Internet Appendix for Short selling in extreme events

NOT FOR PUBLICATION

Marco Valerio Geraci

Tomas Garbaravičius

David Veredas

Abstract

In this online appendix, we present supplementary material and additional results related to our paper.

A. Sample firms

European Banks	European Insurers	North American Banks
Bank of Ireland	Admiral Group plc	Bank of America Corp.
Bankia S.A.	Aegon N.V.	Bank of Montreal
Bankinter S.A.	Ageas S.A.	Bank of Nova Scotia
Banque Cantonale Vaudoise	Allianz SE	BB&T Corp.
Barclays plc	Amlin plc	Canadian Imperial Bank of Commerce
Banca Monte dei Paschi di Siena S.p.A.	Assicurazioni Generali S.p.A.	Citigroup, Inc.
Banca Popolare di Milano S.p.A.	Aviva plc	Comerica, Inc.
Banca Popolare di Sondrio S.C.p.A.	AXA S.A.	Fifth Third Bancorp
Banca Popolare dell'Emilia Romagna S.C.	Baloise Holding AG	Huntington Bancshares, Inc.
Banco Bilbao Vizcaya Argentaria S.A.	Catlin Group Ltd	JP Morgan Chase & Co
Banco Comercial Portugues, S.A.	CNP Assurances S.A.	Keycorp
Banco Espirito Santo, S.A.	Delta Lloyd N.V.	M&T Bank Corp.
Banco Popolare S.C.	Direct Line Insurance Group plc	National Bank of Canada
Banco Popular Espanol S.A.	Gjensidige Forsikring ASA	New York Community Bancorp, Inc.
Banco De Sabadell, S.A.	Hannover Rueck SE	People's United Financial Inc.
Banco Santander S.A.	Helvetia Holding AG	PNC Financial Services Group Inc.
BNP Paribas S.A.	Ing Groep GDR	Regions Financial Corp.
Caixabank S.A.	Legal & General Group plc	Royal Bank of Canada
Commerzbank AG	Mapfre S.A.	Suntrust Banks Inc.
Crédit Agricole S.A.	Muenchener Rueckversicherungs Gesellschaft AG	Toronto-Dominion Bank
Credit Suisse Group AG	Old Mutual plc	U.S. Bancorp
Danske Bank A/S	Prudential plc	Wells Fargo & Co
Deutsche Bank AG	Resolution Ltd	
Julius Baer Gruppe AG	RSA Insurance Group plc	
Jyske Bank A/S	Sampo Oyj	
KBC Groupe S.A.	SCOR SE	
Lloyds Banking Group plc	St. James's Place plc	
Mediobanca Banca Di Credito Finanziario S.p.A.	Standard Life plc	
Natixis S.A.	Storebrand ASA	
Nordea Bank AB	Swiss Life Holding AG	
Pohjola Bank plc	Swiss Re AG	
Royal Bank of Scotland Group plc	Topdanmark A/S	
Skandinaviska Enskilda Banken AB	Tryg A/S	
Standard Chartered plc	Vienna Insurance Group AG	
Svenska Handelsbanken AB	Zurich Insurance Group AG	
Dnb ASA		
Erste Group Bank AG		
Société Générale		
HSBC Holdings plc		
Intesa Sanpaolo S.p.A.		
Swedbank AB		
Sydbank A/S		
Unione Di Banche Italiane S.C.p.A.		
UBS AG		
Unicredit S.p.A.		
Valiant Holding AG		

Table A1: List of financial institutions in the sample

B. Graphical Inspection of Data

Figure A1 shows the aggregate Short Loan Quantity as a ratio of total shares outstanding (bold solid, left axis) for Canadian, Italian, Spanish, and US banks in our sample. Figure A1 also shows the equally weighted stock prices (light dashed, right axis) relative to the first period of each chart and the ban periods affecting these stocks.

