	0.0440	-0.2838	2.3680	16.698*	270.57*
DM	0.0503* (3.0527)	0.00 (0.00)	0.9900* (26.761)	0.0503	-0.1086	0.8484	11.976*	42.551*
JY	0.0307* (2.0016)	0.00 (0.00)	0.1652* (30.247)	0.0307	0.1573	1.6936	21.962*	34.105*
SF	0.0684* (4.1228)	0.00 (0.00)	0.2526* (28.971)	0.0684	-0.0498	1.1649	10.787	39.380*

Notes: Number in parentheses are t-statistics. LB(6) and $LB^2(6)$ refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags. *Indicates statistically significant at 5% level.

Table 6.18: GARCH (p,q) - Unexpected Contemporaneous Volume Model

	GARCH (p,q) + Unexpected Volume			
	BP	DM	JY	SF
(p,q)	(2,2)	(3,4)	(2,4)	(3,3)
C	0.0209 (1.4990)	-0.0041 (-0.2707)	-0.0074 (-0.4924)	-0.0123 (-0.6485)
R(-1)	-0.0815* (-2.7824)	-0.0486 (-1.6705)	-0.0409 (-1.4308)	-0.0032 (-0.1038)
α_0	0.0147* (3.2953)	0.0678* (6.1172)	0.0563* (3.2705)	0.0862* (3.9921)
α_1	0.1235* (6.6205)	0.1662* (6.1172)	0.1121* (4.8412)	0.1662* (6.2152)
α_2	0.1965* (7.3589)	0.0829* (4.3834)	0.1035* (4.5059)	0.0012 (0.0733)
α_3	-	0.0422 (1.7588)	-	0.0637* (3.3391)
β_1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
β_2	0.5542* (19.842)	0.00 (0.00)	0.0266 (0.5166)	0.00 (0.00)
β_3	-	0.0395 (0.7822)	0.0888 (1.5799)	0.4870* (13.065)
β_4	-	0.2372* (4.0940)	0.2576* (4.6588)	-
α 's + β 's	0.8742	0.5680	0.5886	0.7181
δ (10^6)	0.9696* (9.2771)	0.6717* (8.5847)	0.2576* (10.559)	0.1802* (7.6644)
Skewness	-0.0186	-0.1142	0.0946	-0.0635
Kurtosis	1.3898	0.5958	1.1025	1.2011
LB(6)	16.995	13.505*	17.426*	8.7007
LB(12)	21.767*	16.039	29.522*	14.603
$LB^2(6)$	6.7781	3.2955	3.1012	1.5131
$LB^2(12)$	18.729	23.180*	25.022*	17.186

Notes: p and q are the order of the autoregressive and moving average specifications of the GARCH model, respectively. δ is the coefficient of unexpected volume. * Indicates statistically significant at 5% level.

Table 6.19: GARCH Model with Lagged Volume

Currency futures	GARCH (1,1) + Lagged Volume							
	α_1	β_1	δ (10^6)	$\alpha_1 + \beta_1$	Skewness	Kurtosis	LB(6)	$LB^2(6)$
BP	0.3361* (10.503)	0.9610* (255.30)	0.00 (0.00)	1.2971	-0.0367	3.6979	17.821*	6.8788
DM	0.0289* (5.8629)	0.9588* (135.41)	0.1035 (1.8519)	0.9877	0.0118	1.9937	12.045*	4.1456
JY	0.0328* (5.7439)	0.9460* (124.42)	0.3096* (3.4298)	0.9788	0.4273	4.4674	13.882*	2.7579
SF	0.0259* (5.6805)	0.9629* (151.29)	0.3595* (3.5261)	0.9888	0.1094	1.8848	8.0874	10.882

Notes: Number in parentheses are t-statistics. LB(6) and $LB^2(6)$ refer to the Ljung-Box Portmanteau statistic for standardized residuals and standardized residuals squared, respectively, over 6 lags. * Indicates statistically significant at 5% level.

Table 6.20: GARCH (p,q) - Unexpected Lagged Volume Model

	GARCH (p,q) + Unexpected Lagged Volume			
	BP	DM	JY	SF
(p,q)	(2, 2)	(3, 4)	(2, 4)	(3,3)
C	0.0123 (0.8671)	-0.0139 (-0.8115)	-0.0058 (-0.3378)	-0.0263 (-1.3649)
R(-1)	-0.0634* (-2.3311)	-0.0034 (-0.1174)	0.0077 (0.2349)	0.0147 (0.5244)
α_0	0.0051* (3.8655)	0.0108* (3.0925)	0.0270* (4.9379)	0.0024 (0.4841)
α_1	0.0260* (5.8587)	0.0632* (5.2826)	0.1225* (9.4193)	0.0629* (7.0074)
α_2	0.0455* (5.9875)	0.00 (0.00)	0.00 (0.00)	0.0052 (0.7257)
α_3	-	0.0332* (2.5482)	-	0.0077 (0.9726)
β_1	0.00 (0.00)	0.00 (0.00)	0.2608* (4.4291)	0.00 (0.00)
β_2	0.9167* (109.12)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
β_3	-	0.7526* (9.8923)	0.00 (0.00)	0.9083* (67.542)
β_4	-	0.1269 (1.7746)	0.5661* (10.147)	-
α 's + β 's	0.9882	0.9759	0.9494	0.9841
δ (10^6)	0.00 (0.00)	0.4271 (0.3648)	0.00 (0.00)	0.1517* (2.4226)
Skewness	-0.0489	-0.0187	0.3197	0.0092
Kurtosis	3.6368	1.8671	3.9245	1.4818
LB(6)	17.284*	12.230	14.663*	10.206
LB(12)	20.652	17.065	27.545*	19.278
$LB^2(6)$	6.8053	1.8645	1.1894	5.3951
$LB^2(12)$	9.4937	5.1543	4.4188	9.6496

Notes: p and q are the order of the autoregressive and moving average specifications of the GARCH model, respectively. δ is the coefficient of unexpected volume. * Indicates statistically significant at 5% level.

6.7 Conclusion

The relationship between volume and volatility in the futures markets has been of considerable interest to researchers as well as practitioners (traders) for many years. Recently, there has been a dramatic increase in the interest in exploring the role of volume in explaining price variability in the futures markets. The main reason for this development is the critical role that trading volume plays in the modelling of price variability. As noted by Blaum, *et.al.*, (1994) volume statistics provide information to the market that cannot be conveyed by the price. Therefore, it becomes natural for the trader to watch volume because it compliments the information provided by prices.

In this chapter, the conditional variance for four daily currency futures returns has been modelled using the generalized ARCH specification with contemporaneous and lagged trading volume proxied for information flow as a regressor in the conditional variance equation. The summary of the results are as follows:

1. It can be shown that the contemporaneous trading volume is positively correlated with the returns which supports the mixture of distribution hypothesis (MDH). Specifically, these results suggest that the level of trading volume positively influences the conditional variance of the futures price changes for all the currency futures examined. Moreover, the GARCH effects disappear when volume is included in the conditional variance equation, thus supporting the findings of Lamoureux and Lastrapes (1990).

2. Since trading volume is highly serially correlated, which can lead to a high correlation

between the explanatory variables, this study has replaced volume with unexpected volume in the conditional variance, following the procedure of Bessembinder and Seguin (1992). We find similar results of a significant positive relationship between variables but with reduced values of *t*-statistics. Similarly, volatility persistence has also reduced considerably. However, the GARCH effects have not disappeared, contradicting our first finding using correlated volume.

3. To overcome the problem of simultaneity, Harvey (1989) points out that lagged values of endogenous variables should be used because they are classified, together with exogenous variables, as predetermined. In this study, we treat uncorrelated volume as exogenous and reestimate the model using lagged values of uncorrelated volume. The results show that lagged uncorrelated volume has little explanatory power in the conditional variance equation which suggests that there is no simultaneity problem in the equation, as dicussed by Najang and Yung (1991) and that therefore, lagged volume may be a poor proxy for contemporaneous volume.

To sum up, these results suggest that the introduction of unexpected volume as an explanatory variable in the conditional variance equation does not remove the GARCH effects completely. However, it reduces the volatility persistence for all the series examined.

Therefore, employing unexpected volume in addition to the lagged squared residuals or lagged squared variance contributes additional information in explaining the conditional variance of the currency futures markets. The results for the subperiods are almost identical to those of the full periods for most of the currencies under analysis, suggesting structural stability in the entire sample period.

Chapter Seven

Mean and Volatility Spillover

7.1. Introduction

Most of the studies on mean and volatility transmission have focused on the spot equity markets instead of the futures markets and have, in general, concentrated on stock price movements across international stock markets. For example, Eun and Shim (1989), who were among the earliest to study spillover, found that innovations (shocks) in the U.S market are rapidly transmitted to the rest of the world, although innovations in other national markets do not have much effect on the U.S. market.

In the futures markets, Najang, *et.al.*, (1992) were the first to examine volatility spillover employing Generalized Autoregressive Conditional Heteroscedasticity (GARCH) methodology. They explored the extent to which foreign currency futures shocks impinge on other currencies and also the channels through which these are transmitted. Four currency futures were examined over a 10 year period from January 1980 to December 1989, using daily data from the Chicago Mercantile Exchange for the British pound, the German mark, the Japanese yen and the Swiss franc. In general, their findings indicated that during some period or other all the currencies were involved in transmitting volatility to other currencies.

The present study re-examines volatility transmission across the four currency futures and extends the current methodology in a number of ways. First, following Theodossiou and Lee (1993) and Susmel and Engle (1994), the volatility mechanisms on both the conditional first and second moments in currency futures returns are examined across the four currency futures. We allow for changing conditional variances as well as conditional mean returns; in other words, we introduce information from one currency futures contract into the mean and conditional variance of another currency futures contract. As Engle (1982) argues, it is reasonable for asset return variances to be conditional on current information given that their means are conditional on this data set. We extend his argument to include both the mean and the variance of price changes and suggest that they are related directly to the rate of flow of information. Thus, through examining the mean and volatility mechanism, a thorough understanding of the information transmission process may be gained. In addition, diagnostic tests are applied to assess the robustness of the model and to identify possible time structure changes (using subperiods) in the correlation of returns among the four markets.

Secondly, following Hamao *et.al.,* (1990), the present study applies both pairwise analysis between currency futures and an examination of the expanded exogenous variables; *i.e.,* multi-currency futures analysis in the conditional mean and conditional variance equations. In the pairwise analysis, we include the past returns and past squared residuals from only one other foreign currency futures contract in the conditional mean and conditional variance equations. However, in the multi- currency futures analysis, we include the past returns and past squared residuals from the other three markets in the conditional mean and conditional variance equations. This analysis is important since it tests whether expanding variables to include the third and fourth currency futures in the equations has any effect on their mean and volatility coefficients. This common economic effect, as discussed by Hamao et al., (1990), needs to be validated. Finally, the present study uses a sample which begins on January 1 , 1986 and ends on April 30, 1997. As a result, the series is not affected by the removal of the daily price limit by the Chicago Mercantile Exchange on February 22, 1985, thus avoiding the data truncation problem discussed by Hsieh (1993a).

In this chapter, the empirical findings on the mean and volatility spillover across currency futures over the period 1986-1997, based on the data given in Subsection 4.2.1 and the methodology describe in Section 4.7, are presented and discussed. Section 7.2 reports the preliminary statistics and univariate analysis of daily currency futures returns. Section 7.3 estimates pairwise mean spillover, volatility spillover and the Autoregressive Conditional Heteroscedasticity (ARCH) effects from one currency futures market to another. Section 7.4 presents multi-currency futures means, volatility spillover and the ARCH effects across four currencies. In Section 7.5, we report on the consistency of results across subsamples. Section 7.6 concludes the chapter.

7.2 Preliminary Statistics and Univariate Analysis

The preliminary analysis for the daily returns of four currency futures markets is reported in Table 7.1. These include the mean and standard deviations, the measure of skewness and kurtosis (see Appendix 3 for more details on the computation of mean, standard deviation, variance, skewness and excess kurtosis). The Ljung-Box Q-statistic for 6 and

12 lags applied on both the returns, denoted by LB(6), LB(12) respectively, and on the squared return series, denoted by $LB^2(6)$, $LB^2(12)$ respectively, are also presented. The asymptotic distribution of the Ljung-Box statistics, LB(.), is the chi square (χ^2) distribution under the null hypothesis of no serial correlation in the series.

The means of the returns for all the currency futures are positive and range from between 0.0042 percent for the British pound and 0.0156 percent for the German mark. The standard deviations of returns range between 0.7117 percent for the British pound and 0.8016 for the Swiss franc. The measures for skewness and excess kurtosis indicate that the distributions of returns for the British pound and the German mark are negatively skewed, and the Japanese yen and the Swiss franc are positively skewed and all have excess kurtosis relative to the normal distribution. The Ljung-Box portmanteau test statistic for 6 and 12 lags employed on both the return and squared return series, indicates the presence of significant linear dependence at higher lags only for the Japanese yen and significant nonlinear dependence for all four currency futures. The linear dependencies may be due to some form of market inefficiency. On the other hand, nonlinear dependencies may be due to autoregressive conditional heteroscedasticity effects, as documented by several recent studies on currency futures returns (Hsieh, 1993b and Laux, *et. al.,*1993, among others).

Table 7.2 shows the correlation matrix of returns among the four currency futures returns. The cross correlations between the contemporaneous returns for all currency futures returns are very high, particularly between the German mark and the Swiss franc at 0.9166. This result is expected because of the geographical proximity of the two markets. The correlations are also high between the British pound and the German mark, and the British pound and the Swiss franc at 0.7293 and 0.6994, respectively. This result is also expected since they come from the same geographical location of Europe. However, the correlations between the contemporaneous returns and own lagged returns, and the contemporaneous returns and lagged returns from other currency futures are absent across all the four series.

Table 7.1 Preliminary Statistics on Currency Futures Returns

Currency Futures	BP	DM	JY	SF
No. of Observations	2954	2954	2954	2954
Standard Deviation	0.7117	0.7182	0.7058	0.8016
Mean	0.0042	0.0117	0.0156	0.0113
Skewness	-0.3290	-0.0347	0.2316	0.0466
Kurtosis	3.5737	2.2295	4.0605	1.8750
LB(6)	10.393	8.0420	10.179	7.8026
LB(12)	13.582	11.981	35.437*	11.374
$LB^2(6)$	88.764*	65.049*	48.606*	65.728*
$LB^2(12)$	151.881*	107.631*	73.829*	125.687*

Notes: BP = British pound; DM = German mark; JY = Japanese yen; SF = Swiss franc. LB(6) and LB (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. $LB^2(6)$ and $LB^2(12)$ refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. Kurtosis refers to excess kurtosis where 0 denotes normality. * Significant at the 5 % level.

Table 7.2: Correlations Matrix of Lagged and Contemporaneous of Currency Futures Returns

Currency Futures	BP	DM	JY	SF
BP_t	1.0000	0.7293	0.4946	0.6994
BP_{t-1}	-0.0140	-0.0103	-0.0382	-0.0220
BP_{t-2}	0.0021	0.0031	-0.0008	-0.0170
BP_{t-3}	-0.0034	0.0056	0.0037	0.0136
DM_t	0.7293	1.0000	0.6461	0.9166
DM_{t-1}	0.0132	0.0038	-0.0243	0.0082
DM_{t-2}	-0.0158	-0.0271	-0.0079	-0.0393
DM_{t-3}	-0.0134	0.0013	0.0088	-0.0038
JY_t	0.4946	0.6461	1.0000	0.6368
JY_{t-1}	0.0172	-0.0004	-0.0101	0.0006
JY_{t-2}	-0.0269	-0.0361	-0.0187	-0.0350
JY_{t-3}	-0.0098	-0.0053	-0.0109	-0.0143
SF_t	0.6994	0.9166	0.6368	1.0000
SF_{t-1}	0.0176	0.0196	-0.0162	0.0087
SF_{t-2}	-0.0039	-0.0161	0.0027	-0.0327
SF_{t-3}	-0.0177	0.0018	0.0043	-0.0081

Notes: BP = British pound; DM = German mark; JY = Japanese yen; SF = Swiss franc. The t-1, t-2 and t-3, respectively, denote lagged 1, 2 and 3 days futures returns.

7.3 Pairwise Spillover

The results of the pairwise spillover for the univariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model are reported in Tables 7.3A, B, C and D. Our analysis uses the methodology described in Section 4.7.1. Also, several robustness tests are performed on the standardized residuals and the standardized squared residuals for lags 6 and 12.

As explained earlier, the test procedures for the spillover of mean and volatility across two currency futures (pairwise) employed lagged price change and the squared residuals from the currency futures under investigation as well as lagged price change and the squared residual terms of other currency futures which were examined using the GARCH formulation. Altogether , six pairs of currency futures were analysed.

In order to examine whether there is a common economic effect in the explanatory variables, we expand the exogenous variables in the GARCH formulations to include all currency futures, with the expectation that the significant levels of explanatory variables will be reduced considerably since most of the price changes between currency futures provide evidence of a large positive correlation. As a result, these currency futures are closely related and move in the same direction according to common economic fundamentals, as discussed by Tse and Booth (1996).

Our multi-currency futures analysis includes lagged price changes and residuals from the currency under investigation as well as from the other currency futures; all are tested simultaneously in the conditional mean and conditional variance equations. In other words, we add the third and fourth currency futures in the conditional mean as well as in the conditional variance in order to see whether this inclusion will change the results from the previous findings of pairwise spillover.

Tables 7.3A, B, C and D present the coefficient estimates for the conditional mean and conditional variance equations of returns for the British pound, the German mark, the Japanese yen and the Swiss franc, respectively.

7.3.1 Estimates of Mean Spillovers

The results of the estimation for the pairwise conditional mean equation are reported in Tables 7.3A, B, C and D. In Table 7.3A for the British pound, the results show a significant positive mean spillover effect from the German mark but a negative significant own currency spillover; *i.e.*, a lagged one day of the British pound at the 5 percent level. The *t*-statistics are 2.6237 and -2.6365, respectively. Similarly, the British pound receives a significant positive mean spillover from the Swiss franc and a significant negative mean spillover from its own currency, with *t*-statistics of 2.4685 and -2.5108, respectively. On the other hand, the results of pairwise spillover between the British pound and the Japanese yen show an insignificant relationship.

Table 7.3B shows the results of pairwise mean spillover between the German mark and the British pound; the German mark and the Japanese yen; the German mark and the Swiss franc as well as between their own lagged currency futures. Overall, significant pairwise relations are only observed between the German mark and the Swiss franc and the German mark's own currency lagged returns, at the 5 percent level. The *t*-statistics are respectively, 2.3986 and -2.2793. As for the pairwise mean spillover between the Japanese yen and other currency futures returns as well as their own lagged returns, Table 7.3C shows significant effects only from the British pound, with a *t*-statistic of -2.0876.

Table 7.3 D presents the results of pairwise spillover between the Swiss franc and other currency futures returns as well as its own lagged currency futures. The pairwise relationships are all insignificant, even at the 10 percent level. This means that the Swiss franc does not receive any mean spillover effects from any other currency futures returns, nor from its own lagged returns.

Finally, for all the pairwise mean spillover analysed, the R^2 are extremely low, suggesting that, overall, the returns from one currency futures contract are not affected by the returns of another currency futures returns contract or by that currency's own lagged returns. In other words, currency futures returns are not forecastable in the conditional means.

7.3.2 Volatility Spillover Effect and ARCH Effect

The results of the examination of the coefficients estimation on volatility spillover are also shown in Tables 7.3A, B, C and D. The analysis covers both volatility spillover as well as the Autoregressive Conditional Heteroscedasticity (ARCH) effect. Significant positive pairwise volatility spillover effects are reported in Table 7.3A for the British pound from the German mark and the Swiss franc with t-statistics of 2.6192 and and 3.0120, respectively. In addition, the spillover from the own lagged residual or the ARCH effect between the British pound and all its pairs indicates a highly significant positive relationship. For example, the ARCH effect for the pairwises regressions of the British pound and the German mark, the British pound and the Japanese yen, and the British pound and the Swiss franc have a t-statistics of 11.840, 12.707 and 11.735, respectively.

Table 7.3B presents the results of pairwise volatility spillover and the ARCH effect between the German mark and the British pound, the German mark and the Japanese yen, and the German mark and the Swiss franc. Significant volatility spillover is found only from the British pound, with a t-statistic of 2.1347. However, similar to the results of the British pound, the German mark pairwise regression shows a highly significant ARCH effect. As for the Japanese yen pairwise volatility spillover and the ARCH effect, significant spillover occurs from the British pound and the Swiss franc, with t-statistics of 2.2650 and 2.9771, respectively, and there are also significant positive high ARCH effects.

Finally, Table 7.3D shows the results for pairwise volatility spillover in the Swiss franc as well as the ARCH effect. Again, the British pound together with the German mark are the main sources of volatility spillover to the Swiss franc, with significant t-statistics of 2.4090 and 2.0800, respectively. The ARCH effect is also found for pairwise regression.

The results for pairwise spillover reported above suggest that, in general, the British pound and the Swiss franc are the main exporters of volatility to other currency futures. For example, spillover from the British pound affects the volatility of all other currency futures while the Swiss franc exports volatility spillover to two other currency futures: the British pound and the Japanese yen. The own volatility spillover or the ARCH effects for the Swiss franc are all positively significant, indicating that the past own shocks explain present volatility in the same currency futures.

The above results for pairwise mean and volatility spillovers need to be validated because only two currencies at a time have been considered. In a currency futures market where simultaneous trading occurs for all currencies, it is necessary for all currency futures to be included in a single regression. This point is very important since the traders in the market take clues not only from the price information on currency futures of interest but also from information contained in other currency futures traded in the same market. Therefore, in the next section, we shall go on to analyse the mean and volatility spillover using multi-currency futures.

The residuals based diagnostic tests of Ljung-Box statistics show no evidence of linear or non-linear dependence in the standardized residuals for any of the currency futures markets except for the Japanese yen. The Ljung-Box statistics for the Japanese yen for lag 12, denoted by LB(12), show significant evidence of serial correlation in the standardized residuals. These significant linear dependencies may be due to some form of market inefficiency [Koutmos and Booth (1995)]. The measures of skewness and kurtosis reported in last six rows of Table 7.3A, B, C, D remain low and are close to normality particularly for the German mark and the Swiss franc. It seems that the Generalized Autoregression Conditional Heteroscedasticity, GARCH (1,1) is well specified.

Table 7.3: Univariate GARCH Model Estimates.

