ANALYSIS OF MARKET QUALITY BEFORE AND AFTER THE 2011 SHORT SELLING BANS

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Abstract

We measure the impact of the August 2011 ban on covered short-selling adopted by some European countries. Our results evidence that the impact on prices was temporary; in the longer term the ban was neutral in its effects on stock prices. We also conclude that the post-ban volatility was not lower than the pre-ban volatility. As for the permanent impact, the volatility of closing prices and the intraday volatility increased in comparison with the other financial stocks not covered by the ban. We also find that the short-selling ban did have a negative impact on liquidity in the weeks following the event, even though there was an initial and transitory negative (but not statistically significant) impact on the bid-ask spread that could indicate otherwise.

Introduction

The years of 2010 and 2011 were characterized by a high degree of uncertainty in the equity and debt markets. Volatility reached new peaks, particularly amid financial companies. The sovereign debt crisis started in Greece, Ireland and Portugal, but soon began to threaten Italy and Spain, contributing to this increase in volatility. During the second quarter of 2011, political measures were deployed to mitigate the possible consequences of a Greek debt restructuring. This period was also rife with countless rumours related to the resolution of the European sovereign debt crisis and the disclosure of the results of stress tests carried out at several European banks.

Within this context, some European Regulators temporarily banned short-selling in financial stocks on 11th August 2011 aimed to reduce volatility and to stop or at least mitigate the downward spirals in prices. This ban was also justified by evidence of rumours with the purpose of market manipulation. The countries that implemented such bans are France, Italy, Belgium and Spain (hereinafter, FIBS).

This paper addresses the impact of this ban on covered short-selling in FIBS' financial stocks. We first investigate the short-term impact on the prices of securities covered by the ban. Then, we evaluate the effects on market quality, i.e., on liquidity, volatility and price discovery mechanisms.

Most neo-classical models in finance assume that some market players (arbitrageurs) have the ability to 'enforce' the law of one price. A key tool to ensure that is the possibility of market players carrying out short-selling strategies and exploit assets mispricing. Therefore, since long ago, the topic of short selling's ban has been subject of investigation.

Most of the literature investigates the effects of short-selling restrictions on liquidity, volatility, price discovery and overpricing.[1] Boehmer et al. (2008, 2011), Fotak et al. (2009), Gagnon and Witmer (2010), Kolasinski et al. (2010), Battalio and Schultz (2011), Beber and Pagano (2013) and Marsh and Payne (2012) find that short selling restrictions had an adverse effect on liquidity. However, Jones and Lamont (2002) and Charoenrook and Daouk (2005) present conflicting evidence. In terms of price discovery, Diamond and Verrecchia's (1987) theoretical model predicts that the existence of trade restrictions slows down price discovery asymmetrically – less in upward movements than in downward movements. Miller (1977), Harrison and Kreps (1978), Biais et al. (1999), Bris et al. (2007), Boehmer and Wu (2013), Saffi and Sigurdsson (2011), Chang (2010) and Beber and Pagano (2013) provide similar empirical findings. Jones and Lamont (2002), Chang et al. (2007), Autore et al. (2011) and Lobanova et al. (2010) provide evidence consistent with the overpricing hypothesis (ie, short selling restrictions lead to stock overpricing), but Diether et al. (2009), Boehmer et al. (2010) and Beber and Pagano (2013) do not. Boehmer et al. (2010) find that stocks with relatively high short open interest subsequently experience negative abnormal returns, but the effect can be transient and of debatable economic significance. Finally, higher volatility associated to short selling restrictions has been unveiled by Abreu and

[1] See Beber and Pagano (2013) for a recent literature review.

Brunnermeier (2002, 2003), Scheinkman and Xiong (2003), Hong and Stein (2003), Charoenrook and Daouk (2005) and Bris et al. (2007).

Most studies support the hypothesis that short-selling constraints contribute to decreasing market efficiency. However, this conclusion is not shared by all researchers. Besides, the literature is relatively scarce given that the experiences of short selling bans are occasional, and therefore the effects of each one of them deserve to be studied. Moreover, up to now, most studies have focused on the U.S. stock market, albeit a few (Beber and Pagano 2013, and Bris et al. 2007, among others) discuss the short-selling impact on a multi-country setup. Despite the recent global trend of harmonization, the U.S. markets have had different rules and market architecture (characterized by a market-driven order book and by the importance of market-makers and specialists in providing liquidity and immediacy) for a long time. The 'up-tick rule' prevailed during 70 years and prohibited short-selling after price declines, and is an example of this idiosyncrasy. The rule was adopted to restrict short selling in a declining market in order to avoid an out of control negative spiral and was only eliminated by SEC on 2007. Because market architecture and rules are important and affect market players' behaviour, it is important to evaluate the effects of short-selling bans in jurisdictions and markets other than the U.S.

Hence, the 2011 episode in some E.U. markets gives us an opportunity to assess the effects of short-selling bans in other markets. As far as we know, little attention has been paid to the effects of this ban in the financial literature.[2] Besides, there is scarce evidence about the performance of the impacted shares before the ban because, in general, the literature focuses on the post ban effects. This papers aims to contribute to fill these gaps.

Specifically, the research questions we address in the paper are the following: i) *Did financial stocks perform differently from normal (ie, exhibit abnormal returns) prior to the ban?* ii) *Did FIBS financial stocks perform differently than Non-FIBS financial stocks prior to the short-selling ban?* iii) *What was the immediate impact (on prices, liquidity and volatility) of the ban on FIBS stocks?* iv) *What was the permanent impact of the short-selling ban (on prices, volatility and pricing efficiency) on FIBS financial stocks?*

The paper is structured as follows. In section 2 we discuss the sample. Section 3 discusses the initial results related to the (non-)existence of abnormal returns in the five and ten sessions before the short-selling ban. The immediate impact of the ban on prices, liquidity and volatility is also analysed in section 3, and section 4 discusses the permanent impact. Some concluding remarks are made in the final section of the paper.

[2] A more recent study by Roqueiro (2013) also covers the bans on short-selling in Europe in the span 2011/2012.

1. Sample and Market Conditions

Our sample consists of 170 financial stocks listed in Western Europe (virtually all the listed financial institutions and insurance companies). The shares of 58 of them were subject to the covered short-selling ban, whereof 10 companies are domiciled in France, 29 in Italy, 5 in Belgium and 14 in Spain.

The major European capital markets recorded a sharp decline in prices during 2011. Between 10th February 2011 and 29th July 2011, the CAC 40, FTSE/MIB, BEL20 and IBEX Indices fell down -10.8%, -20.7%, -11.4% and -12.7%, respectively. However, the comparison between domestic market and financial sector performance shows that the decline was sharper in the financial sector companies: the non-weighted average of the cumulative returns of stocks subject to the ban was -22.2%, -34.3%, -32.4% and -23.2% in France, Italy, Belgium and Spain, respectively. All in all, the average decline was -29.3% among financial institutions of countries that introduced the ban, in comparison to an average -20.6% drop for companies in the financial sector of other Western European countries and -24.5% in the DJ Euro Stoxx 600 Banks Index.

