Short Selling in the Tails

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Abstract

Short selling plays a crucial role for price discovery and liquidity purposes yet national governing authorities decided to ban short selling in periods of extreme price movements, on the grounds that short selling can exacerbate price downturns. Whereas most of the literature analyses the average relation between short selling and price changes, our study focuses on the relation that occurs during extreme events, using a new paradigm that stems from the literature on tail correlations. For the largest European and US banks, as well as European insurers, we uncover a very strong relation when both variables are in their tails. In normal times, no negative association is found, which favours the view that short sellers act as price stabilizers. But during turmoil, short selling relates with excessive price drops that can put the market under serious stress.

Keywords: short selling, tail correlation

JEL Classification: G15, G18, G28

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1 Introduction

The problem

Although most of the academic literature converges around the consensus that short selling is a market practice that has mostly positive effects, regulators are nonetheless of the view that short selling bans could be a justified and necessary measure in the exceptional circumstances of a severe financial crisis. While the consensus is that short selling may contribute to market liquidity, increase market efficiency and aid price discovery, the concern remains that in a falling market, prices are more vulnerable to (potentially predatory) short selling that can exacerbate downfalls and even lead to market crashes.

Financial firms and banks in particular are especially vulnerable to the potentially adverse effects of short selling. Amid extreme market uncertainty and widespread concerns about the quality of banks’ balance sheets, short selling of bank shares has a potential to trigger and reinforce downward price spirals. Bank share prices can fall significantly below their book value and this could aggravate a crisis by alarming both counterparties and clients and by hindering banks’ efforts to recapitalise themselves by issuing new shares.

Concerns about potential adverse effects of short selling prompted a significant number of regulators around the world to prohibit short selling during the various episodes of the global financial crisis that started in 2007. On 18 September 2008, following the bankruptcy of Lehman Brothers, the US Securities and Exchanges Commission (SEC) was the first financial market authority to issue a temporary ban on short selling of financial stocks. The SEC explained that “this emergency action should prevent short selling from being used to drive down the share prices of issuers.”

On 18 May 2010, similar concerns brought BaFin, the German Federal Financial Supervisory Authority, to ban naked short selling of bonds issued by euro area sovereigns: “massive short selling of the debt securities concerned [...] [was] resulting in further excessive price movements which could result in further serious disadvantages for the financial market, and could jeopardize the stability of the financial system as a whole.”

These bans and accompanying justifications highlight the concern among policy makers that large increases in short selling can induce large price declines. In this paper, our objective is to shed more light on these concerns by studying the association between extreme changes in short selling activity and stock prices of financial companies.

Literature review

The academic literature has attempted to explain the relation between short selling and stock prices through theoretical and empirical studies. Various theoretical models show that short selling aids price discovery. Starting from Miller (1977), the intuition behind these studies is that markets act as aggregators of participants’ beliefs. If agents that hold strictly negative views on the future stock performance are prohibited from entering the market, then the resulting prices will be overvalued, giving rise to the possibility of bubbles. However, if

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2 The official release can be found at http://www.bafin.de/SharedDocs/Pressemitteilungen/EN/Pressemitteilung/2010/pm_100518_cds_leerverkauf_allgemeinverfuegungen_en.html?nn=2821494
agents have rational expectations (and are risk-neutral), as in the model of Diamond and Verrecchia (1987), investors will anticipate the overpricing effect during bans, causing prices to be correct on average, but slower at incorporating negative information.

Our study relates more specifically to theoretical models that analyse short selling and the occurrence of large price downfalls. In Brunnermeier and Oehmke (2014), so-called “predatory” short selling can induce institutions that are close to their capital constraints to initiate fire sales, thereby causing asset prices to plummet. The effect is worsened if short sellers are able to coordinate, as this would require a smaller initial drop in prices to trigger a complete liquidation of the firm’s assets. They conclude that temporary short selling bans could be beneficial in reducing the effects of predatory short selling. However, Hong and Stein (2003) show that if market participants who possess negative beliefs are not allowed to sell assets short, then the unrevealed negative information will accumulate and potentially discharge into a crash, once the market starts to decline. In their view, bans should be associated with more frequent price crashes.3

Turning to empirical studies, Boehmer, Huszar, and Jordan (2010) and Asquith, Pathak, and Ritter (2005) find a positive association between short interest—i.e. the number of shares shorted as a proportion of the total shares outstanding—and future negative abnormal price changes over the following trading days. These studies, however, point towards the informativeness of short sellers in forecasting stock performance rather than to short selling driving down stock prices. Boehmer et al. (2010) also note that short interest may have two different interpretations: low short interest can be the result of stock supply constraints or it can be taken as an indication that short sellers are avoiding the stock. The former explanation contrasts with the findings of Asquith et al. (2005), who show that in normal times short selling constraints are unlikely. Moreover, Saffi and Sigurdsson (2011) demonstrate that stock utilisation (the number of shares on loan divided by the number of shares available for lending) is relatively stable across issuers of different size, indicating that short interest should not be constrained by the supply side of the stock lending market.

Rather than using an indicator of short selling activity per se, a number of papers opt for examining stock price changes during different short selling regimes. The bans implemented in 2008 represent a natural experiment to study the effects of short selling restrictions on prices. Beber and Pagano (2013) and Boehmer, Jones, and Zhang (2008) study the effect of the 2008 short selling bans and do not find price-supporting impact. Bris, Goetzmann, and Zhu (2007) test the impact of short-sales constraints on the frequency of extreme negative price changes and the skewness of returns. They find that in markets in which short selling is either prohibited or not practised, stock price changes at the market level tend to be less negative. Similarly, Chang, Cheng, and Yu (2007) study the Hong Kong stock market and provide evidence that, on average, allowing short selling decreases negative skewness. According to Saffi and Sigurdsson (2011), however, lower skewness when short selling is unconstrained is actually due to fewer instances of large price increases rather than to more cases of extreme negative price changes.

Short selling can also occur through the use of derivatives (Danielsen and Sorescu, 2001) or exchange traded funds (ETFs). Although it would be costlier, a synthetic short position

3Their model is supported by the empirical findings of Ofek and Richardson (2003) on Internet stocks during the Dotcom bubble.
can also be obtained by selling at-the-money calls and buying an equivalent amount of at-the-money put options. Kolasinski, Reed, and Thornock (2013) explain that, even during bans, substantial short selling can occur when market makers hedge options written for synthetic short positions. They find that daily short selling volume changes are negatively associated with price changes, and even more so in periods during which short selling is prohibited. However, the volume of traded options on banned stocks actually declined during the US SEC ban of 2008 (Grundy, Lim, and Verwijmeren, 2012). Most probably this was due to the increased option hedging costs. An alternative to options can be to short sell an ETF that tracks a portfolio containing the underlying stock. In fact, Karmaziene and Sokolovski (2014) found a strong increase in the shorting of ETFs during a ban, thereby suggesting that these are close substitutes when it comes to the short selling of underlying stocks.

The literature reviewed above focuses mainly on assessing the average impact of short selling, as opposed to its impact during a strongly bearish market, when prices are much more susceptible to significant downfalls. To our best knowledge, only two recent papers have assessed the relation between short selling and stock prices on days of extreme price changes. First, Shkilko, Ness, and Ness (2012) study intraday price reversals and find that short sellers exacerbate price declines, but to a lesser extent than long sellers. By contrast, Boehmer and Wu (2013) find that short sellers act as liquidity providers during transient price turnarounds, buying when the price drops and selling when the price jumps unusually high. This is interpreted as evidence that short sellers trade on the basis of superior information rather than speculation. These contrasting results may be attributable to the narrow criteria used in these studies to select price reversal episodes. To investigate this further, an analysis that concentrates on the association between short selling and price changes during extreme situations, without restricting observations, is therefore very relevant.

What we do

We propose to examine the relation between short selling and price changes under a new paradigm that stems from the literature on tail association. We adopt TailCoR, a measure of tail correlation, developed by Ricci and Veredas (2013). TailCoR can uncover the relationship between short selling and price changes when both are at the extremes of their distribution. That is, TailCoR is able to quantify the relation between large changes in short interest (that can be linked to aggressive short selling) and large price downfalls. Moreover, such analysis can be implemented under general and mild assumptions, as it does not depend on specific distributional assumptions, and it is straightforward to compute, as no optimisations are needed.