A. Pairwise Mean and Volatility Spillover: British Pound

Conditional Mean Coefficient	Currency Futures		
	British Pound		
β_0	0.0145 (1.3120)	0.0139 (1.2553)	0.0146 (1.3089)
$\beta_{BP,i}$	-0.0672* (-2.6365)	-0.0356 (-1.6153)	-0.0610* (-2.5108)
$\beta_{DM,i}$	0.0563* (2.6237)		
$\beta_{JY,i}$		0.0172 (0.9552)	
$\beta_{SF,i}$			0.0444* (2.4685)
R^2	0.0013	0.0007	0.0016
Conditional Variance Coefficient	**Currency Futures**		
	British Pound		
α_0	0.0021* (3.7899)	0.0026* (4.9023)	0.0019* (3.4517)
$\alpha_{BP,i}$	0.00298* (11.840)	0.0304* (12.707)	0.0295* (11.735)
$\alpha_{DM,i}$	0.0036* (2.6192)		
$\alpha_{JY,i}$		0.00 (0.00)	
$\alpha_{SF,i}$			0.0031* (3.0120)
γ_1	0.9624* (319.42)	0.9646* (338.27)	0.9627* (319.89)
Skewness	-0.2684	-0.2654	-0.2747
Kurtosis	2.7506	2.9270	2.7458
LB(6)	6.5003	6.7840	6.3292
LB(12)	8.3371	8.5223	8.2717
$LB^2(6)$	7.3440	7.6985	7.2403
$LB^2(12)$	11.140	11.347	11.231

B. Pairwise Mean and Volatility Spillover: German Mark

Conditional Mean Coefficient	Currency Futures		
	German Mark		
β_0	0.0067 (0.5430)	0.0062 (0.5052)	0.0063 (0.5138)
$\beta_{BP,i}$	-0.0293 (-1.0938)		
$\beta_{DM,i}$	0.0176 (0.6958)	-0.0103 (-0.4381)	-0.0923* (-2.2793)
$\beta_{JY,i}$		0.1000 (0.4381)	
$\beta_{SF,i}$			0.0855* (2.3986)
R^2	0.0004	0.0000	0.0016
Conditional Variance Coefficient	**Currency Futures**		
	German Mark		
α_0	0.0067* (4.8899)	0.0069* (4.338)	0.0066* (4.6798)
$\alpha_{BP,i}$	0.0062* (2.1347)		
$\alpha_{DM,i}$	0.0325* (7.4958)	0.0382* (8.2268)	0.0368* (5.7943)
$\alpha_{JY,i}$		0.0004 (0.2077)	
$\alpha_{SF,i}$			0.0006 (0.1303)
γ_1	0.9488* (149.74)	0.9482* (152.21)	0.9500* (156.08)
Skewness	-0.0012	0.0072	0.0045
Kurtosis	1.8143	1.7658	1.7420
LB(6)	6.0704	5.9094	5.9359
LB(12)	11.137	11.115	11.067
$LB^2(6)$	6.6114	6.0082	6.1840
$LB^2(12)$	9.0667	8.4300	8.3049

C. Pairwise Mean and Volatility Spillover: Japanese Yen

Conditional Mean Coefficient	Currency Futures		
	Japanese Yen		
β_0	0.0105 (0.8612)	0.0105 (0.8649)	0.0105 (0.8601)
$\beta_{BP,i}$	-0.0432* (-2.0876)		
$\beta_{DM,i}$		-0.0364 (-1.6578)	
$\beta_{JY,i}$	0.0081 (0.3877)	0.0109 (0.4665)	0.0051 (0.2189)
$\beta_{SF,i}$			-0.0241 (-1.2018)
R^2	0.0017	0.0007	0.0004
Conditional Variance Coefficient	**Currency Futures**		
	Japanese Yen		
α_0	0.0101* (2.0876)	0.0111* (6.3246)	0.0095* (5.4969)
$\alpha_{BP,i}$	0.0031* (2.2650)		
$\alpha_{DM,i}$		0.0001 (0.0580)	
$\alpha_{JY,i}$	0.0380* (5.9248)	0.0388* (10.178)	0.0349* (9.1332)
$\alpha_{SF,i}$			0.0058* (2.9771)
γ_1	0.9384* (161.73)	0.9386* (160.43)	0.9384* (158.57)
Skewness	0.3136	0.3199	0.3129
Kurtosis	3.5032	3.5392	3.5364
LB(6)	7.5136	7.6896	7.4382
LB(12)	37.508*	37.429*	37.732*
$LB^2(6)$	6.2584	6.0658	6.4526
$LB^2(12)$	10.922	10.739	11.048

D. Pairwise Mean and Volatility Spillover: Swiss Franc

Conditional Mean Coefficient	Currency Futures		
	Swiss Franc		
β_0	0.0049 (0.3547)	0.0063 (0.4489)	0.0038 (0.2724)
$\beta_{BP,i}$	-0.0560 (-1.9429)		
$\beta_{DM,i}$		0.0068 (0.1376)	
$\beta_{JY,i}$			0.0061 (0.2351)
$\beta_{SF,i}$	0.0431 (1.7574)	0.0042 (0.0959)	0.0056 (0.2322)
R^2	0.0017	0.0000	0.0000
Conditional Variance Coefficient	**Currency Futures**		
	Swiss Franc		
α_0	0.0100* (4.5063)	0.0108* (4.6013)	0.0095* (4.3972)
$\alpha_{BP,i}$	0.0077* (2.4090)		
$\alpha_{DM,i}$		0.0144* (2.0800)	
$\alpha_{JY,i}$			0.00 (0.00)
$\alpha_{SF,i}$	0.0276* (6.4857)	0.0227* (3.6398)	0.0316* (7.5328)
γ_1	0.9508* (137.06)	0.9490* (133.27)	0.9536* (146.05)
Skewness	0.0793	0.0921	0.0859
Kurtosis	1.4623	1.4336	1.4496
LB(6)	5.5732	5.6053	5.8793
LB(12)	11.235	11.686	12.598
$LB^2(6)$	9.6502	8.9964	10.037
$LB^2(12)$	17.9382	16.335	17.490

Notes: Numbers in parentheses are t-statistics. Kurtosis refers to excess kurtosis where 0 denotes normality. LB(6) and (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. LB2(6) and (12) refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. * Indicates statistically significant at the 5 % level.

7.4 Multi-Currency Spillover

The results of fitting the GARCH model to the futures mean and volatility to account for spillover between currencies are reported in Table 7.4. The analysis is based on the methodology described earlier in Section 4.7.2.

7.4.1 Estimates of Mean Spillover

The results of the estimation for expanded exogenous variables in the conditional mean are reported in Table 7.4. There are statistically significant positive mean spillovers at the 5 percent level in the mean returns from currency futures of the Swiss franc to the German mark and significant negative spillovers in the mean return from currency futures of the British pound to the Swiss franc. Their coefficients and *t*-statistics are, respectively, 0.0911(2.4985) and -0.064 (-2.1110). The results of the effect of past returns on its own current returns; *i.e.*, own mean spillover effect, are significant only for the British pound at the 5 percent level, suggesting *prima facie* inefficiency in the currency futures returns.

The above results for multi-currency mean spillover seem to differ greatly from the findings for pairwise mean spillover. While the pairwise has five significant mean spillover effects and three significant own mean spillover effects, the multi-currency futures shows a lesser number of significant mean spillover effects and own mean spillover effects.

In order to evaluate the extent to which the mean spillover or past returns can predict current currency returns, Table 7.4 also shows the univariate coefficient of determination R^2, for all four conditional mean equations. All R^2 values are about 2 percent which is considered very low, thus suggesting low explanatory power. The conditional mean equations for the British pound, the German mark, the Japanese yen and the Swiss franc explain only 0.14 percent, 0.22 percent, 0.19 percent and 0.17 percent , respectively, of the total variation in the currency futures market returns. On the basis of these estimates, it can be concluded that even though there is significant mean spillover form the Swiss franc to the German mark and from the British pound to the Swiss franc, the conditional mean equations are not strong enough to be used in predicting currency futures returns. If they could be used effectively by traders to improve short-term price forecastibility, the weak form of the efficient market hypothesis would be violated.

7.4.2 Volatility Spillover Effects and ARCH Effect

After determining the appropriate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) specifications for each of the four currency futures returns, an exogenous variables are introduced into the conditional variance equations of the model. These expanded exogenous variables are the past squared innovations derived from the return series for three other currency futures as well as from the own innovation series. They are interpreted either as volatility suprise or as news from another currency futures or as volatility surprise or news from the own currency futures. Najang, *et.al.*, (1992), refer to these residuals in terms of other currency futures as a "rate of information arrival". We can conclude that there is a volatility spillover effect from one currency futures contract to another if the past squared innovation terms of one currency futures contract are found to be significant in the conditional variance equations. Two distinct effects can be observed in our results: the first is the spillover effect; *i.e.*, volatility spillover from other currency futures, and the second other is the Autoregressive Conditional Heteroscedasticity (ARCH) effect; *i.e*, the own spillover effect.

The results for volatility spillover are also reported in Table 7.4 which shows that all the coefficients for the one-lag conditional variance are large and highly significant, suggesting high volatility persistence in currency futures returns. The persistence of volatility coefficients (*t*-statistics in brackets) are as follows: 0.9626 (312.88)for the British pound, 0.9500 (151.85) for the German mark, 0.9386 (158.15) for the Japanese yen and 0.9479 (129.22) for the Swiss franc. Statistically significant positive own-volatility spillovers are present in the returns for all currency futures. These results suggest that the lagged conditional variance alone does not capture all of the explanatory power but that the information impounded in the past squared innovation also contributes toward explaining conditional variance; *i.e.*, the presence of the Autoregression Conditional Heteroscedasticity (ARCH) effect. For example, the own-volatility spillover coefficients for the Japanese yen, the German mark and the British pound are (0.0350), (0.0315) and (0.0297), respectively. These figures are approximately 50 percent, 45 percent and 35 percent larger than the coefficient of the Swiss franc (0.0220). This means that the past-currency futures volatility surprise in the German mark or the Japanese yen has a greater impact on the current volatility of the German mark or the Japanese yen than does the past-market volatility surprise on the

Swiss franc.

As for cross-volatility spillovers among currency futures, a statistically significant at the (5 percent level) spillover occurs only from the British pound to the German mark and from the Swiss franc to the British pound, with coefficients (t-statistics in the brackets) of 0.0062 (2.1409) and 0.0031 (3.0049), respectively. Volatility spillover also occurs from the British pound to the Swiss franc and from the Swiss franc to the Japanese yen but at a low level of significance. These results suggest that innovations (lagged residual terms) in both the British pound and the Swiss franc are the most frequently transmitted to other currency futures. On the other hand, there is no clear sign that any particular currency futures contract dominates the volatility spillover effect since each of the currency futures received only one spillover from other currency futures. These results are quite different from those of Najand, *et.al.*,(1992) who found highly significant cross-currency volatility spillover effects for the British pound, the German mark and the Japanese yen. As noted by Susmel and Engle (1994), if a market is informationally efficient in variance, there should be very little predictive power from one market to another market. In our case, currency futures efficiency should be ruled out for the British pound and the German mark since the volatility spillover effect is highly significant. However, for the Japanese yen and the Swiss franc, the evidence of efficiency should not be ruled out completely since the volatility effects are significantly low, with t-statistics of 1.8144 and 1.7579, respectively.

Our results show that both the lagged conditional variance and the lagged residual variable for all currency futures does capture most of the explanatory power for the conditional variance. In addition, both the British pound and the German mark futures reveal additional evidence: they not only exhibit high ARCH effects but also a significant spillover effect. These exist simultaneously in the conditional variance equation. In other words, shocks from the past as well as shocks contained in other currency futures have similar valuable information content which can affect the volatility of these two currency futures. Thus, the British pound and the German mark are forecastable in the short run. These results are, consistent with those of Najang and Yung (1991) who find that the Generalized Autoregression Conditional Heteroscedasticity (GARCH) effect persists in the Treasury-Bond futures market even after correlated volume is accounted for in the model. However, our results differ from of those reported by Najand, Rahman and Yung (1992) who observe that the ARCH effects become significant when there are nonexistent or weak spillover effects but disappear when there are strong spillover effects.

Similar to the results for mean spillover, the findings for volatility spillover indicate a great difference between multi-currency futures and pairwise currency futures. Expanding the exogenous variables in the conditional variance equation; *i.e.*, moving from pairwise to multi-currency futures analysis, appears to significantly reduce the spillover effect. In other words, inclusion of the third and the fourth currency futures returns in the equation appears to diminish the volatility spillover effect on the first currency futures market and also on other currency futures, a finding that differs greatly from the results of Hamao, *et.al.*, (1990) who reported the opposite. The simple explanation is that all the four currency futures contain a common economic effect. Thus, if the spillover effect reflects the influence of this common economic effect on the volatility of all currency futures, introducing the third and fourth currency futures is unlikely to add much incremental explanatory power to the conditional variance.

Table 7.4A gives a summary of the differences in significant levels between the volatility spillover effect and the Autoregressive Conditional Heteroscedasticity (ARCH) effect for pairwise and multi-currency futures. For example, in the pairwise analysis, there are seven significant volatility spillover effects, all at the 5 percent level, compared to four in the multi-currency futures analysis, of which two are at a lower level of significance. However, both the pairwise and multi-currency futures have significant ARCH effects.

Robustness Tests for Full Sample

In order to assesss the general validity of the univariate Generalized Autoregressive Conditional Heteroscedasticity, GARCH (1,1) model and the results obtained, a series of misspecification tests were performed. The diagnostic tests results on the standardized residuals ($\varepsilon_{i,t}/\sigma_{i,t}$) for each currency futures are reported in the last six rows of Table 7.4. The measures for kurtosis show a great improvement with all values reduced dramatically compared to the original series. The coefficients for skewness, however, report improvement only for the British pound and the German mark.

The Ljung-Box portmanteau statistics applied on the standardized residuals for lags 6 and 12 , denoted by LB(6) and LB(12), are all insignificant except for the Japanese yen at higher lags, thus supporting the assumption of no serial correlation. It appears that the autoregression models of the conditional mean equations have captured most of the serial correlation in the return series.

The validity of the correct model specification in the conditional variance requires that the standardized residuals be conditionally constant over time. The Lung-Box portmanteau statistics for 6 and 12 lags, denoted by $LB^2(6)$ and $LB^2(12)$, show no serial correlation, supporting the evidence of no non-linear dependence in the squared standardized residuals for any of the currency futures. Thus, the residual based diagnostic tests results indicate that the univariate Generalized Autoregressive Conditional Heteroscedasticity, GARCH (1,1) specification of the conditional variance equations provides a satisfactorily explanation of the heteroscedastic behaviour and interaction of the four currency futures returns.

To summarise, the tests performed do not present any serious evidence against the estimated univariate, GARCH (1,1) model. The assumption of constant conditional correlation suggests a robust representation of the correlation structure of return series in all four currency futures returns. With regard to the finding which contradicts Najand, *et.al.,* (1992), there may be two reasons for this discrepancy. First, more than half of their sample covers the period of effective imposition of daily price limits. Secondly, their investigation uses five currency futures and includes the Canadian dollar in the sample. This means that their study hypothesizes that information arrival is a function of the residual terms of five other currency futures instead of four.

Table 7.4: Univariate GARCH Model Estimates: Multi-Currency Futures Mean and Volatility Spillover

Conditional Mean Coefficient	Currency Futures			
	BP	DM	JY	SF
β_0	0.0145 (1.3027)	0.0068 (0.5516)	0.0110 (0.8978)	0.0067 (0.4762)
$\beta_{BP,i}$	-0.0682* (-2.6632)	-0.0356 (-1.3162)	-0.0371 (0.4773)	-0.0643* (-2.1110)
$\beta_{DM,i}$	0.0462 (1.0577)	-0.0742 (-1.7096)	-0.0312 (-0.6721)	0.0403 (0.7621)
$\beta_{JY,i}$	-0.0075 (-0.3371)	0.0031 (0.1294)	0.0113 (0.4730)	0.0070 (0.2583)
$\beta_{SF,i}$	0.0155 (0.4065)	0.0911* (2.4985)	0.0209 (0.6170)	0.0118 (0.2658)
R^2	0.0014	0.0022	0.0019	0.0017
Conditional Variance Coefficient	**Currency Futures**			
	BP	**DM**	**JY**	**SF**
α_0	0.0019* (3.2666)	0.0063* (4.6674)	0.0095* (5.4292)	0.0108* (4.6148)
$\alpha_{BP,i}$	0.0297* (11.615)	0.0062* (2.1409)	0.0006 (0.3026)	0.0064 (1.7579)
$\alpha_{DM,i}$	0.00 (0.00)	0.0315* (6.8707)	0.00 (0.00)	0.0103 (1.3763)
$\alpha_{JY,i}$	0.00 (0.00)	0.0005 (0.2473)	0.0350* (8.8370)	0.00 (0.00)
$\alpha_{SF,i}$	0.0031* (3.0049)	0.00 (0.00)	0.0051 (1.8144)	0.0220* (3.5538)
γ_1	0.9626* (312.88)	0.9500* (151.85)	0.9386* (158.15)	0.9479* (129.22)
Skewness	-0.2718	0.0036	0.3115	0.0854
Kurtosis	2.7339	1.7722	3.5081	1.4450
LB(6)	6.4095	6.0813	7.4646	5.4332
LB(12)	8.3138	11.066	37.638*	10.857
$LB^2(6)$	7.2793	6.3505	6.3637	8.8113
$LB^2(12)$	11.275	8.5244	10.884	16.997

Notes: Numbers in parentheses are t-statistics. Kurtosis refers to excess kurtosis where 0 denotes normality. LB(6) and (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. LB2(6) and (12) refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. * Indicates statistically significant at the 5 % level.

Table 7.4A: Comparison of Results Between Pairwise and Multi-Currency Futures Volatility Spillover and the ARCH Effect.

Currency Futures	Pairwise				Multi-Currency Futures			
	BP	**DM**	**JY**	**SF**	**BP**	**DM**	**JY**	**SF**
$\alpha_{BP,i}$	ARCH Effect (YES)	Significant 5%	Significant 5%	Significant 5%	ARCH Effect (YES)	significant 5%	No	Significant 10%
$\alpha_{DM,i}$	Significant 5%	ARCH Effect (YES)	No	Significant 5%	No	ARCH Effect (YES)	No	No
$\alpha_{JY,i}$	No	No	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No
$\alpha_{SF,i}$	Significant 5%	No	Significant 5%	ARCH Effect (YES)	Significant 5%	No	Significant 10%	ARCH Effect (YES)
γ_1	Significant 5%	Significant 5%	Significant 5%	Significant 5%	Significant 5%	Significant 5%	Significant 5%	Significant 5%

Notes: ARCH effects refers to past own shock spillover. The 10% and 5% critical levels are 1.645 and 1.960, respectively.

7.5 Consistency of Results Across Subsamples

Pairwise Subsample Results

Tables A-4 and A-7 report the summary statistics for Subperiods I and II, respectively, and Tables A-5 and A-8 report the correlations matrix results for Subperiods I and II, (see Appendix 5 for both). To judge the sensitivity of the results on whether the subperiod provides the same type of inference as a full sample, we repeat the same analysis of mean and volatility spillover for Subsample I and Subsample II for the periods from January 1, 1986 to September 18, 1991 and from September 19, 1991 to April 30, 1997, respectively. Tables A-6A, A-6B, A-6C and A-6D report the univariate

GARCH estimated results in Subsample I for the BP, the DM, the JY and the SF, respectively. Tables A-9A, A-9B, A-9C and A-9D report the univariate GARCH estimated results in Subsample II for the BP, the DM, the JY and the SF, respectively (see Appendix 5 for both subperiods).

The spillover in the conditional mean in Subsample I shows that only the British pound has a highly significant spillover effect. No mean spillover effect from other currency futures appears to exist for the German mark, the Japanese yen or the Swiss franc. In Subsample II, the mean spillover effect is significantly strong only for the German mark from the Swiss franc. All the other relationships are either non-existent or significantly low. Thus, the results for Subsamples I and II are quite different. Table A-10 in Appendix 5 gives summary of comparison for mean spillover between Subperiods I and II.

Turning to the second moment interdependencies (volatility spillover) in Subsample I, it can be seen that interactions between currency futures returns are almost non-existent. None of them either export volatility to other currency futures or receive volatility from other currency futures, a result which is completely different from the findings for the entire sample. However, the same argument does not hold for Subsample II, where the spillover effect and the interaction between currency futures are tremendous. For example, there are highly significant volatility spillover effects for three currency futures: for the British pound from the German mark and Swiss franc; for the Japanese yen from the British pound, the German mark and the Swiss franc; and for the Swiss franc from the British pound and German mark. Table 7.4B gives summary of comparison between Subperiods I and II.

Our results thus demonstrate that the structures of each of the subperiods are very different. Subperiod II seems to suggest a more volatile period than Subperiod I, since the interactions between currency futures are quite active. In addition, it appears that Subperiod II has more influence on the results for entire period than does Subperiod I.

Table 7.4B: Summary Comparison of the Results Between Subsample I and Subsample II: Pairwise Volatility Spillover

	Subsample I				Subsample II			
	BP	DM	JY	SF	BP	DM	JY	SF
$\alpha_{BP,i}$	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	Significant 10%	Significant 5%	Significant 5%
$\alpha_{DM,i}$	No	ARCH Effect (YES)	No	No	Significant 5%	ARCH Effect (YES)	Significant 5%	Significant 5%
$\alpha_{JY,i}$	No	No	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No
$\alpha_{SF,i}$	No	No	No	ARCH Effect (YES)	Significant 5%	No	Significant 5%	ARCH Effect (YES)
γ_1	Significant 5%	Significant 5%	Significant 5%	No	Significant 5%	Significant 5%	Significant 5%	Significant 5%

Notes: ARCH effects refers to past own shock spillover. The 10% and 5% critical levels are 1.645 and 1.960, respectively.

Pairwise Robustness Tests for Subsamples

Diagnostic tests based on the standardized residuals of the two subsamples appear to suggest that the univariate Generalized Autoregressive Conditional Heteroscedasticity, GARCH (1,1) model satisfactorily explains the interaction of the currency futures under investigation. There is no indication of serious model misspecification for any of the currency futures time series except for the Japanese yen in both Subsamples I and II, a problem which is shown in the results for the entire sample. The Ljung-Box values for lags 6 and 12 of standardized residuals squared for the Swiss franc, denoted by $LB^{\cdot}(6)$ $LB^{\cdot}(12)$, respectively, are significant at conventional levels, indicating evidence of linear dependencies in the series. On the other hand, the Ljung-Box statistics for lags 6 and lags 12 of the standardized residuals squared, denoted by $LB^{2\cdot}(6)$ $LB^{2\cdot}(12)$, are free of nonlinear dependencies at conventional levels. Overall, the results of skewness and the kurtosis of standardized residuals for both subperiods show no improvement when compared to those of full sample.

Multi-Currency Futures Subsample Results

Again, the results of the two subsamples for the multi-currency futures spillover effect between currency futures are analysed. In this section, we discuss the results for the multi-currency futures mean spillover, and the volatility spillover effects as well as Autoregressive Conditional Heteroscedasticity (ARCH) effects for both Subperiods I and II followed by the test for robustness of the results.

Subsample I Results

The results for the multi-currency futures mean and volatility spillover in Subsample I are reported in Table 7.5. The inclusion of expanded exogenous variables in the conditional mean produced inconclusive results. While some show results which are opposite to those for pairwise spillover effects, the majority remain the same. For example, the multi-currency futures shows evidence of significant mean spillover similar to that for pairwise spillover in only one case; *i.e.*, spillover effects from the Japanese yen to the British pound. The other significant interactions in the multi-currency futures occur from the British pound to the German mark and from the British pound to the Swiss franc with *t*-statistics of -2.0959 and -2.1514, respectively. The R^2 value for each of the four conditional mean equations shows a dramatic increase compared to the R^2 for the whole sample. The R^2 for the British pound, for example, increases from 0.14 percent to 0.9 percent. However, this value is still very low for the past returns to have an impact on the prediction of the current currency futures returns.

As for the conditional variance equation, theBritish pound, the German mark and the Japanese yen exhibit highly significant Autoregressive Conditional Heteroscedasticity (ARCH) effects with the inclusion of expanded exogenous variables. These results are similar to those for the full sample except for the Swiss franc. However, the spillover effect is absent in all cases, in contrast to the results for the full sample. These results, suggest that, in Subsample 1, currency futures interactions were greater only for the conditional mean. The conditional volatility, however, shows no interaction among currency futures, a very different result from that for the full sample. This suggests that in Subsample I, all four currency futures returns exhibit a high degree of informational efficiency with respect to news or shocks from other currency futures. In addition, in the Swiss franc, neither the lagged conditional variance nor the lagged residual contributes toward explaining the conditional variance.

