ON THE IMPACT OF THE AUGUST 2011 BAN ON COVERED SHORT SELLING – An Empirical Analysis

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Abstract

This paper seeks to identify the impact of the 11th August 2012 ban on covered short-selling in some European countries' financial stocks. The evidence presented suggests that the impact on prices tends to be temporary; in the longer term the ban seems to have been neutral in its effects on stock prices. We also conclude that the post-ban volatility is not lower than the pre-ban volatility, and that 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 have increased, at least in comparison with the other financial stocks not covered by the ban. In terms of market efficiency, our analysis shows an immediate and transient lower bid-ask spread. However, this transient effect disappears after 20 trading sessions and it becomes even slightly positive. This negative effect on liquidity is confirmed by the evolution of the Amihud Illiquidity Indicator.

1. Introduction

The years of 2010 and 2011 were characterized by a high degree of uncertainty in the equity and debt markets. Volatility has remained at high levels, particularly amid financial companies. The sovereign debt crisis that spread to Greece, Portugal, Ireland and, more recently, Italy and Spain contributed to this increase in volatility.

During the course of the second quarter of 2011, a political process was 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 transactions in financial stocks on 11th August 2011. This ban was justified by evidence of rumours with the purpose of market manipulation. Amid the countries that adopted such bans are France, Italy, Belgium and Spain (hereinafter, FIBS).

This paper seeks to identify the impact of this ban on covered short-selling in FIBS' financial stocks. We first investigate the short-term impact on prices of securities covered by the ban. Then, we evaluate the effects of those measures on 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 the law of one price is the possibility of market players carrying out short-selling strategies. For a long time now, this issue was the subject of investigation. All in all, the empirical literature seems to support the theoretical point of view that restrictions on short-selling negatively influence the price discovery process, especially for the case of negative news.

Most of the literature on this subject concerns 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 (2011) and Marsh and Payne (2010) 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 bull than in bear markets. Miller (1977), Harrison and Kreps (1978), Biais et al. (1999), Bris et al. (2007), Boehemer and Wu (2010), Saffi and Sigurdsson (2011), Chang (2010) and Beber and Pagano (2011) provide similar 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. (2005), Boehmer et al. (2010) and Beber and Pagano (2011) do not. Boehmer et al. (2010) find that stocks with relatively high short interest subsequently experience negative abnormal returns, but the effect can be transient and of debatable economic significance. Finally, higher volatility associated to short selling

[1] See Beber and Pagano (2011) for a recent literature review.

restrictions has been unveiled by Abreu and Brunnermeier (2002, 2003), Scheinkman and Xiong (2003), Hong and Stein (2003), Charoenrook and Daouk (2005) and Bris et al. (2007).

In short, most studies support the hypothesis that short-selling constraints contribute to decreasing market efficiency. In particular, the evidence points to a slowing down of price adjustment in the downswing and an increase in transaction costs/decreased liquidity. However, the recent bans have not been analysed. Besides, there is scarce evidence about the performance of the impacted shares before the ban. This papers aims to contribute to fill these gaps.

Effectively, the impact of the short-selling ban on 11th August 2011 is assessed in the following sections of this paper, with particular regard to the consequences on price dynamics and volatility, and also on market efficiency. 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. Sample

Our sample consists of 170 financial stocks in Western Europe (virtually all the listed financial institutions and insurance companies). The shares of 58 of said companies 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 (altogether the FIBS countries).

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 (Table 1 – Panel A). However, the comparison between domestic market and financial sector performance shows that the decline was particularly sharper in the financial sector companies: the unweighted average of the cumulative returns of stocks subject to the covered short selling 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 on covered short selling, 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 decided after the close of the markets on 11th August 2011 and came into force in the stock exchange session of the following 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.

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 10 trading sessions subsequent to the event's date.

