Short Seller Skills in the Global Context: Public News Processing vs. Private Information Gathering

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Abstract

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Keywords: Short selling, informed traders, news media, international stock market
JEL Code: G12, G14, G15

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Abstract

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1. Introduction

Much empirical evidence indicates that short sellers are informed investors. Stocks with high short-selling activity tend to underperform those with low short-selling activity (see, e.g., Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009). The literature attributes short sellers' ability to predict future returns to their superior skills at processing public news (Engelberg, Reed, and Ringgenberg, 2012) and to their private information-gathering activities, which help them to anticipate future negative corporate events (see, e.g., Christophe, Ferri, and Angel, 2004; Karpoff and Lou, 2010). Ultimately, short sellers appear to profit both from interpreting public news and from using their private information (Boehmer, Jones, Wu, and Zhang, 2020).

However, the existing evidence is based on the U.S. market, with many relevant information sources publicly available there, along with stronger investor protection laws and stricter insider trading regulations than exist in most other countries (Karolyi, 2015). If short sellers lack access to high-quality news or are not well protected against competing insider traders, they may be unable to benefit from trading on public news.[1] To capture profits from trading on the news, short sellers need prices to respond to news, and such a response would be impossible if the news were untrustworthy or if the information in the news were incorporated into prices by insider traders before the public news dissemination. Indeed, Griffin, Hirshey, and Kelly (2011) find that many countries exhibit little stock price reactions to the news in financial media due to widespread insider trading and low-quality journalism and news transmission mechanisms. It is thus unclear whether short sellers outside the United States trade on public news or profit entirely from using their private information.

To fill this gap in the literature, I analyze short-selling activities around news in 29 countries. Surprisingly, I find that in most markets, short sellers derive their informational advantage from their superior ability to process public news rather than from their access to private information. Specifically, I

[1] Insider traders can incorporate most information into prices before it is publicly released, thus leaving little information to trade on for short sellers on the news days. Massa, Qian, Xu, and Zhang (2015) show that short sellers and insider traders compete with each other, prompting insiders to trade on their negative information faster.

find that high short-selling activities on news days, as compared to non-news days, predicts market-adjusted returns about ten times lower in the subsequent five to 20 days. In contrast, short selling before news releases is not associated with sizable returns on news days. These results indicate that short sellers profit more from trading on the news than in anticipation of it.

My analysis requires correct identification of the timing of short position initiations—on or before public news releases—to differentiate between short selling on the news and on private information. Engelberg et al. (2012) and Boehmer et al. (2020) use transaction-level short sales data for U.S. stocks around the Regulation SHO implementation for such identification. However, comparable data are not widely available internationally. In this paper, I use daily data on outstanding equity loans instead (an analog of short interest in the United States), and I propose a novel method that uses these data to distinguish whether short sellers anticipate or trade on the news.

The issue with using equity loans is that they cannot identify short sales timing precisely. Equity loans on a day reflect the cumulative quantity of all short positions not yet covered by that day, not the short positions opened on that day.[2] The number of outstanding equity loans observed on a day can then underrepresent the number of shorts on that day. Specifically, short sales on a negative news day increase equity loans on that day, whereas short sellers anticipating negative news increase their equity loans before this news and close them on the news day when the price drops to reflect negative information. Consequently, an empiricist cannot use equity loans on negative news days to estimate the number of shorts on such days. However, short sellers' activities before and on the *positive* news day do not interfere, since news anticipators would not short stocks before this news (hence, they would not need to cover their positions on the news day), while news traders may want to do that if the stock price overshoots its fundamental value.[3] Thus, I use outstanding equity loan amounts on positive news days as a measure of

[2] Here, I ignore the settlement cycle for illustration purposes. Since equity delivery is instantaneous in equity lending markets, short sellers borrow stocks on day $T + n$ when they must deliver them to the buyers in the stock market. Thus equity loans on day T reflect the uncovered short positions up to day $T - n$. I adjust for the settlement cycle in my analysis to focus on the number of short sales associated with outstanding equity loans observed on day T.

[3] In principle, news anticipators and news traders do not have to be different subsets of traders for this logic to work. If they are the same, they would increase their short positions before negative news and close them once the price

short sales on those days to examine whether short sellers trade on (positive) news in international stock markets.

Engelberg et al. (2012) show that short sellers do trade on positive news—that is, news days with positive returns on those days—in the U.S. market. The likely reason is that the market overreacts to positive news (Frank and Sanati, 2018), and short sellers trade on return reversals associated with these overreactions. I confirm that overreaction to positive news is prevalent in other regions. In an average country from my sample, the mean abnormal market-adjusted return on positive news days is 1.81%, but it reverses by 0.32% in the subsequent 20 days. Thus, short sellers can capitalize on overreaction to positive news if they trade quickly.

My analysis of equity loans around news shows that a one-standard-deviation increase in equity loans on positive news days is associated with market-adjusted returns 0.19% to 0.52% lower in the next five to 20 days, respectively. The economic effect on future returns is about ten times larger than that of increased equity loans on non-news days. For comparison, a similar increase in equity loans on negative news days is associated with a 0.02% lower (0.11% higher) market-adjusted returns in the next five (20) days; moreover, this effect is smaller than that from equity loans on non-news days. These findings support the notion that outstanding loan quantities on positive news days can be used to examine whether short sellers trade on positive news. Nevertheless, if short sellers were trading only on the news and not on private information, one would also expect to see significant economic results for equity loans observed on negative news days, since there would be no anticipatory short sales before such news.

To examine short sellers' usage of private information, I investigate whether equity loans taken before the dissemination of the day's news have a varying predictive power for future returns depending on the news type. I hypothesize that short sellers could prefer to concentrate on predicting news that has more direct implications for stock prices, since this news likely signals price responses on which short sellers can capitalize. I split news into three types, from the lesser to greater importance for investors:

adjusts to its intrinsic value—that could happen on the news day or after it if there is a price drift. On the other hand, they would decrease their positions before positive news and increase them on the news day if there is an overreaction.

informative, tangible, and earnings. I then examine whether equity loan variation preceding relevant news has greater predictive power for returns of more important news. Informative news includes all news stories with novel non-historical information; this news does not concern past record prices or trading volumes. Tangible news presents more quantitative information, easier to interpret in terms of market expectations; it includes news about earnings, revenues, analyst ratings, price targets, stock picks, and credit ratings.[4] Since intangible news contains mostly qualitative data with little implication for stock prices (von Beschwitz, Chuprinin, and Massa, 2017), tangible news is more important for investors as it has a more direct mapping into prices via cash flows or discount rates. Finally, I put earnings news into a separate news category of the greatest importance, as this news directly features in many valuation models.

My empirical results support my hypothesis. The association between equity loan variations before news and stock returns on the news days increases with the importance of the news, indicating that short sellers more successfully predict more important news. The effect is especially strong for earnings news: a one-standard-deviation increase in equity loans before this news predicts 0.11% lower five-day stock returns around the news days. This effect is approximately two times stronger than the one around tangible news and more than three times stronger than the one around all informative news. These findings suggest that short sellers utilize their private information to predict more price-relevant news. Nevertheless, the economic effect of short-selling activities before the news resembles that of short selling on other days. Accordingly, short-selling activities before the news bring short sellers less money than short sales on the news.

This paper contributes to several strands of literature. First, I add to the literature investigating the origins of short sellers' informational advantage. Engelberg et al. (2012) and Gao and Wang (2021) show that short sellers' skills at processing public news help them generate profits. A number of papers suggest that access to private information enables short sellers to predict future adverse events about companies, such as unexpectedly low earnings (Christophe et al., 2004), analysts' stock downgrades (Christophe, Ferri,

[4] I use RavenPack news classification, which categorizes news into these and other groups.

and Hsieh, 2010), financial misconduct (Karpoff and Lou, 2010), and negative returns on private placement announcements (Berkman, McKenzie, and Vermijeren, 2017). Boehmer et al. (2020) and Hu, Jones, and Zhang (2021) conclude that short sellers profit from both interpreting public news and using their private information. These studies examine U.S. short sellers, however, and the informational advantage of short sellers outside the United States is less understood.