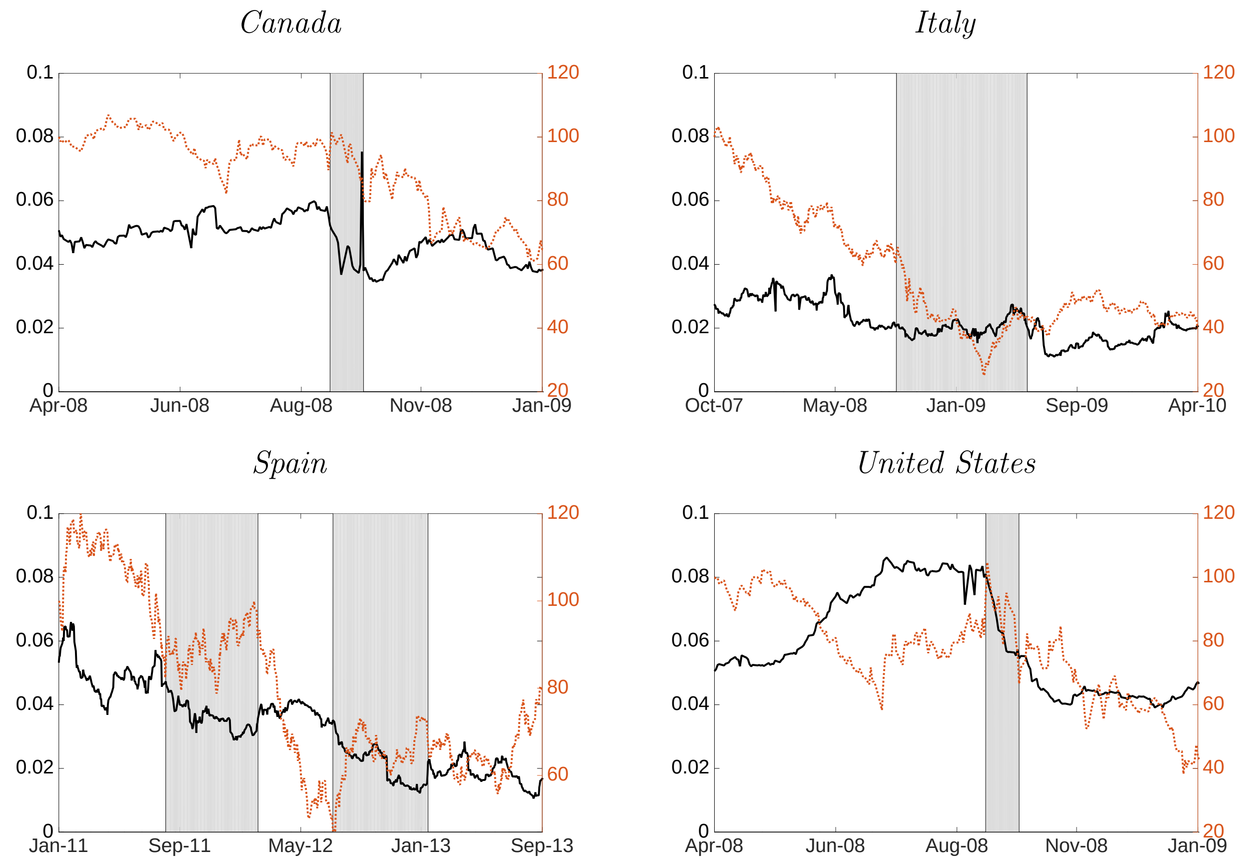

Figure A1: Short interest and ban periods

The figure depicts the aggregate Short Loan Quantity (bold solid, left axis) as a ratio of shares outstanding and the average price level (light dashed, right axis) for Canadian, Italian, Spanish, and US bank stocks. The average price level is computed as an equally weighted average of the stock prices relative to the stock price on the first period of the chart. For each country, the figure also depicts covered short selling ban periods (shaded regions) involving bank stocks. The horizontal axis is different for each chart.

For the four cases shown in Figure A1, short interest is high during the pre-ban period and falls during the ban period. It seems that the bans have lowered short selling activity, measured as short interest on these stocks. Moreover, the price level appears to be falling in the pre-ban period and, to some extent, recovering during the ban period.

Figure A1 also shows that short interest continues to decrease after the ban is lifted. This observation has led us to distinguish the pre-ban period from the post-ban period as different regimes. In the paper, we restrict our analysis to the first ban period for those countries that have implemented several bans throughout the sample period. This is because, in some particular cases, it is non-obvious how to distinguish the pre-ban period from the post-ban period after the first ban implementation (see e.g., the case of Spain in Figure A1).

C. Additional results

C.1. Price reversions during extreme events

We conducted an analysis of the tail episodes characterised by large changes in short selling and large price downfalls, $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q_{\Delta SI}^{\pi}]$.

In our sample, there were 15,388 events of this type. Among these, 7,136 such episodes involved European bank stocks, 4,964 involved European insurance company stocks, and 3,288 involved North American bank stocks.

We analysed the days successive to these events and checked for price reversions. Similarly to Shkilko et al. (2012), we identified price reversions as a recovery of at least 90% of the initial downfall. Results are given in Figure A2.

Figure A2 shows the percentage of reversions that occurred following the event. For example, Figure A2 shows that two days after the event $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q_{\Delta SI}^{\pi}]$, 50% of the North American stocks would recover the price downfall. After 5 days, this percentage goes up to 54%.

As price changes that reverse quickly involve no new information, the results in Figure A2 seem to suggest that about half of the joint extreme movements in prices and short selling activity cannot be associated to informative short selling. On the other hand, just less than 50% of these episodes involve price downfalls that continue to persist, which can be associated to short selling aiding price discovery.

As an additional analysis, we also looked at the level of abnormal short interest on the day associated with the event. Following Boehmer & Wu (2013), we defined abnormal short interest with respect to the previous 20-day median short interest. Results regarding abnormal short selling are shown in the hatched area of Figure A2.

The hatched area of Figure A2 shows the percentage of $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q_{\Delta SI}^{\pi}]$ episodes