The ban on new short positions in financial stocks was announced after the close of the markets on 11th August 2011 and came into force on the following trading day. In the five sessions prior to this ban coming into force, the financial stocks recorded, on average, a higher devaluation than that of the domestic Indices in France (-9.3% in the financial stocks as against -7.2% of the CAC 40 Index) and Belgium (-9.3% versus -3.6%). Furthermore, in the same period the devaluation of financial stocks was less sharp in countries that banned covered short selling, in comparison to the financial stocks of other Western European countries and the DJ Euro Stoxx 600 Banks Index.[3]

Following the ban, the stock markets and particularly the financial stocks continued to experience a decline. Notwithstanding this and excluding the positive effect on the trading session wherein this ban was effective, the financial stocks price trend was less negative than the domestic benchmarks in three of the four countries in the five sessions subsequent to 12th August 2011. However, this result remains valid only in one of the four countries when the 10 trading sessions after 12th August 2011 are considered. Furthermore, the financial stocks subject to the ban exhibit a higher depreciation than the financial stocks that were not subject to this ban. This conclusion is valid for the 5 and the 10 trading sessions subsequent to the event's date.

2. Short-Run Impact

[3] The treatment group of stocks exhibits positive and statistically significant CAR, while the control group of stocks records negative and statistically significant CAR. The CAR difference (between the two groups) is also statistically significant.

The event study methodology is used to assess the impact of the covered short selling ban on prices. Abnormal returns in the trading sessions that follow the ban are computed using the Market Model and the Multi-Index Model:

i) Market Model:

$$R_{it} = \alpha_i + \beta_i \times R_{mt} + \varepsilon_{it} \qquad (1)$$

ii) Multi-Index Model:

$$R_{it} = \alpha_i + \beta_i \times R_{mt} + \delta_i \times R_{st} + \varepsilon_{it} \qquad (2)$$

where R_{it} is the stock's *i* return at *t*; R_{mt} is the market's return at *t*; and R_{st} is the financial sector's return at *t*.

The use of the Market Model (perhaps the most frequently used model in event studies) aims to isolate idiosyncratic shocks from systematic or macroeconomic shocks. By using the Multi-Index Model, we control for the existence of sectorial information impacts (in addition to economic or macroeconomic information that impacts the entire market).

The estimation window comprises 120 trading sessions, and covers the period $[t_{-129}; t_{-10}]$, where t_0 refers to the trading session of the 11th August 2011. Four different alternatives are considered for the event window (t_0 as previously defined): 1) $[t_{-9}; t_{-1}]$; 2) $[t_{-5}; t_{-1}]$; 3) $[t_1; t_5]$; and 4) $[t_1; t_{10}]$.

2.1. Individual Cumulative Abnormal Returns

In Table 1 we show, for different event windows, the percentage of stocks that exhibit statistically significant positive (upper panel) or negative (lower panel) cumulative abnormal returns (CAR), at the 5% significance level.

The results depend on the event window dimension. When we compare the two five-day windows we conclude, for both the market model and the multi index model, that after the ban the percentage of stocks of the FIBS group (i.e., the stocks subjected to the ban) with positive abnormal CAR increases and that the percentage of stocks with negative abnormal CAR decreases. For example, using the market model, the percentage of FIBS stocks with positive abnormal CAR increases from 27.6% to 39.7%, and the percentage of FIBS stocks with negative abnormal CAR decreases from 6.9% to 1.7%.[4] However, when we compare the ten-days windows we conclude, once again for both models, that in the FIBS group the percentage of stocks with positive abnormal CAR decreases and that the percentage of stocks with negative abnormal CAR increases. This evidence is consistent with

[4] The differences are statistically significant at the usual levels of significance (results not reported).

the idea that the immediate (i.e., five-days horizon) impact of the ban on prices was positive but transitory, given that in a ten-days horizon the positive price impact disappears or is even transformed in a negative price impact. This suggests that the eventual impact of the ban on stock prices is temporary.

This table also shows that the FIBS group of stocks performs better than Non-FIBS stocks on the immediacy of the ban. Effectively, in the windows [-9;-1] and [-5;-1], the percentage of positive (negative) CAR is higher (lower) for the FIBS stocks. Finally, Table 1 also shows that the percentage of negative CAR significantly decreases among the Non-FIBS stocks. Therefore, even if the percentage of positive CAR does not increase, the increase of positive CAR (in a five-days horizon) and, specially, the lower percentage of FIBS stocks with negative CAR might not be necessarily related to the ban itself. A further (likelihood ratio) test to examine if the proportion of financial firms exhibiting (positive or negative) statistically significant CAR is similar for the FIBS and Non-FIBS groups is implemented. Indeed, the percentage of firms exhibiting positive (and negative) statistical significant CAR is statistically different for FIBS and Non-FIBS groups both before and after the announcement of the ban (results not reported).

2.2. Aggregated Cumulative Abnormal Returns

We next aggregate the CAR of the analysed securities. The statistical techniques used hereinafter generally follow the MacKinlay (1997) and Brown and Warner (1985) methodology. Therefore, for each event window we compute the t-statistic of the cumulative abnormal returns:

$$T\ stat = \frac{\overline{CAR}(\tau 1,\tau 2)}{\sqrt{var[\overline{CAR}(\tau 1,\tau 2)]}} \qquad (3)$$

where,

$$\overline{CAR}(\tau 1,\tau 2) = \frac{1}{n}\sum_{i=1}^{n} CAR_i(\tau 1,\tau 2) \qquad (4)$$

$$var[\overline{CAR}(\tau 1,\tau 2)] = \frac{1}{n^2}\sum_{i=1}^{n} \sigma_i^2(\tau 1,\tau 2) \qquad (5)$$

$\mathrm{CAR_i}(\tau 1,\tau 2)$ is the cumulative abnormal return in the event window $(\tau 1,\tau 2)$ for stock i; $\sigma_i^2(\tau 1,\tau 2)$ is the abnormal return variance in the event window $(\tau 1,\tau 2)$ for stock i; and n is the number of observations in the cross sectional sample.

To ascertain the robustness of the results, we compute: i) classical standard errors (as in equation (3)), ii) Boehmer standard errors (see Boehmer et al. 1991), and iii) cross dependency adjusted standard errors (see Brown and Warner 1985). In ii) and iii) we aim at controlling for variance changes in the event windows and for cross dependency of the abnormal returns of the various firms, respectively.

In the following paragraphs we discuss the results presented in Table 2.

H1: Financial stocks do not perform differently than normal prior to the short-selling ban.

With regard to the Market Model's results (Table 2 – Panel A, "all companies"), we conclude that financial stocks exhibit CAR which are not statistically different from zero for the [-9; -1] and [-5; -1] windows. From Table 1 we know that 14.1% (15.9%) of the stocks present positive (negative) statistically significant CAR in the 5-days window prior to the ban. Results are similar for the Multi-Index Model and thus we do not reject H1, and conclude that, prior to the ban, the overall performance of financial stocks is normal.

H2: FIBS stocks do not perform differently than Non-FIBS stocks prior to the ban.

