



LUND UNIVERSITY

School of Economics and Management

Testing the effects of short-selling constraints in Europe on stock return volatility using
GARCH models

Master Thesis

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Abstract

By betting on market downturns, short sellers make profits from asset declines. Thus, critics often blame short sellers for being responsible for market downturns and as a consequence, short selling restrictions became a popular phenomenon worldwide post the 2008 financial crisis. During the European sovereign debt crisis regulators in France, Belgium, Spain and Italy imposed a short selling bans for financial stocks in order to prevent further market downturns. The ban, with the purpose of reducing market volatility and the effect of false rumours, was active between August 2011 and February 2012. This paper studies the impact on market volatility from this short selling ban and attempts to ascertain whether or not it achieved its objective. In order to test for the stock market volatility in the four European countries where the ban was imposed, we use a variety of Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. We apply these models to portfolios of stocks that were subject to a short selling ban, as well as to portfolios of stocks that were not. We find some evidence of an increase in the volatility of returns for stocks on which short selling was not banned and attempt to explain why this is the case.

Acknowledgements

We would like to express our sincere gratitude to our advisor Frederik Lundtofte for his help, guidance and useful feedback. Additionally, we would like to thank our conversants Daniel Mohall and Can Telmen for valuable insights and feedback during our midterm seminars.

Keywords: GARCH, Short selling, short sale restrictions, EGARCH, volatility

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1. Introduction

Short sellers tend to receive elevated scrutiny from regulators and the financial press. In past periods of financial instability, regulators have often imposed bans on short selling of stocks with the goal of calming the markets and preventing further price declines. The appropriateness of these bans is a matter of debate, and their effects on stock markets have been studied. We want to add to this research by studying their effect on stock market volatility.

The common investor who invests their money in the stock market is interested in seeing prices increasing over time, giving them a positive return on their money. In contrast, the short seller profits from a decrease in stock prices. This puts these two types of agents at odds with each other. When markets are decreasing, short sellers are often in the awkward position of profiting while everyone else are losing their shirts. Short sellers nonetheless play an important role in the market. By short selling overvalued assets, they help these assets reach their fair value, making the market as a whole more efficient.

Occasionally, during periods of high financial market volatility and significant market declines, regulators restrict or ban short selling, possibly in the hope of preventing prices from declining further, or perhaps in order to calm markets, reducing their volatility to 'normal' levels. This has for instance happened during the 2008 financial crisis in many countries around the world, as governments scrambled to contain the fallout from the bankruptcy of the investment bank Lehman Brothers. The focus of our paper will be a subsequent short selling ban imposed in four countries in the Eurozone: Italy, Spain, France and Belgium, which was in place from August 2011 until February 2012, during the height of the European sovereign debt crisis.

The purpose of this paper is to investigate if short selling restrictions have an effect on stock return volatility. Previous papers have focused on the effect of these short selling bans on market liquidity and on their ability to prevent prices from declining further. Comparatively little research has been made on the relationships between short selling bans and market volatility. We will test the effects of one of these bans on stock market volatility, using Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models on portfolios of stocks that were subject to a short selling ban, compared to portfolios of stocks that were not. This should allow us to see if the imposition of the ban was able to reduce the volatility of the affected stocks. Our paper thus adds to the research by examining a recent event

from a new perspective and providing empirical evidence for whether or not short selling regulations are effective.

The rest of our paper will proceed as following. Section 2 will give a short theoretical background and discuss prior research in the area of short selling and bans on short selling. Section 3 gives an overview and theoretical background to using GARCH models to estimate volatility. In section 4, we discuss our data and methods. In section 5 we will examine our results, and finally in section 6 we will provide a brief summary and a conclusion.

2. Theoretical background and literature review

Short selling

Short selling is a trading strategy where an investor wants to profit from a future decrease in the price of an asset that they have anticipated. In a short sale, the investor sells an asset first, then buys it back again at a later date, hopefully at a lower price. In order to accomplish this, the investor will arrange to borrow the asset that they wish to short from someone else. This asset will then be returned once the investor has repurchased the asset on the market, closing out his position. Often, the investor will also pay a fee to the owner of the asset for the privilege of borrowing it (Fabozzi et al, 2004, pp. 9-16).

There is more than one reason to short sell. An investor may be making a purely speculative bet that a particular asset is overvalued by the market, hoping to profit as new information is revealed and the market brings the price back down to the asset's intrinsic value.

Alternatively, an investor might short sell for the purpose of hedging an investment. For instance, if the investor was concerned that a portfolio they are holding would decrease in value during a market downturn, they might sell short a basket of similar assets. The loss on their portfolio would then be made up by the gain on the short sale. This is particularly useful for financial institutions who may occasionally need to hold certain assets on their books whose risk they want to avoid being exposed to¹. Short selling can also be used in relatively more sophisticated trading strategies where an investor buys one asset and short sells another, hoping to profit from convergence or divergence in their prices. Such a trading

¹ For example, when underwriting a stock issue by HBOS, Morgan Stanley took a large short position in the stock of HBOS in order to hedge their risk, as they would have had to hold any shares they could not sell. See Farrell (2008).

strategy was for instance employed with some success by the hedge fund Long-Term Capital Management (Lowenstein, 2002).

It is a somewhat controversial practice. On the stock market, short sellers find themselves on the opposite side of both traditional long investors as well as company management, hoping that a particular company's stock will decline. Managers of companies whose stock is falling have often blamed short sellers for their troubles², and it seems that, by adding selling pressure to a stock, short sellers may have a hand in causing a stock price to decline. On the other hand, short sellers may simply be doing the market a favour by bringing the prices of overvalued assets back to their intrinsic value, protecting other investors from purchasing an asset at an inflated price.

In periods of significant market declines and increased volatility regulators have often imposed short selling bans in the hope of calming markets and preventing things from getting worse. Gruenewald et al. (2010) has a comprehensive overview of short selling bans around the world in response to the 2008 financial crisis. These bans and regulations take various forms - on the lighter end some countries have required that investors make disclosures about their net short positions once they reach a certain threshold of their capital. Commonly, regulators have banned so-called "naked" short selling where a stock is sold short before the seller has located and borrowed the stock³. On the stricter end regulators have outright banned short selling of any kind, occasionally just on stocks of financial institutions, but at other times of all listed stocks. It is one of these outright short sale bans that we focus on in our paper.

Citing high volatility and the spread of false rumours, the European Securities and Markets Authority (ESMA) announced on August 11th, 2011 the imposition of a ban on the short selling of the stocks of financial companies in four countries: Belgium, France, Italy and Spain. This was accompanied by statements from the financial regulators in each of the four countries detailing specifically which companies on which short selling was banned. Originally intended to be in place for only 15 days, this particular short-selling ban was extended several times and in place until February of 2012, and it is this period which is our study focuses on. If the regulators were able to reduce volatility with a short selling ban, it might prove a useful tool in future financial crises for keeping markets calm. Conversely, if

² For example, CEO of Lehman Brothers Richard Fuld blamed a "plague of naked short selling" for the failure of the firm. See Kirchgaessner and Farrell, (2008).

³ This is possible because settlement of stock trades is not instant

banning short selling proved unable to reduce volatility, such a ban might be a mistake, especially if there are other negative effects associated with the ban. Félix et al. (2013) has an overview of the specific stocks subject to the short-selling ban.

Background for the ban

Prior the ban the European markets had faced weeks of turmoil and high volatility due to the ongoing European sovereign debt crisis, and banks especially were under the most pressure. Causing increased concern in the European markets, the ESMA introduced the ban with the aim of restricting the benefits arising from spreading false rumours and misleading signals and information (ESMA, 2011).

Following a sharp price decline, the 15-day short sale ban was introduced in Belgium, France, Italy and Spain in August 2011. The banks in France were under severe short sale pressure from speculators, and the country therefore took the first initiative for the short sale ban. The four countries intended to get other regulators in other European countries to follow, but they were unable to do so. The UK for instance had introduced a ban in 2008 and was sceptical towards establishing another one. All four countries introduced short selling restrictions to financial stocks, however the restrictions in Belgium and France did not include short selling of derivatives, which was covered by the Spanish ban (Financial Times, 2011).

At the time, the short-sellers viewed the European banks as being fragile and weak institutions, and the combination of declining trust in Europe's politicians, and the problems with sovereign debt gave them plenty of reasons for speculating in falling bank stocks (McCrum, 2011). Kenneth S. Rogoff, a professor of economics at Harvard University, commented that, "the crisis in Europe goes far beyond falling stock prices and has more to do with the state of banks there" (Story and Castle, 2011). Generally, financial institutions in Europe were still weakly capitalised following the financial crisis and recession of 2008, and as European sovereign bonds came under some pressure during 2011, this translated into further negative pressure on the stocks of these financial institutions, as they typically held many of these bonds as part of their capital.