3. Short-Run Impact

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 followed the ban are computed using the Market Model and the Multi-Index Model:

i) Market Model:

$$R_{it} = \alpha_i + \beta i \times R_{mt} \qquad (1)$$

ii) Multi-Index Model:

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

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 is justified because it isolates idiosyncratic shocks (specific information which only affects the analysed company) from systematic or macroeconomic shocks (information that affects all companies in the market). By using the Multi-Index Model, one assumes that there is sectorial information that may influence the performance of securities in a certain sector in addition to economic or macroeconomic data that affects 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 on 12th August 2011. Six alternatives are considered for the event window, with t_0 as previously defined:

(i) $[t_{-9}; t_{-1}]$;
(ii) $[t_{-5}; t_{-1}]$;
(iii) $[t_1; t_5]$;
(iv) $[t_1; t_{10}]$;
(v) $[t_0; t_5]$;
(vi) $[t_0; t_{10}]$.

3.1. Results for Individual Stocks

Upon estimation of the Market Model, we compute the proportion of stocks with statistically significant positive cumulative abnormal returns (CAR). Overall, only 18.8% and 11.8% of stocks exhibit statistically significant positive CAR at the 5% significance level in the event windows which include the five and the ten trading sessions right after 12th August 2011 (Table 2).

By dividing the sample between the financial stocks of FIBS and non-FIBS countries, we find a higher percentage of securities with significant positive CAR in the first group in all event windows considered. Among the FIBS countries, Italy and Spain exhibit higher percentages (51.7% and 24.1%, and 42.9% and 21.4%, respectively, in the event windows which include the five and the ten trading sessions after 12th August 2011).

The use of the Multi-Index Model produces similar results. Notwithstanding this, one notices an increased number of stocks in France with statistically positive CAR after the ban on covered short selling.

3.2. Overall Results

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 of the above mentioned event windows 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,

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

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

$CAR_i(\tau1, \tau2)$ is the cumulative abnormal return in the event window $(\tau1, \tau2)$ for stock i; $\sigma_i^2(\tau1, \tau2)$ is the abnormal return variance in the event window $(\tau1, \tau2)$ for stock i; and n is the number of observations in the cross sectional sample.

We start our investigation testing the hypothesis:

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

With regard to the Market Model's results (Table 3, 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] event windows. Results are similar for the Multi-Index Model (Table 4, Panel A) and thus we do not reject H1, and conclude that, prior to the ban, the overall performance of financial stocks was normal.

We next test the hypothesis

H2: FIBS financial stocks did not perform differently than non-FIBS stocks prior to the ban.

From Table 3, 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%). To the contrary, 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 (Table 3, Panel B) rejects the null hypothesis of no difference. Thus, we reject H2. The evidence runs contrary to the idea that FIBS stocks did 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 was positive and higher than that of other European banks. The use of the Multi-Index Model provides similar results.

As regards the impact of the short-selling ban, we test the following hypotheses:

H3: Post-ban CAR are non-significant

H4: Post-ban CAR of FIBS are not different than those of non-FIBS stocks

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 3, Panel A). Nevertheless, the CAR is not statistically different from zero within 10 days after this ban came into force. Table 3, 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).

The results for other financial stocks in the other European countries (control group) are in contrast with the results reported in the previous paragraph. The CAR of these securities are statistically not different from zero, when calculated for the post-ban event windows.

We further compare the CAR of financial stocks of FIBS and the control group (Table 3, Panel B). The difference between the CAR of these groups is positive and statistically different from zero at the 5% significance level for the pre-ban event windows and for the event window containing the five trading sessions after the ban. In the case of the event window that includes the 10 trading days after the ban, the evidence indicates that the CAR of the two groups are not statistically different.

The analysis is also carried out using the Multi-Index Model. The results are generally similar to those from the Market Model (Table 4). However, we obtain evidence of statistical significant CAR for the whole sample, for stocks subject to the ban and for the difference between the FIBS and non-FIBS stocks in the 10 trading sessions after the ban (but statistical significance declines with the robustness corrections which we undertook).