My paper is the first to show that short sellers in international stock markets trade primarily on the news rather than on private information. I also contribute to the literature methodologically by demonstrating how to identify short selling on the news by analyzing data on outstanding equity loans. Since international transaction-level short sales data are not widely available, my method should facilitate further research about short selling in a global context.

Second, this paper deepens the understanding of short-selling trading strategies in international stock markets. Most international short-selling studies focus on short sale constraints and regulations (e.g., Bris, Goetzmann, and Zhu, 2007; Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Jones, Reed, and Whaler, 2016). The research on short sellers themselves and their trading strategies is largely limited to the U.S. market (e.g., Diether et al., 2009; Engelberg et al., 2012; Boehmer et al., 2020). To my knowledge, the only exceptions are Boehmer, Huszár, Wang, Zhang, and Zhang (2022) and Gorbenko (2022), who find that short-selling activities negatively predict future returns at the stock and market levels in most countries worldwide. These results indicate that short sellers have an informational advantage. I find that this advantage primarily comes from short sellers' superior skills at processing public news.

This study is also related to the literature examining the role of financial media in transmitting information into prices. Literature on U.S. news illustrates that stock prices react to the content of the news stories in the financial press (see, e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008). However, this reaction changes depending on the price shocks observed on the news days. According to Frank and Sanati (2018), positive news price shocks are usually followed by reversals, while negative shocks are followed by drifts suggesting that the market overreacts to positive news and underreacts to negative news. In international stock markets, the price response to the news information is often muted due to this

information being incorporated into prices by insider traders before the news and due to poor news transmission mechanisms (Griffin et al., 2011). I find that stock-price responses to the news have improved since Griffin et al.'s (2011) study, indicating a globally improving informational environment around trading. Nevertheless, the asymmetric response to the news—return reversals after positive news price shocks and drifts after negative shocks—prevails in markets outside the United States, suggesting that the drivers of these asymmetries are common across countries.

2. Data

2.1. Data Sources and Sample Construction

I use several data sources in the paper. International daily data on equity lending transactions come from S&P Global Securities Finance Buyside Analytics Data Feed (previously IHS Markit). The database covers 85–90% of securities lending transactions worldwide and is widely used in short-selling research (e.g., Saffi and Sigurdsson, 2011; Engelberg, Reed, and Ringgenberg, 2018; Muravyev, Pearson, and Pollet, 2022). International intraday data on news stories come from RavenPack News Analytics, a leading global news database used for quantitative trading strategies and finance research (e.g., Kolasinki, Reed, and Ringgenberg, 2013; Dang, Moshirian, and Zhang, 2015; Yu, Zhang, and Zhang, 2017). I collect daily data on U.S. stocks from the Center for Research in Security Prices (CRSP) and Compustat. Similar data for non-U.S. stocks come from Datastream. I follow Ince and Porter (2003) and Griffin, Kelly, and Nardari (2010) to eliminate errors and outliers when calculating returns in Datastream.

My main sample covers 29 countries from January 2007 to December 2021. I start sample construction with the same set of 38 countries analyzed in Boehmer et al. (2022), which is the first paper to examine the predictive power of short-selling activities for future returns in the global capital market. Following Boehmer et al. (2022), I merge the data from S&P Global, Datastream, CRSP, and Compustat based on available stock identifiers (ISIN, SEDOL, or CUSIP). The sample includes only common stocks traded on each country's major exchanges. Further, since this paper is about short-selling activities around

news, I filter out all stock-year observations in which a stock has no news stories in RavenPack or no equity loans in S&P Global. Finally, I exclude countries with less than 30 stocks per year and less than ten years of data. The news filter essentially eliminates nine countries from the original sample of 38 countries used in Boehmer et al. (2022): Chile, China, Greece, Hungary, Indonesia, Ireland, Philippines, Portugal, and Russia. However, this filter is necessary to analyze short-selling activities around the news.

I apply a number of filters to select and time relevant news stories from RavenPack. The database reports intraday timestamps for each news story in Coordinated Universal Time (UTC). I convert these timestamps to the time zones of the local exchanges, considering daylight savings changes as necessary, and I assign a news story to the next available trading day if it occurs outside regular trading hours. Because some companies may be mentioned in news stories not directly dedicated to them—for example, as a part of a general economic overview or a story about a rival company—I also apply a set of filters to ensure that the analyzed news stories are about particular companies (*ENTITY_TYPE = "COMP"* and *RELEVANCE = 100*). In addition, since this paper focuses on trading around the information content of the news, I include only those news stories based on factual data, not expert opinions or forecasts (*FACT_level = "fact"*).[5]

Table 1 reports the descriptive statistics for the main sample. The average number of stocks per year with available data on news and equity loans (*NStocks*) varies from 41 in Austria to 4,043 in the United States. The news stories emerge predominantly from the United States: the final sample consists of 4,787,228 days with at least one news story (*NNewsDays*) based on U.S. stocks. These news days comprise about 60% of the sample, as expected given that the U.S. stock market constitutes about half of the global equities market capitalization. The average stock in the United States has about 33% of its yearly trading days covered by news (*%NewsDaysPerStock*), while in other countries, news covers only about 12% of trading days for the average stock. Therefore, short sellers outside the United States have much less public

[5] This filter does not exclude analyst ratings or stock picks.

news to trade on. In this situation, short sellers may be better to focus on trading on their private information, since they have fewer opportunities to profit from processing public news.[6]

[Table 1]

2.2. Equity Loans and Short Selling

This paper uses data on outstanding equity loans as a proxy for short-selling activities. The primary reason equity loan transactions occur is that short sellers borrow stocks to deliver them to their buyers in the stock market. After a short sale transaction on day *T*, a short seller must deliver the stock to the buyer by the end of trading day $T + n$, where n depends on the settlement cycle adopted by regulators in a particular country.[7] Since stock delivery occurs immediately in equity lending markets, short sellers borrow stocks from lenders on day $T + n$ to deliver them to the buyers. Consequently, outstanding equity loans on day *T* reflect the uncovered short positions up to day $T - n$. I thus use outstanding equity loans on day $T + n$ to approximate the amount of open short positions on day *T*. A similar approach has been used by Geczy, Musto, and Reed (2002), Thornock (2013), and von Beschwitz et al. (2017).

I follow the literature and standardize outstanding equity loans by the number of shares outstanding in a given stock to get the short interest ratio (*SIR*) or by trading volume to get the days-to-cover ratio (*DTCR*). Both variables have been used to predict future stock returns in the cross-section, but *DTCR* has been shown to be a more powerful predictor internationally (Boehmer et al., 2022). Table 1 reports the time-series average values of the daily within-country cross-sectional medians for *SIR* and *DTCR*. Short interest is much lower outside the United States, mainly because short selling is more constrained in other countries. However, *SIR* in my sample is higher than in Bohmer et al.'s (2022) study because I focus on

[6] Previous studies do not report such news disproportions across regions because they usually analyze a random selection of news rather than all news and oversample some markets to ensure a large enough sample for analysis (e.g., Griffin et al., 2011).

[7] Table A1 of Appendix A reports settlement cycles adopted across my sample countries. Figure A1 of Appendix A illustrates the changes in settlement cycles across my sample countries during the 2007–2021 period.

stocks covered by news media.[8] These stocks are likely to be less short-sale constrained, as the news coverage is associated with fewer limits to arbitrage (Fang and Peress, 2009). As Bohmer et al. (2022) demonstrate, the predictive power of shorts for future returns is concentrated in stocks with more limits to arbitrage (e.g., those with low liquidity or high shorting fees). Thus, it is important to see whether short-selling activities will continue to predict return in my stock sample with relatively fewer limits to arbitrage.