Following the ESMA, the regulators of the four countries also released their own statements. The Italian Companies and Stock Exchange Commission (CONSOB), August 12, 2011, resolution No. 17902 Restrictive Measures on Net short positions on shares, states that "with the aim of ensuring the transparency of the markets regulations will be imposed. In

order to protect investors and certify orderly conduct of trading, an urgent yet temporarily solution will be introduced, due to the current market situation, where net short position on shares or increase in existing net short position will be prohibited” (CONSOB, 2011).

For France, the ban on taking net short position in French securities in the financial sectors was decided by the AMF, Article L.421-16 II of the Monetary and Financial Code. Similar to the decision made by CONSOB, any net short position or increasing any existing net short position, including intraday, was prohibited. However, the ban did not apply to financial intermediaries acting as market makers or liquidity providers when they are operating under a contract with the relevant market undertaking or with the issuer concerned, or when acting as counterparty for block trades in equity (AMF, 2011).

In Belgium, the Financial Services and Market Authorities (FSMA) modified the rules of short selling restrictions on Euronext Brussels. Belgium, which had already restricted so-called “naked” short selling in shares or derivatives on the Euronext Brussels in 2008, altered the restrictions in The Royal Decree 23 September 2008, to prevent covered short selling as well. The rule did not apply to any existing net economic short positions, but they could not be increased. Jean-Paul Servais, Chairman of the FSMA did not regard misleading information to have a remarkable effect on the financial securities listed on Euronext Brussels, rather, the FSMA undertook this decision mainly because of the increased volatility in the financial markets. (FSMA, 2011).

Followed by the end of the ban in France on February 12th, 2013, the FSMA altered the short-selling restrictions on Belgian financial institutions once again on February 13th. The FSMA decided to gradually adapt its temporary ban into a permanent system. To reach its decision, the FSMA took into account that while there was a lower volatility in the market, they continued to observe the development of the market carefully. The new regulations stated that there is an obligation to report net short positions as long as they are not prohibited, and that naked short selling is still subject to the ban. Furthermore, in order to reduce the risk of undesired market disturbance, the “locate rules” states that if a person without ownership or having borrowed the shares want to sell them are thus required to make certain arrangements to make sure that they have a reasonable assumption that the shares can be delivered in time (FSMA, 2012).

Previous bans

There have been several previous short selling constraints in the past, for instance in September 2008 the Security Exchange Commission (SEC) in US, together with Financial Services Authorities (FSA), in the UK, imposed a short sale ban on financial stocks. The main reason for the ban was based on concern for the financial companies and to maintain the integrity and quality of those companies as well as rehabilitate market equilibrium (SEC, 2009). While the ban in UK covered a longer time period between September 2008 until January 2009 (FSA, 2008) and applied to 32 financial stocks (FSA, 2008), the ban in the US was limited to just a few weeks and started off by covering 799 financial stock (SEC, 2009).

Following the short sale ban in the US, just a few days after the ban, financial stocks took another downturn and people started to question whether the short sellers were the ones to blame at all, and whether the problem was in fact the financial institutions (Story, 2008). Furthermore, according to then chairman of the SEC Christopher Cox (2008), imposing the short sale ban was his biggest regret during his tenure at the SEC (Younglai, 2008).

Literature review

Short selling and restrictions to it has been examined from both theoretical and empirical angles. Miller (1977) produces a theoretical model in which the price of a given stock is affected by divergence of opinion among investors. He argues that since the short-term supply of a particular stock is fixed, the price of it will be determined by the subset of investors who are most optimistic about the prospects of the stock (similar to how in bidding for oil prospecting rights, the prospectors with the highest expectations for a particular field will tend to submit the highest bids). Short sellers are however able to effectively create new stock with their short positions, which allows them to shift the supply curve to the right, allowing more pessimistic investors to express their opinion on the stock's fair value. The implication is then that restrictions on short selling leads to securities being overvalued, especially securities that have the greatest divergence of opinion among investors, such as very risky stocks where future outcomes are subject to a great deal of uncertainty.

Diamond and Verrecchia (1987) model an economy with three types of agents - market makers, informed traders and uninformed traders. In any given period, the informed traders know the true value of a security, whereas uninformed traders will trade based on inferences they make from the actions of other traders. Informed traders will short based on their

information about a stock, whereas uninformed traders will only short if they find themselves in need of liquidity in order to consume today (noise traders, essentially). Diamond and Verrecchia find that restricting short selling in the market increases the time it takes for prices to adjust to new private information, as the informed traders are not as easily able to impact their private information in the stock price. Another implication of the study is that when traders are restricted from short selling they will simply choose not to trade instead. The existence of non-trading periods under short selling constraints then imply that informed traders who would have sold a stock short instead choose to remain on the bench. This implies that future returns will be lower.

Taken together, these two studies imply that the presence of short sellers in a market helps informational efficiency by allowing prices to reflect the intrinsic value of a security, and increasing the speed at which prices adjust to new information. The corollary is then that restrictions on short selling reduce informational efficiency.

On the empirical side, there has been several studies of prior short selling bans. Beber and Pagano (2013) study a large sample of stocks around the world on which short selling was banned in the period around the 2008 financial crisis and find that the imposition of short selling bans affected market liquidity negatively, which was visible in widening bid-ask spreads for banned stocks. They find less evidence of any effect on stock prices - given other events at the time, such as TARP⁴, it is hard to tease out the effect of short selling bans alone on stock prices.

There is also Félix et al. (2013) who study the same short selling ban as us. Using implied volatility skews as a proxy for investor risk aversion, they find that the ban increased risk aversion across the market. This increase in risk aversion increased the price of put options on stocks, preventing speculators from further placing bets on declining share prices. The short selling ban thus accomplished its goal of preventing short sales, “restricting both outright and synthetics shorts”, but this came at a cost.

It is not immediately clear how short selling and volatility are linked. By helping keep stock prices near their intrinsic value, as in Miller (1977), short sellers might actually help keep price volatility down, as adjustments to new information would not be nearly as drastic as they would be if stock prices were far above their intrinsic value. In an empirical study,

⁴ The Troubled Asset Relief Program, an effort by the US Treasury to stabilise financial markets in 2008

Charoenruek and Daouk (2005) find support for this, showing that “when short-selling is possible, aggregate stock returns are less volatile and there is greater liquidity”. Using an ARCH model and a binary variable indicating whether or not short-selling is feasible, they find a negative and significant effect on stock return volatility in both developed and emerging countries whenever short selling is feasible.

Boehmer et al. (2013) study 727 US stocks that were subject to short selling bans in 2008 and match them to other stocks that were not banned. Among their findings, they note that the imposition of the short selling ban lead to an increase in firm-level volatility, as measured by intraday volatility. This effect was strongest for the largest firms. They also find that any positive effect on prices concurrent with the imposition of the ban were likely due to TARP.

Most studies support the hypothesis that short-selling constraints contribute to a decrease market efficiency, however, this conclusion is not shared by all investors. The research conducted by Alves et al. (2015), adds to the literature by analysing the impact of the short sale ban imposed by France, Belgium, Spain and Italy in 2011. In order to assess whether the bans were successful in reducing the risks of negative price spirals, they examined the market quality, volatility, liquidity and the price discovery process, before and during the ban, as well as the impact on the restricted stocks price dynamics. In order to examine whether the short sale ban was successful in reducing price uncertainty they investigated the pattern of short-term volatility before and during the ban, and one of the hypotheses in their research was that short selling bans did not have an impact on volatility. 170 financial Western European stock were included in their research, whereas 58 of them were subject to the ban. In order to analyse the pattern a control group were created consisting of all the financial stocks in the sample which were not subject to the ban. Thereafter a Logit model was estimated which included a dummy variable with the value one if the stock is subject to the ban and zero otherwise. A Garman-Klass volatility estimator was then used as a proxy for volatility. Their results show that subsequent to the bans announcements the median volatility between the treatment and the control group peaked several times, which support the idea of a greater volatility increase among the treatment stocks. Further, it shows that as the ban was established the volatility change is 10.3 percentage points higher for banned stocks. They conclude that the ban did not contribute to reduced volatility of the financial stocks during the ban period and thus, the intention of reducing volatility failed.