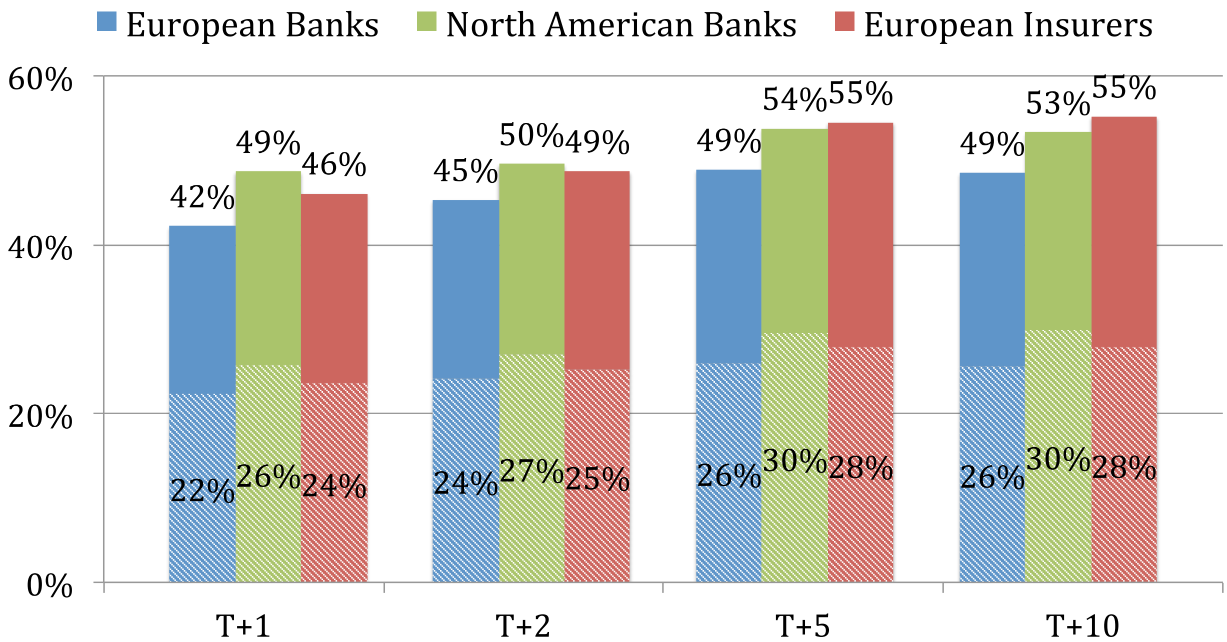

Figure A2: Price reversions

Figure A2 shows the percentage of reversions that occurred in the days following the event $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q_{\Delta SI}^{\pi}]$. A reversion is defined as a price recovery of at least 90% of the initial loss during the event. The hatched area of Figure A2 shows the percentage of $[r_t < Q_r^{1-\pi}, \Delta SI_t > Q_{\Delta SI}^{\pi}]$ episodes that reversed and were associated with positive abnormal short interest relative to the previous 20-day average.

that recovered and were associated with positive abnormal short interest. The results show that slightly more than half of the short-term recovery episodes were associated with positive abnormal short interest. On average, the abnormal increase in short interest is of 54% for European banks, 55% for North American banks, and 52% for European insurers. These results reinforce the idea that at least part of the joint extreme movements in prices and short selling activity can be associated to non-informative (potentially speculative) short selling.

C.2. Lagged conditional tail frequencies

Figure A3 shows the median conditional tail frequencies between returns and the change in short interest using different leads and lags of ΔSI. Points in the negative domain of the horizontal axis show the empirical frequency of a large negative movement of r that is *preceded* by a large positive movement in ΔSI i.e., $P[r_t < Q_r^{1-\pi} \mid \Delta SI_{t+h} > Q_{\Delta SI}^{\pi}]$ for $h = [-10, -1]$.

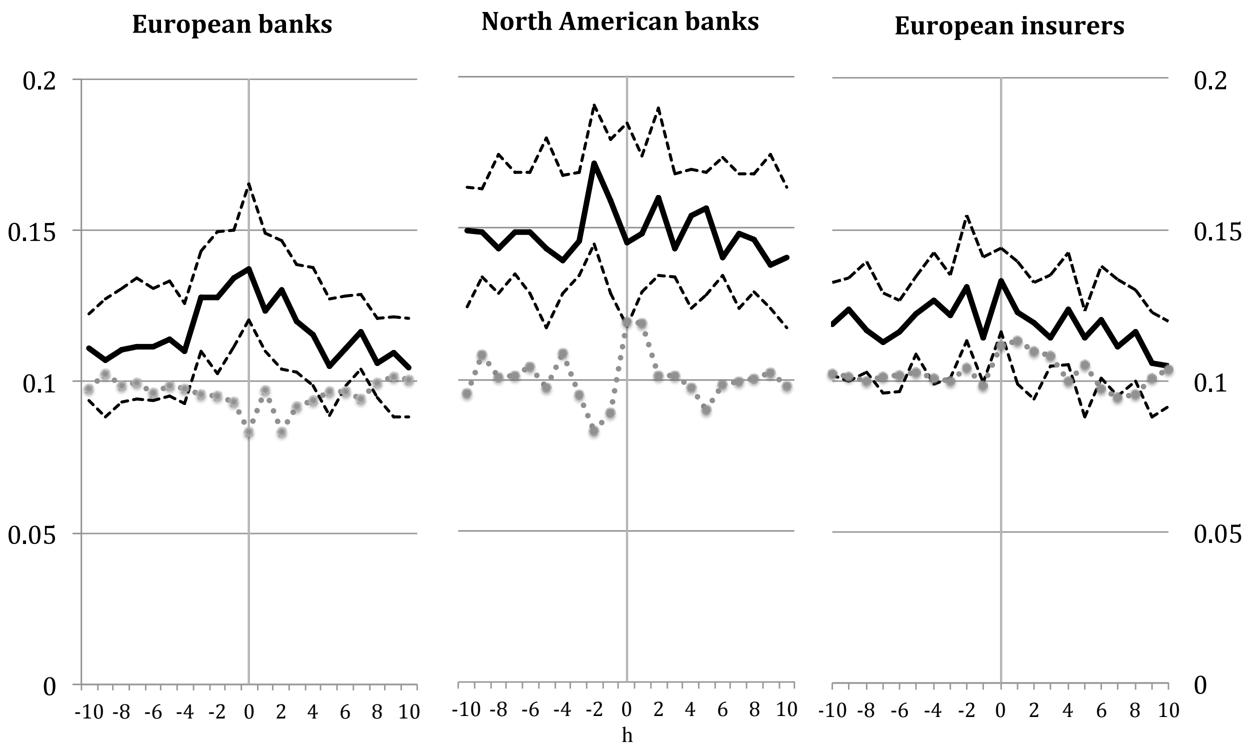

Figure A3: Conditional tail frequencies with different lead and lags of SI_t and r_t.

