# The 2011 European Short Sale Ban: A Cure or a Curse? *

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**Abstract**

This paper examines whether the 2011 European short sale ban on financial stocks proved to be successful or had a negative impact on financial markets. We explicitly take an options market perspective and focus on market participants' changes in beliefs and expectations. During the ban, short positions in banned stocks decreased, whereas they increased for non-banned stocks. Our results indicate that the ban increased implied jump risk levels, thereby negatively impacting the banned financial stocks. However, we also observe that after the announcement of the ban, financial contagion risk actually dropped for banned stocks. Instead of a substitution effect between regular short selling and synthetic shorting through single stock puts, we observe a migration out of single stock puts into the EuroStoxx 50 index options market. We conclude that this type of migration diversified selling pressure initially concentrated in financial stocks across a larger share of the stock market, thereby reducing systemic risks and enhancing overall financial stability.

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## 1. Introduction

On August 11, 2011, Belgium, France, Italy, and Spain imposed short sale bans on financial stocks. The European Securities and Markets Authority (ESMA) stated that the reason for the short sale bans was to curb market abuse and the spread of false rumors[1]. The spread of false rumors is dangerous because it may increase the risk of financial contagion[2], thereby endangering financial stability.

Recent academic studies argue that short sale bans, at best, do not affect stock price levels and, at worst, contribute to their decline and negatively impact market quality. For instance, Boehmer et al. (2013) conclude that it is unclear whether the SEC's 2008 imposition of short sale bans achieved the goal of providing a floor for U.S. equity markets. Beber and Pagano (2013) investigate the impact of the 2008 bans on stock markets in 30 different countries and find that banned stocks underperform stocks not included in the bans.

In this paper, we explicitly take an options market perspective, as opposed to employing only the stock market itself. Our paper focuses on market participants' changes in beliefs and expectations, as in the work of Yan (2011), Chang et al. (2013), and Chira et al. (2013). Forward-looking probabilities implied by options prices, i.e., risk neutral densities (RND), and the implied volatility (IV) skew, are used to assess how the ban affects implied jump risk on banned and non-banned stocks. We employ a data set of daily IV across a range of different moneyness levels for all optionable European stocks listed in Belgium, France, Italy, and Spain. We note that using option-implied data is a novel approach in the literature to analyze the impact of short sale bans on financial markets.

We focus not only on the outmost tails of RNDs but also on the tails of realized returns. We argue that it is the more extreme parts of the distributions that best reflect implied jump risk. We use extreme value

[1] ESMA stated on August 11, 2011: "European financial markets have been very volatile over recent weeks. The developments have raised concerns for securities markets regulators across the European Union. [....] While short selling can be a valid trading strategy, when used in combination with spreading false market rumors this is clearly abusive. [...] Today some authorities have decided to impose or extend existing short selling bans in their respective countries. They have done so either to restrict the benefits that can be achieved from spreading false rumors or to achieve a regulatory level playing field, given the close inter-linkage between some EU markets."

[2] Financial contagion occurs when a relatively contained shock, which initially affects only one or a few institutions, sectors or countries, propagates via larger shocks to the rest of the financial sector, economy or other countries.

theory (EVT) to assess how investors, through their perception of implied jump risk, differentiated between banned and non-banned stocks upon the introduction of the 2011 European short selling ban.

Our work is related to that of Melick and Thomas (1997) and Birru and Figlewski (2011) because it examines the behavior of RNDs over specific events. The rationale of using RND and IV skews to assess how the ban affected implied jump risk is also supported by Bates (2000) and Rubinstein (1994). They show that before the 1987 crash, the probability of large negative stock returns was small and fairly close to that suggested by the normal distribution. Just prior to the crash, however, the option-implied probability of jumps rose considerably at the same time that the IV skew became steeper. The left tail of the RND of returns became considerably fatter and thus negatively skewed with increased kurtosis, a phenomenon attributed to crash fear (Rubinstein, 1994). As a result, out-of-the-money (OTM) puts are systematically priced at a higher level relative to at-the-money (ATM) ones.

The main contributions of our paper are threefold. First, we provide evidence that the ban increased implied jump risk levels, particularly impacting the banned financial stocks. We show that it is the imposition of the ban itself that led to the increase in implied jump risk, rather than other causes, such as information flow, options-trading volumes, or stock-specific factors. This finding is important because increased implied jump risk may provoke financial contagion (see Ait-Sahalia et al., 2015) and increase systemic risk. Because of the connection between implied jump risk and contagion, shifts in implied jump risk are closely monitored by regulators[3].

Second, we find that after the announcement of the ban, financial contagion risk actually drops for banned stocks. This finding seems to run contrary to what one might expect, given the documented increases in implied jump risk levels for banned stocks. Interestingly, for the non-banned stocks, we document that contagion risk levels do indeed increase after the ban, thus behaving in line with the rise in implied jump risk levels. We argue that this difference may be caused by (formal and informal) market makers' reluctance to further increase their options' inventory risk, leading to relatively steep IV skews, reduced volumes, and widened bid-ask spreads for banned stocks.

[3] For instance, Poon and Granger (2003) note that the Bank of England uses implied volatilities to assess market sentiment.

Third, we compare the effects of the 2011 European ban to its 2008 American counterpart. Investors may be able to obtain economic short exposure to banned stocks through a derivatives-based strategy that replicates the payoff of a stock's short sale. Such a "substitution effect" (see Battalio and Schultz, 2011; Grundy et al., 2012) is characterized by a migration of trading volume from one instrument to another. We find that no substitution effect occurred between regular short selling and synthetic shorting through single stock puts during the 2011 European ban. Instead of a substitution effect, our results show a migration out of single stock puts into the EuroStoxx 50 index options market. We conclude that this type of migration diversifies selling pressure initially concentrated in financial stocks across a larger share of the stock market, thereby reducing systemic risks and enhancing overall financial stability.

## 2. Data and methodology

The 2011 short sale ban on financial stocks in the euro member countries Belgium, France, Italy, and Spain was established by a coordinated act of the European Securities and Market Authority (ESMA) and the national financial market regulators of those countries on August 11, 2011. The announcement was made via a public statement issued by the ESMA and was followed by publications on the same day by the Belgian Financial Services and Markets Authority (FSMA), the French Autorité Des Marchés Financiers (AMF), the Italian Commissione Nazionale per le Societá e la Borsa (Consob), and the Spanish Comision Nacional Del Mercado de Valores (CNMV). The ban entered into effect on August 12, 2011. Table 1 provides an overview of the banned financial stocks.

*< Please insert Table 1 about here >*

The ban on covered short selling not only prohibited the creation of new net short positions but also banned increases in existing ones, including intra-day operations. Naked short selling had already been prohibited in these four markets since 2008. Positions arising from formal market-making activities were exempted from the ban. The ban targeted not only public markets but also over-the-counter (OTC) markets. In terms of scope, the national announcements differed. The Belgian FSMA announced that the ban applied to net economic short positions of any kind, while the French AMF communicated that derivatives could only be used to hedge, create or extend net long positions. For the Italian Consob, the ban covered only shares and not exchange-traded funds (ETFs) or any derivatives, while the Spanish CNMV imposed the ban on all trades in equities or indices.

During the ban, holders of financial stocks were still allowed to use single stock derivatives or simply sell their holdings to hedge their portfolios. Investors exposed to stocks were allowed to hedge their overall equity market exposure by trading the market index or single stock derivatives. It was the short selling of banned stocks that was prohibited, not hedging them or reducing equity market risk. The creation or extension of marginal net short positions in banned securities as a result of hedging equity market risk was still allowed.

The European short sale ban was initially intended to be in place for the next 15 days only, with the exception of Belgium, which announced that the ban would remain in effect indefinitely. Nevertheless, the ban was extended by the Spanish CNMV, the French AMF, and the Italian Consob several times. On February 13, 2012, both FSMA and AMF announced the lifting of the ban with immediate effect in Belgium and with retroactive effect, to February 11, in France. On February 15, the CNMV announced the lifting of the ban from February 16 onwards, and on February 24, the Italian ban expired.

Our sample covers the period from February 15, 2008, to March 27, 2012, and includes 1,073 trading days. It consists of all stocks that had listed options as of February 2012 on the Belgian (Brussels Stock Exchange/Euronext Brussels), French (Paris Bourse or Euronext Paris), Italian (Milan Stock Exchange or Borsa Italiana), and Spanish (Bolsa de Madrid) stock exchanges. Overall, our sample comprises 185 stocks, of which 105 are included in these stock exchanges' main indices, i.e., the Belgian BEL20, the French CAC40, the Italian MIB, and the Spanish IBEX35.

From Bloomberg, we source daily trading volumes and the number of shares outstanding per stock, trading volumes, and put-call volume ratios for listed options. Trading volumes for listed puts on the EuroStoxx 50 index, the V2X index (the IV index from the EuroStoxx 50 index), and generic series of five-year sovereign credit default swaps (CDS) for Belgium, France, Italy, and Spain are also collected from Bloomberg. Daily short stock positions (utilization rates) and costs of short selling (simple average fee, simple average rebate, and cost of borrow score) were kindly provided by Markit Securities Finance (formerly Data Explorers).

We implement the method by Figlewski (2009) for obtaining RNDs. He builds on the Breeden and Litzenberger (1978) formulae and interpolates and smooths the IV structure instead of interpolating option prices. A clear strength of the Figlewski (2009) approach is its ability to fill in intermediate grid values of the IV curve between the available strikes (the body of the RND) with reduced noise and to extrapolate the RND beyond such observable strikes with tails of flexible and reasonable shape.

To calculate RND for the stocks of interest, we obtain daily IV data for seven moneyness levels, i.e., 80, 90, 95, 100, 105, 110, and 120, at the three-month maturity. Implied volatilities are extracted by reverse engineering the Black-Scholes model from Bloomberg's 16:00 hours closing mid-prices (Bloomberg, 2008). In line with Figlewski (2009), IVs for the 80 to 95 moneyness levels are obtained from puts, while IVs for the 105 to 120 moneyness levels are obtained from calls. For consistency with our IV skew measure, we use ATM IV from puts. Because we intend to compare RND from banned stocks to non-banned ones, we compute IV skews and extract RNDs for these two groups of stocks separately. More details on the application of the method are included in Appendix 1.1.

We make use of extreme value theory (EVT) to measure implied jump risk[4] because it focuses on tail events, such as jumps in return distributions. EVT allows us to compare the value-at-risk (VaR) implied by RNDs for banned and non-banned stocks. We first estimate the tail shape estimator ($\varphi$), using Hill (1975) to compute the VaR using the semi-parametric quantile estimator ($\hat{q}_p$) of Hartmann et al. (2004). In a next step, we employ a bivariate EVT method to calculate commonality in jumps and, hence, contagion risk from historical returns. EVT is well suited to measure contagion risk because it does not assume any specific return distribution. Our approach estimates how likely it is that one stock will experience a crash beyond a

[4] We acknowledge that the expression "jump risk" can also refer to the physical or actual, real-world jump risk. However, in this paper, we work with the implied, risk-neutral jump risk measure only. This measure of jump risk can be viewed as the sum of the actual (real-world) jump risk plus a risk premium. Hence, implied jump risk increases may be caused by increases in physical jump risk, increases in the risk premium, or both.

specific extreme negative return threshold conditional on another stock crash beyond an equally probable threshold.[5]

We use the daily IV skews of individual European equities as a second measure of implied jump risk[6]. The IV skew is calculated as the difference between the IV of three-month OTM listed puts at the 80 percent moneyness level and ATM puts with the same maturity for every stock in our sample. As with RNDs, we construct two indices of IV skew, one for banned and the other for non-banned stocks, by equally averaging the stock-specific IV skews of the constituents of each index. We also calculate single country versions of the banned and non-banned IV skews for Belgium, France, Italy, and Spain. Table 2 presents descriptive statistics for our IV skew measures for the entire sample period, both for the overall and single-country levels.

< *Please insert Table 2 about here* >

Table 2 shows that the average and median IV skews for banned stocks are higher than for non-banned stocks, an observation that pertains not only to the overall numbers but also to each country separately. The standard deviation of the IV skew is higher for banned stocks. As expected, the distributions of the IV skews are all positively skewed. All IV skew distributions reported here have fat right tails and are not normal; thus, we use a non-parametric Mann-Whitney U-test to make statistical inferences.

