# Are single stock futures used as an alternative during a short-selling ban?

Benzennou, Bouchra; ap Gwilym, Owain; Williams, Gwion

**Journal of Futures Markets**

*DOI:*
10.1002/fut.21849

Published: 01/01/2018

Peer reviewed version

Are single stock futures used as an alternative during a short-selling ban?

Bouchra Benzennou, Owain ap Gwilym* and Gwion Williams

Bouchra Benzennou is a Lecturer in Finance at Coventry University, Coventry, United Kingdom.

Owain ap Gwilym is a Professor of Finance at Bangor Business School, Bangor University, Bangor, United Kingdom.

Gwion Williams is a Lecturer in Finance at Bangor Business School, Bangor University, Bangor, United Kingdom.

* Corresponding author, Bangor Business School, Bangor University LL57 2DG, United Kingdom. Tel: + 44-1248-382176, email: owain.apgwilym@bangor.ac.uk

Acknowledgment:

The authors are very grateful for comments and suggestions received from the editor and an anonymous reviewer.

# Are single stock futures used as an alternative during a short-selling ban?

The response of the single stock futures (SSF) market to a short-selling ban is investigated. The hypothesis is that traders use SSF as a substitute instrument for short-selling. A significant increase in SSF trading activity is documented, accompanied by narrower spreads. SSF market volatility did not react during the ban, which suggests that the increased trading activity did not weaken SSF market quality. The quality of the underlying market during the ban period is also assessed, with the results suggesting that changes in SSF market activity had neither positive nor negative effects on the stocks' liquidity, volatility, and volume.

## 1. Introduction

Single stock futures (SSF) are a cost-effective trading instrument and offer advantages over trading in stocks. Ang and Cheng (2005a) argue that these derivatives are a potentially vital instrument for institutional and individual investors. Mitchell (2003, p.4) states that "*investing, speculating, hedging, and market making can be facilitated with the use of SSF*". Moreover, SSF represent an alternative to securities lending/borrowing. Taking a long (short) SSF position provides similar advantages to lending (borrowing) the underlying stock while reducing fees and counterparty risk. Since SSF have lower margin requirements, they represent a cheap and less risky alternative mechanism to short-selling. Danielsen et al. (2009) examine the impact of the launch of SSF on the short-selling and trading features of underlying stocks in the US. Their evidence is consistent with the hypothesis that SSF represent a plausible alternative to short-selling because costs related to short sales and the level of short-selling decrease after the introduction of SSF.

Short-sellers are heavily criticised for contributing to stock market crashes. Following the Lehman Brothers collapse in September 2008, many market regulators implemented restrictions on short-selling. On September 18th, 2008, the UK Financial Services Authority (FSA) announced a ban on short-selling financial stocks, which was in place until January 16th, 2009.[1] This emergency measure was an effort to stabilise markets, especially in bank stocks, whereby short-selling was a strong contributor to the massive selloff occurring globally.[2] However, many researchers question the effectiveness and benefits of such intervention. Based on theoretical models and empirical findings, short-selling enables traders to react to bad news, therefore any constraint on short-sales will decelerate price discovery and reduce market liquidity, without necessarily stemming price declines.[3] This liquidity shock, especially during

[1] The FSA announced the end of the ban on January 5th, 2009.
[2] See "Short sale ban spreads around the globe", Wall Street Journal, September 22, 2008.
[3] For example, Jones and Lamont (2002); Diamond and Verrecchia (1987); Bai et al. (2006).

the severe conditions of a crisis, is demonstrated to have a negative impact on stocks and fixed income markets (e.g. Danciulescu, 2009). Under these short-sale constraints, sophisticated traders may migrate to SSF to establish similar short positions to those they would have achieved by short-selling.

This paper aims to identify whether short-sellers acknowledge SSF to be low-cost alternatives to short-selling. If this is the case, they will migrate to SSF if they can no longer short sell due to a ban. The reaction of trading activity, liquidity, and volatility are examined during the UK short-selling ban in 2008-09. A shift to SSF trading would imply that these instruments could be used by market participants to circumvent bans on short-selling. This paper offers a unique contribution in these respects.

A difference-in-differences analysis is conducted whereby the Lisbon SSF market acts as a control group. The results indicate a significant increase in the number of quotes for SSF in the London market, accompanied by an increase in market liquidity. The volatility of the SSF market in London did not react, which suggests that SSF markets can absorb elevated trading activity while maintaining market quality.

Prior literature suggests that SSF trading leads to more efficient pricing in the underlying market (e.g. Ang and Cheng, 2005b; Shastri et al., 2008; Danielsen et al., 2009). Based on this argument, the quality of the underlying stock trading in the presence of SSF is assessed during the short-selling ban. SSF are expected to mitigate the effect of the ban on their underlying stocks such that the latter are more liquid, more frequently traded, and less volatile than stocks without SSF. This study finds no evidence that SSF improve the underlying market's quality during the ban. Finally, the impact of the ban on SSF mispricing is investigated. In the absence of short-sale constraints, futures underpricing can be exploited by shorting the stock and going long futures, thus reducing the magnitude of the mispricing. Therefore, SSF mispricing is expected to be more prevalent during the short-selling ban. Consistent with theoretical prediction, the findings suggest that the level of SSF mispricing increases during the ban.

This paper is structured as follows. Section 2 discusses prior literature on SSF and short-selling. The data and methodology are explained in Section 3. Section 4 presents the empirical results, and Section 5 concludes.

## 2. Literature Review and Hypotheses

### 2.1. SSF and the underlying market

There is an established debate about the impact of derivatives trading on the underlying stock market. Some researchers argue that derivative markets destabilise the spot market as they are used by speculators as tools for price manipulation and thus increase volatility.[4] Others argue that derivatives encourage arbitrageurs to trade against uninformed trading demand, hence correcting any mispricing and maintaining asset prices at their fundamental values.[5]

Several studies examine the impact of the introduction of SSF on the underlying market in terms of metrics such as volatility, pricing efficiency and cost reduction. Lee and Tong (1998) find that the introduction of SSF at the Sydney Futures Exchange did not induce any changes in volatility. McKenzie et al. (2001) find that SSF listing induces a significant decline in the systematic risk in the underlying market, where the response of volatility is firm-dependent. Ang and Cheng (2005b) demonstrate that the presence of SSF improves market efficiency and stability. This is revealed by a decline in the price volatility of stocks with SSF listings after their introduction to the US market in 2002. Ang and Cheng (2005b) provide evidence suggesting that informed traders (arbitrageurs) might prefer SSF to options as they

[4] e.g. Kuprianov (1995).
[5] e.g. Figlewski and Webb (1993); Phillips (2011).

represent a cheaper mechanism to exploit mispricing in the spot market. Hence, SSF trading contributes to more efficient pricing in the underlying market. These results are supported by Shastri et al. (2008), who show that the information efficiency and market quality of the underlying market improved significantly compared to the pre-SSF period.

Overall, prior literature suggests that the introduction of SSF contributes to the stabilisation of the underlying stock markets by reducing price volatility, improving price efficiency, and increasing market quality. Indeed, trading in SSF offers two major advantages over trading in the spot market. First, SSF relax short-selling constraints by enabling investors to establish a short position in an asset. Short-selling is subject to higher costs and risks, plus legal and institutional restrictions. In order to short a stock, an investor must find an owner willing to lend the stock in question and the lender requires a fee. Once the stock is borrowed, the borrower bears the risk of the lender recalling the stock at any time. Second, SSF have lower margin requirements than spot market trades.[6] Hence, SSF enable holding a short position on a certain stock at lower costs while incurring less risk. Danielsen et al. (2009) provide evidence that short-sellers migrate to SSF at their introduction in the US market, while the underlying market's bid-ask spreads (quoted and effective) fall after SSF introduction, accompanied by a decrease in short-selling costs and the level of short sales.

One might argue that options offer similar advantages. However, options have non-linear payoffs and require buying and selling options with the same strike and maturity as the SSF contract in order to create a similar short position. In relation to market quality improvements, SSF are found to contribute a higher proportion of the price discovery process compared to options (Chakravarty et al., 2004).

[6] See Table 2.1 (p. 11) in Mitchell (2003) for a detailed comparison of equities and SSF.

## 2.2. Market reactions to short-selling bans

Several researchers have investigated the effect of short-selling restrictions on asset prices and market efficiency. Diamond and Verrecchia (1987) argue that short-sales constraints hinder price discovery as they prevent asset prices from promptly reflecting private information known to sophisticated traders. The delay caused in the price discovery process implies uncertainty and consequently reduced liquidity. Bai et al.'s (2006) model shows that a short-selling ban's effect on prices could take two directions. It has an upward effect on prices as it lessens market liquidity and selling pressure, and a downward effect on prices as it weakens the information content of prices.

