Short selling in extreme events⋆

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Abstract

We study the association between daily changes in short selling activity and financial stock prices during extreme events using TailCoR, a measure of tail correlation. For the largest European and US banks, as well as European insurers, we uncover a strong relation during exceptional (extreme) days and a weak relation during normal (average) days. Examining days with large increases in short positions and large downfalls in stock prices, we find evidence of both momentum and contrarian short selling taking place. For North American bank stocks, contrarian short selling appears more practiced than for European bank and insurance stocks. We find that the uncovered relationship decreases with firm size and increases during ban periods, which is in line with short selling becoming more informative when constrained.

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1. Introduction

In this paper, our objective is to shed more light on the concern among policy makers that short selling can exacerbate price downfalls. Whereas most of the literature has analysed the average relation between short selling and price changes, our study focuses on the relation that occurs during extreme events. We propose to use TailCoR, a new measure developed by Ricci & Veredas (2013) that stems from the literature on tail correlations. TailCoR allows to decompose the relation between short selling activity and stock returns into the relation that occurs during normal (average) days and the relation that occurs during exceptional (extreme) days.

We examine the relation between short selling and stock returns for the largest European and North American banks, as well as for the largest European insurers, from July 2006 to September 2013. Our indicator for short selling activity (short interest) is the daily number of shares on loan. This is a well-established indicator of short selling activity that has been used by, among others, Richardson et al. (2017) and Jones et al. (2016). We find that the average association between short selling and price changes, is quite weak, whereas it is strong in the tails of the empirical distribution i.e., during extreme events. Moreover, large changes in short selling positions are strongly and negatively related to large changes in stock prices.

Previous studies have focused on US stock markets, and have found that short selling is associated, on average, with positive contemporaneous returns and negative future returns (Dechow et al., 2001; Asquith et al., 2005; Diether et al., 2009b; Boehmer et al., 2010). These studies show that short sellers are capable of predicting future returns and concentrate on stocks that are overpriced relative to fundamentals. Our results for large North American banks confirm these findings by showing that there is a strong relationship in the *positive* tails of the joint distribution of short interest changes and returns. That is, we find that for North American banks, extreme short interest changes are more strongly related to extreme positive returns than extreme negative returns. This indicates that there is evidence of short sellers acting as contrarian traders.

Consistent with the findings of Curtis & Fargher (2014), we also find evidence of momentum trading by short sellers taking position against large North American bank stocks. Our analysis using conditional tail frequencies highlights that, in episodes of extreme short selling activity, contemporaneous returns are extremely negative (i.e., in their 10% empirical quantile) 14.5% of the time. We find that, during 50% of these episodes, prices tend to revert within 1 to 2 trading days, which suggests that part of these price downfalls are not due to informative short selling.

Our sample spans banks of several European countries, which allows us to compare our results obtained for North American banks. We find that, in the case of European bank stocks, contrarian short selling is much less prevalent. Our measure of tail correlation shows that, for 70% of the European banks in our sample, extreme positive short interest changes are more strongly related to extreme negative returns than to extreme positive returns. This suggests that there are differences between short selling on European markets and North American markets. Moreover, results for European banks provide some basis for the concerns of European regulators that banned short selling during the European sovereign debt crisis.

For European financial companies, we find that the relationship between extreme negative price changes and extreme positive returns is stronger for firms with smaller market capital. There can be two possible explanations for this result. First, smaller firms are likely to have a lower absolute (and possibly relative) amount of free float capital, which makes their shares less liquid (Glosten & Harris, 1988). Second, smaller firms are more susceptible to information asymmetry between specialist short sellers and buyers.

Our paper is close in spirit to the studies of Boehmer & Wu (2013) and Shkilko et al. (2012), who assessed the relation between short selling and stock prices on days of extreme price changes. Compared to their approach, we do not impose selection criteria but use TailCoR, a non-parametric measure that makes use of the entire sample of observations. Our results are closer to those of Shkilko et al. (2012), who found that short sellers exacerbate price declines, than those of Boehmer & Wu (2013), who found that short sellers act as liquidity providers during transient price turnarounds, buying when the price drops and selling when the price jumps unusually high.

Our study also contributes to the literature on short selling bans. Whereas, prior studies have focused on the effect of short selling bans on price levels and returns (e.g., Boehmer et al., 2008; Chang et al., 2007), we study the impact of covered short selling bans on the association between (remaining) short selling activity and returns. In addition to the bans introduced in the US and many European countries following the financial crisis, we also analyse the more recent joint ban of five European regulators introduced in August 2011, which were not included in the prior studies of Beber & Pagano (2013) and Bris et al. (2007).

For Canadian and European banks, we find that the 2008 bans were associated with a higher relationship between short selling changes and returns. In line with the results of Boehmer et al. (2013) and Kolasinski et al. (2013), this points towards short selling becoming more informative during ban periods. Conversely, we did not find similar results for the 2011 ban period, perhaps indicating that this more recent ban was less effective towards impeding uninformative short selling.

Although TailCoR has several advantages (it does not depend on specific distributional assumptions, and it is straightforward to compute, as no optimisations are needed), similarly to linear correlation, it does not make it possible to draw conclusions about the direction of causality. This is a limitation of our study that we address in the supplementary online material. We provide several additional results using different leads and lags of our short selling measure and find that short sellers can anticipate large price declines by about one to four trading days.

Overall, our study provides evidence on the relationship between short selling and extreme price changes that could motivate future work in this direction. For example, our analysis could be extended using a bivariate autoregressive model of conditional quantiles, such as that of White et al. (2015), applied to short selling and price changes.

The remainder of the paper is structured as follows. In Section 2, we introduce the securities lending market, from which our data comes from. In Section 3, we describe our data in more depth 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.[1] 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. 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.

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

[1] Regulation (EU) No 236/2012 of the European Parliament and of the Council of 14 March 2012 on short selling and certain aspects of credit default swaps.

lending is often outsourced to intermediaries such as 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.

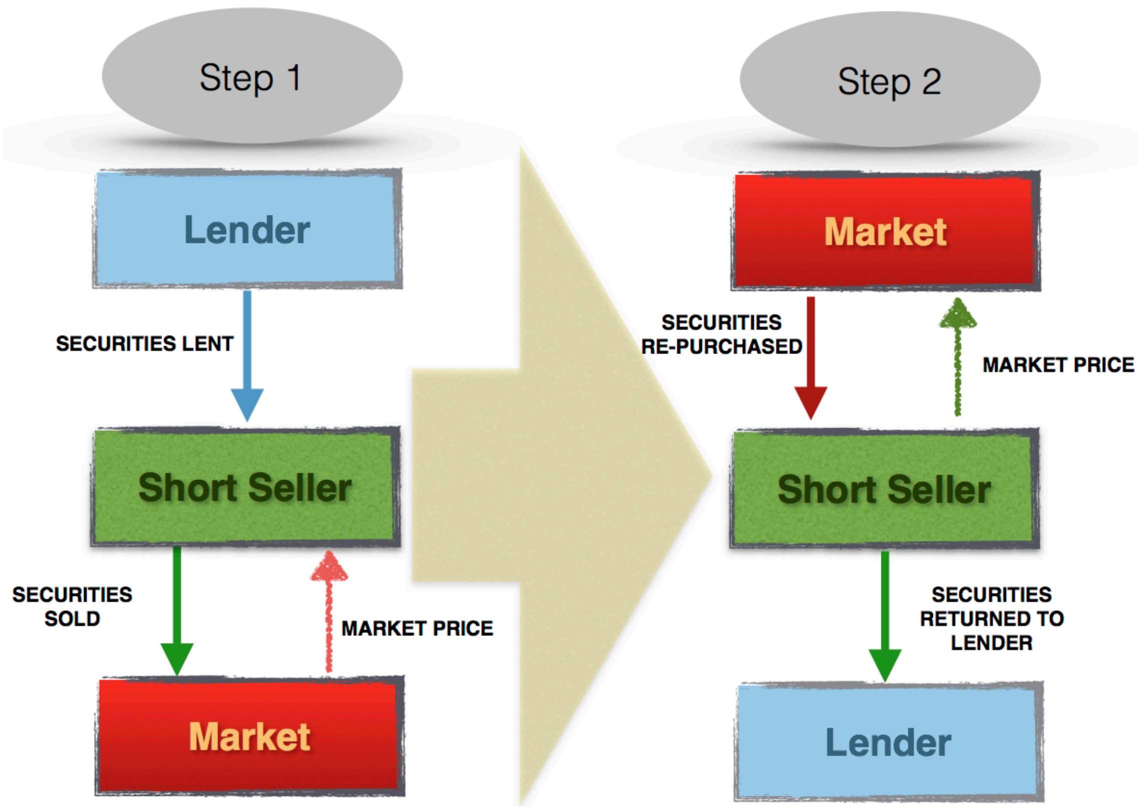

Fig. 1. Covered short selling. The figure shows the steps involved in a covered short sale. In the first step, the short seller borrows the security from a lender. The short seller then sells the borrowed security in the market. In the second step, the short seller buys an equivalent security back from the market so to return it to the original holder, the security lender. If the price has declined between step 1 and step 2, the short seller will have made a profit from the trade.