Subsample II Results

When we examine Subperiod II, in which the model is reestimated with the inclusion of expanded variables, the picture changes quite substantially, as shown in Table 7.6. The results for currency futures interaction in mean spillovers are very different from those for Subsample I and for the full period. There are significant mean spillovers from the German mark to the British pound and from the British pound to the Japanese yen, which are absent in Subsample I. However, regarding conditional volatility, interactions among the currency futures are similar, a finding which is very similar to those documented for the entire period, with the exception of spillover from the Swiss franc to the British pound. The currency futures interaction in the second moment shows highly significant volatility spillovers from the British pound to the German mark. Similar spillover effects also occur from the British pound to the Swiss franc and from the Swiss franc to the Japanese yen but at a low level of significance.

A comparison of the results from Subsample I and Subsample II reveals that, overall, the subsamples are quite independent in the conditional mean. Moreover, they do not influence the results for the full period. However, the same cannot be said of the conditional volatility. Although the subsamples are independent of one another, Subsample II appears likely to have a greater influence on the results of the full period than Subsample I. A summary of the comparison between the results of pairwise and multi-currency futures spillovers are presented in Tables 7.5A and 7.6A for Subsamples I and II, respectively. In addition, Table 7.7 reports the summary of our comparison between the results of Subsample I and Subsample II.

Our results suggest that the inclusion of the third and fourth currency futures returns in the conditional variance variables appears likely to be influenced by the common economic effect for all currency futures, as discussed in Hamao, *et.al.*, (1990), except for the German mark. In other words, expanding the exogenous variables in the conditional variance is unlikely to add much incremental explanatory power of the return generating process. It appears that all the currency futures are close substitutes and that they move in the same direction according to common economic principles. Moreover, the ARCH effects; *i.e.*, own spillovers are highly significant for all the currency futures, suggesting that the past own shocks can explain more of the current volatility than the past information of other currency futures. If shocks from other currency futures contain more valuable information on a given currency futures than the currency futures itself, the ARCH effects should weaken or disappear.

Tests for Robustness of the Subsamples

The robustness of the results was tested by reestimating some of the models using two shorter sample periods of almost equal length. Diagnostic tests based on the standardized residuals of the subsamples were then carried out. These show that the univariate Generalized Autoregresive Conditional Heteroscedasticity, GARCH (1,1) model satisfactorily explains the interaction of the currency futures markets. No serious model misspecification is indicated, except for the Swiss franc in Subsample I, and for the British pound and the Japanese yen in Subsample II. The Ljung-Box values for lagged 6 and 12 of the standardized residuals squared, denoted by LB·(6) and LB·(12), for the Swiss franc are significant at conventional levels, indicating evidence of non-linear dependence in the series. On the other hand, the Ljung-Box statistics for lagged 6 and 12 of standardized residuals squared, denoted by $LB^2(6)$ $LB^2(12)$, show significant linear dependence for the British pound and the Japanese yen at conventional levels. The measures of the skewness and kurtosis of the standardized residuals improve dramatically in Subsample I but remain the same in Subsample II when compared to the full sample. The statistics, however, are still too large to accept the null hypothesis of a normal distribution.

Table 7.5: Univariate GARCH Model Estimates. (Subsample I)

Multi-Currency Futures Mean and Volatility Spillover

Conditional Mean Coefficient	Currency Futures			
	BP	DM	JY	SF
β_0	0.0170 (0.8737)	0.0271 (1.5014)	0.0271 (1.4471)	0.0211 (0.9871)
$\beta_{BP,i}$	-0.0660 (-1.8106)	-0.0749* (-2.0959)	-0.0065 (-0.1829)	-0.0896* (-2.1514)
$\beta_{DM,i}$	-0.0387 (-0.5226)	-0.0747 (-1.2365)	-0.1039 (-1.5710)	0.0627 (0.8866)
$\beta_{JY,i}$	0.0852* (2.1912)	0.0681 (1.9145)	0.0113 (0.3096)	0.0696 (0.8866)
$\beta_{SF,i}$	0.0694 (1.0894)	0.0713 (1.3243)	0.0671 (1.1751)	-0.0390 (-0.6273)
R^2	0.0091	0.0043	0.0022	0.0045
Conditional Variance Coefficient	**Currency Futures**			
	BP	DM	JY	SF
α_0	0.0089* (3.0156)	0.0180* (3.2064)	0.0244* (3.3152)	0.6656* (28.103)
$\alpha_{BP,i}$	0.0245* (5.0358)	0.00 (0.00)	-0.0065 (-0.1829)	0.0166 (0.5652)
$\alpha_{DM,i}$	0.00 (0.00)	0.0538* (5.7202)	-0.1039 (-1.5710)	0.0009 (0.0437)
$\alpha_{JY,i}$	0.0039 (1.3613)	0.00 (0.00)	0.0481* (5.6822)	0.00 (0.00)
$\alpha_{SF,i}$	0.00 (0.00)	0.00 (0.00)	0.0671 (1.1751)	0.00 (0.00)
γ_1	0.9559* (108.29)	0.9152* (56.847)	0.9054* (44.065)	0.00 (0.00)
Skewness	-0.3552	0.0074	0.2399	0.0812
Kurtosis	2.0637	1.4318	2.4389	1.1116
LB(6)	4.6531	2.6064	1.6144	3.2854
LB(12)	8.3174	5.4612	18.576	13.185
LB^{2}(6)	2.5207	14.252	11.184	24.054*
LB^{2}(12)	8.1293	7.0160	15.771	47.659*

Notes: Numbers in parentheses are t-statistics. Kurtosis refers to excess kurtosis where 0 denotes normality. LB(6) and (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. LB2(6) and (12) refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. * Indicates statistically significant at the 5 % level.

Table 7.5A : Summary Comparison of the Results Between Pairwise and Multi-Currency Futures Volatility Spillover: Subsample I

Currency Futures	Pairwise				Multi-Currency Futures			
	BP	DM	JY	SF	BP	DM	JY	SF
$\alpha_{BP,i}$	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No	No	No
$\alpha_{DM,i}$	No	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No	No
$\alpha_{JY,i}$	No	No	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No
$\alpha_{SF,i}$	No	No	No	ARCH Effect (YES)	No	No	No	ARCH Effect (No)

Notes: ARCH effects refers to past own shock spillover. The 10% and 5% critical levels are 1.645 and 1.960, respectively.

Table 7.6: Univariate GARCH Model Estimates. (Subsample II)

Multi-Currency Futures Mean and Volatility Spillover

Conditional Mean Coefficient	Currency Futures			
	BP	DM	JY	SF
β_0	0.0162 (1.1604)	-0.0007 (0.0394)	0.0001 (0.0037)	0.0006 (0.0293)
$\beta_{BP,i}$	-0.0935* (-2.3520)	0.0003 (-0.0074)	-0.0740* (-2.0048)	-0.0454 (-0.9357)
$\beta_{DM,i}$	0.1300* (2.2679)	-0.0929 (-1.3623)	0.0551 (0.8093)	0.0063 (-0.0723)
$\beta_{JY,i}$	-0.0599* (-2.1194)	-0.0496 (-1.5380)	0.0016 (0.0016)	-0.0477 (-1.3082)
$\beta_{SF,i}$	-0.0446 (-0.8857)	0.1220* (2.3162)	-0.0257 (-0.4492)	0.0757 (1.1099)
R^2	0.0030	0.0058	0.0038	0.0047
Conditional Variance Coefficient	**Currency Futures**			
	BP	DM	JY	SF
α_0	0.0013* (2.1945)	0.0051* (2.3162)	0.0064* (3.6773)	0.0201* (4.9019)
$\alpha_{BP,i}$	0.0299* (8.2435)	0.0072 (1.7157)	0.0008 (0.2680)	0.0134 (1.8115)
$\alpha_{DM,i}$	0.0077* (4.4328)	0.0186* (2.1097)	0.00 (0.00)	0.0170 (0.9900)
$\alpha_{JY,i}$	0.00 (0.00)	0.0001 (0.0424)	0.0339* (6.0729)	0.00 (0.00)
$\alpha_{SF,i}$	0.00 (0.00)	0.0043 (0.6984)	0.0074 (1.8089)	0.0266* (2.0940)
γ_1	0.9583* (220.83)	0.9579* (118.44)	0.9423* (130.15)	0.9179* (72.454)
Skewness	-0.0530	0.0044	0.4539	0.0965
Kurtosis	3.2820	2.1218	4.8172	2.0551
LB(6)	17.017	11.258	12.428	8.7564
LB(12)	18.896	16.042	28.248*	12.194
$LB^2(6)$	6.9358	5.2081	3.0575	7.8764
$LB^2(12)$	10.190	7.6330	7.5091	20.270

Notes: Numbers in parentheses are t-statistics. Kurtosis refers to excess kurtosis where 0 denotes normality. LB(6) and (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. LB2(6) and (12) refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. * Indicates statistically significant at the 5 % level.

Table 7.6A: Summary Comparison of the Results Between Pairwise and Multi-Currency Futures Volatility Spillover: Subsample II

Currency Futures	Pairwise				Multi-Currency Futures			
	BP	DM	JY	SF	BP	DM	JY	SF
$\alpha_{BP,i}$	ARCH Effect (YES)	No	Significant 5%	Significant 5%	ARCH Effect (YES)	Significant 10%	No	Significant 10%
$\alpha_{DM,i}$	Significant 5%	ARCH Effect (YES)	Significant 5%	Significant 5%	Significant 5%	ARCH Effect (YES)	No	No
$\alpha_{JY,i}$	No	No	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No
$\alpha_{SF,i}$	Significant 5%	No	Significant 5%	ARCH Effect (YES)	No	No	Significant 10%	ARCH Effect (No)

Table 7.7: Summary of Comparison of the Results Between Subsample I and Subsample II: Multi-Currency Futures Volatility Spillover

Currency Futures	Subsample I				Subsample II			
	BP	DM	JY	SF	BP	DM	JY	SF
$\alpha_{BP,i}$	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	Significant 10%	No	Significant 10%
$\alpha_{DM,i}$	No	ARCH Effect (YES)	No	No	Significant 5%	ARCH Effect (YES)	No	No
$\alpha_{JY,i}$	No	No	ARCH Effect (YES)	No	No	No	ARCH Effect (YES)	No
$\alpha_{SF,i}$	No	No	No	ARCH Effect (YES)	No	No	Significant 10%	ARCH Effect (YES)
γ_1	Significant 5%	Significant 5%	Significant 5%	No	Significant 5%	Significant 5%	Significant 5%	Significant 5%

Notes: ARCH effects refers to past own shock spillover. The 10% and 5% critical levels are 1.645 and 1.960, respectively.

7.6 Conclusion

For many years, researchers as well as practitioners have shown considerable interest in the mean and volatility spillover of equity and currency markets. The public information hypothesis has been one of the main factors encouraging this interest as it has been found that the way in which news information is transmitted across currencies has an impact on the return of currencies traded in the same market, thus allowing speculators to make more accurate forecast and to improve the opportunities for making abnormal profits.

The purpose of this chapter has been to examine whether information on one currency futures contract has an impact on the mean and the volatility of other currency futures. We have employed both pairwise and multi-currency futures analyses across four currency futures returns, for the British pound, the German mark, the Japanese yen and the Swiss franc, in order to test whether if there is more explanatory power in the expanded variables.

Using the Autoregression Conditional Heteroscedasticity (GARCH) model, for either pairwise or multi-currency futures, we have found that during certain periods all currency futures are involved in transmitting mean spillover to other currency futures. However, our results exhibit an extremely low univariate coefficient of determination, R^2, indicating that past returns have little explanatory power in predicting current currency returns. Such a situation raises a serious question as to whether investors can employ them to predict the future course of currency futures prices for hedging purposes.

The results from the conditional variance equation reveal that the British pound and the Swiss franc futures currency are the main exporters of volatility to the other currency futures. However, there is no clear evidence of any currency futures which import volatility. In addition, we have found that significant Autoregressive Conditional Heteroscedasticity (ARCH) effects and spillover effects exist simultaneously when explaining the conditional variance equation for the British pound and the German mark. Our results also show that the inclusion of the third and the fourth currency futures returns in the equation appears to diminish the volatility spillover effect on the first currency futures returns and also on the other currency futures returns. The common economic effect is cited as a possible explanation for these phenomena.

As for the structure of the series in both subperiods, it seems that they behave very differently, as shown in Table 7.7. From the results for the multi-currency futures, it appears that Subperiod II has more volatile interactions than Subperiod I. This may be explained by the increase in volume - the larger the amount of information flowing to the market (as proxied by trading volume), the more the traders' expectations spread, and therefore the observed increase in volatility in this case is consistent with a well documented comovement between volatility and trading volume

Finally, we tested the model specifications of pairwise and multi-currency analysis for the entire period as well as for the individual subperiods and found that, in general, the GARCH (1,1) normal distribution seems to fit the data satisfactorily. Overall, the diagnostic tests based on the residuals suggested no serious model misspecification for any of the four currency futures returns.

Chapter Eight

Summary and Conclusions

8.1 Introduction

The preceding chapters have presented the results of the empirical analysis of this study. In this chapter, we summarize the methodology employed and compare the findings of the present study to those reported in other published work. Finally, the implications of our results for traders and other futures market participants are discussed and possible directions for further research in the currency futures market are outlined.

8.2 Summary of Research Methods and Finding

This study began with the idea of examining nonlinear dependence in currency futures returns, since investigations of many other financial instruments have shown that data tend to exhibit nonlinear behaviour. Each of the four nonlinear dependence testing procedures used in this study have revealed significant nonlinearity in the data. Furthermore, the BDS test rejected the null hypothesis of i.i.d.. Thus, as the third moment test failed to reject multiplicative dependence, the overall evidence suggests that nonlinearity occurs in the variance of the process.

Because the results show substantial significant ARCH effects; *i.e.*, that large and small changes in returns tend to be systematically clustered together over time, the study has employed the specifications of conditional heteroscedasticity, with Bollerslev's GARCH generalization of the ARCH process (1986) providing a parsimonious model that represents the data satisfactorily. Other analyses conducted in this study used GARCH (1,1) throughout. Indeed, perhaps the most important point which emerged from our empirical analysis is the ability of the GARCH (1,1) model to capture the nonlinear dependence in all the series

In the classical empirical work by Lamoureux and Lastrapes (1990) on the heteroscedasticity in stock returns, in which the GARCH effects diminished when volume was introduced as a proxy for the mixing variable, the authors attempted to test the hypothesis of a mixture of distributions in which the stochastic mixing variable was hypothesized to be the rate of information arrival. The second part of our empirical study, therefore, concentrated on investigating the relationship between the trading volume and price variability in the currency futures markets. Two competitive hypotheses were investigated: namely, the sequential information model and the mixture of distributions hypothesis. Our findings on the contemporaneous relationship between volume and returns are consistent with the mixture of distributions hypothesis which suggests *prima facie* efficiency in currency futures pricing. However, when we reconsidered the informational role of volume using a GARCH specification, we found that trading volume explained the conditional variance of currency futures to a significant degree and that the GARCH effects diminished in all cases examined, a finding which is similar to those of Lamoureux, *et.al.,* (1990) in the stock market. As trading volume is highly autocorrelated, these test results could therefore be biased. In order to overcome this problem, we replace the correlated volume in the conditional variance equation by the unexpected volume, which was estimated using an AR procedure. We then reestimated the above equation using GARCH (p,q), since this model exibited a better fit than merely GARCH (1,1). It was found that the GARCH effects remain significant (*i.e.*, they do not vanish) when unexpected volume is included.

The final stage of the empirical research reported in this thesis was to explore the possibility of volatility spillover among currency futures. We took a substantially different approach from the analysis of volume, by examining the hypothesis that the rate of information arrival is a function of the residual terms of other currency futures. Thus, instead of using volume in the conditional variance equation, our analysis included the residuals from each currency futures estimation in the conditional variance equation of the other currency futures. In this context, Najang, *et.al.* (1992) have shown that ARCH effects disappear when there are strong spillover effects but that when the spillover effects are nonexistent or weak, the ARCH effects become significant. Our results show that, in some cases, both the ARCH and spillover effects remain significant, implying that the residuals from a particular future contract's conditional mean equation and those from the conditional mean equation of other currency futures have different information content and are thus highly significant in explaining the conditional variance. In the last part of our analysis, we tested whether there were common economic effects in the series. In general, our results show that the mean and volatility spillover effects diminish after the inclusion of expanded exogenous variables in the equations.

Our general conclusions are that since nonlinearity enters through the variance of the process, the general form of conditional heteroscedasticity in Engle (1982) should be used. Indeed, the generalized autoregressive conditional heteroscedasticity (GARCH) model appears to fit reasonably well to the returns generating process for all the contracts examined. This can be seen from the diagnostic tests in Chapters 5, 6 and 7 which reveal that the model can account for most of the second order moment in all the currency futures return series.

8.3 Comparison with Previous Studies

The preliminary results of this study are similar to those of Hsieh (1989a) on the spot market for foreign exchange and also to those of Fujihara and Morgoué (1997a) on the petroleum futures market. Using the BDS test, these authors rejected the null hypothesis of i.i.d. in all cases, as has the present study of currency futures returns. As for the third moment test, the findings reported here indicate a failure to reject the null hypothesis of multiplicative dependence and this is similar to Hsieh (1989a), implying that nonlinearity arises solely from the variance of the process and that nonlinear predictability for the conditional mean of the currency futures returns can be ruled out.

With respect to the relation between trading volume and price variability, our results for contemporaneous observations are similar to those of Grammatikos and Saunders (1986) who also analysed currency futures returns. They found a positive relationship between volume and price variability which is consistent with the mixtures distribution hypothesis (MDH). However, this result opposes to those of McCarthy and Najang

(1993), who found an insignificant relationship between contemporaneous trading volume and currency futures price changes. However, the two studies mentioned above use linear methods only. It should be emphasised, therefore, that the results presented in this thesis, which are in agreement with some past studies but which disagree with others, have been obtained from GARCH models which have better fit.

In relation to the examination of GARCH effects when trading volume is included as a proxy for information arrival in the conditional variance equation, the previous findings in other markets are mixed. For example, Najang and Yung (1991), who studied Treasury-bond futures contracts, found that the GARCH effects remained significant when volume was included in the equation, which is in contrast to our findings. Similar results were also reported by Fujihara and Mougoue (1997a) for petroleum futures, whereas the finding of Lamoureux and Lastrapes (1990) for the equity market are consistent with those of the present study: that GARCH effects vanish completely in most cases when expected volume is included in the conditional variance equation. This study has built on prior work in other markets by replacing the expected volume of currency futures trading with the unexpected volume. Our results show that while the unexpected volume remains significant, the GARCH effects do not disappear. Hence, our findings suggest that contemporaneous unexpected volume contributes information about the conditional variance in addition to lagged error and lagged conditional variance.

Finally, with regard to spillover effects on currency futures returns, our results show that ARCH effects from one contract and spillover effects from other contracts are found to exist simultaneously, particularly for the British pound and the German mark. These results differ from those of Najang, Rahman and Yung (1992) who, using currency futures data which may have been affected by the price limit introduction in 1985, reported evidence that ARCH effects disappear when there are strong spillover effects and that ARCH effects remain significant when the spillover effects are nonexistent or weak. In the present study, however, the continuous dataset (1986-1997) does not lead to the same conclusion. We have found evidence that information relating to one futures contract cannot be treated as a substitute for information arising in the trading of another contract.

8.4 Implications and Directions for Further Research

It may be argued that this type of research has particular relevance to the theory and practice of futures markets. In particular, a better understanding of the volatility of currency futures prices is important since this has significant implications for long-term hedging strategies in exchange risk management. For example, hedgers enter futures contracts to stabilize their future income flows, with the amount traded being determined by their expectations of the futures price and of future spot price variability. This is particularly important with respect to the capital requirements when a firm involved in hedging uses currency futures since the futures position is marked to market and gains and losses are settled at the end of the each trading day. If a firm's futures position is sustaining losses, it may need additional funds to meet margin requirements. Therefore, the ability to forecast futures price movements is crucial in assessing how much capital (e.g, additional funds) may be needed to maintain this futures position.

Given the evidence of second order serial dependence in currency futures prices, a better understanding of the volatility of currency price movements and trading volume would allow traders to forecast more accurately. They appear to believe that intrinsic knowledge of price changes and trading volume will enhance their understanding of the market dynamics and thus their financial success (Kocagil and Shachmurove, 1998). Indeed, there is some evidence that traders base their forecasts of futures price movements directly on the amount of volume traded. As suggested by Harris and Raviv (1993), trading volume can be considered to reflect information about changes and agreement in investors' expectations. Therefore, the results of the present study are relevant to technical analysis as trading volume has been found to play an important role in determining the quality of information contained in the price statistics.

Finally, the evidence of significant spillover effects and ARCH effects provides a better understanding of how the transmission mechanism works in the currency futures market, enabling investors to formulate better strategies for hedging in the currency futures markets. Our findings show that, on average, the ARCH effects; *i.e.* learning from errors in predicting rate changes in a single currency, dominate spillover effects between currencies. This indicates that investors should rely more on shocks in a particular currency when designing hedging positions. However, they should not neglect completely the price movements of other currency futures since our findings show that such returns exhibit a significant common economic effect.

Although in this thesis we have tried to uncover the source of GARCH effects using both the trading volume and shocks from other currency futures, it appears that these variables have not been able to explain much of the observed nonconstancy of the return variance. Further research should be directed toward uncovering these sources of heteroscedasticity. The possible exogenous variables which should be considered in place of volume as proxies of information arrival include the basis (the difference between the spot price and the futures price), open interest (outstanding contracts) and trading volume relative to open interest. An examination of these variables could shed considerable light on the time varying variance in the return series which cannot be fully captured by the unexpected volume.

It should be recalled that, in our study, the positive contemporaneous correlation between price change and trading volume is attributed to the equilibrium pricing by market participants who have received new information. However, as argued by Jennings and Barry (1983), examining the total price change and volume traded using daily data only may misspecify this contemporaneous association. Goodhart *et.al.,* (1993), Takezawa (1995) and Watanabe (1996) have examined intraday volume and price changes and provide statistical techniques for determining when the price adjustment process has attained a new equilibrium. In future research, a similar methodology could perhaps be used to investigate the relationship between price change and volume in the currency futures market.

Another area of potential future research is the spillover effect of currency futures in markets located in different parts of the world. For example, in the interest rate futures market, Abhyankar (1995) and Lim, Terry and How (1998) have examined the inter-market transmission of returns, volatility and trading volume for Eurodollar futures on the Chicago Mercantile Exchange (CME) and the Singapore Monetary Exchange (SIMEX). Here, identical contracts are traded in two distinct time zones but linked with a mutual offset system allowing for round-the-clock trading. Extending this to currency futures would shed light on the importance of transmission effects when the observations are drawn from non-overlapping time zones.

To summarise, this thesis provides important evidence on which to base hedging strategies. We have used a nonlinear model to show that today's unexpected trading volume in the currency futures market dominates past forecasting errors in the returns series and also the spillover of information between currencies. Our results are statistically significant and stable across subperiods. However, some unresolved issues can be identified, particularly the potential relevance of other explanatory variables such as basis and open interest. There is also the possibility of further refinement using alternative return periods as well as quotations across markets in different time zones.