A similar research was conducted by Bohl et al (2012) where they investigated whether short selling restrictions destabilized the Taiwanese stock market, during the short sale ban

from 1998 until 2005. They argue that short sale bans are counterproductive since they anticipate a volatility increase during the period when short sale ban takes place since restrictions will inhibit investors' ability to find the fundamental price of the asset, as in Miller (1977). Further, a short sale ban will lead to a destabilization of stock prices when the market is in a decline and in some cases, worsen stock prices declines. By using a Markov-switching GARCH model and several different asymmetrical GARCH models and they found evidence that short selling restrictions increased stock return volatility.

Morales-Zumaquero and Sosvilla-Rivero (2015) have been investigating the impact from the short selling ban on the Spanish stock exchange in 2011 and the financial market volatility. Their research covers the impacts on the volatility of the underlying index, Ibex-35, and financial stocks from when the Comisión Nacional del Mercado de Valores (CNMV) introduced the short selling ban. In order to test for the effect of the ban on the volatility from the closing price and the trading volume, they applied structural changes in variance to address possible structural breaks. Their results show several structural breaks; however, they do not correspond with the time of the ban, instead they are linked with country-specific incidents or other events happening in Europe. Thus, there is no indication that the ban had an impact on the Spanish market and whether CNMV achieved their goal, rather, the resulting effect of the ban might have contradicted effects on the Spanish market due to the reduction in market liquidity.

Bohl et al's (2016) research focuses on short sale restrictions' impacts on stock return volatility on the German stock market during the period 2008-2010. Their main focus is on volatility persistence rather than changes in volatility levels, in which volatility persistence is described as investors limited ability find the fundamental price during periods of short selling constraints. In order to analyse the volatility persistence an asymmetric Markov-switching GARCH model is applied to the short sale ban. They argue that the model main advantages are firstly its ability to capture any form of regime-specific asymmetric volatility effects and secondly, it allows to estimate alternative GARCH equations of entirely differential functional forms across the volatility regimes. They created two indices, one on those stocks restricted from the short sale constraints and another, the control group, consisting of all the stocks on DAX which were not subject to the short sale constraints. In their research, they estimated two separate versions of a two-regime Markov-switching asymmetric GARCH model for the stock return on the two indices. Their findings show, despite the overall increase in the conditional variances for whole German during that time period as an effect of the breakdown of Lehman brothers, that the short sale restriction,

during the period of downturn, did not contribute to a stabilization of stock prices. Further, they end their paper with a recommendation that regulators should avoid imposing short selling restrictions.

Baklaci et al (2016) adds to the literature by being the first to cover both the short and long-run causality between volatility and short selling. They examined the causality between short selling trades and volatility in the US market by using the Granger causality link. The result of their study shows that when there is an increase in short selling activities there is an increase in return volatility. They found a bilateral causality between the short-selling trades and the volatility of price changes and conclude that short selling increases volatility and thus there is a possibility that it will have a destabilizing effect on the market. Further, in order to deter market destabilization, they are suggesting that regulators should strengthen their supervision in monitoring the market and even impose stricter short selling restriction.

Short sale restrictions tend to come during periods of elevated market uncertainty, and if they have an effect on uncertainty it might transmit through to volatility. Liu and Zhang (2015) look into the economic policy uncertainty (EPU) ability to predict stock market volatility. Further, they are testing if the forecasting prediction of the volatility models can be improved by adding EPU to the models. In order to calculate daily realized volatility (RV), they used 5 minutes high-frequency return of the S&P500 and where several different volatility models were used to capture RV. Disregarding which of the different volatility models that were being used, the results demonstrate that different impacts of previous EPU on current RV are highly significant as well as EPU's ability on predicting market RV. Moreover, since business-cycle fluctuations is one of the main explanations to market activity, their results indicate that EPU indexes can thus, play a part in foreseeing economic recessions. In other words, increased economic uncertainty seems to lead to increases in volatility and by measuring economic uncertainty it can be easier to predict an economic decline.

3. Overview of estimation of Autoregressive Conditional Heteroscedasticity models

ARMA models

To model financial time series such as stock prices or returns, an ARMA model is often applied, where the variable of interest is regressed on its own past values. The ARMA model is a combination of the properties from the autoregressive AR(p) and moving average MA(q) parts. The autoregressive processes states that the value of y_t is dependent on its values in previous periods, y_{t-i} , as well as a stochastic error term, u_t , and is shown in equation 1. (Brooks, 2014, p. 259):

$$y_t = \mu + \sum_{i=1}^p \phi_i y_{t-i} + u_t \quad (1)$$

The moving average processes express y_t as dependent on the current and previous values of the white-noise error term, u_t , with a constant mean, $E(u_t) = 0$ and constant variance $var(u_t) = \sigma^2$. Thus, an MA(q) process is expressed as follows (Brooks, 2014, p. 256):

$$y_t = \mu + \sum_{i=1}^q \theta_i u_{t-i} + u_t \quad (2)$$

The combination of the MA(q) and AR(p) parts creates an ARMA model, where y_t depends linearly on its own value in a previous period together with the white noise term and past values of the white noise term, and it is given by the equation (Brooks, 2014, p. 268):

$$\phi(L)y_t = \mu + \theta(L)u_t \quad (3)$$

Stock prices have often been argued to follow a random walk process (see for instance Fama, 1965), meaning that the stock price today is a function of the stock price yesterday, plus today's random error. This is due to the efficient markets hypothesis, the idea being that the price today incorporates all publicly available information on the company. If this is true, it then follows that stock prices tomorrow can't be predicted based on what they are today (or more precisely, stock prices tomorrow will be the same as today, plus an unknown

stochastic shock). A return series, which is simply a price series differenced once, will then solely be a function of a stochastic error term.

ARCH models

One of the assumptions of the Classical Linear Regression Model (CLRM) is that the variance of the errors is constant, that is, the errors are homoscedastic, and the variance of the entire process is then also a constant term. However, it would be implausible to assume that the errors for financial data remain constant over time. Financial time series often show what is known as volatility clustering where the variance of the error term appears to vary over time. Periods of low volatility tend to be followed by periods of low volatility, and periods of high volatility tend to be followed by periods of high volatility. In order to better model this property, a non-linear estimation method is required, (Brooks 2014, p. 416).

Some of the most widespread non-linear models applied to financial data for modelling volatility are the Autoregressive Conditionally Heteroscedastic (ARCH) models and Generalised Autoregressive Heteroskedasticity (GARCH) models. The ARCH model was specified by Engle (1982). If volatility tends to cluster as described above, it could be modelled as an autoregressive process, and by using an ARCH model the autocorrelation in the variance can be estimated by letting the conditional variance of the error term be dependent on the previous value of the squared errors. The conditional variance of u_t which can be written as σ_t^2 is then given by the following equation:

$$\sigma_t^2 = \text{var}(u_t | u_{t-1}, u_{t-2}, \dots) = E[u_t^2 | u_{t-1}, u_{t-2}, \dots] \quad (4)$$

The general case of an ARCH(q), where the error variance is dependent on q lags of squared errors can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_q u_{t-q}^2 \quad (5)$$

Or in sigma notation, the expression is:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i u_{t-i}^2$$

By adapting an ARCH model, the errors do not need to be constant, and accordingly heteroscedasticity in the errors is now allowed (Engle, 2001). In order to ensure that the model gives positive values for conditional variance (as a negative variance would be nonsense), the α -parameters must be restricted to being positive. This is known as the non-negativity constraint (Brooks 2014, p. 425).

GARCH models

There are a few restrictions and difficulties regarding the use of the ARCH(q) model. Firstly, deciding the number of lags of the squared residual can involve some problems, as the conditional variance process tends to have a long memory. The more parameters are included in the conditional variance equation, the higher the likelihood that one of them is negative, which would violate the non-negativity constraint. One way to deal with these problems is using a GARCH model, which is an extension of an ARCH(q) model, (Brooks 2014, p. 428, 430):

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i u_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (6)$$

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is presented by Bollerslev (1986), and the models have been used in modelling the relation between conditional variance and asset risk premium (Nelson, 1991). The GARCH model allows the conditional variance to be dependent upon on past values of the squared errors and also on past conditional variance, where σ_{t-j}^2 represent the variance from the previous period and u_{t-i}^2 represents the squared residuals, (Engle, 2001). Generally, a GARCH (1,1) will be used in practice since, among the different volatility models, it is perceived as being more simple and robust, (Engle, 2001). The GARCH (1,1) is given by the equation (Brooks 2014, p. 428):

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (7)$$

Where the conditional variance is a weighted function of the constant term ω , the shocks in volatility which is measured as yesterday's squared error from the conditional mean equation, u_{t-1}^2 and yesterday's forecast variance, σ_{t-1}^2 . α and β determine the persistence of volatility shocks and can be estimated by maximum likelihood. Engle and Bollerslev (1986) used the GARCH (1,1) to model the risk premium on the foreign exchange market, and by

extending the GARCH (1,1) into a multivariate model, Engle and Bollerslev together with Woolridge tested a conditional CAPM with time varying covariances of asset returns.