## 3. Discussion of results

We first examine the short selling utilization rate[7] and the performance of banned and non-banned stocks around the ban announcement day. Figure 1 shows that the imposition of the 2011 European ban strongly affects the short selling of stocks in Belgium, France, Italy, and Spain. Plot A indicates that the short selling utilization rates fall for banned stocks from 32 to 27 percent in the months of August and September 2011, especially after the ban announcement on August 11. This drop in short selling utilization is widespread

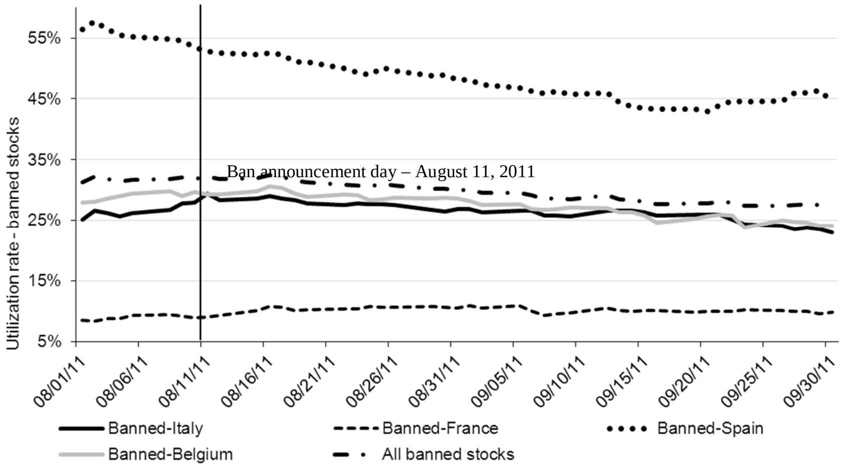
[5] We refer to Hartmann et al. (2004) and Balla et al. (2014), who use the conditional co-crash (CCC) probability estimator, which is applied to each pair of stocks in our sample. Appendix 2 includes a detailed discussion of both our employed univariate and bivariate EVT-methodologies.

[6] A fat left tail in the RND of returns is a corollary to the fact that the IV skew is steep, see Bakshi et al. (2003).

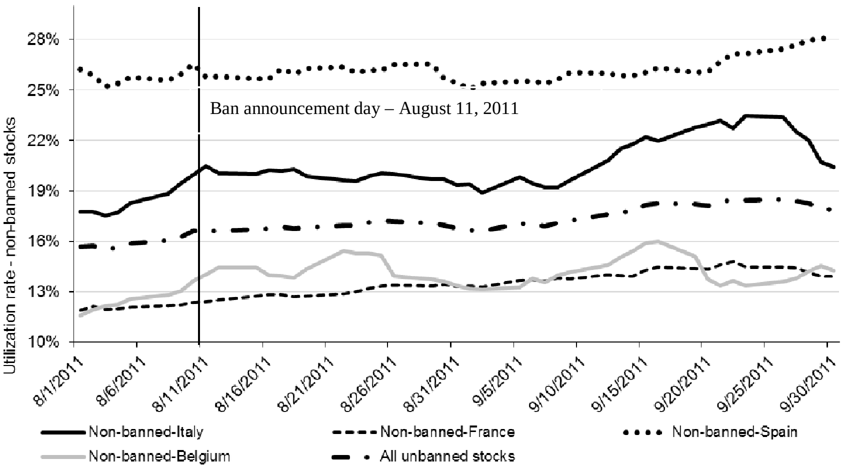
[7] The short selling utilization rate is calculated as *Utilization*=100*(*ValueOnLoan*/*InventoryValue*), where *ValueOnLoan* is the beneficial owner value of the loan and *InventoryValue* is the beneficial owner inventory value. *Utilization* measures the value of a stock utilized for securities lending against the total value of inventory available for lending, i.e., its short selling demand.

across the four crisis countries. For Belgium and Italy, short selling utilization drops from 29 to 23 percent and 24 percent, respectively. For France, it remains unchanged at approximately 10 percent during this period. For Spain, it drops from 53 percent on the ban announcement day to 45 percent on September 30. We observe that such drops in the utilization rate come from the decrease in the value of short selling, the numerator of the utilization rate, as inventories of stocks available for lending in the four countries remain relatively unchanged. The decreasing utilization rates indicate that the ban was effective in reducing short selling, despite market makers still being allowed to short banned stocks.

**Figure 1. Short positions around ban date**
**Plot A. Banned stocks**




**Plot B. Non-banned stocks**




This figure presents the average short utilization rates calculated for banned (Plot A) and non-banned (Plot B) stocks in our sample. Utilization rates have been calculated for the full sample of banned and non-banned stocks as well as separately for the stocks in Belgium, France, Italy, and Spain.

The reduction in short selling of financial stocks is especially noteworthy when utilization rates for banned and non-banned stocks are compared. Plot B shows that the utilization rate for non-banned stocks increases from 16 to 18 percent, on average, during August and September 2011, an increase observed across all four euro countries.

Despite such changes in utilization rates, short selling of banned financial stocks far exceeds the level measured in non-banned stocks. In August 2011, the average short selling utilization rate for financial stocks is twice the level reported for stocks of the other sectors (32 percent in Plot A vs. 16 percent in Plot B). Short sellers would have benefited much more from further deterioration of financial stocks rather than from a potential weakness in the average stock. Despite such a dichotomy, utilization rates for the overall market around the ban announcement day were at their highest levels since 2010 for the four crisis countries. For Italy and Spain, the short selling activity was concentrated in mid-caps (Data Explorers Limited, 2011), which matches a large short selling interest in their banks.

From the end of June until the ban announcement, the EuroStoxx Banks index dropped by 32 percent, whereas the EuroStoxx 50 index fell by 22 percent. In the first ten days of August 2011, before the ban, shares in European banks fell by 23 percent, whereas the European index corrected by 17 percent. In the subsequent month after the ban was announced, European banks' stocks lost an additional 18 percent, while non-financial equity dropped by only 6 percent. Our data on short selling positions and returns suggest that financial stocks were indeed under strong pressure.

### *3.1. VaR levels and volatility skews*

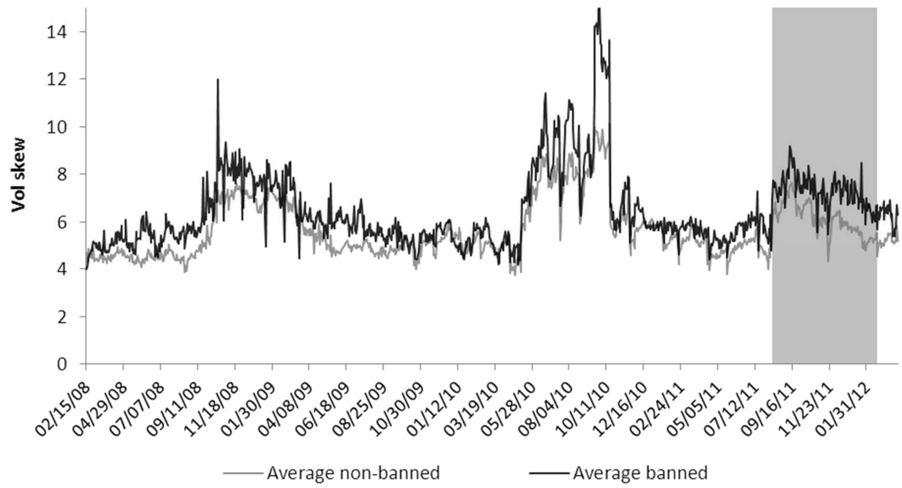
In the following analysis of VaR levels implied by RNDs, we distinguish five sub-periods: (1) the U.S. recession period (February 15, 2008, to June 30, 2009); (2) the 2009/2010 stock market rally (July 1, 2009, to April 26, 2010); (3) the European crisis period (April 27, 2010, to August 10, 2011), initiated by Standard and Poor's downgrade of Greece's sovereign bonds to "junk" status; (4) the ban period (August 11, 2011, to February 16, 2012); and (5) the post-ban period (February 17, 2012, to March 27, 2012).

Panel A of Table 3 shows that during the ban period, the RND-implied VaR levels for banned stocks, i.e., the perceived implied jump risks, are significantly higher than for non-banned stocks. The same conclusion holds for the post-ban period. We observe that the VaR levels from RNDs during the ban period are significantly higher than during the pre-ban period. The ten percent VaR for banned stocks increases from 38 to 62 percent for banned stocks, whereas for non-banned stocks, it increases to a much lesser extent, from 35 to 46 percent. We observe similar differences in extreme downside risk for these two sub-samples at both the five- and one-percent VaR levels. Interestingly, the VaR levels for the post-ban period are not significantly different from the ban period for both banned and non-banned stocks. The other sub-sample that had very distinct downside risk features in comparison to the preceding period was the 2009 stock market rally. The latter period had significantly lower VaR priced in RND returns than the U.S. recession period, especially for banned stocks but also for non-banned equity. The ten percent VaR for banned stocks was 50 percent during the recession and 40 percent during the rally, whereas for non-banned stocks it was 47 and 41 percent, respectively. We find that the VaR levels for banned stocks were generally higher than for non-banned stocks, and downside risk priced in RND reached its peak during the ban.

*< Please insert Table 3 about here >*

Figure 2 depicts the historical behavior of our proxy for implied jump risk, the average IV skew, for banned and non-banned stocks. The ban period is highlighted, with the beginning of the shadowed part representing the ban announcement day. We observe that between 2008 and 2012, spikes in average IV skews were well above their mean, coinciding with periods of market turmoil. Figure 2 shows that the IV skews rise strongly in 2008, around the Lehman collapse, and wane after the market trough in March 2009. In 2010, the IV skews jump on April 27, the day the Greek government bonds were downgraded by Standard and Poor's to "junk" status. The IV skew then strongly reverses on October 18, 2010, when a task force of European leaders agreed on a rescue package to improve the European Union's economic governance in an effort to tackle the financial crisis. The 2011 jump in IV skews coincides with the ban announcement day on August 11. The announcement was not accompanied by any major event related to the European financial crisis, to equity markets in general or to the financial sector. We observe that on all three occasions, the IV skew of banned stocks exceeded the IV skews for non-banned stocks.

**Figure 2. Averaged implied volatility skews**




This figure depicts the average IV skew for banned and non-banned stocks over the entire sample period. Averages are calculated over all stocks in Belgium, France, Italy, and Spain that have listed options. The IV skew per stock is calculated as the difference between the IV of the 80 percent moneyness OTM put option and the ATM put option. The European short selling ban period (August 12, 2011, to February 16, 2012) is shadowed.

Figure 2 shows that implied jump risk rises strongly just prior to the ban announcement for both banned and non-banned stocks. Such spikes in implied jump risk occur during the day on August 11, 2011, whereas the ban was officially announced only after the market closed[8]. The increase in the average IV skew on August 11 for banned stocks is equivalent to 2.16 volatility points, while for non-banned stocks it is equivalent to 1.05 volatility points. Both differences exceed the 99$^{th}$ percentile of all daily IV skew changes in our sample. On August 12, the average IV skew continued to rise sharply, by 0.78 volatility points for banned stocks, a movement exceeding the 94$^{th}$ percentile of all daily IV skew changes in our sample. On that same day, the IV skew for non-banned stocks rose by 0.55 volatility points, exceeding the 96$^{th}$ percentile. We observe that jumps in the IV skews around the ban announcement day are outliers in our sample. More importantly, the rise in the IV skew for banned stocks is much more pronounced than for non-banned stocks.

[8] It is unclear whether any information on the upcoming short selling ban leaked before the market closed on August 11. However, given that a ban on covered short selling on all stocks was already introduced in Greece on August 8, the extension of the ban to other European countries might have been expected by some market participants.

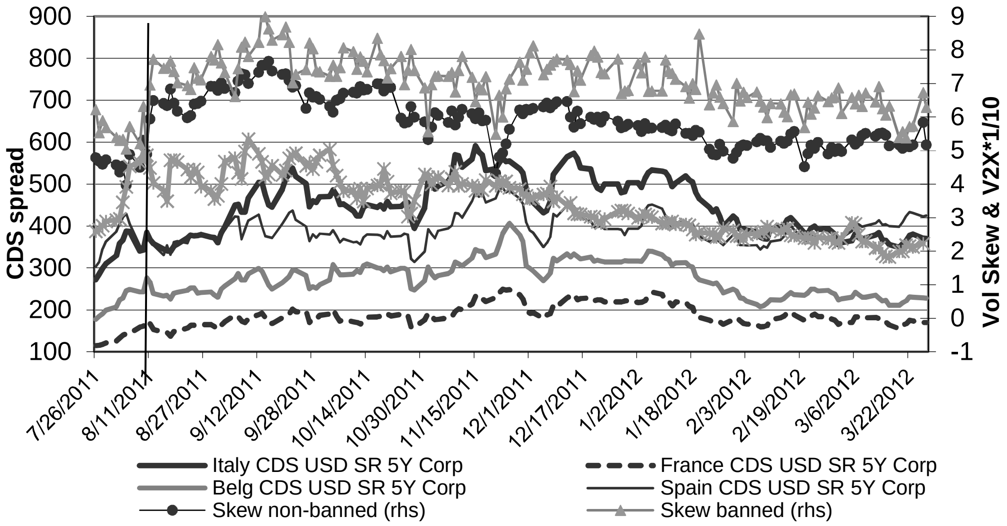
We also observe from Figure 2 that after the announcement of the short sale ban, the IV skew levels of both banned and non-banned stocks remained elevated for several weeks. During the entire ban period, the IV skew of banned stocks remained relatively high, whereas the IV skew for non-banned stocks slowly declined to pre-ban levels. This persistence in the high level of implied jump risk indicates that the ban did not diminish market participants' concerns regarding European financial stocks.