In short, the empirical evidence is stronger when one uses the Multi-Index Model and thus we reject H3 in favour of the alternative that post-ban CAR are positive. However, the positive impact of the ban is stronger in the 5 than in the 10 post-ban trading sessions. This result 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.

3.3. Impact on volatility

In this section, the following hypotheses 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.

The F-test results are reported in Table 5. 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 (Table 5, Panel A2).

When the abnormal returns are considered, the percentage of stocks with higher variance in the five trading days after the ban remains at less than 5% and is 0% for FIBS financial stocks. When considered the ten trading days after the ban, almost 1/3 of FIBS stocks record an increase in variance. 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 (Table 5, Panels A2 and B2, *versus* Panels A1 and B1).

The overall sample t-test on the ratio of (raw and abnormal return) variances also shows that this risk measure increased in the 10 trading days prior to and after the ban. These results are valid for both FIBS and non-FIBS stocks (Table 6).

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 7 displays the percentage of stocks with structural changes 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. It is also interesting to note that the percentage of stocks with a negative impact on volatility is considerably higher within the non-FIBS. In effect, that percentage is 6.9% and 5.2%, and 30.4% and 19.6% in the five and the ten trading sessions after the ban for the FIBS and non-FIBS stocks, respectively.

The Beaver's U-Test is based on:

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

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:

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

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 10 post-ban trading days event windows.

The combination of the above mentioned results allows us to reject H5. In fact, the t-test (Beaver's U test – Table 8) 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 that exhibit a decline in that risk measure 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.

4. 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. The analysis covers the period from January to September 2011, and the data were collected on a weekly basis.

We follow the econometric panel data approach of Beber and Pagano (2011) to model the impact of the ban on the liquidity and price discovery indicators.

4.1. Liquidity

Two alternative liquidity indicators are considered for assessing the short-selling ban impact in the FIBS: the Bid-Ask Spread and the Amihud's Price Impact Indicator. The bid-ask spread is defined as the percentage difference between bid and ask prices.[2] The average bid-ask spread increased in France and Spain after the short-selling ban (Table 9), whereas Belgium and Italy only recorded a temporary reduction in the second half of August (that did not persist in September).

In order to measure the permanent impact of the ban, the following model is estimated:

$$D(bid - ask\ spread) = \beta_0 + \beta_1 \times D(vol_t) + \beta_2 \times \mathrm{D}(volume_{t-1}) + \gamma_1 \times BANNED_t + \gamma_2 \times D(BANNED_t) + \sum_{j=1}^{3} \theta_j \times u_{j-1} \quad (9)$$

where vol_t is the volatility at t; $volume_t$ is the value of stock transactions in week t; $BANNED$ is equal to 1 if the stock is subject to short-selling constraints at time t, and zero otherwise; and the prefix D(.) is the first difference operator. The model includes an AR(3) process.

We test the following hypothesis:

[2] Relative to the average bid-ask.

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

The estimation of the panel dynamic model allows us to conclude that the bid-ask spread decreased after the ban (Table 10 – Panel A). Nonetheless, this impact appears to be merely transitory. In fact, the stocks covered by the ban exhibit an average change of -0.19 (=-0.39+0.2) percentage points in the bid-ask spread variable in the first post-ban week, in comparison with the stocks included in the control group. However, in the three weeks that followed, there is a weekly average 0.2 percentage points bid-ask spread increase amid the stocks subject to the short-selling ban. This means that, four weeks after the event, the bid-ask spread is higher than the pre-ban level.

Regarding the Amihud's Indicator (Amihud, 2002), France, Italy, Belgium and Spain exhibit a higher value after the ban (Table 9). A dynamic model similar to the one used for the bid-ask spread is estimated:

$$D(\ln(Amihud + 1)) =$$
$$\beta_0 + \beta_1 \times D(vol_t) + \beta_2 \times \mathrm{D}(volume_t) + \gamma_1 \times BANNED + \gamma_2 \times D(BANNED) + \sum_{j=1}^{4} \theta_j \times u_{j-1} \quad (10)$$

The results reported in Table 10 – Panel A show positive *BANNED* and *D(BANNED)* coefficients. This means that the impact of the ban on the Amihud illiquidity indicator was permanent (i.e. a level shift after the announcement of the ban, which persisted over the course of the following weeks).