Equation 7 can be rewritten as (Nelson, 1991):

$$\sigma_t^2 = \omega + \sum_{k=1}^{\infty} \phi_k z_{t-k}^2 \sigma_{t-k}^2 \quad (8)$$

By equalizing the conditional variance to the weighted average of squared residuals in addition to a constant term, the GARCH (1,1) captures the volatility clustering in asset returns, (Nelson, 1991). The GARCH model can thus be viewed as analogous to an ARMA model for the conditional variance.

Asymmetric models

While having less parameters decreases the likelihood of some being negative, the GARCH model is still limited by the non-negativity constraints on ω and ϕ_k , which are supposed to assure a positive σ_t^2 for all t , (Nelson). Further, the basic GARCH is limited by the fact that it assumes symmetry. As it depends on the square of past values of the error term and of itself, it is affected equally by positive and negative shocks to the process. However, in practice we deal with a phenomenon known as the leverage effect, where negative shocks to returns tend to increase volatility more than positive shocks. In order to account for these limitations there are several asymmetric extensions to the basic GARCH model which can be adapted. (Brooks, 2014, p. 440).

Firstly, the GJR model has an additional term added to account for possible asymmetries. The conditional variance is given by the following equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \quad (9)$$

where $I_{t-1} = 1$ if $u_{t-1} < 0$
 $= 0$ otherwise

Where the indicator variable I works as a dummy variable, which activates whenever the previous period's shock was negative. If there would be a leverage effect, then the value of γ will be greater than zero ($\gamma > 0$), and the model will return a higher conditional variance.

Secondly, the exponential GARCH (EGARCH) model, introduced by Nelson (1991), is considered to have a numerous of advantages to the basic GARCH model and can be described as following (Brooks, 2014, p. 441):

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_t^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (10)$$

Where the parameters ω , α , β and γ are being estimated. Even if the parameters in the model would appear to be negative, the conditional variance, σ_t^2 , will however always be positive. This is because $\log(\sigma_t^2)$ is modelled, and it is therefore no longer necessary to apply any non-negativity constraints on the parameters. $\sqrt{\sigma_t^2}$ is the last period's shocks in standardized value and the last expression, given in parenthesis, accounts for the absolute value of the last period's volatility shocks. Additionally, since asymmetries are allowed for under the EGARCH formulation, the term measuring the leverage effect, γ , will again appear negative if the relationship between the volatility and returns are negative, (Nelson, 1991).

Estimation in practice

When estimating linear model, the method of ordinary least squares (OLS) can be applied, however, this method cannot be implemented for non-linear models and an alternative method needs to be adapted. The maximum likelihood method can be applied to both linear and non-linear models and are thus helpful when working with GARCH models or other models with conditional heteroscedasticity. By giving an assumption about the distribution of the errors, a likelihood function is composed by finding the parameters which maximizes the value of the function. The procedure of estimating the maximum likelihood for a GARCH model is to first identify the GARCH equation. The second step is to identify the log-likelihood function, given by equation 11, which will be maximized. Finally, using EViews, the appropriate parameter values which maximizes equation 11 can be found (Brooks, 2014, p. 431).

$$L = \frac{T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^T \log(\sigma_t^2) - \frac{1}{2} \sum_{t=1}^T \frac{(y_t - \mu - \phi y_{t-1})^2}{\sigma_t^2} \quad (11)$$

In our case, in order to account for the non-normality of the data, a Student's t-distribution will be used for the error terms. The t-distribution, which looks similar to a normal distribution except from its higher kurtosis and smaller peak around the mean, has an additional parameter compared to the normal distribution, the degrees of freedom. In the limit, a t-distribution will approach a normal distribution due to the fact it has infinite of degrees of freedom. The normal distribution has kurtosis equal to 3, however financial asset returns are usually leptokurtic and thus do not follow a normal distribution. The degrees of freedom estimate in a student's t-distribution has the advantage of controlling the fatness of the tails fitted from the model. (Brooks (2014, p. 101, 463).

Goodness of fit

As GARCH models do not use least squares for estimation, we cannot use R-squared to determine which model fits the data best. Indeed, in this case the R-squared parameter is essentially meaningless. An alternative method is to use information criteria, which do not need any normality assumptions regarding the distributions of the errors. When a large number of parameters are included, information criteria are the process of determining between competing models which incorporate automatic correction penalties. For the information criteria, two factors are included, firstly, a term which is a function of the residual sum of squares, (RSS). Secondly, a penalty for the loss in degrees of freedom caused by adding extra parameters. The aim is to select the number of parameters which minimize the value of the information criteria. By adding a new variable to a model will result in competing effects on the information criteria, the residual sum of squares will fall whereas the value of the penalty term will increase. There are several information criteria which can be applied, however, the most common information criteria are Akaike's, the Schwarz Bayesian information criterion (SBIC) and the Hannan-Quinn criterion (HQIC), and are given by the following equations:

$$AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \quad (12)$$

$$SBIC = \ln(\hat{\sigma}^2) + \frac{k}{T} \ln T$$

$$HQIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \ln(\ln T)$$

Where $\hat{\sigma}^2$ is the estimator of the variance of regressions disturbances u_t , T is the sample size and k is the numbers of parameters. None of the criterion is with certainty pre-dominating over the other ones, however SBIC has much harder penalty than AIC and the HQIC is somewhere in between them. Further, SBIC strongly consistent, however, it is not efficient. AIC, on the other hand, is efficient but not consistent and will on average deliver a model which is too large whereas SBIC will asymptotically deliver the correct model order. (Brooks (2014, p. 275).

4. Data and methods

Data

Using Thomson Reuters Datastream we collect time series of daily prices for all stocks on the Italian, Belgian, Spanish and French stock markets for the period 01-01-2008 to 01-01-2013. We use daily data in order to capture the most variation in prices, which should give us a more precise estimation of volatility. That is, using daily data we avoid the smoothing effect of using weekly or monthly data. We discard stocks of companies that had no trading at all during the period (such as companies that went bankrupt prior to the period). This leaves us with a sample of 1865 stocks. We further divide this sample into different subsamples containing stocks on which short selling was banned, stocks on which it wasn't, and then divide these subsamples again by country. Félix et al (2013) has an overview of the stocks on which short selling was banned, the list comprises 60 stocks representing the largest banks and insurance companies in the four countries, with Italy having by far the largest share of banned stocks at 29, and Belgium having the smallest share at 4. The remaining 1805 stocks form our portfolios of non-banned stocks.

We transform the price series into return series by taking the natural log of the ratio of today's price over yesterday's price and multiply the result by 100 (for the purpose of scaling), losing one daily observation in each time series in the process.

$$R_{it} = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \quad (13)$$

Taking a sample from all four countries should allow us to account for country-specific factors, while also allowing us to examine closer where any potential effect is strongest.

For each subsample, we construct an equally-weighted portfolio, and with these portfolios generate time series of returns. Some summary statistics about these portfolios can be found in Table 1 in the appendix. Of note is that all portfolios had a negative mean return in the period, which is likely a consequence of the economic conditions of the period, as it covers the peak of the European sovereign debt crisis. All subsamples have a higher kurtosis than 3, exhibiting the “fat tails” that are found so often in stock market data. This of course means that none of the subsamples are normally distributed, with all of them showing high Jarque-Bera test scores. Finally, the portfolios of stocks that were subject to the short-selling ban all show a higher standard deviation than the portfolios of stocks that were not banned, meaning that over the entire period they had a higher volatility of returns than the stocks that were not banned. This could be due to factors specific to the banned stocks, as all of these stocks are financial firms, whereas the portfolios of non-banned stocks are much more diversified. Based on Beta estimates from Datastream, the banned stocks also have a higher beta on average (1.08) compared to the non-banned stocks (0.57), indicating that overall they have a higher systematic risk.

Next, we also generate time series of indicator variables for each country, set to 1 when the short-selling bans were active and 0 otherwise. While the short-selling bans were announced on 11-08-2011, Félix et al. (2013) suggests that investors may have anticipated the implementation of these bans due to a similar ban being announced a few days earlier for Greek stocks, therefore we set the indicator variables to 1 from 08-08-2011 onwards. While the ban was initially intended to only remain in place for 15 days, regulators in all four countries eventually extended it until February 2012, where it expired on the 15th in Spain, 13th in Belgium and France, and 24th in Italy, so our indicator variables also revert back to 0 on those dates.