To examine the predictive power of short-selling activity, I run panel regressions of market-adjusted stock returns on the lagged *DTCR* values separately for each country in my sample:

$$r_{i,t:t+n} = \alpha + \beta DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n}, \quad (1)$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-1}$ is the number of shares on loan (adjusted for the settlement cycle) divided the trading volume in stock i on day t–1, $\boldsymbol{X_{i,t-1}}$ is a set of stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects. Control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). To facilitate the comparison of the results across countries, I standardize all *DTCR* coefficients to have a mean of zero and a standard deviation of one within each country-year. Standard errors are clustered by stock and year.

Table 2 reports the coefficients on *DTCR* in basis points for each country in my sample. In 27 (28) out of 29 countries, *DTCR* coefficients are negative, and in 14 (13) countries, they are also statistically significant at a 10% level or better at a five-day (20-day) return horizon. Comparable to those of Boehmer et al. (2022), these results indicate that short-selling activities negatively predict future returns in international stock markets. Nevertheless, the effect of *DTCR* on future returns is less economically

[8] The current and all future comparisons between my sample and Boehmer et al.'s (2022) sample are based solely on the 29 countries included in my and their sample.

significant than Boehmer et al. (2022) report. For example, at a 20-day return horizon, the *DTCR* coefficient is approximately four times smaller than that found by Boehmer et al. (2022), suggesting that *DTCR* has less predictive power for future returns in my sample. Since my sample includes fewer short-sale-constrained stocks, these results are consistent with the Bohmer et al.'s (2022) finding that the shorts' predictive power for future stock returns decreases with fewer limits to arbitrage.

[Table 2]

3. News Informativeness and Short Selling

As skilled processors of public information, short sellers can trade on the information content of the news in different ways. They can profit from negative news by trading on it more quickly than others or by trading on the negative return drift. They can also trade on positive news if they understand when prices overreact to such news, causing return reversals afterward. However, not all news types are equally informative; hence, not all news is associated with significant price responses on which short sellers could trade. For example, von Beschwitz et al. (2017) find that intangible news, containing mostly qualitative data and minimal numeric information, has few implications for stock prices. As a result, short sellers use this news mainly for liquidity reasons, that is, to benefit from lower trading costs associated with high trading volumes on such news. Therefore, to understand short sellers' informational advantage in international stock markets, I rely on news with potential price implications on which short sellers can trade.

3.1. News Categorization: More and Less Informative

I use RavenPack news story categorization to separate news into more and less informative and center my analysis on more informative news. Specifically, RavenPack categorizes news into 50 groups based on their content (variable *GROUP*). First, I put the news story in the "informative" category if it is not about past prices or trading volumes. A news story about a record price or trading volume observed for a stock in the past does not directly affect stock prices, as it contains little information unknown to the

market, so I exclude this news group from my analysis. Next, I create the "tangible" news category that is easier to interpret regarding its effect on companies' cash flows or discount rates: news about earnings, revenues, analyst ratings, price targets, stock picks, or credit ratings. A more straightforward interpretation of the news assumes a more direct impact on stock prices, and short sellers can trade on this impact. The idea of news tangibility draws on the work of von Beschwitz et al. (2017), who use the numerical content of the news to identify information that is easier to interpret in terms of market expectations. Finally, I put all news in the "earnings" group in a separate, most-informative news category, as this news directly features in many valuation models (Table A2 of Appendix A further details the news categorization).

Figure 1 presents the distribution of news days by news type (category). Days with at least one informative news story comprise 77% of my sample, indicating that almost a quarter of my sample consists of news days with little new information for the market. About 44% of the news days contain at least one tangible news story, and about 29% contain at least one earnings news story. By the number of articles in each country examined, the earnings news category is the largest. Overall, a substantial proportion of the news in my sample is not informative according to my categorization. However, the ultimate informativeness of a news category can be determined only by examining price responses to the news.

[Figure 1]

I adopt Griffin et al.'s (2011) approach and compare abnormal stock return volatilities on the news days versus non-news days. A price shock should punctuate informative news. Conversely, if the news does not provide novel information to market participants (e.g., because insider traders have already incorporated this information into prices), the price response to such news should be muted. Ultimately, the more informative the news, the larger the price shock compared to that of non-news days. To measure price shocks, I apply Griffin et al.'s (2011) measure of abnormal stock return volatility: the absolute value of a stock's return in excess of its local value-weighted market return. I then compare these volatilities between news days and non-news days. On news days, I expect abnormal volatilities to be bigger for more informative news categories.

Figure 2 plots the average difference in abnormal volatilities on news days and non-news days separately for informative, non-informative, tangible, and informative non-tangible news. All positive values in the figure signify that the average volatility on particular news days is higher than on non-news days, indicating a price shock and, thus, informativeness of the news. Conversely, near-zero or negative values signify that the average volatility on the news day is similar to or lower than on non-news days, suggesting this news contains mundane information. Large negative values are especially interesting, as they indicate much lower volatility on the news vs. non-news days—a potential sign of insider trading ahead of the news.

[Figure 2]

As seen in Panels A and C, stock prices respond well to informative and tangible news, but tangible news is associated with more drastic price responses (higher absolute return volatility differences on the *y*-axis).[9] For comparison, return volatility on uninformative news days containing stories only about past prices and trading volumes in Panel B is lower than on non-news days, confirming that these news stories are uninformative for the market. Large negative values confirm the logic of assigning news stories about past record prices or trading volumes to an uninformative news category: these news stories discuss what has already happened on non-news days. Therefore, they cannot generate price shocks as large as those shocks they discuss. Interestingly, in about half of the sampled countries the return volatility on news days with informative but non-tangible (i.e., mostly qualitative) news stories (Panel D) is lower than on non-news days. Thus, intangible (qualitative) news stories seem not to contain much price-relevant information, consistent with von Beschwitz et al.'s (2017) findings for the U.S. market. In untabulated results, I find larger absolute return volatilities on earnings news compared to non-news days, again supporting the logic of categorization into more and less informative news. In addition, tangible non-earnings news days are associated with higher price shocks than are non-news days, suggesting that all types of tangible news are informative. Since news informativeness is crucial for analysis of short selling based on the news, my

[9] All these absolute return volatility differences are also statistically significant. I confirm these results, including larger price responses to tangible than informative news, in a regression framework in Table A3 of Appendix A.

further analysis targets the news category having an unambiguous price response in most regions: tangible news.[10]

Compared to previous studies, Figure 2 reports interesting results across developed and emerging countries (blue and orange bars, respectively). Specifically, for the earlier period 2003–2009, Griffin et al. (2011) document large differences in volatilities on news versus non-news days for developed countries, but few differences for emerging countries. They argue that this pattern arises due to more insider trading and weak news dissemination mechanisms in emerging countries. My results for a more recent 2007–2021 sample contrast those of Griffin et al. (2011). Figure 2 demonstrates the tendency of developed countries to exhibit larger return volatilities on news versus non-news days, especially for tangible news. However, all emerging countries have larger price shocks on the news versus non-news days as well. The implication is that stock price responsiveness to the news has increased since Griffin et al.'s (2011) study and, in turn, that the informational environment around trading has improved in emerging countries. This improvement may be driven by global technological developments enhancing news dissemination via access to news hosted by online analytical platforms like Seeking Alpha (Ding, Zhou, and Li, 2020).

3.2. Asymmetric Response to Positive and Negative News

Short sellers can trade on the news content or in anticipation of the news if their private information helps predict firm fundamentals, which are eventually revealed during public news releases. To differentiate between short selling on the news and on private information, I need to correctly identify the timing of short position initiations—on or before public news releases. However, the short sales data that allows that identification—such as that used by Engelberg et al. (2012) and Boehmer et al. (2020) for the U.S. market—is internationally scarce. In this section, I propose a method to identify short selling on the news from equity loans. This method requires the asymmetric price response to positive and negative news—that is, return

[10] The results for all informative news are qualitatively similar. I report results from the analysis of short selling around informative news, which are analogous to results in Tables 4 and 5, in Tables A4 and A5 of Appendix A.

reversals and drifts after positive and negative news price shocks, respectively. This section describes and documents such responses for my sample countries.