In addition to purely directional short selling, there are also other motives to borrow and short sell a stock. For example, various arbitrage trading strategies also use short selling and stock borrowing—e.g. convertible arbitrage, pairs trading, or index arbitrage.[2] Given that short selling is a high-risk operation, sophisticated market participants, such as investment banks and hedge funds, usually adopt these strategies.

Particularly in Europe, where taxes on dividend payments vary greatly from country to country, dividend arbitrage is yet another motive for stock borrowing. 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 may lend out the shares to an agent in another country and agree to receive in return a negotiated percentage of a dividend pay-out (usually from 95% to 98%), which is much larger than an after-tax payment in a home country.

It is worth mentioning here the role of the securities lending market during periods in which short selling is banned. Covered short selling bans prohibit the short sale of stocks that are not owned by the seller at the time of the sale. This means that short selling borrowed stocks is prohibited, but it is still possible to short a stock through other means.

For example, synthetic short positions are still achievable using put options, credit default swaps, and inverse exchange traded funds (ETFs). Grundy et al. (2012) show that, during the September 2008 ban implemented in the US, the transaction prices for options substantially increased due to their higher demand. During the same period, Karmaziene & Sokolovski (2017) found that shorting of ETFs increased as short sellers were trying to circumvent the short selling prohibition. Traders engaging in short selling through options are more sophisticated than ordinary short sellers (Kolasinski et al., 2013). Moreover, the higher costs of short selling through options makes it likely that these short sellers are also more informed.

Short selling during the ban was also possible for registered market makers, including liquidity providers, specialists, and options market makers, that were exempted from the short selling prohibition Boehmer & Wu (2013). The exemption was put in place to allow market makers to continue making markets smoothly, but was not valid for informal market makers, such as high frequency traders and algorithmic traders, who often make markets in large-cap and active stocks

[2]See Faulkner (2007) for an overview of the role of stock lending in these strategies.

(Hendershott et al., 2011; Menkveld, 2013). For the US, the ban exemption was paired with a borrow requirement i.e., market makers were required to locate and borrow shares prior to short selling them (Blocher & Ringgenberg, 2018).

Our indicator of short selling activity, which is based on shares on loan, should capture part of the synthetic short selling by entities trying to circumvent the ban. This is because market makers engaging in the other side of the trade might resort to the securities lending market to hedge their exposure. For example, imagine an entity would like to buy a put option to create a synthetic short position in the underlying asset. The market maker facing this trade, might hedge its exposure by shorting the underlying asset.

As argued by Boehmer & Wu (2013), market makers might have multiple reasons for borrowing and short selling a stock apart from hedging. For example, they might engage in a covered short sale simply to provide liquidity to a buyer. For this reason, during ban periods, our indicator based on shares on loan represents only an upper limit of the short selling by entities trying to circumvent the ban.

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 claims that it offers the most comprehensive dataset on securities lending activities 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 and Short Interest Indicator

Our data sample includes daily information on prices and stock borrowing activity of 104 constituents of the Stoxx Europe 600 Banks, the Stoxx Europe 600 Insurance, and the Stoxx

North America 600 Banks stock indices.[3] We chose stocks that are included in major stock indices to ensure that these are relatively liquid in the secondary trading market and securities lending market.

The sample consists of 47 European banks, 35 European insurance companies and 22 North American banks.[4] Our data comprises over 8,895 daily observations in eight countries from 3 July 2006 and ends on 30 September 2013.[5]

During some periods of our sample, short selling—both naked and covered—was banned. We collected short selling ban dates from the websites of national financial markets authorities of six countries: Canada, France, Italy, Spain, the UK, and the US. We concentrated on covered short selling bans because our indicator of short selling activity primarily accounts for covered short selling.

We constructed subsamples of the pre-ban and post-ban periods as follows. For a given stock, with d ban observations, we considered the last d observations prior to ban implementation for the pre-ban sample. Similarly, we considered the first d observations after the end of the ban for the post-ban sample. In this way, we kept the number of observations relating to pre- and post-ban periods equal to the number of ban period observations. For those stocks that were banned several times during the sample period (e.g., Italian or Spanish bank stocks), we only considered the first ban period for the construction of the ban, pre-ban, and post-ban subsamples. This was done so to avoid pre- and post-ban periods overlapping in the case of several bans.

To construct the best indicator for short selling activity on a given stock, 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 short selling activity. Based on transaction-level data, the proprietary algorithm applied by MSF removes those stock borrowing transactions that are clearly unrelated to short selling, because, for example, they are financing trades or are part of dividend arbitrage or convertible arbitrage trades.[6]

Short Loan Quantity is settlement data, which implies that it refers to transactions that

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[3] We provide a detailed list of the firms in our sample in the online supplementary material.

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

[5] 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.

[6] In the online supplementary material, we show that our main results are robust to the dividend arbitrage effect.

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).[7] Due to $T+3$ settlement, for our calculation we have shifted 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:

$$SI_{i\,t} = \frac{SLQ_{i\,t}}{SO_{i\,t}}, \tag{1}$$

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.

$$\Delta SI_{i\,t} = SI_{i\,t} - SI_{i\,t-1}, \tag{2}$$

$$r_{i\,t} = \log(p_{i\,t}) - \log(p_{i\,t-1}). \tag{3}$$

To avoid self-created jumps in our proxy for change in short interest $\Delta SI_{i\,t}$, we excluded observations that related to days on which the number of shares outstanding changed. By discarding such observations, we remove the instances of abrupt changes in our short selling indicator that are not due to short selling.

Our indicator overcomes some of the limitations of other similar measures for short selling activity .

First, in the past, short interest was generally publicly available bi-monthly, and this low frequency posed an analytical limitation in early studies. 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. Boehmer et al., 2008; Christophe et al., 2009; Diether et al., 2009a), which only collects trades flagged as short sales, short interest can capture both subtractions from and additions to short sales.

[7] 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.

Despite these advantages, our indicator is still an imperfect measure of short selling activity. According to Cohen et al. (2007), $\Delta SI_{i\,t}$ 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.

Another limitation is that our indicator does not capture short positions opened and closed within the same day. Reed (2002) reports that, for the US equity market, the median loan duration is three days, but the mode is 1 day. Thus, potentially, we could be missing short selling activity that occurs at the intraday frequency. According to Boehmer et al. (2013) and Menkveld (2013), however, a substantial part of intraday short selling activity may be attributed to high-frequency liquidity providers (including, but not limited to, algorithmic traders), whose trades should not be, at least a priori, extreme.

3.2. Descriptive Data Analysis

Table 1 provides a comparison of data characteristics during pre-ban, ban, and post-ban periods. Panel A of Table 1 reports median values and interquartile ranges of the variables in levels, $SI_{i\,t}$ and $p_{i\,t}$.[8] To make prices comparable across firms, we divided each firm's stock price by the its stock price on October 17, 2012.

Panel A of Table 1 shows that the median level of short interest was lower by 4% and 50% for, respectively, European banks and insurers during ban periods compared to non-ban periods. For North American banks, short interest was lower by 27% during ban periods compared to non-ban periods. For all three groups of stocks, short selling activity has decreased during ban periods, in line with the primary intent of bans.

As mentioned in the previous section, at least part of the remaining short selling activity that is observed during ban periods may be attributed to market makers (including specialists and option market makers) that were exempted from the ban. The short selling activity of these exempted market makers may be the result of hedging synthetic short positions provided to short sellers that were trying to circumvent the ban. Thus, our results give us an indication of the potential magnitude of this type of short selling.

[8]We thank an anonymous referee for suggesting this analysis.

Panel A of Table 1 also shows that the median prices of European bank and insurance stocks were respectively 39% and 30% lower during the ban period compared to the pre-ban period. In contrast, during ban periods affecting North American banks, the median price rose by 13% compared to the pre-ban period. This might be in part the effect of the Trouble Asset Relief Program, which coincided with the ban period in the US and might have had a positive effect on the stock prices. Thus, it seems that bans did not effectively sustain price levels of European financial stocks, whereas they were effective, to some extent, for North American bank stocks.

Panel B of Table 1 reports descriptive statistics for the differenced variables, $\Delta SI_{i\,t}$ and $r_{i\,t}$. For all three groups of financial firms, Panel B of Table 1 shows that the median changes in short interest $\Delta SI_{i\,t}$ were large and negative during the ban period. This suggests that, short sellers were closing their short positions during ban periods in order to comply with the new regulation.

For the median European banks and insurers in our study, Panel B of Table 1 shows that the interquartile range of short interest changes ($\Delta SI_{i\,t}$) was lower during ban periods than during non-ban periods. Since market makers were the only agents allowed to short during ban periods, this result suggests that they generate less dispersed short interest changes than banned short sellers, including informed sellers and speculators. A similar argument can be made if we consider the median interquartile range of short interest in levels ($SI_{i\,t}$), shown in Panel A of Table 1.

