
A Study on the Impact of the Short Selling Ban on FIBS

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Abstract:

In this paper we investigate how the short selling ban affected stock markets in France, Italy, Belgium and Spain and whether the required response was really achieved and reflected in the market. Although some argue that the short selling ban was needed for the market to get back on its feet, others argue that short selling is a tool that improves market efficiency and banning such trading strategy might lead to detrimental effects on the market.

Therefore, the purpose of this study was to show whether the short selling ban had a positive or negative effect, both in the short-term and long-term, on the financial markets. Moreover, to determine whether short selling is an effective tool and whether it really drives the stock prices down when the financial markets are going through bad moments. Consequently, uncover whether the short selling ban has had a permanent impact on the financial markets and whether it really had an effect on the FIBS. To do this we used market data and a selection of stock returns, which included banned stocks in the FIBS financial markets and non-banned financial stocks from non-FIBS before, during and after the short-selling ban in August 2011.

It was found that the short selling ban led to higher volatility in the FIBS countries and also had a spill over effect on non-FIBS countries. Furthermore, the impact of the short selling ban on volatility was only deemed to be for a short-term period, with the exception of Spain. Also, the short selling ban slowed down price discovery in Belgium, France and non-FIBS countries, whereas the short selling ban did not affect Spain and Italy. Furthermore, all countries including the non-FIBS countries illustrated a better price discovery position after the ban was lifted; therefore the short selling ban only had a short-term impact on price discovery. Moreover, there was a long-term positive effect on prices with improvement in stock market prices for all FIBS countries with a positive impact on non-FIBS countries. However, liquidity in all FIBS and non-FIBS countries suffered a short-term negative impact.

Keywords: *Short Selling Ban, FIBS, Non-FIBS, Price Discovery, Volatility, Liquidity, Financial Stock Prices, Pre-Ban Period, Ban Period, Post-Ban Period.*

JEL classification: *G01, G15.*

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1. Introduction

Short selling is considered to be a risky type of trading strategy. This due to the fact that some professional investors use a trading strategy known as naked short selling, whereby the investor does not borrow the stock or insure the feasibility of borrowing the stocks before short selling them. Furthermore, it is widely known that some investors will do anything in order to have an advantage over their competitors and therefore they might make use of false rumours in order to make them believe a false story and therefore artificially try to manipulate the price of a stock. (Securities and Exchange Commission, 1999).

Regulators have in fact, on several occasions highlighted short selling to be one of the factors contributing to the financial crisis. They were convinced that short selling activity was a factor of instability in the financial markets and the European Markets and Securities Commission (ESMA) decided to impose, on August 2011, a ban on France, Italy, Belgium and Spain (FIBS) stock markets (Handjani, Ali, 2012).

Stock exchange regulators argued that short selling activity led to sudden price declines in the stock market, which led to higher volatility in the market and lower liquidity. However, on the other hand, other analysts and theorists suggest that short selling does not really lead to such repercussions (Avgouleas, Emilios, 2010). The shares of 56 companies were subject to the short selling ban, of which 10 companies are domiciled in France, 28 in Italy, 4 in Belgium and 14 in Spain.

In 2011, the European stock markets saw a huge decline in its stock prices, where in the FIBS the most notable price declines were between July and August, with the BEL20 (Belgian stock index), CAC40 (France's stock index), FTSE/MIB (Italian stock index) and IBEX (Spanish stock index) declining by approximately 8%, 7.8%, 7.5% and 7.9% respectively.³

Furthermore, the comparison between the financial stocks and the market's stock as a whole indicate that the decline was even bigger when it came to financial stocks. When looking at the financial stocks of the FIBS, the results show that in France the decline in the CAC financial stocks in July and August 2011 was 12.61% and 18.55% respectively. On the other hand, in Belgium the decline in financial stocks was similar to the decline in the market as a whole with approximately an 8% decline in July and August. In Italy, the FTSE/MIB financial stocks were close to 8% in July, however the financial stocks suffered a 15.57% decline in August. Furthermore, in Spain the IBEX financial stocks were close to the market's stocks with 7.04% and 9.47% in July and August respectively. However, the study can conclude that there was a higher devaluation in financial stocks compared to the market as a whole, which makes the analysts question such a discrepancy.

³ Data collected from: [<http://www.euroinvestor.com/markets/stocks/europe>] [viewed on: 25/10/14]

Another interesting observation is that there was a 29.3% decline in financial stocks of the FIBS compared to the 20.6% decline in financial stocks in other European countries.⁴

As noted in this study, short selling is a controversial subject amongst various analysts and researchers due to the impact it has on the liquidity, volatility and market prices. Moreover, although many studies have been carried out on short selling bans in general and during the 2008 recession, few researchers have studied the impact of the 2011 short selling ban on the FIBS. Therefore, we aim to evaluate how the market in the FIBS fared during the 2011 short selling ban and the effects it had on such markets. We analyse whether short selling bans really have a negative effect on price discovery and whether price discovery tends to slow down when there is some negative news. Basically, we investigate whether stock discovery is affected negatively by short selling bans. We feel that a study of this kind will be of benefit to both academics and regulators in search of solutions to the risks the European economies are facing.

1.1 Research Questions

We based our studies on answering the following research questions and the following hypothesis:

- a. *Did the financial stocks perform differently in terms of returns prior to the ban?* - here we seek to understand whether the financial stocks were performing differently prior to the ban as compared to financial stocks performing during normal market environment. If the financial stocks performed differently, then the effects of the short selling ban on financial stocks would raise another question, i.e. whether the ban really had an impact or whether it was due to the financial stocks not performing normally that such repercussions occurred during and after the short selling ban.
- b. *How did FIBS financial stocks compare to the non-FIBS financial stocks during the short selling ban?* – here we seek to determine how the banned financial stocks in the FIBS fared as compared to the non-banned financial stocks in non-FIBS countries. This to show whether the short selling ban has a positive impact or not. However it should be noted that different countries may have different market scenarios to trade in so certain effects could be unrelated to the short selling ban.
- c. *What was the impact both in the short-term and long-term of the short selling ban on the FIBS' liquidity, volatility and prices?* – here, we seek to determine how the short selling ban effected the FIBS' liquidity, volatility and prices and whether the effects were only for a short period or whether the effects were of permanent, or long-term nature.

⁴ Data collected from: [<http://www.investing.com/indices>] [viewed on: 25/10/14]

1.2 Hypothesis

H0: As suggested by Beber and Pagano (2010) and Boehmer *et. al* (2008), short selling ban in the FIBS, as well as the short selling ban in general, does not contribute to market and stock price stabilisation but leaves stock prices unaffected or even worse have the opposite effect on the stock market regulators' intentions to stabilise the market. The study's results should indicate that the higher the average daily number of transaction, the higher the market liquidity. The latter therefore suggests that there is no major imbalance between supply and demand.

H1: Short selling ban in the FIBS, as well as the short selling ban in general, will contribute to market and stock price stabilisation.

2. Literature Review

Concerned with the impacts of the European Sovereign debt crisis on their respective countries, European Regulators, conducted stress tests on European banks. This led to a temporarily ban on short-selling transactions of financial stocks in France, Italy, Belgium and Spain (FIBS). Several researchers have tried to test and provide evidence for the impact of short selling both on the law of one price (no arbitrage opportunities in the markets) and on the financial markets as a whole (Gagnon, L., Witmer, J., 2009).

2.1 Impact of Short Selling Restrictions on Liquidity

Beber and Pagano (2011) and Boehmer *et al.* (2012), in their studies, found that short selling bans have a negative effect on liquidity. The former, concluded that short selling bans have a detrimental effect on the market's liquidity. They question the regulator's decision in the U.S. to ban short selling during a time where liquidity was fundamental to the markets. They highlight that the median bid-ask spread was larger during the short selling ban as compared to bid-ask spreads outside the short selling ban period. Noting, that the bid-ask spread was on average 2.27 times larger as compared to the pre-ban period and over 3 times larger as compared to the post-ban period, with Italy's short selling ban having the most devastating negative effect on the market's liquidity.