Figure A3 shows the median conditional tail frequencies (bold solid) between returns and the change in short interest using different leads and lags (days) of ΔSI. It also shows the lower and upper quartile (light dashed) across three groups of firms: European banks, European insurers, and North American banks. Points in the negative domain of the horizontal axis $h = [-10, -1]$ show the empirical frequency of a large negative movement of r that is *preceded* by a large positive movement in ΔSI i.e., $P[r_t < Q_r^{1-\pi} \mid \Delta SI_{t+h} > Q_{\Delta SI}^{\pi}]$. Points in the positive domain of the horizontal axis $h = [1, 10]$ of the charts in Figure A3 show the empirical frequency of a large negative movement of r that is *followed* by a large positive movement in ΔSI i.e., $P[\Delta SI_{t+h} > Q_{\Delta SI}^{\pi} \mid r_t < Q_r^{1-\pi}]$. The vertical line at $h = 0$ gives the contemporaneous tail frequency $P[r_t < Q_r^{1-\pi} \mid \Delta SI_t > Q_{\Delta SI}^{\pi}] = P[\Delta SI_t > Q_{\Delta SI}^{\pi} \mid r_t < Q_r^{1-\pi}]$. The figure also shows the median tail frequency for a multivariate normal (light dotted with circle markers) with the same correlation coefficient as the sample.

Points in the positive domain of the horizontal axis of the charts in Figure A3 show the empirical frequency of a large negative movement of r that is *followed* by a large positive movement in ΔSI i.e., $P[\Delta SI_{t+h} > Q_{\Delta SI}^{\pi} \mid r_t < Q_r^{1-\pi}]$ for $h = [1, 10]$.

For all three charts shown in Figure A3 we can notice that the empirical tail frequency is stronger for small lead/lags and diminishes as lead/lags increase. This is especially evident for European bank stocks. The empirical tail frequency is higher than the same tail frequency measured for a bivariate normal with the same linear correlation coefficient (shown in light dotted with circles).

For European and North American banks, Figure A3 shows that the tail frequency in the negative domain of the horizontal axis, $P[r_t < Q_r^{1-\pi} \mid \Delta SI_{t+h} > Q_{\Delta SI}^{\pi}]$ for $h = [-10, -1]$, is higher than the tail frequency in the positive domain of the horizontal axis, $P[\Delta SI_{t+h} > Q_{\Delta SI}^{\pi} \mid r_t < Q_r^{1-\pi}]$ for $h = [1, 10]$. This seems to suggest that large positive movements in short interest are often followed by large negative movements in prices. For 25% of our European bank sample, this occurs more than 15% of the time. For the North American bank stocks in our sample this effect is particularly strong when short interest movements precede stock price movements by two trading days, i.e., when $h = -2$.

Given the daily frequency of the data, this seems to suggest that short sellers are predicting stock price downfalls rather than causing stock price falls. This is also consistent with a large part of the previous literature that studies the predictive ability of short sellers (Dechow et al., 2001, Diether et al., 2009).

Points on the positive domain of the horizontal axis of the charts, which shows $P[\Delta SI_{t+h} > Q_{\Delta SI}^{\pi} \mid r_t < Q_r^{1-\pi}]$ for $h = [1, 10]$, are lower than points on the negative domain of the horizontal axis, which shows $P[r_t < Q_r^{1-\pi} \mid \Delta SI_{t+h} > Q_{\Delta SI}^{\pi}]$ for $h = [-10, -1]$. However, for North American banks, $P[\Delta SI_{t+h} > Q_{\Delta SI}^{\pi} \mid r_t < Q_r^{1-\pi}]$ for $h = [1, 10]$ is still quite high, with median values over 15%, which might suggest that some momentum short selling is still taking place, with short sellers increasing their short positions following large price downfalls.

C.3. Full sample TailCoR

Table A2 presents positive and negative TailCoR computed for the full sample of European banks, North American banks, and European insurers. The full sample TailCoR is computed by pooling observations of all firms for each of the three groups of firms in our sample.

	Panel A: Positive TailCoR			
	TailCoR	ρ	Linear component	Tail component
European banks	2.42	-0.03	0.98	2.46
North American banks	2.24	0.02	1.01	2.21
European insurers	2.61	0.02	1.01	2.58
	Panel B: Negative TailCoR			
	TailCoR	ρ	Linear component	Tail component
European banks	2.51	-0.03	1.02	2.47
North American banks	2.20	0.02	0.99	2.23
European insurers	2.59	0.02	0.99	2.61

Table A2: Full sample TailCoR

Table A2 shows TailCoR estimates computed using the full sample of observations, by pooling data points for every firm in each of the three groups of firms in our sample—European banks, North American banks, and European insurers—for tail level $\xi = 95\%$. Panel A shows positive TailCoR, which is computed by projecting standardised data points across the 45° line. Panel B shows negative TailCoR, which is computed by projecting standardised data points across the 135° line.