To illustrate the issue with using equity loans to identify short selling on the news, consider the following scenario. The negative news about a stock is publicly released on day *T*. Short sellers trading on this news, "news traders," increase the number of their equity loans observed on that day.[11] However, short sellers anticipating this news, "news anticipators," have already built up their short positions, increasing the quantity of borrowed stocks before the public news release. When the negative news is publicly released, the stock price drops, and news anticipators close their positions with profit; these position closures reduce the outstanding equity loans observed on the news day.[12] Since the observed equity loans on the negative news day reflect both covered and newly opened short positions, an empiricist cannot use equity loans on negative news days to estimate the number of shorts initiated on those days.

Conversely, short sellers' activities before and on the *positive* news do not interfere because news anticipators would not short stocks before this news (i.e., they would decrease or close their short positions in anticipation of future positive news). Hence, they would not need to cover their short positions on the news days. However, news traders may still want to short sell on positive news if there is a stock price overreaction to this news. Indeed, Frank and Sanati (2018) find that positive news price shocks are usually followed by return reversal in the United States, indicating an initial overreaction of the market to positive news. Thus, I use outstanding equity loans observed on positive news days as a measure of short sales on those days to examine whether short sellers trade on (positive) news in international stock markets. For this logic to work, however, an overreaction to positive news should manifest among my sample countries; otherwise, short sellers would not have incentives to trade on positive public news.

[11] Here, for simplicity I ignore the settlement cycle, assuming that shorting a stock on day T is reflected in equity loans on day T. In fact, due to the settlement cycle, short sales on day T are reflected in equity loans on day $T + n$. I adjust for the settlement cycle in all my analyses (see Section 2.1).

[12] If the price drop is not big enough on the news day, due to the market underreaction to the news, news anticipators could leave their positions open. However, empirical evidence indicates that short sellers are prone to the disposition effect and tend to close their profitable positions prematurely (von Beschwitz and Massa, 2020).

I begin by examining stock price reactions to positive and negative news for my sample countries. For brevity, I focus only on countries in which short-selling activities have significant predictability for future returns in Table 2 (at least at one of the return horizons considered)—these are 18 countries with negative, statistically significant *DTCR* coefficients. However, other countries exhibit parallel patterns.

Figure 3 plots return drifts and reversals in the [1,20] day window following positive and negative price shocks on tangible news days on Day 0. Positive and negative price shocks are defined as positive and negative market-adjusted returns on news days. Return drifts (reversals) are the postnews market-adjusted returns of the same (opposite) sign as the news-day return; thereby, all positive and negative values in Figure 3 represent return drifts and reversals, respectively. In all countries except New Zealand, the United Kingdom, and the United States, positive news price shocks are followed by reversals (green dots in the lower part of the graph). On the contrary, negative news price shocks in most countries are followed by drifts (red squares in the upper part of the graph).

[Figure 3]

To measure the significance of the return drifts and reversals in Figure 3, I conduct an event-study analysis. Specifically, I compare market-adjusted returns in the event window around positive and negative news days with the market-adjusted returns in the estimation period [t–120,t–10]. I present the results from this event study in Table 3. To account for event-induced variance when estimating statistical significance, I use Boehmer, Musumeci, and Poulsen's (1991) t-statistics.

Table 3 reports negative abnormal returns in the [1,5] and [1,20] event windows for nearly all the countries, both for positive and negative news price shocks. Concentrating on the [1,20] event window, $ARet_{[1,20]}$, the positive news is followed by negative returns in 14 out of 18 countries, and in 12 countries, these negative returns are statistically significant. The negative news is also followed by negative returns in almost all countries. These results indicate that reversals follow positive news price shocks, while drifts follow negative news price shocks (as in Figure 3). Concerning economic significance, the mean abnormal market-adjusted return on positive news days across my sample countries is 1.81%, but it reverses by 0.32% in the following 20 days. Given an average number of 5,660 positive news days per year in a country

(1,838 days outside the United States), short sellers have enough opportunities to capitalize on an average overreaction of 0.32% (0.36% outside the United States) to positive news.

[Table 3]

My results in Figure 3 and Table 4 for countries outside the United States are consistent with those reported for the U.S. news by Frank and Sanati (2018), suggesting that asymmetric responses to positive and negative news stem from similar drivers worldwide.[13] Frank and Sanati (2018) explain the asymmetric response to the news with two stylized facts. As they argue, retail investors trade primarily in response to positive news, generating excess demand that temporarily overshoots prices relative to their fundamental values and induces return reversals. Simultaneously, capital scarcity hinders arbitragers from correcting stock prices quickly in response to negative news shocks; this effect induces return drifts following negative news price shocks. Since this paper focuses on trading around news, I continue to investigate short-selling activities on and before the news and leave the examination of drivers of asymmetric response to news in the global capital market to future research.

4. Main Results

4.1. Short Selling on the News

The previous section has established that positive news price shocks are followed by reversals internationally. Thus, following my identification strategy, I can now investigate whether short sellers are trading on positive news by analyzing outstanding equity loans on these news days. Specifically, I want to understand whether equity loans observed on the positive news days, which proxy for short sales on those days, predict future returns. To do that, I run regressions as in Eq. (1) but limit the observations to equity

[13] Interestingly, my results for the U.S. news differ from those in Frank and Sanati (2018). The difference is likely driven by different samples and news data sources. My paper analyzes all stocks in a more recent period, 2007–2021, with all news sources covered by RavenPack (*DowJones Newswires*, all editions of the *Wall Street Journal*, *Barron's*, the *Financial Times*, *Morningstar*, *Bloomberg*, and other major publishers and Web aggregators, including local and regional newspapers and financial websites). Frank and Sanati (2018) analyze news in the *Financial Times* for S&P 500 firms for an earlier 1982–2013 period.

loans observed on the news days and five- and 20-day returns following these news days. I run regressions separately for positive and negative news to see whether the logic of my identification strategy works, namely using only positive news price shocks to identify short selling on the news. As in Eq. (1), to facilitate international comparison I adjust the equity loan variable (*DTCR*) for the settlement cycle and standardize it to a mean of zero and a standard deviation of one within each country-year.

Table 4 reports the results. The first two columns show negative *DTCR* coefficients in 13 out of 18 countries, and in 7 countries, these coefficients are statistically significant, indicating that high short-selling activities on positive news days predict low future stock returns in many markets worldwide. Concerning an average economic significance across countries, a one-standard-deviation increase in equity loans on positive news days corresponds to market-adjusted returns 19 basis points lower in the next five days and 52 basis points lower in the subsequent 20 days. However, this significance varies markedly across countries: a similar increase in *DTCR* leads to a 59 basis point future 20-day return *increase* in South Africa and to a 356 basis point return *decrease* in Mexico. Interestingly, no discernable pattern appears in short sales' return predictability across emerging and developed countries: the two countries with the most and least predictability—Mexico and South Africa, respectively—are both emerging countries. Overall, for my sample countries the findings indicate that short sellers' trades on (positive) news are profitable on average, suggesting that short sellers do trade on the news. In certain countries (e.g., South Africa), however, this does not seem to be the case.

[Table 4]

For comparison, the last two columns in Table 4 report *DTCR* coefficients for regressions run on negative news days. An average *DTCR* coefficient across countries is only marginally negative at a five-day return horizon and even becomes positive at a 20-day horizon, suggesting little association between equity loans on the negative news days and future returns. I emphasize that these results do not mean that short sellers do not trade on negative news or that their trades do not predict future stock returns. Instead, these results confirm my identification strategy: It is hard to use equity loans observed on negative news

days to measure short positions opened on those days. However, it is possible to use equity loans on positive news days to measure short-selling activities.