From Table 2 – Panel A, one concludes that FIBS stocks exhibit overall positive and significant CAR in the two event windows that include the 5 and the 9 trading sessions prior to the ban (respectively 2.54% and 3.55%). In contrast, Non-FIBS stocks exhibit negative CAR in those event windows. Moreover, the t-test of the equality of CAR for both FIBS and Non-FIBS stocks (column "Treatment Group minus Control Group") rejects the null hypothesis of no difference. Additionally, Table 1 shows that 29.3% of FIBS stocks display positive and statistically significant CAR in the nine trading days prior to the ban, which contrasts with 6.3% amid Non-FIBS stocks. In terms of negative and statistically significant CAR, the differences among these groups are also striking (5.2% against 21.4% for FIBS and Non-FIBS, respectively, in the nine trading days prior to the ban). Thus, we reject H2. The evidence runs contrary to the argument that FIBS stocks have poor returns, worse than those of Non-FIBS stocks, and in favour of the hypothesis that, prior to the ban, the performance of FIBS financial stocks is positive and higher than that of other European banks. The use of the Multi-Index Model (Table 2 – Panel B) provides similar results. This means that the countries that adopted the ban are not the ones where the financial stocks perform worst. If we add to this conclusion the previous one that financial stocks do not perform differently than normal prior to the short-selling ban, we must conclude that the ban was based on (political or) other reasons instead of the effective market conditions of financial stocks listed in their respective jurisdictions.

H3: Post-ban CAR are non-significant

H4: Post-ban CAR of FIBS and Non-FIBS stocks are not different

With regard to the Market Model's results, we find a statistically significant 1.78% CAR in the 5 days window after the ban (Table 2 – Panel A). Nevertheless, the CAR is not statistically different from zero within 10 days after the ban. Table 2 – Panel A further confirms the divergence of the financial stocks' abnormal performance in FIBS *vis-a-vis* other financial companies in Western Europe (that is, in Non-FIBS countries). In fact, the CAR for the five trading sessions after the event are statistically different from zero (4.23%) among the FIBS stocks. The CAR for the 10 trading sessions after the event are 1.20% (but not statistically significant even at the 10% level when the variance changes in the event window are considered or the cross-sectional independence assumption is dropped). However, the CAR for the control group are statistically not different from zero in the post-ban windows.

We further compare the CAR of financial stocks of FIBS and the control group (Table 2, column "Treatment Group minus Control Group"). The difference between the CAR of these groups is positive and statistically different from zero at the 5% significance level in all but one (the [1; 10]) windows. Results are similar when we use the Multi-Index Model (Table 2 – Panel B). Thus, using a five-day horizon we reject H3 in favour of the alternative that post-ban CAR are positive. This evidence is mostly due to FIBS stocks which exhibit positive post-ban CAR; Non-FIBS stocks show positive, albeit non-significant, CAR after the ban, allowing us to reject H4.

2.3. Impact on volatility

In this section, the hypotheses related with the impact on volatility are tested.

H5: The post-ban volatility is equal to the pre-ban volatility

H6: The post-ban volatility of FIBS is lower than that of Non-FIBS stocks.

Three alternative tests are used to assess the impact of the ban on volatility: (i) the F-test for equality of the (raw/abnormal) returns' variance in the estimation and event windows; (ii) the t-test to detect structural changes in the volatility equation (assuming that the variable follows a GARCH process); (iii) the Beaver's U test.

The F-test results are not reported. The percentage of stocks with higher variance of raw returns in the 5 post-ban trading days (vis-à-vis the variance in the estimation window) is less than 5% for the whole sample and 1.7% for FIBS. These percentages increase considerably for the ten post-ban trading days (19.0% for FIBS and 26.8% for Non-FIBS). On the other hand, the percentage of stocks with lower volatility in the five and the ten post-ban trading days is substantially higher among the Non-FIBS. Results are similar for abnormal returns. Moreover, with the exception of the [1, 5] window, the percentage of stocks with higher post-ban variance of (raw and abnormal) returns is higher than the percentage of stocks with lower post-ban variance.

As for the analysis of structural changes in the volatility equation, we consider the following GARCH (1, 1) Model:

$$R_{it} = \alpha_i + \beta i \times R_{mt} + v_t$$

$$v_t^2 = \gamma_0 + \gamma_1 \times v_{t-1}^2 + \rho_1 \times \sigma_{t-1}^2 + \emptyset \times DUM_t \qquad (6)$$

where R_{it} is the stock's i return at t; R_{mt} is the market return at t; DUM_t is a dummy variable that takes the value 1 in the event window and 0 otherwise; v_t is an error term and σ^2 represents the variance.

Table 3 – Panel A displays the percentage of stocks with a positive structural change in the variance equation: 9.5% and 6.5% in the event windows that include the five and the ten trading sessions after the ban, respectively. These percentages fall to 8.6% in the abovementioned two event windows for FIBS stocks. Interestingly, the percentage of stocks with a negative impact on volatility is considerably higher within the Non-FIBS.

The Beaver's U-Test is based on:

$$\mathrm{U_i} = \left(\frac{\mathrm{ARi}}{\sigma\ (\mathrm{ARi})}\right)^2 \sim \mathrm{F}(1, \mathrm{T} - \mathrm{d}) \qquad (7)$$

where ARi is the abnormal return of stock *i*; σ(ARi) is the standard deviation of the abnormal return of stock *i*; T is the number of observations used for computing the standard deviation of abnormal returns; and d is the number of variables used in the expected return equation.

In aggregate terms, the test statistics is:

$$\mathrm{Z} = \frac{\sum_{i=1}^{N} \mathrm{U_i} - \mathrm{N} \times \frac{(\mathrm{T-d})}{(\mathrm{T-d-2})}}{\sqrt{2 \times \mathrm{N} \times \frac{(\mathrm{T-d})^2 \times (\mathrm{T-d-1})}{(\mathrm{T-d-2})^2 \times (\mathrm{T-d-4})}}} \sim \mathrm{N}(0,1) \qquad (8)$$

Simulations by Dodd et al. (1984) indicate that the Z-statistic is poorly specified, and in particular is "fat-tailed", rejecting the null hypothesis too often. Pattel (1976) notes that this measure should not be used to evaluate changes in variance, but rather changes in mean and variance concurrently. We conclude that there are CAR and/or changes in variance in the 5 and the 10 post-ban trading days event windows (Table 3 – Panel B).

The combination of the above mentioned results allows us to reject H5. In fact, the t-test (Beaver's U test) rejects the null hypothesis of equal variance (variance and/or CAR). Moreover, there are cases where the variance of returns is higher after the ban, and this means that there is no generalized variance decrease after the ban. We also reject H6; our results do not indicate a generalized volatility decrease in the post-ban period for the FIBS stocks. The analysis also shows that the percentage of stocks with lower volatility is substantially higher within the Non-FIBS financial stocks. Given these results, one may conclude that, from a statistical point of view, the short-selling ban did not contribute to reduce the volatility of FIBS financial stocks.