We do not observe the same result for North American banks, for which the median interquartile ranges of short interest and short interest changes are higher during ban periods than during non-ban periods. This might be due to the small sample size available for North American banks during the ban period, which was, at most, only 14 trading days long. Short sellers closing their short positions to comply with the ban will induce a higher interquartile range of SI and ΔSI. Moreover, as noted by Boehmer & Wu (2013), the first day of the ban was a "triple witching day" i.e., the last day of trading before expiration of index options, equity options on individual stocks, and index futures. Such days are characterised by large order imbalances and excess volatility in the equity markets. This might explain the large interquartile range of SI and ΔSI observed during ban periods for North American banks.

Panel B of Table 1 also shows that, during ban periods, the median European bank witnessed less negative daily changes in its stock price than during the pre-ban period. We do not observe this effect for North American banks, for which median pre-ban returns were positive and the median ban returns were heavily negative. This might be due to the fact that bans for North American banks were implemented after the bankruptcy of Lehman Brothers in mid-September 2008, in an extremely bearish and volatile market, as can also be noticed from the rows of Panel B of Table 1 relating to median interquartile ranges of returns.

		Panel A: Variables in levels							
		$SI_{i\,t}$				$p_{i\,t}$			
		All sample	Pre-ban period	Ban period	Post-ban period	All sample	Pre-ban period	Ban period	Post-ban period
Median of medians	European banks	1.475	1.993	1.918	1.905	141.2	220.0	134.5	128.9
	North American banks	2.825	6.413	4.702	3.733	96.630	101.9	114.6	94.40
	European insurers	1.438	2.995	1.495	1.907	94.830	116.7	81.830	82.840
Median of interquartile ranges	European banks	1.487	0.930	0.666	0.863	131.5	29.90	22.40	22.35
	North American banks	2.108	0.532	0.947	0.595	26.950	7.025	9.237	7.543
	European insurers	1.394	0.693	0.578	0.826	30.790	8.639	8.817	8.188
		Panel B: Variables in first differences							
		$\Delta SI_{i\,t}$				$r_{i\,t}$			
		All sample	Pre-ban period	Ban period	Post-ban period	All sample	Pre-ban period	Ban period	Post-ban period
Median of medians	European banks	0.000	-0.016	-0.035	-0.011	0.000	-0.313	-0.121	0.000
	North American banks	-0.002	-1.994	-6.821	-4.210	0.000	0.918	-1.524	-0.643
	European insurers	-0.029	0.000	-0.133	0.114	0.019	-0.147	-0.167	-0.334
Median of interquartile ranges	European banks	7.265	12.97	6.587	8.433	2.472	2.576	4.161	3.435
	North American banks	13.52	37.81	46.14	31.03	2.214	6.761	7.876	8.402
	European insurers	5.938	9.727	7.891	11.09	1.981	2.850	3.729	3.523

Table 1. Descriptive statistics. Panel A shows the median values and interquartile ranges of daily short interest and stock prices, $(SI_{i\,t}, p_{i\,t})$. Medians and interquartile ranges of SI are multiplied by 100 for visibility reasons, so that they are percentage points. For each firm, i, prices, $p_{i\,t}$, are computed relative to firm i's stock price on October 17, 2012, so that prices are 100 at the base date. Panel B shows the median values and interquartile ranges of daily changes in short interest and stock prices, $(\Delta SI_{i\,t}, r_{i\,t})$. Medians and interquartile ranges of ΔSI are multiplied by 10,000 for visibility reasons, so that they are basis points. Medians and interquartile ranges of r are multiplied by 100, so that they are percentages.

To describe the average dependence between short interest changes and returns, we examined the linear correlation between the two variables.[9] For the three groups of firms in our sample, Figure 2 shows the median correlation between $\Delta SI_{i\,t+h}$ and $r_{i\,t}$ for leads and lags of up to ten days, $h = [-10, 10]$, of changes in short interest. The dashed lines represent the interquartile range of the correlation estimates as a measure of cross-sectional dispersion.

For all leads and lags, the median correlations are low, between 0.03 and -0.03, and with an interquartile range between -0.1 and 0.1. At a first glance, Figure 2 could suggest that there is no relation between changes in short interest and stock prices. However, correlation largely measures the association that occurs between two variables in normal times or, graphically, the association around the centre of the joint probability distribution. It does not capture the association at the tails, i.e. the relation between extreme changes in short selling and stock prices.

To examine the dependence that occurs during extreme events, we computed the empirical conditional tail frequencies for each of the 103 firms in our sample. This is the frequency of observing one of the two variables in its empirical tail given that the other variable is also in its empirical tail.[10]

Figure 3 shows the medians and interquartile ranges of the conditional tail frequencies across the three groups of firms. Panel A of Figure 3 shows the conditional tail frequency when both variables are in the same extreme side of their empirical distribution, whereas Panel B of Figure 3 shows the conditional tail frequency when the two variables are in opposite extremes. The tail event referred to in the table is for the $\pi = 90\%$ quantile of the variables.[11] The last row of each panel shows the corresponding probability calculated for a bivariate normal distribution, with variance-covariance matrix equal to that of the sample variance-covariance matrix between changes in short interest and stock prices.

Figure 3 shows that the tails of ΔSI and r are substantially heavier than Gaussian i.e., the probability of observing a joint tail event is usually larger than in the bivariate normal distribution. Moreover, across all three groups of firms, Panel B of Figure 3 shows that the probability of r being

[9]Throughout the paper, we measure linear correlation using the highly robust and efficient Fisher consistent version of Kendall's correlation for the normal model, defined as: $\tilde{\rho}_K = \sin(\frac{\pi}{2}\rho_K)$, where ρ_K is Kendall's correlation (Lindskog et al., 2003; Croux & Dehon, 2010).

[10]For a similar exercise using stock return pairs, see Fortin & Kuzmics (2002).

[11]Results for different levels of π are available on request.

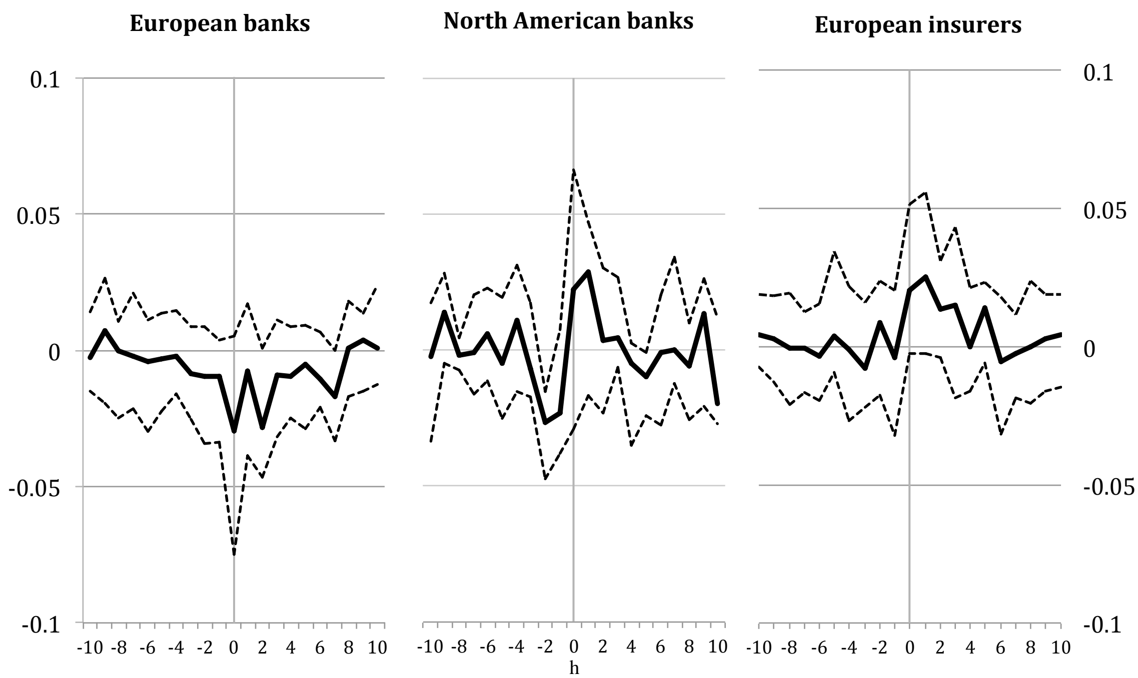

Fig. 2. Correlation between changes in short interest and stock price returns. The figure shows the median correlation between changes in short interest and stock price returns for different leads and lags (in days) of the changes in short interest. The figure also plots the upper and lower quartiles of the correlation across all firms in the three groups.

in its lower tail given that ΔSI is in its upper tail, $Pr[r_t < Q_r^{1-\pi}, \Delta SI_t > Q^{\pi}_{\Delta SI}]$ is high. For European banks and insurers, $Pr[r_t < Q_r^{1-\pi}, \Delta SI_t > Q^{\pi}_{\Delta SI}]$ is higher than all other conditional tail frequencies, indicating that there is asymmetry in our data.