In both studies it was found that short selling bans increase the end of day bid-ask spreads in the financial markets and therefore implying that liquidity suffers when short selling is banned. They also highlight the fact that bid-ask spreads can be viewed as an illiquidity measure where the wider the spread, the less liquid the stock is. Moreover, they note that even after the ban was lifted, there was illiquidity. However the reason could be because the market's volatility remained very high.

Fotak *et al.* (2010) agreed with Boehmer *et al.*'s (2012) findings, that short selling bans tend to have an adverse effect on liquidity. However they look at naked short

sales (short selling without borrowing). They, highlight the fact, that naked short sales have the same impact on the market as covered short sales during trading time. Moreover, they note that an increase in naked short selling will lead to a reduction in spreads and therefore an increase in liquidity. Furthermore, Fotak *et al.* (2010) argue that naked short selling leads to lower order imbalances (reducing the gap between excess supply and demand when major news hits the markets), and therefore improving the liquidity.

These views are shared by other researchers namely Gagnon and Witmer (2009) who looked at the Canadian markets short selling bans; Battalio and Schultz (2010) who reviewed the U.S. stock market during the short selling ban and found that the spreads resulted in liquidity costs amounting to over \$600 million; Marsh and Payne (2010), who looked into the U.K. markets finding that financial stocks had a greater impact on liquidity as compared to non-financial stocks in the U.K. markets.

On the other hand, Jones and Lamant (2002) did not agree with the researchers above. They argued that during the Great Depression in the U.S., when in 1932 there was a requirement that brokers should secure written authorisation before lending a shares, reduced liquidity. However, the 1938 requirement, which required short selling strategies, only to be executed if there was an increase on the stock, resulted in increased liquidity (Beber and Pagano, 2011). Charoenrook and Daouk (2005) concur with this finding and note that short selling restrictions in 111 countries they studied correlate with greater market liquidity.

2.2 Impact of Short Selling Restrictions on Price Discovery

Diamond and Verrecchia (1987) concluded that market restrictions tend to slow down price discovery and therefore result in an increase in the bid-ask spreads. Furthermore, the study concludes that short selling restrictions tend to slow the price more in bear markets as compared to the bull markets.

Although, Miller (1977) agrees to this, but contrary to Diamond and Verrecchia (1987) argues that short selling restrictions tend to move the price upwards, leading to 'overpricing' of the stock.

Harrison and Kreps (1978) also conclude that short selling restrictions tend to slow down price discovery in the markets. Harrison and Kreps, however assume that all investors have the same information and no inside information is known to investors.

Biais *et al.* (1999) conclude similarly, that in the French market when market restrictions are imposed good information about the market tends to be reflected faster than bad news on the market.

Bris *et al.* (2003) analysed the stock of 47 equity markets around the world and came up with two conclusions about the impact of short selling restrictions on price discovery. The first conclusion was that short selling does in fact help price discovery in the stock markets. The second conclusion was that short selling might lead to greater price declines in individual stocks, hence concluding that short selling constraints have little or no impact on severe price declines in the markets.

Boehmer and Wu (2010) suggest that being informed does not mean that the market prices will immediately reflect the information being given to the traders involved. On the contrary, traders who receive information would want to keep that information for themselves and not leak it into the market. They suggest that when short selling is allowed on the market, market prices tend to react faster to new public information, thus concluding that short selling can be a marketing strategy that helps the market to reflect price information. Furthermore, they suggest that short selling leads to smaller pricing errors and therefore price discovery is reflected faster in the market. However, when analysing the impact of short selling restrictions on price discovery, they concluded that restrictions tend to hinder price discovery in the market.

Saffi and Sigurdsson (2011) studied over 25 countries over the period of three years in order to analyse how short selling restrictions affect price efficiency. They concluded that short selling restrictions do not lead to price instability or high negative returns on the affected stocks.

Beber and Pagano (2011) also analyse the impact of the 2008 short selling ban in the U.S. on price discovery. They concluded that short selling restrictions tend to slow down price discovery especially when bad news is announced on the market. Beber and Pagano's (2011) conclusions are in line with Diamond and Verrecchia's (1987) conclusions, that short selling restrictions tend to slow down price discovery more in the bear market as compared to the bull market.

When testing whether it is a good idea for regulators to impose short selling restrictions in order to limit the activity of traders in bearish markets and therefore slowing down price discovery more in bearish markets as compared to bullish markets, Beber and Pagano (2011) found that, short selling bans slow down price discovery more in bearish markets as compared to bullish markets.

2.3 Impact of Short Selling Restrictions on Prices and Returns

Jones and Lamont (2001) conclude that stocks tend to be overpriced when short selling bans are imposed on stock markets. They find that some stocks tend to be too expensive to be shorted; therefore they are considered to be overpriced in the market and yield lower returns.

Chang *et al.* (2007) conclude similarly after analysing the Hong Kong stock markets and notes that this impact happens especially for individual stocks. However, in their analysis they also consider the investors' opinion about the stock and conclude that the more different the investors' opinions are the more overvalued the stocks are.

Similar conclusions were reached by Autore *et al.* (2011), who focused their studies on the illiquidity shock and the overpricing of the stocks and Lobanova *et al.* (2010), who focused their studies on the impact of the short-selling ban in the U.S. on liquidity, volatility and market efficiency and found that during the 2008 short selling restriction in the U.S. returns on banned stocks reduced as compared to other periods.

Diether *et al.* (2007) tested whether short sellers are able to make future decisions about their stocks based on new laws enacted by the SEC in 2005. They conclude that short sellers tend to be more active in the market when stock prices increase and they tend to short less when stock market prices tend to decrease. The latter shows that Diether *et al.* (2007) come to the same conclusion as Biais *et al.* (1999), that short sellers and traders in general tend to react more to bad news than good news. However, on the other hand, Diether *et al.* (2007), do not agree with most researchers that the larger the difference between the investors' opinions, the more overpriced the stocks are. In fact, Diether *et al.* (2007), state that as uncertainty and difference of opinions amongst investors grows larger, the more short selling activities tend to be executed, therefore having a more efficient market.

Boehmer *et al.* (2012) agree with Diether *et al.*'s (2007) reasoning and conclude that short selling restrictions do not have any effect on stock market prices. They studied banned stocks both during the ban, before and after the ban on those stocks. They concluded that there were no exaggerated price changes when comparing the pre-ban period and the ban period on the stocks involved, noticing that banned stocks were subject to underperformance in the stock market during the ban. Boehmer *et al.* (2007) analysed the abnormal returns of the original banned stocks as compared to the cumulative returns to similar never banned stocks. They concluded that the day after the ban was imposed, the banned stocks made an average of 6.68% returns as compared to the 3.48% for the never banned stocks. Boehmer *et al.* (2007) also state that such a difference could be permanent.

However, the abnormal returns made by the affected institutions could be due to the Troubled Asset Relief Program (TARP) announcement (a program that was intended to strengthen market stability and financial institutions) on that same date, on which the short selling restriction was imposed. They also found that the day the ban was enacted on them the average excess return on the banned stocks was very close to zero. Boehmer *et al.* (2007), suggest that the reason for a close to zero average excess return could be that the SEC's intention to boost the share prices by imposing the short selling ban is outweighed by the negative price effects of the short selling restriction.

Furthermore, Beber and Pagano (2011) also conclude that short selling restrictions do not lead to overpricing of stocks in the markets and decline again when the restriction is no longer imposed. They, in fact find some overpricing in the U.S. data stock market, which could be due to the TARP announcement. However when analysing other countries they do not find any overpricing of the stocks when a ban is imposed but rather no changes in the stock prices.

2.4 Impact of Short Selling Restriction on Volatility

Charoenrook and Daouk (2005) concluded that short selling leads to less volatility in aggregate stock returns and decline the claims that short selling leads to higher market volatility.

Bris *et al.* (2003) study the effect of short selling restrictions on volatility by calculating the average standard deviation of individual stock returns and use its logs, in order to arrive at the stocks' real value. They conclude that short selling restrictions do lead to higher volatility in the stock market returns. They also notice that volatility is even higher in less-developed countries as compared to countries with more prestigious governments. These findings are similarly concurred to by Beber and Pagano (2011) and Boehmer *et al.* (2012).