Our proxy for short selling (short interest) is the daily number of shares on loan for large listed European and US banks, as well as for European insurers, from July 2006 to September 2013. Our sample of financial institutions includes all banks and insurers that are included in the Stoxx Europe 600 and Stoxx North America 600 stock indices, so as to also ensure that selected stocks are sufficiently liquid in both the secondary trading and the securities lending markets. The sample includes financial firms listed in a number of countries, which allows us to investigate the heterogeneous impact of short selling bans that were implemented in various countries from 2008. The provider of data used in this study, Markit Securities Finance, claims that it offers the most comprehensive dataset on securities
lending activities by using, among other things, so-called “give-to-get” data gathering and distribution model that involves key players in the securities lending market—banks, prime brokers, hedge funds, custodians and agent lenders.

**What we find**

We report three main results. The first and the most important is that the association between short selling and price changes can become very strong under exceptional circumstances, while being weak in normal times. Moreover, large changes in short selling positions are strongly and negatively related to large changes in stock prices. By contrast, the linear correlation, which largely captures “normal” changes in short selling and prices, is close to zero. Furthermore, we find that extreme negative price changes are more strongly associated with extreme positive rather than negative changes in short interest.

The second result is that the tail relationship was much stronger for small cap firms. Intuitively, a smaller firm is likely to have a lower absolute (and possibly relative) amount of free float capital, which makes its shares less liquid (Glosten and Harris, 1988). In our sample, the market capitalizations of European insurance companies were generally lower and tail correlations tended to be higher than those for US and European banks. Although we are unable to indicate the precise causes of this result, we can propose two non-mutually exclusive explanations. First, the insurance sector was not the main concern for regulators in Europe and short selling bans affected only a few insurers in our sample. Second, a small market capitalization of a firm makes its shares less liquid and their price more vulnerable to large changes in short sellers positions.

Third, we relate to studies examining the effect of bans by comparing the adverse tail relationship during ban and non-ban periods. Our results show that the adverse tail correlation between increases in short selling and declines in stock prices was not always lower during ban periods, but had declined markedly towards the end of the analysis window.

The remainder of the paper is structured as follows. In Section 2 we introduce the securities lending market. In Section 3 we describe our data, and in Section 4 we explain our methodology. In Section 5 we report our results and in Section 6 we present our conclusions.

## 2 Short Selling and Securities Lending

A short sale relates to the sale of a security that is not owned by the seller at the time of the agreement.\(^4\) There are two main mechanisms to sell a security short. The first is to engage in a covered short sale by which the seller borrows the security before selling it short.\(^5\) By contrast, a short sale is considered naked or uncovered if the seller has not borrowed the stock beforehand, potentially giving rise to a failure to deliver the security to the buyer at the time of settlement. The European Securities and Markets Authority (ESMA) banned naked short selling of all securities in November 2012, while the Regulation SHO imposed


\(^5\)According to the European Securities and Markets Authority, an arrangement to borrow the shares or confirmation by a third party that the shares have been located is a sufficient requirement for considering the short sale covered, as opposed to naked. A similar definition is adopted by the US SEC.
by the SEC in 2005 requires short sellers to locate securities before selling them and enacts a close-out requirement to limit delivery failures.\(^6\)

The number of shares borrowed of a given stock can be interpreted as a proxy for the number of shares sold short of that very same stock (Diether, Lee, and Werner, 2009, Massa, Zhang, and Zhang, 2015, Saffi and Sigurdsson, 2011). In fact, in order to perform a covered short sale one must first borrow the given stock from a securities lender, as shown in Figure 1.

Figure 1 highlights the two steps that occur in a covered short sale. In the first step, the short seller borrows the security from a securities lender, either directly or through an intermediary. Securities lenders are generally institutional investors, such as pension funds or insurance companies that have securities in their portfolios as longer-term investments and from which they wish to obtain some additional revenue. Securities lending is not their primary activity, which is why securities lending is often outsourced to intermediaries that can be custodian banks, asset managers, or dealers lending securities on behalf of beneficial owners. Once the short seller has obtained the shares in step one, these shares will be sold at the market price to a buyer who is usually unaware of participating in a short sale. In the second step of the operation, the short seller will buy back the shares from the market. If expectations were correct, the short seller will buy the shares back at a lower price, thereby making a gain from the price difference. Finally, the short sale is closed when the short seller returns the securities to the lender.

In a securities lending transaction, the transfer of securities to the borrower occurs in \(T + 3\), meaning that it takes 3 trading days to settle the transaction. Since in most equity markets a stock sale is also settled at \(T + 3\), then in order to minimise borrowing costs a short seller will borrow a stock on the same day when the short sale is implemented in order to deliver the shares to the buyer by the deadline, at \(T + 3\).

The borrower of a stock has to provide the lender with collateral in the form of cash or other securities. For a lender, a security loan that is collateralised with cash can also be a viable alternative for financing. However, the typical and economically equivalent operation for such cash—rather than security-driven transaction—is a repurchasing agreement or a buy/sell back, whereby received security serves as collateral for a cash loan. When security lending is collateralised with other securities (usually of higher quality), it can become part of a collateral swap/transformation/upgrade transaction, with a view to using the received high-quality collateral to obtain cash.

In addition to purely directional short selling, there are also other motives to borrow a stock. For example, various arbitrage trading strategies also use short selling—e.g. convertible arbitrage, pairs trading or index arbitrage.\(^7\) Given that short selling is a high-risk operation, such investment strategies are usually used by sophisticated market participants such as investment banks and hedge funds.

Dividend arbitrage is another important motive for stock borrowing. It is driven by the fact that a stock loan represents an absolute transfer of title without having to actually purchase the stock. This could be used to vote on a given company’s corporate decisions, although this is not a frequent practice. More commonly, the transfer is made to perform tax

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\(^6\)Market makers are generally exempt from these requirements.

\(^7\)See Faulkner (2007) for an overview of the role of stock lending in these strategies.
arbitrage on dividend pay-outs, a widely used strategy in Europe where taxes on dividend payments vary greatly from country to country. Contractually, beneficial owners always retain the right to receive any dividend payments made on the shares they own. However, it is the holder of the stock who physically receives the dividend payment and is thus subject to a tax obligation. For this reason, a stockholder can lend out the shares to an agent in another country and agree to receive in return a negotiated percentage of a dividend payout (usually from 95% to 98%), which is much larger than an after-tax payment in a home country.

3 Data

Our dataset is composed of securities lending data provided by Markit Securities Finance (MSF) that acquired Data Explorers, the former provider of such data. MSF collects and distributes to subscribers daily information on demand and supply in the securities lending market by using, among other things, a so-called “give-to-get” data gathering and distribution model that involves key players in the securities lending market—banks, prime brokers, custodians, agent lenders, hedge funds and other institutional investors. Security lenders provide data on the inventory of securities they make available to borrow (i.e. supply) as well as the amount of securities that they actually lend out (i.e. demand). Security borrowers report information on the securities that they borrow (i.e. demand). MSF then cleans the data to avoid double counting.
3.1 Sample, Indicators and Data Cleaning

Our data sample includes daily information on prices and stock borrowing activity for stocks traded on the main domestic stock exchanges of 104 constituents of the Stoxx Europe 600 Banks, the Stoxx Europe 600 Insurance, and the Stoxx North America 600 Banks stock indices. The sample thus consists of 47 European banks, 35 European insurance companies and 22 North American banks. Choosing stocks that are included in a major stock index also ensures that selected stocks are relatively liquid in the secondary trading market and thus should also be sufficiently liquid in the securities lending market.

Our data comprises over 8,895 daily observations in eight countries from 3 July 2006 and ends on 30 September 2013, during which timeframe short selling—both naked and covered—was banned. Bans were applied for different periods and for the shares of different firms, as decided by the national authority in charge. In the US, for example, short selling prohibitions were in force from 18 September 2008 to 8 October 2008 for a list of 700 financial stocks. The most extreme case was Italy, which imposed a short selling ban on the stocks of banks and insurance companies in September 2008 and which lasted for over a year. In 2012, the financial market authorities of both Italy and Spain reintroduced short selling restrictions, although in Italy only financial stocks were affected, whereas in Spain restrictions applied to all stocks.

The ban dates were obtained from the websites of national financial markets authorities of eight countries: Canada, France, Germany, Italy, Spain, Switzerland, the UK, and the US. A detailed list of firms in our sample is provided in Appendix A.

In our study, in order to construct the best proxy for short selling, we make use of a variable provided by MSF called Short Loan Quantity ($SLQ$). $SLQ$ is the number of shares on loan of a given stock, filtered in order to estimate pure directional short selling. Based on transaction-level data, the proprietary algorithm applied by MSF removes those stock borrowing transactions that are clearly unrelated to pure directional short selling, because, for example, they are financing trades or are part of dividend arbitrage or convertible arbitrage trades.