We note that several of the stocks are listed on more than one exchange – for instance the bank Santander is listed both in its home market Madrid and in Milan, however the statements from the regulators do not mention if short-selling Santander was banned on both exchanges. If this is not the case, the short selling ban could have had the effect of shifting short seller activity from one exchange to another.

Estimation

Using these time series and indicator variables, we are ready to estimate GARCH models for each of the portfolios.

A priori, we expect no autocorrelation in stock returns. We should not be able to predict today's stock returns based on yesterday's, hence we do not at first include any ARMA (p,q) terms in the mean equation:

$$R_t = u_t \quad (14)$$

Where R_t is today's portfolio return and u_t is today's stochastic shock, a random variable with mean 0 and a conditional variance we will model using our GARCH models.

For the conditional variance equation, we stick to GARCH (1,1) as it has been found to be sufficiently adequate in most cases (Brooks 2014, p. 430). In addition to the GARCH terms, we also include the indicator variable J in the variance equation for each regression.

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 + \theta J_t \quad (15)$$

We are interested in whether this term is significant ($p < 0.10$) and if so, the magnitude (the absolute value of the coefficient θ). This will indicate whether or not the short-selling ban had a significant effect on volatility, and if so, to what degree. As mentioned above, since financial asset returns are usually leptokurtic, the student's t-distribution will be used for the error distribution because of its advantage of controlling for the fatness of the tails. For our GJR and EGARCH estimations, we use a similar variance equation specification, including the indicator variable in each estimation.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} + \theta J_t \quad (16)$$

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_t^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \theta J_t \quad (17)$$

We are both interested in testing the effect of the short-selling ban on the stocks that were banned, and on the wider stock market, since the ESMA's overall goal was supporting the integrity of the entire financial market. We therefore use this indicator variable in all estimations, not just the portfolios of stocks on which short selling was banned.

Alternate specifications

It is worth noting that several of the time series of returns show some autocorrelation. As mentioned earlier, under the classic assumptions about efficient markets we expect no

significant autocorrelation in a time series of returns (as in Fama, 1965), however it may still be worthwhile to test the effect on the model of adding some ARMA terms.

By adding an AR(1) term to the estimation we slightly improve the Schwarz information criterion for most of the models, however it has very little effect on the ban coefficient, which is the variable we are interested in. Brooks (2014, p. 411) mentions that asset return series sometimes show signs of being “fractionally integrated” wherein the series has persistent statistically significant autocorrelation over several lags. This seems to fit what we are seeing here. For theoretical reasons as discussed above, we stick with the purely random mean equation given above in (14).

We also tested GARCH models of higher order than (1,1), but generally the additional terms were not statistically significant, and information criteria were not improved either.

Primary results

Table 2 in the appendix shows our estimated coefficients and significance for the indicator variable showing when the ban is active, using GARCH, GJR and EGARCH estimations. Across the four countries and three estimation methods, none of them show statistical significance, with the lowest p-value achieved being 0.104, which was found using an EGARCH estimation on the subsample of Italian stocks that were subject to the short-selling ban.

Looking closer at the different subsamples, the short-selling ban seems to generally be associated with an increase in volatility, both for stocks on which short-selling was banned and for the rest, with the exception of Spain, where all estimation methods gave a negative and very small coefficient. However, none of these increases in volatility are statistically significant. For illustration, table 3 in the appendix shows graphs of the estimated variance of the portfolio representing the entire sample, with the three different estimation methods. Clearly visible are the peaks in volatility following the Lehman Brothers bankruptcy in 2008, as well as another peak in volatility around mid to late 2011, the period of interest.

Shorter sample

We originally select the time period 2008 to 2013 for the sake of having a large number of observations around the period of interest to help make the GARCH estimates as accurate as possible. However, the period includes the very extraordinary period around late 2008 to

early 2009 where volatility spiked to very high levels. We are concerned that this period may have skewed our results in some way and we therefore perform another estimation, using the same sample and methods, but this time only using data from 2010 to 2013.

Secondary results

Table 4 in the appendix shows the estimates for the short selling ban variable coefficient and their p-values, across the three estimation methods and four country samples. In this case the vanilla GARCH estimates still show no statistical significance for the short-selling ban, but the two asymmetric methods both show significance on some of the samples. In particular, for the overall sample the short selling ban is associated with an increase in volatility, not in the stocks on which short selling was banned, but in all the other stocks.

Looking closer at the individual countries, the effect is most visible in France and Italy, where both countries show a positive and significant effect on the stock volatility of the non-banned stocks. In Spain on the other hand, the ban was associated with only a very small negative effect on the volatility of the banned stocks, and no significant effect on the volatility of the non-banned stocks. Finally, in Belgium the ban is associated with a positive effect on the volatility of the banned stocks. In both the long and the short sample, the coefficients associated with the ban variable have the curious property of a very high coefficient value and also a high p-value in the GARCH and GJR estimations. This is possibly due to the sample size – the Belgian stocks subject to a short sale ban was the smallest subsample, with only four stocks.

Table 5 in the appendix shows graphs of estimated conditional variance for the portfolio representing the entire sample across the three estimation methods. The EGARCH estimation in particular generates a very jittery graph around the time of the short selling ban, compared to the previous smaller volatility spikes.

5. Discussion of results

The results are somewhat counterintuitive. If we thought of short sellers as actors that manipulate or destabilise the market, preventing short selling in some shares should have the effect of reducing volatility in these shares. Conversely, if we thought of short sellers as actors that stabilise the market by keeping prices closer to intrinsic values (as in Miller, 1977), preventing short selling in some shares should have the effect of increasing the volatility of these shares. In this case the short selling ban appears to have increased volatility in the shares on which short selling was not banned.

The first thing to consider is which model specification and sample length is most accurate. We are fairly confident, based on Nelson (1991), that the EGARCH model is superior to the plain vanilla GARCH model and the GJR model, as it allows for negative parameters and accounts for the leverage effect. But it is less clear which of the two time periods give the best estimate for the coefficients. A priori, a longer sample is probably better, however with the longer sample period we find no significant effect from the ban for any of the portfolios, with any of the estimation methods. The other studies we have examined that looked at the same period tended to find some significant effects, and we therefore put somewhat more weight on the results we found with the shorter sample.

One explanation could be that the market took the short selling ban as a signal that the wider economy might be in a worse state than previously thought. This point was made in a comment in *The Guardian* (Pratley, 2011) - the short-selling bans in 2008 preceded a series of bank bailouts and a large recession that reduced stock prices across the market. In the climate of the ongoing European sovereign debt crisis, investors may have anticipated that another short-selling ban is a signal that regulators expect things to get much worse, and the resulting increase in uncertainty would then lead to an increase in volatility, similar to Liu and Zhang (2015). In this view, the ban contained some additional information for investors on the state of the economy, since regulators presumably wouldn't have implemented it if they didn't see a need for action. This also fits with the findings of Félix et al (2013), who find that risk aversion for all stocks, both banned and non-banned, increased after the short-selling bans were put into place. They also found that the volume of put options on the non-banned stocks significantly increased in the ban period, whereas the volume of put options on the banned stocks did not change significantly, which could go some way in explaining why the short-selling bans seemed to only affect the volatility of the non-banned stocks. Our results also fit with the results of Morales-Zumaquero and Sosvilla-Rivero (2015) - like them, we found no discernible effect on the Spanish stocks from the short-selling ban.

This does not fully explain why we saw little to no effect on the volatility of the banned stocks. In Félix et al (2013) risk aversion appeared to increase even more for the banned stocks than for the non-banned stocks, and if increased risk aversion leads to higher volatility, we should then have a positive and significant effect on the volatility of the banned stocks as well. Likewise, Alves et al (2015) find an increase in volatility associated with the ban for both banned and non-banned stocks. Neither of these two papers appear to account for the leverage effect however, and it is possible that this effect explains the lack of an effect in the banned stocks. Section 6 of the appendix shows a graph of the price evolution for three portfolios – the overall portfolio containing all stocks, and the two portfolios containing all banned stocks and all non-banned stocks, across all four countries. Particularly striking is the heavy decline in the average price of the stocks on the ban list, especially in the period around the time the short-selling ban was implemented. As the asymmetric models predict increased volatility after declines in prices, this alone would probably explain the increased volatility in the period, leaving the dummy ban variable insignificant. Meanwhile, the non-banned stocks did not decline by nearly the same magnitude, and so in this case the dummy ban variable has more explanatory power.