3. Methodology

Using non-probability judgmental sampling we chose 52 banned stocks and 17 non-banned stocks. The main demographic variable for the study was the weekly excess returns of the relevant FIBS (France, Belgium, Italy and Spain) and non-FIBS (Germany, Austria, Greece and the Netherlands) financial stocks pre, during and post the ban between August 2011 and February 2012. The total frequency of the demographic variable (the weekly excess returns) amounted to 8,112 observations for the 52 banned stocks and 2,652 observations for the 17 non-banned stocks. Data was collected to measure liquidity, volatility and prices before, during and after the ban.

One of the main reasons why non-probability judgmental sampling was used for this study is due to the accessibility of the stocks and the research requiring a very specific group, where specific financial stocks that were subject to the short selling ban were needed. Furthermore, some of the financial stocks required for the study had either merged or went bankrupt during the period that the study was carried out.

Furthermore, when sampling the non-FIBS stocks, non-probability, judgmental sampling was chosen due to the fact that they were influential countries during the period the study was carried out. Furthermore, other countries such as Norway were not selected due to the stock prices being in their home currency not in Euro. The

stocks gathered were then identified from Thomson Reuters and downloaded using the add-on onto Ms Excel.

In order to analyse what impact the short selling ban had on liquidity in FIBS countries, the average daily number of transactions was deemed to be the most appropriate measurement tool. The volume of the respective stocks was downloaded from Thomson Reuters. Moreover, in order to determine the daily number of transactions, the total number of trades was divided by the number of trading days.

3.1 Price Discovery Approach

In order to estimate the market model, we made use of weekly returns for each stock on the corresponding national stock market index from August 2011 to February 2012 (the ban period). The weekly return data for both the individual stocks and the stock market indexes was again downloaded from Thomson Reuters. The reason why we chose a weekly frequency is motivated by previous studies, mainly those of Beber and Pagano (2011) and Bris, Goetzmann and Zhu (2007), that find such frequency to be the optimal balance between noise and information. To test the prediction of price discovery in the study, an estimation of a market model regression was made using EViews. The market model makes use of the formula:

$$Y = a + bX$$

where Y = the weekly returns of the stock (dependent variable); and X = the weekly returns of the national stock market index (independent variable).

Furthermore, the reason why we chose the market model to identify price discovery is due to the fact that the ban should affect price discovery in terms of a firm-specific basis rather than a market-wide informational effect.

3.2 Stock Price Effect Approach

The stock prices of 52 banned stocks from FIBS countries were collected from Thomson Reuters, leading to a total of 8,112 observations. On the other hand, 17 stocks from non-FIBS countries were collected, therefore having a total of 2,652 observations. The stock market indexes for both the FIBS and non-FIBS countries were also collected from Thompson Reuters.

One of the main principles why the short selling ban was enacted in August 2011 was to provide effective support to the prices of financial stocks. In order to test whether the previous statement was true or not, the study focuses on the excess returns of the banned stocks in the FIBS and the non-banned stocks in the following European countries: Austria, Germany, Greece and the Netherlands (Non-FIBS). Excess returns, as defined by Beber and Pagano (2010), is the difference between individual stock returns and the respective country's market index. The stock market

indexes chosen for the FIBS are CAC40, FTSE MIB, BEL20 and IBEX respectively. The reason why we chose these respective stocks was due to the fact that the stock index represents the most financially liquid and stable companies in their respective country.

3.3 Volatility Approach

Volatility defined as the standard deviation of the return provided by the variable unit per unit over time when the return is expressed as continuous compounding. In this study, only business days are assumed, since volatility tends to be much higher during business days than on non-business days, such as weekends and holidays.

In order to calculate volatility, the study makes use of the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) Model, which was proposed by Bollerslev in 1986. The assumption of the GARCH Model is that volatility changes with the passage of time. A further benefit of the GARCH model is that if it is working efficiently, then autocorrelation should be removed.

Furthermore, in order to work out the GARCH (1,1) Model, we use an add-in of Microsoft Excel®, NumXL. The study first identified the weekly returns of the respective stock, with the data downloaded from Yahoo! Finance. The next step in determining the GARCH (1,1) Model was to work out the weighted moving average and the exponential moving averages in order for the study to get an idea of the trend of the stock price before, during and after the short selling ban. Furthermore, the study calculates and plots the autocorrelation function (*acf*) and the partial autocorrelation function (*pacf*) in order to measure the correlation between the observations, after controlling for observations with intermediate lags. The final step of the calculation of the GARCH (1,1) Model was to run the GARCH Model itself using the weekly percentage returns of the stock.

3.4 Liquidity Approach

It is only natural that the average daily number of transactions during times of distress is lower than during normal periods. However in order to counter such an effect the study takes into account both the pre- and post-ban periods, which fall within the European Sovereign Debt Crisis period.

3.5 Limitations and Assumptions of the Methodology

The average daily number of transactions analysis may have its restrictions, whereby volatility may not be due to the short selling ban but due to other factors, especially when considering that the analysis is being conducted during the European Sovereign Debt Crisis. The market model only assumes the weekly returns for the stock market index; however the weekly returns for the financial stocks may be

affected by other factors, which are not portrayed in the market model run by the study.

The excess returns calculation includes the market benchmark indexes for their respective countries. The benchmark indexes however do not represent the whole market but rather a small portion with the most powerful companies in the country. Furthermore, the benchmark index does not only represent financial industry stocks but stocks from the market as a whole, whereas this study focuses only on financial stocks.

The GARCH model operates best under stable market conditions; whereas the research in question is operating during a crisis therefore the market conditions may be fairly unstable.

Although these limitations and assumptions we were still able to give a clear indication of the impacts on the short selling ban on financial markets and whether the impacts were of a short or long-term nature. The study also used several tests that were not used in other papers and analysis of the impacts of short selling bans, hence giving an alternative analysis and viewing of the impacts of the short selling ban.

4. Findings and Results

The weekly excess returns for each of the 52 banned stocks grouped by their respective countries and the 17 non-banned stocks grouped altogether are shown in

Table 1. An illustration of the weekly excess returns of the FIBS and non-FIBS countries for the period February 2010 to June 2013.

EXCESS RETURNS					
Period	Belgium	France	Italy	Spain	Non-FIBS
<i>Pre-Ban Period</i>	-1.14595%	-0.35514%	-0.48431%	-0.31697%	-0.75827%
<i>Ban Period</i>	-0.02556%	0.30488%	1.00363%	0.38407%	0.08546%
<i>Post-Ban Period</i>	-0.08606%	0.47606%	1.01357%	-0.14271%	-0.00522%

4.1 Volatility: Belgium

Pre-Ban Period: The volatility proxy by the exponentially moving average (EWMA) moved smoothly unlike the weekly returns of the Belgian banned financial stocks. Furthermore, it was noted that the volatility proxy by EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Belgian financial stocks interpreted that the weekly returns are negatively skewed. However, the skewness of the Belgian financial stocks was not

significant at the 5% level of significance. Moreover, the White-noise test did not show any signs of serial correlation between returns. As illustrated in Figure 2, the GARCH model results were calibrated and all the results, those being the White-noise, the normal distribution and ARCH, were significant. The GARCH Model estimated volatility to be 5.24% before the short selling ban began.

Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Belgian financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. As illustrated in Figure 3 after the GARCH model was calibrated all the results were significant. The volatility during the ban period was 9.58%, which is a lot higher than the pre-ban period.

Post-Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Belgian financial stocks showed that the skewness was negative, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. As illustrated in Figure 4 after the GARCH model was calibrated all the results were significant. The volatility during the ban period was 5.46%, which is lower compared to the ban period. Furthermore, the results showed that volatility returned to the same approximate value as the pre-ban period values.