Dividend arbitrage trades have a particularly notable impact on stock borrowing data. Dividend arbitrage-related demand to borrow stocks increases significantly before the dividend record date. This surge in demand affects lending rates and effectively makes it more difficult to borrow (Saffi and Sigurdsson, 2011).

The effect of dividend arbitrage trades is illustrated in Figure 2. The plot shows the number of Banco Santander shares on loan before (lighter dashed line) and after the removal of trades that are clearly unrelated to pure directional short selling ($SLQ$, bold solid line).

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8Classified as such by the Industry Classification Benchmark. The main criterion is the main source of revenue.

9We did not consider days during which markets were closed for trading because of local festivities. In fact, during some holidays markets were closed for trading, but open for settlement. In these cases prices were reported as constant by MSF, while borrowing amounts still varied. Since our prime interest is the relationship between short selling and stock price changes, we excluded these days.

10The dividend record date is the day at the end of which the company looks at its shareholder records in order to establish who the actual owners of its shares are, and therefore who is entitled to receive the dividend. Effectively, only those investors who are shareholders at the end of this date, will receive the dividend.
The number of shares on loan visibly peaks on the dividend record date (vertical line) and then declines within 5 to 10 days, as dividend arbitrage-related borrowing transactions are being unwound. Despite transaction-level filters applied by MSF, the filtered $SLQ$ data series still show some spikes on the dividend record dates, suggesting that data quality and/or the filter do not allow for a complete removal of dividend arbitrage trades.

**Figure 2:** Shares on loan (lighter dashed line) and the Short Loan Quantity ($SLQ$, solid bold line) for Banco Santander. The $SLQ$ is the number of shares on loan cleaned for stock borrowings that are clearly unrelated to pure directional short selling. The $SLQ$ is an indicator of pure directional short selling activity. The vertical lines refer to the dividend record dates and represent the last day used to determine shareholders who will receive the dividend.

It is important to note that Figure 2 shows settlement data, which implies that it refers to transactions that were executed three days prior to the reported date, given that in the securities lending market transactions generally settle at $T + 3$ (as also stock purchase/sale in most equity markets).\textsuperscript{11} In terms of dividend arbitrage this means that in order to avoid a dividend tax, the investor must lend out the share at least three days prior to the dividend record date. Moreover, due to $T + 3$ settlement, for our calculation we have shifted

\textsuperscript{11}Settlement does not mean that the loan is closed. Rather, it implies that the transfer has taken place and the securities have been delivered to the borrower. The loan is open until expiry or a recall from the lender, according to contractual agreements.
observations of $SLQ$ backwards by three trading days, so that on a particular date the $SLQ$ would relate to the trading and price change on that same day.

We standardise $SLQ$ by the number of shares outstanding ($SO$) and call this new variable short interest ($SI$). Thus, for firm $i$ on day $t$, the short interest is:

$$SI_{it} = \frac{SLQ_{it}}{SO_{it}},$$

i.e. the number of shares sold short as a percentage of the shares outstanding.

Since we are interested in day-to-day changes in short selling and stock prices, we work primarily with first differences.

$$\Delta SI_{it} = SI_{it} - SI_{it-1},$$

$$r_{it} = \log(p_{it}) - \log(p_{i,t-1}).$$

Our proxy for short selling activity overcomes some of the limitations of other similar measures in at least three ways.

Firstly, in the past, short interest was generally publicly available bi-monthly, and this low frequency posed an analytical limitation in early studies. In fact, short selling positions are often brief, lasting 3 to 5 trading days (Reed, 2002, Diether et al., 2009). By contrast, our $SI$ is a daily measure capable of capturing changes in short positions in a timely manner.

Second, unlike order/trade data (as used in e.g. Christophe, Ferri, and Angel, 2009, Boehmer et al., 2008), which only collects trades flagged as short sales, short interest can capture both subtractions from and additions to short sales. Thus, order/trade data cannot capture long trades (stock purchases) that might be used to cover short sales.

Third, according to Cohen, Diether, and Malloy (2007), $\Delta SI_{it}$ can be related to shifts in the demand for shorting of stock $i$, or shifts in the supply, or both. Since stocks in our sample are relatively liquid, they should not be subject to supply constraints (Asquith et al., 2005), and thus our proxy should principally capture changes in demand to sell short.

Boehmer et al. (2008) show that the largest short sales are the most informed, meaning that they predict the largest price declines in future returns. Thus, large positive $\Delta SI_{it}$ can capture short sellers (potentially speculators or manipulators, as in Grundy et al., 2012) that target firm $i$, while large negative $\Delta SI_{it}$ movements can signify that short sellers are avoiding that stock.

For most firms we have between 1,792 and 1,885 daily observations of stock prices, $SLQ$, and shares outstanding. In some cases, observations are missing because either the shares of a given company started being traded after the sample start date or simply because MSF was unable to provide daily observations due to data collection problems. We excluded data of one European bank because its shares on loan remained basically unchanged for most of the sample period. Our initial sample thus contains 186,558 observations.

Subsequently, we implemented three further steps of data cleaning. First, stock prices provided by MSF were crosschecked with prices and trading volumes reported by Yahoo Finance. As a result, we discarded observations on days when both (i) volume traded on Yahoo Finance was zero and (ii) stock prices provided by MSF were unchanged from the previous day. Effectively, this was an additional way to check for days during which the given stock did not trade.
Second, we excluded observations that related to days on which the number of shares outstanding changed. This was done in order to avoid self-created jumps in our proxy for change in short interest $\Delta SI_{it}$. To be clearer, suppose there is a new issue of shares on day $t$ by a given company $i$. This would cause $SI_{it}$ to drop even though we do not observe a fall in the number of shares borrowed. The differenced variable $\Delta SI_{it}$ would wrongly indicate that the short selling activity on the stock of firm $i$ is decreasing. By discarding such observations, we remove the instances of abrupt changes in our proxy variable that are not due to short selling.

Third, despite filters applied by MSF, $SLQ$ still includes some dividend arbitrage-related stock borrowings. In order to control for this phenomenon, we excluded observations in an interval of 10 trading days before and after the dividend record date. All in all, the number of eligible observations was reduced by about one-fifth to 148,503 (see Table 1).

<table>
<thead>
<tr>
<th>ORIGINAL SAMPLE</th>
<th>186,550</th>
</tr>
</thead>
<tbody>
<tr>
<td>Removing days with zero trades on Yahoo Finance</td>
<td>6,185</td>
</tr>
<tr>
<td>Differencing and removing days on which shares outstanding changed</td>
<td>4,834</td>
</tr>
<tr>
<td>Removing 20-day intervals susceptible to dividend arbitrage trades</td>
<td>27,028</td>
</tr>
<tr>
<td><strong>FINAL SAMPLE</strong></td>
<td>148,503</td>
</tr>
<tr>
<td>of which ban-related observations</td>
<td>8,895</td>
</tr>
</tbody>
</table>

Table 1: Number of daily observations of change in short interest and share price for the stocks of 103 firms and the impact of data processing and cleaning.

### 3.2 Descriptive Statistics

Basic descriptive statistics of $\Delta SI_{it}$ and $r_{it}$ are reported in Table 2. These statistics include the median values, interquartile ranges, skewness and kurtosis for North American and European banks, as well as for European insurance companies. Table 2 also provides a comparison of data characteristics during ban and non-ban periods, which allows making the following four observations.

First, during ban periods, the median firm witnessed either less negative or larger positive daily changes in its stock price than outside ban periods. Although this is consistent with the theoretical overpricing arguments of Miller (1977) and the results of Aitken, Frino, McCorry, and Swan (1998), it would be speculative to say that it was caused by the bans. In fact, most of the bans affecting our sample related to the extraordinary prohibitions on covered short selling that were introduced after the bankruptcy of Lehman Brothers in mid-September 2008. Beber and Pagano (2013) provide an in-depth study of different bans applied in 2008 across several countries.

12 Beber and Pagano (2013) provide an in-depth study of different bans applied in 2008 across several countries.
In fact, the median daily change in the stock price of a median North American bank was 0.49% during bans.

Second, the median changes in short interest $\Delta SI_{it}$ were negative and smaller during the ban periods for all three groups of financial firms, suggesting that, as one would expect, short sellers were closing their short positions in order to comply with the ban.

Third, while the interquartile ranges of $\Delta SI_{it}$ were not distinctly wider during the ban periods, the interquartile ranges of $r_{it}$, by contrast, were larger during the ban periods.

Fourth, both short interest and stock price changes were much more variable (as measured by their interquartile ranges) for North American banks than for European firms. This might be due to the fact that short selling is more frequently used in the US and Canada than in Europe. In addition, the median decrease in short interest during bans was stronger for North American banks than for European firms. This could be an indication of bans being more stringently applied in the US and Canada.