We analysed the tail episodes characterised by large changes in short selling and large price downfalls, $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q^{\pi}_{\Delta SI}]$, with particular attention. Specifically, we examined the days successive to these events and checked for price reversions.[12] Results provided in full in the supplementary online material show that in almost 50% of the $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q^{\pi}_{\Delta SI}]$ cases analysed, the price downfall recovered within one to two days. Given that price changes that reverse quickly involve no new information, this seem to suggest that a considerable part of the short selling

[12]We thank an anonymous referee for suggesting this exercise.

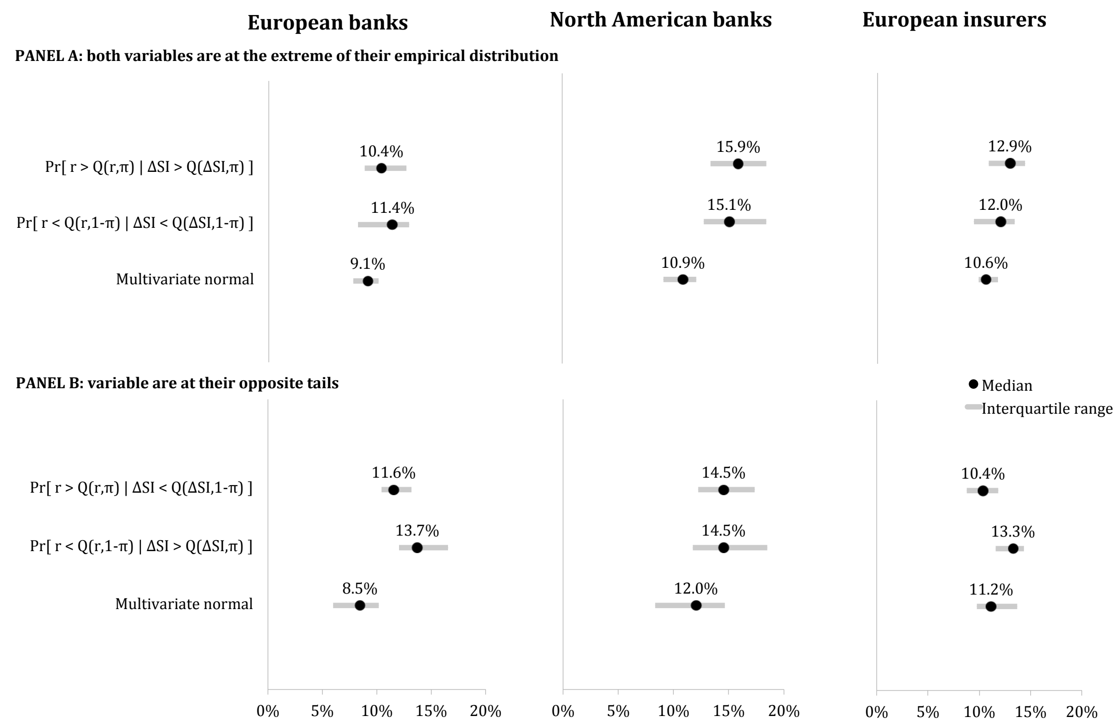

Fig. 3. Conditional tail probabilities of short interest and stock returns. The figure shows the median and interquartile range of the empirical conditional tail frequencies between returns and changes in short interest at the empirical quantile $\pi = 90\%$. The last row of each panel indicates the corresponding probabilities for a multivariate normal with variance-covariance matrix equal to the sample variance-covariance matrix of the firms in the given group. Results for different levels of π are available on request.

activity occurring during these $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q_{\Delta SI}^{\pi}]$ episodes was non-informative.

Although conditional tail frequencies do not allow us to make statements about the direction of causality, high levels of $P[r_t < Q_r^{1-\pi} \mid \Delta SI_t > Q_{\Delta SI}^{\pi}]$ are feared by policy makers. In an attempt to explore the potential causal relationship in more depth, we studied the conditional tail frequencies for different lags (in days) of ΔSI and r. Results fully reported in the supplementary online material show that $P[r_t < Q_r^{1-\pi} \mid \Delta SI_{t+h} > Q_{\Delta SI}^{\pi}]$ is highest when $h = [-1, -4]$, which suggests that short sellers anticipate price downfalls one to four days before they occur.

Lastly, Panel A of Figure 3 shows that, for North American banks, the probability of large positive returns conditional on large positive movements in short interest, $P[r_t > Q_r^{1-\pi} \mid \Delta SI_t > Q^{\pi}_{\Delta SI}]$, is high (15.9%), evidencing the occurence of contrarian short selling. These results are also consistent with the study of Boehmer et al. (2013) and Diether et al. (2009b), who show that short sellers in the US equity markets act as contrarian traders, providing liquidity when it is needed.

We do not observe similar evidence of contrarian short selling for European bank stocks and this might be because short selling is more constrained in European markets. With the exception of the UK, which has lending supply and borrowing fees similar to those of Canadian and US stocks, Saffi & Sigurdsson (2011) show that short sellers are less constrained in North American equity markets than in European equity markets.

Overall, the data show a lack of linear correlation between changes in short interest and stock prices, but provides strong evidence of tail relationships.

4. Methodology

To quantify the dependence between tail changes in short selling and stock prices, we rely on TailCoR, a measure that takes into account both linear and tail relationships.

4.1. TailCoR

We give an intuitive derivation of the measure in Figure 4 and we refer an interested reader to Ricci & Veredas (2013) for an in-depth discussion. Figure 4 shows the scatter plot of changes in short interest (horizontal axis) and stock prices (vertical axis) for an unnamed bank. Both variables are standardised (i.e. centred at their medians and scaled by their interquartile ranges) so to mitigate dependencies between short interest changes and returns that are due to their respective marginal distributions.[13] For notational convenience, we drop the firm subscript, i, and denote the standardised variables $\Delta\widetilde{SI}_t$ and $\tilde{r}_t$.

All pairs of observations are projected on the 135-degree line, thereby producing a new random variable:

$$Z_t = \frac{1}{\sqrt{2}}\big(\tilde{r}_t - \Delta\widetilde{SI}_t\big). \tag{4}$$

[13] An alternative step, proposed by Ricci & Veredas (2013), would be to standardise the variables by their cumulative marginal distributions, so to eliminate marginal dependencies that go beyond the location and scale. However, under the assumption of ellipticity, standardising using the median and interquartile range is sufficient.

As illustrated in Figure 4, the projected observations Z_t sit on the 135-degree line.[14]

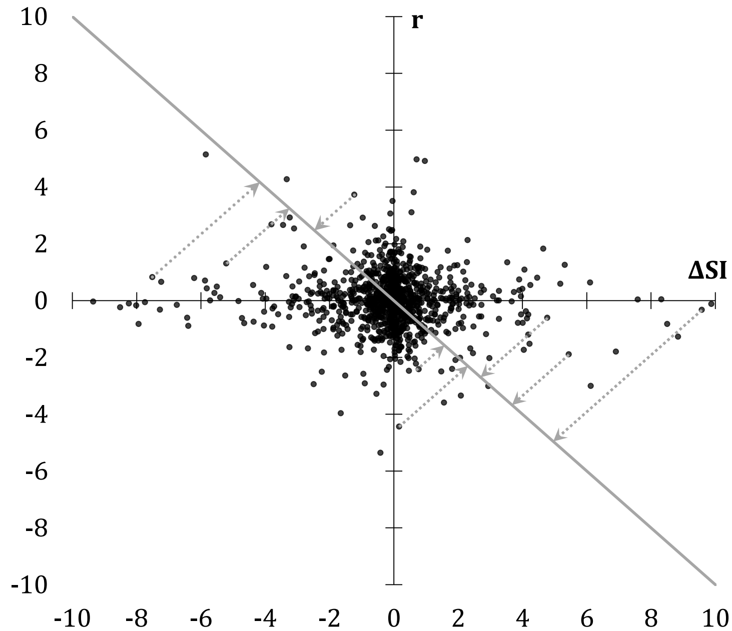

Fig. 4. Scatter plot of $\Delta\widetilde{SI}_t$ and $\tilde{r}_t$ for an unnamed bank. The figure illustrates changes in short interest and stock prices centred at their medians and scaled by their interquartile ranges to render them comparable. To calculate TailCoR, all points are then projected on the 135-degree line.

The degree of dispersion of Z_t depends on the strength of the relationship between changes in short interest and stock prices. With extreme events, the cloud of observations spreads along the 135-degree line more widely, either in the northwest or the southeast quadrants, or both.

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

$$\text{TailCoR}^{\xi} = s_g(\xi) IQR_Z^{\xi}, \tag{5}$$

where $IQR_Z^{\xi} = Q_Z^{\xi} - Q_Z^{1-\xi}$ 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 function of a normal distribution). The aim of the normalisation is to have a reference number: under

[14]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_t is the first principal component.

Gaussianity and no correlation (and hence independence), TailCoR$^\xi$ equals 1.

If r_t and ΔSI_t were positively related, then projecting on the 45-degree line would yield a higher TailCoR. In that case, $Z_t = (1/\sqrt{2})\big(\tilde{r}_t + \Delta\widetilde{SI}_t\big)$ and IQR_Z^ξ can be interpreted as a measure of contrarian short selling.[15] However, since we are primarily interested in the negative association between changes in short interest and stock prices, we will primarily analyse TailCoR obtained by projecting along the 135-degree line. If the true relationship is positive, then projecting on the 135-degree line will yield a more conservative value of TailCoR.