Table 3, Panel B presents the corresponding medians for the whole period and for the five sub-periods separately. We observe that the sub-periods 1, 3, and 4 have the highest IV skews. They also roughly match the periods of market turmoil and volatility humps highlighted in Figure 2: the global financial crisis, the European sovereign debt crisis, and the 2011 European ban period. The median IV skew for banned stocks is 7.34, significantly higher during the ban period than before, when it was 6.05. For non-banned stocks, the median IV skew during the ban period is 6.05, only slightly higher than during the European crisis, when it was 5.78. Moreover, the median IV skew during the European crisis period is also significantly higher than during the stock market rally. Figure 2 also indicates that the IV skew for banned stocks exceeds that for non-banned stocks in most periods. We observe similar patterns in the country-specific data. We find that the short selling ban contributes to an increase in implied jump risk, especially with respect to banned stocks. Conversely, once the ban is lifted on February 16, 2012, IV skews drop significantly for both banned and non-banned stocks.

Our empirical findings indicate that the short sale ban did not reduce the implied jump risk during the European financial crisis. Otherwise, VaR levels and IV skews would have receded. On the contrary, we find significant evidence that VaR levels increased strongly and that IV skews jumped instantly when the ban was introduced and remained high during the period of the ban, particularly for banned stocks.

A potential flaw in the empirical analysis so far is that large movements in the IV skew, observed during the ban or at the time of its announcement, may have been contemporaneous to the dissemination of other relevant information. If so, we cannot draw a clear connection between the ban announcement and IV skew behavior. Figure 3 indicates that the IV skews rise on August 11, even though we do not observe negative shocks within country-specific CDS spreads and the V2X index[9].

**Figure 3. Sovereign CDS spreads, V2X and implied volatility skews**




This figure depicts the five-year sovereign CDS spreads for Belgium, France, Italy, and Spain as well as the V2X and the IV skews for non-banned and banned stocks. Sovereign CDS spreads proxy for country-specific information flow. V2X is the implied volatility index from the EuroStoxx 50 index, and it proxies for market-wide information flow. The V2X series is multiplied by 0.10 to fit the same scale as the IV skew. The IV skew per stock is calculated as the difference between the IV of the 80 percent moneyness OTM put option and the ATM put option. The ban announcement on August 11, 2011, is indicated by the vertical line.

Figure 3 displays that information flow for the four crisis countries was relatively benign around the ban announcement date, as CDS spread levels remain unchanged, whereas the V2X even decreases after showing a large spike in the days preceding the ban. Equity market movements around that period further support the presence of such positive information flow[10]. The EuroStoxx 50 index rose by 2.86 percent on August 11 and by 4.15 percent on August 12, whereas the EuroStoxx Banks index rose by 2.96 and 5.26 percent, respectively. Moreover, no other major announcement was made during these days. The absence of negative information strongly suggests that the ban announcement itself catalyzed the rise in implied jump risk.

[9] We use CDS spreads to proxy the country-specific information flow. We adopt the V2X, the European counterpart of the VIX (the IV index for S&P500 index options), as a proxy for the European equity market information flow.

[10] Figure 3 shows that moves in the country-specific IV skew match the sovereign CDS spread behavior in this period very well. CDS spreads moved sideways for Belgium, France, and Italy, while they rose for Spain. This divergence can be explained by the fact that on February 13, 2012, Spain's sovereign debt rating was downgraded two notches by Moody's, from A3 to A1, which was much more severe than the rating changes for the other three crisis countries.

### *3.2. Financial contagion risk*

In this section, we assess the development of financial contagion risk, using average conditional co-crash (CCC) probabilities. The average CCC probability measures the likelihood that a banned (non-banned) stock crashes, given that another banned (non-banned) stock crashes. We estimate the bivariate CCC probabilities for all pairs of banned and all pairs of non-banned stocks using realized daily returns. Table 4, Panel A presents the results from the estimation of equation (A.13) for the full sample and individual sub-samples. Over the full sample, the CCC probability for the banned stocks is 32 percent, while for the non-banned stocks, it is 29 percent, which is not significantly different. In the first sub-sample periods, the contagion risk of the banned stocks reaches a similar level, as it does for the other stocks. However, during the pre-ban European crisis period, we find that contagion risk for banned stocks (42 percent) becomes significantly different from that for non-banned stocks (33 percent). Surprisingly, this substantial difference is no longer observed during the ban period, when the CCC probability for banned stocks decreases to 32 percent, while it increases to 41 percent for non-banned stocks. This decrease in contagion risk for banned stocks is one of the major findings of our paper. Apparently, the imposition of the ban decreased systemic risk. This effect occurred despite the increase in forward-looking implied jump risk across the same sample and period.

In a next step, we analyze whether the CCC probabilities for banned and non-banned stocks are different across samples. We observe that the CCC probabilities for banned stocks during the U.S. recession (27 percent) and the 2009 equity market rally period (28 percent) are not significantly different. The same assessment holds for non-banned stocks, where Panel A indicates CCC probabilities at 26 and 23 percent for these two sub-periods, respectively. The pre-ban period, however, witnesses an abrupt and statistically significant increase in the CCC probability for banned (from 28 to 42 percent) and non-banned (from 23 to 32 percent) stocks. Clearly, contagion risk is higher across the board once the European crisis is triggered, but it is especially higher for financial stocks. After the ban is announced, banned stocks' contagion risk falls from 42 to 32 percent, while for non-banned stocks, contagion risk rises from 32 to 41 percent.

*< Please insert Table 4 about here >*

Another variable that potentially plays a major role for financial contagion risk is trading activity. Bollen and Whaley (2004) suggest that the IV skew might be closely linked to trading activity in the options market. They find that changes in the shape of the IV function are directly related to net buying pressure on options from end-users' public order flow. They argue that end-users trade options for portfolio insurance, agency, and speculative reasons, rather than for market-making reasons. Gârleanu et al. (2009) confirm their findings and observe that the size of the IV skew is positively and significantly related to demand pressures from institutional investors seeking portfolio insurance.

We inspect daily put and call trading volumes as well as the put-call volume ratio as proxies for trading pressure, as suggested by Dennis and Mayhew (2002). We measure volume as the median number of contracts traded on a specific day for all stocks in the sample. We obtain an overall put-call volume ratio by averaging the single-stock contracts. Again, we evaluate these measures over the five periods previously identified in our data set. Table 4, Panel B documents that the median number of single-stock puts for each banned stock traded per day decreases significantly from 1,905 during the pre-ban European crisis period to 1,727 during the ban period. For non-banned stocks, the median volume of puts also drops, from 1,157 during the pre-ban period to 943 during the ban. The median put-call volume ratio for non-banned stocks significantly increases during the ban, from 6.3 to 8.7, whereas the median put-call volume ratio for banned stocks hardly changes.

The findings in Panel B provide no evidence that individual stock options, particularly puts, experienced a large rise in trading activity. Thus, we find no evidence of a substitution effect of the short selling of common stock into single-stock put options. We also find no evidence that trading activity completely dried up during the ban period. This result is in line with Grundy et al. (2012), who show that the overall volume of options trading dropped during the 2008 U.S. short selling ban. This behavior of trading volumes indicates that during the ban, the IV skew does not increase as a result of increased selling pressure, as originally suggested by Bollen and Whaley (2004) and Gârleanu et al. (2009).

We assume that once short selling activity in banned stocks diminishes, the demand for synthetic shorts via put options should increase. During the ban, informal market makers in options (high-frequency traders and hedge funds)[11] can no longer delta-hedge by short selling stocks. Hence, they become less willing to sell protection, significantly impairing the supply of puts.

As securities-lending programs were in less demand by short sellers during the ban, it became cheaper to borrow stocks. In unreported results, we find that three common measures of borrowing costs (the simple average fee, the simple average rebate, and the daily cost of borrow score) indeed fall for banned stocks, from the date the ban was introduced until the end of September 2011. Borrowing costs constitute, however, only one component of hedging costs, and, depending on market circumstances, not necessarily the largest one. Costs incurred by bid-ask spreads and price impact may easily outpace borrowing costs in times of thin trading activity. Beber and Pagano (2013) illustrate that the 2008 U.S. ban is associated with an increase in bid-ask spreads ranging between 1.64 and 1.98 percentage points among international stocks where the average bid-ask spread is 3.93 percentage points[12]. Likewise, Battalio and Schultz (2011) and Grundy et al. (2012) note that bid-ask spreads on options on banned stocks also rose significantly during the 2008 U.S. short sale ban. In contrast, on August 11, 2011, the fee for borrowing from the Spanish bank Santander was only 51 bps per annum. Therefore, lower borrowing costs may not have helped much in encouraging market makers to write puts during the ban.

A final explanation for a smaller supply of puts during the ban is that option sellers became more risk-sensitive following equity market declines. Gârleanu et al. (2009) find that end-users have a net long-position in equity index options with a corresponding large net position in OTM puts. Conversely, market makers are short in OTM puts. Following a market decline, they become more reluctant to write additional puts. In the days before the introduction of the European short sale ban, equity markets strongly corrected on the back of an intensifying European financial crisis; thus, it is not difficult to envision high risk aversion among market makers during the ban and a diminished willingness to sell puts. Holders of financial stocks suddenly had to pay much higher prices to buy protection: three-months 80 percent moneyness OTM puts on

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[11] Boehmer et al. (2013) note that approximately 50 percent of all options trading is currently supplied by such informal market makers.

[12] Sobaci et al. (2014) provide similar results for emerging markets.

financial stock, on average, became 16 percent more expensive on August 11, compared to the average of the previous 21 trading days.

On the ban announcement day, the trading volume for puts on the EuroStoxx 50 index reached 2,573,868, which is the second-highest daily trading volume for this instrument in our sample[13]. A potential explanation for such a high trading volume is that after the imposition of the ban, the skew from stock options relative to index options became too costly. The spread between the IV skew from the Eurostoxx 50 index put options and single-stock puts, which is normally highly positive, was just marginally positive during the ban, reaching zero on December 20, 2011. Because index puts are far more liquid than single-stock puts, a liquidity premium no longer existed, and a migration from single stock puts to index puts took place. Such an explanation is also in line with the "flight-to-liquidity" models suggested by Pástor and Stambaugh (2003) and Acharya and Pedersen (2005).

### *3.3. Panel regression analysis*

To further assess the effect created by the short selling ban and trading activity on IV skews, we run a panel regression analysis with the IV skew (*IVSkew*) as the dependent variable. This regression allows us to isolate the relationship between the IV skew, banned stocks, and trading activity by controlling for other determinants of the IV skew, such as information flow and idiosyncratic factors. We use the following firm-specific control variables: daily turnover (*Turnover*), systematic risk (*Beta*), and firm size (*Size*). We use turnover as a proxy for stock liquidity, following Dennis and Mayhew (2002).

We calculate an individual stock's daily turnover by dividing its daily trading volume by its number of shares outstanding. The stock's beta is our control variable for systematic risk. The market return is assumed to be the equal-weighted average daily return for all stocks in our sample. The daily estimation of the beta uses a rolling window of one year's worth of data, where the data begin one year before the first

[13] The heaviest trading in EuroStoxx 50 index puts took place on October 10, 2008, when the Belgian bank Dexia was bailed out and 2,604,185 contracts were traded.

sample date. Firm size is calculated as the number of shares outstanding on a specific day multiplied by the stock price.

Control variables are uncorrelated with each other in both the cross-sectional and the time-series dimension (unreported here). We employ de-trended levels of sovereign CDS spreads for Belgium, France, Italy, and Spain (*CCDS*) and the V2X volatility index (*V2X*) as a control variable for country-specific and equity market information flows[14]. Additionally, we proxy firm-specific information flows with daily stock returns (*R*), trading pressure via single-stock put option trading volume (*PVlme*), and trading volume of puts on the EuroStoxx 50 index (*E50PVlme* )[15]. Our resulting Model 1 is given as follows:

$$IVSkew_{i,t} = c + V2X_t + CCDS_{i,t} + R_{i,t} + Turn_{i,t} + Size_{i,t} + Beta_{i,t} + D_t^B + D_t^{Bned} + D_t^B * D_t^{Bned} + D_t^{PostB} + D_t^{PostB} * D_t^{Bned} + PVlme_t + E50PVlme_t + \varepsilon_t, \quad (1)$$

where $D_t^B$ is a dummy variable equal to one if the date is within the ban period (August 11, 2011, to February 16, 2012), and zero otherwise. $D_t^{Bned}$ is a dummy variable equal to one if the underlying stock is a banned stock, and zero otherwise. $D_t^{PostB}$ is a dummy variable equal to one if the date is after the lifting of the ban (from February 17, 2012, onwards), and zero otherwise. An additional dummy variable is created as an interaction term for these two dummies, $D_t^B{*}D_t^{Bned}$. This variable captures the effect on the IV skew when two conditions hold: the stock is banned and the ban is in place.

We use generalized least squares (GLS) to account for potential serial correlation in the residuals. We estimate our panel regression over three different periods: (a) the full period, ranging from February 15, 2008, to March 27, 2012; (b) the period that starts on April 27, 2010, when the European sovereign crisis is deemed to have begun, to March 27, 2012; and (c) the ban period, ranging from August 11, 2011, to February 16, 2012. Table 5, Panel A reports the regression results. Over the full sample period (column a), all

[14] Based on the Johansen cointegration test, we find no cointegration between the de-trended CDS spreads of the four crisis countries and the V2X index at the five-percent significance level.