Prior studies document negative effects of short-selling bans on market quality. Marsh and Payne (2012) study the extent to which the UK short-sale restrictions (2008-09) were effective in supporting the UK stock markets, and find that the ban failed to support both financial and non-financial stocks. Prices were following a downward trend and strong selling pressure existed before the ban. Compared to non-financial stocks, the ban undermined the liquidity of financial stocks. Moreover, the efficiency and information content of trading deteriorated during the ban for financials compared to non-financial stocks. Boehmer et al. (2013) examine the implications of short-sale restrictions in the US during autumn 2008 by comparing the liquidity (bid-ask spread and price impact) of financial stocks subject to the ban and those that were not. Stocks targeted by the ban were significantly less liquid than others. Considering data from around the world, Beber and Pagano (2013) explore the implications of short-sale restrictions on market liquidity, the price discovery process, and stock prices. They find that the regulatory interventions are accompanied by wider spreads and inferior price discovery, without improving stock price performance.

Counter-intuitively, Battalio and Schultz (2010) find that short-sellers did not shift to options as an alternative to short-selling. Grundy et al. (2012) provide similar evidence on the reaction of options markets to the US short-sale ban. They explain that traders' ability to establish a short-sale-like position by buying a put option depends on finding a writer able to short-sell the underlying. The only participants allowed to short sell during the US ban were options market makers. Grundy et al. (2012) also report a significant widening of spreads for options on stocks targeted by the ban, and a dramatic drop in option trading volumes.

The above evidence suggests that short-sale restrictions did not necessarily meet regulators' expectations. In the presence of bans, market quality (measured by liquidity, price impact, and volume) worsened for both equity and options markets. This study offers a substantial contribution by linking a short-selling ban to SSF contracts in a unique setting.

### 2.3. Hypotheses

Following the collapse of Lehman Brothers in 2008, several financial authorities in Europe announced restrictions on short sales (covered and/or naked). Table 1 lists these bans, their durations and their nature. The UK FSA announced on September 18$^{th}$, 2008 a ban on net position short-selling in financial stocks at the London Stock Exchange, which was lifted on January 16$^{th}$, 2009.

[Insert Table 1 here]

This paper tests the hypothesis that SSF constitute a viable substitute to short-selling. On this basis, an immediate increase in demand for trading in SSF should be observed when the ban begins. Second, if a negative relationship exists between spread and trading activity, narrower spreads in SSF during a ban period are expected. The SSF market's reactions to a short-selling ban are assessed by testing three hypotheses:

*Hypothesis 1*: Short-sellers migrate to SSF trading after the introduction of the ban, which will be revealed by an increase in trading activity;

*Hypothesis 2*: If a negative relationship exists between trading activity and spread, any increase in SSF trading activity will lead to narrower bid-ask spreads;[7]

*Hypothesis 3*: SSF volatility will decrease during the ban period if narrower spreads are accompanied by lower volatility in this market structure.[8]

Moreover, the paper examines the impact of SSF trading on the underlying market quality (measured by liquidity, volume, and volatility). Prior literature reports that SSF improve the underlying market quality as their introduction is accompanied by a decline in information asymmetry and trading costs in the stock market. However, there is contrasting prior evidence on whether SSF trading has an impact on the underlying market's volatility.

## 3. Data and Methodology

### 3.1. Data

SSF began trading in London in June 2003. In this SSF market structure, liquidity is provided by designated market makers (DMM) who facilitate customer order flow by setting bid-ask spreads for a stipulated level of demand.[9] The trading day starts at 08:00 and ends at 18:00. The SSF data comprise time-stamped observations on all SSF quotes including contract type, expiration date and price in the London and Lisbon markets, from January 2008 until December 2010.[10] The dataset comprises 135 SSF contracts in London and 13 in Lisbon. For the analysis, different maturities for each contract are defined as follows: short-maturity contracts with less than 30 days to expiry; medium-maturity contracts with between 30 and 60 days to expiry; long-maturity contracts with more than 60 days to expiry. Daily data on SSF open interest are collected from Bloomberg and Datastream for the sample period.

---

[7] See George and Longstaff (1993); Wang et al. (1997); among others.
[8] See Wang et al. (1994); among others.
[9] See https://derivatives.euronext.com/en/stock-futures/liquidity-provider-programmes
[10] A number of days' data between January 5th and February 9th 2009 do not contain bid prices, which rules out estimates of spreads on those days. The exchange confirmed that the data was indeed missing and there were no alternative sources to supply data for those days.

The SSFs' underlying stocks trade in NYSE Euronext markets including Amsterdam, Brussels, and Paris. Data on the underlying assets (including bid and ask prices, volume, earnings per share, dividend per share, and market capitalisation) are collected from Bloomberg and Datastream. Similar data are collected for stocks traded in NYSE Euronext Amsterdam, Brussels, and Paris without SSF. For the London SSFs, there are 135 stocks with SSF (treatment group) and 1,019 stocks without SSF (control group). Euribor data are collected from the European Central Bank's (ECB) Statistical Data Warehouse.[11] Data from January 2008 until December 2009 are used to assess the ban effect, and data from 2010 are used for placebo tests.

In order to pursue the paper's objectives, daily data is created from the intraday SSF data. Let t represent the time when the bid and ask quotes are observed. The quoted percentage spread is calculated by dividing the difference between ask and bid prices by the midpoint, for each SSF contract i for each maturity (short, medium, long):[12]

$$\%BAS_{i,t} = \frac{p_{i,t}^{A} - p_{i,t}^{B}}{P_{i,t}^{M}} \tag{1}$$

Where $p_t^A$ and $p_t^B$ are the ask and bid prices, respectively. The midpoint price is the average of the bid and ask prices:

$$P_{i,t}^{M} = \frac{p_{i,t}^{A} + p_{i,t}^{B}}{2} \tag{2}$$

In order to create daily data, the average percentage spread is calculated over each trading day d, for each SSF contract i for each maturity:

[11] See http://sdw.ecb.europa.eu/.
[12] Note that contracts with less than 7 days to maturity are not included, as is standard practice in related derivatives literature.

$$\mathrm{BAS}_{i,d} = \sum_{t=1}^{N} \frac{\%\mathrm{BAS}_{i,t}}{N_{i,d}} \tag{3}$$

Where $N_{i,d}$ is the number of quotations of a given contract with a given maturity on trading day d.

For each SSF contract i, for each maturity, the daily volatility is measured by the absolute return defined as in Ding et al. (1993):

$$\mathrm{RISK}_{i,d} = \left| \frac{P_{i,d}^{M} - P_{i,d-1}^{M}}{P_{i,d-1}^{M}} \right| * 100 \tag{4}$$

Where $P_{i,d}^{M}$ and $P_{i,d-1}^{M}$ are the last observed midpoint SSF prices on days d and $d-1$, respectively.

Finally, the daily trading activity is estimated by the number of quotes on each trading day d, for each contract i in each maturity group.

All measures are calculated for both the London and Lisbon SSF markets.

The underlying market's quality is measured by the bid-ask spread, trading volume, and volatility. For each stock s, the daily bid-ask spread is calculated as expressed in Equation (1). The volatility measure for a stock s traded in the underlying market is also given by the absolute return:

$$\mathrm{RISK}_{s,d} = \left| \frac{P_{s,d} - P_{s,d-1}}{P_{s,,d-1}} \right| * 100 \tag{5}$$

Where $P_{s,d}$ and $P_{s,d}$are the closing prices on days d and $d-1$, respectively.

### 3.2. Methodology

#### 3.2.1. Spread – volatility – trading activity relationship

Prior to considering the market reactions to the short-selling ban, the spread-volatility-trading activity relationship is investigated. The SSF market structure is similar to that of a specialist market because of the presence of DMMs. In such a context, microstructure literature predicts an inverse spread-trading activity relationship and a direct spread-volatility relationship, where trading activity and volatility are two of the main determinants of spreads.[13] Existing literature suggests that higher trading activity is expected to narrow spreads. Providing liquidity in infrequently traded assets will be costly because market makers are exposed to greater risk, i.e. there exists an inverse relationship between spreads and trading activity. Microstructure models predict that higher volatility is expected to widen spreads because market makers will aim to protect their positions. The spread-volatility relationship is normally positive. Therefore, SSF bid-ask spreads are expected to respond to changes in trading activity and volatility.

In order to test this relationship, the following equation is estimated:

$$\mathrm{BAS}_{\mathrm{i,d}} = \beta_0 + \beta_1 \mathrm{Activity}_{\mathrm{i,d}} + \beta_2 \mathrm{Risk}_{\mathrm{i,d}} + \varepsilon_{\mathrm{i,d}} \tag{6}$$

Where $\mathrm{Activity}_{\mathrm{i,d}}$ is defined as the daily trading activity of an SSF contract i on a day d.