Under the assumption of ellipticity (i.e. that the probability contours of the bivariate distribution of changes in short interest and stock prices are ellipsoids), all dependence is due to the scatter matrix (a multiple of the covariance matrix) and a common shape parameter, α, which generates the tail thickness. This assumption allows to decompose TailCoR$^\xi$ into

$$\text{TailCoR}^\xi = s_g(\xi)s(\xi,\alpha)\sqrt{1-\rho}. \tag{6}$$

where $s(\xi,\alpha)$ is a monotonically decreasing function of the shape parameter, α. In other words, the larger α, the thinner the tails, the smaller $s(\xi,\alpha)$.

For every firm, we tested for bivariate elliptical symmetry of $\{\Delta SI_t, r_t\}_{t=1}^T$ using an extension of the multivariate runs test developed by Marden (1999).[16] Controlling for multiple testing using the Šidák (1967) correction, the null hypothesis of bivariate elliptical symmetry about the origin is rejected for, respectively, 8.7% and 13.6% of European and North American bank stocks. The rejection rate for European insurer was of 11.4%. Overall, the null hypothesis of bivariate elliptical symmetry of $\{\Delta SI_t, r_t\}_{t=1}^T$ was rejected for just 6.7% of the firms in our sample. Therefore, we conclude that there is support for elliptical symmetry in our data.

TailCoR can be estimated from the interquantile range of Z at probability level ξ, whereas the tail component, $s(\xi,\alpha)$ can be estimated as the ratio of $\widehat{IQR}_Z^\xi$ and $\sqrt{1-\widehat{\rho}}$. The choice of ξ is contextual and is typically above 0.90. In some sense, ξ is the "depth" at which we explore the tails.

Ricci & Veredas (2013) show that, under ellipticity, the estimate of TailCoR is consistent and asymptotically unbiased. Although Ricci & Veredas (2013) derived analytical expressions for the

[15] The vector $\big(1/\sqrt{2}, 1/\sqrt{2}\big)$ is the eigenvector associated with the largest eigenvalue of a standardised elliptical random vector with positive relation.

[16] An interested reader may refer to Dyckerhoff et al. (2014) for additional details on this test.

standard errors for TailCoR, based on the variance of quantile estimators, the sample estimates of these expressions are far from straightforward to estimate. Hence, we restrict our analysis to the dispersion of TailCoR estimates among the groups of firms analysed, measured by the interquartile group range of TailCoR estimates.

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 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. 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.

To assess this relationship, we make use of Southeast TailCoR, which focuses on observations in the southeast quadrant of Figure 4, as more clearly shown in Figure 5.

Southeast TailCoR (SE-TailCoR) is defined as

$$\text{SE-TailCoR}^{\xi} = 2 s_g(\xi) IQR_Z^{\xi +}, \tag{7}$$

where $IQR_Z^{\xi +} = \left(Q_Z^{\xi} - Q_Z^{0.5}\right)$ is the interquantile range between the ξ^{th} quantile and the median of the projection Z.

Under the assumption that returns and short interest changes follow a normal mean-variance mixture with uniform asymmetry, Southeast TailCoR can also be decomposed as:

$$\text{SE-TailCoR}^{\xi} = 2\, s_g(\xi)\, s_{SE}(\xi, \alpha) \sqrt{1 - \rho^{(+\,-)}}, \tag{8}$$

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

$$\rho^{(+\,-)} = \frac{\sigma^{(+\,-)}}{\sigma^{+}_{\Delta SI} \sigma^{-}_{r}}, \tag{9}$$

and where $\sigma^{+}_{\Delta SI}$ is the positive semi-variance of ΔSI_t, and σ^{-}_{r} is the negative semi-variance of r_t.

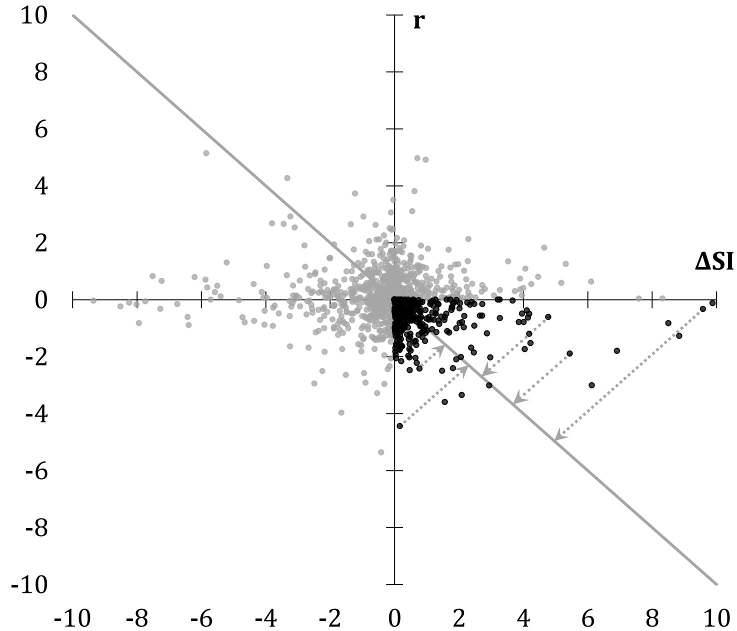

Fig. 5. Scatter plot of $\Delta\widetilde{SI}_{i\,t}$ and $\tilde{r}_{i\,t}$ for an unnamed bank focusing on the southeast quadrant. The figure illustrates positive changes in short interest and negative changes in stock prices. As in the case of TailCoR, all points are projected on the 135-degree line, but only the southeast part of the interquantile range is used to compute the Southeast TailCoR.

We call $\sigma^{(+-)}$ the positive-negative semi-covariance.[17]

The normal mean-variance mixture is considered a flexible family of multivariate asymmetric distributions that nests several elliptically symmetric and asymmetric distributions (Mencía & Sentana, 2009). It allows the dependence between ΔSI and r to become stronger at some extremes of the joint distribution of the variables. Uniform asymmetry means that short interest changes and returns are assumed asymmetric by the same extent.

The asymptotic distribution of Southeast TailCoR (SE-TailCoR) is not given by Ricci & Veredas

[17]We define the positive-negative semi-covariance between the changes in short interest and stock price returns as

$$\sigma^{+\,-} = \mathbb{E}\Big[\Big((\Delta SI_t - \overline{\Delta SI}) \cdot \mathbb{I}(\Delta SI_t > \overline{\Delta SI})\Big)\Big((r_t - \bar{r}) \cdot \mathbb{I}(r_t < \bar{r})\Big)\Big] \tag{10}$$

where $\overline{\Delta SI}$ is the mean of ΔSI and $\bar{r}$ is the mean of r. The indicator function $\mathbb{I}(\Delta SI_t > \overline{\Delta SI})$ is equal to one when $\Delta SI_t > \overline{\Delta SI}$ and zero otherwise. Similarly, $\mathbb{I}(r_t < \bar{r})$ is equal to one when $r_t < \bar{r}$ and zero otherwise.

(2013) but it can easily be derived as,

$$\sqrt{T}(\widehat{\text{SE-TailCoR}^{\xi}} - \text{SE-TailCoR}^{\xi}) \xrightarrow{\mathcal{D}} \mathcal{N}(0, 4s_g(\xi)^2\Sigma) \tag{11}$$

where,

$$\Sigma = \frac{\Gamma(Q_Z^{\xi})}{f^2(F^{-1}(\xi))} + \frac{\Gamma(Q_Z^{0.5}}{f^2(F^{-1}(0.5))} - 2\frac{\Gamma(Q_Z^{\xi}, Q_Z^{0.5})}{f(F^{-1}(\xi))f(F^{-1}(0.5))} \tag{12}$$

The proof follows that of Corollary 1 in Ricci & Veredas (2013).

5. Results

We calculate TailCoR between changes in short interest and stock price for every firm and we then analysed group medians. For the remainder of the paper, we display results for $\xi = 95\%$. Results for TailCoR computed using the full sample of observations and for different values of ξ are provided in the online supplementary material.

5.1. TailCoR between short interest and stock price changes

Table 2 shows that the level of TailCoR is high across all firms, reflecting strong tail dependence between changes in short interest and stock prices. The median values of TailCoR for the three groups of firms are around 2.08. 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.

For North American banks, the first and third quartiles (shown in parentheses) of TailCoR suggest that coefficients are tightly dispersed around their median values, whereas for European banks and insurers the coefficients are more widely dispersed. European insurance companies have the largest TailCoR, possibly because the market capitalisation of insurers is smaller than that of banks and thus the liquidity of the former stocks is likely to be lower.

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 72% of European banks, 36% North American banks, and 49% European insurers.[18] This result is in line with the tail conditional frequencies presented in Section 3.2, which showed that North American banks had

[18]Results for TailCoR computed using the 45-degree line projection is provided in the online supplementary material.

a high empirical frequency when both r and ΔSI are in their positive tails, further evidencing that contrarian short selling is taking place in North American markets.