The full sample results given in Table A2 show that the level of TailCoR obtained projecting across the 45° line is very close to that obtained projecting across the 135° line. For the European bank sample, negative TailCoR is higher than positive TailCoR, confirming firm specific results. For North American banks the opposite is true. Across all three groups of firms the tail component of TailCoR is higher when computed using the negative projection.

C.4. Additional TailCoR results

Table A3 reports the median TailCoR measured using the 45° line (i.e., assuming a positive relationship between short selling and returns) across the three groups of firms in our sample. Median negative TailCoR is higher than the median positive TailCoR for European banks and insurers. However, for North American banks, median positive TailCoR is higher than the median negative TailCoR. This might indicate that contrarian short selling is more prevalent for the largest North American bank stocks than the largest European financial stocks. This is also consistent with the fact that North American markets are more efficient in terms of liquidity and price-discovery than European markets.

	Panel A: Positive TailCoR			
	$\xi = 99\%$	$\xi = 95\%$	$\xi = 90\%$	$\xi = 75\%$
European banks	3.69	2.05	1.65	1.26
	(2.66 ; 5.51)	(1.78 ; 2.61)	(1.52 ; 1.92)	(1.18 ; 1.33)
North American banks	3.00	1.96	1.60	1.21
	(2.82 ; 3.58)	(1.88 ; 2.12)	(1.55 ; 1.67)	(1.17 ; 1.24)
European insurers	4.48	2.26	1.77	1.28
	(3.42 ; 8.46)	(1.91 ; 3.04)	(1.60 ; 1.94)	(1.22 ; 1.35)
	Panel B: Negative TailCoR			
	$\xi = 99\%$	$\xi = 95\%$	$\xi = 90\%$	$\xi = 75\%$
European banks	3.71	2.08	1.66	1.29
	(2.81 ; 5.33)	(1.88 ; 2.59)	(1.59 ; 1.97)	(1.22 ; 1.32)
North American banks	3.06	1.95	1.55	1.13
	(2.83 ; 3.55)	(1.81 ; 2.13)	(1.48 ; 1.71)	(1.11 ; 1.23)
European insurers	4.49	2.33	1.79	1.23
	(3.27 ; 8.36)	(1.93 ; 2.87)	(1.56 ; 1.95)	(1.18 ; 1.29)

Table A3: Positive and Negative TailCoR

Table A3 shows median TailCoR across the three groups of firms in our sample, European banks, North American banks, and European insurers, for different tail levels, ξ.. Panel A shows results relating to positive TailCoR, computed by projecting standardised points of $(\Delta SI, r)$ across the 45° line. Panel B shows results relating to negative TailCoR, computed by projecting standardised points of $(\Delta SI, r)$ across the 135° line. Interquartile ranges are reported in parenthesis.

C.5. Scaling of short interest by volume of trades

As argued by Shkilko et al. (2012), scaling the number of shares sold short by the total number of shares outstanding captures deviations from the unconditional level of short selling. On the other hand, scaling the number of shares sold short by the total volume of trades relates changes in short selling to changes in long volume.

In their paper, Shkilko et al. (2012) use two measures of relative short selling. The first is based on a measure of short selling volume scaled by total shares outstanding. The second is a measure of short selling volume scaled by total volume of trades. The results of their analysis of price reversal episodes shows that short selling volume scaled by shares outstanding tends to increase during price declines, indicating that short sellers are consuming liquidity rather than providing it. On the other hand, short selling scaled by volume tends to decrease during price declines, indicating that long volume increases more than short volume during these episodes.

Similarly, Boehmer & Wu (2013) analyse short selling volume relative to total trade volume during price decline episodes and find that their measure decreases around these episodes. They interpret this result as evidence that short sellers are contrarian traders, decreasing their short selling when the price decline is temporary, thus aiding price-discovery.

We computed TailCoR and Southeast TailCoR using the alternative scaling method i.e., scaling Short Loan Quantity (SLQ) by total volume of trades. We obtained total volume of trades from Yahoo Finance.

Panel A of Table A4 shows negative TailCoR between returns and changes in SLQ scaled by volume of trades. When compared to results shown in Table 2 of the paper, Table A4 shows that TailCoR computed using SLQ scaled by volume of trades is lower than TailCoR computed using SLQ scaled by shares outstanding. Across all groups of firms, both the component based on linear correlation and the tail component are lower when scaling SLQ by current volume of trades. Moreover, European insurers now have the lowest value of TailCoR among the three groups of firms, whereas they had the highest value when TailCoR was computed using SLQ scaled by shares outstanding.