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, even though there was an initial and temporary negative impact on the bid-ask spread that could indicate otherwise. Thus, H7 is rejected.

4.2. 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 9).

We assume that the evolution of the closing prices' volatility is modelled by:

$$vol = \beta_0 + \beta_1 \times \mathrm{D}(volume_t) + \gamma_1 \times BANNED \qquad (11)$$

where the variables have been defined previously. We estimate equation (11) in a cross-section and period fixed effects framework.

The stocks of the treatment group display higher volatility than the stocks of the control group in the BAN window after taking into account the cross-section and period fixed effects. This means that the stocks affected by the ban exhibit relatively higher volatility. The results are statistically significant at the 10% level - Table 10 – Panel B.

As regards the daily price range, broadly speaking, all the countries witnessed a decline in intra-day volatility after the ban. This lasted until 9th September 2011 (Table 9). The following panel fixed effects model is used to explain the evolution of the daily price range.

$$Daily\ Price\ Range = \beta_0 + \beta_1 \times \ln(volume_{t-1}) + \gamma \times BANNED \quad (12)$$

Equation (12) is estimated in a cross-section and period fixed effects framework. Our results suggest a positive and statistically relevant effect of the ban on the daily price range of FIBS's financial stocks (Table 10 – Panel B); stocks influenced by the ban display a higher daily price range than those not affected by the ban, when individual characteristics of firms and period effects are considered.

In light of the above, one can conclude that the impact of the short selling ban on volatility is positive since both the volatility of closing prices and intraday volatility seem to have increased. Consequently, H8 is rejected.

4.3. Pricing Efficiency

Three different indicators are used to examine price discovery: Market Efficiency Coefficient (MEC), MYY and Cross-Autocorrelation.

The MEC exploits the fact that price movements are more continuous in the most liquid markets, even when new information influences equilibrium prices. Accordingly, a permanent price change will be accompanied by minimum temporary changes in prices of more resilient markets. The MEC is calculated as follows:

$$MEC = Var\ (R_t)/\left(T * Var(r_t)\right) \quad (13)$$

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 will tend to be nearer 1 in the more resilient markets. As a general rule, 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. 1999)[3] 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 greater 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:

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

$$\mathrm{R_{it}} = \alpha_i + \beta_i \times \mathrm{R^+_{mt}} + \phi i \times \mathrm{R_{Wt}} \quad \text{; obtain } \mathrm{R}^{2+} \qquad (14)$$

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

$$\mathrm{MYY} = \mathrm{DIF\,R^2} = \mathrm{R^{2-}} - \mathrm{R^{2+}} \qquad (15)$$

In efficient markets, MYY should be close to 0, displaying a symmetric adjustment of 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,

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

$$\rho_i^- = corr(\mathrm{R_{it}}, \mathrm{R^-_{mt-1}}) \qquad (16)$$

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

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

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

[3] Morck et al. (1999) show that R2 and other measures of stock market synchronicity are higher in countries with less developed financial systems and poorer corporate governance.

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

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

with *Indicator* = MEC, MYY and 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

$$Indicator_{i,t} = \beta_0 + \gamma_1 \times BANNED_{i,t} + \gamma_2 \times PER_{i,t} \quad (17)$$

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.

4.3.1.Results

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 sample stocks 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 were 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 11, 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 were 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 11, 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 securities covered by the ban.

The MYY variable experienced 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 11, Panels A and B). Furthermore, the results do not show a structural change in this variable after the regulatory 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 was faster among the first group of stocks. Nevertheless, the results are also not statistically relevant (Table 11, 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 experienced 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 news (market) appear to have been incorporated faster in prices than positive news among FIBS in comparison to stocks in the control group; however, these results lack statistical significance.