[15] Single-stock put option trading volume is computed as the average daily trading volume of puts divided by 1,000. Put trading volume is not used as an additional cross-sectional variable because data are only available for a limited set of stocks (122 of 186). *E50PVlme* is the daily trading volume of puts on the EuroStoxx 50 index divided by 1,000,000 and is used to capture the potential indirect substitution effect of trading pressure on single-stocks' puts by index puts.

coefficients are statistically significant at the one-percent level, except for the dummy variable $D_t^B$ and the post-ban dummy variables. The results for *V2X*, country CDS spreads, *Beta*, and *Turnover* are in line with the results reported in the literature and with our expectations. We expected V2X and CDS spreads to be positively related to the IV skew, as implied jump risk priced for individual stocks is likely to increase with equity market volatility and country credit risk. Contrary to our expectations, stock returns and size are positively related to the IV skew. Nevertheless, our size-skew estimates are in line with the results reported in Engle and Mistry (2008). They suggest that size proxies for beta, warranting a positive relationship between size and skew.

The results obtained from our dummy variables over the full sample period confirm that the ban positively affected the IV skew for banned stocks: $D_t^B * D_t^{Bned}$ has a positive sign and is statistically significant. The interaction coefficient of this dummy variable indicates that the ban increases IV skews for banned stocks by 0.3 volatility points, which is economically relevant because it amounts to approximately five percent of the median IV skew in our data set. This is a strong result, given the large set of control variables used. This finding suggests that the IV skew for banned stocks during the European short sale ban was abnormally high compared to that for non-banned stocks and that for banned stocks in other periods. Furthermore, the estimated coefficient of $D_t^{Bned}$ implies that financial stocks have IV skews that are, on average, 0.72 volatility points higher than IV skews for non-banned stocks. This finding is consistent with our descriptive statistics provided in Table 2. The three dummy estimates confirm that the IV skew for all stocks was higher during the ban, and the effect was more pronounced for banned stocks.

*< Please insert Table 5 about here >*

Column b of Panel A shows that during the euro crisis pre-ban period, all parameter estimates for control variables have identical signs and comparable statistical significance levels compared to the results obtained in estimating Model 1 over the full period (column a). The impact in IV skews of banned stocks caused by the ban is even stronger though. On average, the ban increases the IV skew for banned stocks by 0.45 volatility points, which amounts to roughly nine percent of the median IV skews across our data set. At the same time, for the average stock, IV skews decreases by -1.1 volatility points during the ban. These results support our hypothesis that investors seem to have differentiated between banned and non-banned stocks upon the ban introduction.

Empirical results change more strongly when we estimate Model 1 for the 2011 European ban period. Column c shows that all control variables still have the same signs and the results are strongly statistically significant; however, the estimate of $D_t^{Bned}$ is no longer statistically significant. Because we use such a short period, the dummies $D_t^{B}$, $D_t^{PostB}$, $D_t^{B}*D_t^{Bned}$, and $D_t^{PostB}*D_t^{Bned}$ are no longer applicable. This outcome suggests that, within the ban period, financial stocks are no longer associated with higher IV skews relative to the average stock. The lack of significance of $D_t^{Bned}$ is, however, connected to its cross-correlation with beta for financial stocks during the ban (i.e., 1.30 relative to 0.90 for non-banned stocks). Additionally, *PVlme* becomes negative and significantly related to *IVSkew*. Thus, a rise in the skew during the ban period is associated with a lower volume of single-stock puts. This result is consistent with our hypothesis that a supply shift drove the IV skew during the ban rather than a change in demand. In such a setting, large upward movements in the skew could have been caused by low trading volumes in OTM puts. At the same time, the link between *E50PVlme* and *IVSkew* turns positive and significant. This relation is explained by the above-noted increase in the volume of index puts traded, in parallel with the supply-led rise in the IV skew during the ban.

A ban may be considered ineffective when selling pressure migrates from banned securities to alternative instruments. However, in the case of the 2011 European short sale ban, we observe that the migration of selling pressure from financial stocks to put options on European indices has not jeopardized the efficacy of the short sale ban. As a result of the migration, the ban appears to have diverted selling pressure initially concentrated in financial stocks to a larger share of the market. This hypothesis is consistent with the fact that contagion risk decreased for banned stocks during the ban but increased for non-banned stocks.

When the short sale ban was introduced on August 11, 2011, any further selling pressure on financial stocks could have led to destabilizing shocks and financial contagion. The price of OTM puts on banned stocks rose as a result of lower trading volume rather than through a substitution effect. The richness of OTM puts made it substantially more expensive for market participants to take a synthetic short position. Hence, imposition of the ban likely helped to curb downward price pressure, which benefited financial sector stability.

In a next step, we analyze whether a supply shift in the options market was an important driver of IV skews during the ban. As market makers use their bid-ask quotes for inventory management, spread measures from options markets indicate whether a supply shift occurred around the ban or not. We calculate two bid-ask spread-based measures for put options—i) *percentage spread*, i.e., $(ask - mid)\ /\ mid,$ and ii) *IV spread*, i.e., $\delta IV = \delta C/Vega$—to evaluate the impact on IV caused by market makers' inventory management[16]. *Percentage spread* represents the percentage of the put mid-price that market makers charge to supply an option. *IV spread* represents the translation of *percentage spread* into volatility points, i.e., how many volatility points market makers charge to supply an option. We evaluate the behavior of *percentage spread* and *IV spread* in the full sample and in our sub-samples by calculating median spreads of these two metrics across put options on the 28 stocks in our sample that belong to the EuroStoxx 50 index[17]. The results are shown in Table 6.

*< Please insert Table 6 about here >*

We observe that *percentage spread* is relatively low during both the U.S. recession and the 2009 stock market rally, but becomes significantly higher when the pre-ban period begins. For non-banned stocks, the spread increases from 0.081 to 0.099, whereas for banned stocks, it rises from 0.058 to 0.076. The ban period is the sub-sample where *percentage spread*, at 0.089, is the highest for banned stocks, significantly higher than during the preceding period (0.076). For non-banned stocks, the metric drops during the ban period from 0.099 to 0.090. Thus, *percentage spread* indicates that during the ban, market makers became more averse to supplying puts on financial stocks but not on the other stocks. In the post-ban period, spreads for both non-banned and banned stocks fall, suggesting the unwinding of this supply shift.

[16] *IV spread* uses options' Greek *Vega*, i.e., $\delta C/\delta IV$, to obtain $\delta IV$, where $\delta C$ is the difference between ask and mid-prices. Option prices and *Vegas* are from ATM options and are obtained from Bloomberg and Datastream. Although the *IV spread* measure only estimates the impact on IV caused by changes in spreads from ATM options, we assume that such increase in spread is also indicative of supply shift on OTM options and, consequently, on the IV skew. This assumption is conservative, as bid-ask spreads of OTM options are typically higher than those of ATM options due to the lower liquidity of OTM options.

[17] From the full Eurostoxx 50 index sample, we discard those stocks for which the required options data are not available.

The *IV spread* metric behaves in line with *percentage spread.* The *IV spread* is relatively low during both the U.S. recession and the 2009 stock market rally, with the latter period reporting statistically significant lower spreads than the former. The pre-ban period experiences a sudden and statistically significant rise in *IV spread*, from 0.050 to 0.075, for non-banned stocks and from 0.039 to 0.082 for financial stocks. The *IV spread* continues to rise during the ban period for banned stocks, from 0.082 to 0.149. In contrast, it falls by two-thirds for non-banned stocks, from 0.075 to 0.025. During the post-ban period, *IV spread* continues to rise for banned stocks, whereas it falls for non-banned stocks[18]. These results from our two spread measures confirm that during the ban, market makers widened their spreads for options on financial stocks, while no such supply shift seems to have occurred for options on the other stocks.

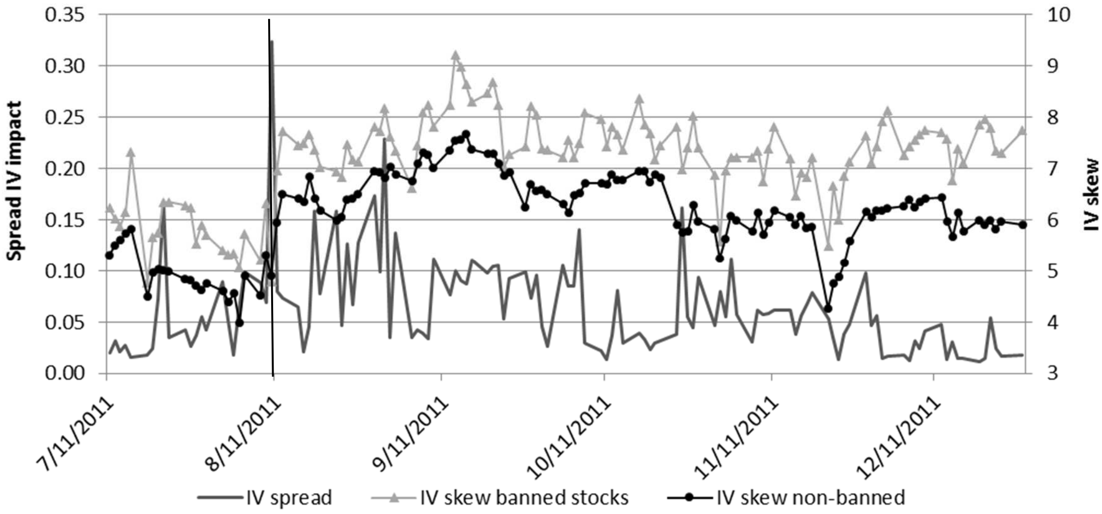
To formally test the overall impact of options bid-ask spread on IV skew, we specify our Model 2, which comprises Model 1 with the addition of the *IV spread* as an explanatory variable, as follows:

$$IVSkew_{i,t} = c + V2X_t + CCDS_{i,t} + R_{i,t} + Turn_{i,t} + Size_{i,t} + Beta_{i,t} + D_t^B + D_t^{Bned} + D_t^B * D_t^{Bned} + D_t^{PostB} + D_t^{PostB} * D_t^{Bned} + PtVlme_t + E50PtVlme_t + IVspread_t + \varepsilon_t. \qquad (2)$$

Table 5, Panel B presents the estimates of Model 2. We observe that *IV spread* has a statistically significant (positive) relation with IV skews during the ban period but not during the other two periods. During the ban period, on average, a one volatility point increase in *IV spread* is linked to a 3.30 increase in IV skew. Within the full sample and during the pre-ban period, however, rises in *IV spread* provoke no statistically significant impact on IV skew. Most explanatory variables in Model 2 have the same signs and similar significance levels as observed in the estimation of Model 1. This is always the case for the joint dummy $D_t^B * D_t^{Bned}$. More intuitively, Figure 4 shows the jump in IV skews around the ban announcement day and a coincident large spike in *IV spread.*

[18] The rise in *IV spread* during the post-ban period is mainly caused by Spain, which matches the behavior of Spanish stocks' IV skew and sovereign CDS in such periods. This rise is likely caused by the country's sovereign debt rating downgrade by Moody's on February 13, 2012.

**Figure 4. Implied volatility skews and IV spread**




This figure depicts the average IV skews for banned and non-banned stocks as well as the average *IV spread* for the 28 stocks in our sample that belong to the EuroStoxx 50 index from July 11, 2011, to December 30, 2011. The IV skew per stock is calculated as the difference between the IV of the 80 percent moneyness OTM put option and the ATM put option. The ban announcement on August 11, 2011, indicated by the vertical line, coincides with a large spike in *IV spread* and with large increases in the IV skew for banned and for non-banned stocks.

We see that on August 11, 2011, the banned stocks' average IV skew rose by 2.16 volatility points, whereas for our sample of 28 stocks, this increase was 1.77 volatility points. Of these 1.77 volatility points, a rise of 0.32 volatility points in IV skew (approximately 18 percent) was caused by a widening of the bid-ask spread, as suggested by the *IV spread* variable shown in Figure 4. Due to the conservative nature of this variable, which is based on ATM options rather than on OTM options, such an impact on IV skew coming from bid-ask spreads is material. These findings reinforce our view that IV skews have risen due to a supply shift among market makers and other options providers, rather than further selling pressure on financial stocks via options.