4.2 Volatility: France

Pre-Ban Period: The volatility proxy by the exponentially moving average (EWMA) moved smoothly unlike the weekly returns of the French banned financial stocks. Furthermore, it was noted that the volatility proxy by EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the French financial stocks interpreted that the weekly returns are negatively skewed. However, the skewness of the French financial stocks was not significant at the 5% level of significance. Moreover, the White-noise test did not show any signs of serial correlation between returns. As illustrated in Figure 5, the GARCH model results were calibrated and all the results, those being the White-noise, the normal distribution and ARCH, were significant. The GARCH Model estimated volatility to be 5.53% before the short selling ban began.

Ban Period : The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the French financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs

of serial correlation between returns. After the GARCH model was calibrated all the results were significant as illustrated in Figure 6. The volatility during the ban period was 7.06%, which is a higher than the pre-ban period.

Post-Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the French financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. After the GARCH model was calibrated all the results were significant as illustrated in Figure 7. The volatility during the ban period was 3.58%, which is a lot lower compared to the ban period.

4.3 Volatility: Italy

Pre-Ban Period: The volatility proxy by the exponentially moving average (EWMA) moved smoothly unlike the weekly returns of the Belgian banned financial stocks. Furthermore, it was noted that the volatility proxy by EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Italian financial stocks interpreted that the weekly returns are negatively skewed. However, the skewness of the Italian financial stocks was not significant at the 5% level of significance. Moreover, the White-noise test showed some signs of serial correlation between returns, therefore the GARCH model had to be calibrated. The GARCH Model estimated volatility was 8.40% before the short selling ban began (Figure 8).

Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Italian financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. After the GARCH model was calibrated all the results were significant. The volatility during the ban period was 9.47%, which is higher than the pre-ban period implying that volatility increases during the short selling ban period as illustrated in Figure 9.

Post-Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. the volatility during the ban period was 6.26%, which is lower compared to the ban period. Furthermore, it can be concluded that volatility during the short selling ban period increased as compared to periods were the short selling ban was not in place.

4.4 Volatility: Spain

Pre-Ban Period: The volatility proxy by the exponentially moving average (EWMA) moved smoothly unlike the weekly returns of the Spanish banned financial stocks. Furthermore, it was noted that the volatility proxy by EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Spanish financial stocks interpreted that the weekly returns are negatively skewed. However, the skewness of the French financial stocks was not significant at the 5% level of significance. Moreover, the White-noise test did not show any signs of serial correlation between returns. The GARCH model results were calibrated and all the results, those being the White-noise, the normal distribution and ARCH, were significant. The GARCH Model estimated volatility was 2.88% before the short selling ban began as Figure 11 illustrates.

Ban Period : The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Spanish financial stocks showed that the skewness was negative, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. After the GARCH model was calibrated all the results were significant. The volatility during the ban period was 3.77%, which is a higher than the pre-ban period implying that the short-selling ban did have a negative effect on volatility (Figure 12).

Post-Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the Spanish financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. After the GARCH model was calibrated all the results were significant. The volatility during the ban period was 4.20%, as illustrated in Figure 13, which is a higher compared to the ban period.

4.5 Non-FIBs (Austria, Greece, Germany and the Netherlands)

Pre-Ban Period: The volatility proxy by the exponentially moving average (EWMA) moved smoothly unlike the weekly returns of the non-FIBs financial stocks. Furthermore, it was noted that the volatility proxy by EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the non-FIBs financial stocks interpreted that the weekly returns are negatively skewed (-0.74). The skewness of the non-FIBs financial stocks was statistically significant at the 5% level of significance. Furthermore, the White-noise test was significant and did not show any signs of serial correlation. The GARCH Model estimated volatility was 3.99% (Figure 14) before the short selling ban began.

Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the non-FIBS financial stocks showed that the skewness was negative, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. The volatility during the ban period was 7.25% (Figure 15), which is higher than the pre-ban period implying that volatility did not only increase in FIBS countries but also in non-FIBS countries.

Post-Ban Period: The exponentially moving average (EWMA) volatility proxy moved fairly smooth and the study showed that the EWMA is more sensitive to positive returns as compared to negative returns. The descriptive statistics of the financial stocks showed that the skewness was positive, however the skewness was not significant at the 5% level. Furthermore, the White-noise test did not show signs of serial correlation between returns. The volatility during the ban period was 3.87%, which is a lot lower than the ban period imposed on the FIBS countries.

4.6 Price Discovery

In order to test price discovery, a market model regression was used, where we made use of weekly returns for each stock on the corresponding national stock market index from February 2010 to February 2013.

4.6.1 Belgium

Pre-Ban Period: The R^2 value of the pre-ban period regression was 0.5227, indicating that 52.27% of the total variation in the weekly returns of the financial stocks in Belgium is explained by the variation in the explanatory variable (the Belgian stock index). Furthermore, the Durbin-Watson statistic is very close to two, which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Belgium by 1.701 units.

Ban Period: The R^2 value of the pre-ban period regression was 0.3467, indicating that 34.67% of the total variation in the weekly returns of the financial stocks in Belgium is explained by the variation in the explanatory variable (the Belgian stock index). Furthermore, the Durbin-Watson statistic is fairly close to two, which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Belgium by 2.04 units.

Post-Ban Period: The R^2 value of the pre-ban period regression was 0.1856, indicating that 18.56% of the total variation in the weekly returns of the financial stocks in Belgium is explained by the variation in the explanatory variable (the Belgian stock index). Furthermore, the Durbin-Watson statistic is close to two, which implies that there is no serial autocorrelation in the model. The regression

stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Belgium by 1.84 units. The latter shows that price discovery was fairly less after the ban period.

4.6.2 France

Pre-Ban Period: The R^2 value of the pre-ban period regression was 0.5048, indicating that 50.48% of the total variation in the weekly returns of the financial stocks in France is explained by the variation in the explanatory variable (CAC40). Furthermore, the Durbin-Watson statistic is very close to two (1.995), which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of the banned financial stocks increased the CAC40 by 1.16 units.

Ban Period: The R^2 value of the pre-ban period regression was 0.5234, indicating that 52.34% of the total variation in the weekly returns of the financial stocks in France is explained by the variation in the explanatory variable (CAC40). Furthermore, the Durbin-Watson statistic is a bit higher but close to two, which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Belgium by 1.323 units.

Post-Ban Period: The R^2 value of the pre-ban period regression was 0.4412, indicating that 44.12% of the total variation in the weekly returns of the financial stocks in France is explained by the variation in the explanatory variable (CAC40). Furthermore, the Durbin-Watson statistic is lower but close to two (1.809), which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of France by 1.297 units. The latter shows that price discovery was fairly less but relatively close to the ban period's conclusion.

4.6.3 Italy

Pre-Ban Period: The R^2 value of the pre-ban period regression was 0.3374, indicating that 33.74% of the total variation in the weekly returns of the financial stocks in Italy are explained by the variation in the explanatory variable (FTSE MIB). Furthermore, the Durbin-Watson statistic is close to three, which implies that there is some degree of serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Italy by 1.024 units.

Ban Period: The R^2 value of the pre-ban period regression was 0.3254, indicating that 32.54% of the total variation in the weekly returns of the financial stocks in Italy is explained by the variation in the explanatory variable (the FTSE MIB). Furthermore, the Durbin-Watson statistic is approximately 2.67, which implies that there is some degree of serial autocorrelation in the model. The regression stated that

on average, a one unit increase in the price of a banned financial stock increased the stock market index of Italy by 1.0312 units.

Post-Ban Period: The R^2 value of the pre-ban period regression was 0.2857, indicating that 28.57% of the total variation in the weekly returns of the financial stocks in Italy is explained by the variation in the explanatory variable. Furthermore, the Durbin-Watson statistic is close to 2.50, which implies that there is some degree of serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Belgium by approximately 1 unit. The latter shows that price discovery was fairly less but very similar after the ban period.

4.6.4 Spain

Pre-Ban Period: The R^2 value of the pre-ban period regression was 0.695, indicating that 69.50% of the total variation in the weekly returns of the financial stocks in Spain is explained by the variation in the explanatory variable (IBEX). Furthermore, the Durbin-Watson statistic is fairly close to two (1.704), which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of the banned financial stocks increased the IBEX by 0.711 units.