	TailCoR	ρ	$\sqrt{1-\rho}$	$s(\xi,\alpha)$
European Banks	2.08	-0.03	1.01	5.08
	(1.88 ; 2.59)	(-0.08 ; 0.00)	(1.00 ; 1.04)	(4.53 ; 6.30)
North American Banks	1.95	0.03	0.99	4.87
	(1.81 ; 2.13)	(-0.03 ; 0.07)	(0.97 ; 1.01)	(4.56 ; 5.11)
European Insurers	2.33	0.02	0.99	5.69
	(1.93 ; 2.87)	(0.00 ; 0.05)	(0.97 ; 1.00)	(4.77 ; 7.05)

Table 2. TailCoR between changes in short interest and stock prices. The table shows TailCoR and linear correlation between changes in short interest and stock prices for 46 European banks, 35 European insurers and 22 North American banks. The table also shows the components of TailCoR that depend on the linear correlation (ρ) and on the tail index (α). The table reports median group values as well as the first and third quartiles (in parentheses). Here, $\xi = 95\%$. Additional results for different values of ξ are provided in the supplementary online material.

Table 2 also shows the decomposition of the computed TailCoR coefficients into the component that depends on the linear correlation between short selling and returns, $\sqrt{1-\rho}$, and the component that depends on the tail association, $s(\xi,\alpha)$. The values indicate that TailCoR is primarily driven by the association between extreme changes in short interest and extreme changes in stock prices. For all three groups of firms, $\sqrt{1-\rho}$ is close to 1, indicating weak linear association. The tail components, however, are high, indicating that large positive (negative) changes in short interest are associated with large negative (positive) changes in stock prices.

5.2. Southeast TailCoR between short interest and stock price changes

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 3 and can be interpreted as follows: for 70% of the European banks in our sample, for example, Southeast TailCoR was found to be greater than Northeast TailCoR.

As was highlighted in Section 3 with the conditional tail frequencies, Table 3 shows evidence of a tail relationship when short selling is positive and returns are negative. For North American

	Northeast-TailCoR	Northwest-TailCoR	Southwest-TailCoR
European banks	70%	70%	76%
North American banks	36%	59%	45%
European insurers	60%	74%	57%

Table 3. Percentage of firms for which Southeast TailCoR was greater than TailCoR computed using other quadrants. The table shows the percentage of firms for which Southeast TailCoR was greater than TailCoR computed using other quadrants of the scatter plot of standardized points.

banks, Table 3 also shows evidence of a strong relationship in the northeast quadrant, which can be associated with contrarian short selling. We do not find the same level of Northeast TailCoR for European stocks.

To quantify the relationship in the southeast quadrant, we calculated Southeast TailCoR for all firms and present results in Table 4 (which reads similarly to Table 2).

	SE-TailCoR	$\rho^{(+\,-)}$	$\sqrt{1-\rho^{(+\,-)}}$	$s^{SE}(\xi,\alpha)$
European Banks	2.16	-0.20	1.10	2.41
	(1.9 ; 2.73)	(-0.24 ; -0.14)	(1.07 ; 1.11)	(2.10 ; 3.10)
North American Banks	1.93	-0.19	1.09	2.16
	(1.83 ; 2.16)	(-0.20 ; -0.17)	(1.08 ; 1.10)	(2.04 ; 2.40)
European Insurers	2.42	-0.14	1.07	2.81
	(1.96 ; 2.85)	(-0.21 ; -0.12)	(1.06 ; 1.10)	(2.19 ; 3.24)

Table 4. Southeast TailCoR and its components. The table shows Southeast TailCoR (SE-TailCoR) and the positive-negative semi-correlation correlation, as defined in Eq. 9, between changes in short interest and stock prices for 46 European banks, 35 European insurers and 22 North American banks. The table also shows the components of Southeast TailCoR that depend on the positive-negative semi-correlation ($\rho^{(+\,-)}$) and on the tail index (α). The table reports median group values as well as the first and third quartiles (in parentheses). Here, $\xi = 95\%$. Additional results for varying levels of ξ are available on request.

The median value of Southeast TailCoR is around 2.14 for all firms. Table 4 also displays, across the three group of firms in our sample, the median values of the components of Southeast TailCoR: $\sqrt{1-\rho^{+-}}$ and $s^{SE}(\xi, \alpha)$.

The positive-negative linear correlation is larger in absolute terms than the full-fledged linear correlation that we had presented previously in Table 2. 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 tail component, which indicates that extreme positive short interest changes are associated with extreme negative returns.

Similarly to Table 2, Table 4 shows that European insurance companies have the highest Southeast TailCoR while European and North American Banks show lower levels of tail association.

To retrieve a market measure of Southeast TailCoR, we repeated this analysis using portfolios of stocks of European banks and insurance companies, and North American banks. Results, given in the online supplementary material, showed that the market Southeast TailCoR of North American banks was higher than the Southeast TailCoR for the median North American bank. Moreover, across the three groups of firms, market Southeast TailCoR of North American banks was higher than the market Southeast TailCoR of European banks and insurance companies. This suggests that there are extreme cases in the group of firms analysed that increase the overall tail correlation between the market return and short selling occurring on the market. These extreme cases appear more important for North American banks.

High Southeast TailCoR values do not allow us 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 directional short selling activity. To shed more light on causality, we studied Southeast TailCoR at different leads and lags (in days) of $(\Delta SI, r)$. Results are reported in the supplementary online material and show that Southeast TailCoR tends to be highest for lags of ΔSI between 1 and 4 days. For North American banks, for example, Southeast TailCoR peaks at lag 2 (days) of ΔSI, suggesting that short sellers can predict extreme negative price movements of North American bank stocks with two days anticipation.

Our results presented above are in line with the findings of Shkilko et al. (2012), who found 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.

The contrasting results of Boehmer & Wu (2013) may be attributable to different standardisation of the short selling indicator. Similarly to Shkilko et al. (2012), we standardised our indicator of shares short sold (shares on loans) by the number of shares outstanding. Boehmer & Wu (2013), on the other hand, standardised the number of shares short sold by total volume of trades.

In the online supplementary material, we re-calculated results standardising SLQ by volume of trades.[19] We found a weaker tail relationship than that found using the standardisation by shares outstanding. Nonetheless, the relationship uncovered is still much higher than that between independent random variables, and we conclude that the standardisation does not alter our main findings.

5.3. Southeast-TailCoR and firm size

We ranked firms according to market capitalization and analysed Southeast TailCoR for groups of firms of different size. Figure 6 depicts the median and interquartile 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 and second quartile in terms of firm size) have the highest Southeast TailCoR. Such results are not observed for North American banks, for which the largest banks appear to have the highest Southeast TailCoR.

Across all firms, Southeast TailCoR is highest for the companies with the lowest market capital. All firms in the smallest size quartile have a market capital of between \$1.6 billion and \$7.2 billion and are predominantly insurance companies (out of 26 firms composing the smallest size quartile across all firms, 15 are insurance companies and 11 are European banks). Thus, European insurance firms in our sample are generally smaller than the European banks in our sample and this might explain the high Southeast TailCoR result for European insurers found in Table 4 of Section 5.2.

There are two possible channels through which firm size can affect the relationship between short interest changes and returns.

First, small firms are affected by the liquidity channel. Boehmer et al. (2013) found that liquidity can have important implications for the impact of short selling on prices and a smaller firm is likely

[19] We thank an anonymous referee for suggesting this exercise.