In a final step, we incorporate information from the fixed income market into our panel regression analysis. We use the probability of default, following Hull et al. (2005), who build on the Merton (1974) credit risk model. Hull et al. (2005) find that implied volatility skews from single-stock options are linked to the firms' default risk. We specify the probability of default both as a stock-specific information flow proxy (Model 3) and to replace the dependent variable in Model 1, which leads to Model 4. Models 3 and 4 are estimated for the full sample, ranging from February 15, 2008, to March 27, 2012. We use the same GLS panel regression approach as in Model 1, with the following specifications:

$$IVSkew_{i,t} = c + V2X_t + CCDS_{i,t} + R_{i,t} + Turn_{i,t} + Size_{i,t} + Beta_{i,t} + D_t^B + D_t^{Bned} + D_t^B * D_t^{Bned} + D_t^{PostB} + D_t^{PostB} * D_t^{Bned} + PtVlme_t + E50PtVlme_t + PD_{i,t} + \varepsilon_t \quad (3)$$

and

$$PD_{i,t} = c + V2X_t + CCDS_{i,t} + R_{i,t} + Turn_{i,t} + Size_{i,t} + Beta_{i,t} + D_t^B + D_t^{Bned} + D_t^B * D_t^{Bned} + D_t^{PostB} + D_t^{PostB} * D_t^{Bned} + PtVlme_t + E50PtVlme_t + \varepsilon_t \quad (4).$$

$PD_{i,t}$ is the probability of default[19] implied by the 5-year CDS for firm *i* at time *t*. Because CDS data are not available for all firms in our sample, the number of cross-sections used in Model 3 and Model 4 equals 83. Table 5, Panel C reports the regression results for both models.

The second-to-last column in Panel C shows that the Model 3 estimates for the full period are consistent with the Model 1 estimates (column a) for the joint dummy $D_t^B * D_t^{Bned}$, with a significant coefficient of 0.3. The dummy $D_t^{Bned}$ has the same sign and statistical significance as in Model 1. The coefficient of the $PD_{i,t}$ variable is negative and strongly statistically significant. This negative link supports our hypothesis that the ban itself is responsible for an increase in implied jump risk for banned stocks.

The results in Panel C show that the risk premium priced in CDS default probabilities does not increase during the ban, like it was observed for the IV skews in Table 3. We argue that the implied jump risk rose due to an increase in physical jump risk, not to an increase in the risk premium. This result seems to be in line with our conclusion that the increase in implied jump risk during the ban was due to a supply shift instead of further selling pressure or increased risk premium required by investors to hold financial stocks. The explanatory power for Model 3 (14.5 percent) is higher than for Model 1 (10.5 percent), indicating that $PD_{i,t}$ is a powerful variable in explaining the dynamics of jump risk.

The last column of Panel C reports the estimates for Model 4, where $PD_{i,t}$ is the dependent variable. We see that the ban period has increased the probability of default for banned stocks by 1.8 percent, on average, as evidenced by the coefficient of the joint dummy $D_t^B * D_t^{Bned}$. The dummy $D_t^B$ is also positive,

[19] Probability of default implied by CDS spreads is calculated using the ISDA standard model. The recovery ratio is 40 percent.

meaning that the probability of default rose across the board once the ban was introduced. These findings suggest that the ban has negatively impacted fixed income markets because the increase in the probability of default slightly increased after the introduction of the ban.

### *3.4. Robustness Tests*

In Model 1, we observe shifts in the signs of *PVlme* and *E50PVlme* across different sample periods. Hence, we run now an additional GLS panel regression as a robustness check to control for any influence of the short sale ban. We estimate a reduced form of Model 1 that excludes all dummies related to the ban, while using only pre-ban data. Thus, our Model 5 is specified as follows:

$$IVSkew_{i,t} = c + V2X_t + CCDS_{i,t} + R_{i,t} + Turn_{i,t} + Size_{i,t} + Beta_{i,t} + PVlme_t + E50PVlme_t + \varepsilon_t \quad (5)$$

where the variables are defined as in Model 1. We estimate Model 5 for (a) the entire pre-ban period (from February 15, 2008, to August 10, 2011); (b) the U.S. recession period (from February 15, 2008, to June 30, 2009); (c) the stock market rally period (from July 1, 2009, to April 26, 2010); and (d) the European sovereign crisis until the last trading before the ban was implemented (from April 27, 2010, to August 10, 2011). Panel A of Table 7 presents the regression results of Model 5.

*< Please insert Table 7 about here >*

The first column of Table 7 shows that the Model 5 estimates for the pre-ban period are consistent with the Model 1 estimates (Table 5, Panel A, column a) for the full sample period. Hence, we find that increased trading activity in single-stock puts is linked to a high IV skew of single-stock options. This relation confirms the findings of Bollen and Whaley (2004) and Gârleanu et al. (2009), who link trading pressure to IV skews. Columns b and c of Panel A show that the estimates of the Model 5 parameters during all three sub-periods have the same signs and statistical significance levels as those obtained over the full pre-ban period (column a). Hence, the findings remain stable across various time periods and within two different model specifications.

As an additional robustness check, we analyze whether the IV skews for stocks in other European countries increased around the date of the short sale ban announcement. Such an increase could be evidence of financial contagion effects in options markets. If so, the steep rise in implied jump risk would also be observed in other European countries that did not adopt the ban and that were vulnerable to or already hit by the financial crisis. European countries that fit such criteria are Greece, Ireland, and Portugal (Grammatikos and Vermeulen, 2012). We compile the IV skew data for only Ireland and Greece because Portugal does not have a public equity options market. In unreported results, we find no indication that implied jump risk for these stocks materially changes when the short selling ban is introduced. These observations strengthen our earlier conclusion that the rise in the level of implied jump risk on the day of the ban announcement is connected to the ban itself, as opposed to other reasons, such as financial contagion.

In another robustness check, Panel B reports the results of estimating Model 1 after removing the Belgian shares from the sample. A potential justification for excluding the Belgian data from the analysis is that the Belgian banks in particular experienced relatively heavy government intervention during the crisis period. This intervention may distort the estimations for Belgium. However, Panel B of Table 7 shows that the results do not materially change after the removal of the Belgian data.

Our findings are also not altered when we use the IV slope measure of Yan (2011), which is the IV of close-to-ATM puts minus the IV of calls, as the dependent variable instead of our IV skew measure (see Panel C). Because our measurement of the IV skew is based on mid-prices, which may be unaffected by bid-asks widening due to market makers' response to the market turmoil, we also test whether our results hold if our IV skew measure comes from ask prices. We hypothesize that the ask price-based IV skew is biased upwards by the wider than normal bid-ask spreads during the European sovereign crisis and the ban period. Our analysis shows that the main findings still hold when we add the *IV spread* variable to the IV skew on the left-hand side of Model 1. This result, reported in Panel C, proves that our regressions are not biased by the use of IV from mid-prices in the construction of our explained variable, the IV skew.

As a final robustness test of Model 1, we substitute CDS spreads with sovereign spreads from government bonds. The intuition behind this check for robustness test is that uncovered positions in sovereign European CDS were also banned on November 1, 2012. We calculate spreads vis-à-vis Germany, using a maturity of ten years. Panel D indicates that our findings are affected rather little by this substitution and remain robust.

## 4. Conclusion

Recent research suggests that the short sale bans introduced during the 2008 financial crisis have reduced market quality around the world, perhaps even to the extent that the bans' benefits were outpaced (see, for example, Battalio and Schultz, 2011; Grundy et al., 2012; Boehmer et al., 2013; and Beber and Pagano, 2013). Nevertheless, market regulators in Belgium, France, Italy, and Spain re-introduced a short sale ban on financial stocks in August 2011 to combat the European financial crisis.

To analyze the effects of the European 2011 short sale ban on financial market stability and contagion risk, we extracted RNDs and IV skews from single-stock options. Our results indicate that implied jump risk of banned stocks was higher during the ban period than in any other period analyzed. We find that on the day of the ban announcement, implied jump risk levels for both banned and non-banned stocks showed a significant rise. Implied jump risk tended to increase for banned stocks even more than for non-banned stocks. Furthermore, during the imposition of the ban, the banned stocks' average IV skews remained at an elevated level, whereas this metric dropped for the other stocks. During the ban, the median IV skews for both the banned and non-banned stocks reached their highest levels when compared to any other period in the sample. Thus, the short sale bans themselves increased implied jump risk, especially for the banned stocks, even after controlling for information flow and stock-specific factors.

We further document that contagion risk for both banned and non-banned stocks already increased significantly during the pre-ban period. For non-banned stocks, contagion risk rose even more upon imposition of the ban. However, we find that contagion risk for banned stocks decreased during the ban relative to the pre-ban period.

Our approach of using option-implied data to analyze the impact of short sale bans on financial markets is only a first step. We believe that our knowledge on this topic would benefit from additional future research. Of particular interest would be the analysis of ban-driven increases in implied jump risk using the mutually exciting jumps model of Ait-Sahalia et al. (2015). We hypothesize that a lack of coordination by country regulators in introducing bans may be undesirable, as shocks in jump risk caused by subsequent bans may cross-excite each other and lead to financial contagion, which is of great importance to the supervisory policy agenda.

While we observe that the short sale ban is effective in restricting both outright and synthetic shorts on banned stocks, we do find evidence of trading migration to the Eurostoxx 50 index options market. Investors seem to switch from single-stock puts to index puts because of "flight-to-liquidity" incentives. The selling pressure potentially diverted from the financial stocks to a larger share of the stock market, thereby reducing the destabilizing effects in the financial sector.

The question remains whether the 2011 European short selling ban was a cure or a curse. If the first and foremost goal of imposing a ban is reducing systemic risk, then the 2011 bans do seem to fulfill this purpose. However, we note that this success comes at a cost, which is that the implied jump risk increases. Despite the fact that this effect in implied jump risk indicates market failure and may have adversely influenced market participants' expectations, it helped to preserve market stability by reducing contagion risk. Thus, what is the appropriate balance between market failure and systemic risk? Bans should be avoided if possible, and should only be used as a last resort when all other means have failed, as government and regulators should prioritize financial market stability over transitory market failure.

## Appendix 1 – Methodology to estimate implied jump risk

*1.1. Implied jump risk from risk-neutral distributions*

In this section, we describe how we compute IVs for the groups of banned and non-banned stocks. The banned group constituents are the stocks that were prohibited from short sales. The non-banned group constituents are the remaining stocks in our sample. We compute IVs for banned and non-banned stocks separately by equally averaging IV[20] on each moneyness level available across all stocks belonging to either the banned group or the non-banned group. This step produces one IV structure across our seven moneyness levels (80, 90, 95, 100, 105, 110 and 120) for both groups for every day in our sample. Then, we apply the Black-Scholes model to our IV data to obtain options prices for the banned and non-banned groups of stocks. We set the instantaneous price level of both groups equal to 100, and as a result, the percentage moneyness level automatically reflects strike prices per group. When applying the Black-Scholes model, we calculate contemporaneous dividend yield for banned and non-banned stocks by equally weighting dividend yield from the individual stocks. The risk-free rate applied is the Euribor three-month maturity.

Once options prices for the average banned and non-banned stocks are obtained, we can extract the RND of equity returns using the Breeden and Litzenberger (1978) formulae for the strikes along the body of our distribution, i.e., from the 80 to 120 moneyness levels:

$$RND(S) = \exp(rT)\left.\frac{\delta^2 C(T,K)}{\delta K^2}\right|_{K=S}, \tag{A.1}$$

where *RND(S)* is the risk-neutral probability of observing the terminal index level ($S$) at time $T$, $r$ is the risk-free rate for the specific maturity, $K$ is the strike price, and $C$ is the index option price. Computing the second derivative of the option price relative to strike prices via central differences leads to:

$$RND(S) \approx \exp(rT)\frac{C(T,S-\Delta K)-2C(T,S)+C(T,S+\Delta K)}{(\Delta K)^2}. \tag{A.2}$$

Following Figlewski (2009), extrapolation beyond the body of the RND[21] is performed by fitting a generalized extreme value (GEV) distribution using two extreme anchor points on each side of the body of the RND and extending a tail with the same shape[22]. The GEV-based extrapolation is then used to model the tails of the RND toward the moneyness levels 0 and 200. We initially use the first and third percentiles of the

[20] IV is calculated through reverse engineering the Black-Scholes model, while assuming constant interest rates and discrete dividends. Interpolation is used to calculate the IV at a fixed level of moneyness and at a fixed time to maturity.

[21] The Figlewski (2009) method is close to the method used by Bliss and Panigirtzoglou (2004), where body and tails are also extracted separately. These authors use a weighted natural spline algorithm for interpolation, which has the same decreasing noise effect in RNDs. Extrapolation is done by the introduction of pseudo data points, which has the effect of pasting lognormal tails into the RND. One advantage of both approaches is that extrapolation does not result in negative probabilities, which is possible when the spline interpolation is applied. We favor the approach by Figlewski (2009) because the use of the lognormal tails by Bliss and Panigirtzoglou (2004) assumes that the IV is constant beyond the observable strikes, resembling the Black-Scholes model and being largely inconsistent with empirical evidence.

[22] Figlewski (2009) argues that interpolation using fourth-order splines is superior to cubic splines because it avoids kinks in the RND. The translation from interpolated IV curve into RND would require taking higher-order derivatives than those used by the construction of the spline.