Ban Period: The R^2 value of the pre-ban period regression was 0.7837, indicating that 78.37% of the total variation in the weekly returns of the financial stocks in Spain is explained by the variation in the explanatory variable (IBEX). Furthermore, the Durbin-Watson statistic is very close to two, which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the stock market index of Belgium by 0.714 units.

Post-ban Period: The R^2 value of the pre-ban period regression was 0.8092, indicating that 80.92% of the total variation in the weekly returns of the financial stocks in Spain is explained by the variation in the explanatory variable (IBEX). Furthermore, the Durbin-Watson statistic is a bit higher but close to two (2.11), which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a banned financial stock increased the IBEX by 1.017 units. The latter shows that price discovery was higher than the previous periods.

4.6.5 Non-FIBS

Pre-Ban Period: The R^2 value of the pre-ban period regression was 0.6491, indicating that 64.91% of the total variation in the weekly returns of the financial stocks in non-FIBS countries is explained by the variation in the explanatory variable. Furthermore, the Durbin-Watson statistic is very close to two, which implies that there is no serial autocorrelation in the model. The regression stated that

on average, a one unit increase in the price of financial stock increased the stock market index of non-FIBS by 1.035 units.

Ban Period: The R^2 value of the pre-ban period regression was 0.6901, indicating that 69.01% of the total variation in the weekly returns of the financial stocks is explained by the variation in the explanatory variable. Furthermore, the Durbin-Watson statistic is lower but rather close to two, which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of a non-FIBS financial stock increased the stock market index by 1.292.

Post-Ban Period: The R^2 value of the pre-ban period regression was 0.4216, indicating that 42.16% of the total variation in the weekly returns of the financial stocks is explained by the variation in the explanatory variable. Furthermore, the Durbin-Watson statistic is very close to two (1.95), which implies that there is no serial autocorrelation in the model. The regression stated that on average, a one unit increase in the price of non-banned financial stock increased the stock market index by 0.778 units. The latter shows that price discovery was fairly less after the ban period.

4.7 Stock Price Effect

The excess returns were calculated in order to conclude whether the short selling ban provided support for the prices of financial stocks. The excess returns for all the respective FIBS and non-FIBS countries are illustrated in Table 1.

4.7.1 Belgium

Pre-Ban Period: The pre-ban period's excess returns for the financial stocks was -1.15%, which means that of the pre-ban period's excess returns performed negatively on average.

Ban Period: The ban period's excess returns for the financial stocks was -0.03%, which showed that the short selling ban had a positive impact on stock prices.

Post-Ban Period: The post-ban period's excess returns for the financial stocks was -0.09%, which showed that the stocks price returns after the ban was lifted remained fairly stable.

4.7.2 France

Pre-Ban Period: The pre-ban period's excess returns for the financial stocks was -0.355%, which means that of the pre-ban period's excess returns performed slightly negative on average.

Ban Period: The ban period's excess returns for the financial stocks was 0.305%, which concluded that the short selling ban had a positive impact on the stock price and stocks even achieved a positive return during the ban period.

Post-Ban Period: The post-ban period's excess returns for the financial stocks was 0.476%, which showed that the stocks price returns after the ban was lifted achieved even higher returns than during the short selling ban period.

4.7.3 Italy

Pre-Ban Period: The pre-ban period's excess returns for the financial stocks was - 0.484%, which means that of the pre-ban period's excess returns performed negatively on average.

Ban Period: The ban period's excess returns for the financial stocks was 1.004%, which showed that the short selling ban had a very positive impact on stock prices and the short selling ban helped the financial stock prices to stabilise and even achieve positive returns.

Post-Ban Period: The post-ban period's excess returns for the financial stocks was 1.014%, which showed that the stocks price returns after the ban was lifted remained fairly similar as compared to the ban period.

4.7.4 Spain

Pre-Ban Period: The pre-ban period's excess returns for the financial stocks was - 0.317%, which means that of the pre-ban period's excess returns performed negatively on average.

Ban Period: The ban period's excess returns for the financial stocks was 0.384%, which showed that the short selling ban had a positive impact on stock prices and the short selling ban helped the financial stock prices to stabilise and even achieve positive returns on the Spanish financial stock market.

Post-Ban Period: The post-ban period's excess returns for the financial stocks was - 0.143%, which showed that the financial stocks achieved negative returns after the ban was lifted. The latter therefore implied that the short selling ban had a positive impact on the stock returns.

4.7.5 Non-FIBS

Pre-Ban Period: The pre-ban period's excess returns for the financial stocks was - 0.758%, which means that of the pre-ban period's excess returns performed negatively on average.

Ban Period: The ban period's excess returns for the financial stocks was 0.085%, which showed that the short selling ban also had a positive impact on non-FIBS countries and the impact of the short selling ban had a positive spill over effect on European markets.

Post-Ban Period: The post-ban period's excess returns for the financial stocks was -0.005%, which showed that the stocks price returns remained fairly stable as compared to the ban period.

4.8 Liquidity Effect

The average daily number of transactions helped us to determine how liquidity was effected during the ban period. The average daily number of transactions and the number of days used for the sample period are illustrated on Table 2.

Table 2. The average daily number of transactions estimating the liquidity effect on both FIBS and non-FIBS countries

<u>Period</u>	<u>Number of Trading Days</u>	<u>Belgium</u>	<u>France</u>	<u>Italy</u>	<u>Spain</u>	<u>Non-FIBS</u>
<i>Pre-Ban Period</i>	240	1,287,297	8,560,709	63,713,976	10,184,796	12,461,315
<i>Ban Period</i>	210	1,126,516	5,900,042	47,520,115	3,501,143	10,392,511
<i>Post-Ban Period</i>	240	1,558,545	9,306,577	85,467,063	9,756,563	12,610,011

4.8.1 Belgium

Pre-Ban Period

The average daily number of transactions on the banned financial stocks before the ban period was enacted was approximately 1.29 million, which is a lot lower than the 5.014 million average traded on Euronext BEL20.

Ban Period: On the other hand, the ban period's average daily number of transactions was 1.127 million, which shows a lower amount of number of transactions traded and therefore implying lower liquidity.

Post-Ban Period: The post ban period's average daily number of transactions was 1.559 million, which shows a higher amount of transactions than the ban period and also than the pre-ban period. The latter showed that the liquidity increased significantly after the ban period and investors had more confidence to invest in the financial markets.

4.8.2 France

Pre-Ban Period: The average daily number of transactions on the banned financial stocks before the ban period was enacted was approximately 8.561 million.

Ban Period: On the other hand, the ban period's average daily number of transactions was 5.9 million, which shows a significant amount of reduction in the average daily number of transactions traded and a huge loss in market liquidity.

Post-Ban Period: The post ban period's average daily number of transactions was 9.307 million, which again shows that after the ban was lifted the average amount of number of transactions increased after the ban was lifted implying that the short selling ban did have a negative effect on liquidity.

4.8.3 Italy

Pre-Ban Period: The average daily number of transactions on the banned financial stocks before the ban period was enacted was approximately 63.714 million.

Ban Period: On the other hand, the ban period's average daily number of transactions was 47.520 million, which shows an alarming amount of lack of transactions traded and a therefore huge loss in market liquidity.

Post-Ban Period: The post ban period's average daily number of transactions was 85.467 million, which again shows a huge increase of transactions after the ban was lifted. The latter implies that the short selling ban reduced significantly market liquidity in the Italian financial stock market.

4.8.4 Spain

Pre-Ban Period: The average daily number of transactions on the banned financial stocks before the ban period was enacted was approximately 10.185 million.

Ban Period: On the other hand, the ban period's average daily number of transactions was 3.501 million, which shows a decline in market liquidity during the period the short selling ban was in place.

Post-Ban Period: The post ban period's average daily number of transactions was 9.757 million, which again shows a huge increase of transactions after the ban was lifted. The latter implies that the short selling ban reduced significantly market liquidity in the Spanish financial stock market.