Equation (6) is estimated with the Generalised Method of Moments (GMM). This is efficient in producing robust estimates, particularly when facing potential endogeneity problems. The purpose of this estimation is solely to establish the nature of the relationship between spreads, trading activity, and volatility. The estimation is run for the London and Lisbon markets separately, and for each maturity group separately.

---

[13] These models explain the bid-ask spread as (i) the price of immediacy, i.e. the cost of processing and fulfilling an order (e.g O'Hara and Oldfield, 1986); or (ii) the cost arising from information asymmetry (e.g. Bessembinder, 1994).

### 3.2.2. Difference-in-differences test

The primary focus is to assess the SSF market response to the short-selling ban, which is achieved using a difference-in-differences approach. The treatment is the short-selling ban and the aim is to estimate the average treatment effect of the treated (ATT). The treatment group comprises SSF contracts traded in London while the control group is the Lisbon SSF market (both of which are in the same exchange ownership group).[14] The short-selling restrictions were implemented shortly after the sudden collapse of Lehman Brothers, therefore, it is assumed that the market could not "prepare" for this event, and indeed, that short-sellers were profiting from trades in financial stocks up to this point (due to other events in the crisis). Two categorical variables are defined: $\mathrm{ban}$ and $\mathrm{treat}$. The ban variable represents the treatment and takes the value of 1 during the period of short-selling restrictions and 0 otherwise. The $\mathrm{treat}$ variable represents the categories for the treatment/control group, i.e. $\mathrm{treat} = 0$ for the control group and $\mathrm{treat} = 1$ for the treatment group (London).

A shift to the SSF market would cause an increased demand for trading, i.e. would be captured well by the number of quotes. Variations in the liquidity of the market (measured by the bid-ask spread) and its volatility are hypothesised to follow as a response to the increase in trading activity. Because the variables of interest could be influenced by the underlying equity's firm size, it is appropriate to add market capitalisation to the model specification.

The difference-in-differences coefficient is obtained by estimating the following model:

$$\mathrm{Var}_{i,d} = \beta_0 + \beta_1 \mathrm{ban}_d + \beta_2 \mathrm{treat}_i + \beta_3 \mathrm{treat}_i * \mathrm{ban}_d + \beta_4\, \mathrm{CAP}_{i,d} + \varepsilon_{i,d} \qquad (7)$$

[14] A different specification was also considered, where, for each contract, the treatment variable takes the value of 1 with respect to the ban period in the home market of its underlying asset; and the treatment group comprised SSF written on stocks subjected to the ban. The results from such a specification imply that all SSF react to the ban, regardless of their underlying market. This reaction is most evident during the UK ban period.

Var represents one of trading activity, spreads, or volatility. $\beta_0$ represents the level of $\mathrm{Var}_{i,d}$ in the control group (Lisbon) outside of the treatment (ban). $\beta_1$, the coefficient of the categorical variable $\mathrm{ban}_d$, captures the difference in $\mathrm{Var}_{i,d}$ in the control group (Lisbon) during the ban. $\beta_2$, the coefficient of the dummy variable $\mathrm{treat}_i$, captures differences between the treatment market (contracts traded in London) and control (contracts traded in the Lisbon market) groups before and after the ban.[15] The coefficient of interest here is $\beta_3$, which captures the effect of the ban on the treated group. Finally, $\mathrm{CAP}_{i,d}$ is the control variable for firm size. Equation (7) is estimated for the three variables, using the pooled data and for each maturity group separately.[16]

In a separate exercise, a model similar to (7) is used to evaluate the underlying market's quality during the ban period in the presence of SSF. The dependent variable $\mathrm{Var}_{s,d}$ then represents stocks' spreads, trading activity and volatility. The treated group comprises stocks with SSF and the control group comprises stocks without SSF (traded in NYSE Euronext Amsterdam, Brussels, and Paris).

The difference-in-differences approach assumes that the trend in the control and treatment groups in the absence of the treatment is similar. Here, if there had been no ban, the assumption is that the trend in the variables of interest would be similar in contracts traded in both London and Lisbon. A placebo difference-in-differences test which consists of using a "fake" treatment group is performed to test this assumption. Specifically, the same difference-in-differences model is estimated using data from 2010 and using a "fake" ban period from September 18th, 2009 until January 16th, 2010. If the assumption is valid, the difference-in-

[15] The only SSF contract written on a Portuguese financial stock subject to short selling restrictions (Banco Espírito Santo) is dropped from the control group.
[16] Both contracts written on financial and non-financial stocks are used for the estimation.

differences estimator computed on the placebo data should not be significant, i.e. the fake ban should not have any impact on the variables of interest.

### 3.2.3. Propensity score matching and difference-in-differences

An issue arises from the fact that units in the treatment and the control groups are not assigned randomly. Because contracts traded in London (treated) and Lisbon (control) differ in certain specific characteristics, the direct comparison of the outcome of the ban might be subject to potential bias. A matching exercise, using a propensity score, is used to improve the quality of the inference from the difference-in-differences estimates. The propensity score refers to the conditional probability that a unit will be assigned to the treatment group. It is most commonly defined by a logistic regression/probit model where the treatment is a function of a set of independent variables x (e.g. Austin, 2011):

$$p(x) = \text{prob}(\text{treat} = 1|x) \tag{8}$$

Estimating model (8) yields the predicted probability $\hat{p}(x)$. The independent variables x should represent factors based on which a unit receives the treatment or not. Ang and Cheng (2005a) report that SSF exchanges tend to list larger stocks. The SSF trading in London are written on larger firms than is the case for Lisbon SSF. Therefore, the covariate chosen for the calculation of propensity scores is firms' market capitalisation.

Once propensity scores are calculated, the conditioning method considered is n:1 matching. Blundell and Costa Dias (2000) note that combining the difference-in-differences method and propensity score matching produces high-quality results for the evaluation of a non-experimental treatment. Smith and Todd (2005a) demonstrate that cross-sectional matching estimators are weaker and find that the most robust estimators are given by the difference-in-differences matching. The matching exercise combines an observation j from the control group with one or more observations i in the treatment group on the basis of their scores. The best match for observation i is found using a caliper, i.e. a pre-specified range $|p_i - p_j|$ where p refers to the propensity score. Following Rosenbaum and Rubin (1985) and Austin's (2011) recommendations, the caliper is set to a value of 0.20. Only matched units are then included in the difference-in-differences estimation method, following Girma and Görg (2007).

This process will be reliable if the balance property is verified. The balancing condition is assessed by calculating the standardised mean difference for the covariate x between the treated and the control groups (e.g. Smith and Todd, 2005b). If the standardised differences exceed an arbitrary criterion, the balancing condition is not satisfied. Here, 0.20 is considered as the threshold, following Rosenbaum and Rubin (1985). For a covariate x, the standardised difference, or bias, is calculated as:

$$D(x) = \frac{100 * |\bar{x}_T - \bar{x}_C|}{\sqrt{\frac{s^2{}_T + s^2{}_C}{2}}} \tag{9}$$

Where T and C refer to the treatment and control groups, respectively; $\bar{x}_T$ and $\bar{x}_C$ are the sample means of the covariate x, respectively; and $s^2{}_T$ and $s^2{}_C$ are the sample standard deviations of the covariate x in the treatment and control groups, respectively.

### 3.2.4. Nature of the shift to SSF and arbitrage opportunities

After assessing the effect of the ban on SSF trading activity, the origins of any changes are investigated. The ban coincides with a financial crisis, which implies that trading could be driven by hedging (or an increase in investors' risk aversion) and/or speculation. A plot of the number of quotes before, during and after the ban period conveys easily the nature of the effect of the ban on trading activity. The dynamics of trading activity for London and Lisbon SSF around September 18th, 2008 is depicted in Figure 1.[17] There is a clearly discernible effect on London SSF trading at the start of the ban period. Any effect in Lisbon is captured in the difference-in-differences design.

[Insert Figure 1 here]

Distinguishing between speculative and hedging activity is based on the length of the holding period, i.e. shorter for speculators. According to Bessembinder and Seguin (1993), daily open interest can be used to capture hedging activity in derivative markets. Changes in open interest are combined with daily volume to proxy for speculative demand. For day d, $\mathrm{R_d}$ is calculated as follows:

$$\mathrm{R_d} = \frac{\mathrm{Activity_d}}{|\mathrm{OI_d} - \mathrm{OI_{d-1}}|} \tag{10}$$

Where $\mathrm{OI_d}$ and $\mathrm{OI_{d-1}}$ are the daily open interest for days d and $\mathrm{d} - 1$, respectively. $\mathrm{R_d}$ is used to measure the relative importance of speculators' trading activity compared to hedgers' activity. Therefore, high speculative demand would increase trading activity within the day but closure of positions would imply little impact on open interest. An increase in $\mathrm{R_d}$ suggests either an increase (decrease) in speculative activity or a decrease (increase) in hedging activity. Therefore, relatively higher speculative demand is associated with high $\mathrm{R_d}$.