3. Permanent Impact

In addition to the immediate effect of the short selling ban on prices and volatility, this study also aims to determine more permanent effects on market efficiency. Three important vectors relating to market efficiency are assessed: liquidity, volatility and price discovery. We follow the econometric panel data approach of Beber and Pagano (2013) to model the impact of the ban, and we use weekly data for the period from January to September 2011 (a total of 36 weeks).

3.1. Liquidity

We test the following hypothesis:

H7: The short selling ban did not have a permanent impact on liquidity.

Two liquidity indicators are considered for assessing the impact of the short-selling ban: the Bid-Ask Spread (BAS, henceforth) and the Amihud's Price Impact Indicator (APII, hereinafter). BAS is defined as the percentage difference between ask and bid prices.[5] BAS increases in France and Spain after the ban (Table 4), whereas Belgium and Italy only record a temporary reduction in the second half of August (but not in September).

In order to separate the immediate and the permanent impact of the ban, we estimate the following fixed effects model:

$$(9) \qquad BAS_{i,t} = \beta_0 + \sum_{j=2}^{7} \beta_j \times month(j)_t + \sum_{h=32}^{36} \gamma_h \times WEEK(h)_t + \sum_{k=33}^{36} \theta_k \times BANNED_i \times WEEK(k)_t + \overline{\delta_i} + u_{i,t}$$

where $BAS_{i,t}$ is the bid-ask spread; $month(j)_t$ is a dummy variable equal to 1 in month j and zero otherwise; $WEEK(h)_t$ is a dummy variable equal to 1 in week h and zero otherwise; $BANNED_i$ is equal to 1 if the stock i is subject to short-selling constraints and zero otherwise; and $\overline{\delta_i}$ is a fixed effect dummy variable.

We use the month of July (WEEKS 26 to 30) and the first week of August (WEEK31) as our baseline, that is, the time span before the ban turns effective.[6] This allows us to directly compare periods that usually display similar liquidity patterns (the months of July and August). We use a set of dummy variables associated with $month(j)$ to account for the seasonality of the dependent variable (suggested by the results of Table 4). $WEEK(h)$ captures the common (banned and non-banned stocks) BAS change in week h in relation to the baseline. $BANNED_i \times WEEK(h)$ captures the marginal impact on the stocks subject to the ban.

The model is firstly estimated using the standard Least Square Dummy Variable (LSDV) approach. However, because BAS tends to exhibit serial dynamics and cross-correlation dependence, we also use other methods to gauge the robustness of the results. The first alternative is the fixed effects model with a first-order autoregressive disturbance term. The second and third alternatives employ the Arellano–Bond estimator for linear dynamic panel-data models that uses lagged levels of the endogenous variables as well as first differences of the exogenous variables as instruments. The Arellano–Bond estimator eliminates the panel-specific heterogeneity by first-differencing the regression equation. The second and third alternatives use robust and GMM standard errors, respectively. Finally, we use a robust method based on the Driscoll and Kraay standard errors that corrects the standard errors of the estimated LSDV parameters with the aim of removing not

[5] Relative to the average bid-ask.

[6] The ban became effective in WEEK33.

only heteroskedasticity and autocorrelation, but also cross- correlation dependence. The Driscoll and Kraay methodology applies a Newey-West type of correction to the sequence of cross-sectional averages of the moment conditions and guarantees that the covariance matrix estimator is consistent regardless of the cross-sectional dimension (Hoechle, 2007).

We begin with the analysis of WEEK32, the week prior to the ban (Table 5 - Panel A). The estimated coefficient is positive and statistically significant in all cases, which means that BAS is higher in the trading days before the ban. We also report a higher BAS in the week after the ban for the whole sample (WEEK33). Nonetheless, that increase is lower for the set of stocks subject to the ban (the coefficient of WEEK33*BAN is negative, although only statistically significant for the FE model and the Driscoll and Kraay methodology).

Without prejudice of this immediate negative marginal impact on the treatment group of stocks, the overall marginal impact, that is, the aggregate impact on the four weeks after the ban is positive. This is more evident for the last two weeks of the sample (WEEK35 and WEEK36), where the stocks subject to the prohibition record a statistically significant higher BAS. Indeed, the accrued BAS change for the stocks subject to the ban is positive and higher than the one in the control group.

We next turn to the Amihud's Indicator (Amihud, 2002). In order to mitigate the excessive volatility of APII, skewness, and multiplicative heteroskedasticity, a log transformation is carried out prior to the estimation. Thus, equation (9) is estimated with $\ln(1 + APII_{i,t})$ as the dependent variable. Results are in Table 5 - Panel B. The weeks after the BAN are characterized by higher APII (all stocks). The surge is particularly strong in WEEK34 and WEEK36, where the increase is statistically significant regardless of the approach used. Regarding the marginal impact on the stocks subject to the prohibition, the results differ slightly with the methodology used to compute the standard errors. In the four weeks after the prohibition, the price impact is higher amid the stocks subject to the ban than on the stocks of the control group. That difference is statistically significant in the FE, the FE with AR(1) disturbances and the FE with Driscoll and Kraay standard errors models, but if Arellano-Bondt is used the difference is only statistically significant in WEEK35. Therefore, in general APII increases in all stocks of the sample, but the rise is larger within the stocks subject to the ban.

In view of these results, we conclude that the short-selling ban did have a negative impact on liquidity in the weeks following the event (i.e., both the bid-ask spread and the Amihud indicator increase), even though there was an initial and transitory negative (but not statistically significant) impact on BAS that could indicate otherwise. Thus, H7 is rejected.

3.2. Volatility

Two alternative volatility measures are analysed (the volatility of the closing prices and the daily price range, the latter being a proxy for intraday volatility) to test the hypothesis

H8: The short-selling ban did not have a permanent impact on (the reduction of) volatility.

The securities traded in France, Belgium and Italy exhibit a decline in closing price volatility after the ban. In contrast, an increase in volatility appears to have taken place in Spain (Table 4).

We assume that the evolution of the closing prices' volatility is given by a model similar to (9) with $\mathrm{vol}_{i,t}$ as the volatility of firm i at t (or $\mathrm{DR}_{i,t}$ as the daily range of firm i at t). Again, we estimate equation (9) in a cross-section effects framework. A fixed effects model with a first-order autoregressive disturbance term, Arellano–Bond setup and Driscoll and Kraay standard errors are also estimated. The stocks not subject to the prohibition display lower volatility in the week that immediately follows the ban (WEEK33) – see Table 5 - Panel C. Nevertheless, that decline does not appear to be statistically significant if autocorrelation is accounted for. That decrease in volatility continues in WEEK34, but in WEEK36 there is a statistically significant rise in volatility. Concerning the stocks subject to the ban, they exhibit a higher accrued change in volatility than the stocks of the control group. That difference is statistically significant in WEEKS 35 and 36 using a standard fixed-effects model (Table 5 – Panel C). Overall, the stocks subject to the ban experience higher volatility after the event, albeit moderate. Putting in differently, the volatility of the stocks subject to the ban is not influenced by this event, in contrast with the control group of stocks that witness lower volatility in WEEK34 and higher volatility in WEEK36.