Appendix 1

Figure A-1: British Pound Futures Price (Number of Observations = 2954)

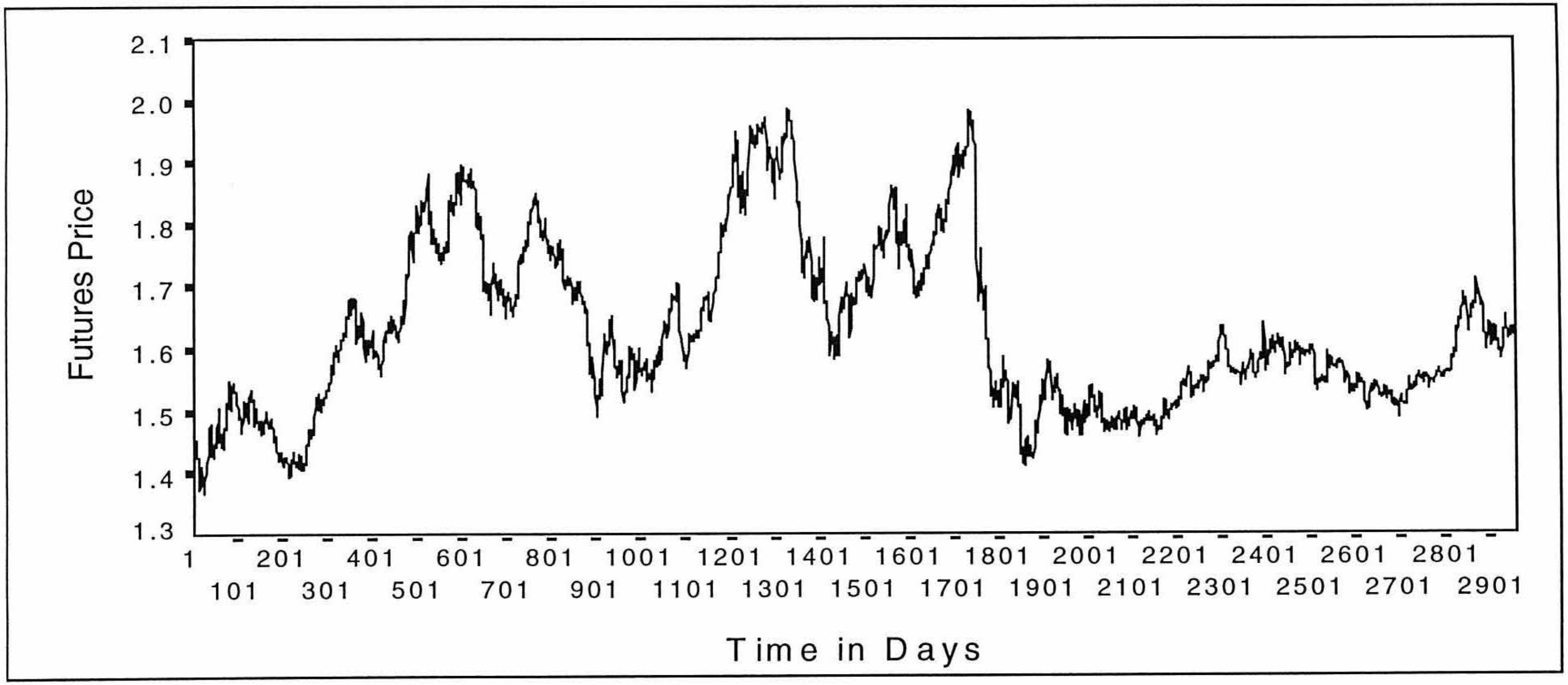


Figure A-2: British Pound Futures Returns (Number of Observations = 2954)

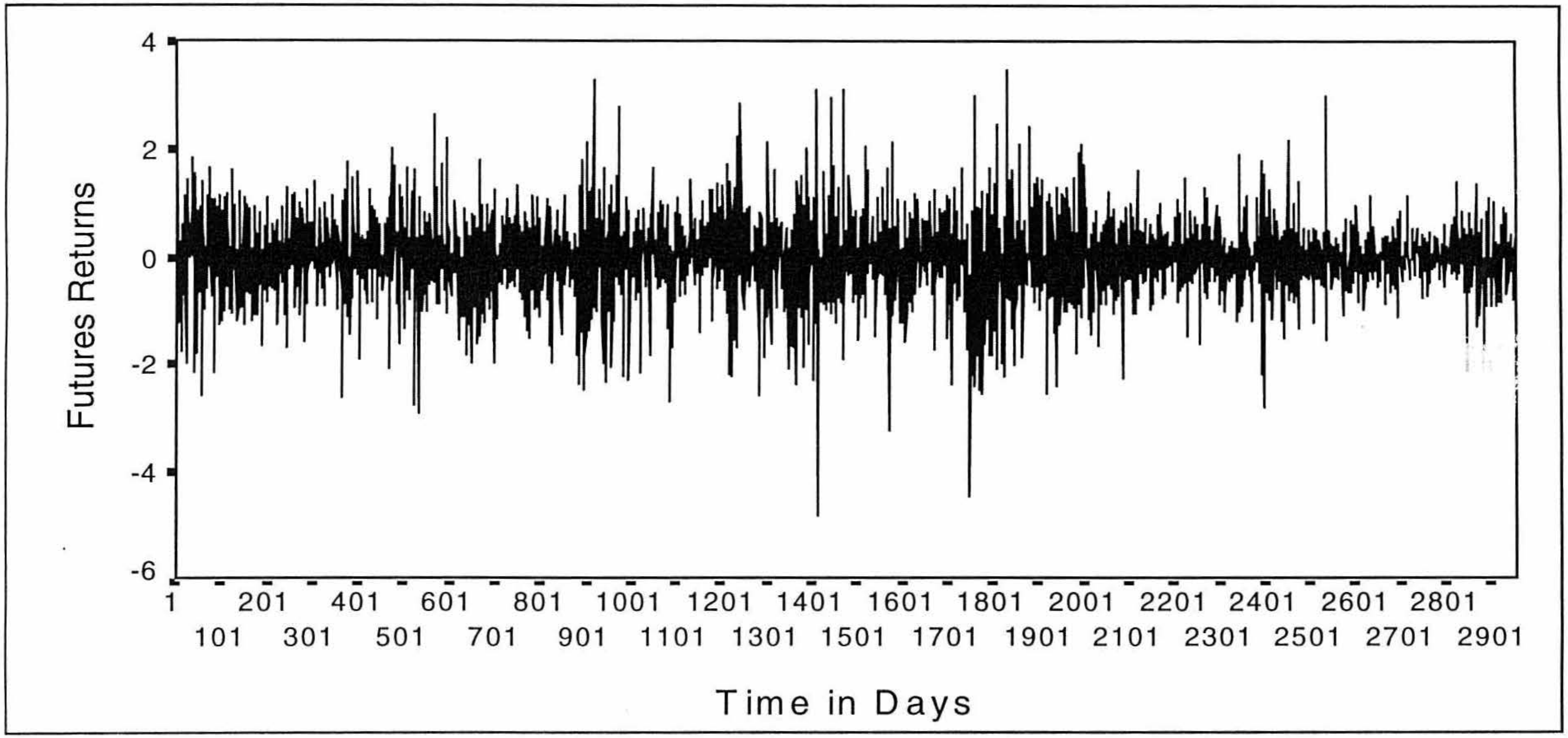


Figure A-3: German Mark Futures Price (Number of Observations = 2954)

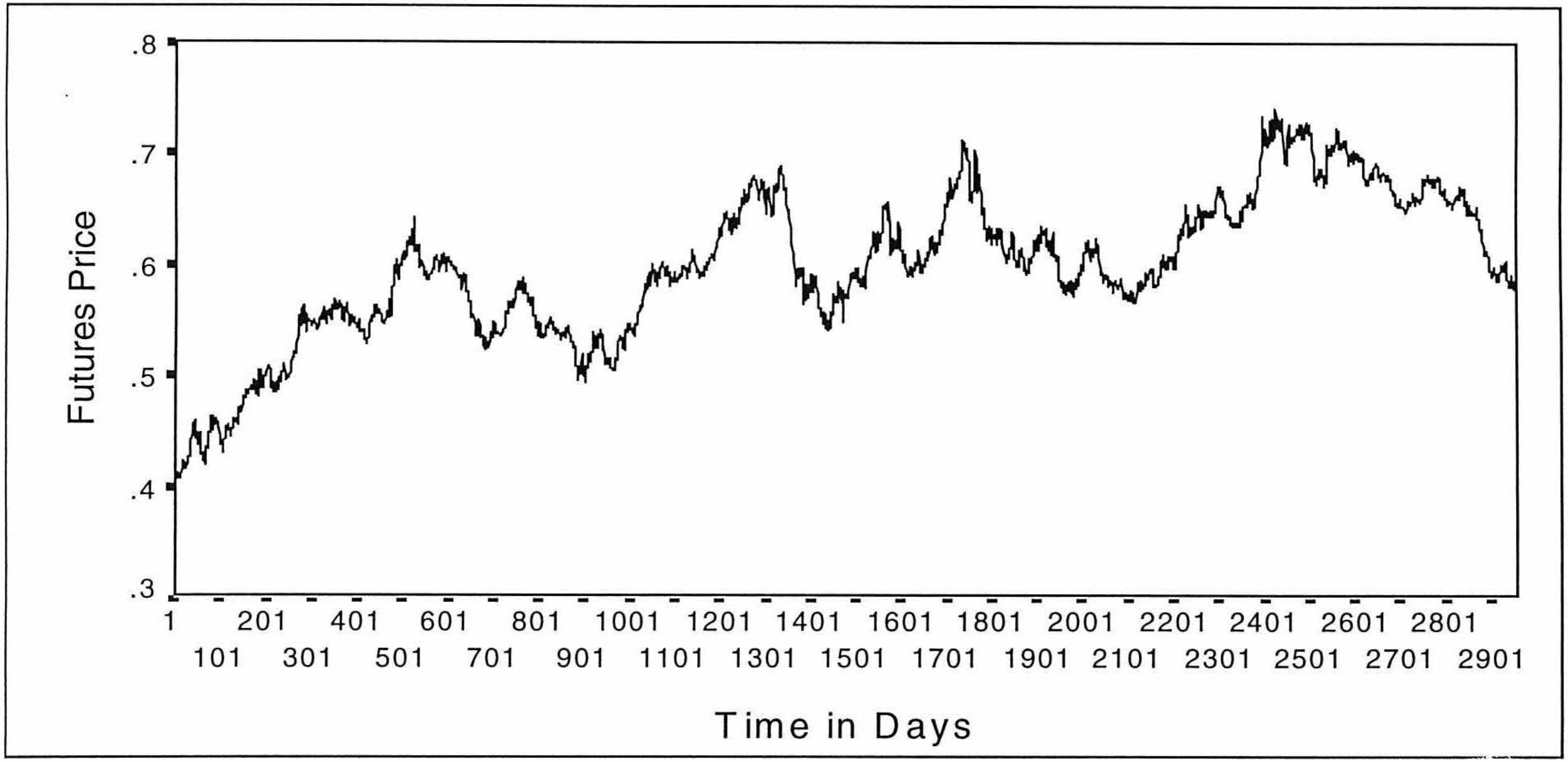


Figure A-4: German Mark Futures Returns (Number of Observations = 2954)

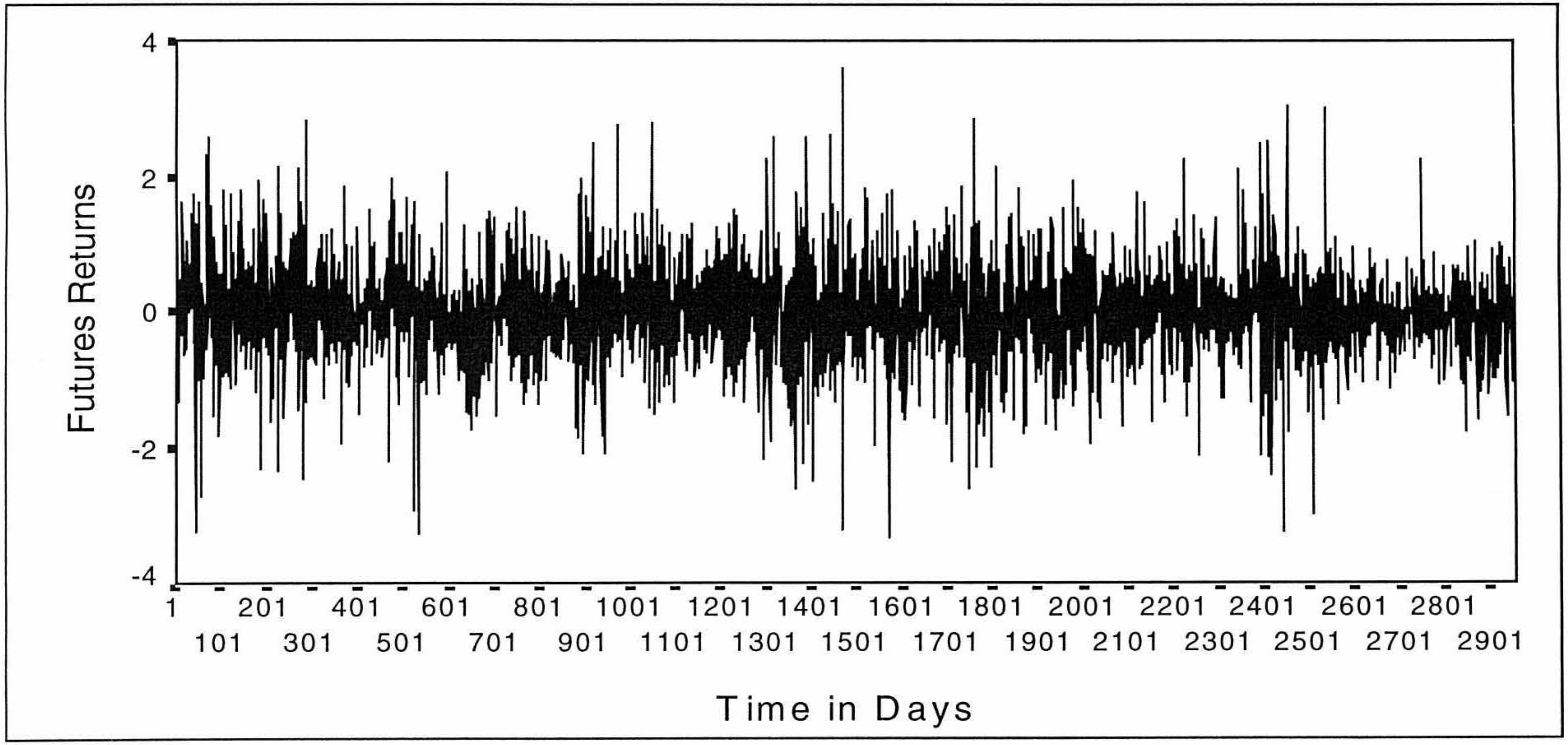


Figure A-5: Japanese Yen Futures Price (Number of Observations = 2954)

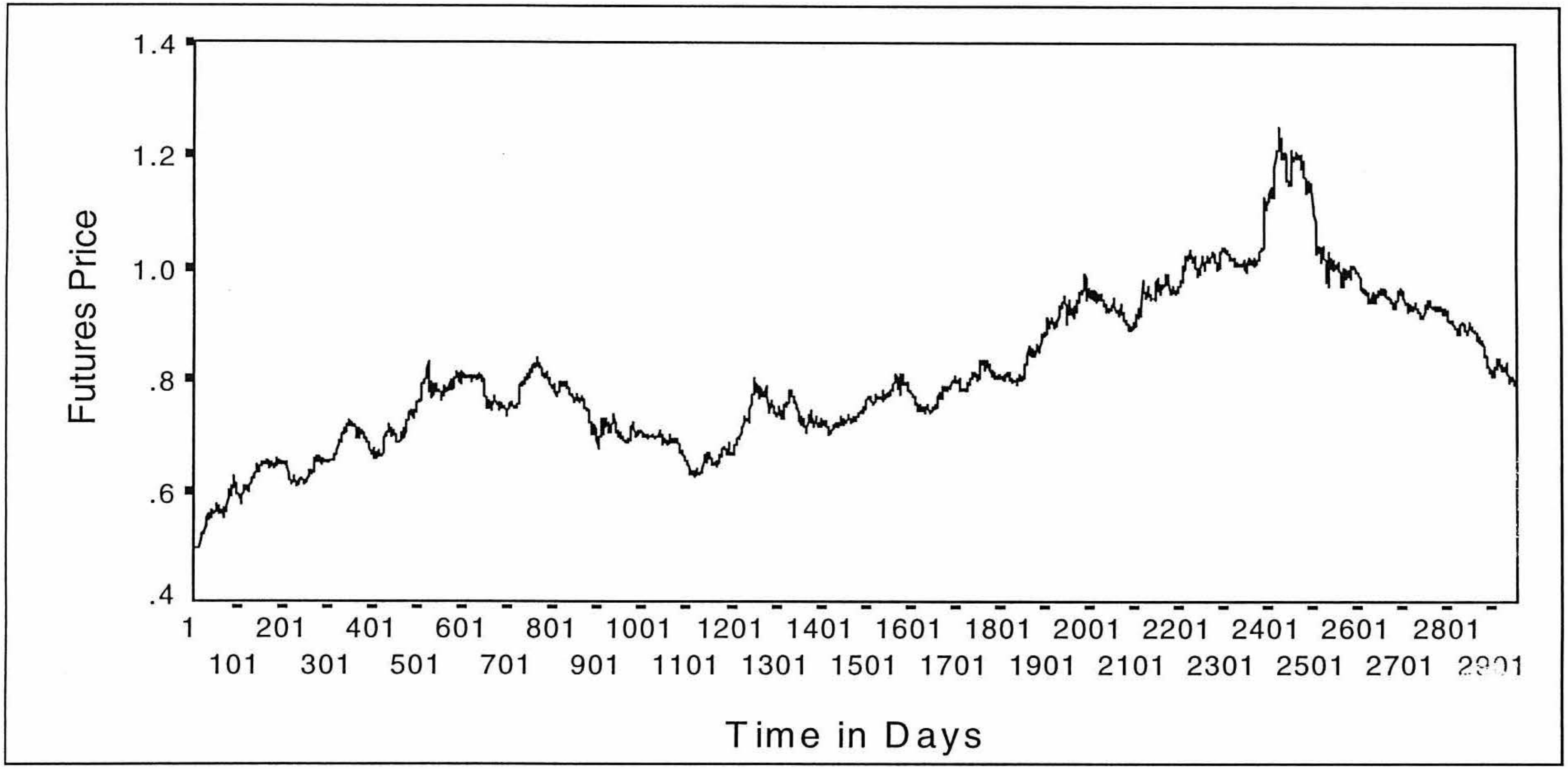


Figure A-6: Japanese Yen Futures Returns (Number of Observations = 2954)

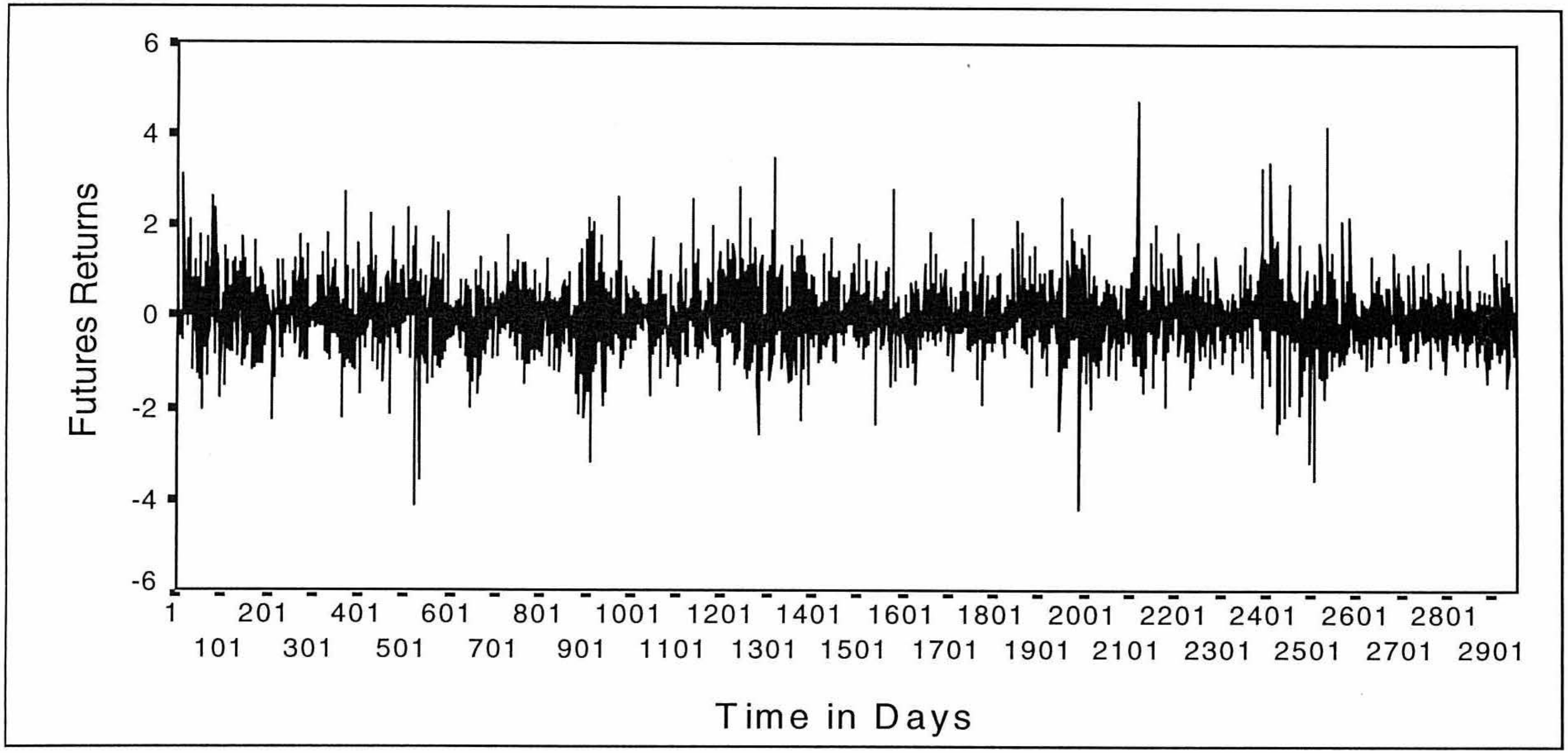


Figure A-7: Swiss Franc Futures Price (Number of Observations = 2954)