RND's body as (outer and inner) anchor points for the left tail and the 99th and 97th percentiles as (outer and inner) anchor points for the right tail. We extend the approach of Figlewski (2009) by allowing these anchor points to change if the fitted GEV curves produce implausible tails, e.g., zero probability under the tails. Equations (A.3) and (A.4) give, respectively, the GEV's cumulative distribution function and probability distribution function:

$$F_{GEV}(S_T) = \exp\left[-\left(1+\omega\left(\frac{S_T-\mu}{\sigma}\right)\right)^{-1/\omega}\right], \tag{A.3}$$

and

$$f_{GEV}(S_T) = \frac{1}{\sigma}\left[1+\omega\left(\frac{S_T-\mu}{\sigma}\right)\right]^{\left(-\frac{1}{\omega}\right)-1} \exp\left[-\left(1+\omega\left(\frac{S_T-\mu}{\sigma}\right)\right)^{-1/\omega}\right], \tag{A.4}$$

where $\omega > 0$ sets a fat tail relative to the normal, $\omega = 0$ sets a normal tail, and $\omega < 0$ sets a distribution tail that is thinner than the normal. The $\mu$ and $\sigma$ are location and dispersion parameters. Because fitting GEV curves entails setting these three parameters, Figlewski (2009) also imposes three conditions on the tail: i) that the total probability in the tail of the body (up to the inner anchor point) is the same for the RND and the GEV approximation, ii) that the shape of the RND equals the shape of the GEV curve in the inner anchor point, and iii) that the shape of the RND equals the shape of the GEV curve in the outer anchor point. We refer to Appendix 1.2 below for more details.

Once the body and tails of the RND for terminal index levels are obtained for banned and non-banned stocks, we convert them into return RNDs by calculating log-returns relative to the starting index level $S_0$. Finally, we compute probabilities for every percentage return quantile of the PDF via linear interpolation, which are normalized to integrate to one.

*1.2. The Figlewski (2009) approach for extracting RND from implied volatilities*

In this section, we describe the Figlewski (2009) approach and how we apply it to our sample. In the Figlewski (2009) method, the following three conditions are imposed for the right tail:

Condition 1: $F_{GEV}(X(\alpha_{innerR})) = \alpha_{innerR}$,

Condition 2: $f_{GEV}(X(\alpha_{innerR})) = f_{Body}(X(\alpha_{innerR}))$,

Condition 3: $f_{GEV}(X(\alpha_{outerR})) = f_{Body}(X(\alpha_{outerR}))$, (A.5)

where $X(\alpha_{innerR})$ represents the exercise price corresponding to the $\alpha$-quantile of the RND used as the inner anchor point in the right tail, whereas $X(\alpha_{outerR})$ denotes the same but for the outer anchor point in the right tail. For the left tail, these conditions are modified to:

Condition 1: $F_{GEV}(-X(\alpha_{innerL})) = 1 - \alpha_{innerL}$,

Condition 2: $f_{GEV}(-X(\alpha_{innerL})) = f_{Body}(X(\alpha_{innerL}))$, Condition 3: $$f_{GEV}(-X(\alpha_{outerL})) = f_{Body}(X(\alpha_{outerL})). \quad \text{(A.6)}$$

We fit the GEV curves by implementing the following optimization:

$$GEV(\omega, \mu, \sigma) = arg\ min(y), \quad \text{(A.7)}$$

where the objective function $y_R$ for the right tail following the three conditions above is:

$$y_R = [F_{GEV}\big(X(\alpha_{innerR})\big) - \alpha_{innerR}]^2 + [f_{GEV}\big(X(\alpha_{innerR})\big) - f_{Body}(X(\alpha_{innerR}))]^2 + \cdots$$
$$[f_{GEV}\big(X(\alpha_{outerR})\big) - f_{Body}(X(\alpha_{outerR}))]^2, \quad \text{(A.8)}$$

and whereas, for the left tail, the objective function $y_L$ is:

$$y_L = [F_{GEV}\big(-X(\alpha_{innerL})\big) - 1 + \alpha_{innerL}]^2 + [f_{GEV}\big(-X(\alpha_{innerL})\big) - f_{Body}(X(\alpha_{innerL}))]^2 + \cdots$$
$$[f_{GEV}\big(-X(\alpha_{outerL})\big) - f_{Body}(X(\alpha_{outerL}))]^2. \quad \text{(A.9)}$$

The approach by Figlewski (2009) performs nicely for many observations in our sample. However, for some observations, the fitted GEV curves are implausible. We illustrate the problem encountered in Figure 5, where the right tail of the RND is reasonably fitted by GEV, but the left tail is not. To avoid ending up with implausible tails, we allow the inner anchor points to change by a predefined amount (ΔIAnchor), following a loop-algorithm from iteration *m* = 1,…, *M*. Within this algorithm, the inner anchor points are mainly the ones to shift to accommodate a better-behaved GEV curve. Exceptionally, however, the outer anchor points are also shifted. The algorithm for the left tail is given as:

1. Let the $\alpha$-quantile inner anchor point ($\alpha_{innerL}$) increase by ΔIAnchor as $m \rightarrow M$ loop until $y_L^m > 5^{-25}$ and median of $\frac{\delta^2 f_{GEV}}{\delta K^2}\Big|_{K=0}^{K=X(\alpha_{innerL})} < 0$, otherwise stop loop.
2. If $y_L^{m-1} < y_L^m$, then evaluate if median of $\frac{\delta^2 f_{GEV}}{\delta K^2}\Big|_{K=0}^{K=X(\alpha_{innerL})} > 0$. If yes, stop loop and use $\alpha$-quantile inner anchor point ($\alpha_{innerL}$) of $y_L^m$ for GEV estimation. If median of $\frac{\delta^2 f_{GEV}}{\delta K^2}\Big|_{K=0}^{K=X(\alpha_{innerL})} < 0$, continue loop by increasing $\alpha$-quantile inner anchor point ($\alpha_{innerL}$) by ΔIAnchor.
3. If $y_L^{m-1} < y_L^m$, then evaluate if $0.05 > \int_0^{X(\alpha_{outerL})} F_{GEV}^{m-1} > 0.1$. If so, stop loop and use $\alpha$-quantile inner anchor point ($\alpha_{innerL}$) of $y_L^{m-1}$ for GEV estimation, otherwise continue loop.
4. If the $\alpha$-quantile inner anchor point ($\alpha_{innerL}$) increases up to the mode (peak) of the RND, then it stops increasing and the $\alpha$-quantile outer anchor point ($\alpha_{outerL}$) starts increasing by a very small step of 0.01 percent. If the $\alpha$-quantile outer anchor point ($\alpha_{outerL}$) increases more

than 10 times, then stop loop and use $\alpha$-quantile outer and inner anchor points from the iteration with lowest $y_L$ for GEV estimation.

Thus, our modification to the Figlewski (2009) approach is that the RND body is always extracted from the IV by using the Breeden and Litzenberger (1978) formulae. In contrast, Figlewski (2009) substitutes the original RND in the interval between the inner anchor point and the end of the original RND.

**Appendix 2 – Extreme value theory**

When applying EVT, we first estimate the tail shape estimator ($\varphi$), using Hill (1975):

$$\hat{\varphi} = \frac{1}{k} \sum_{j=1}^{k} ln\left(\frac{x_j}{x_{k+1}}\right), \tag{A.10}$$

where $x_j$ are ranked returns in ascending order *j* = 1, …, *n*; *n* is the sample size; *k* is the number of extreme returns used in the tail estimation; and $x_{k+1}$ is the return "tail cut-off point". The tail shape estimator $\varphi$ measures the curvature, i.e., the fatness of the tails of the return distribution: a high (low) $\varphi$ indicates that the tail is fat (thin).

After extracting RNDs for both banned and non-banned stocks, we next determine the optimal number of observations *k* used to estimate parameter $\varphi$ in equation (A.10). For this purpose, we produce Hill-plots for the left tail of our two RNDs. Such Hill-plots depict the relationship between *k* and $\varphi$ as a curve. The optimal value of *k* is selected as the minimum level for which the value of $\varphi$ stabilizes, thus where a stable trade-off between the approximation of the tail shape by the Pareto distribution and the uncertainty of such approximation occurs (because of the use of fewer observations). We set *k* equal to four percent or 43 observations, which matches the level used in, e.g., Hartmann et al. (2004).

Once $\varphi$ is obtained, we compute extreme downside risk, hereafter VaR, using a semi-parametric quantile estimator used in Hartmann et al. (2004):

$$\hat{q}_p = x_{k+1} \left(\frac{k}{pn}\right)^{\hat{\varphi}}, \tag{A.11}$$

where *n* is the sample size, *p* is a chosen exceedance probability, which means the likelihood that a return $x_j$ exceeds the tail value *q*, and $x_{k+1}$is the 'tail cut-off point'. Note that $\hat{q}_p$ has as one of its inputs the estimated tail shape parameter $\hat{\varphi}$. The $\hat{q}_p$ statistic indicates the level of the worst return occurring with probability *p*. Since the tail quantile statistic $\frac{\sqrt{k}}{ln\left(\frac{k}{pk}\right)}\left[ln\frac{\hat{q}\,(p)}{q\,(p)}\right]$ is asymptotically normally distributed, we follow Hartmann et al. (2004) and use the following *T*-statistic for this estimator:

$$T_q = \frac{\hat{q}_1 - \hat{q}_2}{\sigma[\hat{q}_1 - \hat{q}_2]} \quad \sim N(0,1), \tag{A.12}$$

where the denominator is calculated as the difference between the two estimated VaRs, using 1,000 bootstraps. The null hypothesis of this test is that $\hat{q}_1$ and $\hat{q}_2$ do not come from independent samples of normal distributions, therefore, the VaRs are equal.

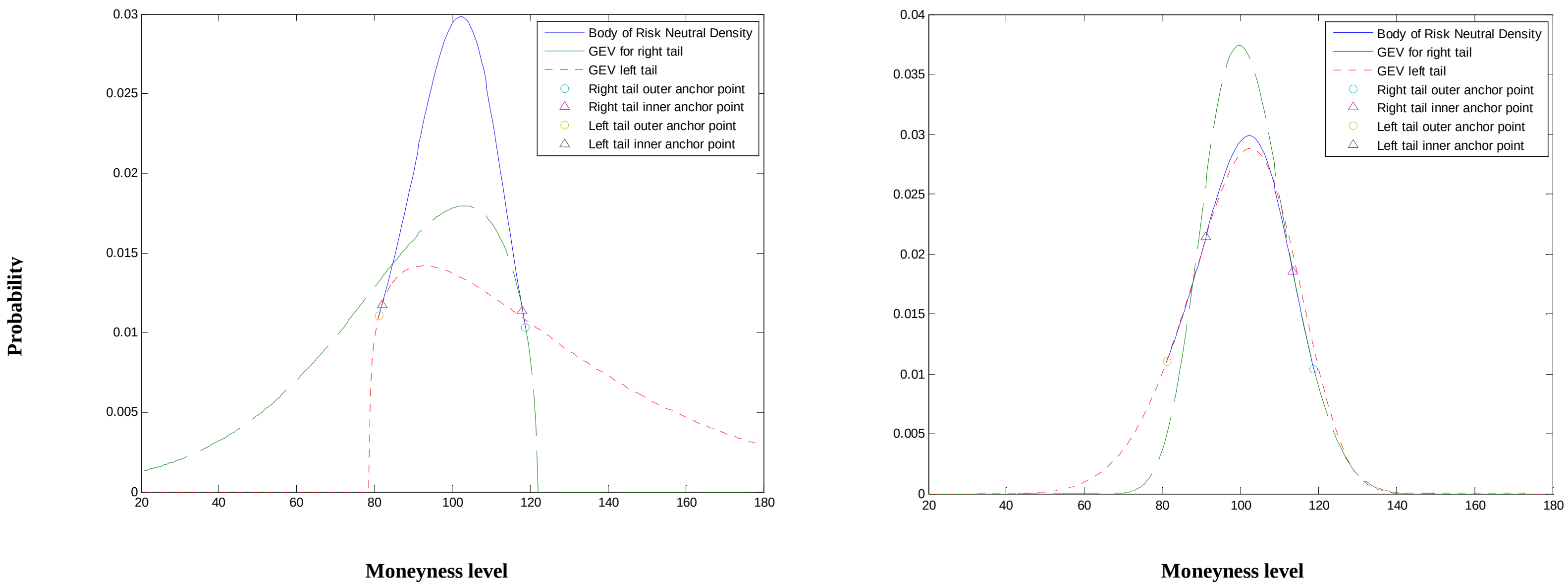
In the next step, we employ a bivariate EVT method to calculate commonality in jumps, hence, contagion risk from historical returns. EVT is well suited to measure contagion risk because it does not assume any specific return distribution. Our approach estimates how likely it is that one stock will experience a crash beyond a specific extreme negative return threshold conditional on another stock crash beyond an equally probable threshold. We refer to Hartmann et al. (2004) and Balla et al. (2014) who use the conditional co-crash (CCC) probability estimator, which is applied to each pair of stocks in our sample, as follows:

$$\widehat{CCC}_{ij} = 2 - \frac{1}{k}\sum_{t=1}^{N} I\{V_{it} > x_{i,N-k} \; or \; V_{jt} > x_{j,N-k}\}, \quad \text{(A.13)}$$

where the function *I* is the crash indicator function, in which *I* = 1 in case of a crash, and *I* = 0 otherwise, $V_{it}$ and $V_{jt}$ are returns for stocks *i* and *j* at time *t*; $x_{i,N-k}$, and $x_{j,N-k}$ are extreme crash thresholds. The estimation of the CCC-probabilities requires setting $k$ as the number of observations used in equation (A.13). For consistency with our Hill-estimator, we again use $k$ = 43 as the minimum level for which the value of $\varphi$ is stable in our Hill-plots. Furthermore, because the CCC-probability is asymptotic normal if $k/N \to 0 \; as \; k,$ $N \to \infty$ (see Hartmann, 2004), a *t*-test for such estimator is obtained by the same bootstrap-based approach that is used in equation (A.12).