With respect to the daily price range, broadly speaking, all the countries witness a decline in intra-day volatility after the ban, which lasts until 9th September 2011 (Table 4). Table 5 – Panel D also shows the results of the estimates of model (9) with DR as dependent variable, and we conclude that the treatment group of stocks experiences higher daily price range than the control group after the announcement of the ban.

In light of the above, one can conclude that the short selling ban did not have a significant impact on the volatility of the treatment group of stocks. After the ban, the accrued volatility change of closing prices and the accrued intraday volatility change are negative and statistically significant for the stocks of the control group. However, the stocks of the treatment group experience a lower decline of the daily range and a positive, albeit moderate, volatility increase. Consequently, H8 is not rejected.

3.3. Pricing Efficiency

Three different indicators are used to examine price discovery: Market Efficiency Coefficient (MEC), MYY and Cross-Autocorrelation. MEC exploits the fact that price movements are more continuous in the most liquid markets, even when new information influences equilibrium. Accordingly, a permanent price change will be accompanied by minimum temporary changes in more resilient markets. MEC is calculated as:

$$MEC = Var\,(R_t)/\big(T * Var(r_t)\big) \qquad (10)$$

where $Var\,(R_t)$ is the variance of returns measured at a longer time frequency, $Var(r_t)$ is the variance of returns measured at a shorter time frequency, and T is the ratio between the number of short periods and the number of long periods.

MEC tends to be close to 1 in the more resilient markets. In general, stocks trading in less resilient markets display higher short-term volatilities, arising from greater transitory price changes when the equilibrium is disturbed (overshooting).

We define MYY (Morck et al. 2000)[7] as the ratio of idiosyncratic risk. This indicator relies on the assumption that more efficient markets exhibit a higher idiosyncratic risk (the ratio between the company's idiosyncratic information and market information should be higher in information environments that enable market players to acquire and rapidly use cheap information). According to Bris et al. (2007), one may use MYY to measure the potential price adjustment asymmetry to positive and negative information. Accordingly, the coefficient of determination of the market model is calculated by taking into account the ups and downs of the market for each stock. The following two equations are estimated and the respective coefficients of determination obtained:

$$\mathrm{R_{it}} = \alpha_i + \beta_i \times \mathrm{R^-_{mt}} + \phi i \times \mathrm{R_{Wt}} \qquad \text{; obtain } \mathrm{R^{2-}}$$

$$\mathrm{R_{it}} = \alpha_i + \beta_i \times \mathrm{R^+_{mt}} + \phi i \times \mathrm{R_{Wt}} \qquad \text{; obtain } \mathrm{R^{2+}} \qquad (11)$$

where $\mathrm{R_{it}}$ is the return of asset *i* in *t*; $\mathrm{R^+_{mt}}$ is the positive or zero market return in *t*; $\mathrm{R^-_{mt}}$ is the negative market return in *t* and $\mathrm{R_{Wt}}$ is the return of the sector index in *t*.

Thus

$$\mathrm{MYY} = \mathrm{DIF\,R^2} = \mathrm{R^{2-}} - \mathrm{R^{2+}} \qquad (12)$$

In efficient markets, MYY should be close to 0, displaying a symmetric adjustment to the news with positive and negative impact. If the short-selling constraints prevent the incorporation of negative information in prices, this indicator will record a positive value.

One disadvantage of MYY is that only the amount of private information assimilated into prices is taken into account and not the timing of price adjustments. Hou and Moskowitz (2005) suggest that efficiency can be modelled as a delay in price adjustments and that the cross-autocorrelation between the return on securities and the lagged market return should be used. Diamond and Verrecchia (1987) argue that prices adjust slowly to negative market news in the presence of short-selling constraints. Thus,

$$\rho_i^+ = corr(\mathrm{R_{it}}, \mathrm{R^+_{mt-1}})$$

$$\rho_i^- = corr(\mathrm{R_{it}}, \mathrm{R^-_{mt-1}}) \qquad (13)$$

$$\rho_i^{Diff} = \rho_i^- - \rho_i^+$$

[7] Morck et al. (2000) show that R2 and other measures of stock market synchronicity are higher in countries with less developed financial systems and poorer corporate governance.

where R_{it} is the return of asset *i* at *t*; and R_{mt}^{+} and R_{mt}^{-} were previously defined.

The ρ_i^{Diff} variable displays the asymmetry in incorporating positive and negative news in the market.

Tests are performed to the mean and median of the three indicators in order to assess the impact of the short-selling ban. Therefore, the following hypothesis is tested

$$D(Indicator^{FIBS}) - D(Indicator^{Others}) = 0$$

with *Indicator* = MEC, MYY or ρ_i^{Diff} , and *D* refers to the change between the periods before and after the ban.

Furthermore, the following fixed effects model is also estimated

$$Indicator_{i,t} = \beta_0 + \gamma_1 \times BANNED_{i,t} \times PER_{i,t} + \gamma_2 \times PER_{i,t} + u_{i,t} \quad (14)$$

where *Indicator* and *BANNED* are as previously defined and PER is a binary variable equal to 1 in the post ban period.

We use MEC to test the hypothesis

H9: The short-selling ban did not have an impact on the informational efficiency of markets

and use both MYY and ρ_i^{Diff} to test the hypothesis

H10: The short-selling ban did not have an impact on the asymmetry of the price adjustment to positive and negative information.

Three alternatives are used for the computation of MEC:

- Daily and weekly frequencies in calculating returns - MEC(DW);
- Weekly and monthly frequencies in calculating returns - MEC(WM);
- Daily and monthly frequencies in calculating returns - MEC(DM).

In general, the stocks of the sample witness a decline in the MEC(DW) and MEC(DM) variables after the ban. It turns out, however, that this reduction is higher in the stocks covered by the ban. As for the MEC(WM) variable, only stocks covered by the short-selling constraints record a negative change in the post-event period. This is in contrast to the stocks that are not subject to the ban. Mean tests reject the hypothesis of an equal variation for both types of stocks in the post-event period (Table 6 - Panel A).

The mean tests are generally parametric tests and assume that the variable under analysis asymptotically follows a normal distribution. This assumption is often unrealistic. Accordingly, and in order to test the robustness of the previous results, non-parametric tests to the median are conducted. They corroborate the findings of the parametric tests (results not reported).

The fixed effects model provides an indication of whether, on average, there is a significant change in MEC after the ban (as measured by the PER coefficient). This coefficient is negative and statistically significant for the MEC(DW) and MEC(DM) models. However, when the dependent variable is MEC(WM), PER displays a positive coefficient, although not statistically significant. In other words, the analysed stocks (whether covered or not by the short-selling ban) record negative and statistically significant variations in the efficiency levels of the price discovery process when this is measured by the MEC(DW) and MEC(DM) variables.

The analysis of the *BANNED* coefficient shows that, in comparison to other stocks, the stocks covered by the ban exhibit higher negative MEC variations in the post-event period. Furthermore, these variations are statistically significant (Table 6 - Panel B).

In light of the abovementioned results, we reject H9 and conclude that there is evidence of a reduction in the informational efficiency of markets after the short selling ban. This reduction is clearly more evident among the stocks covered by the ban. Thus, the higher short term volatility increase (*vis-à-vis* the longer term volatility) is evidence of overshooting among the securities covered by the ban.