<table>
<thead>
<tr>
<th></th>
<th>$\Delta SI_{it}$</th>
<th></th>
<th></th>
<th>$r_{it}$</th>
<th></th>
<th></th>
</tr>
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<tbody>
<tr>
<td></td>
<td>All sample</td>
<td>Ban period</td>
<td>Non-ban period</td>
<td>All sample</td>
<td>Ban period</td>
<td>Non-ban period</td>
</tr>
<tr>
<td><strong>Median of medians</strong></td>
<td>European banks</td>
<td>0.000</td>
<td>-0.002</td>
<td>0.000</td>
<td>-0.041</td>
<td>-0.268</td>
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<tr>
<td></td>
<td>North American banks</td>
<td>0.000</td>
<td>-0.085</td>
<td>-0.014</td>
<td>0.000</td>
<td>0.487</td>
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<tr>
<td></td>
<td>European insurers</td>
<td>0.000</td>
<td>-0.002</td>
<td>0.000</td>
<td>-0.007</td>
<td>-1.373</td>
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<tr>
<td><strong>Median of interquartile ranges</strong></td>
<td>European banks</td>
<td>0.069</td>
<td>0.073</td>
<td>0.104</td>
<td>2.528</td>
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<td></td>
<td>North American banks</td>
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<td></td>
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<td>0.073</td>
<td>1.994</td>
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<td><strong>Median of skewness</strong></td>
<td>European banks</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.011</td>
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<td>0.000</td>
<td>0.000</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>European insurers</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.001</td>
<td>0.003</td>
</tr>
<tr>
<td><strong>Median of kurtosis</strong></td>
<td>European banks</td>
<td>6.036</td>
<td>6.011</td>
<td>4.388</td>
<td>1.560</td>
<td>1.055</td>
</tr>
<tr>
<td></td>
<td>North American banks</td>
<td>4.815</td>
<td>0.445</td>
<td>0.290</td>
<td>2.962</td>
<td>-0.446</td>
</tr>
<tr>
<td></td>
<td>European insurers</td>
<td>7.115</td>
<td>6.193</td>
<td>4.913</td>
<td>1.535</td>
<td>0.907</td>
</tr>
</tbody>
</table>

**Table 2**: The median values, interquartile ranges, skewness and kurtosis of daily changes in short interest and stock prices of North American and European banks, as well as of European insurers, during both ban and non-ban periods. Medians (50th quantile, $Q^{0.50}$), and interquartile ranges ($IQR$) were multiplied by 100 for visibility reasons, so that $\Delta SI_{it}$ is in percentage points, while $r_{it}$ is in percentages. The excess kurtosis and the skewness were computed using quantile-based measures. The kurtosis was calculated as excess with respect to the Gaussian as $IQR^{0.975}/IQR^{0.75} - 2.91$. The skewness was computed as $(Q^{0.975} - Q^{0.50}) - (Q^{0.50} - Q^{0.025})$.

Figure 3 shows the median correlation between changes in short interest and stock prices at different leads and lags (up to ±10 days) of changes in short interest for the three groups of firms in our sample. The dashed lines represent the interquartile range of the estimators.
as a measure of cross-sectional dispersion. Correlations are estimated using the measure developed by Lindskog, McNeil, and Schmock (2003), which is robust to outliers.

The median correlations are very low, always between 0.01 and -0.01 and with an interquartile range between -0.1 and 0.1, for all leads and lags. The data in Figure 3 could suggest that there is no relation between changes in short interest and stock prices. However, these Pearson correlations, which are the most commonly used, capture only the linear association between the two variables. They largely measure the association that occurs between the two variables in normal times or, graphically, the association around the centre of the joint probability distribution. They do not capture the association at the tails, i.e. the relation between extreme changes in short selling and stock prices.

![Figure 3: Median correlation between changes in short interest and stock prices for different leads and lags of changes in short interest. The chart also plots the upper and lower quartiles of Pearson $corr(\Delta SI_{t+h}, r_{it})$.](image)

To capture the tail association, we computed the empirical conditional tail probability for each of the 103 firms in our sample, calculated as the frequency of observing one of the two variables in its empirical tail given that the other variable is also in its empirical tail (see Fortin and Kuzmics (2002) for a similar exercise with stock return pairs). Figure 4 shows the medians and interquartile ranges of these empirical probabilities across the three
groups of firms. Panel A shows the conditional tail frequency when both variables (properly standardised) are in the same extreme side of their empirical distribution. Panel B shows the conditional frequency when the two variables are in opposite tails. Here, the tail event referred to in the table is for $\theta = 2$ standard deviations from their mean. The last row of each panel shows the corresponding probability calculated for a bivariate standardised normal distribution (with correlation equal to the sample correlation between changes in short interest and stock prices).

**European banks**

**North American banks**

**European insurers**

<table>
<thead>
<tr>
<th></th>
<th>European banks</th>
<th>North American banks</th>
<th>European insurers</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Pr { r &gt; \theta \mid \Delta SI &gt; \theta }$</td>
<td>2.9%</td>
<td>9.0%</td>
<td>3.1%</td>
</tr>
<tr>
<td>$\Pr { r &lt; -\theta \mid \Delta SI &lt; -\theta }$</td>
<td>2.8%</td>
<td>6.5%</td>
<td>3.2%</td>
</tr>
<tr>
<td>$\Pr { \Delta SI &gt; \theta \mid r &gt; \theta }$</td>
<td>2.2%</td>
<td>6.4%</td>
<td>2.7%</td>
</tr>
<tr>
<td>$\Pr { \Delta SI &lt; -\theta \mid r &lt; -\theta }$</td>
<td>2.0%</td>
<td>4.2%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Multivariate normal</td>
<td>1.9%</td>
<td>2.6%</td>
<td>2.6%</td>
</tr>
</tbody>
</table>

**PANEL A:** both variables are at the same extreme of their empirical distribution

**PANEL B:** variables are at their opposite tails

![Graph showing conditional tail probabilities](image)

**Figure 4:** Conditional tail probabilities of short interest and stock returns. Each series of $\Delta SI_{i,t}$ and $r_{i,t}$ for each firm was centred at its mean and standardised by its standard deviation. Then conditional empirical probabilities of the variables being $\theta$ standard deviations from their mean were computed. Here $\theta = 2$. The last row of each panel indicates the corresponding probabilities for a multivariate normal with correlation equal to the correlations of the firms in the given group.

We draw four main conclusions. First, the tails of $\Delta SI_{i,t}$ and $r_{i,t}$ are significantly heavier than Gaussian and the probability of observing a joint tail event is usually larger than in

---

13 We computed conditional tail frequencies for different levels of $\theta$. Results are available upon request.

14 Note that by symmetry of the Gaussian distribution $\Pr(\Delta SI_{i,t} > \theta \mid r_{i,t} > \theta) = \Pr(r_{i,t} > \theta \mid \Delta SI_{i,t} > \theta) = \Pr(\Delta SI_{i,t} < -\theta \mid r_{i,t} < -\theta) = \Pr(r_{i,t} < -\theta \mid \Delta SI_{i,t} < -\theta)$. The last rows for panels A and B are not numerically equal due to sample variability.
the multivariate normal. This is especially true for both the North American and European banks in our sample. For European insurance companies, the conditional tail frequencies are closer to those found between two random variables following a multivariate normal distribution.

Second, the probability of \( r_{it} \) being in its lower tail given that \( \Delta SI_{it} \) is in its upper tail (\( r_{it} < -\theta \mid \Delta SI_{it} > \theta \)) is rather high, especially for European and North American banks. For North American banks, however, extremely large increases in short interest (larger than 2 standard deviations) are somewhat more often associated with positive (\( r_{it} > \theta \mid \Delta SI_{it} > \theta \)) rather than negative extreme changes in stock prices.

Third, the probability of a large increase in short interest conditional on a large change in stock price is also high and somewhat more so in the case of extreme negative (\( \Delta SI_{it} > \theta \mid r_{it} < -\theta \)) rather than positive changes in stock prices.

Fourth, the data suggest that amid large price declines (usually in times of crisis, when financial stock prices are low and vulnerable), there is greater likelihood of observing an extremely high increase in short selling (possibly targeting a firm) (\( \Delta SI_{it} > \theta \mid r_{it} < -\theta \)) than extremely high unwinding of short positions (\( \Delta SI_{it} < \theta \mid r_{it} < -\theta \)).