4.8.5 Non-FIBS

Pre-Ban Period: The average daily number of transactions on the non-FIBS financial stocks before the ban period was enacted was approximately 12.461 million.

Ban Period: On the other hand, the ban period's average daily number of transactions was 10.392 million, which shows a lower amount of number of transactions traded and therefore implying lower liquidity.

Post-Ban Period: The post ban period's average daily number of transactions was 12.610 million. The post-ban period's results were fairly similar to the pre-ban period's results.

4.8 Theoretical and practical implications

4.8.1 Volatility

The FIBS' financial stocks showed relatively higher volatility during the ban period as compared to the pre-ban period, which implies that the short-selling ban did have a negative impact on volatility in the FIBS stock markets. We came to the same conclusions that Bris et al (2003) came to, that is, that short selling restrictions do lead to higher volatility in the markets.

The study analysis of the non-FIBS financial stocks yielded the same conclusions as that of the FIBS, that is, that during the ban period the volatility was higher than before the ban was imposed. The result could be seen from two different point of views. The first point of view being that volatility increased due to other circumstances rather than the short-selling ban, whilst on the other hand, the second conclusion could be that the short-selling ban had a spillover effect on the volatility of other European countries.

Moreover, the study also analysed the period (one year) after the short selling ban was imposed. All the FIBS countries, except for Spain, showed that volatility decreased significantly after the short-selling ban was lifted. We can then conclude that the short-selling ban only had a short-term impact on volatility and there was no permanent impact on the financial stocks' volatility. The reason why Spain had a higher volatility after the ban was lifted could be the huge financial stress it was under during the time period chosen for the study.

4.8.2 Price Discovery

The Belgian and French financial stocks were affected by the short-selling ban and price discovery slowed down as compared to the period before the ban was lifted. However, on the other hand, the Spanish and Italian financial stocks were not affected in terms of price discovery when the short-selling ban was imposed. One reason for such results could be that the Spanish and Italian financial stocks were already under huge stressful conditions (lack of demand and supply for the financial stocks), therefore the autocorrelation between the financial stocks and the stock market indexes remained fairly similar.

We find that during the ban period, the price discovery of non-FIBS financial stocks was also affected, even though the effect was minimal. The reason for such, could be that the non-FIBS investors feared that the short-selling ban could be imposed on other European countries, therefore the demand for financial stocks in non-FIBS countries decreased, affecting the price discovery.

The post-ban short-selling period had similar results for Belgium, France and Italy, where price discovery improved after the ban period was lifted. In the case of Italy, price discovery remained fairly stable over the whole sample period. On the other hand, in the case of Spain, price discovery was affected even further after the ban was lifted. The main reason for such a conclusion could be the “mini-bailout of Bankia” (Financial Times, 2012), which further reduced the demand for Spanish financial stocks. The latter implied that in all cases, apart from in the Spanish financial stocks, the impact of the short-selling ban on price discovery was only temporary.

4.8.3 Stock Price Effect

Similar to what Boehmer *et al.* (2012), concluded in their study, we found that short-selling ban had a positive influence on the financial stock prices of all FIBS countries. Similar conclusions resulted for non-FIBS countries. One of the reasons for such could be that the short-selling ban on FIBS countries helped European markets instil stability and more confidence in the market. The stock prices of the banned financial stocks after the ban was lifted remained fairly stable or showed slight improvements in all FIBS countries. Therefore, we concluded that the short-selling ban did not just have a temporary impact on stock market prices but also had a positive long-term impact on the financial stock prices of the banned stocks.

4.8.4 Liquidity Effect

We came to similar conclusions as Beber and Pagano (2011), that the short-selling ban has an adverse effect on market liquidity. The conclusions of the study show that all the FIBS countries suffered heavily in terms of market liquidity during the short-selling ban period. This could be due to the reason that investors fear that more stocks will be banned therefore the market flow stagnates leading to less liquidity.

The analysis of the non-FIBS countries liquidity yielded to the same conclusions as that for the FIBS countries, however the impact on liquidity was far less. These findings could be due to the instability that surrounded the Greek financial crisis, whilst on the other hand, non-FIBS countries, such as Germany and Austria, had a new record in terms of exports (Spiegel, 2013) and a strong economic performance (Deutsche Borse Group, 2012) respectively.

After the ban was lifted, the study concluded that liquidity was higher and at par with the pre-ban period in all FIBS countries. Therefore, the short-selling ban did not have a long-term impact on liquidity but liquidity was only negatively affected during the ban period.

5. Conclusions

The short selling ban led to higher volatility in the FIBS countries and also had a spill over effect on non-FIBS countries. Furthermore, with the exception of Spain,

the impact of the short selling ban on volatility was only deemed to be for a short-term period.

Although, the short selling ban did not affect Spain and Italy, it slowed down price discovery in Belgium, France and non-FIBS countries. Furthermore, all countries including the non-FIBS countries illustrated a better price discovery position after the ban was lifted; therefore the short selling ban only had a short-term impact on price discovery.

The short selling ban was enacted in order to achieve stability and improve stock market prices. This was achieved for all FIBS countries and also had a positive impact on non-FIBS countries. Furthermore, the impact of the short-selling ban on stock prices was not just temporary but had a long-term positive effect on prices.

One of the main criticisms of the imposition of a short selling ban is that it reduces liquidity and the latter was proved in this research, where liquidity in all FIBS and non-FIBS countries suffered when the short selling ban was imposed. However, the short selling ban only had a short-term impact on liquidity.

As noted, the financial stocks of FIBS countries performed differently in terms of returns prior to the ban. In fact, the financial stocks showed more positive results during the ban period as compared to the period before the ban was enacted. Furthermore, both the FIBS and non-FIBS countries performed in a similar pattern during the short selling ban period, with the exception of price discovery where Spain and Italy performed differently from the other countries analysed during the study.

The short selling-ban affected liquidity, volatility and price discovery negatively, however the impact was only of a short-term nature. On the other hand, stock prices were affected positively by the short selling ban and the impact was that of a long-term nature. The latter conclusions contradicted the findings of Beber and Pagano's (2010), that short selling bans leave stock prices unaffected or has a negative effect.

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Figure 7 – GARCH model’s results estimating volatility for France after the ban was lifted

GARCH(1,1)			Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value		LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.00		84.87	-163.75	1	0.05	0.98	1.08	2.91	TRUE	FALSE	FALSE
α_0	0.00					Target	0.00	1.00	0.00	0.00		
α_1	0.80		\sqrt{L}			SIG?	FALSE	FALSE	TRUE	TRUE		
β_1	0.00		8.39589%									

Figure 8 – GARCH model’s results estimating volatility for Italy before the ban was enacted

GARCH(1,1)			Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value		LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.01		25.01	-44.03	1	-0.01	1.00	1.45	4.03	TRUE	FALSE	FALSE
α_0	0.01					Target	0.00	1.00	0.00	0.00		
α_1	0.17		\sqrt{L}			SIG?	FALSE	FALSE	TRUE	TRUE		
β_1	0.00		9.46654%									

Figure 9 – GARCH model’s results estimating volatility for Italy during the ban period

GARCH(1,1)			Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value		LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.01		74.78	-143.56	1	0.01	1.01	0.66	1.86	TRUE	FALSE	FALSE
α_0	0.00					Target	0.00	1.00	0.00	0.00		
α_1	0.15		\sqrt{L}			SIG?	FALSE	FALSE	FALSE	TRUE		
β_1	0.00		6.26104%									

Figure 10 – GARCH model’s results estimating volatility for Italy after the ban was lifted

GARCH(1,1)			Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value		LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.00		121.06	-236.12	1	-0.01	0.95	-0.01	-0.06	TRUE	TRUE	FALSE
α_0	0.00					Target	0.00	1.00	0.00	0.00		
α_1	0.16		\sqrt{L}			SIG?	FALSE	FALSE	FALSE	FALSE		
β_1	0.16		2.88176%									

Figure 11 – GARCH model’s results estimating volatility for Spain before the ban was enacted