How big are short sellers' profits from trading on positive news compared to their activities on other days? The simple comparison between the *DTCR* coefficients in Tables 4 and 2 suggests that, on average, short sellers make about ten times more money from trading on positive news than from trading on all other days. To quantify this difference more formally, I run the following regressions:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_2 PosNews_{i,t-1} + \beta_3 NegNews_{i,t-1} + \beta_4 PosNews_{i,t-1} \times DTCR_{i,t-1} + \beta_5 NegNews_{i,t-1} \times DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n}, \quad (2)$$

where $PosNews_{i,t-1}$ ($NegNews_{i,t-1}$) is a dummy variable equal to 1 if stock *i* has a positive (negative) tangible news story on day *t*–1. The interaction coefficient can tell how different the effect of an increase in *DTCR* on a positive (negative) news day is in comparison with a non-news day.

Table 5 reports the regression results from Eq. (2). The average interaction coefficient of *DTCR* with a positive news dummy is approximately ten times larger (in absolute terms) than the *DTCR* coefficient. These results indicate that the predictive ability of increased short-selling activities on positive news days for future returns is about ten times larger than that of short-selling activities on non-news days.

[Table 5]

The average interaction coefficient of *DTCR* with a negative news dummy in Table 5 is positive. These results confirm the difficulty of using equity loans observed on negative news to examine short-selling activities on those days. Nevertheless, if short sellers were mostly news traders, one would expect mostly negative interaction coefficients on *DTCR* and negative news dummies, since there would be minimal short position coverages by news anticipators. For example, in Hong Kong and Taiwan, the interaction coefficients on *DTCR*s and negative news dummies are negative, which implies that short sellers do not trade much in anticipation of the negative news in these countries. However, the interaction coefficients with positive news dummies remain greater in magnitude than those with negative news dummies, indicating some news anticipation. Otherwise, these interaction coefficients would be of a similar

or larger magnitude for negative news, since short sellers specialize in trading on negative information.[14] In Section 4.2, I investigate short sellers' ability to predict news in more detail.

4.2. Short Selling ahead of the News

If they trade on private information, short sellers may be able to predict future stock news price responses. Short sellers often conduct in-depth firm investigations to estimate the degree of the company's overvaluation. Ljungqvist and Qian (2016) describe how short sellers gather and analyze private information, including an examination of documents like purchase agreements or customer orders, personal conversations with managers, and on-site visits to production facilities or customers. Once the information is gathered and short positions are established, short sellers need only wait until the market realizes that the shorted company is overvalued. The latter often happens when a new piece of information is publicly released via news media. Thus, short sellers could predict future news price shocks if they utilize private information in their trades. This section examines whether short-selling activities before news predict returns on news days.

I begin by running regressions, as in Eq. (1), for a subsample of news days returns and outstanding equity loans (variable *DTCR*) observed before these news days. My regressions for *DTCR*s with different time lags varying from one to 20 days prior to the news examine the persistence of the predictive power of equity loans on future news returns. I use both positive and negative news returns for regressions, as informed short sellers would avoid underpriced companies and decrease or close their short positions in anticipation of future positive news.[15]

Table 6 reports the results. The *DTCR* coefficients are negative for most countries, indicating that short sellers build up their positions before negative news and reduce them before positive news. The

[14] Engelberg et al. (2012) show that short sales initiated on the negative news days predict future returns around five times lower than short sales initiated on the non-news days and around two times lower returns than short sales initiated on the positive news days.
[15] Boehmer, Huszár, and Jordan (2010) find that stocks with low short interest experience significant future abnormal returns.

predictive power of *DTCR* for the news-days returns reduces with a 20-day lag, suggesting that the predictive power of equity loans for future news returns is relatively short-term. On average, a one-standard-deviation increase in *DTCR* a day before the news predicts a 6.25 basis point lower market-adjusted return in the next five days. This effect is higher than that in Table 2 (a 1.75 basis point lower return), indicating that short sellers anticipate news returns more than average returns. Yet, the predictive power of *DTCR* prior to news remains weaker than that on the positive news days (compare the *DTCR* coefficient of –6.25 in Table 6 with the *DTCR* coefficient of –19.07 in Table 4). These findings indicate that short sellers' private information helps them predict future news, but these short-selling activities still appear to bring them less profit than those on news days.

[Table 6]

However, whether these differences are statistically significant remains unclear. To investigate more formally, I run the following regressions:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_2 News_{i,t} + \beta_3 News_{i,t} \times DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n}, \quad (3)$$

where $News_{i,t}$ is a dummy variable equal to 1 if stock *i* has a tangible news story on day *t.* Notice that all equity loans (variable *DTCR*) are measured at *t*–1, while the news-day dummies are for day *t.* Thus, the interaction coefficient can signal the difference in the effect of an increase in *DTCR* before the news compared to *DTCR* increases observed on all other days. Table 7 reports the regression results.

Overall, the interaction coefficients in Table 7 are only marginally significant. For the results at the one-day return horizon in the first two columns, on average an increase in *DTCR* prior to the news day predicts a return 1.27 basis point *higher* on the next day, as compared to a similar *DTCR* increase on other days. This effect is opposite the expected negative predictive power of equity loans for future returns, suggesting that the predictive power of short-selling activities before the news resembles that on all other days. The results for a five-day return horizon in the last two columns are qualitatively similar: most countries exhibit positive interaction coefficients, although an average coefficient is marginally negative.

[Table 7]

Table A6 of Appendix A presents regressions with interaction coefficients for equity loans observed both on the positive and negative news days and before the news, confirming the results in Tables 5 and 7. The average interaction coefficients on *DTCR* and contemporaneous positive news-day dummies are negative and much larger in magnitude than those on *DTCR*s themselves. In contrast, the other interaction coefficients—with contemporaneous negative news-day dummies and with lead news-day dummies—are either positive or only marginally negative. These findings confirm that short sellers extract more profit from trading on the news than from anticipating it.

My prior analysis centered on short sellers' ability to predict returns on tangible news days. However, short sellers may prefer to concentrate on predicting news with more direct implications for stock prices, since this news is likely to be associated with price responses on which short sellers can capitalize. I thus split news into three types, from least to most relevant to investors: informative, tangible, and earnings (see Section 3.1 for details). Running regressions as in Table 5 but for these different news types, I then examine whether equity loan variation before news has higher predictive power for returns on more important news.

Table 8 reports the results. The *DTCR* coefficients increase in magnitude with the news informativeness, suggesting that short sellers more successfully predict more important news. The effect of *DTCR* variations on future news returns is especially strong for earnings news. A one-standard-deviation increase in equity loans before this news predicts 11 basis points lower five-day stock returns around the news days.[16] This effect is approximately two times stronger than that for tangible news and more than three times stronger than that for all informative news. At the same time, it is only two times smaller than that from short-selling activities on positive tangible news in Table 4. These results indicate that short sellers focus on the prediction of news having more direct implications for stock prices.

[Table 8]

[16] I also run regressions with interactions (similar to those in Table 7), finding that the *DTCR* coefficient prior to earnings news is 2.20 (1.37) basis points more negative than that on all other days at a one-day (five-day) predictive return horizon (see Table A7 of Appendix A).

6. Conclusion

This paper investigates the origins of short sellers' informational advantage in international stock markets. Surprisingly, I find that in most markets, short sellers derive their informational advantage from their superior ability to process public news rather than from their access to private information. Specifically, I find that high short-selling activities on news days predict about ten times lower market-adjusted returns in the next five to 20 days, as compared to high short-selling activities on non-news days. In contrast, short selling before news releases is not associated with sizable returns on news days. These results indicate that short sellers profit more from trading on than from anticipating the news. Additional analysis of short-selling activities before the news reveals that they more accurately predict future price shocks on tangible news—that is, news that is easier to interpret in terms of market expectations. These findings suggest that short sellers acquire more tangible private information that helps predict future earnings or similar figures, but does not help anticipate price shocks from qualitative news about companies' businesses.