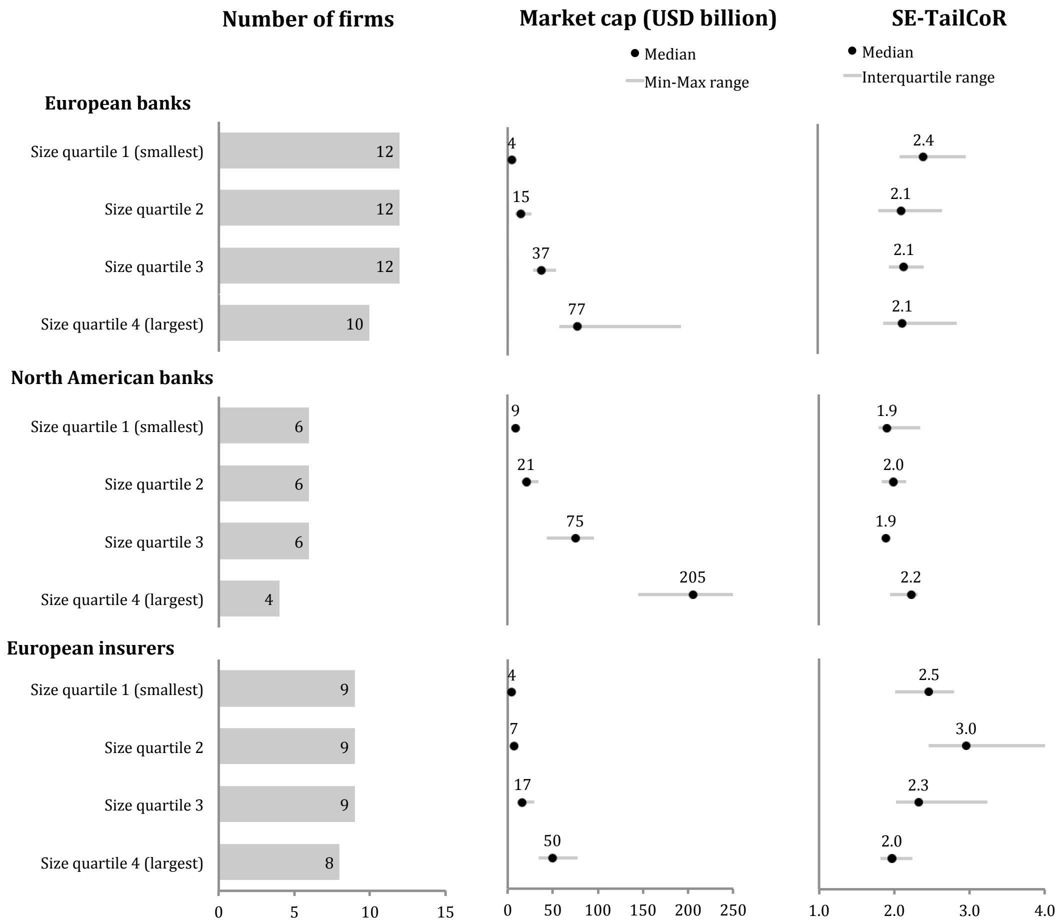

Fig. 6. Southeast TailCoR for firms of different size. Our sample firms are generally mid to large-cap as we used membership of the Stoxx600 indices to construct our database.

to have less free float capital available to borrow and sell short (Beber & Pagano, 2013).

Second, small firms are susceptible to the asymmetric information channel. As pointed out by Diether et al. (2009b), short sellers may act as opportunistic risk bearers when there is high uncertainty due to asymmetric information. In the model of Glosten & Harris (1988), a market specialist engaging in a trade faces an adverse selection problem because the customer on the other side of the trade may have some insider information that the specialist does not have. Especially in the case of small companies, which have low trading volume and liquidity, specialists may have to short in order to meet the trade with the informed trader. In return for holding the risk, the short sellers would require compensation in the form of negative returns (a high ask price).

Results for North American banks in Figure 6 concur with the liquidity channel and information asymmetry channel explanations. North American banks are larger across all size quartiles than European banks and, apart from the largest size quartile, North American banks also have a lower Southeast TailCoR than their European counterparts. This could be because North American bank stocks are more liquid and have less information asymmetry than European bank stocks. However, the fourth size quartile of North American banks is associated with a higher Southeast TailCoR than the fourth size quartile of European banks. One explanation could be that these extremely large North American banks are global and highly complex, and thus could be treated as a different case.

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 & Pagano, 2013; Bernal et al., 2014). In a regime of low liquidity, 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 trades and the negative impact of short selling on returns.

The above-mentioned studies concentrate primarily on the bans adopted by the SEC. However, it is particularly difficult to identify the effects of bans in the US because these were implemented for a short period of time (14 trading days) and were concomitant with the Troubled Asset Relief Program (TARP). 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 contrast, Boehmer et al. (2013) and Kolasinski et al. (2013) find that the magnitude (but not in frequency) of negative extreme returns increase when short selling is allowed.[20] Our data, which span several

[20] This result is consistent with the notion that short selling does not affect the frequency of crashes but affects their depth. Saffi & Sigurdsson (2011) however ascribe this result to less over pricing when short selling is allowed.

countries and policy regimes, can help shed light on these results.

The sample of bans includes the short selling prohibitions enacted during the 2008 crisis by the financial market authorities of Canada, Italy, the UK, and the US. Additionally, we also examine the ban imposed by the financial market authorities of France and Spain between August 2011 and February 2012, which was not analysed in prior studies.

For stocks involved in these bans, we compared the level of Southeast TailCoR obtained with ban observations to the level of Southeast TailCoR obtained using pre-ban and post-ban observations.[21]

Figure 7 shows median Southeast TailCoR for the stocks examined, grouped by country of listing and sector. The vertical axis displays the level of Southeast TailCoR, whereas the horizontal axis shows the pre-ban, ban, and post-ban periods. Southeast TailCoR was computed using the relevant standardisation for each period (see Section 4).

Figure 7 shows that, regarding bans, the effects on the relationship between short interest and returns were not uniform across sectors or short selling regime. For example, for Italian and UK bank stocks that were banned during the 2008 financial crisis, Southeast TailCoR increased during the ban and returned to pre-ban levels after the ban. For French and Spanish bank stocks, which were banned during the European debt crisis in August 2011, Southeast TailCoR did not change substantially between pre-ban, ban, and post-ban periods.

Canadian bank stocks, which were banned for 14 days during September 2008, also displayed a similar pattern to Italian and UK bank stocks, whereas US bank stocks, which were banned for the same period, showed a decline in Southeast TailCoR during and after the ban. Thus, for Canadian, Italian, and UK banks, results seem to confirm the findings of Boehmer et al. (2013) and Kolasinski et al. (2013), who showed that the price reaction to short selling activity increased during ban periods. According to their studies, this is due to the increased informativeness of those short sellers who continued their activity after the ban.

We found more consistent results across European insurers. For all European insurers studied, Figure 7 shows a decrease in Southeast TailCoR during the ban compared to the pre-ban period. Once the ban expired, Southeast TailCoR rose again to pre-ban levels or higher. The only exception was for Spanish insurers, for whom Southeast TailCoR declined during the ban and then remained roughly stable thereafter.

[21] We thank an anonymous referee for this suggestion.

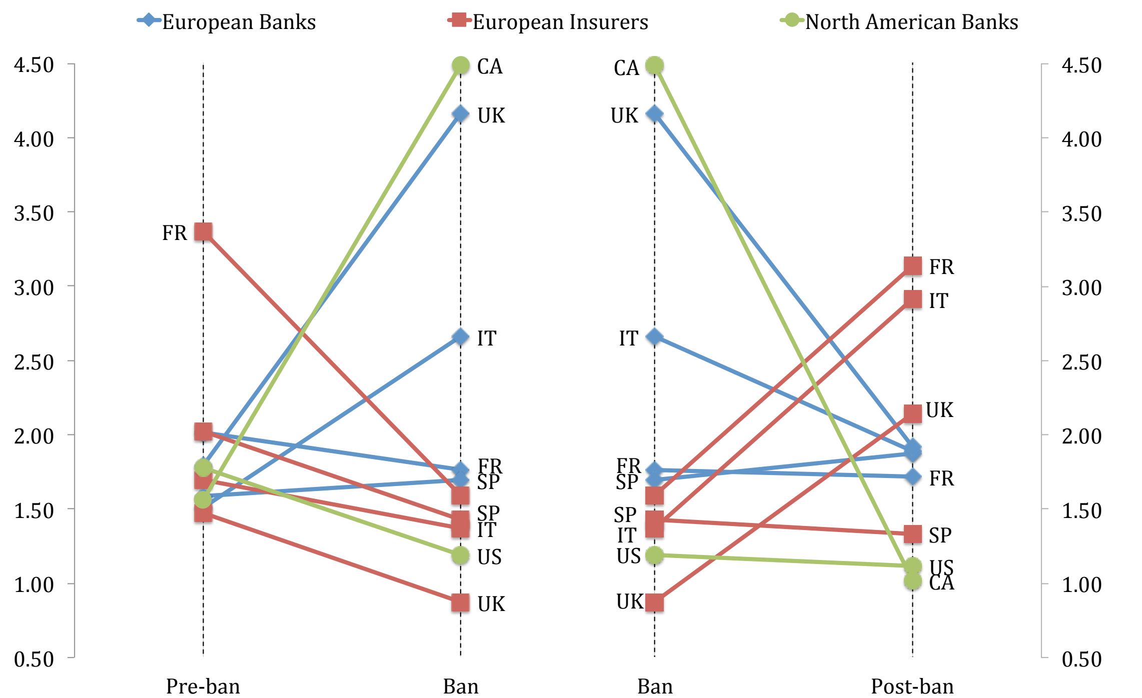

Fig. 7. Median Southeast TailCoR according to country-listing and financial sector for pre-, ban, and post-ban periods. The figure shows the median Southeast TailCoR for the groups of firms in our study computed using observations from three subsamples of observations relating to different covered short selling regulatory periods, which we name pre-ban, ban, and post-ban periods. We constructed the subsamples as follows. For a given stock, with d ban observations, we considered the last d observations prior to ban implementation for the pre-ban sample. Similarly, we considered the first d observations after the end of the ban for the post-ban sample. For those stocks that were banned several times during the sample period (e.g., Italian or Spanish bank stocks), we only considered the first ban period for the construction of the pre- and post-ban subsamples.

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 daily estimates of Southeast TailCoR over rolling windows of a year. We grouped the dynamic Southeast TailCoR results of European and North American banks according to stock country listings. Figure 8 depicts the medians and interquartile ranges of Southeast TailCoR for banks listed in the six countries studied. The shaded areas in Figure 8 depict periods of short selling bans affecting banks in those countries.