5. Conclusions

This paper assesses the impact of the short-selling ban on 11th August 2011, with particular regard to the consequences on price dynamics and volatility, and also on market efficiency. The research questions we addressed in the paper were 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 started out by concluding that, prior to the ban, financial stocks exhibited positive abnormal returns. Moreover, financial stocks in countries which applied the ban exhibited 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 and 10 trading days after the ban among the stocks covered by the said ban. The financial stocks that were 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, we conclude that the post-ban volatility is not lower than the pre-ban volatility, and we find cases where the volatility is higher 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 have increased, at least in comparison with the other financial stocks not covered by the ban.

In terms of market efficiency, our analysis shows an immediate and transient lower bid-ask spread. However, this transient effect disappears after 20 trading sessions and it becomes even slightly positive. This 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.

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. 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; thus, if it was expected that the ban would bring about a different market reaction to bad news, then this goal was not achieved.

Table 1 : Descriptive Analysis of the Sample

Panel A - ACRR - Average Cumulative Raw Return [Equal Weight]

	EW	[-9;-1]	[-5;-1]	[1;5]	[1;10]
FIBS	-29,3%	-15,4%	-4,6%	-4,1%	-6,0%
Non-FIBS	-20,6%	-13,3%	-6,0%	-4,0%	-3,7%
DJ Euro Stoxx Banks	-24,5%	-19,3%	-7,8%	-9,7%	-10,8%

Panel B - ACRR - Average Cumulative Raw Return [Market Value Weight]

	EW	[-9;-1]	[-5;-1]	[1;5]	[1;10]
FIBS	-25,7%	-21,9%	-7,8%	-7,2%	-6,9%
Non-FIBS	-	-	-	-	-

Note: EW-Estimation Window

Table 2 : Individual results - Percentage of stocks with statistical significant (5% level) positive abnormal returns in the event window

Market Model

Event Window	**[-9;-1]**	**[-5;-1]**	**[1;5]**	**[1;10]**	**[0;5]**	**[0;10]**
All Comp.	14,1%	14,1%	18,8%	11,8%	20,0%	14,7%
FIBS	**29,3%**	**27,6%**	**39,7%**	**20,7%**	**41,4%**	**27,6%**
Non-FIBS	**6,3%**	**7,1%**	**8,0%**	**7,1%**	**8,9%**	**8,0%**

Multi-Index Model

Event Window	**[-9;-1]**	**[-5;-1]**	**[1;5]**	**[1;10]**	**[0;5]**	**[0;10]**
All Comp.	20,6%	15,9%	22,9%	15,9%	25,9%	17,6%
FIBS	**37,9%**	**32,8%**	**46,6%**	**31,0%**	**53,4%**	**36,2%**
Non-FIBS	**10,0%**	**6,4%**	**10,9%**	**8,2%**	**10,9%**	**8,2%**

Table 3: Aggregate results - Market Model

Panel A

Event Window	All Companies				FIBS Financial Companies				Other European Banks				Event Window
	CAR	*t-stat*			CAR	*t-stat*			CAR	*t-stat*			
		Standard	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*		*Standard*	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*		*Standard*	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*	
[-9;-1]	-0,36%	-0,554	-0,438	-0,326	3,55%	5,417(***)	3,738(***)	2,122(**)	-2,38%	-2,559(**)	-2,589(***)	-2,139(**)	**[-9;-1]**
[-5;-1]	-0,11%	-0,239	-0,158	-0,14	2,54%	5,211(***)	3,199(***)	2,041(**)	-1,49%	-2,184(**)	-1,846(*)	-1,799(*)	**[-5;-1]**
[1;5]	1,78%	3,732(***)	3,308(***)	2,194(**)	4,23%	8,658(***)	6,097(***)	3,391(***)	0,52%	0,761	0,781	0,627	**[1;5]**
[1;10]	1,10%	1,626	1,298	0,956	1,20%	1,744(*)	0,777	0,683	1,04%	1,079	0,927	0,892	**[1;10]**
[0;5]	2,13%	4,063(***)	3,557(***)	2,389(**)	5,28%	9,876(***)	6,916(***)	3,868(***)	0,49%	0,663	0,660	0,545	**[0;5]**
[0;10]	1,44%	2,035(**)	1,63	1,196	2,26%	3,119(***)	1,421	1,222	1,02%	1,005	0,867	0,830	**[0;10]**