Taken together, the above results for (\( r_{it} < -\theta \mid \Delta SI_{it} > \theta \)) and (\( \Delta SI_{it} > \theta \mid r_{it} < -\theta \)) suggest a vicious cycle where stock price declines induce active short selling and high short selling leads to lower stock prices.\(^{15}\) Although we are not able to make statements about the direction of causality, this is exactly the relation feared by policy makers during the financial crisis, which had prompted them to impose short selling bans. Overall, the data show a lack of linear correlation between changes in short interest and stock prices, but provide strong evidence of tail relationships.

4 Methodology

To quantify the dependence between tail changes in short selling and stock prices, we rely on TailCoR, an indicator that takes into account both linear and tail relationships. The linear relation is usually associated with normal times, while the tail relation is typical for periods of exceptional circumstances. TailCoR is suitable for both thin- and heavy-tailed random variables, does not depend on specific distributional assumptions, is simple, and no optimisations are needed. Moreover, it performs well in small samples, and disentangles easily linear and tail (non-linear) relations.

4.1 TailCoR

We give an intuitive derivation of the measure in Figure 5 and we refer an interested reader to Ricci and Veredas (2013) for an in-depth discussion. The chart shows the scatter plot of changes in short interest (horizontal axis) and stock prices (vertical axis) for Banco Santander. Both variables are standardised (i.e. centred at their medians and scaled by their interquartile ranges). We denote them \( \Delta \tilde{SI}_{it} \) and \( \tilde{r}_{it} \) respectively. All pairs of observations are projected on the 135-degree line, thereby producing a new random variable:

\(^{15}\)As a robustness check, we looked also at the conditional tail frequencies for different lags of \( \Delta SI_{it} \) and \( r_{it} \). The results broadly confirm our findings and are available upon request.
\[
Z_{it} = \frac{1}{\sqrt{2}} (\tilde{r}_{it} - \Delta \tilde{S}_{Iit}).
\]

**Figure 5:** Scatter plot of \(\Delta \tilde{S}_{Iit}\) and \(\tilde{r}_{it}\) for Banco Santander. Both variables were centred at their medians and scaled by their interquartile ranges to render them comparable. To calculate the TailCoR, all points are then projected on the 135-degree line.

The projected observations \(Z_{it}\) sit on the 135-degree line.\(^{16}\) The degree of dispersion of \(Z_{it}\) depends on the strength of linear and tail relations between changes in short interest and stock prices. Banco Santander is an archetypical example of the relation we find: weak linear relation and strong (negative) tail relation. Indeed, linear correlation is only -0.081, i.e. there is no real direction in the relationship at the centre of the distribution. This is a characteristic of our data and the reason behind low correlation coefficients found in Section 3.2. With tail events, the cloud of observations spreads along the 135-degree line more widely, either in the north-west or the south-east quadrants, or both (see arrows in Figure 5).

TailCoR is defined as the normalised tail interquantile range (at probability level \(\xi\)) of \(Z\):

\[
\text{TailCoR}_i^\xi = s_g(\xi) IQR_{R_i^{c,\xi}}^\xi,
\]

where \(IQR_{R_i^{c,\xi}} = Q_i^{c,\xi} - Q_i^{c,1-\xi}\) is the tail interquantile range of the projection, and \(s_g(\xi)\) is the normalisation (equal to \(\Phi^{-1}(0.75)/\Phi^{-1}(\xi)\), where \(\Phi^{-1}(\cdot)\) is the inverse cumulative density

\(^{16}\)Note that the vector \((1/\sqrt{2}, -1/\sqrt{2})\) is the eigenvector associated with the largest eigenvalue of a standardised elliptical random vector with negative relation. In other words, \(Z_{it}\) is the first principal component.
function of a normal distribution). The aim of the normalisation is to have a reference number: under Gaussianity and no correlation (and hence independence), TailCoR\textsubscript{i} equals 1.

If \( r_{i,t} \) and \( \Delta SI_{i,t} \) were positively related, then projecting on the 45-degree line would yield a higher TailCoR. In that case \( Z_{i,t} = (1/\sqrt{2})(\tilde{r}_{i,t} + \Delta SI_{i,t}) \).\(^{17}\) However, since we are primarily interested in the negative association between changes in short interest and stock prices, we always project on the 135-degree line, as suggested by Ricci and Veredas (2013). If the true relationship is positive, then projecting on the 135-degree line will yield a more conservative value of TailCoR.

To get a sense of the order of magnitude of TailCoR, random simulations from a Student t-distribution with tail parameter \( \alpha = 2.5 \) (so heavy tailed) result in average TailCoR of 1.46 (see Ricci and Veredas (2013) for an in-depth discussion of these results). For Banco Santander \( IQR z;0.95 = 4.39 \). Multiplying this by \( s_g(0.95) = 0.41 \), thus obtaining a TailCoR of 1.80, which highlights a strong tail relation between changes in short interest and stock returns. The choice of \( \xi \) is contextual and is typically above 0.90. In some sense, \( \xi \) is the “depth” at which we explore the tails.

So TailCoR\textsubscript{i} larger than 1 points to the existence of linear and/or tail relations, but its value does not indicate the contributions of each relation. However, under a very general and reasonable assumption of ellipticity (i.e. that the probability contours of the bivariate distribution of changes in short interest and stock prices are ellipsoids), TailCoR\textsubscript{i} can be decomposed into two parts. One part depends on a function of the tail index \( \alpha \), whereas the other depends on the coefficient of linear correlation between the two variables, \( \rho_i \):

\[
\text{TailCoR}_i^\xi = s_g(\xi)s_i(\xi, \alpha)\sqrt{1-\rho_i}.
\]

Since the linear correlation between changes in short interest and stock prices is close to zero, we expect almost the entirety of TailCoR\textsubscript{i} to come from the tail relation \( s_i(\xi, \alpha) \) that occurs between \( \Delta SI_{i,t} \) and \( r_{i,t} \).\(^{18}\) The relation between the tail index \( \alpha \) and \( s_i(\xi, \alpha) \) is monotonically decreasing: the larger \( \alpha \) (and hence the thinner the tails), the smaller \( s_i(\xi, \alpha) \) is. Under Gaussianity, \( s_g(\xi) \) and \( s_i(\xi, \alpha) \) cancel out and the TailCoR\textsubscript{i} is exclusively a function of the linear relation.

The tail (non-linear) component is easy to estimate: it is the ratio of the \( IQR z;0.95 \) and \( \sqrt{1-\rho_i} \). For Banco Santander the linear component equals to \( \sqrt{1-(-0.081)} = 1.04 \), and thus the tail component \( s_i(0.95, \alpha) = 4.39/1.04 = 4.22 \), indicating high tail correlation between changes in short interest and bank stock price.\(^{19}\)

### 4.2 Southeast-TailCoR

TailCoR, as we have defined it so far, measures the association of tail events symmetrically. That is, it picks up the association between both the lower tail (negative changes in short

\(^{17}\)The vector \((1/\sqrt{2}, 1/\sqrt{2})\) is the eigenvector associated with the largest eigenvalue.

\(^{18}\)In the case of a positive relation, the linear component of TailCoR is calculated as \( \sqrt{1-\rho_i} \).

\(^{19}\)If we had used the projection on the 45-degree line, we would have uncovered a weaker TailCoR of 1.70 and thus a weaker tail correlation component of 4.00.
interest and positive changes in stock prices) and the upper tail (positive changes in short interest and negative changes in stock prices).

As discussed earlier, policy makers often motivated the use of bans by fears that short selling and stock prices are negatively related in times of crisis. In particular, the concern is that predatory short selling could induce negative price spirals. For this reason, it is of particular interest to us to quantify the tail association between positive changes in short interest and negative changes in stock prices.

In order to assess this relationship, we make use of the so-called Southeast TailCoR, which focuses on observations in the southeast quadrant of Figure 5, as more clearly shown in Figure 6. Southeast TailCoR is calculated in the same manner as TailCoR. The key difference is that only the southeast part of the interquantile range is used to compute the Southeast TailCoR, i.e. only the part between the median and the southeast tail.