Further, the impact of the ban on SSF mispricing is investigated. Theory suggests that prices can deviate from their fundamental value as a result of investors' over- or under-reaction to information. Short-sellers' attempts to take advantage of these deviations move prices closer to their fair value (e.g. Diamond and Verrecchia, 1987). MacKinlay and Ramaswamy (1988) argue that, in the absence of short-sale constraints, short-sellers are able to establish futures

[17] The time period of partial missing data is excluded in Figure 1. See footnote 10.

arbitrage portfolios. Arbitrageurs can exploit futures underpricing by shorting the stock and going long futures, thus reducing the magnitude of the mispricing. This can only be achieved without short-selling constraints in the underlying market, but this latter condition does not apply to futures overpricing. Therefore, the magnitude of futures underpricing is larger than that of futures overpricing with short-selling constraints in the underlying market. Based on this argument, SSF mispricing is expected to be larger, especially on the lower bound, during the short-selling ban.

Following Fung and Draper (1999), the fair price of an SSF contract on day d is calculated as:

$$F_d^* = S_d\,(1 + r - D)^t \tag{11}$$

Where $S_d$, r , D, and t are stock price on day d, the daily risk-free rate (proxied by the Euribor rate), the dividend payout ratio (dividends per share divided by earnings per share), and time to maturity as a fraction of a year, respectively.

The mispricing is defined in Yadav and Pope (1994):

$$\pi_d = \frac{F_d - F_d^*}{S_d} \tag{12}$$

Where $F_d$ is the closing price of the SSF contract on the trading day d. $\pi_d^-$ ($\pi_d^+$) represent negative (positive) values of $\pi_d$, suggesting underpricing (overpricing).

A one-way ANOVA test is used to compare the means of $R_d$, the trading activity, the level of mispricing, $|\pi_d|$, $\pi_d^+$ and $\pi_d^-$ during four phases. Phase 0 is defined as the 20 days prior to the ban. Phase 1 is defined as the first 20 days of the ban; Phase 3 is defined as the last 20 days before January 5th, 2009, while Phase 2 is the period in between.

## 4. Results

### 4.1. Spread – Volatility – Trading relationship

This sub-section documents the relationship between the SSF bid-ask spread, volatility, and trading activity. As suggested by previous literature, a narrower spread is expected to be accompanied by a larger number of quotes and lower volatility. Table 2 presents the results of the estimation of Equation (6).[18]

Based on Table 2, there exists a significant direct relationship between liquidity and trading activity. Higher levels of trading activity are therefore accompanied by narrower spreads. This is consistent for both the London and Lisbon markets and across maturities. Moreover, the results suggest a significant positive relationship between spreads and volatility, i.e. wider spreads are accompanied by higher volatility. The relationships found are in accordance with theoretical predictions and prior empirical findings (see Section 2).

[Insert Table 2 here]

### 4.2. SSF and the short-selling ban

The purpose of this section is to answer the question: Are SSF acknowledged as a viable substitute for short-selling? If the answer to this question is affirmative, short-sellers are expected to migrate to trading in SSF when they no longer have the ability to short sell. This is investigated with equation (7), whereby $\beta_3$ is expected to be positive for the number of quotes, and negative for both spreads and volatility.

Prior to the difference-in-differences estimation, a placebo test is conducted to investigate the common trend assumption. A fake treatment is created one year after the actual ban, i.e.

[18] The full dataset from 2008 to 2010 is used to estimate Equation (6).

from September 18th, 2009 until January 16th, 2010, in order to address any potential seasonal effects. Table 3 displays the results of the placebo test.

[Insert Table 3 here]

The placebo difference-in-differences results show a significant negative effect of the "fake" treatment on trading activity, suggesting that trading activity dropped during the last third of 2009.[19] The lower level of trading activity is accompanied by wider spreads and slightly lower volatility. The common trend assumption could not be verified with this fake ban. The assumption is, however, valid when other fake treatment dates are considered (e.g. June 1st, 2010 to August 1st, 2010). However, most importantly, these placebo tests do not indicate any upward trend in trading activity.

Table 4 presents the results of estimating Equation (7). The estimated coefficient for the effect of the ban on trading activity is positive and strongly significant. Therefore, there is an increase in London SSF trading activity during the ban period resulting from a shift to trading in SSF. This is consistent for all maturity groups.

[Insert Table 4 here]

For the bid-ask spreads, the estimated $\beta_3$ is negative and strongly significant, which indicates that spreads are narrower after the ban takes effect. This is expected due to the negative relationship between spreads and trading activity, as reported in Table 2. The increase in trading activity is accompanied by narrower spreads, for the three maturity groups. Volatility shows a much weaker, statistically insignificant reaction. This suggests that volatility in SSF markets is robust to increased trading activity, i.e. an increase in trading in SSF is not associated

[19] This could be due to the drop in electronic trading volume in 2009 as announced by the London Stock Exchange news release. See 'LSE Reveals Year-On-Year Declines In Order Book Trading Volumes In December'. London Stock Exchange, January 8th, 2010.

with a change in market quality.[20,21] The model's goodness of fit is higher for the number of quotes and spreads, where estimates are the most significant.

The n:1 matching exercise reduces the number of contracts to 45 in London and 9 in Lisbon. First, the balance of the matched groups is tested. Table 5 reports the results of the balancing condition based on the n:1 matching approach. The comparison of standardised differences across groups (treatment and control) for both unmatched and matched samples, for the three maturities separately, show that the matching improves the balance of the sample by reducing the size bias by about 82% on average. The standardised differences of size are less than 0.21, which confirms the balancing property of the propensity score adjustment.

[Insert Table 5 here]

The matching and difference-in-differences results are presented in Table 6. The number of quotes and liquidity react as expected to the short-selling ban. The difference-in-differences matching estimates show that the level of trading activity increases significantly and that spreads are significantly narrower during the ban period. The reaction of volatility is benign which shows that SSF markets' quality is not sensitive to the level of trading activity and that these markets can absorb high demands for trading without recording any change in volatility levels. These results strongly confirm the 'pre-matching' findings of Table 4.

[Insert Table 6 here]

These results contrast with Grundy et al. (2012) who find that SSF trading in the US is unaffected during the US short-selling ban. The duration of the bans in the UK and the US differ. The US ban was much shorter, from September 19th to October 8th, 2008. Comparing

[20] Similar tests are performed where volatility is measured by the standard deviation of the midpoint prices within each trading day and similar results are found. The ban does not have any effect on volatility.

[21] Several studies link market quality to short-term volatility and conclude that a decrease in volatility is a sign of enhanced market quality, e.g. Chordia et al. (2011).

the number of SSF contracts traded in the US and the UK suggests that SSF became more popular in the UK. In 2008, a total of 2.5 million SSF contracts were traded in the UK market compared to 4 million in the US. In 2009 (2010), the total number of contracts traded in the UK increased to 9.5 million (11.2 million), while US trading amounted to 2.9 million (4.9 million) contracts.[22] Also, the context of the UK ban is that similar bans are in place in several other European countries (see Table 1).

### 4.3. SSF and underlying market quality

Attention now turns to the quality of the underlying market during the ban in the presence of SSF. Section 2.1 discusses the relevant prior literature on this aspect. This subsection presents how the underlying stocks react during the ban compared with stocks on which no SSF are written.[23] The treated and control groups are unbalanced in terms of firm size. Most stocks with SSF are considerably larger than those without SSF. Hence, the stocks are matched as described in Section 3.2.3. The matching exercise reduces the size bias in the unmatched sample by 85%.[24]

Table 7 reports the results of the difference-in-differences estimation in the unmatched and matched stock samples. In the unmatched sample, stocks with SSF are found to be more liquid, to have higher trading volume and volatility during the ban, compared to stocks without SSF. However, these effects disappear when the samples are matched by size, which implies that the effects of the ban are more prevalent in the largest firms which have listed SSF. This suggests that the presence of SSF does not improve the liquidity, the trading volume, nor the volatility level of the underlying stocks under restrictions on short sales. Consistent with Lee

---

[22] The figures are obtained from the OneChicago and Eurex press releases in January of each year.
[23] Similar to Table 3 for SSF, a placebo test is conducted with a fake treatment to test the parallel trend assumption. The fake treatment is again set one year after the actual UK ban, i.e. from September 18$^{th}$, 2009 until January 16$^{th}$, 2010. The results indicate that liquidity and volume have similar patterns in both the treated and control stocks outside the ban period. However, this assumption is not verified for volatility. The results are available on request.
[24] The results of the balance test are available on request (i.e. the equivalent of Table 5 for the stocks).

and Tong (1998) and Dennis and Sim (1999), SSF are not found to influence the effect of the ban on the market quality for their underlying stocks. The ban was implemented as a response to extreme market conditions, which can explain why the matched sample test does not support findings in McKenzie et al. (2001) and Danielsen et al. (2009).