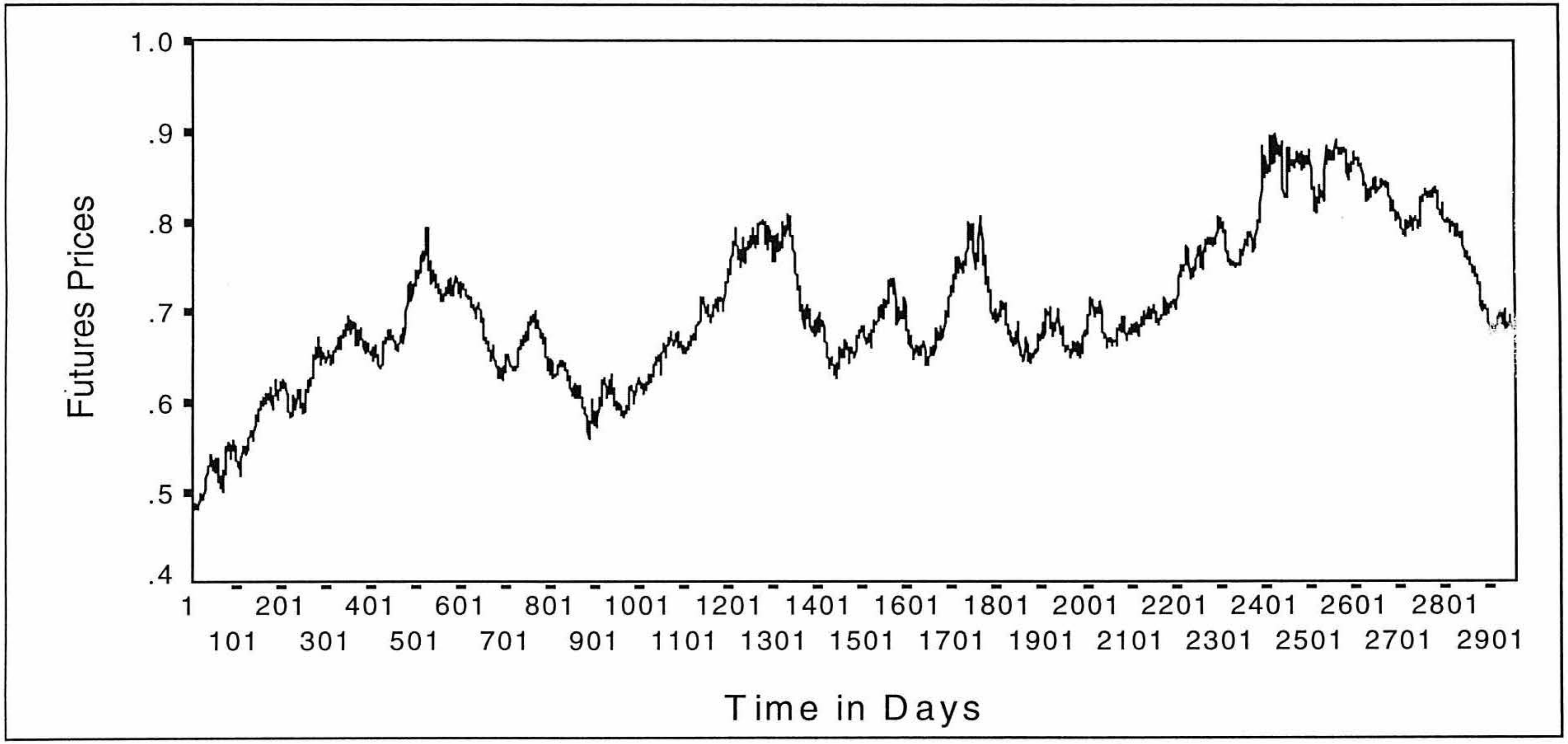
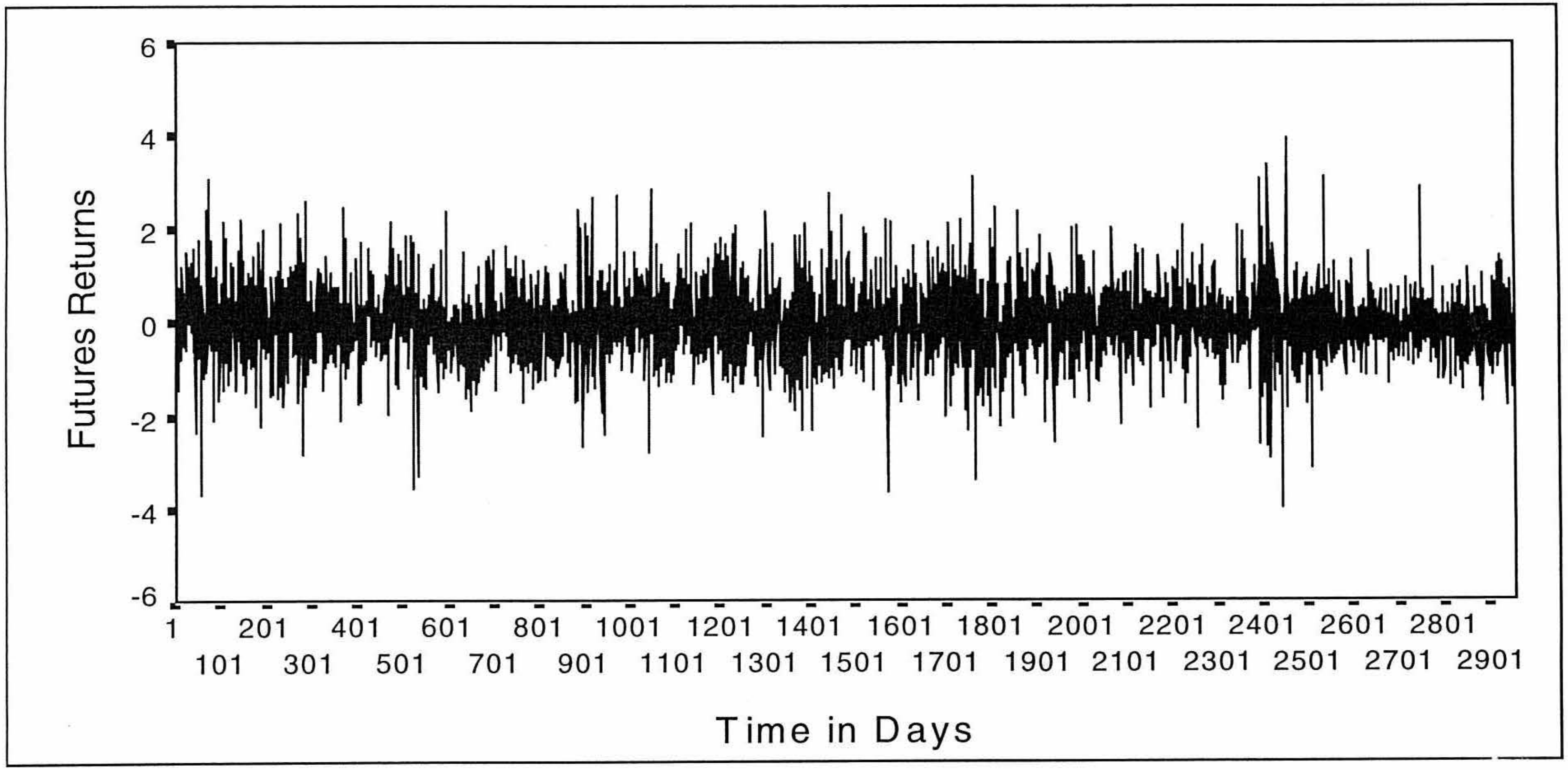


Figure A-8: Swiss Franc Futures Returns (Number of Observations = 2954)



Appendix 2

Figure A-9: British Pound Futures Price (Synchronised with Volume Data: Number of Observations = 2863)

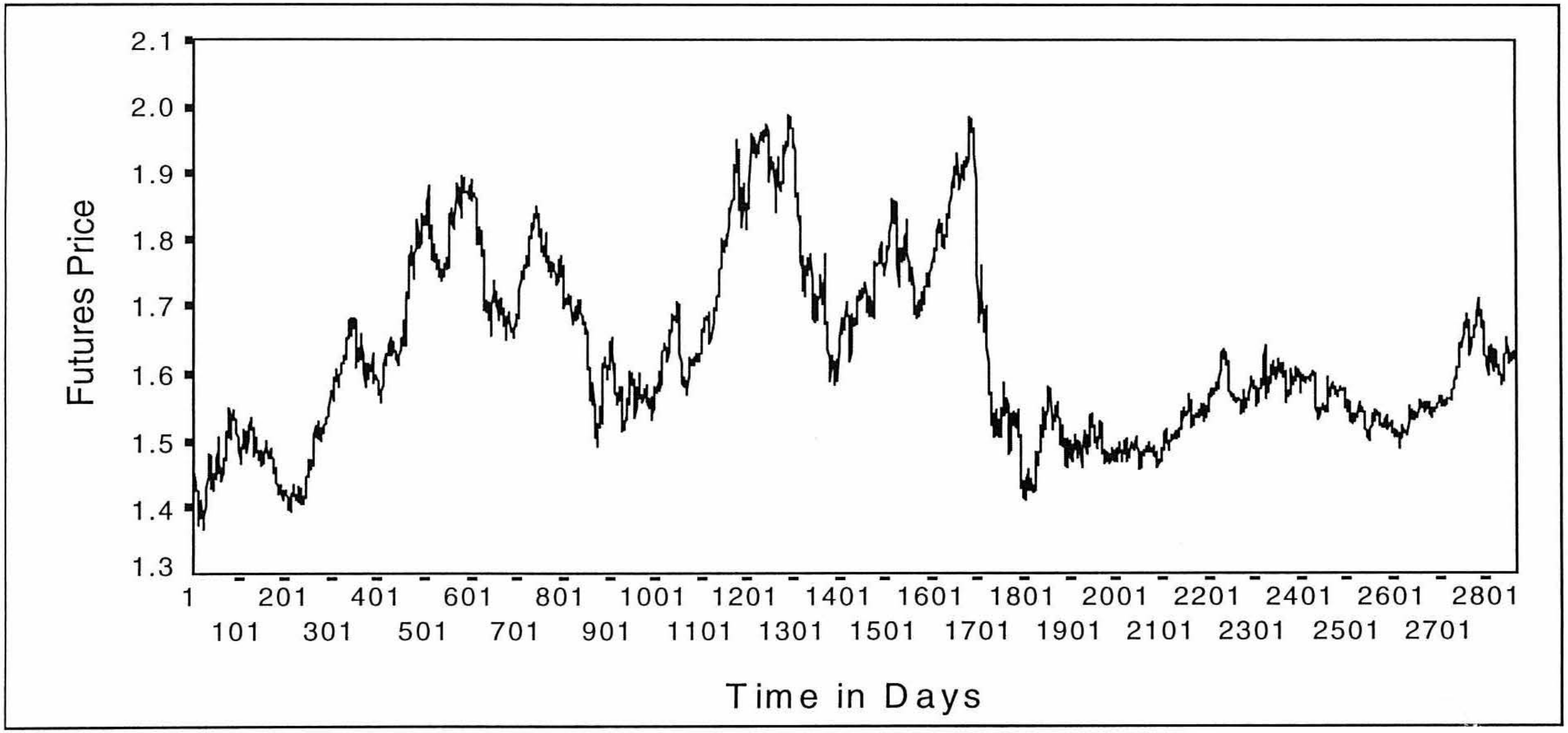


Figure A-10: British Pound Futures Returns

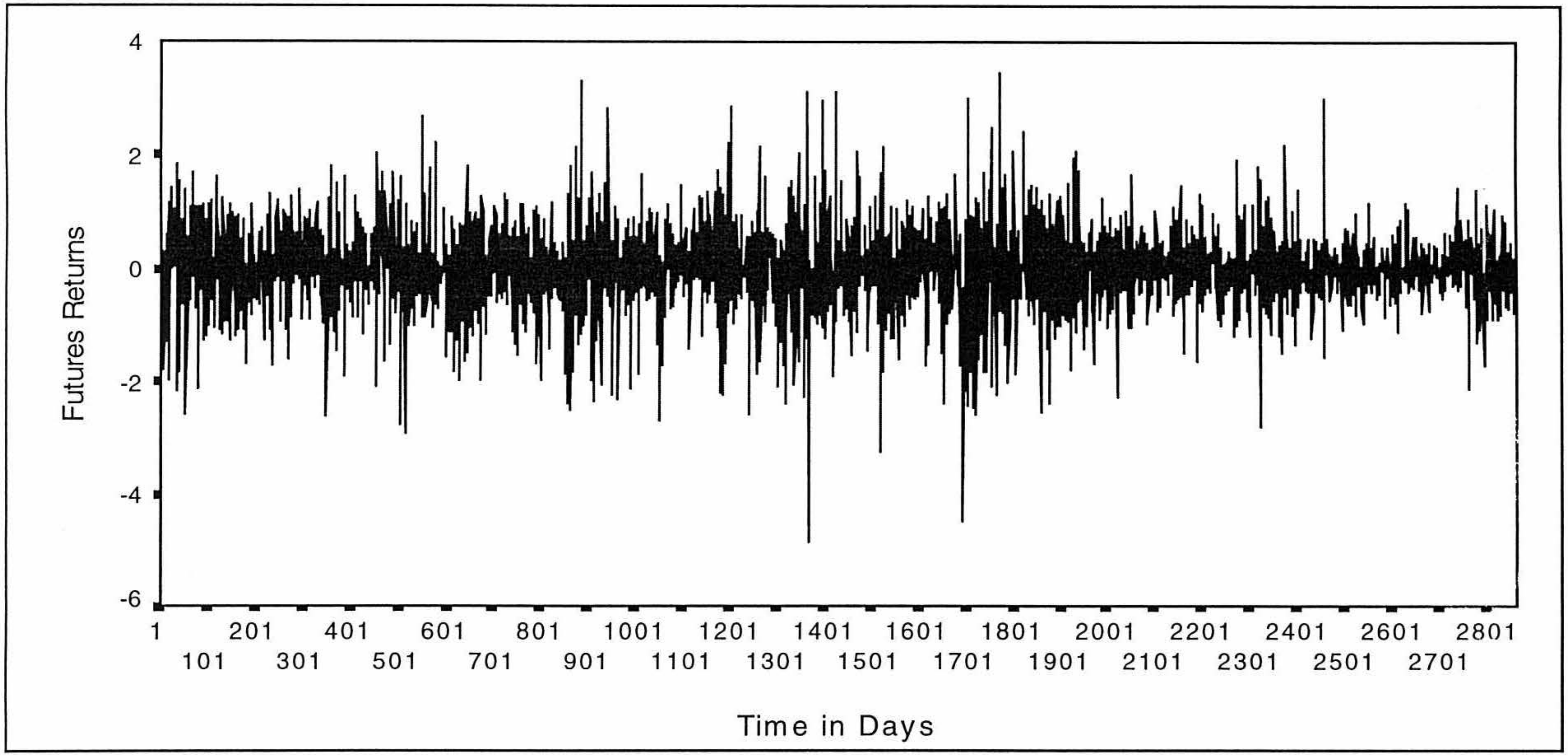


Figure A-11: British Pound Futures Volume

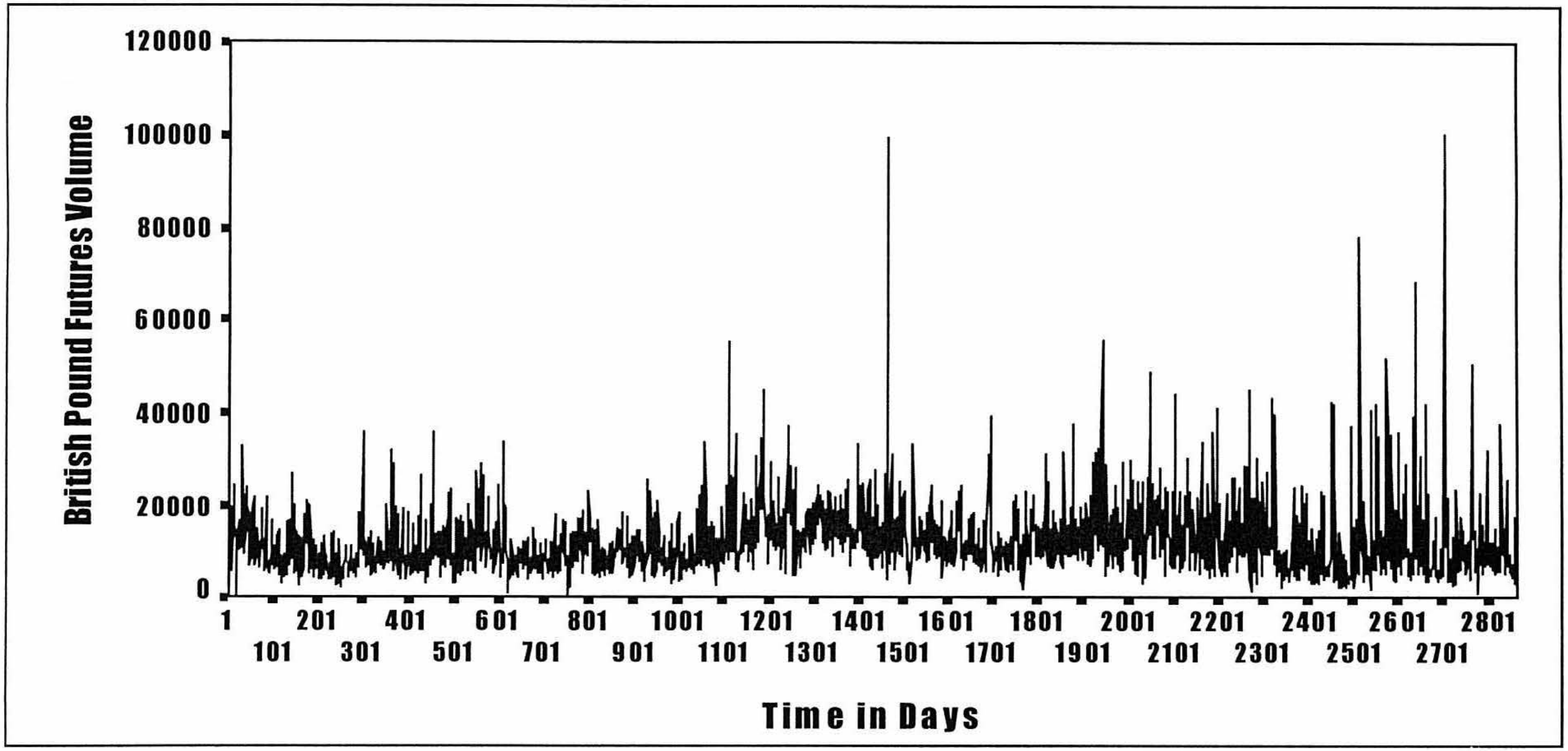


Figure A-12: British Pound Uncorrelated Volume

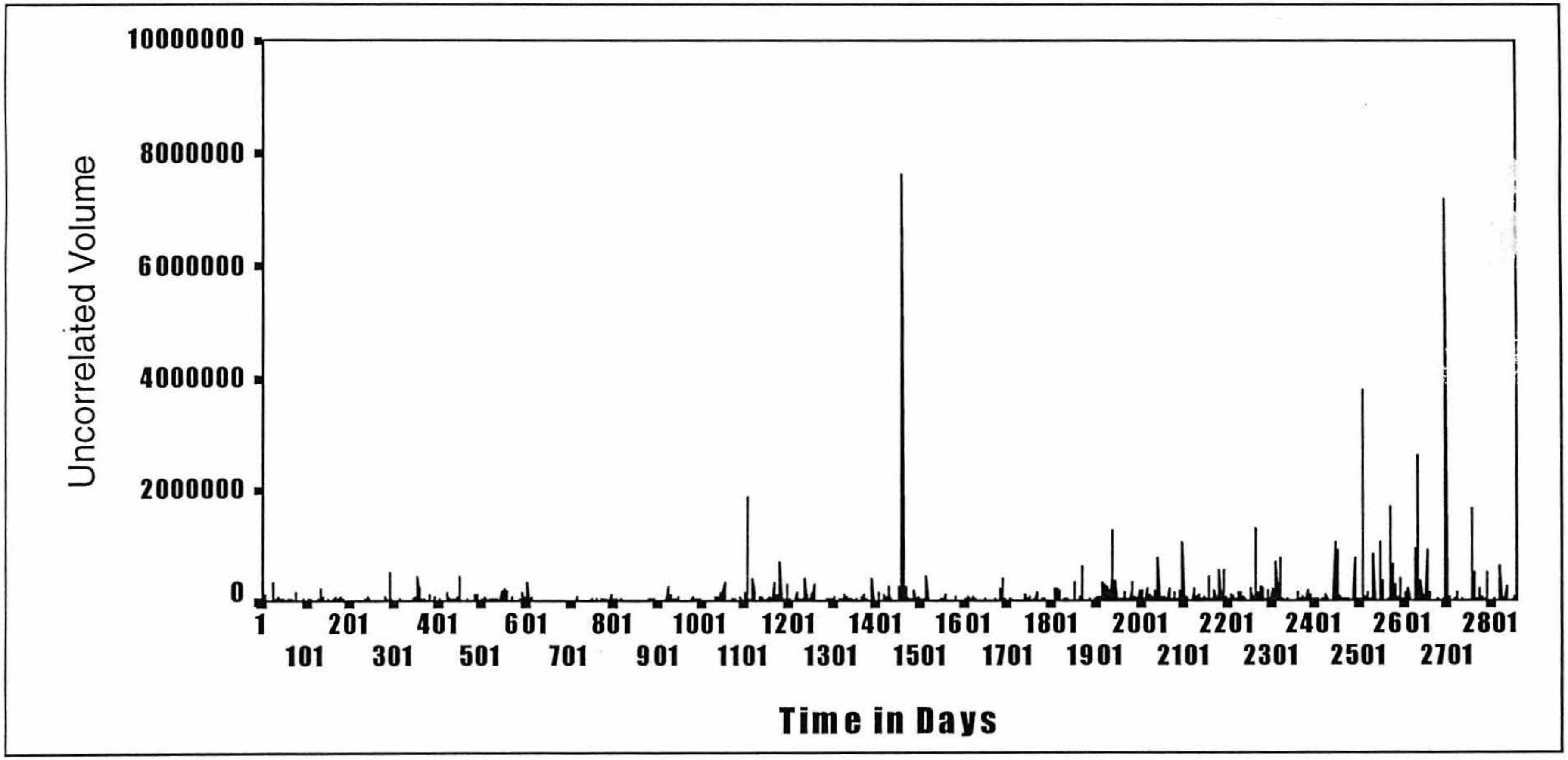


Figure A-13: German Mark Futures Price (Synchronised with Volume Data: Number of Observations = 2865)