![Figure 6: Scatter plot of $\Delta SI_{it}$ and $\bar{r}_{it}$ for Banco Santander focusing on the southeast quadrant where changes in short interest are positive and changes in stock prices are negative. As in the case of TailCoR, all points are projected on the 135-degree line, but only the southeast part of the interquantile range is used to compute the Southeast TailCoR.](image)

More formally, the Southeast TailCoR (SE-TailCoR) is defined as

$$SE\text{-TailCoR}^\xi_i = 2s_g(\xi)IQR^\xi_i,$$

where $IQR^\xi_i = (Q_{i,0.5}^\xi - Q_{i,\xi}^\xi)$ is the interquantile range between the $\xi$th quantile and the median of the projection $Z$. For Banco Santander, the SE-TailCoR$^{0.95}$ is 1.89, i.e. slightly higher than the TailCoR$^{0.95}$ of 1.80, pointing to an even higher tail association between changes in short interest and bank stock prices when the former is positive and the latter are negative.
Southeast TailCoR can also be decomposed into linear and non-linear components under the assumption of ellipticity:

$$\text{SE-TailCoR}_i^\xi = 2s_g(\xi)s_i^{SE}(\xi, \alpha)\sqrt{1 - \rho_i^{(+,-)}},$$

where $\rho_i^{(+,-)}$ is a positive-negative semi-correlation defined as

$$\rho_i^{(+,-)} = \frac{\sigma_i^{(+,-)}}{\sigma_{\Delta SI_i} \sigma_{r_i}},$$

where $\sigma_{\Delta SI_i}$ is the positive semi-variance of $\Delta SI_i$, and $\sigma_{r_i}^{-}$ is the negative semi-variance of $r_i$. We call $\sigma_i^{(+,-)}$ the positive-negative semi-covariance.\(^{20}\)

For Banco Santander, positive-negative semi-correlation $\rho_i^{(+,-)} = -0.20$, a much stronger linear association than was found for all observation pairs, and which corresponds to a linear component of $\sqrt{1 - \rho_i^{(+,-)}} = 1.10$. Then, given that the SE-TailCoR\(^{0.95}\) of Banco Santander is 1.89, the non-linear component is computed as follows: $s^{SE}(0.95, \alpha) = 1.89/(2 \times 0.41 \times 1.10) = 2.10$.

## 5 Results

We calculate TailCoR between changes in short interest and stock price for every firm. For the remainder of the paper, we use $\xi = 0.95$.\(^{21}\)

### 5.1 TailCoR between short interest and stock price changes

As shown in the second column of Table 3, the level of TailCoR is high across all firms, reflecting a great deal of tail dependence between changes in short interest and stock prices. The median values of TailCoR for the three groups of firms are around 2. Moreover, the distance between the first and third quartiles (shown in parentheses) of TailCoR suggests that coefficients are tightly dispersed around their median values. European insurance companies have the largest TailCoR, possibly because in our sample market capitalisations of most insurers are substantially smaller than those of banks and thus the liquidity of the former stocks may also be lower (see Section 5.3 for a discussion on implications of low liquidity for the impact of short selling on prices).

As noted in Section 4.1, in the paper all TailCoR coefficients are computed by projecting pairwise observations on the 135-degree line, since we are primarily interested in the negative

\(^{20}\)We define the positive-negative semi-covariance between the changes in short interest of firm $i$ and the stock price returns of firm $i$ as

$$\sigma_i^{+,-} = \mathbb{E} \left[ \left( (\Delta SI_{it} - \overline{\Delta SI}_i) \cdot \mathbb{I}(\Delta SI_{it} > \overline{\Delta SI}_i) \right) \left( (r_{it} - \overline{r}_i) \cdot \mathbb{I}(r_{it} < \overline{r}_i) \right) \right],$$

where $\overline{\Delta SI}_i$ is the mean of $\Delta SI_i$ and $\overline{r}_i$ is the mean of $r_i$. The indicator function $\mathbb{I}(\Delta SI_{it} > \overline{\Delta SI}_i)$ is equal to one when $\Delta SI_{it} > \overline{\Delta SI}_i$ and zero otherwise. Similarly, $\mathbb{I}(r_{it} < \overline{r}_i)$ is equal to one when $r_{it} < \overline{r}_i$ and zero otherwise.

\(^{21}\)Additional results for different values of $\xi$ are available upon request.
association between changes in short interest and stock prices. When the relation is more positive than negative, this yields a lower (i.e. more conservative) value of TailCoR. We compared TailCoR coefficients computed with 135-degree and 45-degree lines and found that using the 135- rather than 45-degree line resulted in a higher TailCoR for 76% of European banks, 32% North American banks, and 54% European insurers.

<table>
<thead>
<tr>
<th></th>
<th>TailCoR</th>
<th>Pearson correlation $\rho$</th>
<th>Linear component</th>
<th>Tail component</th>
</tr>
</thead>
<tbody>
<tr>
<td>European banks</td>
<td>2.02</td>
<td>-0.03</td>
<td>1.02</td>
<td>4.94</td>
</tr>
<tr>
<td></td>
<td>(1.80 ; 2.44)</td>
<td>(-0.08 ; 0.00)</td>
<td>(1.00 ; 1.04)</td>
<td>(4.35 ; 5.83)</td>
</tr>
<tr>
<td>North American Banks</td>
<td>1.96</td>
<td>0.02</td>
<td>0.99</td>
<td>4.80</td>
</tr>
<tr>
<td></td>
<td>(1.76 ; 2.08)</td>
<td>(-0.04 ; 0.08)</td>
<td>(0.96 ; 1.02)</td>
<td>(4.39 ; 5.04)</td>
</tr>
<tr>
<td>European Insurers</td>
<td>2.17</td>
<td>0.03</td>
<td>0.99</td>
<td>5.34</td>
</tr>
<tr>
<td></td>
<td>(1.85 ; 2.42)</td>
<td>(-0.01 ; 0.05)</td>
<td>(0.98 ; 1.01)</td>
<td>(4.35 ; 6.06)</td>
</tr>
</tbody>
</table>

**Table 3:** The TailCoR and Pearson correlation between changes in short interest and stock prices as well as linear and tail components of TailCoR for 46 European banks, 35 European insurers and 22 North American banks. The table shows median group values as well as the first and third quartiles (in parentheses).

Columns 3 to 5 of Table 3 show the decomposition of the computed TailCoR coefficients into their linear and tail components. The values indicate that the relation is primarily driven by the association between extreme changes in short interest and stock prices. In fact, the linear components are close to 1, indicating no linear association. The tail components, however, are very high. In other words, large positive (negative) changes in short interest are associated with large negative (positive) changes in stock prices.

It is important to note, however, that high TailCoR values do not allow to make statements about the direction of causality. It could well be that extreme increases in short positions instigate extreme price declines, but it could also be that extreme price falls induce bursts of short selling activity. In any case, the revealed tail relationship implies the existence of a potential adverse feedback mechanism that has been at the centre of attention of policy makers.

### 5.2 Southeast TailCoR between short interest and stock price changes

As mentioned in the previous section, negative TailCoR weighs tail events equally whether they are found on the southeast quadrant or not. In order to understand the strength of the tail relation occurring between short selling and returns when the latter are negative and when short interest is positive we computed Southeast TailCoR and compared it with
TailCoR of all other quadrants. We found that the former was greater in the majority of pairwise comparisons. Results are shown in Table 4 and can be interpreted as follows: for 74% of the European banks in our sample, for example, Southeast TailCoR was found to be greater than Northeast TailCoR.

<table>
<thead>
<tr>
<th></th>
<th>Northeast-TailCoR</th>
<th>Northwest-TailCoR</th>
<th>Southwest-TailCoR</th>
</tr>
</thead>
<tbody>
<tr>
<td>European banks</td>
<td>74%</td>
<td>76%</td>
<td>73%</td>
</tr>
<tr>
<td>North American banks</td>
<td>50%</td>
<td>64%</td>
<td>73%</td>
</tr>
<tr>
<td>European insurers</td>
<td>54%</td>
<td>49%</td>
<td>60%</td>
</tr>
</tbody>
</table>

Table 4: Percentage of firms for which Southeast TailCoR was greater than TailCoR computed using other quadrants of the scatter plot of standardized points.

As was highlighted in Section 3 with the help of conditional tail frequencies, there is strong evidence of a high tail relationship when short selling is positive and returns are negative. In order to quantify such a relationship, we calculated Southeast TailCoR for all firms and present results in Table 5 (which reads similarly to Table 3):

<table>
<thead>
<tr>
<th></th>
<th>Southeast TailCoR</th>
<th>$\rho^{(+,-)}$</th>
<th>Linear component</th>
<th>Tail component</th>
</tr>
</thead>
<tbody>
<tr>
<td>European banks</td>
<td>1.93 (1.76 ; 2.31)</td>
<td>-0.20 (-0.25 ; -0.14)</td>
<td>1.09 (1.07 ; 1.12)</td>
<td>2.29 (2.04 ; 2.65)</td>
</tr>
<tr>
<td>North American banks</td>
<td>2.09 (1.82 ; 2.20)</td>
<td>-0.20 (-0.24 ; -0.17)</td>
<td>1.10 (1.08 ; 1.11)</td>
<td>2.34 (1.95 ; 2.48)</td>
</tr>
<tr>
<td>European Insurers</td>
<td>2.21 (1.84 ; 2.41)</td>
<td>-0.17 (-0.21 ; -0.14)</td>
<td>1.08 (1.07 ; 1.10)</td>
<td>2.51 (2.05 ; 2.77)</td>
</tr>
</tbody>
</table>

Table 5: Southeast TailCoR and its components for the three groups of firms in our sample. The table gives median values while the first and third quartile values are given in parentheses. Here $\xi = 0.95$. Additional results for varying levels of $\xi$ are available upon request.