GARCH(1,1)			Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value		LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.00		50.40	-94.80	1	0.00	0.92	-0.54	-0.19	TRUE	TRUE	FALSE
α_0	0.00					Target	0.00	1.00	0.00	0.00		
α_1	0.00		\sqrt{L}			SIG?	FALSE	FALSE	FALSE	FALSE		
β_1	0.00		3.76972%									

Figure 12 – GARCH model’s results estimating volatility for Spain during the ban period

GARCH(1,1)			Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value		LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.00		94.64	-183.27	1	0.00	1.00	0.26	-0.40	TRUE	TRUE	FALSE
α_0	0.00					Target	0.00	1.00	0.00	0.00		
α_1	0.02		\sqrt{L}			SIG?	FALSE	FALSE	FALSE	FALSE		
β_1	0.02		4.19850%									

Figure 13 – GARCH’s model results estimating volatility for Spain after the ban was lifted

GARCH(1,1)		Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value	LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	-0.01	97.87	-189.74	1	0.02	0.97	-0.58	2.20	TRUE	FALSE	FALSE
α_0	0.00				Target	0.00	1.00	0.00	0.00	TRUE	FALSE
α_1	0.10	VL			SIG?	FALSE	FALSE	FALSE	TRUE		
β_1	0.10	3.98976%									

Figure 14 – GARCH model results estimating volatility for Non-FIBS before the ban was lifted

GARCH(1,1)		Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value	LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.00	30.77	-55.55	1	0.00	0.98	-0.28	-0.38	TRUE	TRUE	FALSE
α_0	0.01				Target	0.00	1.00	0.00	0.00	TRUE	FALSE
α_1	0.00	VL			SIG?	FALSE	FALSE	FALSE	FALSE		
β_1	0.00	7.25006%									

Figure 15 – GARCH model results estimating volatility for non-FIBS during the ban period

GARCH(1,1)		Goodness-of-fit			Residuals (standardized) Analysis						
Param	Value	LLF	AIC	CHECK	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
μ	0.00	98.95	-191.90	1	0.00	1.02	0.46	-0.03	TRUE	TRUE	FALSE
α_0	0.00				Target	0.00	1.00	0.00	0.00	TRUE	FALSE
α_1	0.00	VL			SIG?	FALSE	FALSE	FALSE	FALSE		
β_1	0.00	3.87167%									

Figure 16 – GARCH model results estimating volatility for non-FIBS after the ban was lifted

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006502	0.002046	-2.467113	0.0148
WRE	1.701995	0.112239	15.16396	0.0000
R-squared	0.522698	Mean dependent var	-0.009849	
Adjusted R-squared	0.520305	S.D. dependent var	0.055445	
S.E. of regression	0.036397	Akaike info criterion	-3.672263	
Sum squared resid	0.309616	Schwarz criterion	-3.640597	
Log likelihood	39.12599	Hannan-Quinn criter.	-3.659454	
F-statistic	239.9467	Durbin-Watson stat	2.304720	
Prob(F-statistic)	0.000000			

Figure 17 – Market model results estimating price discovery for Belgium before the ban was enacted

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006339	0.010447	-0.608794	0.5483
WRE	2.037579	0.278323	7.320923	0.0000
R-squared	0.346884	Mean dependent var	-0.004728	
Adjusted R-squared	0.340215	S.D. dependent var	0.130486	
S.E. of regression	0.105959	Akaike info criterion	-1.631557	
Sum squared resid	1.134804	Schwarz criterion	-1.580357	
Log likelihood	66.02519	Hannan-Quinn criter.	-1.610936	
F-statistic	53.99992	Durbin-Watson stat	1.054261	
Prob(F-statistic)	0.000000			

Figure 18 – Market model results estimating price discovery for Belgium during the ban period

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001683	0.005375	-0.313198	0.7544
WRE	1.852063	0.205125	9.085617	0.0000
R-squared	0.185688	Mean dependent var	0.002780	
Adjusted R-squared	0.181884	S.D. dependent var	0.086715	
S.E. of regression	0.078433	Akaike info criterion	-2.243924	
Sum squared resid	1.316476	Schwarz criterion	-2.212671	
Log likelihood	24.43438	Hannan-Quinn criter.	-2.231298	
F-statistic	48.79885	Durbin-Watson stat	1.840846	
Prob(F-statistic)	0.000000			

Figure 19 – Market model results estimating price discovery for Belgium after the ban was lifted

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000514	0.001290	-0.398282	0.6906
WRE	1.163192	0.047797	24.33611	0.0000
R-squared	0.504793	Mean dependent var	-0.003267	
Adjusted R-squared	0.503940	S.D. dependent var	0.044057	
S.E. of regression	0.031030	Akaike info criterion	-4.104302	
Sum squared resid	0.559421	Schwarz criterion	-4.089317	
Log likelihood	1198.404	Hannan-Quinn criter.	-4.098461	
F-statistic	592.2461	Durbin-Watson stat	1.995116	
Prob(F-statistic)	0.000000			

Figure 20 - Market model results estimating price discovery for France before the ban was enacted

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001731	0.003577	-0.483889	0.6289
WEEKLY_RETURNS	1.323030	0.079058	16.73482	0.0000
R-squared	0.523413	Mean dependent var	0.003084	
Adjusted R-squared	0.521644	S.D. dependent var	0.082039	
S.E. of regression	0.057162	Akaike info criterion	-2.878104	
Sum squared resid	0.833210	Schwarz criterion	-2.856485	
Log likelihood	37.18363	Hannan-Quinn criter.	-2.866997	
F-statistic	280.0543	Durbin-Watson stat	2.282859	
Prob(F-statistic)	0.000000			

Figure 21 – Market model results estimating price discovery for France during the ban period

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002296	0.001435	1.599745	0.1102
WEEKLY_RETURNS	1.295968	0.062579	20.72529	0.0000
R-squared	0.441213	Mean dependent var	0.004795	
Adjusted R-squared	0.440186	S.D. dependent var	0.044661	
S.E. of regression	0.053416	Akaike info criterion	-3.955623	
Sum squared resid	0.607437	Schwarz criterion	-3.940162	
Log likelihood	108.1967	Hannan-Quinn criter.	-3.948762	
F-statistic	429.5375	Durbin-Watson stat	1.809432	
Prob(F-statistic)	0.000000			

Figure 22 – Market model results estimating price discovery for France after the ban was lifted

Dependent Variable: AVERAGE_RETURNS
Method: Least Squares
Date: 03/28/15 Time: 09:37
Sample (adjusted): 8/09/2010 8/08/2011
Included observations: 53 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.51E-05	0.006701	-0.008222	0.9935
WRE_PRE	1.023904	0.200906	5.096432	0.0000
R-squared	0.337435	Mean dependent var		-0.004934
Adjusted R-squared	0.324444	S.D. dependent var		0.058748
S.E. of regression	0.046286	Akaike info criterion		-3.186328
Sum squared resid	0.118910	Schwarz criterion		-3.111977
Log likelihood	86.43768	Hannan-Quinn criter.		-3.157736
F-statistic	26.97362	Durbin-Watson stat		2.915385
Prob(F-statistic)	0.000005			

Figure 23 – Market model results estimating price discovery for Italy before the ban was enacted

Dependent Variable: AVERAGE_RETURNS
Method: Least Squares
Date: 03/28/15 Time: 09:38
Sample: 8/16/2011 2/06/2012
Included observations: 26

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007543	0.015382	0.490343	0.6283
WRE_BAN	1.031941	0.303306	3.402312	0.0023
R-squared	0.325393	Mean dependent var		0.010036
Adjusted R-squared	0.297274	S.D. dependent var		0.093460
S.E. of regression	0.078347	Akaike info criterion		-2.181546
Sum squared resid	0.147316	Schwarz criterion		-2.084770
Log likelihood	30.36010	Hannan-Quinn criter.		-2.153678
F-statistic	11.57572	Durbin-Watson stat		2.665568
Prob(F-statistic)	0.002344			

Figure 24 – Market model results estimating price discovery for Italy during the ban period