Panel B of Table A4 shows Southeast TailCoR between returns and changes in SLQ scaled by volume of trades. Compared with results shown in Table 4 of the paper, Table A4 shows that Southeast TailCoR computed using SLQ scaled by volume is lower than Southeast TailCoR computed using SLQ scaled by shares outstanding. Both the component based on positive-negative semi-correlation and the tail component are lower when scaling SLQ by current volume of trades across all groups of firms. Although the level of Southeast TailCoR is similar across the three groups, North American banks now have the highest

	Panel A: Negative TailCoR			
	TailCoR	ρ	Linear component	Tail component
European Banks	1.79 (1.58 ; 2.19)	0.01 (-0.01 ; 0.03)	1.00 (0.99 ; 1.00)	4.30 (3.90 ; 5.23)
North American Banks	1.79 (1.54 ; 2.33)	0.00 (-0.01 ; 0.02)	1.00 (0.99 ; 1.01)	4.36 (3.74 ; 5.65)
European Insurers	1.70 (1.51 ; 1.99)	0.01 (-0.02 ; 0.03)	1.00 (0.98 ; 1.01)	4.16 (3.66 ; 4.79)
	Panel B: Southeast TailCoR			
	Southeast TailCoR	ρ^{+-}	Linear component	Tail component
European Banks	1.62 (1.48 ; 2.07)	-0.20 (-0.25 ; -0.14)	1.10 (1.07 ; 1.12)	2.29 (2.04 ; 2.65)
North American Banks	1.67 (1.41 ; 2.21)	-0.20 (-0.24 ; -0.17)	1.09 (1.08 ; 1.11)	2.33 (1.95 ; 2.44)
European Insurers	1.64 (1.45 ; 1.94)	-0.17 (-0.21 ; -0.14)	1.08 (1.07 ; 1.10)	2.32 (2.03 ; 2.77)

Table A4: Results with shares on loan are scaled by total volume of trade.

Table A4 results relating to TailCoR and Southeast TailCoR when short interest is computed by scaling shares on loan (measured by Markit's Short Loan Quantity (SLQ)) by total volume traded. Panel A of Tabel A4 shows the median negative TailCoR for European banks, North American banks, and European insurers. Panel B shows the median Southeast TailCoR for the same three groups of firms. Interquartile ranges are shown in parentheses. All results are for tail level $\xi = 95\%$.

value of Southeast TailCoR, whereas they had the lowest value when Southeast TailCoR was computed using SLQ scaled by shares outstanding.

The values of TailCoR and Southeast TailCoR are lower when scaling SLQ by volume of trades than when scaling SLQ by shares outstanding. However, the new values of TailCoR and Southeast TailCoR still show that there is strong tail association in the data that is stronger than the linear association measured by correlation. To get a sense of magnitude, random simulations from a Student t-distribution with tail parameter $\alpha = 2.5$ (so heavy tailed) result in average TailCoR of 1.46. Hence, using volume of trades as the scaling factor rather than shares outstanding decreases the magnitude of our results but does not change the tone of our main conclusion. Short selling and stock returns remain strongly associated in the extremes of their joint distribution but only weakly associated on average, at the centre of their joint distribution.

C.6. Dividend cleaning

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.[1] This surge in demand affects lending rates and effectively makes it more difficult to borrow (Saffi & Sigurdsson, 2011).

The effect of dividend arbitrage trades is illustrated in Figure A4 for the stock of an unnamed bank. Figure A4 shows the number of 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). 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.

To control for these periodic movements of SLQ, we excluded observations before and after the dividend record date. This exclusion reduces number of eligible observations drastically by up to about one-fifth when 10 trading days are excluded around dividend record dates.

In Table A5 below, we show results of Southeast TailCoR (corresponding to Table 4 of the paper), when observations around dividend record dates are excluded.

Table A5 shows that, for European banks and insurers, when we do not exclude observations

[1]The 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.