The median value of Southeast TailCoR is around 2.01 for all firms. The table displays the median values of the linear and nonlinear (tail) components of Southeast TailCoR across the different groups. Values for the first and third quartiles are given in parentheses.

Notice that the linear correlation is much larger in absolute terms than the value we have found previously using full-fledged TailCoR. When looking at points in the southeast quadrant of our data, a linear relationship is clearly distinguishable, such that, on average, higher short interest is associated with lower returns. Moreover, our data have a strong nonlinear component, which indicates that extreme short interest is negatively associated with extreme returns. On a more general scale, our results are interpretable in the following...
way: given that we find ourselves in a situation of negative returns and positive short interest, positive changes in short selling positions are associated both linearly and nonlinearly with more negative returns.

The decomposition of Southeast TailCoR captures into its linear and nonlinear component captures different aspects of the relationship between positive short selling and negative returns. The linear component captures the association between positive short selling and negative returns that occurs in general, when both these variables are in the southeast quadrant of Figure 6 (Section 4.2). The nonlinear component captures the tail association that occurs during exceptional circumstances in periods of severe price drops.

Looking at results across sectors (rows in Table 5) we notice that, as for the results in Section 5.1, European insurance companies have the highest TailCoR while European and North American Banks show lower levels of tail association. Again, we point primarily to the superior liquidity of bank stocks in financial markets as a possible explanation for this. We will turn to these liquidity effects in Section 5.3 below, where we examine how the strength of the tail relationship varies with market capitalization.

5.3 Southeast-TailCoR and firm size

We rank firms according to market capitalization and analyze Southeast TailCoR for groups of firms of different size. Figure 7 depicts the median and interquantile ranges of Southeast TailCoR for different quartiles of firm size. Results show that for the European banks and insurance companies considered, the smallest companies (the first quartile in terms of firm size) have the highest Southeast TailCoR. Such clear-cut results are not observed for North American banks, where the largest banks appear to have the highest Southeast TailCoR.

Notice that the smallest size quartile of European insurance companies has similar market capital to the smallest size quartile of European banks, but nonetheless the former have a higher Southeast TailCoR. This might be due to the higher liquidity of bank stocks on financial markets compared to insurance companies which generally have less free float. The other size quartiles of European banks are much larger in terms of market capital than the remaining size quartiles of insurance companies.

Results for North American banks are inconclusive. Although all size quartiles are larger than the respective size quartiles of European banks, only the two smallest size quartiles have a lower TailCoR. The third and fourth size quartiles are composed of the largest (and therefore probably the most liquid banks), but are associated to a high Southeast TailCoR. One explanation could be that these banks are global and highly complex, and thus could be treated as a different case.

Overall, but not shown in Figure 7, Southeast TailCoR is highest for the companies with the lowest market capital. All firms in this size quartile have a market capital of between $1.6 billion and $7.2 billion and, with respect to our discussion above, the smallest quartile of firms is predominantly composed of insurance companies (out of 26 firms composing the smallest size quartile across all firms, 15 are insurance companies and 11 are European banks). This result reinforces the intuitive argument that short selling can be particularly important for small firms through a liquidity channel.

Across sectors, one can notice from Figure 7 that European insurance companies have the strongest ties between short selling and returns. The higher TailCoR found for insurance
firms can be explained by the fact that most of these companies in our sample are substantially smaller than banks. Boehmer, Jones, and Zhang (2013) found that liquidity can have important implications for the impact of short selling on prices and a smaller firm is likely to have less free float capital available to borrow and sell short (Beber and Pagano, 2013, Glosten and Harris, 1988).

The next subsection focuses on evaluating the impact of covered short selling bans on the relationship we have just uncovered.

5.4 Short selling bans

Several studies show that short selling prohibitions are harmful for market efficiency and liquidity (Beber and Pagano, 2013, Bernal, Herinckx, and Szafarz, 2014). In a regime of low liquidity, however, bans can result in the opposite of the effect intended. Boehmer et al. (2013), for example, show that the short-term price impact of short selling increased by 14 basis points for banned stocks during the SEC ban. Similarly, Kolasinski et al. (2013) show that short selling prohibitions increased the proportion of informed trading and thus the

Figure 7: Southeast TailCoR for firms of different size. Our sample firms are generally mid to large-cap as we used membership of the Stoxx600 indices to construct our database.
negative impact of short selling on returns.

In fact, during bans, short selling is still possible through the use of derivatives and other instruments, as explained in Section 1. Moreover, market makers are allowed to short during bans. Thus even during bans we might observe potentially predatory short selling and a high variability in our proxy of short interest as market makers borrow stocks to hedge synthetic short positions they are counterparties to.\footnote{Grundy et al. (2012) show, however, that during the SEC ban of 2008, the volume of traded options for banned stocks actually declined. They ascribe this to the increased costs for hedging options. On the other hand, Karmaziene and Sokolovski (2014) find a strong increase in shorting of ETFs.}

The above-mentioned studies concentrate primarily on the bans adopted by SEC. However, it is particularly difficult to identify the effects of bans in the US because these were implemented at the same time as the Troubled Asset Relief Program (TARP) was announced. Using international data, Bris et al. (2007) and Chang et al. (2007) show that short selling bans are associated with higher (less negative) skewness of returns. In stark contrast, Boehmer et al. (2013) and Kolasinski et al. (2013) find that negative extreme returns increase in magnitude (but not in frequency) when short selling is allowed.\footnote{This result is consistent with the notion that short selling does not affect the frequency of crashes but affects their depth. Saffi and Sigurdsson (2011) however ascribe this result to less over pricing when short selling is allowed.}

Our data, which span several countries and policy regimes, can help shed light on these contrasting results. We first collected dates during which bans were imposed in eight countries—Canada, France, Germany, Italy, Spain, Switzerland, the United Kingdom and the United States. These bans affected the stocks in our sample that were quoted on the domestic exchanges of these countries. We concentrated on covered short selling bans because our proxy primarily accounts for covered short selling. However, for one of the countries examined, Germany, only naked short selling bans were imposed. We computed Southeast TailCoR between short interest and returns for all ban periods.\footnote{We had to discard observations for Banca Popolare di Sondrio and Banca Popolare dell’Emilia Romagna because during the ban period over 50% of the values of short interest change were zero, causing us to effectively divide by zero in our calculations for TailCoR.}

To compare these results to periods during which short selling was allowed, we also computed Southeast TailCoR excluding prohibition periods for those firms that were banned at least once during our sample. In order to maintain a fair comparison, we kept the number of observations for non-ban periods equal to the number of observations during bans. Also we constructed the sample of non-ban observations so that it contained the same number of days in the pre-ban period as in the post-ban period.\footnote{Italian banks in our sample experienced two bans. Thus, for the non-ban sample of these firms we kept the same number of days in the two pre-ban periods as the two post-ban periods.}

Stocks of firms that were never banned were excluded from calculations. Our final sample of bans includes the prohibitions enacted during the 2008 crisis by the financial market authorities of Canada, Italy, Germany, Switzerland, the UK and the US. France enacted a naked short selling ban, which it kept for the remainder of the sample, so we did not include this date into our comparison. Rather, for France, we analysed the covered short selling ban the Autorité des marchés financiers (AMF) enacted in August 2011. Likewise, no actual ban was enacted in Spain where naked short selling is illegal.\footnote{The CNMV took action by reaffirming the importance of the short selling regulation in an official communication and imposing a disclosure requirement. The official communication can be found at}
In addition to the bans of 2008, we also examine bans that have not been analysed in prior studies, such as the joint ban imposed by France, Italy and Spain in August 2011 or the naked short selling ban imposed by Germany in May 2010. These were enacted in response to aggravations of the European debt crisis.

Figure 8 shows median Southeast TailCoR for the stocks examined, grouped by country of listing and by sector. The horizontal axis shows Southeast TailCoR during non-ban periods whilst the vertical axis shows Southeast TailCoR during ban periods. Some sectors had a lower negative tail relationship during the bans than during non-ban periods. These were French, German and Spanish insurers as well as Canadian and Spanish banks. For most of the remaining sample, we notice little change throughout the two regimes.