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

Panel B

Event Window	FIBS minus Other European Financial Institutions				Event Window
	Dif. CAR	*t-stat*			
		Standard	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*	
[-9;-1]	5,92%	5,212(***)	4,487(***)	2,951(***)	**[-9;-1]**
[-5;-1]	4,03%	4,808(***)	3,560(***)	2,696(***)	**[-5;-1]**
[1;5]	3,71%	4,421(***)	3,861(***)	2,478(**)	**[1;5]**
[1;10]	0,16%	0,134	0,083	0,075	**[1;10]**
[0;5]	4,79%	5,213(***)	4,475(***)	2,920(***)	**[0;5]**
[0;10]	1,24%	0,993	0,626	0,558	**[0;10]**

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

Table 4: Aggregate Results - Multi-Index Model

Panel A

Event Window	All Companies				FIBS Financial Companies				Other European Banks				Event Window
	CAR	*t-stat*			CAR	*t-stat*			CAR	*t-stat*			
		Standard	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*		*Standard*	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*		*Standard*	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*	
[-9;-1]	0,41%	0,631	0,494	0,449	4,86%	7,701(***)	5,009(***)	3,668(***)	-2,11%	-2,241(**)	-2,258(**)	-2,019(**)	**[-9;-1]**
[-5;-1]	0,30%	0,627	0,406	0,440	3,28%	6,982(***)	4,188(***)	3,326(***)	-1,41%	-2,049(**)	-1,722(*)	-1,818(*)	**[-5;-1]**
[1;5]	2,41%	5,070(***)	4,397(***)	3,555(***)	5,44%	11,567(***)	8,002(***)	5,510(***)	0,84%	1,224	1,218	1,086	**[1;5]**
[1;10]	2,23%	3,311(***)	2,635(***)	2,330(**)	3,45%	5,196(***)	2,218(**)	2,475(**)	1,64%	1,677(*)	1,419	1,494	**[1;10]**
[0;5]	2,58%	4,959(***)	4,224(***)	3,474(***)	6,36%	12,345(***)	8,338(***)	5,880(***)	0,62%	0,818	0,788	0,725	**[0;5]**
[0;10]	2,40%	3,400(***)	2,706(***)	2,390(**)	4,37%	6,273(***)	2,737(***)	2,988(***)	1,42%	1,380	1,170	1,227	**[0;10]**

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

Panel B

Event Window	FIBS minus Other European Financial Institutions			
	Dif. CAR	*t-stat*		
		Standard	*Boehmer Adj.*	*Cross-sectional Adj. (Crude Adj.)*
[-9;-1]	6,96%	6,151(***)	5,176(***)	4,131(***)
[-5;-1]	4,70%	5,624(***)	4,137(***)	3,737(***)
[1;5]	4,59%	5,502(***)	4,731(***)	3,655(***)
[1;10]	1,81%	1,530	0,934	1,019
[0;5]	5,74%	6,281(***)	5,250(***)	4,170(***)
[0;10]	2,96%	2,384(**)	1,475	1,587

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

Table 5: F test for equality of two population variances (variance in the estimation window versus variance in the event window)