In other words, both banned and non-banned stocks experienced a volatility spike around August 2011, and this spike could be explained for the banned stocks by the asymmetric properties of the EGARCH model, but not for the non-banned stocks.

While our results show that the short-selling ban was associated with higher volatility in the overall stock market in the four countries, particularly for the stocks on which short selling was not banned, we cannot say with complete confidence that the short-selling ban directly caused this increase in volatility. The second half of 2011 was generally a tumultuous time for the stock market, and it is possible that the increase in volatility around the short selling ban is essentially coincidental. The results of Morales-Zumaquero and Sosvilla-Rivero (2015) point in this direction – while they found an effect on stock return volatility in Spain around the time of the ban, they also found that it appeared to be caused by other events in Europe.

We can however say that the short selling ban does not appear to have been able to reduce volatility, in either the banned stocks or the wider stock markets of these four countries, and it thus appears to be an ineffective tool for the promotion of financial stability.

6. Conclusion

The aim of this paper is to investigate the imposed short selling ban in France, Italy, Belgium and Spain from August 2011 until February 2012 and its impact on stock market volatility, as the main reason that regulators imposed this short sale restriction was in order to mitigate the spread of false rumours and to reduce the volatility on financial stocks. By examining whether the imposed short selling ban in France, Italy, Spain and Belgium was effective this paper adds to the literature on whether imposing regulations can be a successful means for decreasing stock market volatility and improving the overall functioning of the stock market. The study contains series of daily returns of 1865 financial stocks from the four countries imposing the ban. Using these we create subsamples of daily data of all the banned stocks and the non-banned stocks and secondly, generate subsamples based on countries. For each of the subsamples, we create an equally weighted portfolio from which we produce time series of returns. In order to measure volatility, we estimate GARCH, EGARCH and GJR models with an included indicator variable with a value of 1 when the ban was active and 0 otherwise.

We estimate the GARCH models using both a longer sample from 2008 to 2013, and a shorter sample from 2010 to 2013. For the longer sample, none of the specifications show any significance for the indicator variable for the short-selling ban. For the shorter sample, the vanilla GARCH model still shows no significance, but the asymmetric GJR and EGARCH models both show a statistically significant increase in conditional variance associated with the short selling ban. This increase is seen mainly in the stocks on which short-selling wasn't banned. We theorize that the short-selling ban could have worked as a signal, transmitting higher volatility to the wider stock market as investors experienced increased risk aversion, or that the increase in the volatility of these stocks is essentially coincidental.

While the results don't show clearly that the short-selling ban increased volatility, they also don't show that the ban decreased volatility, and therefore the ESMA's stated goal of reducing stock market volatility does not appear to have been achieved. This paper therefore adds to the large pile of evidence that short-selling bans appear to have an overall negative effect on the functioning the stock market. Sadly, while the empirical evidence does not appear to point in favour of short selling bans, regulators may still end up implementing them in times of financial crisis, as they face strong political pressure to appear to be doing something about the crisis, as was the case with the SEC in 2008 (Younglai, 2008).

References

Alves, C., Mendes, V. and da Silva P.P. (2015), Analysis of market quality before and during short-selling bans.

AMF. (2011 August 11). Decision by the AMF Chairman pursuant to Article L. 421-16 II of the Monetary and Financial Code: Ban on taking net short positions in French securities of the financial sector (as listed hereunder). [Press Release]. Retrieved from:
http://www.amf-france.org/en_US/Actualites/Communiqués-de-presse/AMF/annee_2011?xtcr=10&isSearch=true&docId=workspace%3A%2F%2FSpacesStore%2F1039f5d0-4515-41e2-a43e-15dba75bc527&lastSearchPage=http%3A%2F%2Fwww.amf-france.org%2FmagnoliaPublic%2Famf%2Fen_US%2FResultat-de-recherche%3FformId%3DALL%26TEXT%3Dshort%26REFERENCE%3D%26DATE_PUBLICATION%3D01%26%2337%3B2F01%26%2337%3B2F2011%26DATE_OBSOLESCENCE%3D01%26%2337%3B2F01%26%2337%3B2F2012%26DATE_VIGUEUR_DEBUT%3D%26DATE_VIGUEUR_FIN%3D%26LANGUAGE%3Den%26valid_form%3Dstart%26%2343%3Bsearch%26isSearch%3Dtrue&xtmc=short&docVersion=1.0

Baklaci, H. F., Suer, O. and Yelkenci, T. (2016) A closer insight into the causality between short selling trades and volatility.

Beber, A. and Pagano, M. (2011) Short-Selling Bans around the World: Evidence from the 2007-09 Crisis.

Bohal, M.T., Essidb, B. and Siklos, P.L. (2012), Do short selling restrictions destabilize stock markets? Lessons from Taiwan.

Bohl, T.M., Reher, G. and Wilfling, B. (2016), Short selling constraints and stock returns volatility: Empirical evidence from the German stock market.

Bollerslev, T. (1986) Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31 (1986)

Brooks, C. (2014) *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press

Charoenruek, A. and Daouk, H. (2005). A Study of Market-Wide Short-Selling Restrictions.

CONSOB. (2011 August 12). Consob resolution No. 17902 of August 12, 2011. [Press Release]. Retrieved from:

<http://www.consob.it/web/consob-and-its-activities/bullettin/documenti/english/resolutions/res17902.htm>

Diamond, D. and Verrecchia, R. (1987) Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics* 18 (1987)

Engle, R. (1982), Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, vol. 50, no. 4 (Jul 1982)

Engle, R. (2001), GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives*, vol. 15, no. 4 (Fall 2001).

ESMA. (2011 August 11). ESMA promotes harmonised regulatory action on the short-selling in the EU. [Press Release]. Retrieved from:

https://www.esma.europa.eu/sites/default/files/library/2015/11/esma_2011_266_uu_public_statement_on_short_selling.pdf

Fabozzi, F., Abate, J. A., Atzil, L., Bris, A., Cohen, J., Gastineau, G. L., ... Zhu, N. (2004). *Short Selling – Strategies, Risks and Rewards*. Hoboken, New Jersey, United States: Wiley Finance

Fama, E. (1965) Random Walks in Stock Market Prices. *Financial Analysts Journal*, vol. 21, no. 5 (Sep. - Oct. 1965)

Farrell, S. (2008 July 22), Morgan Stanley's shorting of HBOS cleared by FSA. *The Independent*. Retrieved from: <https://www.independent.co.uk/news/business/news/morgan-stanleys-shorting-of-hbos-cleared-by-fsa-874939.html>

Félix, L., Kräussl, R., and Stork, P. (2013) The 2011 European Short Sale Ban on Financial Stocks: A Cure or a Curse? Center For Financial Studies Working Paper Series No.

2013/17. Retrieved from: https://www.ifk-cfs.de/fileadmin/downloads/publications/wp/2013/CFS_WP2013_17.pdf

Financial Times. (2011 August 12). Short-selling ban brings relief on for banks, *Financial Times*. Retrieved from: <https://www.ft.com/content/9a55839a-c42d-11e0-ad9a-00144feabdc0>

FSA. (2008 September 18). FSA statement on short positions in financial stocks. [Press Release]. Retrieved from: <http://www.fsa.gov.uk/pages/Library/Communication/PR/2008/102.shtml>

FSA. (2008 September 18). Callum McCarthy: Comments on short positions in financial stocks. [Press Release]. Retrieved from: <http://www.fsa.gov.uk/library/communication/pr/2008/103.shtml>

FSA. (2008 18 September). [Press Release]. Retrieved from: <http://www.fsa.gov.uk/pages/Library/Communication/PR/2008/102.shtml>

FSMA. (2011 August 11). The FSMA Modifies Short Selling Rules. [Press Release]. Retrieved from: <https://www.fsma.be/en/news/fsma-modifies-short-selling-rules>

FSMA. (2012 February 13). The FSMA Modifies Short Selling Rules. [Press Release]. Retrieved from: <https://www.fsma.be/en/news/fsma-modifies-short-selling-rules-0>

Gruenewald, S., Wagner, F., Weber, R. (2010) Emergency Short Selling Restrictions in the Course of the Financial Crisis. SSRN Electronic Journal (June 2010)

Kirchgaessner, S and Farrell, G. (2008 October 6). Fuld says Lehman victim of short sellers. *Financial Times*. Retrieved from: <https://www.ft.com/content/f59fdd00-93b0-11dd-9a63-0000779fd18c>

Liu, L. and Zhang, T. (2015) Economic Policy uncertainty and stock market volatility

Lowenstein, R. (2002). *When Genius Failed*. London, United Kingdom: Fourth Estate

McCrum, D. (2011 August 8). European banks face short sellers' fire. *Financial Times*.