Figure 8: Median Southeast TailCoR according to country-listing and financial sector.

For US banks, there was no substantial difference in the median Southeast TailCoR during the ban and non-ban period. The SEC announced the 14-day ban in the midst of the financial crisis and, evidently, the level of Southeast TailCoR was influenced very little by the short selling ban, at least for the median bank. However, in terms of dispersion, additional results not reported here showed a lower interquartile range for Southeast TailCoR during the ban.

Generally, across almost all countries, Southeast TailCoR appears not to have decreased during bans and at times to have even increased (e.g., in the case of Italian and UK insurers).
Figure 9: Median Southeast TailCoR computed for non-overlapping windows of 6-months and for 46 European banks, 35 European insurance companies, and 22 North American banks.

Short selling bans through time

In order to analyse a more time-dependent measure of the tail relation between short interest and returns and thus to track the effect of ban implementations, we computed Southeast TailCoR for non-overlapping windows of six months of data, including observations related to bans. We take the median Southeast TailCoR for all firms across sectors for every window. Results are shown in Figure 9.

The first thing we notice in Figure 9 is that the relationship between Southeast TailCoR of different sectors is not as stable as the data in Figure 8 may have suggested. Secondly, even though Southeast TailCoR values for most of the sample of European banks and insurers are very close, at several times the two diverge. Thirdly, North American banks had the lowest level of Southeast TailCoR for most of the time period analysed, even though it increased rapidly and peaked during the financial crisis.

During the first window of data, which includes observations from July 2006 to December 2006, European insurance companies had the highest Southeast TailCoR followed by European and North American banks, respectively. However, starting from the second 6-month window, which dates January 2007 to June 2007, Southeast TailCoR for North American banks began to rise quickly, perhaps picking up the growing trouble linked to the subprime mortgage crisis. Although stock prices only started declining from October of that year, big movements in short interest could indicate that informed short sellers were already taking large bets on the downfall of banks.

During the data windows dating July 2007 to December 2007 and January 2008 to June 2008, Southeast TailCoR...
2008, the Southeast TailCoR of European banks and insurance companies also began to rise. In September, Northern Rock, a UK-based commercial bank, requested security from the Bank of England leading to a bank run. The event was one of the first signs of the crisis spreading across the Atlantic to Europe. For the following two windows, Southeast TailCoR continued to increase, reaching a peak in the data window ending December 2008.

The data window ending January 2009 includes the introduction of short selling bans that occurred in most countries after 18 September 2008, following enactment of the bans by the SEC. The increase in Southeast TailCoR is greatest for North American banks as they were hit the hardest at that time of the financial crisis. The peak window ending December 2008 includes destabilizing events such as Lehman’s bankruptcy on 14 September 2008.

After that window, Southeast TailCoR decreased quickly to around 1.5 points, which can be considered a medium-high tail relationship. For European banks and insurers, Southeast TailCoR started rising again after January 2011 reflecting the unfolding of successive distressing events during the Eurozone debt crisis. The deepening crisis in Portugal led to an IMF-EU bailout in the first half of 2011. Successively, Spanish bank bailouts and the uncertainty of Greek elections increased risks in European financial markets.

The level of Southeast TailCoR of North American banks peaked in the window ending in December 2011. This window includes the August 2011 crisis and the decision of Standard and Poor’s to downgrade the US credit rating from AAA to AA+. In addition to a large drop in stock prices in North American markets, fears of contagion of the Greek crisis to Italy and Spain led to volatility in European markets. The CAC40 dropped 20% in two weeks, while the FTSE 100 suffered four triple-digit losses in a row for the first time in its history. On August 11th, in response to potential speculative attacks, the market authorities of Belgium, France, Italy, and Spain decided to jointly ban creating or amplifying net-short positions in a confined list of financial stocks.

In the remaining part of the sample, from January 2012 to December 2013, the trend is that Southeast TailCoR generally decreased for all three sectors examined. This may have the result of calming financial markets, following moves by the ECB to support Eurozone countries through Outright Monetary Transactions. The only exception to this tendency is the window ending June 2013 window, during which European banks and insurers seem to have had a small jump in Southeast TailCoR levels. This can be linked to the start of the Cypriot crisis in March of the same year. On the other hand, Southeast TailCoR values for North American banks decreased steadily, reaching below the 1-point mark in January 2014. This implies no tail risk between short selling activity and price drops (large negative returns). In fact, a TailCoR of less than 1 is equivalent to tails thinner than Gaussian, meaning a very low probability of extreme events.

**Short selling bans through time and across countries**

We grouped the dynamic Southeast TailCoR results of European and North American banks according to stock country listings. Figure 10 depicts the medians and interquartile ranges of Southeast TailCoR for banks listed in eight countries. The shaded areas in Figure 10 refer to the remaining countries in our sample are available upon request.
depict periods of short selling bans affecting banks in those countries.

There appears to be little association between the ban period and the level of Southeast TailCoR. For Canada and Germany, there seems to be a peak right in the middle of the ban period with Southeast TailCoR declining after the ban is lifted. To a lesser extent, we can notice a decrease in the tail relationship in Spain, Switzerland and the UK. Switzerland and the UK applied a short-term covered short selling ban during the last quarter of 2008.

On the other hand, in the US and in Italy, the ban did not seem to be associated with a reduction in the level of Southeast TailCoR. This also seems to be the case for the naked short selling bans applied in Germany in May 2010 on a list of financial stocks. This policy was purposely aimed at decreasing the chances of speculative attacks on German banks given rumors that they would suffer heavily from a Greek default.

Overall, there is little evidence that the bans reduced the relationship between positive short selling and extreme falls in stock prices. We notice for all countries that the relationship decreased strongly after 2013. This is in concomitance with stronger efforts to regulate short selling in recent years. In fact, in 2010, the SEC amended regulation SHO applying the alternative-upick rule which prohibits short selling a stock at a price lower than the national best bid if that stock has incurred a 10% loss from the previous day’s close. In November 2012, a set of rules enacted by the European Parliament (among which Regulation N. 236/2012) came into force. The upshot is that naked short selling is now banned. For Canada, France, Germany and the US, we notice that Southeast TailCoR is below the level of 1 during this period, which implies low association between short interest and returns as well as a low probability of joint extreme events.
Figure 10: The group medians (straight and circle markers, in blue) of Southeast TailCoR for firms according to country of listing and their interquartile range (dashed, in red). We depict periods during which national bans on covered short selling were introduced (shaded area).
6 Conclusion

We study the association between daily changes in short selling activity and financial stock prices when both are at the extremes of their distribution. To quantify tail dependence, we use TailCoR, a measure of tail correlation. Our proxy for short selling activity is based on securities lending data for the stocks of the largest European and North American banks and European insurance companies. We find a very weak linear relation between short selling and stock prices, which is consistent with the literature. However, when we examine the relation at the tails we discover a strong tail relationship. We also show that the adverse tail correlation between increases in short selling activity and declines in stock prices during short selling bans was not always lower than during non-ban periods.

We analyse the relationship uncovered and find patterns that match previous observations in the literature. First, European insurance companies have the highest tail association, which could be due to insurance companies being relatively smaller than the banks in our sample. In fact, the tail relationship was found to be much higher for small firms, in terms of market capitalisation. This intuitively confirms the empirical finding that stocks with lower liquidity are more price-sensitive to short selling (Boehmer et al., 2013). As explained in Beber and Pagano (2013) and in Glosten and Harris (1988) small firms have generally lower stock liquidity, which explains the stronger tail relationship between short selling and returns for smaller firms.

Second, examining the effects of bans, we find that there is no particular decrease in the relationship between positive short selling positions and negative price changes during short selling prohibitions. In particular, for US banks on which a 14-day ban was imposed, we notice no change in Southeast TailCoR due to the ban. Thus, these results cast doubts on the effectiveness of bans to limit the vicious cycle between price drops and short selling (which can still be carried out during bans by market makers and sophisticated agents using options).

Our results on the effects of bans are confirmed in a time-varying analysis of Southeast TailCoR. No strong decrease is noticed in periods during which bans were in place. Rather, there is a decrease during the post-ban period. Nonetheless, the measure reacts in a timely fashion to crisis events showing that the risk of contemporaneous high short selling and low returns increases during market downturns. Moreover, Southeast TailCoR appears to decrease after 2012 concurrently with calmer financial markets and perhaps, coordinated policy action against abusive short selling in Europe and North America.
## Appendix A

<table>
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<th>European Banks</th>
<th>European Insurers</th>
<th>North American Banks</th>
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<td>Aegon Nv</td>
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**Table 6:** List of financial institutions in the sample
References