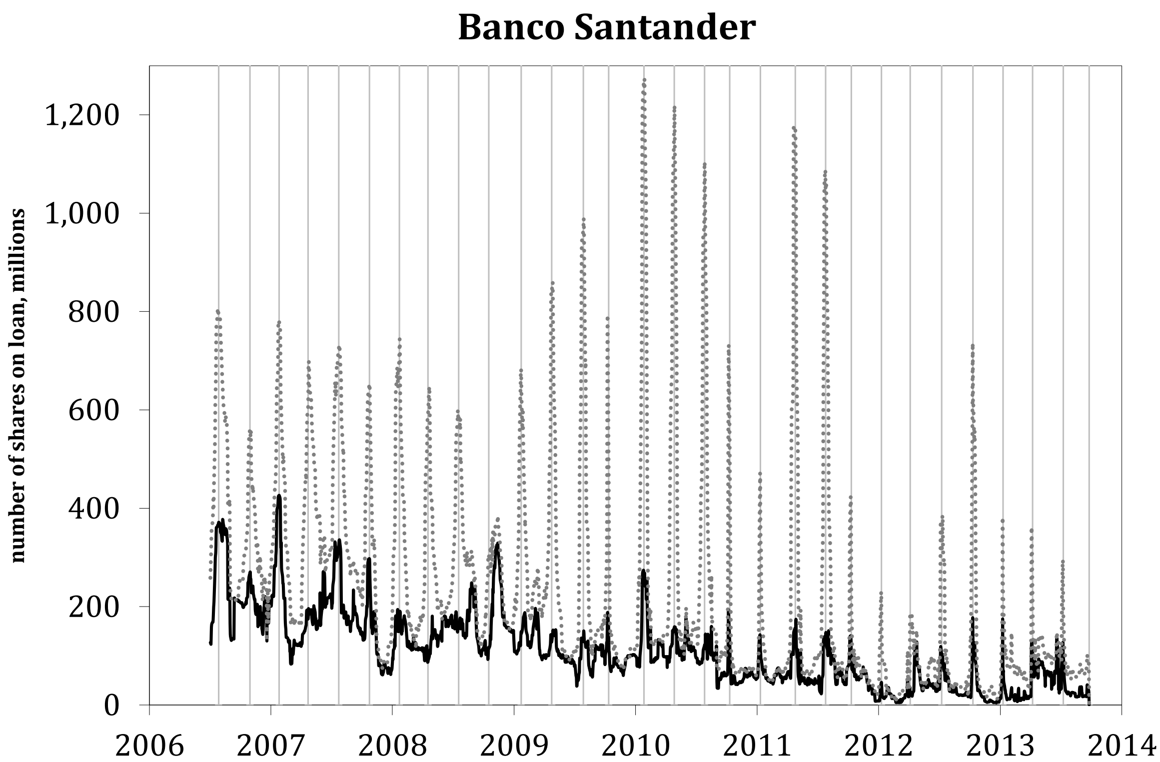

Figure A4: Shares on loan (lighter dashed line) and the Short Loan Quantity (SLQ, solid bold line) for an unnamed bank

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.

	Southeast TailCoR			
	Days (d) removed before/after dividend record date			
	$d = 0$	$d = 5$	$d = 10$	$d = 15$
European Banks	2.16 (1.90 ; 2.73)	2.09 (1.89 ; 2.47)	2.06 (1.86 ; 2.37)	2.10 (1.87 ; 2.37)
North American Banks	1.93 (1.83 ; 2.16)	1.94 (1.81 ; 2.22)	2.09 (1.80 ; 2.17)	2.05 (1.85 ; 2.27)
European Insurers	2.42 (1.96 ; 2.85)	2.17 (1.84 ; 2.45)	2.12 (1.83 ; 2.41)	2.14 (1.83 ; 2.38)

Table A5: Southeast TailCoR when observations around dividend record dates are excluded

The table shows median group values as well as the first and third quartiles (in parentheses). Here $\xi = 95\%$.

around dividend record dates from computations, Southeast TailCoR is slightly higher than with the restricted sample. In fact, for European banks and insurers, Southeast TailCoR appears almost monotonically decreasing with the number of days around dividend dates excluded.

On the other hand, for North American banks, median Southeast TailCoR appears to be increasing with dividend date exclusion. The interquartile range of Southeast TailCoR appears relatively stable.

Overall, there are some differences in median Southeast TailCoR when excluding dividend dates. In most cases these seem small and innocuous to our main conclusions.

C.7. Lagged Southeast TailCoR

Figure A5 shows Southeast TailCoR for leads and lags of short interest. Figure A5 shows that Southeast TailCoR is widely dispersed for European banks and insurers, whereas it is less dispersed for North American banks. Moreover, European insurers appear to have the highest level of Southeast TailCoR across all leads and lags of short interest.

Regarding the relationship between lead and lags of ΔSI and Southeast TailCoR, we notice that, similarly to the preceding conditional tail frequency analysis, for North American banks, median Southeast TailCoR peaks at lag 2 of ΔSI.

C.8. Time-varying Southeast TailCoR

We have attempted to control for serial correlation using a time-varying measure of Southeast TailCoR, based on a rolling window approach. In calculating Southeast TailCoR for every window, we standardised using the window interquartile range and demeaned using the window median. This window-by-window standardisation should limit the effects of heteroskedasticity and serial correlation.

Figure A6 shows Southeast TailCoR computed using the rolling window approach. Notice that Southeast TailCoR is relatively stable over time ranging in level between 1.2 and 1.8,