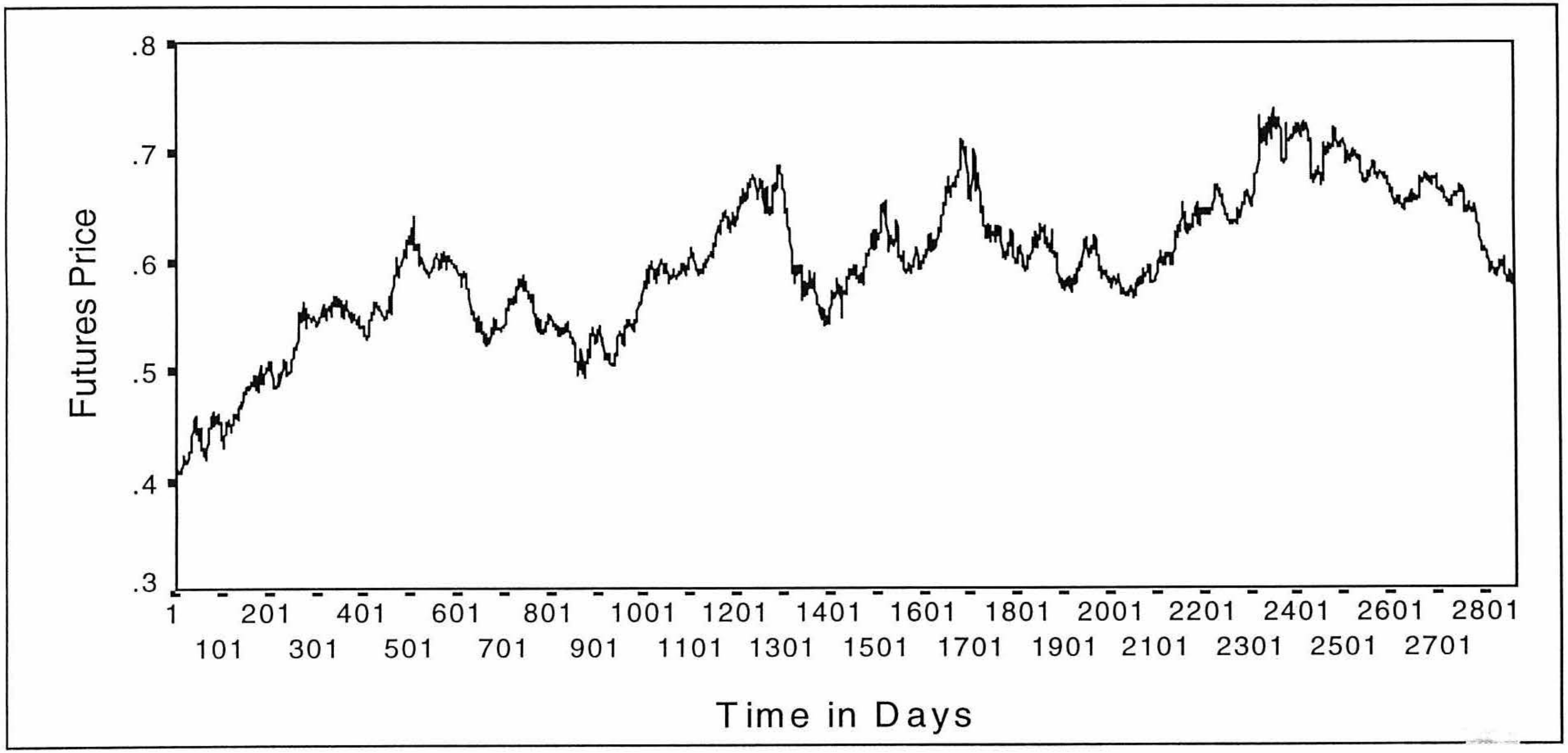


Figure A-14: German Mark Futures Returns

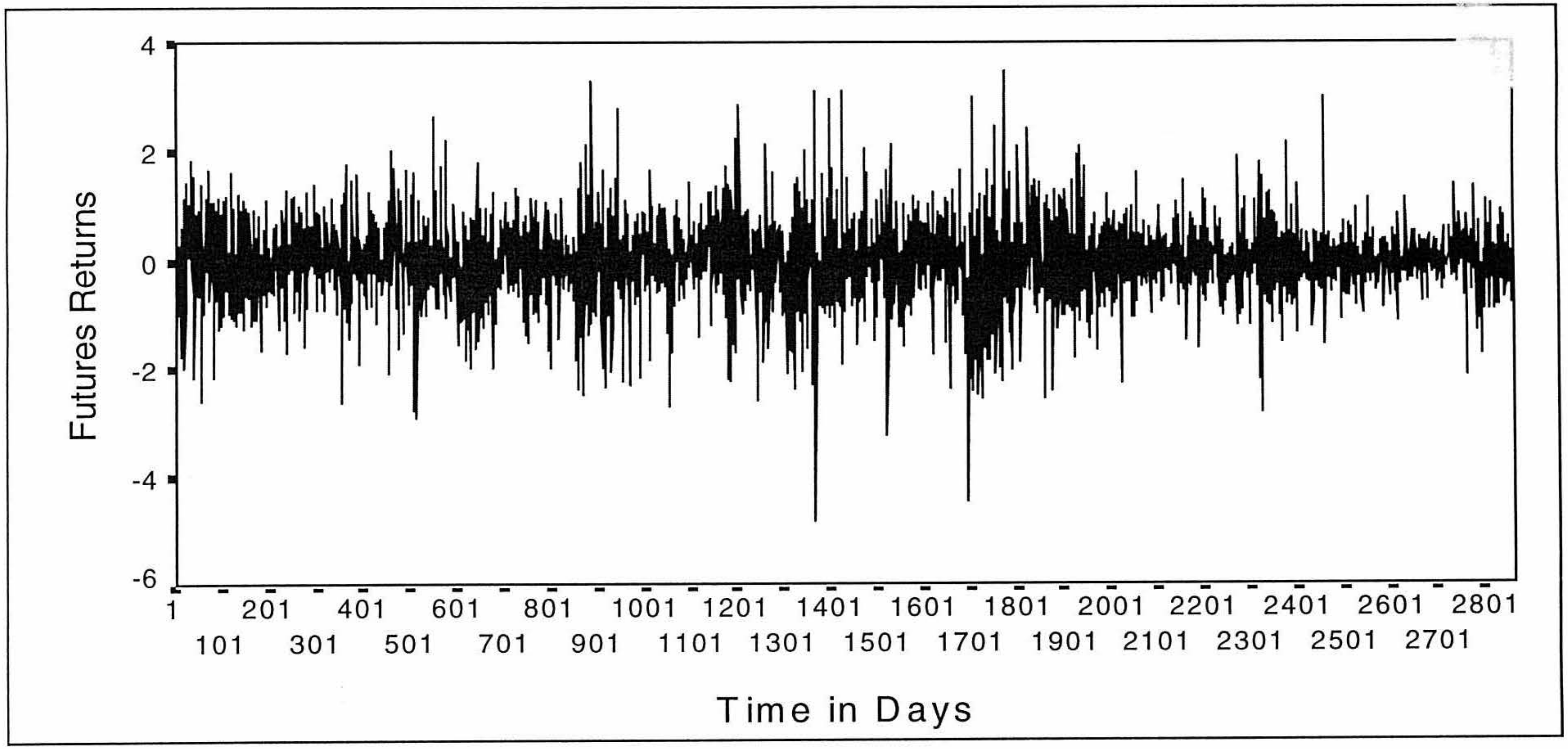


Figure A-15: German Mark Futures Volume

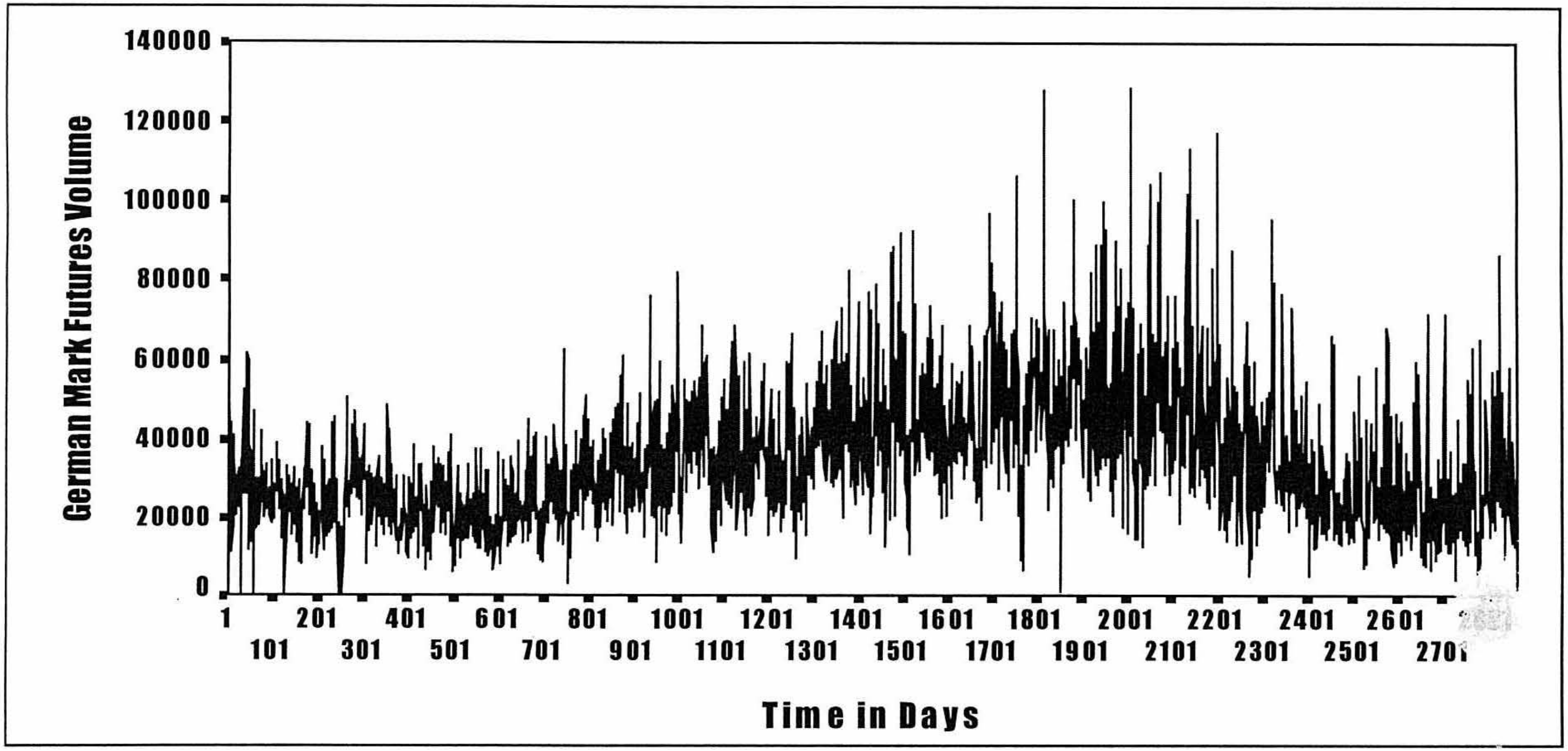


Figure A-16: German Mark Uncorrelated Volume

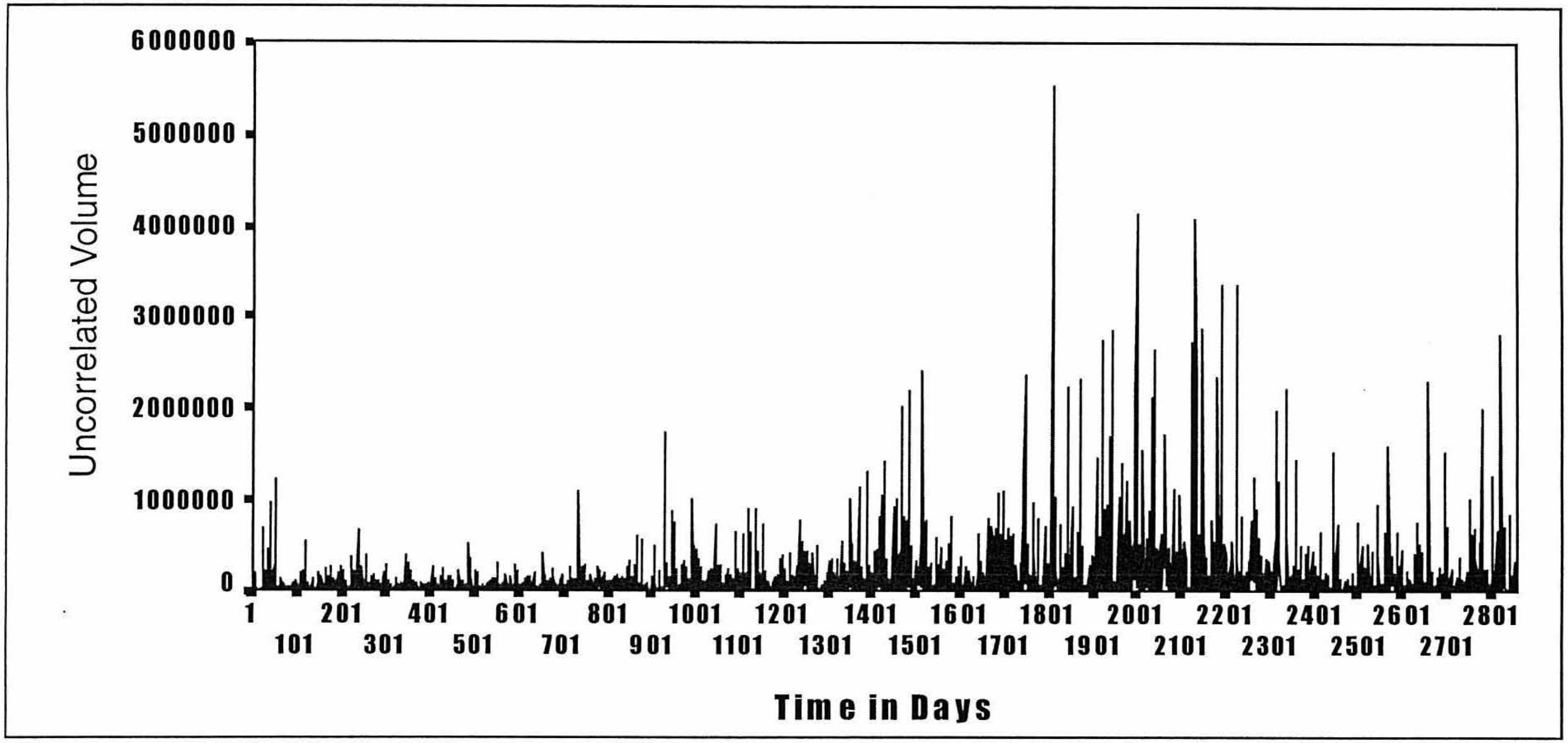


Figure A-17: Japanese Yen Futures Price (Synchronised with Volume Data: Number of Observations = 2861)