## Figure 5. RND extraction

### A. Figlewski (2009) approach B. Modified Figlewski (2009) approach




Plot A depicts the RND of banned stocks for March 24, 2011, using the Figlewski (2009) approach. Plot B depicts the RND of banned stocks for the same date, using the modified Figlewski approach described in Appendix 1.2. We note that in Plot A both the left and the right tails of the RND, fitted by GEV curves, are implausible because they contain abruptly declining tails under which the probability is close to zero. It is not the approach that causes such distortion but the limited range of moneyness in our data set.

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**Table 1. Overview of banned financial stocks**

| Belgium | France | Italy | Spain |
|---|---|---|---|
| Ageas | April Group | Azimut Holding | Banca Cívica, S.A. |
| Dexia | Axa | Banca Carige | Banco Bilbao Vizcaya Argentaria, S.A. |
| KBC Group | BNP Paribas | Banca Finnat | Banco de Sabadell, S.A. |
| KBC Ancora | CIC | Banca Generali | Banco de Valencia |
| | CNP Assurances | Banca Ifis | Banco Español de Crédito, S.A. |
| | Crédit Agricole | Banca Intermobiliare | Banco Pastor, S.A. |
| | Euler Hermés | Banca Monte Paschi di Siena | Banco Popular Español, S.A. |
| | Natixis | Banca Popolare Emilia Romagna | Banco Santander, S.A. |
| | Paris Ré | Banca Popolare Etruria e Lazio | Bankia, S.A., |
| | Scor | Banca Popolare Milano | Bankinter, S.A. |
| | Société Générale | Banca Popolare Sondrio | Bolsas y Mercados Españoles, S.A. |
| | | Banca Profilo | Caixabank, S.A. |
| | | Banco di Desio e Brianza | Caja de Ahorros del Mediterráneo |
| | | Banco di Sardegna Rsp | Grupo Catalana de Occidente, S.A. |
| | | Banco Popolare | Mapfre, S.A. |
| | | Cattolica Assicurazioni | Renta 4 Servicios de Inversion, S.A. |
| | | Credito Artigiano | |
| | | Credito Emiliano | |
| | | Credito Valtellinese | |
| | | Fondiaria – Sai | |
| | | Generali | |
| | | Intesa Sanpaolo | |
| | | Mediobanca | |
| | | Mediolanum | |
| | | Milano Assicurazioni | |
| | | Ubi Banca | |
| | | Unicredit | |
| | | Unipoland | |
| | | Vittoria Assicurazioni | |

This table lists the financial stocks banned from short selling on August 11, 2011, in Belgium, France, Italy, and Spain by their respective national financial market regulators in a coordinated act with the European Securities and Market Authority (ESMA).

**Table 2. Descriptive statistics**

| | Overall | | Belgium | | France | | Italy | | Spain | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Non-banned | Banned | Non-banned | Banned | Non-banned | Banned | Non-banned | Banned | Non-banned | Banned |
| Average | 5.73 | 6.49 | 5.33 | 7.11 | 6.23 | 8.57 | 6.49 | 7.49 | 3.85 | 4.96 |
| Median | 5.31 | 5.98 | 5.14 | 6.94 | 6.09 | 8.16 | 6.23 | 7.24 | 3.19 | 3.98 |
| Standard Deviation | 1.22 | 1.63 | 1.40 | 2.25 | 1.28 | 2.04 | 1.26 | 1.70 | 2.78 | 3.84 |
| Skew | 1.15 | 1.91 | 0.67 | 0.48 | 0.56 | 0.54 | 1.02 | 0.89 | 4.03 | 4.35 |
| Excess Kurtosis | 0.88 | 5.24 | 0.29 | 0.64 | -0.11 | -0.51 | 0.89 | 1.16 | 18.87 | 22.44 |
| Jarque-Bera | 266.0*** | 1835.4*** | 81.0*** | 58.5*** | 54.9*** | 61.9*** | 214.5*** | 195.8*** | 18395.7*** | 25297.4*** |

This table provides descriptive statistics for the IV skews of non-banned and banned stocks calculated over the full sample period (February 15, 2008 to March 27, 2012) for the overall group of stocks as well as separately for Belgium, France, Italy, and Spain. We perform Jarque-Bera normality tests for all groups of stocks to infer whether IV skews are normally distributed or not. The null hypothesis ($H_0$) for the Jarque-Bera test is that data is normally distributed. Rejection of $H_0$ is denoted by ***, **, and *, at the one, five, and ten percent significance level, respectively.

## Table 3. Extreme downside risk and implied volatility skew

**Panel A - Extreme downside risk**

| Sample split | 10% VaR | | | 5% VaR | | | 1% VaR | | |
|---|---|---|---|---|---|---|---|---|---|
| | Non-banned | Banned | NB vs. B | Non-banned | Banned | NB vs. B | Non-banned | Banned | NB vs. B |
| Full sample (02/15/2008 – 03/27/2012) | -0.31 | -0.34 | -1.3 | -0.36 | -0.4 | -1.5 | -0.51 | -0.57 | -1.9 |
| U.S. recession (02/15/2008 – 06/30/2009) | -0.47 | -0.5 | -0.9 | -0.53 | -0.58 | -1.2 | -0.73 | -0.82 | -1.8 |
| 2009 stock market rally (07/01/2009 – 04/26/2010) | -0.41** | -0.40*** | 0.3 | -0.47** | -0.46*** | 0.2 | -0.63*** | -0.63*** | 0.0 |
| Pre-ban European crisis (04/27/2010 – 08/10/2011) | -0.35** | -0.38 | -1.1 | -0.40* | -0.44 | -1.0 | -0.58 | -0.62 | -1.0 |
| Ban period (08/11/2011 – 02/16/2012) | -0.46*** | -0.62*** | -4.0*** | -0.52*** | -0.70*** | -4.0*** | -0.69*** | -0.94*** | -4.1*** |
| Post-ban period (02/17/2012 – 03/27/2012) | -0.45 | -0.56 | -2.1** | -0.5 | -0.64 | -2.2** | -0.66 | -0.84 | -2.2** |

**Panel B - Implied volatility skew**

| Sample split | Overall | | Belgium | | France | | Italy | | Spain | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Non-banned | Banned | Non-banned | Banned | Non-banned | Banned | Non-banned | Banned | Non-banned | Banned |
| Full sample (02/15/2008 – 03/27/2012) | 5.31 | 5.98 | 5.14 | 6.94 | 6.09 | 8.16 | 6.23 | 7.24 | 3.19 | 3.98 |
| U.S. recession (02/15/2008 – 06/30/2009) | 5.02 | 5.99 | 4.70 | 6.97 | 5.46 | 7.83 | 6.31 | 8.02 | 3.47 | 4.87 |
| 2009 stock market rally (07/01/2009 – 04/26/2010) | 5.05* | 5.41*** | 4.46*** | 6.24*** | 5.69** | 7.46*** | 5.99*** | 6.00*** | 2.42*** | 3.26*** |
| Pre-ban European crisis (04/27/2010 – 08/10/2011) | 5.78*** | 6.05*** | 5.63*** | 7.81*** | 6.42*** | 8.14*** | 5.82 | 7.11*** | 3.60*** | 3.98*** |
| Ban period (08/11/2011 – 02/16/2012) | 6.05** | 7.34*** | 5.90*** | 7.28 | 6.99*** | 11.97*** | 7.14*** | 7.98*** | 3.06*** | 3.98 |
| Post-ban period (02/17/2012 – 03/27/2012) | 5.17*** | 6.37*** | 5.32*** | 5.25*** | 5.59*** | 10.65*** | 6.73*** | 5.49*** | 2.73*** | 4.98*** |

Panel A shows the ten, five, and one percent extreme downside risk estimates, or value-at-risk (VaR), of the risk neutral densities (RNDs) for all non-banned and all banned stocks during the full sample period, as well as for the five different sub-periods. Asterisks used as superscript to VaRs denote the outcome of the T-tests specified in equations (A.11) and (A.12) across different sample periods. The column 'NB vs. B' shows the *t*-stats of the test that compares VaRs of non-banned and banned stocks, using equations (A.11) and (A.12). The null hypothesis ($H_0$) is that there is no difference between the VaR from non-banned and banned stocks. Panel B provides the median IV skews for non-banned and banned groups of stocks during the same periods as in Panel A. Mann-Whitney (MW) U-tests are applied to the IV skew of paired sample splits to infer whether the medians are statistically different from each other. The null hypothesis ($H_0$) for the MW U-test is that there is no difference between the two unrelated samples. In both panels, rejection of $H_0$ is denoted by the asterisks $^{***}$, $^{**}$, and $^{*}$, at the one, five, and ten percent significance level, respectively. In Panel B, the superscripts are placed in the cell of the second sub-sample that is compared.

**Table 4. Conditional co-crash probabilities, option trading volumes and put-call ratios**

**Panel A - Conditional co-crash probabilities**

| Sample split | Conditional co-crash-probabilities | | |
|---|---|---|---|
| | Non-banned | Banned | NB vs. B |
| Full sample (02/15/2008 – 03/27/2012) | 0.29 | 0.32* | 1.7 |
| U.S. recession (02/15/2008 – 06/30/2009) | 0.26 | 0.27 | 0.4 |
| 2009 stock market rally (07/01/2009 – 04/26/2010) | 0.23 | 0.28 | 1.6 |
| Pre-ban European crisis (04/27/2010 – 08/10/2011) | 0.32* | 0.42** | 2.2** |
| Ban period (08/11/2011 – 02/16/2012) | 0.41 | 0.32 | -1.3 |
| Post-ban period (02/17/2012 – 03/27/2012) | NA | NA | NA |

**Panel B - Option trading volumes and put-call ratios**

| Sample split | Put volume | | Put-call volume ratio | |
|---|---|---|---|---|
| | Non-banned | Banned | Non-banned | Banned |
| Full sample (02/15/2008 – 03/27/2012) | 1,064 | 1,690 | 7.0 | 3.8 |
| U.S. recession (02/15/2008 – 06/30/2009) | 877 | 1,377 | 7.1 | 4.1 |
| 2009 stock market rally (07/01/2009 – 04/26/2010) | 1,200*** | 1,747*** | 7.0 | 3.4*** |
| Pre-ban European crisis (04/27/2010 – 08/10/2011) | 1,157 | 1,905** | 6.3 | 3.7** |
| Ban period (08/11/2011 – 02/16/2012) | 943*** | 1,727*** | 8.7*** | 3.8 |
| Post-ban period (02/17/2012 – 03/27/2012) | 1,245*** | 2,758*** | 7.9 | 5.7*** |

Panel A shows the average conditional co-crash (CCC) probabilities calculated by equation (A.13) among all non-banned and all banned stocks during the full sample period, as well as for the five different sub-periods. Asterisks used as superscript to CCC-probabilities denote the outcome of the T-tests specified in equations (A.11) and (A.12) across different sample periods. The column 'NB vs. B' shows the *t*-stats of the test that compares CCC-probabilities of non-banned and banned stocks, using equations (A.11) and (A.12). The null hypothesis ($H_0$) is that there is no difference between the CCC-probabilities from non-banned and banned stocks. Panel B shows the median daily trading volume, measured by the number of contracts traded in put options, as well as the median daily put-call volume ratio for all non-banned and banned stocks for the overall sample period and for the five different sub periods. We apply Mann-Whitney U-tests to investigate whether the medians are statistically different from each other. The null hypothesis ($H_0$) is that there is no difference between the populations of the two samples. In both panels, rejection of $H_0$ is denoted by the asterisks ***, **, and *, at the one, five, and ten percent significance level, respectively. In Panel B, the superscripts are placed in the cell of the second sub-sample that is compared.