[Insert Table 7 here]

### 4.4. Nature of the shift to SSF and arbitrage opportunities

Is the increase in SSF trading driven by hedging or speculation? Figure 2 displays the dynamics of $R_d$ (defined in Equation (10)) around the ban period in London.

[Insert Figure 2 here]

Comparing the evolution of $R_d$ and trading activity in Figure 2 gives a better insight into the nature of trading underlying the increased trading activity. The ratio $R_d$ has several peaks before and during the ban. The spikes are in most cases synchronous with those observed in the number of quotes which implies that the increase in trading activity is mainly driven by high speculative demand.

The conclusions drawn from the plot are confirmed by a one-way ANOVA test to compare the means of $R_d$ and the trading activity in four phases. Panel A of Table 8 reports the results. As defined in Section 3.2.4, Phase 0 represents the reference level of $R_d$ and the number of quotes. The other estimates in each phase are the differentials between the variables' mean values in that phase compared with Phase 0. Both $R_d$ and the number of quotes significantly increase in the first 20 days of the ban compared to the pre-ban period. They remain significantly elevated during the ban then $R_d$ falls in the last 20 days of available data.

[Insert Table 8 here]

Further, the level of SSF mispricing is compared across the four phases. Panel B of Table 8 reports that the absolute value of mispricing does not change significantly in the first 20 days of the ban. It is significantly higher during Phase 2 and the last 20 days of data. Similar results are found for negative and positive mispricing, in terms of the phases with statistically significant coefficients. Additionally, the mispricing levels react asymmetrically to restrictions on short-selling. Consistent with theoretical prediction, the magnitude of the negative mispricing increases, i.e. underpriced SSF fall further below their fair value under short-selling constraints. The magnitude of positive mispricing decreases, i.e. the extent of overpricing reduced significantly under short-selling constraints.

Referring back to Figure 1, the number of quotes remains higher than the pre-ban period after the UK ban's expiry and then follows a downward trend to the end of 2009. This implies that speculators gradually (rather than immediately) revert to short-selling, as they are likely to still hold SSF with outstanding maturities. The ban expiry date was announced on January 5$^{th}$, 2009, i.e. only 10 days before the end of the ban. It would take time for some positions to unwind. Also, short-selling bans in other European markets (see Table 1) remained in effect at this time, which is a further reason why short-sellers may not immediately alter their trading behaviour at the end of the UK ban. As suggested by the column for negative mispricing in Table 8, mispricing-related arbitrage demand could be a further important influence in the post-ban period.

## 5. Conclusions

The main purpose of this paper is to answer the question: do market participants employ SSF as an alternative instrument to short-selling? The reaction of SSF markets to the short-selling ban in the UK from September 18$^{th}$, 2008 to January 16$^{th}$, 2009 is examined, considering the trading activity, liquidity, and volatility of SSF in London. The answer to the question is conclusively affirmative. The evidence is that SSF trading activity in London increases at the beginning of the ban period, accompanied with narrowing spreads, while volatility is not sensitive to the ban. The increased trading activity can be explained by an increase in demand from short-sellers as they shift to trading in SSF. Additional tests indicate that the increase in trading is predominantly speculative activity rather than hedging. The change in the trading activity level improves market liquidity as spreads become narrower during the restriction period. Despite the elevated SSF trading, volatility does not increase, which means that the SSF market is able to absorb the extra demand for trading without reducing market quality. In order to ensure reliable inferences, propensity score analysis is used to obtain a randomised treatment variable. The difference-in-differences specification is re-estimated using matched data and consistent estimates are found, which strongly confirms the findings.

The study also investigates how SSFs' underlying stocks react to the ban. In prior literature, restrictions on short selling are associated with deteriorations in market quality (e.g. Boehmer et al. 2013). This paper finds neutral evidence in that increased SSF trading neither improves nor worsens market quality in the underlying stocks during the ban. This could be due to the fact that the period considered is characterised by unique market conditions. However, there is evidence that market quality for the largest stocks is affected.

Another test is conducted to investigate the level of SSF mispricing during the short selling ban. Short sale restrictions prevent arbitrageurs from exploiting futures underpricing by shorting the stock and going long futures. Therefore, the magnitude of any negative mispricing is expected to increase during short selling bans. This is found to be true for SSF as their mispricing, in absolute value, increases during the ban period. The mispricing magnitudes react asymmetrically to restrictions on short-selling, as the negative mispricing became wider, while the positive mispricing narrowed.

The findings strongly imply that market participants use SSF as a viable alternative to short-selling. Therefore, SSF represent a mechanism via which market participants can circumvent a short-selling ban. Further investigation shows that stocks with SSF have similar liquidity, trading volume, and volatility levels as size-matched stocks without SSF during the ban period. The findings have important implications for regulators, exchanges, and investors, and present further evidence on the effectiveness of regulatory interventions during financial crises.

## References


Ang, J. S. & Cheng, Y. (2005a). Financial innovations and market efficiency: The case of single stock futures. Journal of Applied Finance, 15, 38–51.

Ang, J. S. & Cheng, Y. (2005b). Single stock futures: Listing selection and trading volume. Finance Research Letters, 2, 30–40.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivariate Behavioral Research, 46, 399–424.

Bai, Y., Chang, E. C. & Wang, J. (2006). Asset prices under short-sale constraints. Working Paper, MIT.

Battalio, R. & Schultz, P. (2010). Regulatory uncertainty and market liquidity: The 2008 short sale ban's impact on equity option markets. Journal of Finance, 66, 2013–2053.

Beber, A. & Pagano, M. (2013). Short selling bans around the world: Evidence from the 2007-09 crisis. Journal of Finance, 68, 343–381.

Bessembinder, H. & Seguin, P. J. (1993). Price volatility, trading volume, and market depth: Evidence from futures markets. Journal of Financial and Quantitative Analysis, 28, 21–39.

Bessembinder, H. (1994). Bid-ask spreads in the interbank foreign exchange markets. Journal of Financial Economics, 35, 317–348.

Blundell, R. & Costa Dias, M. (2000). Evaluation methods for non-experimental data. Fiscal Studies, 21, 427–468.

Boehmer, E., Jones, C. & Zhang, X. (2013). Shackling the short sellers: The 2008 shorting ban. Review of Financial Studies, 26, 1363–1400.

Chakravarty, S., Gulen, H. & Mayhew, S. (2004). Informed trading in stock and option markets. Journal of Finance, 59, 1235–1257.

Chordia, T., Roll, R., & Subrahmanyam, A. (2011). Recent trends in trading activity and market quality. Journal of Financial Economics, 101, 243–263.

Danciulescu, C. (2009). Cross market effects of stocks short selling restrictions: Evidence from the September 2008 natural experiment. CAEPR Working Paper.

Danielsen, B. R., Van Ness, R. A. & Warr, R. S (2009). Single stock futures as a substitute for short sales: Evidence from microstructure data. Journal of Business Finance & Accounting, 36, 1273–1293.

Dennis, S. & Sim, A. (1999). Share price volatility with the introduction of individual share futures on the Sydney Futures Exchange. International Review of Financial Analysis, 8, 153–163.

Diamond, D. W. & Verrecchia, R. E. (1987). Constraints on short selling and asset price adjustment to private information. Journal of Financial Economics, 18, 277–311.

Ding, Z., Granger, C. W. J. & Engle, R. F. (1993). A long memory property of stock market returns and a new model. Journal of Empirical Finance, 1, 83–106.

Figlewski, S. & Webb, G. P. (1993). Options, short sales, and market completeness. Journal of Finance, 48, 761–777.

Fung, J. K. W. & Draper, P. (1999). Mispricing of index futures contracts and short sales constraints. Journal of Futures Markets, 19, 695–715.

George, T. J. & Longstaff, F. A. (1993). Bid-ssk spreads and trading activity in the S&P 100 index options market. Journal of Financial and Quantitative Analysis, 28, 381–397.

Girma, S. & Görg, H., (2007). Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. Journal of International Economics, 72, 97–112.

Grundy, B., Lim, B. & Verwijmeren, P. (2012). Do option markets undo restrictions on short sales? Evidence from the 2008 short sale ban. Journal of Financial Economics, 106, 331–348.

Jones, C. M. & Lamont, O. A. (2002). Short-sale constraints and stock returns. Journal of Financial Economics, 66, 207–239.

Kuprianov, A. (1995). Derivatives debacles: Case studies of large losses in derivatives markets. Federal Reserve Bank of Richmond: Economic Quarterly, 81, 1–39.

Lee, C. I. & Tong, H. C. (1998). Stock futures: The effects of their trading on the underlying stocks in Australia. Journal of Multinational Financial Management, 8, 285–301.