Dependent Variable: AVERAGE_RETURNS
Method: Least Squares
Date: 03/28/15 Time: 09:39
Sample: 2/13/2012 2/25/2013
Included observations: 55

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.010070	0.007262	1.386620	0.1714
WRE_POST	0.999920	0.217184	4.604021	0.0000
R-squared	0.285686	Mean dependent var		0.010136
Adjusted R-squared	0.272208	S.D. dependent var		0.063134
S.E. of regression	0.053860	Akaike info criterion		-2.969101
Sum squared resid	0.153746	Schwarz criterion		-2.896187
Log likelihood	83.55249	Hannan-Quinn criter.		-2.940954
F-statistic	21.19701	Durbin-Watson stat		2.685723
Prob(F-statistic)	0.000026			

Figure 25 – Market model estimating price discovery for Italy after the ban was lifted

Dependent Variable: AVERAGE_RETURNS
Method: Least Squares
Date: 03/28/15 Time: 10:42
Sample (adjusted): 2/55
Included observations: 55 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001105	0.002160	-0.511638	0.6110
WRE_PRE	0.711158	0.064715	10.98885	0.0000
R-squared	0.694973	Mean dependent var		-0.003216
Adjusted R-squared	0.689217	S.D. dependent var		0.028626
S.E. of regression	0.015958	Akaike info criterion		-5.401986
Sum squared resid	0.013497	Schwarz criterion		-5.329002
Log likelihood	150.5549	Hannan-Quinn criter.		-5.373768
F-statistic	120.7548	Durbin-Watson stat		1.704329
Prob(F-statistic)	0.000000			

Figure 26 – Market model estimating price discovery for Spain before the ban was enacted

Dependent Variable: AVERAGE_RETURNS
Method: Least Squares
Date: 03/28/15 Time: 10:43
Sample (adjusted): 2/27
Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000959	0.003233	0.296699	0.7892
WRE_BAN	0.713842	0.076560	9.323983	0.0000
R-squared	0.783660	Mean dependent var		0.003716
Adjusted R-squared	0.774646	S.D. dependent var		0.034578
S.E. of regression	0.016415	Akaike info criterion		-5.307457
Sum squared resid	0.006467	Schwarz criterion		-5.210681
Log likelihood	70.99995	Hannan-Quinn criter.		-5.279589
F-statistic	86.93665	Durbin-Watson stat		2.073269
Prob(F-statistic)	0.000000			

Figure 27 – Market model estimating price discovery for Spain during the ban period

Dependent Variable: AVERAGE_RETURNS
Method: Least Squares
Date: 03/28/15 Time: 10:43
Sample (adjusted): 2/20/2012 2/25/2013
Included observations: 54 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001167	0.002522	-0.462565	0.6456
WRE_POST	1.017068	0.068494	14.84908	0.0000
R-squared	0.809171	Mean dependent var		-0.001427
Adjusted R-squared	0.805501	S.D. dependent var		0.042025
S.E. of regression	0.018534	Akaike info criterion		-6.102089
Sum squared resid	0.017862	Schwarz criterion		-6.028423
Log likelihood	139.7564	Hannan-Quinn criter.		-5.073679
F-statistic	220.4952	Durbin-Watson stat		2.113754
Prob(F-statistic)	0.000000			

Figure 28 – Market model estimating price discovery for Spain after the ban was lifted

Dependent Variable: AVERAGE_RETURNS
Method: Panel Least Squares
Date: 04/02/15 Time: 10:13
Sample (adjusted): 8/09/2010 8/08/2011
Periods included: 53
Cross-sections included: 4
Total panel (balanced) observations: 212

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.004042	0.001618	-2.497791	0.0133
WRE	1.035452	0.052533	19.71032	0.0000
R-squared	0.649121	Mean dependent var		-0.007583
Adjusted R-squared	0.647450	S.D. dependent var		0.039436
S.E. of regression	0.023415	Akaike info criterion		-6.615250
Sum squared resid	0.115132	Schwarz criterion		-4.629854
Log likelihood	486.1211	Hannan-Quinn criter.		-4.648721
F-statistic	388.4988	Durbin-Watson stat		2.104703
Prob(F-statistic)	0.000000			

Figure 29 – Market model estimating price discovery for non-FIBS before the ban was enacted

Dependent Variable: AVERAGE_RETURNS
Method: Panel Least Squares
Date: 04/02/15 Time: 10:15
Sample (adjusted): 8/22/2011 2/06/2012
Periods included: 25
Cross-sections included: 4
Total panel (unbalanced) observations: 96

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002635	0.004094	-0.643812	0.5213
WRE	1.292056	0.089305	14.46792	0.0000
R-squared	0.690097	Mean dependent var		0.000893
Adjusted R-squared	0.686800	S.D. dependent var		0.071540
S.E. of regression	0.040037	Akaike info criterion		-3.577407
Sum squared resid	0.159579	Schwarz criterion		-3.523983
Log likelihood	173.7155	Hannan-Quinn criter.		-3.555812
F-statistic	209.3208	Durbin-Watson stat		1.770603
Prob(F-statistic)	0.000000			

Figure 30 – Market model estimating price discovery for non-FIBS during the ban period

Dependent Variable: AVERAGE_RETURNS				
Method: Panel Least Squares				
Date: 04/02/15 Time: 10:20				
Sample (adjusted): 2/20/2012 2/25/2013				
Periods included: 54				
Cross-sections included: 4				
Total panel (balanced) observations: 216				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002108	0.002040	-1.033265	0.3026
WRE	0.778101	0.062298	12.48999	0.0000
R-squared	0.421621	Mean dependent var	-5.22E-05	
Adjusted R-squared	0.418919	S.D. dependent var	0.039207	
S.E. of regression	0.029887	Akaike info criterion	-4.173568	
Sum squared resid	0.191152	Schwarz criterion	-4.142315	
Log likelihood	452.7453	Hannan-Quinn criter.	-4.160942	
F-statistic	155.9998	Durbin-Watson stat	1.950583	
Prob(F-statistic)	0.000000			

Figure 31 – Market model estimating price discovery for non-FIBS after the ban was lifted

Appendix B - DEFINITION OF GARCH (1,1) MODEL

GARCH MODEL

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

σ_n^2 - GARCH Model

V_L - Long-Run Average Variance Rate

γ - Weight Assigned to V_L

α - Weight Assigned to u_{n-1}^2

β - Weight Assigned to σ_{n-1}^2

$$\gamma + \alpha + \beta = 1$$

Appendix C – FIBS AND NON-FIBS' CONSTITUENTS

<u>FIBS</u>			
<u>BELGIUM</u>	<u>FRANCE</u>	<u>ITALY</u>	<u>ITALY</u>
Ageas SA_NV	April Group	Assicurazioni Generali	Banca Ifis
Dexia SA	Credit Agricole	Banca Popolare dell'Etruria	Banco di Sardegna
KBC Ancora	AXA	Intesa Sanpaolo	Ubi banca
	Euler Hermes	Azimut Holding	Banca Intermobiliare
	BNP Paribas	Banca Popolare di Milano	Banco Popolare
	Natixis	Mediobanca	UniCredit
	CIC	Banca Carige	Banca Monte dei Paschi
	SCOR	Banca Popolare di	Credito Emiliano

		Sondrio	
	CNP Assurance	Mediolanum	Unipol
	Societe Generale	Banca Finnat	Banca Popolare dell'Emilia Romagna
		Banca Profilo	Credito Valtellinese
		Milano Assicurazioni	
		Banca Generali	
		Banca di Desio e Brianza	
		Societa Cattolica di Ass	

<u>NON-FIBS</u>			
<u>AUSTRIA</u>	<u>GERMANY</u>	<u>GREECE</u>	<u>NETHERLANDS</u>
Erste Group Bank	Aareal Bank AG	Alpha Bank AE	Aegon
Raiffeisen Bank	Allianz SE	Hellenic Exchanges	Delta Lloyd NV
Vienna Insurance Group	Commerzbank AG	Marfin Investment	ING Groep NV
	Deutsche Bank AG	Piraeus Bank SA	Kuka AG
			Nanostart AG
			MLP AG