Retrieved from:

<https://www.ft.com/content/21550128-bf9b-11e0-90d5-00144feabdc0>

Miller, E. (1977). Risk, Uncertainty and Divergence of Opinion. *The Journal of Finance* Vol. 32 No. 4 (Sep 1977)

Morales-Zumaquero, A. and Sosvilla-Rivero, S. (2015) Temporary ban on short positions and financial market volatility: evidence from the Madrid Stock Market.

Nelson, B.D. (1991), Conditional Heteroskedasticity in asset returns, *The Econometric society*.

Pratley, N. (2011 August 12). Short-selling ban sends dangerous message, *The Guardian*.

Retrieved from: <https://www.theguardian.com/business/2011/aug/12/short-selling-ban-ineffective-nils-pratley-analysis>

SEC. (2009 19 September). SEC Halts Short Selling of Financial Stocks to Protect Investors and Markets [Press Release]. Retrieved from:

<https://www.sec.gov/news/press/2008/2008-211.htm>

Story, L. (2008 October 7), A debate as a ban on short-selling ends: Did it make any difference? *The New York Times*. Retrieved from:

<https://www.nytimes.com/2008/10/08/business/08short.html>

Story, L. and Castle, S. (2011 August 11), Four European Nations to Curtail Short-selling, *The New York Times*. Retrieved from:

<https://www.nytimes.com/2011/08/12/business/global/europe-considers-ban-on-short-selling.html>

Younglai, R. (2008 December 31), SEC chief has regrets over short-selling ban. *Reuters*.

Retrieved from:

<https://www.reuters.com/article/us-sec-cox/sec-chief-has-regrets-over-short-selling-ban-idUSTRE4BU3GG20081231>

Appendix

1. Summary statistics for the portfolio returns from each subsample.

Mean, median, maximum, minimum and standard deviation are given in percentage points; for instance a maximum of 3.774369 for the All Stocks portfolio across the entire sample means that the highest return experienced for this portfolio in any given day was 3.77%.

	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera
Entire sample								
All stocks	-0.061049	0	3.774369	-4.038039	0.647973	-0.926110	8.785165	2006.375
Banned stocks	-0.096227	-0.028737	10.70051	-7.414723	1.896628	0.097813	5.280407	284.8447
Non-banned stocks	-0.060161	0	3.667214	-4.010538	0.622468	-1.011238	9.296344	2378.056
Belgium								
All stocks	-0.052755	-0.009543	3.344697	-5.554421	0.625457	-1.081749	11.02995	3760.21
Banned stocks	-0.202870	-0.090702	21.39025	-34.30174	3.996664	-0.499443	10.54404	3148.871
Non-banned stocks	-0.049829	0	3.265182	-5.431076	0.593359	-1.127330	11.93964	4621.911
France								
All stocks	-0.048850	0.001145	2.722313	-4.220489	0.559523	-1.294647	10.07870	3089.179
Banned stocks	-0.057125	0	13.84763	-10.09259	2.385141	0.091833	6.121335	531.5953
Non-banned stocks	-0.048770	0.000264	2.68674	-4.191102	0.548656	-1.334663	10.33734	3314.803
Italy								
All stocks	-0.087560	0	6.466123	-5.916917	1.060434	-0.535342	6.816008	854.1377
Banned stocks	-0.100009	-0.046956	8.934133	-6.984602	1.787205	0.017436	4.989713	215.3345
Non-banned stocks	-0.086560	0	6.253646	-5.831534	1.019878	-0.622032	7.245067	1064.026
Spain								
All stocks	-0.087071	-0.005592	5.746099	-4.903113	0.866936	-0.180120	6.867935	820.5564
Banned stocks	-0.077580	-0.008810	9.352420	-7.821372	1.715055	0.223360	5.474854	343.8926
Non-banned stocks	-0.087648	-0.006329	5.621634	-4.727315	0.831633	-0.218193	7.030312	893.5907

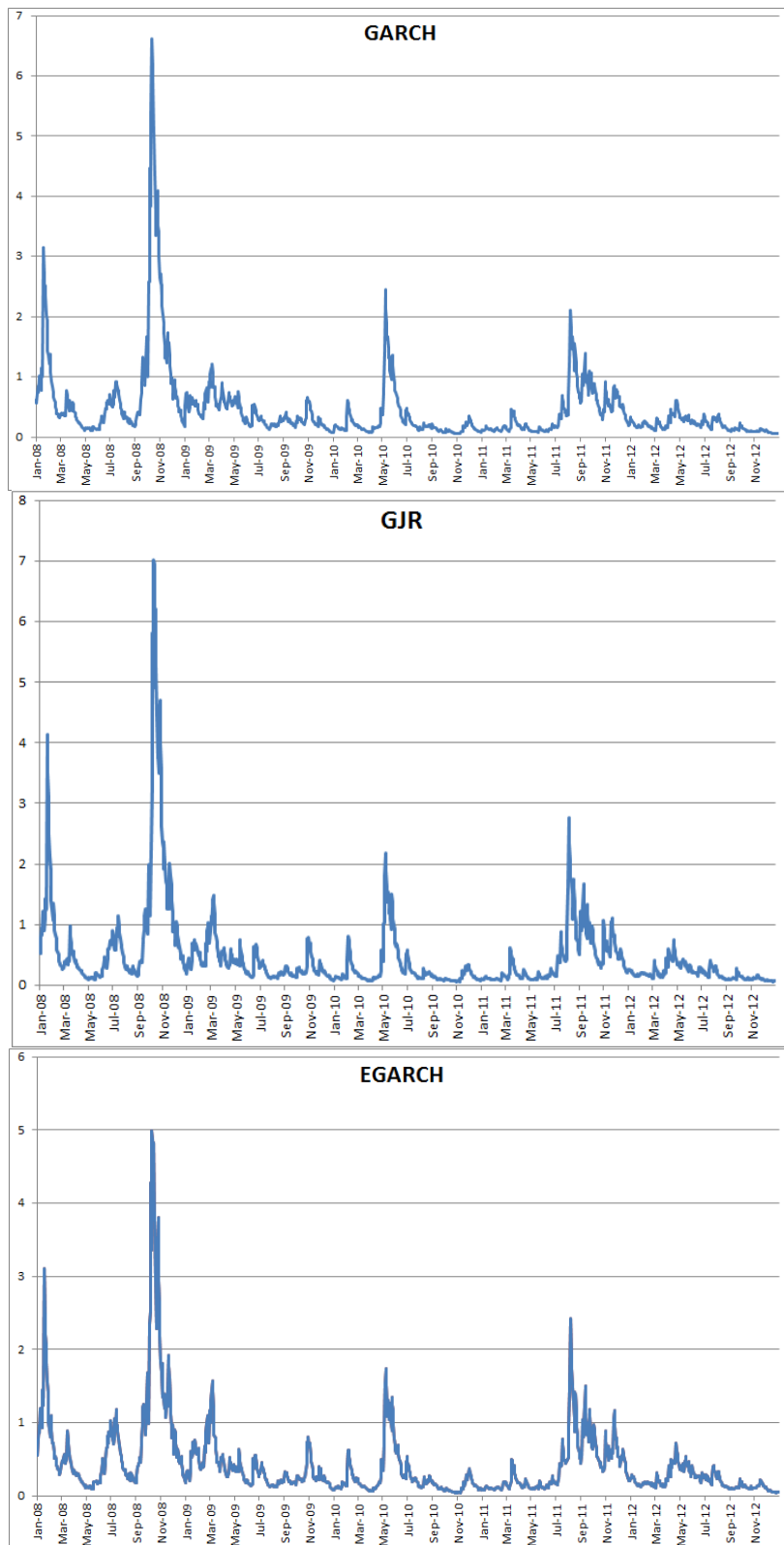
2. Estimation results for the short selling ban variable on the long sample

This table shows the estimated coefficient for the indicator variable set to 1 whenever the short-selling ban is active, along with each estimate's associated p-value in parenthesis underneath, across three different estimation methods and the different subsamples. The indicator variable is included in the variance equation of each estimation. Significance at the 10%, 5% and 1% level is marked by *, ** and *** respectively.