MacKinlay, A. C. & Ramaswamy, K. (1988). Index-futures arbitrage and the behavior of index futures prices. Review of Financial Studies, 1, 137–158.

Marsh, I. W. & Payne, R. (2012). Banning short sales and market quality: The UK's experience. Journal of Banking and Finance, 36, 1975–1986.

McKenzie, M. D., Brailsford, T. J. & Faff, R. W. (2001). New insights into the impact of the introduction of futures trading on stock price volatility. Journal of Futures Markets, 21, 237–255.

Mitchell, K. (2003). Single stock futures: An investor's guide. New Jersey: Wiley.

O'Hara, M. & Oldfield, G. (1986). The microeconomics of market making. Journal of Financial and Quantitative Analysis. 21, 1–376.

Phillips, B. (2011). Options, short-sale constraints and market efficiency: A new perspective. Journal of Banking & Finance, 35, 430–442.

Rosenbaum, P. R. & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. American Statistician, 39, 33–38.

Shastri, K., Thirumalai, R. S. & Zutter, C. J. (2008). Information revelation in the futures market: Evidence from single stock futures. Journal of Futures Markets, 28, 313–415.

Smith, J. A. & Todd, P. E. (2005a). Does matching overcome LaLonde's critique of non-experimental estimators? Journal of Econometrics, 125, 305–353.

Smith, J. A. & Todd, P. E. (2005b). Rejoinder. Journal of Econometrics, 125, 365–375.

Wang, G. H. K., Michalski, R. J., Jordon, J. V. & Moriarty, E. J. (1994). An intraday analysis of bid-ask spreads and price volatility in the S&P 500 index futures market. Journal of Futures Markets, 14, 837–859.

Wang, H. K., Yau, J. & Baptiste, T. (1997). Trading volume and transaction costs in futures markets. Journal of Futures Markets, 17, 757–778.

Yadav, P. K. & Pope, P. F. (1994). Stock index futures mispricing. Journal of Banking and Finance, 18, 921–953.

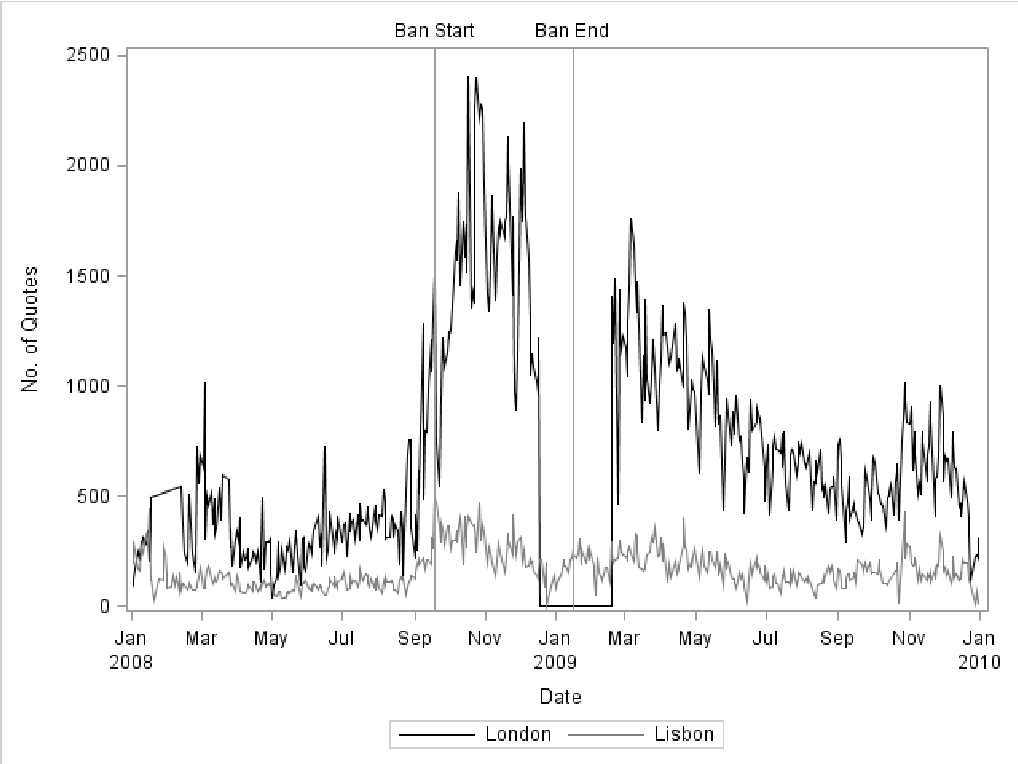


**Figure 1: Trading activity in SSF around the UK short-selling ban**

This figure displays the average number of quotes per day across all contracts traded in London and Lisbon. The UK short selling ban was effective from September 18th, 2008 to January 16th, 2009.

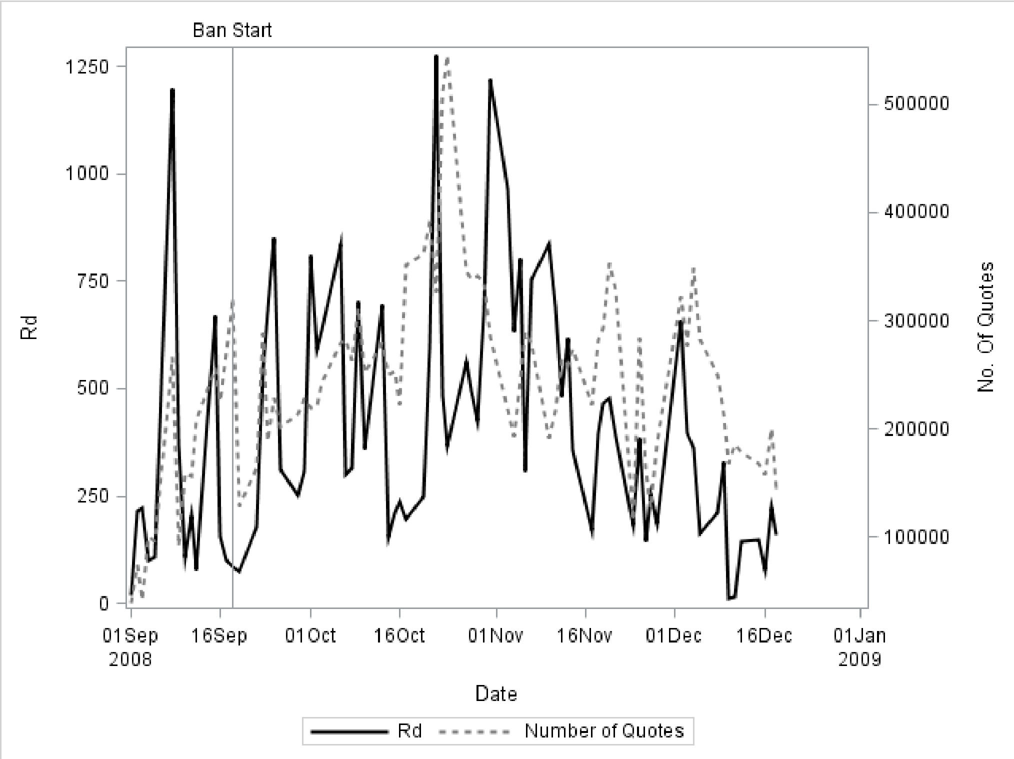


**Figure 2: Ratio Rd and Number of Quotes**

This figure displays the average ratio $R_d$ and the total number of quotes per day during the UK short-selling ban. $R_d$ for day d is defined as follows:

$$R_d = \frac{Activity_d}{|OI_d - OI_{d-1}|}$$

Where $OI_d$ and $OI_{d-1}$ are the daily open interest for days $d$ and $d-1$, respectively. Higher values of $R_d$ indicate relatively high speculative activity.