Panel A: Raw returns - Percentage of cases where the null hypothesis is rejected

A1: $\sigma^2(Event) > \sigma^2(EW)$

	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]
All Comp.	31,8%	14,1%	2,4%	24,1%	20,0%	38,8%
FIBS	**31,0%**	**10,3%**	**1,7%**	**19,0%**	**17,2%**	**39,7%**
Non-FIBS	**32,1%**	**16,1%**	**2,7%**	**26,8%**	**21,4%**	**38,4%**

A2: $\sigma^2(Event) < \sigma^2(EW)$

	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]
All Comp.	6,5%	6,5%	14,1%	10,6%	10,6%	10,0%
FIBS	**3,4%**	**5,2%**	**6,9%**	**6,9%**	**3,4%**	**3,4%**
Non-FIBS	**8,0%**	**7,1%**	**17,9%**	**12,5%**	**14,3%**	**13,4%**

Note: EW- Estimation Window

Panel B: Abnormal returns - Percentage of cases where the null hypothesis is rejected

B1: $\sigma^2(Event) > \sigma^2(EW)$

	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]
All Comp.	24,7%	10,6%	3,5%	26,5%	8,8%	30,6%
FIBS	**22,4%**	**6,9%**	**0,0%**	**32,8%**	**6,9%**	**39,7%**
Non-FIBS	**25,9%**	**12,5%**	**5,4%**	**23,2%**	**9,8%**	**25,9%**

B2: $\sigma^2(Event) < \sigma^2(EW)$

	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]
All Comp.	5,9%	4,1%	15,3%	11,2%	10,6%	11,8%
FIBS	**3,4%**	**1,7%**	**5,2%**	**5,2%**	**5,2%**	**5,2%**
Non-FIBS	**7,1%**	**5,4%**	**20,5%**	**14,3%**	**13,4%**	**15,2%**

Note: EW- Estimation Window

Table 6: T-test: variance ratio (VR = event window variance/estimation window variance) equal to 1.

	Raw returns						Abnormal returns						
	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]	
All Comp.	10,387(***)	11,241(***)	8,345(***)	3,070(***)	11,471(***)	4,151(***)	8,090(***)	8,882(***)	6,489(***)	3,513(***)	7,697(***)	3,839(***)	All Comp.
FIBS	**8,618(***)**	**8,430(***)**	**5,998(***)**	**1,638**	**8,777(***)**	**2,291(**)**	**5,378(***)**	**5,271(***)**	**6,158(***)**	**2,148(**)**	**6,961(***)**	**2,307(**)**	**FIBS**
Non-FIBS	7,696(***)	8,277(***)	6,408(***)	6,789(***)	8,088(***)	7,910(***)	6,417(***)	7,210(***)	4,395(***)	6,015(***)	5,227(***)	6,649(***)	Non-FIBS

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

Table 7: Structural break test in the GARCH(1,1) volatility: Percentage of financial companies without stability in the variance equation

Panel A: Higher Volatility

	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]
All Comp.	26,5%	24,1%	9,5%	6,5%	8,9%	10,0%
FIBS	**32,8%**	**27,6%**	**8,6%**	**8,6%**	**15,5%**	**15,5%**
Non-FIBS	**23,2%**	**22,3%**	**9,8%**	**5,4%**	**5,4%**	**7,1%**

Panel B: Lower Volatility

	[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]
All Comp.	5,9%	8,8%	22,5%	14,8%	18,3%	17,1%
FIBS	**1,7%**	**10,3%**	**6,9%**	**5,2%**	**6,9%**	**10,3%**
Non-FIBS	**8,0%**	**8,0%**	**30,4%**	**19,6%**	**24,1%**	**20,5%**

Table 8: Beavers's U test

[-9;-1]	[-5;-1]	[1;5]	[1;10]	[0;5]	[0;10]	
16,103(***)	17,862(***)	14,899(***)	16,923(***)	19,886(***)	19,664(***)	All Comp.
12,655(***)	**12,710**(***)	**19,531**(***)	**24,653**(***)	**25,945**(***)	**27,840**(***)	**FIBS**
10,732(***)	**12,860(***)**	**4,302(***)**	**3,108(***)**	**5,829(***)**	**4,193(***)**	**Non-FIBS**