The MYY variable experiences a higher average (and median) increase among the FIBS stocks after the regulatory event, which reveals a lower rate of price adjustment to negative news, as opposed to positive news. However, the statistical tests suggest that the differential variation of MYY in the FIBS stocks and other stocks analysed is not statistically significant (mean and statistical significance tests of the *BANNED* variable in Table 6 - Panels A and B). Furthermore, the results do not show a structural change after the event because the PER variable is not statistically relevant.

Regarding ρ_i^{Diff}, the estimated coefficients show that during the post-event period the assimilation rate of negative (market) news on prices was higher than positive (market) news among the stocks covered by the ban. Furthermore, the comparison of the variation rate in the price adjustment between the FIBS stocks and the control group of stocks suggests that the adjustment to negative news is faster among the first group of stocks. Nevertheless, the results are also not statistically relevant (Table 6 - Panels A and B). Thus, H10 is not rejected.

In conclusion, we find evidence of overshooting in all types of stocks, but this is more pronounced in stocks covered by the short-selling ban. In other words, the stocks covered by the ban experience an increasing price discontinuity and short-term volatility, even when compared to the control group. On the other hand, the analysis of the MYY and ρ_i^{Diff} indicators does not confirm any change in the functioning of the FIBS markets after the ban regarding the incorporation of positive and negative news. On the contrary, the negative (market) news appear to be incorporated faster in prices than positive news among FIBS in comparison to stocks in the control group; however, these results lack statistical significance.

4. Conclusions

On 11th August 2011, securities regulators in France, Italy, Belgium and Spain temporarily banned short-selling transactions in financial stocks. The experiences of short selling bans are occasional, and therefore the effects of each one of them deserve to be studied.

This paper assesses for the first time the impact of this short-selling ban, with particular regard to the consequences on price dynamics and volatility, and also on market efficiency. Moreover, there is scarce evidence in prior studies about the performance of the impacted shares before the ban, which we also analyse in this paper. The research questions we address are the following: *i) Did financial stocks perform differently from normal (ie, exhibit abnormal returns) prior to the ban? ii) Did FIBS financial stocks perform differently than Non-FIBS financial stocks prior to the short-selling ban? iii) What was the immediate impact (on prices, liquidity and volatility) of the ban on FIBS stocks? iv) What was the permanent impact of the short-selling ban (on prices, volatility and pricing efficiency) on FIBS financial stocks?*

We start out by concluding that, prior to the ban, financial stocks exhibit positive abnormal returns. Moreover, financial stocks in countries which applied the ban exhibit higher abnormal returns than financial stocks in other European countries.

The evidence presented also suggests that the ban imposed on 11th August 2011 was detrimental to the informational efficiency of stock markets. However, it resulted in statistically significant CAR in the 5 trading days after the ban among the stocks covered by the said ban. The financial stocks not covered by the ban record modest CAR. Also, the CAR of stocks covered by the ban are higher in the five than in the ten trading days after the event, supporting the hypothesis that the impact on prices tends to be temporary. Thus, in the longer term the ban seems to have been neutral in its effects on stock prices. These results are not significantly different from those reported in recent research related to similar events that occurred worldwide in 2008-2009.

As regards volatility, the post-ban volatility is not lower than the pre-ban volatility, and we find cases of higher volatility after the ban. Moreover, the percentage of stocks with lower volatility after the ban is higher among stocks in countries that did not impose the ban. As for the permanent impact, the volatility of closing prices and the intraday volatility seem to increase, at least in comparison with the other financial stocks not covered by the ban. These results are consistent with those from Abreu and Brunnermeier (2002, 2003), Scheinkman and Xiong (2003), Hong and Stein (2003), Charoenrook and Daouk (2005) and Bris et al. (2007), obtained for other time periods.

In terms of market efficiency, there is an immediate and transient lower bid-ask spread which disappears after 20 trading sessions and becomes even slightly positive. The negative effect on liquidity is confirmed by the evolution of the Amihud Illiquidity Indicator. Thus, we conclude that the short-selling ban did not have a permanent impact on market liquidity, which is in line with the findings of Boehmer et al. (2011), Battalio and Schultz (2011) and Beber and Pagano (2013), among others, for similar episodes.

Finally, the study on the impact of the short-selling ban on the information efficiency of markets shows that the stocks subject to such a ban exhibit a higher discontinuity and tendency to overshoot in the post-event period in comparison with the other stocks examined and this is consistent with Lobanova et al. (2010) and Autore et al. (2011), among others. Nevertheless, there is no evidence that the short-selling ban had an impact on price adjustment asymmetry to positive and negative news. This means that the market reaction to good and bad news is similar before and after the ban, which conflicts with the results presented by Saffi and Sigurdsson (2011) and Beber and Pagano (2013), among others; thus, if it was expected that the August 2011 ban would bring about a different market reaction to bad news, then this goal was not achieved.

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Table 1 : Individual results - Percentage of stocks with statistical significant CAR (5% level) in the event window

This table shows the proportion of financial firms with (positive or negative) statistically significant CAR (at the 5% level) in the pre and post-announcement windows. The results are partitioned by group and by the type of model used to obtain the abnormal returns.

	Event Window	[-9;-1]	[-5;-1]	[1;5]	[1;10]
Positive CAR	**Market Model**				
	All Comp.	14.1%	14.1%	18.8%	11.8%
	FIBS	**29.3%**	**27.6%**	**39.7%**	**20.7%**
	Non-FIBS	**6.3%**	**7.1%**	**8.0%**	**7.1%**
	Multi-Index Model				
	All Comp.	20.6%	15.9%	22.9%	15.9%
	FIBS	**37.9%**	**32.8%**	**46.6%**	**31.0%**
	Non-FIBS	**10.0%**	**6.4%**	**10.9%**	**8.2%**
Negative CAR	**Market Model**				
	All Comp.	15.9%	15.9%	5.9%	7.6%
	FIBS	**5.2%**	**6.9%**	**1.7%**	**6.9%**
	Non-FIBS	**21.4%**	**20.5%**	**8.0%**	**8.0%**
	Multi-Index Model				
	All Comp.	12.9%	15.3%	3.5%	6.5%
	FIBS	**3.4%**	**5.2%**	**1.7%**	**5.2%**
	Non-FIBS	**18.2%**	**20.9%**	**4.5%**	**7.3%**

Table 2: Aggregated Cumulative Abnormal Returns

Table 2 shows the CAR in the pre- and post-announcement windows. The results are partitioned by group and by the type of model used to obtain the abnormal returns. Three types of p-values are reported, in accordance with the method used to compute the standard errors: default standard errors, Boehmer standard errors, standard errors with crude adjustment.