**Table 1: Short-Selling Ban Periods around Europe**

This table documents the periods during which short-selling was banned by different European financial authorities. The Nature of Ban column shows whether these restrictions are on naked short positions (NSS) or covered short positions (SS), and whether they are exclusive to financial stocks (FIN) or not (ALL).

| ***Country*** | ***Start*** | ***End*** | ***Nature of Ban*** | ***Source*** |
|---|---|---|---|---|
| Belgium | 23/09/2008 | 12/08/2011 | NSS – FIN | FSMA - Royal Decree of 23 September 2008 |
| France | 23/09/2008 | 01/02/2011 | SS – FIN | AMF instruction n° 2010-08 - AMF article 223-37 |
| Germany | 19/09/2008 | 21/01/2010 | NSS – FIN | BaFin – General Decree Section 49 of the Administrative Procedure Act Verwaltungsverfahrens gesetz (VwVfG) |
| Italy | 22/09/2008 | 01/08/2009 | SS - FIN until 10/10/2008 then SS – ALL | Consob – Resolutions n° 16622 and 16971 |
| Netherlands | 22/09/2008 | 01/06/2009 | NSS until 05/10/2008 then SS - FIN | AFM Press release on September 22, 2008 |
| Portugal | 22/09/2008 | 01/07/2010 | NSS- FIN | CMVM Press release on September 22, 2008 |
| Spain | 22/09/2008 | 23/06/2009 | NSS – FIN | CNMV Communication on September 22, 2008 |
| United Kingdom | 18/09/2008 | 16/01/2009 | SS – FIN | FSA Press release n° FSA/PN/102/2008 |

**Table 2: The Spread-Volatility-Trading Activity Relationship**

This table presents the estimated coefficients of trading activity and volatility as explanatory variables of spread in London and Lisbon for all contracts and each maturity group. The model is estimated using GMM:

$$BAS_{i,d} = \beta_0 + \beta_1 Activity_{i,d} + \beta_2 Risk_{i,d} + \varepsilon_{i,d}$$

Where $i$ is the SSF contract, and $d$ indicates the day on which the observation is recorded.

| | ALL | SHORT | MEDIUM | LONG |
|---|---|---|---|---|
| ***Panel A: Spreads in London*** | | | | |
| Intercept | 0.668 | 0.651 | 0.681 | 0.685 |
| | (184)*** | (178)*** | (180)*** | (59.8)*** |
| Activity (x$10^3$) | -0.040 | -0.070 | -0.070 | 0.062 |
| | (-17.1)*** | (-34.4)*** | (-29.4)*** | (6.80)*** |
| Volatility (x$10^3$) | 0.366 | 1.820 | 0.982 | -1.130 |
| | (2.05)** | (2.50)** | (1.71)* | (-3.31)*** |
| ***R-Squared*** | ***0.004*** | ***0.025*** | ***0.018*** | ***0.003*** |
| ***No. of Obs.*** | ***152102*** | ***53677*** | ***67410*** | ***31015*** |
| ***Panel B: Spreads in Lisbon*** | | | | |
| Intercept | 1.397 | 1.123 | 1.502 | 1.547 |
| | (91.2)*** | (75.8)*** | (59.6)*** | (76.8)*** |
| Activity (x$10^3$) | -0.910 | -0.740 | -1.630 | -0.830 |
| | (-18.7)*** | (-13.0)*** | (-17.9)*** | (-15.3)*** |
| Volatility | 3.997 | 2.328 | 7.081 | 4.414 |
| | (7.30)*** | (5.61)*** | (6.69)*** | (6.05)*** |
| ***R-Squared*** | ***0.023*** | ***0.031*** | ***0.034*** | ***0.030*** |
| ***No. of Obs.*** | ***22901*** | ***6502*** | ***8358*** | ***8041*** |

Significance: 0.01 ‘***’ 0.05 ‘**’ 0.1 ‘*’

**Table 3: Placebo Test for Parallel Trend in SSF**

This table shows results for the "fake" treatment of trading activity, bid-ask spread, and volatility, where the fake treatment is set between September 18th, 2009 and January 16th, 2010. Data from January 1st, 2009 until December 31st, 2010 are used for this estimation.

| | TRADING ACTIVITY | BID-ASK SPREAD | VOLATILITY |
|---|---|---|---|
| Intercept | 186.6 | 1.379 | 0.014 |
| | (60.9)*** | (73.6)*** | (4.09)*** |
| Treat | 730.0 | -0.734 | -0.001 |
| | (112)*** | (-38.3)*** | (-0.05) |
| Fake Ban | -7.734 | -0.234 | -0.007 |
| | (-0.99) | (-6.68)*** | (-13.6)*** |
| Treat*Fake Ban | -286.0 | 0.200 | -0.028 |
| | (-23.9)*** | (5.54)*** | (-1.82)* |
| Cap ($x10^5$) | -141.0 | -0.011 | 0.093 |
| | (-25.5)*** | (-2.22)** | (1.26) |
| ***R-squared* (x10)** | ***0.740*** | ***0.650*** | ***0.001*** |
| **No. of Obs. = 175003** | | | |

Significance: 0.01 '***' 0.05 '**' 0.1 '*'

**Table 4: The Effect of the Short-Selling Ban on SSF – Initial Estimation**

This table represents the estimated coefficients of the difference-in-difference equation:

$$\mathrm{Var}_{i,d} = \beta_0 + \beta_1 \mathrm{ban}_d + \beta_2 \mathrm{treat}_i + \beta_3 \mathrm{treat}_i * \mathrm{ban}_d + \beta_4 \,\mathrm{CAP}_{i,d} + \varepsilon_{i,d}$$

Where Var represents Trading Activity, Spread, and Volatility in each panel, i is the SSF contract, and d indicates the day on which the observation is recorded.

| | ALL | SHORT | MEDIUM | LONG |
|---|---|---|---|---|
| ***Panel A: Trading Activity*** | | | | |
| Intercept | 160.1 | 151.5 | 144.8 | 182.9 |
| | (60.1)*** | (43.5)*** | (51.5)*** | (41.8)*** |
| Treat | 530.5 | 560.8 | 551.6 | 453.1 |
| | (103)*** | (74.2)*** | (86.4)*** | (49.5)*** |
| Ban | 97.28 | 87.98 | 86.33 | 113.5 |
| | (11.0)*** | (8.67)*** | (10.2)*** | (8.06)*** |
| Treat*Ban | 697.2 | 744.3 | 712.8 | 576.8 |
| | (36.4)*** | (29.4)*** | (31.4)*** | (13.8)*** |
| Cap (x$10^3$) | -1.610 | -1.720 | -1.620 | -1.350 |
| | (-40.4)*** | (-34.6)*** | (-35.9)*** | (-20.0)*** |
| ***R-Squared*** | ***0.184*** | ***0.177*** | ***0.188*** | ***0.181*** |
| ***Panel B: Bid-Ask Spreads*** | | | | |
| Intercept | 1.189 | 0.943 | 1.249 | 1.334 |
| | (83.9)*** | (87.9)*** | (54.6)*** | (71.9)*** |
| Treat | -0.556 | -0.335 | -0.609 | -0.671 |
| | (-37.8)*** | (-28.1)*** | (-26.2)*** | (-33.7)*** |
| Ban | 0.697 | 0.401 | 0.885 | 0.725 |
| | (14.3)*** | (16.6)*** | (11.5)*** | (16.5)*** |
| Treat*Ban | -0.654 | -0.348 | -0.838 | -0.713 |
| | (-13.3)*** | (-13.6)*** | (-10.8)*** | (-15.8)*** |
| Cap (x$10^6$) | -0.018 | 0.123 | -0.026 | -0.267 |
| | (-0.32) | (1.49) | (-0.43) | (-4.08)*** |
| ***R-Squared*** | ***0.068*** | ***0.018*** | ***0.071*** | ***0.203*** |
| ***Panel C: Volatility*** | | | | |
| Intercept | 0.016 | 0.017 | 0.016 | 0.016 |
| | (56.9)*** | (33.9)*** | (45.0)*** | (36.5)*** |
| Treat | 0.008 | 0.007 | 0.006 | 0.011 |
| | (16.1)*** | (8.22)*** | (10.4)*** | (14.1)*** |
| Ban | 0.017 | 0.018 | 0.017 | 0.015 |
| | (11.3)*** | (6.30)*** | (7.73)*** | (8.51)*** |
| Treat*Ban | 0.003 | 0.003 | 0.001 | 0.007 |
| | (1.60) | (0.83) | (0.22) | (0.02) |
| Cap (x$10^6$) | -0.029 | -0.027 | -0.026 | -0.041 |
| | (-3.89)*** | (-2.55)** | (-3.15)*** | (-3.31)*** |
| ***R-Sq.* (x10)** | ***0.018*** | ***0.017*** | ***0.017*** | ***0.027*** |
| ***No. of Obs.*** | ***102814*** | ***36212*** | ***44989*** | ***21613*** |

Significance: 0.01 '***' 0.05 '**' 0.1 '*'

**Table 5: Balance Assessment of the Matched SSF groups**

This table shows the results of the balance assessment. The standardised difference of size is calculated as follows:

$$D(\text{size}) = \frac{100 * |\bar{x}_T - \bar{x}_C|}{\sqrt{\frac{s^2{}_T + s^2{}_C}{2}}}$$

Where T and C refer to the treatment and control groups, respectively; $\bar{x}_T$ and $\bar{x}_C$ are the sample means of the covariate x, respectively; and $s^2{}_T$ and $s^2{}_C$ are the sample standard deviations of the covariate size in the treatment and control groups, respectively.