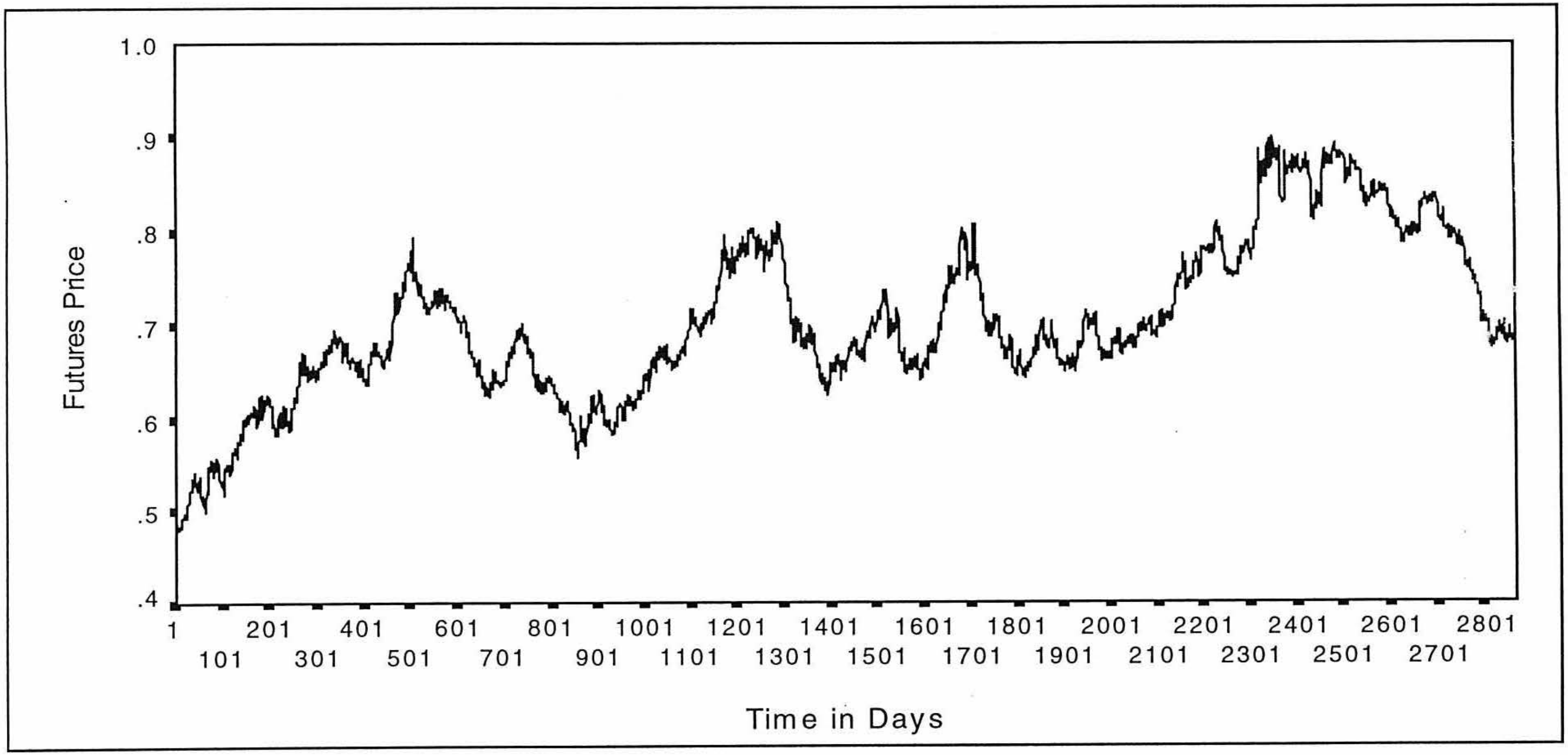


Figure A-18: Japanese Yen Futures Returns

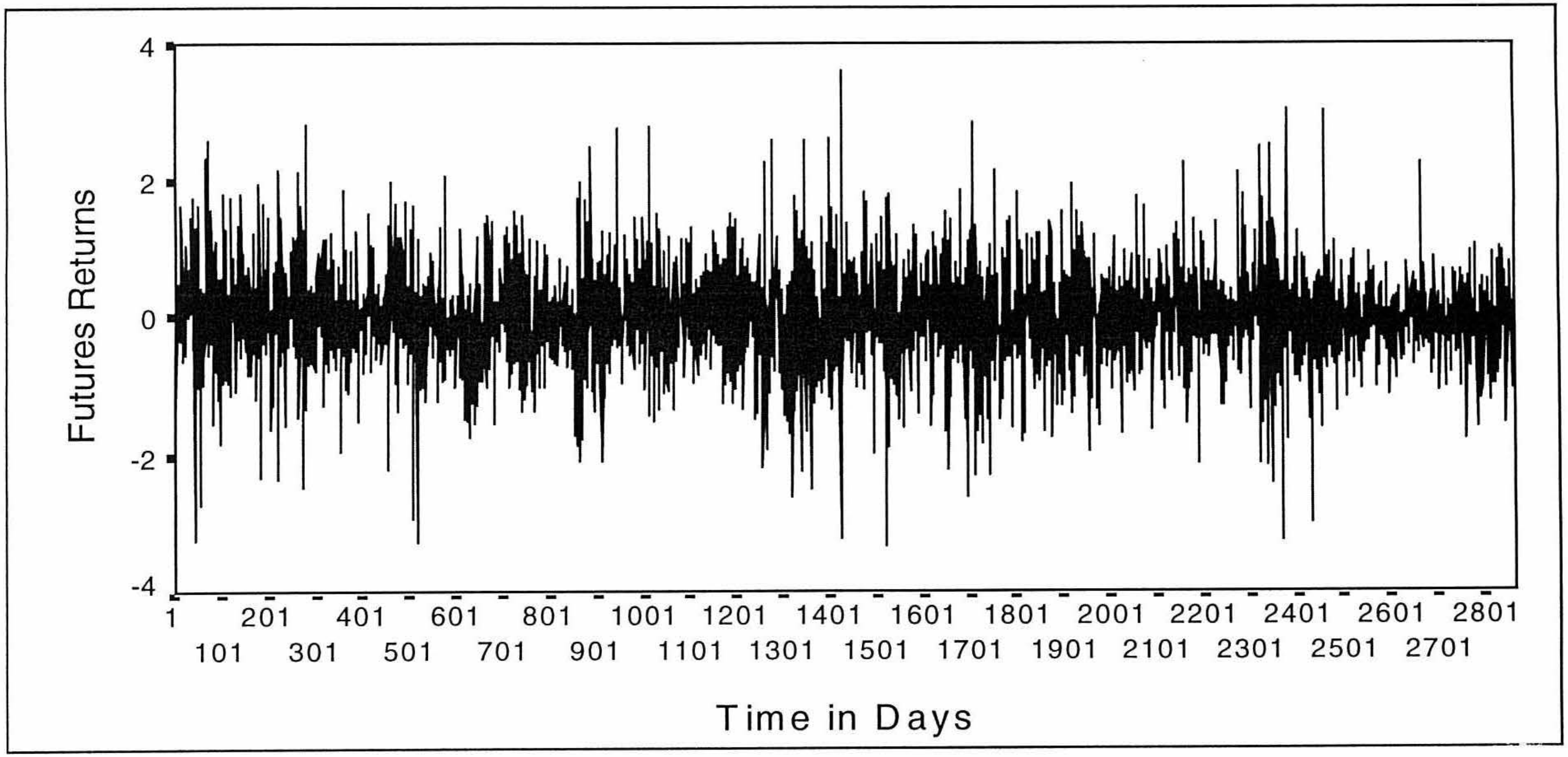


Figure A-19: Japanese Yen Futures Volume

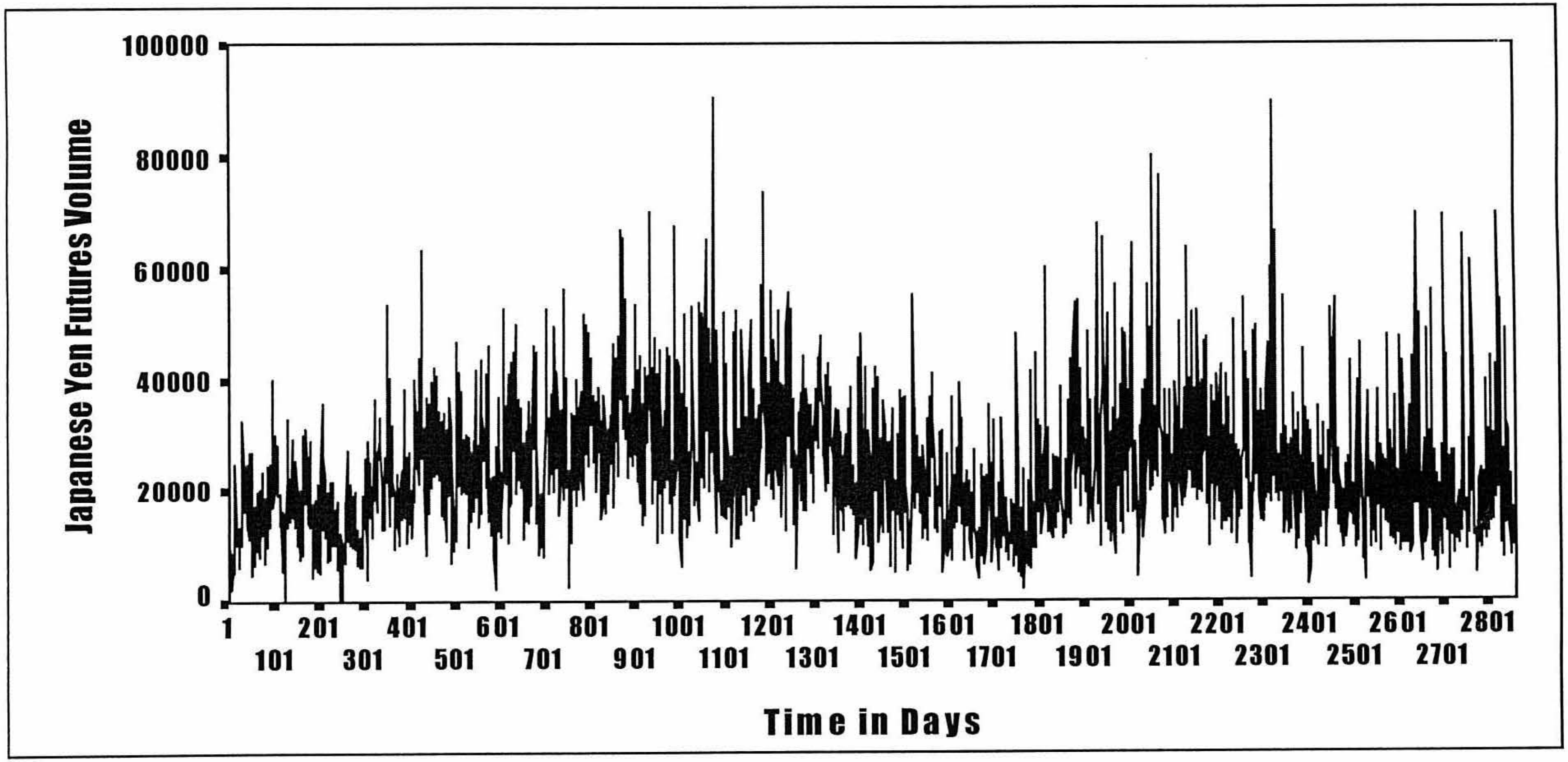


Figure A-20: Japanese Yen Uncorrelated Volume

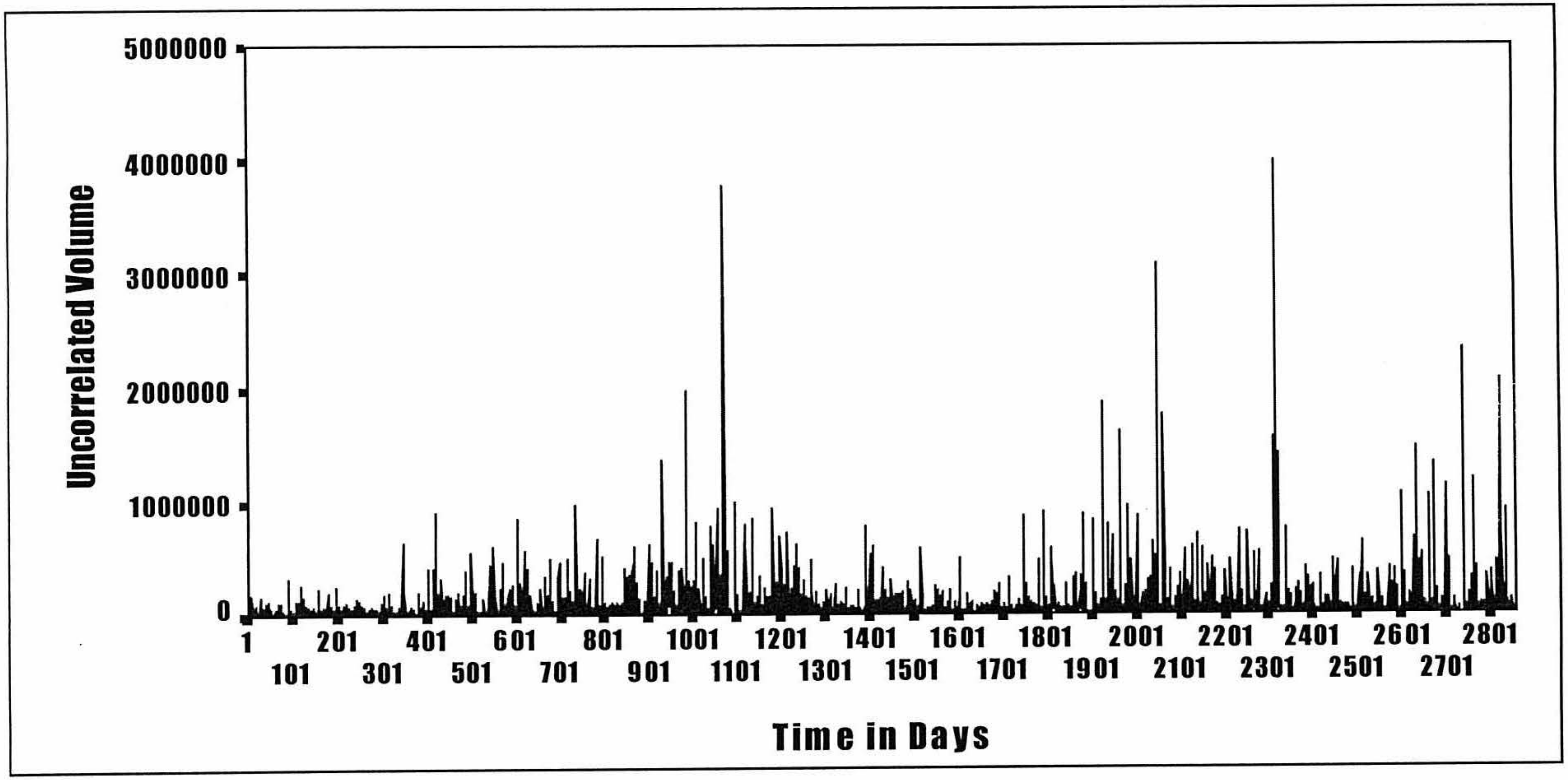


Figure A-21: Swiss Franc Futures Price (Synchronised with Volume Data: Number of Observations = 2865)

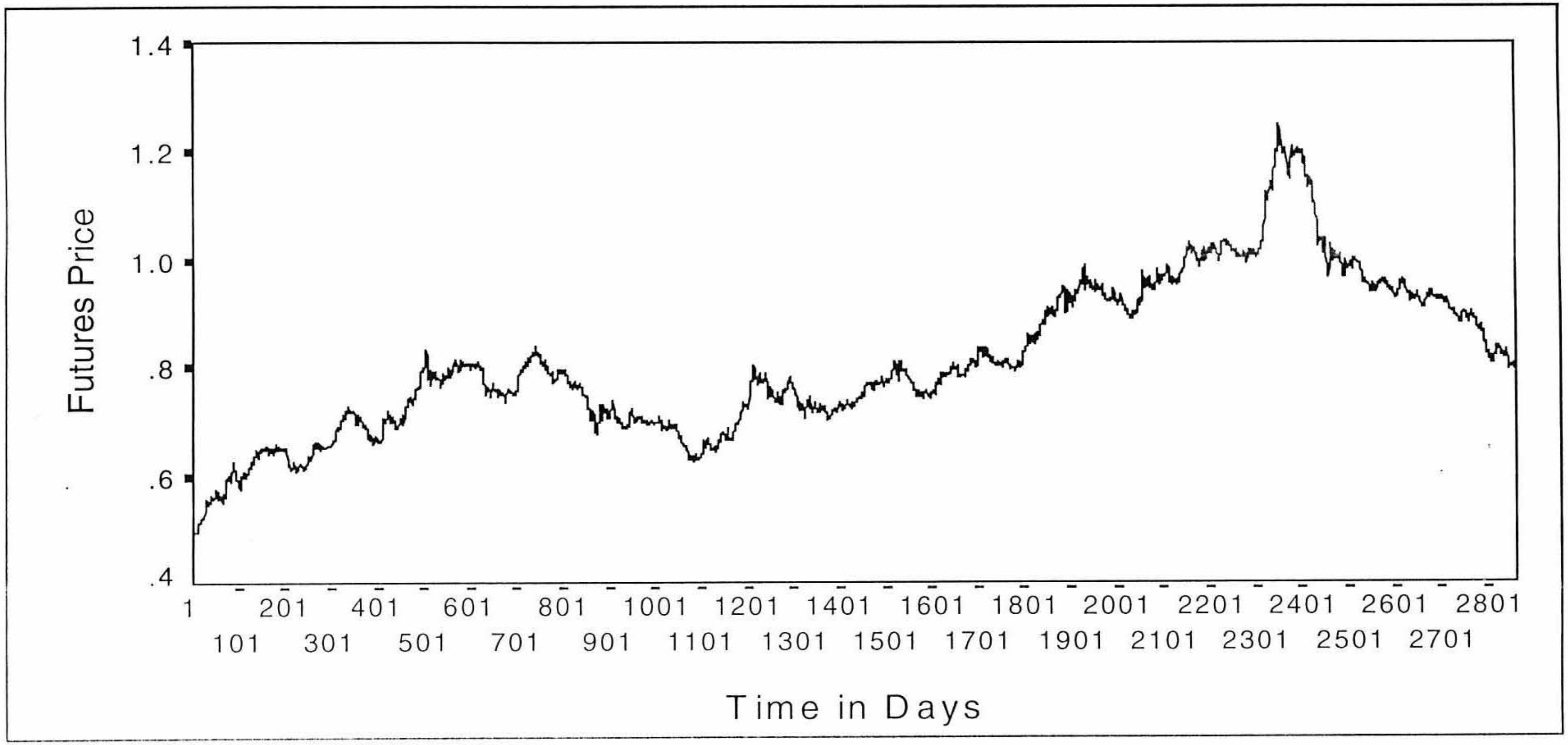


Figure A-22: Swiss Franc Futures Returns

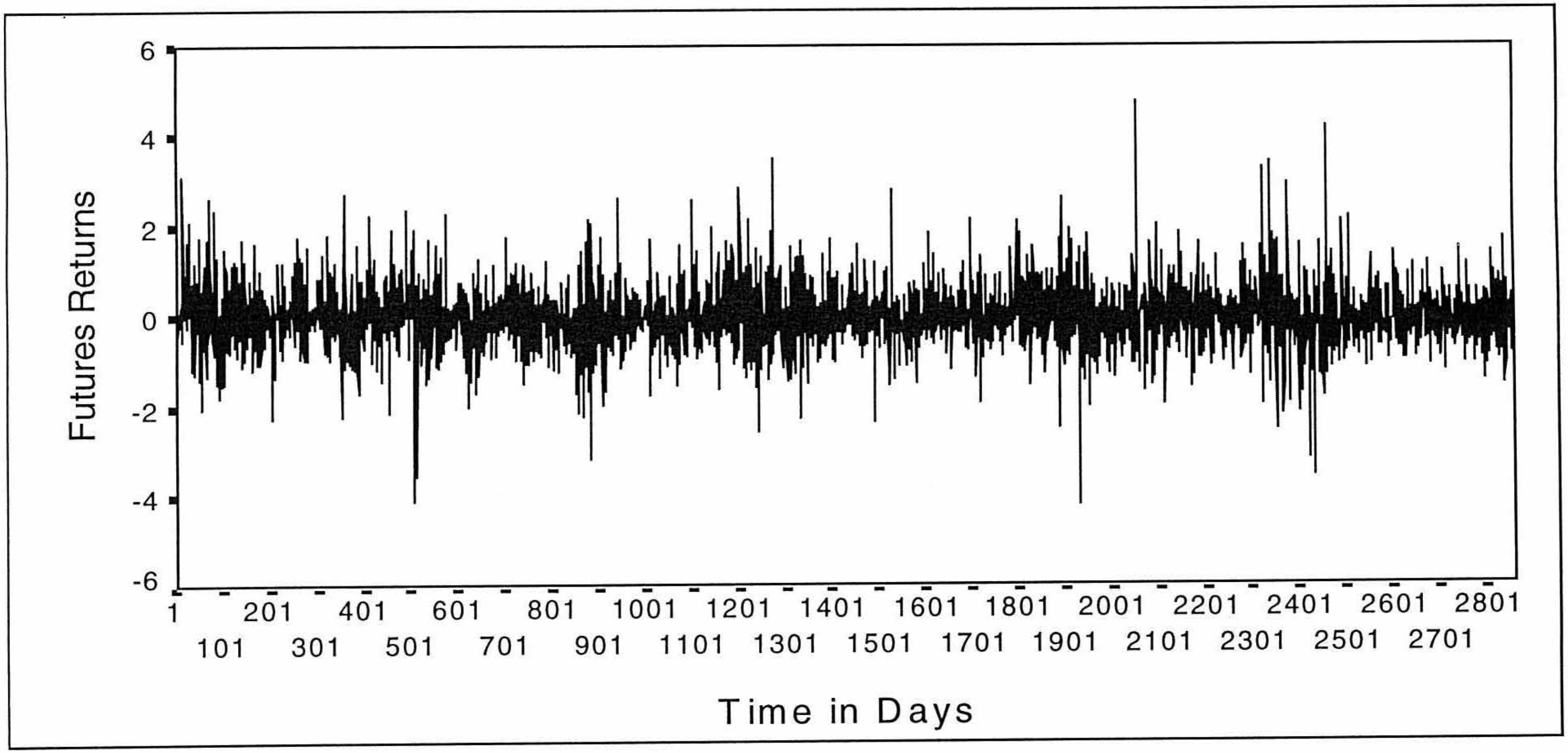


Figure A-23: Swiss Franc Futures Volume

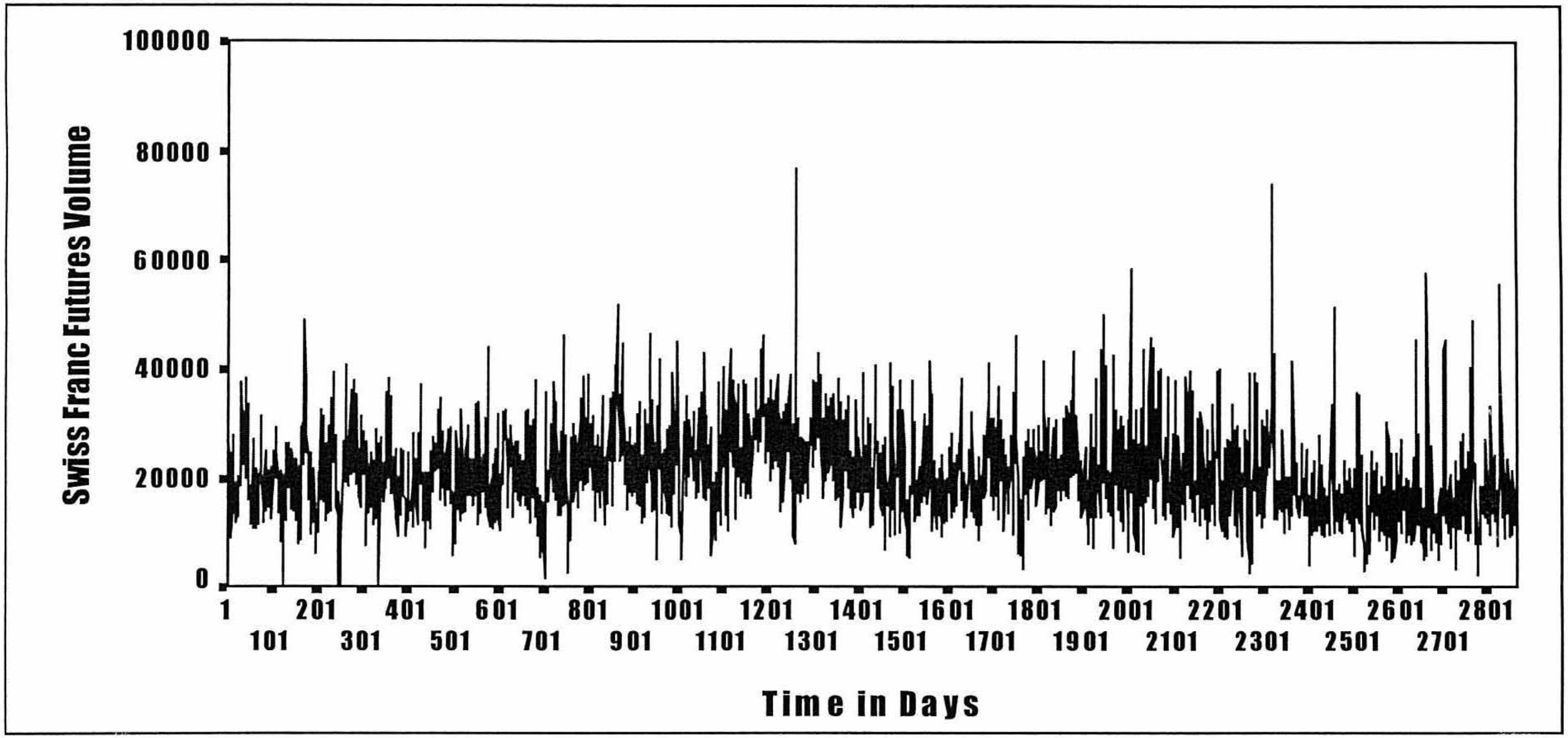
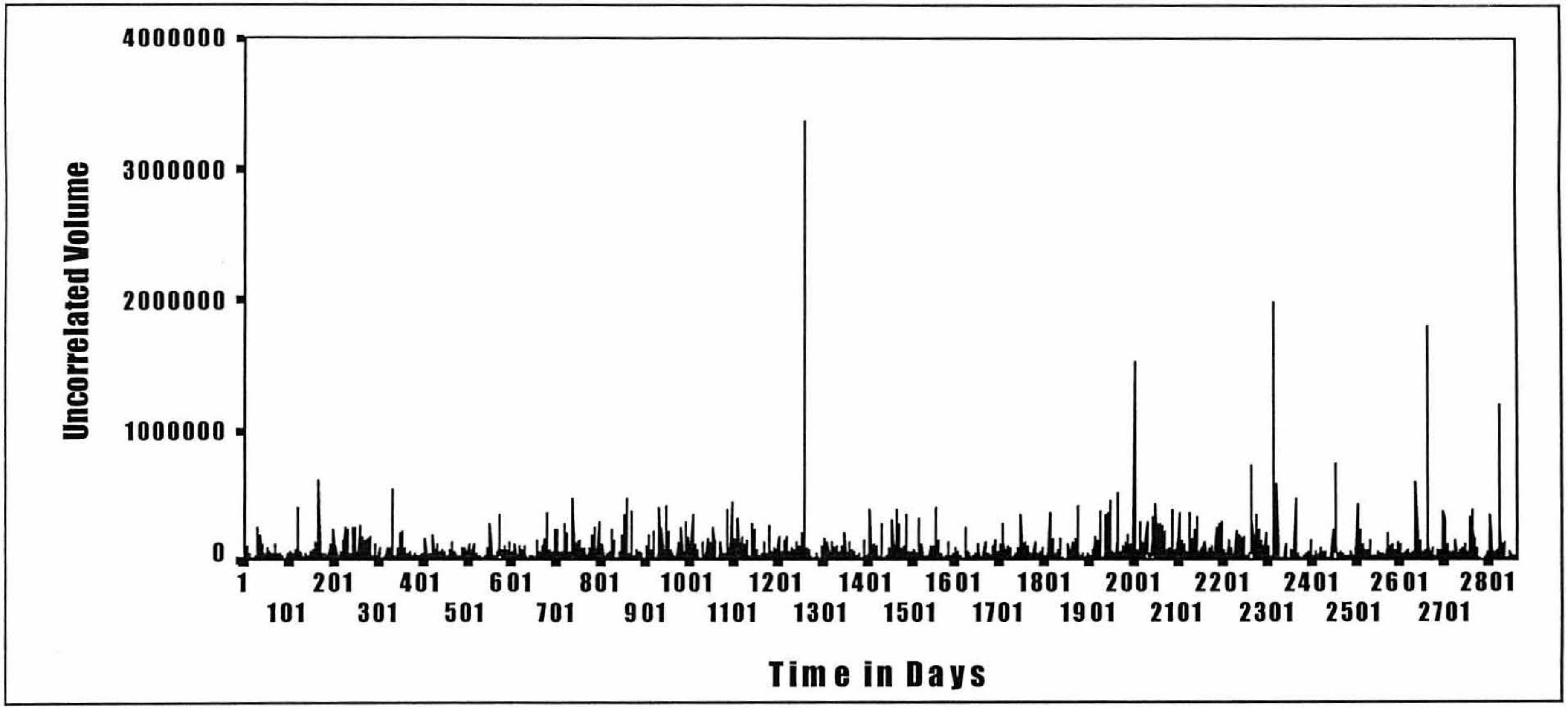


Figure A-24: Swiss Franc Uncorrelated Volume



Appendix 3

The calculation of the mean, the variance, the skewness and the kurtosis for the daily returns and of the trading volume for the four currency futures are as follows:

N (number of observations) for return series = 2954 and;

N (number of observations) for returns series with synchronised trading data = 2863, 2865, 2861 and 2865, for the BP, the DM, the JY and the SF, respectively.

1. The sample mean for currency futures j and for daily returns N, where j = 1, 2, 3 and 4:

$$\mu_j = \frac{\sum_{i=1}^{N} X_{i,j}}{N}$$

2. The sample variance for currency futures j and for daily returns N, where j = 1, 2, 3 and 4:

$$\sigma_j^2 = \frac{\sum_{i=1}^{N} (X_{ij} - \mu_j)^2}{N}$$

3. The sample skewness coefficient for currency futures j and for daily returns N, where j = 1, 2, 3 and 4:

$$SK_j = \frac{\sum_{i=1}^{N} (\frac{X_{ij} - \mu_j}{\sigma_j})^3}{N}$$

4. The sample excess kurtosis coefficient for currency futures j and for daily returns N, where j = 1, 2, 3 and 4:

$$K_j = \frac{\sum_{i=1}^{N} (\frac{X_{ij} - \mu_j}{\sigma_j})^4}{N} - 3$$

Appendix 4

Table A-1: BDS Statistics for the Return Series (n=2954)

Length in Standard Deviation (ε)	Embedding Dimension (m)	W Statistic (BDS/SD)			
		BP	DM	JY	SF
2.0	2	4.5947*	3.3232*	4.9848*	3.2701*
2.0	3	5.8226*	4.0752*	4.8088*	2.8408*
2.0	4	7.7292*	4.0167*	6.4303*	3.5283*
2.0	5	11.423*	-1.9496	7.0612*	3.3956*
2.0	6	12.317*	-0.7707	5.7712*	-6.6772*
2.0	7	17.841*	-7.5892*	3.3684*	-8.0594*
2.0	8	20.793*	-5.8378*	16.792*	-6.2160*
2.0	9	-4.0088*	-4.6055*	-4.6830*	-4.9178*
2.0	10	-3.2050*	-3.7038*	-3.7710*	-3.9668*
1.5	2	4.5634*	2.9211*	5.0230*	2.4577*
1.5	3	5.8049*	2.9933*	4.7439*	2.5227*
1.5	4	7.8593*	4.2115*	4.6495*	4.6254*
1.5	5	11.775*	-2.6992*	3.1465*	1.6024
1.5	6	5.4067*	-9.3948*	2.5743*	-9.9047*
1.5	7	22.134*	-6.9517*	-7.2348*	-7.3477*
1.5	8	-4.8649*	-5.3232*	5.5543*	-5.6416*
1.5	9	-3.8061*	-4.1795*	-4.3727*	-4.4423*
1.5	10	-3.0337*	-3.3443*	-3.5087*	-3.5654*
1.0	2	4.2377*	3.1115*	4.5782*	1.3484
1.0	3	5.0048*	4.9595*	4.0540*	1.2171
1.0	4	8.9692*	1.4194	7.1590*	2.2901*
1.0	5	7.4860*	10.362*	-4.5468*	1.9173
1.0	6	-8.0793*	-8.1057*	-8.7847*	-8.7481*
1.0	7	-5.9344*	-5.9481*	-6.4790*	-6.4453*

1.0	8	-4.5084*	-4.5147*	-4.9438*	-4.9131*
1.0	9	-3.5100*	-3.5119*	-3.8672*	-3.8392*
1.0	10	-2.7834*	-2.7827*	[illegible]	-3.0568*
0.5	2	3.6588*	0.5208	4.2190*	0.8356
0.5	3	8.0122*	4.1811*	5.8569*	1.5329
0.5	4	3.2974*	-4.7211*	12.6870*	4.5299*
0.5	5	63.469*	-8.6032*	-9.9440*	-9.2399*
0.5	6	-6.3184*	-5.8927*	-6.8823*	-6.3600*
0.5	7	-4.5647*	-4.2317*	-4.9975*	-4.5914*
0.5	8	-3.4074*	-3.1390*	-3.7511*	-3.4252*
0.5	9	-2.6039*	-2.3831*	-2.8837*	-2.6161*
0.5	10	-2.0248*	-1.8403	-2.2566*	-2.0333*

Notes: The BDS statistic has a standard normal limiting distribution. The null hypothesis of a random iid process is rejected if the probability of any two M-histories being close together exceeds Mth power of the probability of any two points being close together, where M is the vector dimension. *Indicates statistically significant at 5% level for two-tail tests. The critical value for 5% is 1.960

Table A-2: BDS Statistics for Volume and Uncorrelated Volume

		W Statistic (BDS/SD)							
		BP		DM		JY		SF	
AR(p)		5		7		5		4	
ε/σ	(m)	V	V*	V	V*	V	V*	V	V*
2.0	2	12.865	6.8858	27.226	6.9469	26.453	4.1156	28.779	6.0193
2.0	3	13.134	7.0428	27.589	7.7808	26.133	4.9523	29.546	7.0201
2.0	4	12.892	7.0960	26.976	7.9715	25.594	4.9020	29.243	7.3065
2.0	5	12.754	7.0505	26.188	7.9910	24.906	4.6403	29.126	7.3593
2.0	6	12.483	6.9756	25.635	8.1706	24.379	4.7088	29.152	7.4017
1.5	2	17.822	7.9109	35.315	8.3531	31.193	4.8078	31.230	6.3593
1.5	3	18.938	9.1001	36.136	9.5551	31.544	5.7507	32.486	7.3148
1.5	4	19.087	9.5797	36.083	9.9473	31.637	6.0152	32.832	7.6351
1.5	5	19.306	9.9282	35.997	10.190	31.769	5.8345	33.511	7.6579
1.5	6	19.354	10.112	36.654	10.540	32.208	6.0578	34.355	7.6627
1.0	2	23.934	9.3970	45.452	5.5023	37.107	5.5023	33.527	6.4334
1.0	3	26.201	11.714	48.907	6.4585	39.011	6.4585	35.432	7.4013
1.0	4	27.423	12.509	51.722	7.0806	40.764	7.0806	36.887	7.7287
1.0	5	28.909	13.258	55.010	7.0867	43.044	7.0867	38.999	7.7320
1.0	6	30.034	13.893	59.235	7.4912	46.433	7.4912	41.512	7.8275
0.5	2	30.931	10.442	60.168	9.6093	44.232	6.1957	35.283	6.7989
0.5	3	35.958	13.809	70.667	11.071	49.131	7.2039	37.921	7.9232
0.5	4	40.297	15.542	83.485	12.564	55.038	8.0423	40.288	8.6778
0.5	5	46.109	17.316	101.08	13.352	62.926	8.1425	42.546	9.1984
0.5	6	53.662	18.996	125.52	14.469	72.642	8.4607	45.893	9.5651

Note: V and V* are raw volume and uncorrelated volume, respectively. An AR(p) is lag order of p. All values are statistically significant at 5% level, indicating that none of the series are iid.