	Event Window	All Companies	FIBS (Treatment Group)	Non-FIBS (Control Group)	Treatment Group minus Control Group
Panel A - Market Model	[-9;-1]	-0.36%(./././.)	3.55%(***/***/**)	-2.38%(**/***/**)	5.92%(***/***/***)
	[-5;-1]	-0.11%(./././.)	2.54%(***/***/**)	-1.49%(**/*/*)	4.03%(***/***/***)
	[1;5]	1.78%(***/***/**)	4.23%(***/***/***)	0.52%(./././.)	3.71%(***/***/**)
	[1;10]	1.10%(./././.)	1.20%(*/./.)	1.04%(./././.)	0.16%(./././.)
Panel B – Multi-Index Model	[-9;-1]	0.41%(./././.)	4.86%(***/***/***)	-2.11%(**/**/**)	6.96%(***/***/***)
	[-5;-1]	0.30%(./././.)	3.28%(***/***/***)	-1.41%(**/*/*)	4.70%(***/***/***)
	[1;5]	2.41%(***/***/***)	5.44%(***/***/***)	0.84%(./././.)	4.59%(***/***/***)
	[1;10]	2.23%(***/***/**)	3.45%(***/**/**)	1.64%(*/./.)	1.81%(./././.)

(***), (**) and (*) means that CAR is statistically significant at 1%, 5% and 10%.
(Default Standard Errors/Boehmer Adj./Crude Adjustment)

Table 3: Impact on Volatility

This table depicts the impact of the ban on volatility. Panel A exhibits the proportion of financial firms with statistical significant (positive or negative) volatility changes in the pre- and post-announcement windows under a GARCH(1,1) setup, and in Panel B we show the results of Beaver's U-test.

Panel A: Structural break test in the GARCH(1,1) volatility: Percentage of financial companies without stability in the variance equation

	[-9;-1]	[-5;-1]	[1;5]	[1;10]
Higher Volatility				
All Comp.	26.5%	24.1%	9.5%	6.5%
FIBS	**32.8%**	**27.6%**	**8.6%**	**8.6%**
Non-FIBS	**23.2%**	**22.3%**	**9.8%**	**5.4%**
Lower Volatility				
All Comp.	5.9%	8.8%	22.5%	14.8%
FIBS	**1.7%**	**10.3%**	**6.9%**	**5.2%**
Non-FIBS	**8.0%**	**8.0%**	**30.4%**	**19.6%**

Panel B: Beavers's U test

[-9;-1]	[-5;-1]	[1;5]	[1;10]	
16,103(***)	17,862(***)	14,899(***)	16,923(***)	All Comp.
12,655(***)	**12,710**(***)	**19,531**(***)	**24,653**(***)	**FIBS**
10,732(***)	**12,860(***)**	**4,302(***)**	**3,108(***)**	**Non-FIBS**

(***), (**) and (*) means that U is statistically significant at a 1%, 5% and 10% level.

Table 4: Averages across countries and time

This table shows the evolution of bid-ask spreads, Amihud indicator, volatility and daily price range in Belgium (Be), France (Fr), Italy (It) and Spain (Sp).

		Bid-ask spread (%)				Amihud indicator (times 10^6)				Volatility (%)				Daily price range (%)			
Month		Be	Fr	It	Sp	Be	Fr	It	Sp	Be	Fr	It	Sp	Be	Fr	It	Sp
Jan		0.27	0.23	1.06	0.27	27	195	422	120	2.6	1.9	2.0	2.3	3.6	2.8	2.9	3.3
Feb		0.30	0.24	1.06	0.23	28	76	251	104	2.0	1.6	1.6	1.8	3.0	2.6	2.5	2.9
Mar		0.30	0.21	1.06	0.24	36	75	288	66	1.7	1.7	1.4	1.4	3.0	2.7	2.6	2.7
Apr		0.31	0.20	0.95	0.23	36	81	256	113	1.4	1.4	1.6	1.4	2.4	2.2	2.5	2.5
May		0.33	0.16	1.02	0.25	57	82	533	197	1.5	1.5	1.5	1.3	2.6	2.1	2.5	2.4
Jun		0.33	0.17	1.27	0.28	67	102	1724	135	2.1	1.5	2.2	1.8	2.9	2.0	3.1	2.7
Jul		0.43	0.20	1.87	0.26	74	192	1043	139	3.2	2.2	3.4	2.1	4.4	3.1	4.8	3.4
Aug		0.58	0.25	2.79	0.32	86	131	1044	115	5.0	4.3	4.2	3.1	9.7	8.3	7.9	6.2
	BAN	0.44	0.37	2.35	0.48	94	490	1455	880	3.7	2.6	2.7	3.2	5.0	4.2	4.8	4.1
Sep	BAN	0.59	0.39	3.14	0.45	120	509	2149	220	3.6	3.4	2.9	3.5	4.5	4.2	4.1	4.5

Table 5 – Multivariate Regressions (Panel Least Squares)

In Panels A to D we show the results of a panel data model where the dependent variable is a market quality proxy variable (bid-ask spread – Panel A, Amihud indicator – Panel B, volatility - Panel C and daily price range – Panel D). Three model specifications are analyzed (fixed effects, fixed effects with AR(1) disturbances and a dynamic panel data model wherein the Arellano-Bondt estimator is used). We include six dummy variables in the model to account for the dependent variable seasonality [Jan (January), Feb (February), Mar (March), Apr (April), May and Jun (June)] and three lags of the dependent variable (L1, L2, L3). WEEK[i] are dummy variables equal to one for week [i]. These variables capture the common trend of liquidity/volatility across all the stocks after the enforcement of the ban. WEEK[i]*BANNED assume the value of one for stocks subject to the ban during WEEK[i]. They aim to evaluate the effect of the ban on the liquidity/volatility of the stocks affected by the new regulation.

Panel A – BAS

	FE[(1)]	FE with AR(1) disturbances	Arellano-Bondt[(2)]
JAN	-0.005(***/***)	-0.006(***)	-0.002(./**)
FEB	-0.004(***/***)	-0.004(***)	-0.001(./.)
MAR	-0.003(*/***)	-0.004(***)	-0.001(./.)
APR	-0.005(***/***)	-0.004(***)	-0.003(./***)
MAY	-0.004(***/***)	-0.003(***)	-0.003(**/***)
JUN	-0.003(***/*)	-0.002(***)	-0.001(./**)
WEEK33*BANNED	-0.002(./***)	0.000(.)	-0.001(./.)
WEEK34*BANNED	0.003(./***)	0.001(.)	0.001(./.)
WEEK35*BANNED	0.008(**/***)	0.004(.)	0.004(*/*)
WEEK36*BANNED	0.004(***/***)	0.008(***)	0.006(**/***)
WEEK32	0.004(***/***)	0.002(***)	0.005(***/***)
WEEK33	0.004(**/***)	0.000(.)	0.000(./.)
WEEK34	0.004(**/***)	0.001(.)	0.000(./.)
WEEK35	0.001(./.)	-0.001(.)	-0.003(**/**)
WEEK36	0.003(*/**)	0.001(.)	0.000(./.)
L1.BAS			0.459(***/***)
L2.BAS			0.138(***/***)
L3.BAS			0.106(***/***)
constant	0.019(***/***)	0.019(***)	0.006(**/***)
F	5.993	5.875	
N	5976	5810	5312

Panel B – Log(1+APII)