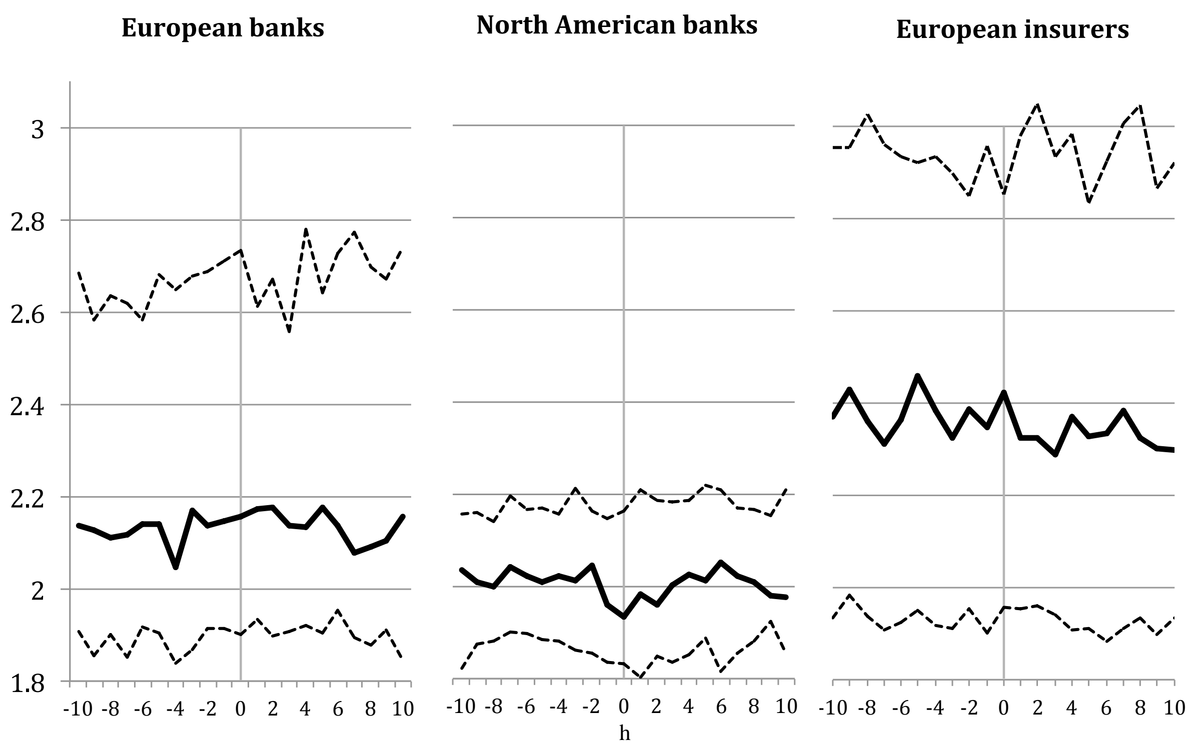

Figure A5: Southeast TailCoR of ΔSI_{t+h} and r_t

Figure A5 shows the median value of Southeast TailCoR (bold solid) for returns and different leads and lags (days) of short interest. It also shows the lower and upper quartile (light dashed) across three groups of firms: European banks, European insurers and North American banks. The vertical line gives the contemporaneous value of Southeast TailCoR i.e., SE-TailCoR$^{\xi}(\Delta SI_{t+h}, r_t)$ at lag $h = 0$ and $\xi = 95\%$.

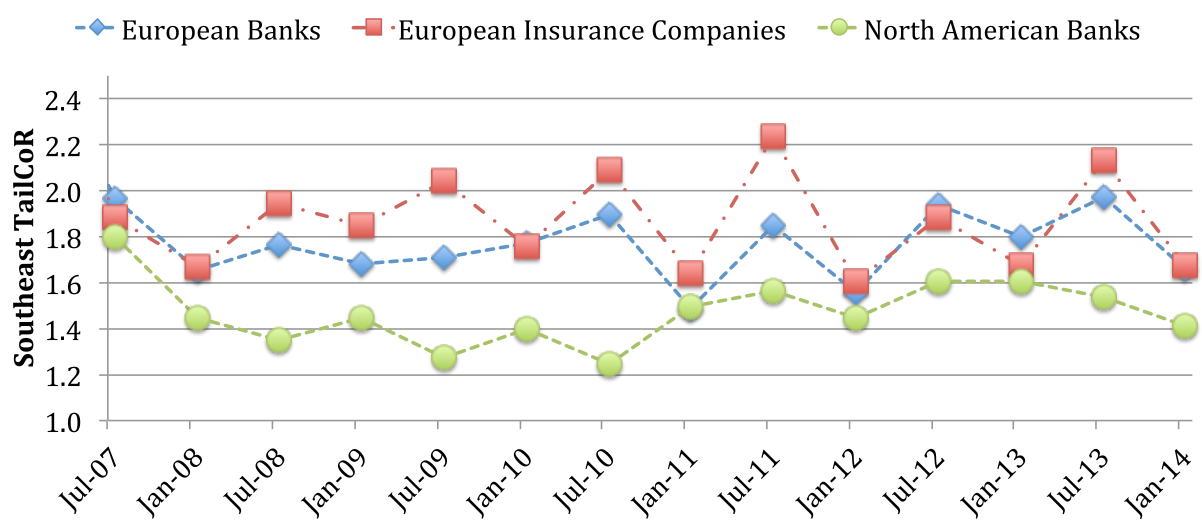

Figure A6: Median Southeast TailCoR computed for non-overlapping windows of 6-months.

for North American banks, 1.4 and 2 for European banks, and 1.6 and 2.2. for European insurers. Figure A6 also shows that European insurers had high levels of Southeast TailCoR across all time periods followed by European banks and successively North American banks. This shows that the results of Table 4 continue to hold over different time periods.

We can also notice some interesting dynamics occurring in Figure A6. In particular, Southeast TailCoR peaks for North American banks in January 2009, the window relating to the 2008 financial crisis. We observe a large peak for European banks and insurers in July 2011 reflecting the unfolding of successive distressing events during the Eurozone debt crisis. Deepening of the 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. There is another peak in Southeast TailCoR of European banks and insurers during the July 2013 window. This follows the Cypriot crisis of March of the same year. On the other hand, Southeast TailCoR values for North American banks decrease steadily. This implies low tail association between short selling activity and large negative price changes.

References

Boehmer, E., & Wu, J. J. (2013). Short selling and the price discovery process. *Review of Financial Studies*, *26*, 287–322. doi:10.1093/rfs/hhs097.

Dechow, P. M., Hutton, A. P., Meulbroek, L., & Sloan, R. G. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics*, *61*, 77–106. doi:10.1016/S0304-405X(01)00056-3.

Diether, K. B., Lee, K., & Werner, I. M. (2009). Short-sale strategies and return predictability. *Review of Financial Studies*, *22*, 575–607. doi:10.1093/rfs/hhn047.

Saffi, P. A. C., & Sigurdsson, K. (2011). Price efficiency and short selling. *Review of Financial Studies*, *24*, 821–852. doi:10.1093/rfs/hhq124.

Shkilko, A., Ness, B. V., & Ness, R. V. (2012). Short selling and intraday price pressures. *Financial Management*, *41*, 345–370. doi:10.1111/j.1755-053x.2012.01189.x.