This paper proposes a novel method to distinguish whether short sellers anticipate or trade on public news from observed equity loans around the news. While previous studies have used transaction-level short sales data from the U.S. market to analyze short selling on the news (Engelberg et al., 2012; Boehmer et al., 2020), internationally such data are scarce, while data on equity loans are abundant. The method introduced in the paper can facilitate further exploration of short-selling trading strategies in the global capital market.

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Panel A: Stock-Days with News Split by the News Types

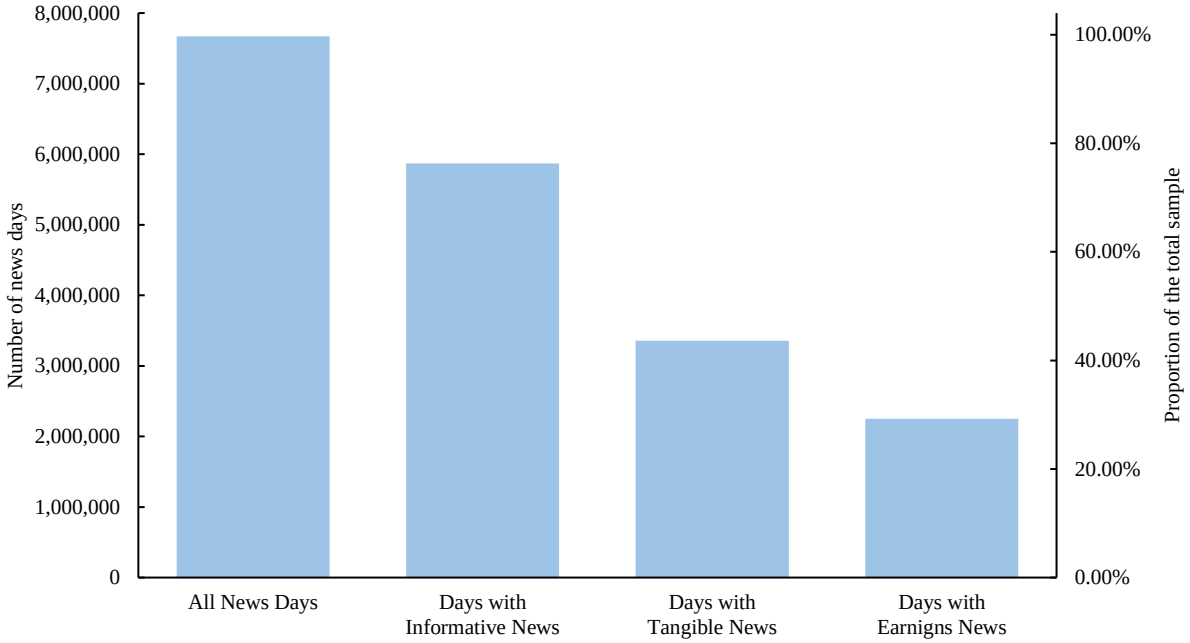

Figure 1. Distribution of the news sample by the news types and regions

This figure plots the total number of stock-days with news split by the news types. Days with informative news are all days in which there is at least one news story with novel non-historical information (i.e., the information in the news story is not about past prices or trading volumes). Days with tangible news are all days in which there is at least one news story about earnings, revenues, analyst ratings, price targets, stock picks, or credit ratings. Days with earnings news are all days in which there is at least one news story about earnings. Section 3 describes the news types in detail. The sample period is January 2007–December 2021.

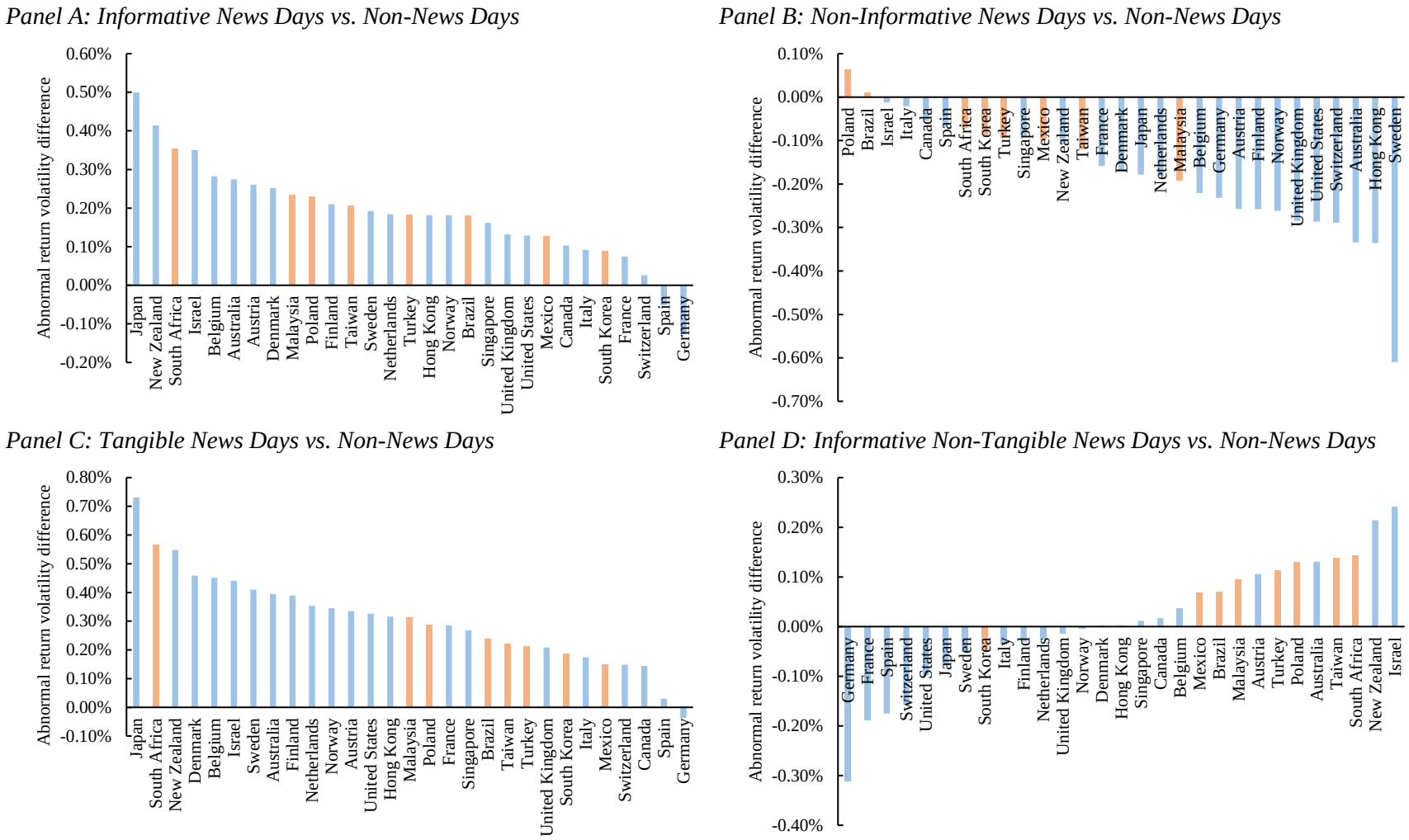

Figure 2. Difference in abnormal volatilities on the news vs. non-news days

This figure plots the difference in daily abnormal return volatilities, defined as the absolute value of a stock's return in excess of the local value-weighted market return, on the news vs. non-news days by region. In Panel A, the news days are all informative news days; in Panel B, the news days are all non-informative news days; in Panel C, the news days are all tangible news days; in Panel D, the news days are all informative but non-tangible news days (see Figure 1 and Section 3 for the definitions of the news types). Non-news days are all days without any news on that day. Blue (orange) bars indicate developed (emerging) economies as classified by MSCI on June 23, 2022. The sample period is January 2007–December 2021.