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

Table 9: Average values across countries and time

		Bid-ask spread				Amihud indicator				Volatility				Daily price range			
Month		Belgium	France	Italy	Spain	Belgium	France	Italy	Spain	Belgium	France	Italy	Spain	Belgium	France	Italy	Spain
January		0,27%	0,23%	1,06%	0,27%	27,5	195,5	422,7	120,0	2,6%	1,9%	2,0%	2,3%	3,6%	2,8%	2,9%	3,3%
February		0,30%	0,24%	1,06%	0,23%	28,4	76,4	251,3	104,7	2,0%	1,6%	1,6%	1,8%	3,0%	2,6%	2,5%	2,9%
March		0,30%	0,21%	1,06%	0,24%	36,9	75,7	288,2	66,2	1,7%	1,7%	1,4%	1,4%	3,0%	2,7%	2,6%	2,7%
April		0,31%	0,20%	0,95%	0,23%	36,7	81,0	256,0	113,3	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%	57,2	82,3	533,0	197,3	1,5%	1,5%	1,5%	1,3%	2,6%	2,1%	2,5%	2,4%
June		0,33%	0,17%	1,27%	0,28%	67,2	102,1	17245,1	135,9	2,1%	1,5%	2,2%	1,8%	2,9%	2,0%	3,1%	2,7%
July		0,43%	0,20%	1,87%	0,26%	74,5	192,3	1043,4	139,4	3,2%	2,2%	3,4%	2,1%	4,4%	3,1%	4,8%	3,4%
August		0,58%	0,25%	2,79%	0,32%	86,7	131,7	1044,4	115,6	5,0%	4,3%	4,2%	3,1%	9,7%	8,3%	7,9%	6,2%
	After the BAN	0,44%	0,37%	2,35%	0,48%	94,3	490,3	1455,2	880,7	3,7%	2,6%	2,7%	3,2%	5,0%	4,2%	4,8%	4,1%
September	BAN	0,59%	0,39%	3,14%	0,45%	120,7	509,2	2149,2	220,8	3,6%	3,4%	2,9%	3,5%	4,5%	4,2%	4,1%	4,5%

Table 10 – Multivariate Regressions (Panel Least Squares)

Panel A

White diagonal standard errors & covariance (d.f. corrected)

	D(BIDASK_S)	D(LOG(1+AMIHUD))
C	0,0002(**)	0,021(***)
D(VOL)	0,0476(*)	11,291(***)
D(LOG(VOLUME(-1)))	-0,0003	-
D(VOLUME)	-	0,000(***)
D(BANNED)	-0,0039(**)	0,335(***)
BANNED	0,0020(***)	0,080(**)
AR(1)	-0,4686(***)	-0,646(***)
AR(2)	-0,2727(***)	-0,470(***)
AR(3)	-0,1065(***)	-0,324(***)
AR(4)	-	-0,193(***)
N.º obs.	5036	5117
R-squared	0,183	0,333
F-statistic	160,61	318,58

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

Panel B

White diagonal standard errors & covariance (d.f. corrected)

Variable	VOL	Daily Price Range
C	-0,008	-0,017(*)
LOG(VOLUME(-1))	0,002(***)	0,004(***)
BANNED	0,004(*)	0,005(***)
Cross-section fixed (dummy variables)		
Period fixed (dummy variables)		
N.º obs.	5854	5854
R-squared	0,364	0,56
F-statistic	15,95	35,56

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

Table 11: Price discovery and the ban

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 a 1%, 5% and 10% level.

Panel B: Price discovery model (Panel Least Squares)

White diagonal standard errors & covariance (d.f. corrected)

Variables	MEC_DW	MEC_DM	MEC_WM	MYY	RHO DIF
C	0,733(***)	0,548(***)	0,726(***)	0,013	0,003
BANNED	-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 a 1%, 5% and 10% level.

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