| | Unmatched Sample | | | Matched Sample | | | |
|---|---|---|---|---|---|---|---|
| | Mean | | D | Mean | | D | % Bias Reduction |
| Maturity | Treatment | Control | | Treatment | Control | | |
| *Short* | 41374.56 | 4557.01 | 0.939 | 5317.76 | 4700.48 | 0.196 | 79 |
| *Medium* | 41349.70 | 4548.71 | 0.935 | 5238.46 | 4618.20 | 0.205 | 78 |
| *Long* | 41273.47 | 4503.12 | 0.938 | 6273.69 | 5938.29 | 0.108 | 88 |

**Table 6: The Effect of the Short-Selling Ban on SSF – Matched Samples**

This table shows the results of the estimated difference-in-difference equation after matching treated and control contracts based on a caliper = 0.20. The model is:

$$\mathrm{Var}_{i,d} = \beta_0 + \beta_1 \mathrm{ban}_d + \beta_2 \mathrm{treat}_i + \beta_3 \mathrm{treat}_i * \mathrm{ban}_d + \beta_4 \, \mathrm{CAP}_{i,d} + \varepsilon_{i,d}$$

The variables are defined in Table 4.

| | ALL | SHORT | MEDIUM | LONG |
|---|---|---|---|---|
| ***Panel A: Trading Activity*** | | | | |
| Intercept | 88.76 | 60.11 | 58.42 | 171.3 |
| | (16.3)*** | (6.99)*** | (7.08)*** | (13.9)*** |
| Treat | 538.1 | 585.1 | 580.4 | 423.3 |
| | (72.0)*** | (42.4)*** | (49.1)*** | (33.7)*** |
| Ban | 112.9 | 102.5 | 98.39 | 142.5 |
| | (16.7)*** | (10.1)*** | (11.2)*** | (8.73)*** |
| Treat*Ban | 266.3 | 307.3 | 253.4 | 222.7 |
| | (10.6)*** | (6.91)*** | (6.92)*** | (4.25)*** |
| Cap | 0.157 | 0.018 | 0.018 | 0.009 |
| | (14.7)*** | (10.2)*** | (10.2)*** | (4.57)*** |
| ***R-Squared*** | ***0.300*** | ***0.318*** | ***0.341*** | ***0.224*** |
| ***Panel B: Bid-Ask Spread*** | | | | |
| Intercept | 1.302 | 1.033 | 1.390 | 1.618 |
| | (81.4)*** | (86.0)*** | (46.6)*** | (49.6)*** |
| Treat | -0.254 | -0.143 | -0.300 | -0.317 |
| | (-19.0)*** | (-9.65)*** | (-13.1)*** | (-11.6)*** |
| Ban | 0.579 | 0.343 | 0.586 | 0.835 |
| | (15.7)*** | (13.4)*** | (8.71)*** | (10.8)*** |
| Treat*Ban | -0.619 | -0.310 | -0.598 | -1.002 |
| | (-15.5)*** | (-9.07)*** | (-8.39)*** | (-11.9)*** |
| Cap ($x10^3$) | -0.042 | -0.027 | -0.053 | -0.064 |
| | (-24.1)*** | (-17.5)*** | (-15.1)*** | (-18.2)*** |
| ***R-Squared*** | ***0.094*** | ***0.092*** | ***0.093*** | ***0.141*** |
| ***Panel C: Volatility*** | | | | |
| Intercept | 0.016 | 0.017 | 0.015 | 0.018 |
| | (29.5)*** | (19.5)*** | (18.5)*** | (13.6)*** |
| Treat | 0.013 | 0.011 | 0.011 | 0.016 |
| | (19.7)*** | (9.87)*** | (12.3)*** | (12.1)*** |
| Ban | 0.018 | 0.019 | 0.019 | 0.017 |
| | (15.7)*** | (9.02)*** | (9.18)*** | (9.80)*** |
| Treat*Ban ($x10^3$) | 3.248 | 3.507 | 1.154 | 7.063 |
| | (1.52) | (0.93) | (0.37) | (0.14) |
| Cap ($x10^6$) | -0.003 | -0.066 | 0.133 | -0.326 |
| | (-0.03) | (-0.39) | (0.79) | (-1.45) |
| ***R-Squared*** | ***0.049*** | ***0.047*** | ***0.056*** | ***0.049*** |
| ***No. of Obs.*** | ***18084*** | ***5832*** | ***7226*** | ***5026*** |

Significance: 0.01 ‘***’ 0.05 ‘**’ 0.1 ‘*’

**Table 7: The Ban's Effect on Underlying Market Quality**

This table shows the results of the estimated difference-in-difference equation after matching treated stocks with control stocks based on a caliper = 0.20. The model is:

$$\mathrm{Var}_{s,d} = \beta_0 + \beta_1 \mathrm{ban}_d + \beta_2 \mathrm{treat}_s + \beta_3 \mathrm{treat}_s * \mathrm{ban}_d + \beta_4\, \mathrm{CAP}_{s,d} + \varepsilon_{s,d}$$

Where Var represents Spread, Trading Activity and Volatility in each panel, *s* is the stock, and d indicates the day on which the observation is recorded.

| | SPREAD | TRADING ACTIVITY | VOLATILITY |
|---|---|---|---|
| ***Panel A: Unmatched Samples*** | | | |
| Intercept | 5.068 | 254.2 | 1.827 |
| | (113)*** | (44.8)*** | (262)*** |
| Treat | -3.544 | 6617 | 0.218 |
| | (-68.3)*** | (32.5)*** | (11.4)*** |
| Ban | 1.862 | 78.49 | 1.041 |
| | (14.9)*** | (5.13)*** | (45.4)*** |
| Treat*Ban | -1.646 | 1090 | 0.717 |
| | (-10.6)*** | (2.60)** | (11.2)*** |
| Cap ($x10^5$) | -0.200 | 224.5 | -0.037 |
| | (-33.1)*** | (13.1)*** | (-13.5)*** |
| ***R-Squared*** | ***0.020*** | ***0.132*** | ***0.025*** |
| ***No. of Obs.*** | | ***492193*** | |
| ***Panel B: Matched Samples*** | | | |
| Intercept | 0.138 | -1678 | 1.851 |
| | (10.7)*** | (-11.6)*** | (71.0)*** |
| Treat | 0.211 | 4486 | 0.143 |
| | (16.1)*** | (28.3)*** | (6.79)*** |
| Ban | 0.238 | 1453 | 1.719 |
| | (2.70)*** | (12.9)*** | (24.4)*** |
| Treat*Ban | -0.056 | 561.2 | 0.081 |
| | (-0.53) | (1.46) | (0.83) |
| Cap ( $x10^5$) | -0.005 | 2709 | -0.033 |
| | (-0.67) | (30.2)*** | (-2.50)** |
| ***R-Squared*** | ***0.005*** | ***0.057*** | ***0.080*** |
| ***No. of Obs.*** | | ***36085*** | |

Significance: 0.01 '***' 0.05 '**' 0.1 '*'

**Table 8: ANOVA Test in the Four Phases of the Ban**

This table contains the results of the ANOVA tests for whether there are significant differences in the average level of $R_d$ (number of quotes divided by the change in open interest), the number of quotes, the level of mispricing $|\pi_d|$, the mean upper bound, $\pi_d^+$, and lower bound, $\pi_d^-$, across four phases of time. Phase 1 is defined as the first 20 days of the ban; Phase 3 is defined as the last 20 days before January 5th, 2009; while Phase 2 is the period in between.

Phase 0 is the reference level; the estimates for phases 1, 2, and 3 represent the differential between the mean in each phase and Phase 0. The test for Phase 0 is whether the variable in question equals zero. For the other phases, the question is whether the difference in the variable compared to its value in Phase 0 equals zero.

***Panel A: $R_d$ and the Number of Quotes***

| | $R_d$ | *No. Of Quotes* |
|---|---|---|
| Phase 0 | 273.9<br>(4.89)*** | 1564<br>(25.1)*** |
| Phase 1 | 144.2<br>(1.83)* | 1011<br>(11.9)*** |
| Phase 2 | 163.5<br>(2.52)** | 1970<br>(27.1)*** |
| Phase 3 | -170.0<br>(-1.91)* | 13.51<br>(0.13) |

***Panel B: Levels of Absolute, Negative and Positive Mispricing***

| | Absolute Mispricing | Negative Mispricing | Positive Mispricing |
|---|---|---|---|
| Phase 0 | 0.717<br>(7.47)*** | -0.783<br>(-5.81)*** | 0.568<br>(25.2)*** |
| Phase 1 | 0.127<br>(0.93) | -0.173<br>(-0.91) | -0.025<br>(-0.74) |
| Phase 2 | 0.475<br>(3.89)*** | -0.701<br>(-4.12)*** | -0.169<br>(-5.71)*** |
| Phase 3 | 0.346<br>(1.88)* | -0.549<br>(-2.16)** | -0.196<br>(-4.38)*** |

Significance: 0.01 ‘***’ 0.05 ‘**’ 0.1 ‘*’