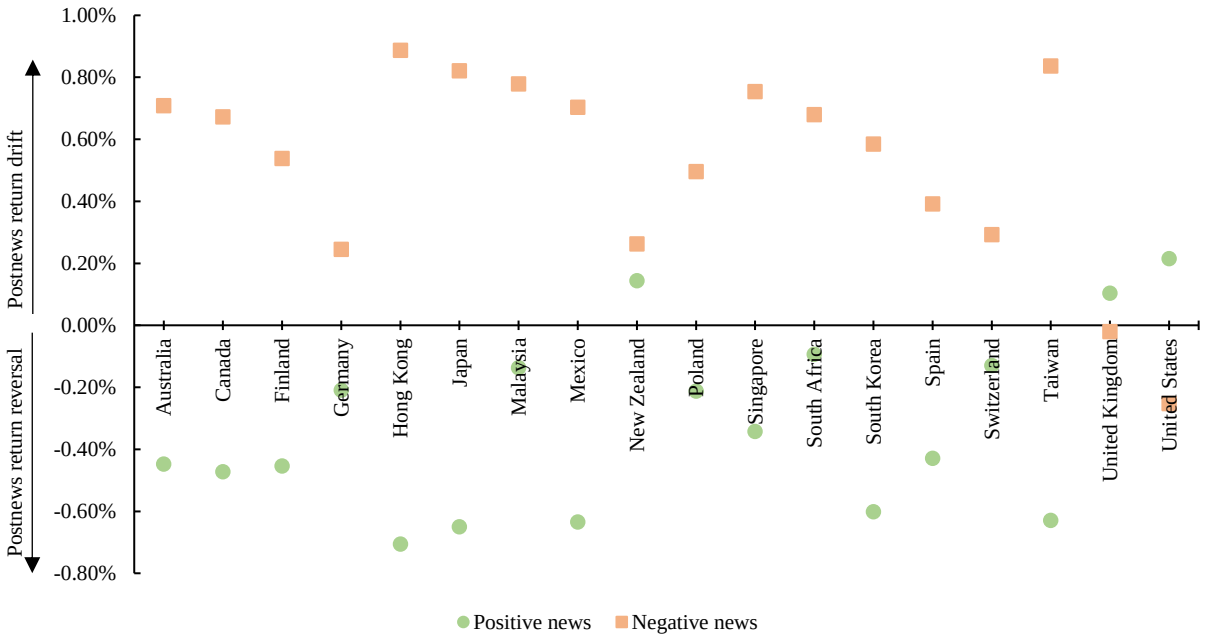

Figure 3. Return drifts and reversals following positive and negative news

This figure plots the average cumulative market-adjusted return drifts and reversals in the [1,20] period (in trading days) following positive and negative tangible news days across stocks by country (see Figure 1 and Section 3 for the definition of tangible news). Based on the market-adjusted returns on those days, news days are split into positive and negative. In the figure, all return drifts (defined as the postnews returns of the same sign as the news-day return) are positive numbers, and all return reversals (defined as the postnews returns of the opposite sign compared to the news-day return) are negative numbers. The sample period is January 2007–December 2021.

Table 1. Descriptive statistics

This table presents descriptive statistics on news coverage and short-selling variables in 29 countries from January 2007 to December 2021. The sample only includes stock-years, for which a stock has at least one news story in RavenPack and at least one day with a positive quantity of shares on loan in S&P Global (previously IHS Markit). *NStocks* is the average number of stocks in a year for a given country. *NNewsDays* is the total number of stock-days with at least one news story about a given stock for a given country. *%NewsDaysPerStock* is the average percentage of news days in a year per stock for a given country. *SIR* and *DTCR* are time-series average values of the daily within-country cross-sectional medians. At the stock-day level, *SIR* (*DTCR*) is calculated as the ratio of the number of shares on loan to the number of shares outstanding (trading volume). The number of shares on loan in *SIR* and *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with the share loans. Sections 2.1 and 2.2 detail the data filtration procedure and settlement cycle adjustment.

Country	Sample period	*NStocks*	*NNewsDays*	*%NewsDays PerStock*	*SIR, %*	*DTCR*
Australia	2007–2021	528	207,617	10.67	0.37	2.44
Austria	2007–2021	41	17,549	11.68	0.68	9.32
Belgium	2007–2021	78	26,788	9.06	0.21	2.87
Brazil	2007–2021	88	51,254	15.88	0.03	0.13
Canada	2007–2021	691	366,352	14.57	0.64	5.16
Denmark	2007–2021	73	35,390	13.15	0.28	2.34
Finland	2007–2021	80	35,219	11.73	0.43	3.92
France	2007–2021	320	194,798	16.03	0.32	3.53
Germany	2007–2021	261	183,912	18.66	0.51	4.00
Hong Kong	2011–2021	166	54,120	12.15	0.18	2.23
Israel	2007–2021	54	25,923	16.55	0.05	0.41
Italy	2007–2021	192	89,011	12.39	0.35	2.64
Japan	2007–2021	2,381	454,498	5.26	0.52	2.40
Malaysia	2012–2021	105	30,882	12.02	0.05	0.93
Mexico	2007–2021	58	28,707	13.56	0.18	3.04
Netherlands	2007–2021	77	49,759	17.19	0.96	4.17
New Zealand	2007–2021	45	18,268	10.89	0.13	2.02
Norway	2007–2021	101	34,772	9.35	0.24	2.79
Poland	2008–2021	61	13,131	6.21	0.07	1.01
Singapore	2011–2021	152	47,119	11.51	0.13	2.03
South Africa	2007–2021	114	43,746	10.35	0.22	1.65
South Korea	2008–2021	547	112,194	6.01	0.35	1.00
Spain	2007–2021	101	47,735	12.59	0.52	3.72
Sweden	2007–2021	239	72,003	8.12	0.32	2.77
Switzerland	2007–2021	171	76,135	11.89	0.53	5.58
Taiwan	2008–2021	491	119,494	6.65	0.34	1.59
Turkey	2007–2021	100	23,841	6.34	0.17	0.43
United Kingdom	2007–2021	677	423,898	16.90	0.40	3.21
United States	2007–2021	4,043	4,787,228	33.38	1.69	3.43
Average outside the United States		285	103,004	11.69	0.33	2.76

Table 2. Predicting future market-adjusted returns with short-selling activity

This table presents the results from the panel regressions predicting future five-day and 20-day market-adjusted returns with the short-selling activity measure, *DTCR*, within each country:

$$r_{i,t:t+n} = \alpha + \beta DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock i on day t–1, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t:t+5}$		Dependent variable: $r_{i,t:t+20}$	
	$DTCR_{i,t-1}$ coeff.	R^2	$DTCR_{i,t-1}$ coeff.	R^2
Australia	–1.38**	0.19%	–3.55***	0.69%
Austria	–4.94	0.26%	–8.83	1.30%
Belgium	0.06	0.77%	–0.02	2.87%
Brazil	–2.27	0.48%	–2.33	1.63%
Canada	–0.98*	0.22%	–1.76	0.59%
Denmark	–0.74	0.93%	–0.18	2.91%
Finland	–1.17	0.32%	–6.90**	1.38%
France	–0.01	0.53%	–0.69	1.72%
Germany	–1.32**	0.25%	–5.02***	1.02%
Hong Kong	–2.81***	0.52%	–5.53**	2.42%
Israel	–1.84	0.55%	–11.27	2.27%
Italy	–0.72	0.56%	–1.45	1.95%
Japan	–1.05**	0.25%	–3.98***	0.84%
Malaysia	–1.38*	0.49%	–2.91**	1.27%
Mexico	–1.28*	0.42%	–1.84	1.36%
Netherlands	0.75	0.43%	1.41	1.65%
New Zealand	–2.57**	0.24%	–3.96	1.03%
Norway	–0.17	0.72%	–0.65	1.93%
Poland	–3.20***	0.23%	–4.85**	0.69%
Singapore	–2.77***	0.27%	–8.39***	1.05%
South Africa	–0.38	0.20%	–3.24*	0.73%
South Korea	–3.69***	0.27%	–8.98**	0.89%
Spain	–1.29	0.51%	–7.06**	1.35%
Sweden	–2.14	0.49%	–2.50	1.55%
Switzerland	–2.10**	0.34%	–5.99***	1.29%
Taiwan	–2.53*	0.12%	–5.61	0.54%
Turkey	–0.42	0.25%	–1.57	0.90%
United Kingdom	–0.54	0.35%	–2.11*	0.99%
United States	–1.05**	0.10%	–1.75	0.38%
Average coeff.	–1.51		–3.85	
# Negative/Total	27/29		28/29	
# Negative & significant at 10%	14		13	