	FE[1]	FE with AR(1) disturbances	Arellano-Bondt[2]
JAN	-0.485(***/***)	-0.471(***)	-0.455(***/***)
FEB	-0.510(***/***)	-0.509(***)	-0.482(***/***)
MAR	-0.414(***/***)	-0.438(***)	-0.437(***/***)
APR	-0.548(***/***)	-0.565(***)	-0.600(***/***)
MAY	-0.350(***/***)	-0.354(***)	-0.356(***/***)
JUN	-0.093(*/.)	-0.079(.)	-0.059(./.)
WEEK33*BANNED	0.476(***/***)	0.471(***)	0.187(./.)
WEEK34*BANNED	0.732(***/***)	0.417(**)	0.158(./.)
WEEK35*BANNED	0.471(***/***)	0.730(***)	0.433(**/**)
WEEK36*BANNED	0.070(./.)	0.466(***)	0.146(./.)
WEEK32	0.163(./.)	-0.022(.)	0.023(./.)
WEEK33	0.361(***/***)	0.083(.)	0.257(*/**)
WEEK34	0.361(***/***)	0.325(***)	0.388(***/***)
WEEK35	0.116(./.)	0.112(.)	0.203(./*)
WEEK36	0.536(***/***)	0.537(***)	0.659(***/***)
L1. Log(1+APII)			0.098(**/***)
L2. Log(1+APII)			-0.008(./.)
L3. Log(1+APII)			-0.075(**/***)
constant	4.537(***/***)	4.552(***)	4.442(***/***)
F	23.517	26.254	
N	5955	5789	5239

Panel C – Volatility

	FE[1]	FE with AR(1) disturbances	Arellano-Bondt[2]
JAN	-0.011(***/***)	-0.010(***)	-0.011(***/***)
FEB	-0.010(***/***)	-0.010(***)	-0.009(***/***)
MAR	-0.010(***/***)	-0.011(***)	-0.008(***/***)
APR	-0.010(***/***)	-0.011(***)	-0.008(***/***)
MAY	-0.011(***/***)	-0.011(***)	-0.008(***/***)
JUN	-0.008(***/***)	-0.009(***)	-0.006(***/***)
WEEK33*BANNED	0.001(./.)	-0.001(.)	0.000(./.)
WEEK34*BANNED	0.002(./.)	0.002(.)	0.004(./.)
WEEK35*BANNED	0.003(./**)	0.002(.)	0.002(./.)
WEEK36*BANNED	0.003(**/.)	0.002(.)	0.003(./.)
WEEK32	0.003(*/.)	0.001(.)	0.004(***/***)
WEEK33	-0.005(***/*)	-0.001(.)	-0.002(./.)
WEEK34	-0.005(***/*)	-0.007(***)	-0.008(***/***)
WEEK35	-0.002(./.)	-0.003(.)	-0.003(./.)
WEEK36	0.005(***/*)	0.004(**)	0.004(**/*)
L1.VOL			0.260(***/***)
L2. VOL			0.005(./.)
L3. VOL			0.051(*/***)
constant	0.029(***/***)	0.029(***)	0.021(***/***)
F	18.87	16.938	
N	5966	5800	5280

Panel D – Daily Range

	FE[1]	FE with AR(1) disturbances	Arellano-Bondt[2]
JAN	-0.017(***/***)	-0.019(***)	-0.011(***/***)
FEB	-0.016(***/***)	-0.018(***)	-0.011(***/***)
MAR	-0.016(***/***)	-0.020(***)	-0.010(***/***)
APR	-0.018(***/***)	-0.020(***)	-0.012(***/***)
MAY	-0.017(***/***)	-0.019(***)	-0.011(***/***)
JUN	-0.014(***/**)	-0.016(***)	-0.009(***/***)
WEEK33*BANNED	0.003(./.)	-0.005(*)	-0.007(*/**)
WEEK34*BANNED	0.000(./.)	-0.003(.)	-0.002(./.)
WEEK35*BANNED	0.008(***/***)	-0.002(.)	-0.003(./.)
WEEK36*BANNED	0.012(***/**)	0.007(*)	0.006(**/*)
WEEK32	0.001(./.)	0.004(***)	0.016(***/***)
WEEK33	-0.004(**/.)	-0.012(***)	-0.012(***/***)
WEEK34	-0.004(**/.)	-0.011(***)	-0.007(***/***)
WEEK35	-0.007(***/.)	-0.012(***)	-0.009(***/***)
WEEK36	-0.005(***/.)	-0.009(***)	-0.004(**/**)
L1. Daily Range			0.450(***/***)
L2. Daily Range			0.006(./.)
L3. Daily Range			0.062(**/***)
constant	0.043(***/***)	0.046(***)	0.024(***/***)
F	31.864	28.095	
N	5976	5810	5312

(***), (**) and (*) means that the variable is statistically significant at the 1%, 5% and 10% level.

[1] Default standard errors/ Driscoll & Kraay standard errors.

[2] Robust standard errors/GMM standard errors.

Li. means that the dependent variable is i-times lagged.

Table 6: Price discovery and the ban

Panel A reports descriptive statistics regarding the pattern of MEC, MYY and rho during the analyzed period for each of the two groups of stocks. Standard univariate tests are computed to assess if the differences of the variables for each of the subgroups are statistically significant. Panel B displays the estimates of a panel data model, in which the dependent variables are MEC, MYY and the correlation between the stock and the lagged market return (rho). D(.) is the first difference operator. DW: returns computed using daily and weekly frequencies; WM: returns computed using weekly and monthly frequencies; DM: returns computed using daily and monthly frequencies. PER is a binary variable equal to 1 in the post ban period.

Panel A: Mean tests

	D(MEC_DW)	D(MEC_DM)	D(MEC_WM)	D(MYY)	D(rho)
	Mean				
FIBS	-0.237	-0.318	-0.221	0.029	0.102
Non-FIBS	-0.092	-0.106	0.150	-0.008	0.034
t-test	2.784(***)	3.170(***)	2.474(**)	-0.686	-0.860
Satterthwaite-Welch t-test	3.055(***)	3.445(***)	3.160(***)	-0.635	-0.934
Anova F-test	7.752(***)	10.050(***)	6.120(**)	0.471	0.740
Welch F-test	9.332(***)	11.866(***)	9.988(***)	0.403	0.873

(***), (**) and (*) means that the variable is statistically significant at the 1%, 5% and 10% level, respectively.

Panel B: Price discovery model (Panel Least Squares)

White diagonal standard errors & covariance (degrees of freedom corrected)

Variables	MEC_DW	MEC_DM	MEC_WM	MYY	D(rho)
Constant	0.733(***)	0.548(***)	0.726(***)	0.013	0.003
BANNED*PER	-0.146(***)	-0.212(***)	-0.371(***)	0.037	0.068
PER	-0.092(***)	-0.106(**)	0.150	-0.008	0.034
Cross-section fixed (dummy variables)					
R-squared	0.656	0.642	0.568	0.473	0.525
F-statistic	1.861	1.748	1.294	0.881	1.087

(***), (**) and (*) means that the variable is statistically significant at the 1%, 5% and 10% level, respectively.