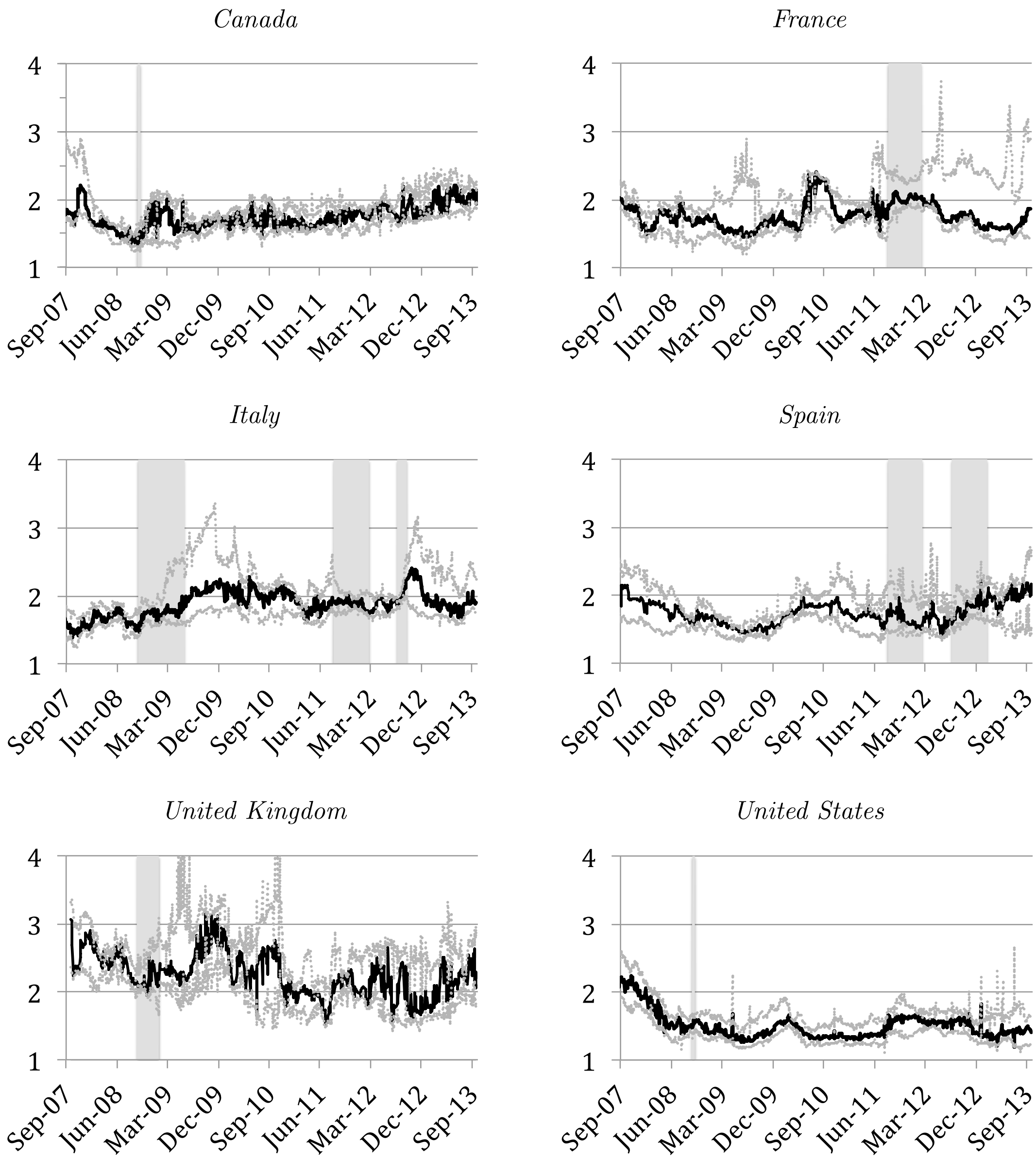

Fig. 8. Southeast TailCoR by country of listing. The figure depicts the group medians (bold solid) of Southeast TailCoR for firms according to country of listing and their interquartile range (light dashed). Southeast TailCoR was computed using rolling windows of 252 trading days, sliding the window by one trading day for each estimation. Periods during which national bans on covered short selling were introduced are indicated with shaded hatched areas.

For Canadian banks, Figure 8 shows that the ban is associated with an increase in Southeast TailCoR, consistent with results shown in Figure 7. Canada implemented an emergency short selling ban following the US SEC on 18 September 2008 on certain Canadian financial stocks. The rise in Southeast TailCoR continues during 2009, then decreases towards the end of the year. Overall, Southeast TailCoR for Canadian banks is tightly dispersed around the median value, which displays a steadily increasing positive trend. After 2012, the value of Southeast TailCoR is above 2, which indicates a strong relationship between extreme price downfalls and extreme increases in short interest.

For French, Italian, Spanish, and UK banks we notice an increase in Southeast TailCoR beginning in early 2010, concomitant with the deteriorating European Sovereign debt crisis. In April 2010 Greece requested a \$ 53-billion bailout and a few days later Standard & Poor's downgraded its sovereign bonds to BB+. Figure 8 suggests a strong relationship between extreme short selling and returns during the European Sovereign debt crisis for French banks. French banks owned a non-residual part of Greek debt and this might explain the large peak in Southeast TailCoR displayed for France around September 2010.

A closer look at the ban period for French banks shows that the upper quartile of Southeast TailCoR decreased steadily during the ban only to increase once the ban was lifted. The French ban of August 2011 was part of a joint action on short selling taken by the financial market authorities of Belgium, France, Greece, Italy, and Spain. A similar Southeast TailCoR reaction to the August 2011 ban is displayed for Italian and Spanish banks.

Italy implemented three bans during the sample period. First, on 22 September 2008, following the US SEC, the Italian market authority (Consob) implemented a covered short selling ban on financial stocks, successively extended to all stocks, listed on the Italian regulated market. After several extensions, the ban was to last until July 2008. Second, as part of the joint action with other European regulators, Consob banned covered short selling in August 2011 until February 2012. Third, in July 2012, Consob banned covered short selling on a list of banking and insurance stocks. This third ban lasted until September of the same year.

During the joint European ban of August 2011, Southeast TailCoR of Italian banks decreased, whereas during the first and the third Italian ban periods (September 2008 to February 2012 and July 2012 to September 2012, respectively), Southeast TailCoR increased. For the bans implemented in Spain, this is also the case. The August 2011 joint European ban is associated with a decrease in Southeast TailCoR for Spanish banks, whereas the subsequent Spanish ban of July 2012 is associated with an increase in Southeast TailCoR. Hence, there is some difference between the joint European ban and other ban periods, perhaps indicating different levels of ban stringency.

The UK presents the highest and most volatile level of Southeast TailCoR. This indicates a stronger relationship between extreme short selling and returns for UK banks, when compared to banks in other countries. During the September 2008 crisis, the UK FCA and the US SEC implemented a short selling ban for financial stock. The US SEC ended the ban in October 2008, whereas the UK FCA extended the ban until January 2009. In both cases, Figure 8 shows a higher Southeast TailCoR during the ban period compared to the pre-ban period.

Overall, for European bank stocks, both Figures 7 and 8 show that the 2008 short selling bans were associated with a decrease in Southeast TailCoR. Furthermore, Figure 8 also illustrates different reactions of Southeast TailCoR to the joint European ban implemented in August 2011. These differences are supported by the results shown in Figure 7, which illustrates the effects of the joint European ban for France and Spain.

For North American bank stocks, results displayed in Figures 7 and 8 were slightly contrasting. Figure 7 shows a steep increase in Southeast TailCoR of Canadian banks during the ban period, which is confirmed by the results shown in Figure 6. On the other hand, for US banks, Figure 7 evidences a slight decrease in the Southeast TailCoR of US banks, whereas Figure 8 displays an increase.

Lastly, regarding the post-ban period, Figure 7 shows a decrease in Southeast TailCoR following the end of the ban period, suggesting that short selling was less informative after the ban was lifted, whereas Figure 8 shows Southeast TailCoR increasing after the ban. This difference could be due to the rolling window approach itself, which continues to account for ban-period observations even after the ban end.

6. Conclusion

We have studied the association between daily changes in short selling activity and financial stock prices when both variables are at the extremes of their joint distribution. To quantify tail dependence, we have used TailCoR, a measure of tail correlation. Our results have shown that the relation between short selling and price changes is stronger during exceptional (extreme) days than during normal (average) days.

Our results have demonstrated that the extremes of the joint distribution of short selling and price changes can conceal additional useful information. Future research could build on our analysis by adopting bivariate models of conditional quantiles. For example, a natural candidate could be the *CoVaR* model developed by Adrian & Brunnermeier (2016). Here, the value at risk (VaR) of returns could be expressed as a conditional function of the change in short interest. Another possibility is a state-dependent value at risk approach, such as the one adopted by Adams et al. (2014), that can model the differential impact of short selling on the VaR of returns, depending on the state of financial markets. Lastly, it may also be possible to model the quantiles of returns and short interest changes simultaneously using an approach that has been proposed by White et al. (2015).

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