## Table 5. Panel regression results

| | Panel A – Model 1 | | | Panel B – Model 2 | | | Panel C – Models 3 and 4 | |
|---|---|---|---|---|---|---|---|---|
| | (a) Full sample | (b) Euro crisis | (c) Ban period | (a) Full sample | (b) Euro crisis | (c) Ban period | (a) Full sample | (b) Full sample PD |
| Intercept | 2.823*** | 2.198*** | -0.283 | 2.951*** | 2.214*** | -0.264 | 2.680*** | 0.011*** |
| | (0.155) | (0.329) | (0.344) | (0.052) | (0.330) | (0.346) | (0.156) | (0.001) |
| V2X | 0.053*** | 0.094*** | 0.035*** | 0.050*** | 0.096*** | 0.029*** | 0.073*** | 0.000*** |
| | (0.004) | (0.011) | (0.009) | (0.001) | (0.011) | (0.009) | (0.004) | (0.000) |
| Country CDS spread | 0.006*** | 0.003*** | 0.008*** | 0.007*** | 0.003*** | 0.009*** | 0.003*** | 0.000*** |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) |
| Stock return | 5.509*** | 9.663*** | 7.055*** | 5.843*** | 9.693*** | 6.997*** | 4.458*** | -0.002 |
| | (0.921) | (1.710) | (1.385) | (0.360) | (1.709) | (1.385) | (0.960) | (0.004) |
| Stock turnover | -19.317** | -22.535** | -25.602** | -18.916** | -22.178** | -26.247** | 4.749** | 0.677*** |
| | (1.834) | (2.468) | (3.313) | (1.376) | (2.466) | (3.318) | (2.318) | (0.020) |
| Stock size | 0.048*** | 0.066*** | 0.109*** | 0.050*** | 0.067*** | 0.109*** | 0.030*** | 0.000*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) |
| Stock *Beta* | 1.015*** | 1.710*** | 3.702*** | 1.037*** | 1.712*** | 3.701*** | 1.482*** | 0.014*** |
| | (0.036) | (0.060) | (0.097) | (0.028) | (0.060) | (0.097) | (0.046) | (0.000) |
| Dummy ban period | -0.180 | -1.104*** | | 0.676*** | 0.358*** | | 1.195*** | 0.011*** |
| | (0.118) | (0.195) | | (0.028) | (0.064) | | (0.116) | (0.000) |
| Dummy stock banned | 0.719*** | 0.357*** | 0.037 | -0.305*** | -1.123*** | 0.030 | 0.475*** | -0.007*** |
| | (0.035) | (0.064) | (0.049) | (0.035) | (0.196) | (0.049) | (0.041) | (0.000) |
| Dummy ban period*stock banned | 0.306*** | 0.451*** | | 0.327*** | 0.474*** | | 0.311*** | 0.018*** |
| | (0.098) | (0.119) | | (0.069) | (0.119) | | (0.110) | (0.001) |
| Dummy post ban | -0.201 | -0.695*** | | -0.293*** | -0.704*** | | 1.025*** | 0.009*** |
| | (0.200) | (0.224) | | (0.059) | (0.224) | | (0.209) | (0.001) |
| Dummy post ban*stock banned | 0.280 | 0.389* | | 0.314** | 0.416* | | 0.491** | 0.010*** |
| | (0.207) | (0.230) | | (0.138) | (0.229) | | (0.247) | (0.002) |
| Put volume | 0.305*** | 0.185 | -0.297** | 0.274*** | 0.182 | -0.333** | 0.442*** | 0.001*** |
| | (0.074) | (0.147) | (0.144) | (0.020) | (0.147) | (0.146) | (0.073) | (0.000) |
| EuroStoxx50 put volume | -0.723*** | -1.358*** | 0.397** | -0.691*** | -1.372*** | 0.428** | -1.114*** | -0.005*** |
| | (0.119) | (0.220) | (0.189) | (0.033) | (0.220) | (0.191) | (0.119) | (0.000) |
| IV spread | | | | 0.062 | -0.619 | 3.304** | | |
| | | | | (0.106) | (0.727) | (1.509) | | |
| Probability of default | | | | | | | -12.356*** | |
| | | | | | | | (0.498) | |
| $R^2$ | 0.1046 | 0.1289 | 0.2757 | 0.1076 | 0.1308 | 0.2765 | 0.1452 | 0.2478 |
| # Obs (Unbalanced Panel) | 146,201 | 73,327 | 21,298 | 142,048 | 73,327 | 21,298 | 74,622 | 84,095 |

Panel A reports the panel regression results for Model 1. Panel B reports the panel regression results for Model 2. Panel C reports the panel regression results for Models 3 and 4. The dependent variable for Models 1, 2 and 3 is the IV skew. Model 4 uses probability of default from single-name CDS *(PD)* as the dependent variable. We distinguish three different periods: (a) full sample (from February 15, 2008 to March 27, 2012), (b) euro crisis (from April 27, 2010 to March 27, 2012), and (c) ban period (from August 11, 2011 to February 16, 2012). The single stock IV skew is the dependent variable and information flow (*Country CDS* and *V2X*), firm-specific control variables (*Return, Turnover, Size, Beta*), trading volume on single put options (*Put volume*) and on index options (*EuroStoxx50 put volume*), a proxy for supply shift on option markets (*IV spread*), firms' probability of default from single-name CDS market (*PD*) and dummies are the explanatory variables. The intercept is estimated as common to all cross-sections and no weighting is used in the cross-sections for estimation. Residuals are not normal for most cross-sections. We apply White-Heteroskedasticity consistent standard error and covariance estimates. The asterisks ***, ***, and * indicate significance at the one, five, and ten percent level, respectively.

**Table 6. Supply shift in the options market**

| *Sample split* | *Percentage spread* | | *IV spread* | |
|---|---|---|---|---|
| | *Non-banned* | *Banned* | *Non-banned* | *Banned* |
| Full sample (02/15/2008 – 03/27/2012) | 0.088 | 0.069 | 0.057 | 0.072 |
| U.S. recession (02/15/2008 – 06/30/2009) | 0.080 | 0.060 | 0.060 | 0.041 |
| 2009 stock market rally (07/01/2009 – 04/26/2010) | 0.081 | 0.058 | 0.050*** | 0.039*** |
| Pre-ban European crisis (04/27/2010 – 08/10/2011) | 0.099*** | 0.076*** | 0.075** | 0.082*** |
| Ban period (08/11/2011 – 02/16/2012) | 0.090*** | 0.089*** | 0.025*** | 0.149*** |
| Post-ban period (02/17/2012 – 03/27/2012) | 0.072*** | 0.083** | 0.018*** | 0.166 |

This table shows the median daily *Percentage spread* measure as well as the median *IV spread* measure for non-banned and banned stocks that belong to the EuroStoxx 50 index for the overall sample period and for the five different sub periods. The *Percentage spread* is defined as *(ask-mid)/mid*, where *ask* is the asking price of an ATM option, and *mid* is the mid-price of an ATM option. This metric represents the percentage of the mid-price that is charged by market makers to sell an option. The *IV spread* is defined as $\delta IV = \delta C / Vega$, where $\delta C$ is the difference between ask- and mid-prices, i.e., the spread, and *Vega* is obtained for ATM options. We apply Mann-Whitney U-tests to assess whether the medians are statistically different from each other. The null hypothesis ($H_0$) is that there is no difference between the populations of the two samples. Rejection of the ($H_0$) is denoted by the asterisks ***, **, and *, indicating significance at the one, five, and ten percent level, respectively.

## Table 7. Robustness checks

| | Panel A – Model 5 | | | | Panel B – Model 1 | | | Panel C– Model 1 | | Panel D-Model 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| | (a) Full (pre-ban) | (b) U.S. recession | (c) Market | (d) Euro crisis | All | Euro crisis | Ban | Yan (2011) | IV skew from ask-prices | Full |
| | Vol skew | Vol skew | Vol skew | Vol skew | Vol skew | Vol skew | Vol skew | 95 minus 105 | | Vol skew |
| Intercept | 3.213*** | 2.196*** | 6.035*** | 2.429*** | 2.893*** | 1.981*** | -0.728** | 0.197** | 4.016*** | 2.574*** |
| | (0.170) | (0.102) | (0.281) | (0.473) | (0.164) | (0.353) | (0.335) | (0.100) | (-0.19) | (0.149) |
| V2X | 0.052*** | 0.052*** | -0.022** | 0.125*** | 0.050*** | 0.103*** | 0.037*** | 0.013*** | 0.076*** | 0.065*** |
| | (0.005) | (0.002) | (0.010) | (0.017) | (0.004) | (0.012) | (0.009) | (0.003) | (-0.005) | (0.004) |
| Country CDS spread | 0.005*** | 0.025*** | 0.024*** | 0.000 | 0.006*** | 0.003*** | 0.009*** | -0.003*** | 0.000 | |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.000) | (-0.001) | |
| Country bond spread | | | | | | | | | | -0.130*** |
| | | | | | | | | | | (0.034) |
| Stock return | 4.861*** | 4.085*** | 3.569*** | 11.958*** | 5.383*** | 9.735*** | 7.090*** | -0.983 | 3.899*** | 5.346*** |
| | (1.060) | (0.667) | (1.234) | (2.927) | (0.995) | (1.832) | (1.374) | (0.670) | (-1.347) | (0.934) |
| Stock turnover | -22.602*** | -18.110*** | -5.120 | -30.131*** | -19.694*** | -23.984*** | -27.241*** | -10.699*** | -39.059*** | -17.274*** |
| | (2.200) | (3.245) | (4.332) | (3.727) | (1.890) | (2.572) | (3.330) | (2.585) | (-4.812) | (1.907) |
| Stock size | 0.042*** | 0.034*** | 0.038*** | 0.054*** | 0.049*** | 0.069*** | 0.114*** | 0.011*** | 0.008*** | 0.048*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (-0.001) | (0.001) |
| Stock *Beta* | 0.939*** | 0.944*** | 0.383*** | 1.262*** | 1.002*** | 1.739*** | 3.893*** | 1.012*** | 0.955*** | 0.990*** |
| | (0.031) | (0.046) | (0.037) | (0.052) | (0.040) | (0.068) | (0.099) | (0.033) | (-0.063) | (0.036) |
| Dummy ban period | | | | | -0.184 | -1.217*** | | 0.304*** | 1.334*** | 0.399*** |
| | | | | | (0.124) | (0.207) | | (0.071) | (-0.066) | (0.117) |
| Dummy stock banned | | | | | 0.712*** | 0.339*** | 0.087 | 0.418*** | 1.987*** | 0.745*** |
| | | | | | (0.036) | (0.068) | (0.056) | (0.023) | (-0.143) | (0.034) |
| Dummy ban period*stock banned | | | | | 0.318*** | 0.497*** | | -0.033 | 0.379** | 0.450*** |
| | | | | | (0.106) | (0.128) | | (0.058) | (-0.151) | (0.097) |
| Dummy post ban | | | | | -0.277 | -0.743*** | | -0.835*** | 1.414*** | 0.194 |
| | | | | | (0.210) | (0.237) | | (0.117) | (-0.261) | (0.203) |
| Dummy post ban*stock banned | | | | | 0.438** | 0.578** | | 0.479*** | 0.392 | 0.343 |
| | | | | | (0.223) | (0.244) | | (0.119) | (-0.314) | (0.210) |
| Put volume | 0.364*** | 0.052 | -0.016 | 0.370* | 0.341*** | 0.236 | -0.274* | 0.490*** | 0.396*** | 0.273*** |
| | (0.081) | (0.054) | (0.056) | (0.201) | (0.077) | (0.156) | (0.140) | (0.047) | (-0.087) | (0.074) |
| EuroStoxx50 put volume | -0.901*** | -0.252*** | -0.165 | -2.188*** | -0.724*** | -1.452*** | 0.423** | -0.710*** | -0.808*** | -0.752*** |
| | (0.132) | (0.082) | (0.164) | (0.308) | (0.124) | (0.233) | (0.184) | (0.077) | (-0.144) | (0.120) |
| $R^2$ | 0.0830 | 0.1412 | 0.2757 | 0.0987 | 0.0994 | 0.1271 | 0.2854 | 0.0315 | 0.2013 | 0.1021 |
| # Obs. | 119,759 | 44,644 | 28,230 | 46,735 | 128,757 | 64,470 | 18,702 | 148,757 | 25,152 | 146,201 |

Panel A reports the panel regression results for Model 5, using only the pre-ban period data. We distinguish four sub-periods: (a) Full pre-ban period: Feb 15, 2008 to Aug 10, 2011; (b) U.S. recession: Feb 15, 2008 to Jun 30, 2009; (c) Market rally: Jul 1, 2009 to Apr 26, 2010; and (d) Euro crisis: Apr 27, 2010 to Aug 10, 2011. Panel B reports the estimates after removal of the Belgian data from the full sample. Here we distinguish three different periods: (a) Full period: 15 Feb, 2008 to 27 Mar, 2012; (b) Euro crisis: 27 Apr, 2010 to 27 Mar, 2012; and (c) Ban period: Aug 11, 2011 to Feb 16, 2012. Panel C reports the regression results for Model 1, where the explained variable IV skew is substituted by (a) Yan (2011) 95 minus 105 IV skew measure, and by (b) our proxy for the IV skew measure from ask-prices. Panel D reports the regression results for Model 1, where the country CDS spreads are replaced by sovereign spreads versus Germany. The single stock IV skew is the dependent variable and information flow (*Country CDS spread*, *Country Bond Spread* and *V2X*), firm-specific control variables (*Return*,*Turnover*, *Size*, *Beta*), trading volume on single put options (*Put volume*) and on index options (*EuroStoxx50 put volume*), and dummies are the explanatory variables. The intercept is set equal in all cross-sections and no weighting is used. Residuals are not normal for most cross-sections. We report White-Heteroskedasticity consistent standard errors in brackets. Asterisks ***, **, and * indicate significance at the one, five, and ten percent level, respectively.