Country	Estimation method	All stocks	Banned stocks only	Non-banned stocks
Entire sample	GARCH	0.002053 (0.7704)	0.060718 (0.4608)	0.001674 (0.79)
	GJR	0.006334 (0.3899)	0.046521 (0.3692)	0.005296 (0.4255)
	EGARCH	0.011656 (0.5387)	0.008752 (0.4031)	0.010062 (0.6075)
Belgium	GARCH	0.0083 (0.3317)	0.790132 (0.1966)	0.008488 (0.2923)
	GJR	0.010716 (0.2491)	0.732665 (0.1544)	0.010361 (0.23)
	EGARCH	0.007437 (0.6994)	0.036459 (0.1497)	0.007063 (0.7167)
France	GARCH	0.002981 (0.686)	0.06998 (0.5803)	0.002939 (0.6795)
	GJR	0.005997 (0.4365)	0.084188 (0.391)	0.005634 (0.4469)
	EGARCH	0.011944 (0.5796)	0.008238 (0.4511)	0.011785 (0.5885)
Italy	GARCH	0.018978 (0.4701)	0.128756 (0.2202)	0.014339 (0.5218)
	GJR	0.03015 (0.1696)	0.087584 (0.1541)	0.026105 (0.1901)
	EGARCH	0.017613 (0.2128)	0.018329 (0.104)	0.016081 (0.2691)
Spain	GARCH	-0.002887 (0.7267)	-0.025 (0.3524)	-0.002367 (0.7719)
	GJR	-0.003988 (0.6175)	-0.010153 (0.5569)	-0.003688 (0.6444)
	EGARCH	-0.011515 (0.4496)	-0.01045 (0.1291)	-0.011164 (0.5065)

3. Graphs of estimated conditional variance for long sample

These graphs show the estimated conditional variance across the three methods for the portfolio representing all stocks in the sample.



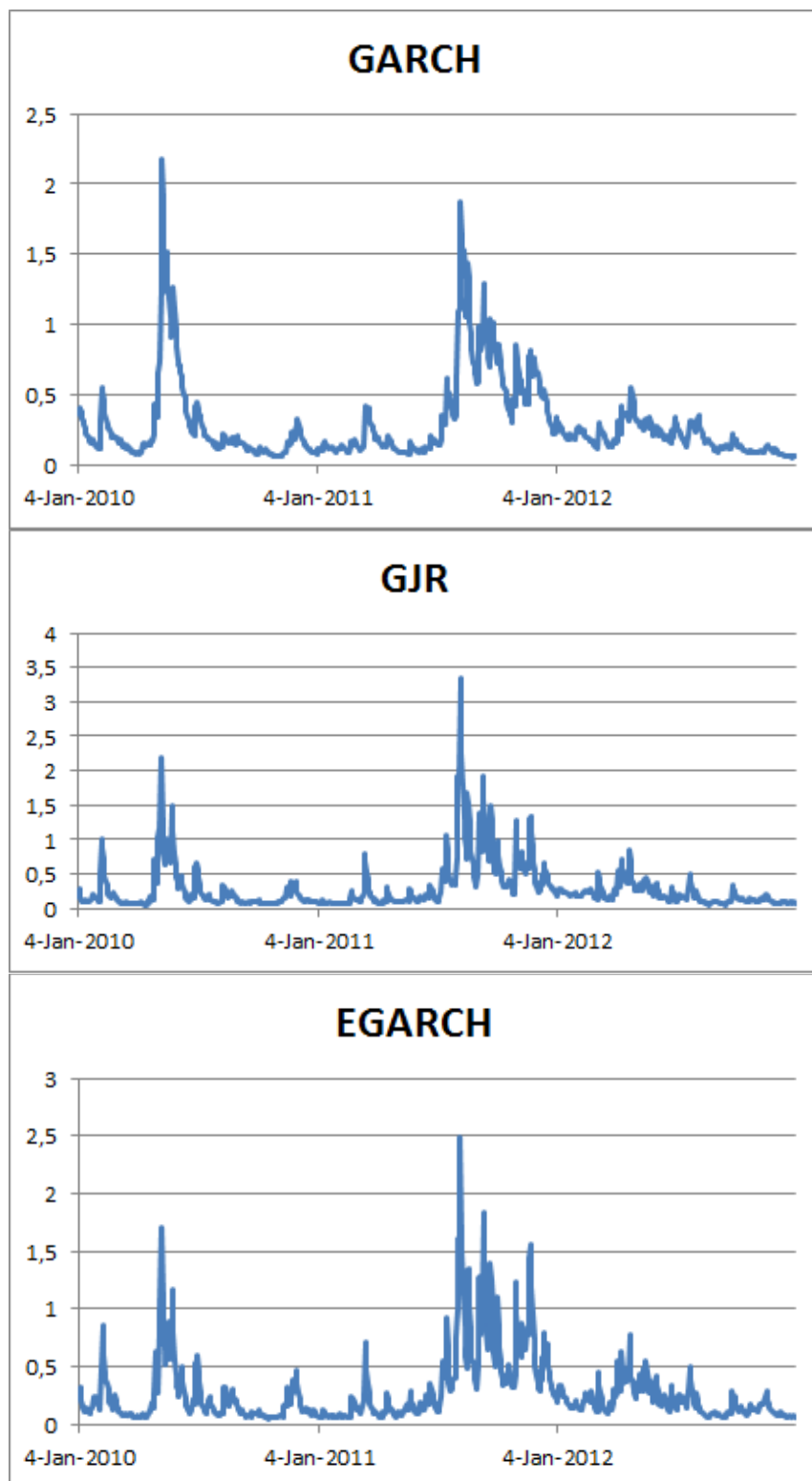
4. Estimation results for the short selling ban variable on the short sample

This table shows the estimated coefficient for the indicator variable set to 1 whenever the short-selling ban is active, along with each estimate's associated p-value in parenthesis underneath, across three different estimation methods and the different subsamples. The indicator variable is included in the variance equation of each estimation. Significance at the 10%, 5% and 1% level is marked by *, ** and *** respectively.

Country	Estimation method	All stocks	Banned stocks only	Non-banned stocks
Entire sample	GARCH	0.005217	0.077322	0.0045
		<i>0.5421</i>	<i>0.4238</i>	<i>0.5517</i>
	GJR	0.029849	0.042438	0.025797
		<i>0.0255 **</i>	<i>0.3988</i>	<i>0.0291 **</i>
	EGARCH	0.111530	0.013218	0.112164
		<i>0.0039 ***</i>	<i>0.2572</i>	<i>0.0046 ***</i>
Belgium	GARCH	0.012608	0.999862	0.011514
		<i>0.2206</i>	<i>0.1368</i>	<i>0.2088</i>
	GJR	0.018833	0.946235	0.016473
		<i>0.1019</i>	<i>0.106</i>	<i>0.1115</i>
	EGARCH	0.058952	0.083738	0.049659
		<i>0.0807 *</i>	<i>0.0307 **</i>	<i>0.1229</i>
France	GARCH	0.006816	0.172897	0.00651
		<i>0.459</i>	<i>0.3531</i>	<i>0.4571</i>
	GJR	0.018802	0.143045	0.017055
		<i>0.1081</i>	<i>0.2931</i>	<i>0.1186</i>
	EGARCH	0.096068	0.028952	0.092801
		<i>0.0299 **</i>	<i>0.171</i>	<i>0.0353 **</i>
Italy	GARCH	0.025685	0.107232	0.022121
		<i>0.3972</i>	<i>0.2931</i>	<i>0.4091</i>
	GJR	0.0959	0.053164	0.081864
		<i>0.0073 ***</i>	<i>0.2491</i>	<i>0.0059 ***</i>
	EGARCH	0.091366	0.010459	0.108073
		<i>0.0023 ***</i>	<i>0.1004</i>	<i>0.0008 ***</i>
Spain	GARCH	0.002411	-0.027299	0.004285
		<i>0.8274</i>	<i>0.3994</i>	<i>0.7171</i>
	GJR	0.00516	-0.017327	0.006771
		<i>0.6818</i>	<i>0.3059</i>	<i>0.611</i>
	EGARCH	0.008875	-0.010584	0.014638
		<i>0.6912</i>	<i>0.0118 **</i>	<i>0.5706</i>

5. Graphs of estimated conditional variance for short sample

These graphs show the estimated conditional variance across the three methods for the portfolio representing all stocks in the sample.



6. Graph of price evolution, 2010-2013

This graph shows the evolution of the average stock price across three portfolios, all stocks (blue), banned stocks (red) and non-banned stocks (green) from 2010 to 2013. Stocks are evenly weighted. Banned stocks are plotted on the right-hand y-axis while the other two portfolios are plotted on the left-hand y-axis.