Table A-3: Third Moments Test for Volume and Uncorrelated Volume

No. of Lags		BP		DM		JY		SF	
i	j	V	V*	V	V*	V	V*	V	V*
1	1	6.0336*	-0.1401	14.470*	-0.1781	15.535*	-0.2933	23.369*	-0.1252
2	1	19.132*	0.0521	19.237*	-0.2175	21.846*	-0.3100	30.214*	-1.2273
2	2	10.784*	-0.2466	16.864*	-0.6075	18.550*	-0.6309	26.631*	-0.7294
1	3	23.481*	-0.5127	20.792*	0.0291	23.589*	0.6629	32.422*	0.1399
1	4	24.272*	0.3780	21.530*	-0.1150	24.205*	1.3258	33.485*	0.9754
1	5	22.137*	0.2487	22.248*	1.3302	26.586*	-0.7496	34.200*	0.7408
2	3	22.451*	-0.4400	20.645*	0.0627	23.796*	0.2708	32.470*	0.8084
2	4	25.885*	0.9909	22.485*	0.3209	26.907*	0.7496	34.387*	1.9345
2	5	27.499*	0.5465	23.133*	-0.0997	27.026*	0.6029	35.710*	2.1911*
3	3	9.8157*	-0.2700	17.609*	-0.4187	18.343*	-0.3729	28.355*	-0.5794
3	4	21.955*	0.9869	21.471*	0.1755	25.093*	-0.5723	33.760*	-0.0407
3	5	27.314*	-1.2194	23.107*	-0.8736	27.220*	0.7444	36.011*	-0.4072
4	4	9.8707*	-0.2775	18.281*	-0.7358	20.886*	-1.2309	28.628*	-0.9860
4	5	21.350*	0.2856	22.234*	-0.1876	25.876*	0.1381	34.529*	-0.6892
5	5	8.2358*	-0.5953	18.968*	-0.7359	21.305*	-1.0612	30.224*	-0.8357

Note: V and V* are raw volume and uncorrelated volume, respectively. *Indicates statistically significant at 5% level for two-tail tests.

Appendix 5

Mean and Volatility Spillovers Effect: Subsample I (January 1, 1986-September 18, 1991)

Table A-4: Preliminary Statistics on Currency Futures Returns

Currency Futures	BP	DM	JY	SF
No. of Observations	1490	1490	1490	1490
Standard Deviation	0.7586	0.7512	0.7299	0.8248
Mean	0.0110	0.0234	0.0259	0.0210
Skewness	-0.3190	0.0187	0.1018	0.0631
Kurtosis	2.8779	2.0072	2.6340	1.1830
LB(6)	6.8825	4.6197	1.5719	3.8768
LB(12)	12.9018	15.457	14.960	13.661
$LB^2(6)$	18.315*	23.460*	31.504*	23.043*
$LB^2(12)$	35.430*	38.647*	59.678*	43.572*

Notes: BP = British pound; DM = German mark; JY = Japanese yen; SF = Swiss franc. LB(6) and LB(12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. $LB^2(6)$ and $LB^2(12)$ refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. Kurtosis refers to excess kurtosis where 0 denotes normality. * Significant at the 5 % level.

Table A-5: Correlations Matrix of Lagged and Contemporaneous of Market Returns

Currency Futures	BP	DM	JY	SF
BP_t	1.0000	0.7369	0.5629	0.7088
BP_{t-1}	-0.0008	-0.0242	-0.0230	-0.0299
BP_{t-2}	-0.0261	-0.0232	-0.0070	-0.0517
BP_{t-3}	-0.0359	0.0000	0.0267	0.0091
DM_t	0.7369	1.0000	0.6970	0.9093
DM_{t-1}	0.0383	0.0006	-0.0248	0.0056
DM_{t-2}	-0.0168	-0.0464	0.0026	-0.0508
DM_{t-3}	-0.0355	-0.0006	0.0146	-0.0131
JY_t	0.5629	0.6970	1.0000	0.6844
JY_{t-1}	0.0722	0.0302	-0.0032	0.0305
JY_{t-2}	-0.0297	-0.0542	-0.0072	-0.0521
JY_{t-3}	-0.0089	-0.0000	0.0053	-0.0168
SF_t	0.7088	0.9093	0.6844	1.0000
SF_{t-1}	0.0514	0.0144	-0.0086	-0.0015
SF_{t-2}	-0.0058	-0.0264	0.0236	-0.0437
SF_{t-3}	-0.0247	0.0087	0.0196	-0.0088

Notes: BP = British pound; DM = German mark; JY = Japanese yen; SF = Swiss franc. The t-1, t-2 and t-3, respectively, denote lagged 1, 2 and 3 days futures returns.

Table A-6: Univariate GARCH Model Estimates

A. Pairwise Mean and Volatility Spillover: British Pound

Conditional Mean Coefficient	Currency Futures British Pound		
β_0	0.0174 (0.8987)	0.0169 (0.8733)	0.0175 (0.9077)
$\beta_{BP,i}$	-0.0487 (-1.3547)	-0.0500 (-1.5814)	-0.0588 (-1.6935)
$\beta_{DM,i}$	0.0774* (2.1664)		
$\beta_{JY,i}$		0.1031* (3.0470)	
$\beta_{SF,i}$			0.0851* (2.7190)
R^2	0.0032	0.0075	0.0054
Log-likelihood			
Conditional Variance Coefficient	**Currency Futures British Pound**		
α_0	0.0101* (3.2821)	0.0090* (3.0470)	0.0099* (3.2676)
$\alpha_{BP,i}$	0.0277* (5.5479)	0.0247* (5.2194)	0.0273* (5.5575)
$\alpha_{DM,i}$	0.00 (0.00)		
$\alpha_{JY,i}$		0.0040 (1.3935)	
$\alpha_{SF,i}$			0.00 (0.00)
γ_1	0.9544* (105.73)	0.9554* (108.50)	0.9550* (106.84)
Skewness	-0.3466	-0.3603	-0.3449
Kurtosis	2.0739	2.0712	2.0764
LB(6)	4.9846	5.1947	4.4082
LB(12)	2.7518	9.0463	8.0917
$LB^2(6)$	8.8684	2.7179	2.4387
$LB^2(12)$	8.6945	8.8774	7.9061

B. Pairwise Mean and Volatility Spillover: German Mark

Conditional Mean Coefficient	Currency Futures		
	German Mark		
β_0	0.0271 (1.5076)	0.0269 (1.4977)	0.0274 (1.5245)
$\beta_{BP,i}$	-0.0622 (-1.7716)		
$\beta_{DM,i}$	0.0315 (0.9724)	-0.0561 (-1.5784)	-0.0812 (-1.4138)
$\beta_{JY,i}$		0.0670 (1.9341)	
$\beta_{SF,i}$			0.0700 (1.3341)
R^2	0.0014	0.0015	0.0011
Log-likelihood			

Conditional Variance Coefficient	Currency Futures		
	German Mark		
α_0	0.0189* (3.2836)	0.0187* (3.2915)	0.0188* (3.2714)
$\alpha_{BP,i}$	0.00 (0.00)		
$\alpha_{DM,i}$	0.0543* (5.7078)	0.0541* (5.7835)	0.0533* (5.7340)
$\alpha_{JY,i}$		0.00 (0.00)	
$\alpha_{SF,i}$			0.00 (0.00)
γ_1	0.9138* (55.673)	0.9138* (56.835)	0.0533* (56.303)
Skewness	0.0048	0.0092	0.0029
Kurtosis	1.4708	1.4583	1.4797
LB(6)	2.6081	2.7556	2.8553
LB(12)	13.649	14.906	14.771
$LB^2(6)$	4.6547	5.1787	5.4264
$LB^2(12)$	6.1423	7.0640	6.8098

C. Pairwise Mean and Volatility Spillover: Japanese Yen

Conditional Mean Coefficient	Currency Futures		
	Japanese Yen		
β_0	0.0261 (1.3963)	0.0257 (1.3779)	**0.0259** **(1.3789)**
$\beta_{BP,i}$	-0.0248 (-0.8541)		
$\beta_{DM,i}$		-0.0492 (-1.4244)	
$\beta_{JY,i}$	-0.0004 (-0.0116)	0.0219 (0.6146)	**-0.0035** **(-0.0976)**
$\beta_{SF,i}$			**-0.0152** **(-0.4838)**
R^2	0.0001	0.0011	**0.0001**
Log-likelihood			
Conditional Variance Coefficient	**Currency Futures**		
	Japanese yen		
α_0	0.0200* (3.3130)	0.0192* (3.3102)	**0.0239*** **(3.3162)**
$\alpha_{BP,i}$	0.00 (0.00)		
$\alpha_{DM,i}$		0.00 (0.00)	
$\alpha_{JY,i}$	0.0433* (5.9707)	0.0427* (5.9909)	**0.0473*** **(5.7014)**
$\alpha_{SF,i}$			**0.00** **(0.00)**
γ_1	0.9184* (54.202)	0.9205* (56.382)	**0.9073*** **(45.172)**
Skewness	0.2362	0.2352	**0.2449**
Kurtosis	2.2976	2.3160	**2.4521**
LB(6)	1.6544	1.5890	**1.7740**
LB(12)	18.758	12.821	**18.451**
$LB^2(6)$	12.805	18.668	**11.689**
$LB^2(12)$	17.752	18.142	**16.043**

D. Pairwise Mean and Volatility Spillover: Swiss Franc

Conditional Mean Coefficient	Currency Futures		
	Swiss Franc		
β_0	0.0225 (1.0535)	0.0187 (0.9026)	**0.0212 (0.9911)**
$\beta_{BP,i}$	-0.0672 (-1.6869)		
$\beta_{DM,i}$		0.0606 (0.8724)	
$\beta_{JY,i}$			**0.0660 (1.6394)**
$\beta_{SF,i}$	0.0403 (1.1196)	-0.0516 (-0.8261)	**-0.0423 (-1.2130)**
R^2	0.0018	0.0002	**0.0017**
Log-likelihood			
Conditional Variance Coefficient	**Currency Futures**		
	Swiss Franc		
α_0	0.6675* (28.376)	0.0322* (2.3465)	**0.67558* (29.161)**
$\alpha_{BP,i}$	0.0176 (0.7918)		
$\alpha_{DM,i}$		0.0168 (1.2074)	
$\alpha_{JY,i}$			**0.00 (0.00)**
$\alpha_{SF,i}$	0.00 (0.00)	0.0259* (2.0716)	**0.0030 (0.1973)**
γ_1	0.00 (0.00)	0.9131* (31.843)	**0.00 (0.00)**
Skewness	0.0679	0.0708	**0.0717**
Kurtosis	1.1464	0.9024	**1.1572**
LB(6)	3.2834	2.7811	**3.7879**
LB(12)	12.509	14.145	**14.249**
$LB^2(6)$	23.300*	13.130	**23.004***
$LB^2(12)$	44.793*	16.192	**45.517***

Notes: Numbers in parentheses are t-statistics. Kurtosis refers to excess kurtosis where 0 denotes normality. LB(6) and (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. LB2(6) and (12) refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. * Indicates statistically significant at the 5 % level.

Mean and Volatility Spillovers Effect: Subsample II (Sept. 18, 1991-April 30, 1997)

Table A-7: Preliminary Statistics on Currency Futures Returns

Currency Futures	BP	DM	JY	SF
No. of Observations	1464	1464	1464	1464
Standard Deviation	0.6607	0.6830	0.6805	0.7774
Mean	-0.0032	-0.0007	0.0046	0.0010
Skewness	-0.3776	-0.1163	0.3884	0.0229
Kurtosis	4.4805	2.4418	5.9311	2.7265
LB(6)	22.754*	13.182*	14.065*	10.574
LB(12)	29.269*	17.514*	28.290*	14.757
LB2(6)	125.47*	53.301*	27.369*	59.570*
LB2(12)	202.07*	85.656*	39.703*	102.68*

Notes: BP = British pound; DM = German mark; JY = Japanese yen; SF = Swiss franc. LB(6) and LB(12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. $LB^2(6)$ and $LB^2(12)$ refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. Kurtosis refers to excess kurtosis where 0 denotes normality. * Significant at the 5 % level.

Table A-8: Correlations Matrix of Lagged and Contemporaneous of Market Returns

Currency Futures	BP	DM	JY	SF
BP_t	1.0000	0.7191	0.4076	0.6879
BP_{t-1}	-0.0318	0.0069	-0.0576	-0.0126
BP_{t-2}	0.0404	0.0363	0.0066	0.0255
BP_{t-3}	0.0399	0.0124	-0.0254	0.0189
DM_t	0.7191	1.0000	0.5829	0.9255
DM_{t-1}	-0.0193	0.0070	-0.0243	0.0108
DM_{t-2}	-0.0149	-0.0040	-0.0211	-0.0263
DM_{t-3}	0.0145	0.0029	0.0013	0.0069
JY_t	0.4076	0.5829	1.0000	0.5806
JY_{t-1}	-0.0518	-0.0376	-0.0187	-0.0343
JY_{t-2}	-0.0237	-0.0151	-0.0326	-0.0156
JY_{t-3}	-0.0113	-0.0121	-0.0303	-0.0119
SF_t	0.6879	0.9255	0.5806	1.0000
SF_{t-1}	-0.0244	0.0253	-0.0254	0.0201
SF_{t-2}	-0.0019	-0.0045	-0.0218	-0.0206
SF_{t-3}	-0.0095	-0.0069	-0.0137	-0.0078

Notes: BP = British pound; DM = German mark; JY = Japanese yen; SF = Swiss franc. The t-1, t-2 and t-3, respectively, denote lagged 1, 2 and 3 days futures returns.

Table A-9: Univariate GARCH Model Estimates

A. Pairwise Mean and Volatility Spillover: British Pound

Conditional Mean Coefficient	Currency Futures		
	British Pound		
β_0	0.0165 (1.1908)	0.0126 (0.9179)	**0.0146** **(1.0636)**
$\beta_{BP,i}$	-0.0926* (-2.3438)	-0.0458 (-1.4143)	**-0.0727** **(-1.9296)**
$\beta_{DM,i}$	0.0450 (1.5263)		
$\beta_{JY,i}$		-0.0353 (-1.5131)	
$\beta_{SF,i}$			**0.0172** **(0.7011)**
R^2	0.0009	0.0023	**0.0009**
Log-likelihood			
Conditional Variance Coefficient	Currency Futures		
	British Pound		
α_0	0.0015* (2.4860)	0.0020* (3.7959)	**0.0016*** **(2.6372)**
$\alpha_{BP,i}$	0.0302* (8.4542)	0.0305* (10.313)	**0.0316*** **(8.8017)**
$\alpha_{DM,i}$	0.0084* (4.6801)		
$\alpha_{JY,i}$		0.00 (0.00)	
$\alpha_{SF,i}$			**0.0048*** **(3.9443)**
γ_1	0.9568* (224.50)	0.9645* (280.29)	**0.9583*** **(220.83)**
Skewness	-0.0755	-0.0382	**-0.0809**
Kurtosis	3.2619	3.9997	**3.4051**
LB(6)	17.350*	17.546*	**17.478***
LB(12)	19.260	18.743	**19.138**
$LB^2(6)$	6.4913	7.3767	**6.2019**
$LB^2(12)$	9.9377	10.053	**9.4917**

B. Pairwise Mean and Volatility Spillover: German Mark

Conditional Mean Coefficient	Currency Futures		
	German Mark		
β_0	-0.0073 (-0.4565)	-0.0092 (-0.5470)	-0.0092 (-0.5487)
$\beta_{BP,i}$	0.0119 (0.3072)		
$\beta_{DM,i}$	-0.0073 (-0.2127)	0.0220 (0.6792)	-0.1113 (-1.8694)
$\beta_{JY,i}$		-0.0387 (-1.2533)	
$\beta_{SF,i}$			0.1052 (2.1101)
R^2	0.0000	0.0026	0.0025
Log-likelihood			

Conditional Variance Coefficient	Currency Futures		
	German Mark		
α_0	0.0040* (3.6103)	0.0037* (3.6248)	0.0038* (3.4574)
$\alpha_{BP,i}$	0.0056 (1.7047)		
$\alpha_{DM,i}$	0.0256* (5.2665)	0.0296* (6.2982)	0.0297* (6.2914)
$\alpha_{JY,i}$		0.00 (0.00)	
$\alpha_{SF,i}$			0.00 (0.00)
γ_1	0.9607* (147.70)	0.9625* (158.80)	0.9579* (118.44)
Skewness	0.0220	0.0295	0.0212
Kurtosis	2.2129	2.1615	2.0360
LB(6)	11.203	11.129	10.914
LB(12)	15.997	16.223	15.579
$LB^2(6)$	5.3673	5.4347	4.9929
$LB^2(12)$	7.3120	7.2162	6.6418

C. Pairwise Mean and Volatility Spillover:Japanese Yen

Conditional Mean Coefficient	Currency Futures		
	Japanese Yen		
β_0	-0.0012 (-0.0741)	-0.0010 (-0.0601)	-0.0007 (-0.0396)
$\beta_{BP,i}$	-0.0554 (-1.8427)		
$\beta_{DM,i}$		-0.0228 (-0.0228)	
$\beta_{JY,i}$	0.0093 (0.3205)	-0.0005 (0.0165)	0.0044 (0.1361)
$\beta_{SF,i}$			-0.0263 (-0.9938)
R^2	0.0033	0.0006	0.0006
Log-likelihood			
Conditional Variance Coefficient	**Currency Futures**		
	Japanese Yen		
α_0	0.0066* (4.1489)	0.0068* (4.3382)	0.0065* (3.8497)
$\alpha_{BP,i}$	0.0052* (3.2333)		
$\alpha_{DM,i}$		0.0090* (3.4659)	
$\alpha_{JY,i}$	0.0377* (7.8211)	0.0347* (7.2407)	0.0332* (6.6689)
$\alpha_{SF,i}$			0.0091* (3.9107)
γ_1	0.9437* (146.63)	0.9420* (143.07)	0.94238 (130.15)
Skewness	0.4474	0.4547	0.4528
Kurtosis	4.7503	5.0028	4.8953
LB(6)	12.155	11.499	11.377
LB(12)	27.535*	26.883*	26.937*
$LB^2(6)$	3.1736	2.8283	2.9821
$LB^2(12)$	7.5944	7.1540	7.3876

D. Pairwise Mean and Volatility Spillover: Swiss Franc

Conditional Mean Coefficient	Currency Futures		
	Swiss Franc		
β_0	-0.0058 (-0.3055)	0.0028 (0.1429)	-0.0088 (-0.4591)
$\beta_{BP,i}$	-0.0479 (-1.1275)		
$\beta_{DM,i}$		-0.0588 (-0.7608)	
$\beta_{JY,i}$			-0.0473 (-1.3540)
$\beta_{SF,i}$	0.0460 (1.4234)	0.0696 (1.0733)	0.0423 (1.3467)
R^2	0.0017	0.0008	0.0035
Log-likelihood			

Conditional Variance Coefficient	Currency Futures		
	Swiss Franc		
α_0	0.0064* (3.7078)	0.0059* (3.7735)	0.0058* (3.5837)
$\alpha_{BP,i}$	0.0090* (2.2980)		
$\alpha_{DM,i}$		0.0313* (3.0672)	
$\alpha_{JY,i}$			0.00 (0.00)
$\alpha_{SF,i}$	0.0242* (5.0287)	0.0668 (0.7201)	0.0289* (6.0506)
γ_1	0.9589* (139.94)	0.9604* (146.10)	0.9615* (149.24)
Skewness	0.1170	0.1407	0.1273
Kurtosis	2.0803	2.0247	2.0324
LB(6)	8.8079	8.3170	8.9365
LB(12)	12.6084	11.961	13.400
$LB^2(6)$	10.486	10.716	11.063
$LB^2(12)$	17.609	16.824	13.529

Notes: Numbers in parentheses are t-statistics. Kurtosis refers to excess kurtosis where 0 denotes normality. LB(6) and (12) refer to the Ljung-Box-Portmanteau statistic for returns over 6 and 12 lags, respectively. LB2(6) and (12) refer to the Ljung-Box-Portmanteau statistic for square returns over 6 and 12 lags, respectively. * Indicates statistically significant at the 5 % level.

Table A-10: Summary Comparison of the Results Between Subsample I and Subsample II: Pairwise Mean Spillover

	Subsample I				Subsample II			
	BP	DM	JY	SF	BP	DM	JY	SF
$\alpha_{BP,i}$	No	No	No	No	No	No	No	No
$\alpha_{DM,i}$	Significant 5%	No	No	No	No	No	No	No
$\alpha_{JY,i}$	Significant 5%	No	No	No	No	No	No	No
$\alpha_{SF,i}$	Significant 5%	No	No	No	No	Significant 5%	No	No

Notes: The 10% and 5% critical levels are 1.645 and 1.960, respectively.

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