Table 3. Return drifts and reversals after positive and negative news

This table presents the abnormal market-adjusted returns from the event study analysis examining stock price reactions to positive and negative news for 18 countries with negative and significant *DTCR* coefficients in one of the regression specifications from Table 2. The table reports abnormal cumulative market-adjusted returns on the event day t=0, $ARet_0$, from day t=*1* to day t=*5*, $ARet_{[1,5]}$, and from day t=1 to day t=20, $ARet_{[1,20]}$, relative to the estimation period [t–120,t–10]. An event day is defined as a day with at least one tangible news story (see Figure 1 and Section 3 for the definition of tangible news). Event days are split into positive and negative news days based on the market-adjusted returns on those days. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from Boehmer et al.'s (1991) t-statistics that account for event-induced variance. All abnormal return estimates are in percentage points.

Country	Positive news			Negative news		
	$ARet_0$	$ARet_{[1,5]}$	$ARet_{[1,20]}$	$ARet_0$	$ARet_{[1,5]}$	$ARet_{[1,20]}$
Australia	2.67***	–0.11***	–0.49***	–2.43***	–0.31***	–0.85***
Canada	2.20***	–0.18***	–0.60***	–2.03***	–0.27***	–0.90***
Finland	1.69***	–0.14***	–0.41***	–1.65***	–0.19***	–0.61***
Germany	1.64***	–0.03	–0.21***	–1.56***	–0.07***	–0.27***
Hong Kong	1.82***	–0.14**	–0.60***	–1.64***	–0.20***	–0.94***
Japan	2.03***	–0.36***	–0.65***	–1.97***	–0.39***	–0.91***
Malaysia	1.59***	0.00	–0.21	–1.49***	–0.23***	–0.93***
Mexico	1.38***	–0.20***	–0.71***	–1.34***	–0.22***	–0.77***
New Zealand	1.62***	0.13**	0.07	–1.54***	–0.22	–0.38
Poland	1.81***	–0.06	–0.10	–1.79***	–0.19**	–0.56***
Singapore	1.48***	–0.08	–0.35***	–1.37***	–0.37***	–0.83***
South Africa	2.18***	0.21***	0.00	–2.01***	–0.09*	–0.72***
South Korea	1.91***	–0.19***	–0.55***	–1.68**	–0.13***	–0.60***
Spain	1.41***	–0.14**	–0.65***	–1.38***	–0.18***	–0.75***
Switzerland	1.34***	–0.03	–0.34***	–1.28***	–0.20***	–0.55***
Taiwan	1.51***	–0.19***	–0.37***	–1.33***	–0.22***	–0.74***
United Kingdom	1.89***	0.09***	0.06***	–1.71***	0.02***	–0.09
United States	2.47***	0.02	0.31***	–2.29***	0.10***	0.38***
Average *ARet*	1.81%	–0.08%	–0.32%	–1.69%	–0.19%	–0.61%
# Negative/Total	0/18	13/18	14/18	18/18	16/18	17/18
# Negative & significant at 10%	0	9	12	18	15	15
# Positive/Total	18/18	5/18	4/18	0/18	2/18	1/18
# Positive & significant at 10%	16	3	2	0	2	1

Table 4. Predicting future market-adjusted returns with short-selling activity on news days

This table presents the results from the panel regressions predicting five-day and 20-day market-adjusted returns after positive and negative news days with the short-selling activity on the news days within each country:

$$r_{i,t:t+n} = \alpha + \beta DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock i on day t–1, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects. Day t–1 in the regression is a day with at least one tangible news story (see Figure 1 and Section 3 for the definition of tangible news). News days are classified as positive or negative based on the market-adjusted returns on those days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Predicting returns after positive news		Predicting returns after negative news	
	$r_{i,t:t+5}$	$r_{i,t:t+20}$	$r_{i,t:t+5}$	$r_{i,t:t+20}$
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.
Australia	–60.42*	–107.63***	–0.26	9.50
Canada	3.27	17.16	0.11	–0.37
Finland	9.43	19.69	14.42	101.57
Germany	–79.59***	–156.16***	–83.47	–27.01
Hong Kong	–73.03*	–145.96**	–19.82***	–37.83***
Japan	1.16	–3.94*	4.94	2.30
Malaysia	–2.10	–19.45	–13.18	–100.80*
Mexico	–60.40**	–355.67**	45.14	164.95
New Zealand	–32.87	–30.42	–7.57***	–8.65***
Poland	–17.34**	20.09	–5.35	46.31***
Singapore	–10.72	–47.80***	6.89	–1.86
South Africa	39.32	58.94	10.59	85.60
South Korea	–20.17***	–0.84	–25.29***	–44.75***
Spain	–18.73***	–34.55	–21.75*	–15.32
Switzerland	–10.30	–80.96	50.94	103.74
Taiwan	–9.06	–18.05	–11.43***	–17.77***
United Kingdom	–1.85	–38.14	20.01	–48.83
United States	0.09	–7.63	–0.18	–11.02**
Average coeff.	–19.07	–51.74	–1.96	11.10
# Negative/Total	13/18	14/18	10/18	11/18
# Negative & significant at 10%	7	6	5	6

Table 5. Predicting power of short-selling activity on news vs. non-news days

This table presents the results from the panel regressions predicting future five-day and 20-day market-adjusted returns with the short-selling activity measure, *DTCR*, within each country:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_2 PosNews_{i,t-1} + \beta_3 NegNews_{i,t-1} + \beta_4 DTCR_{i,t-1} \times PosNews_{i,t-1} + \beta_5 DTCR_{i,t-1} \times NegNews_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock *i* from day *t* to day *t* + *n*, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock *i* on day *t*–1, $PosNews_{i,t-1}$ ($NegNews_{i,t-1}$) is a dummy variable equal to 1 if stock *i* has a positive (negative) tangible news story on day *t*–1, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock *i* on day *t*–1, and $Year\ FE_t$ denotes calendar-year fixed effects (see Figure 1 and Section 3 for the definition of tangible news). News days are classified as positive or negative based on the market-adjusted returns on those days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t:t+5}$			Dependent variable: $r_{i,t:t+20}$		
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times PosNews_{i,t-1}$	$DTCR_{i,t-1} \times NegNews_{i,t-1}$	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times PosNews_{i,t-1}$	$DTCR_{i,t-1} \times NegNews_{i,t-1}$
Australia	–1.38**	–56.59	1.62	–3.55***	–101.97**	15.89
Canada	–1.14**	4.12	1.28	–2.22*	19.37*	1.86*
Finland	–1.21	–0.04	16.78	–7.03***	13.69	80.69
Germany	–1.29**	–74.61***	–52.89	–4.97***	–118.56**	71.13
Hong Kong	–2.68***	–73.73	–16.26***	–5.26**	–137.75*	–30.24***
Japan	–1.16***	3.06	5.88	–4.08***	1.23	4.74
Malaysia	–1.36*	–1.56	–11.81	–2.74**	–16.72	–107.12*
Mexico	–1.28*	–43.37**	64.65	–1.84	–233.29	229.97
New Zealand	–2.09	–44.04	–6.09***	–3.52	–55.59***	–5.22
Poland	–3.12***	–12.80*	–1.43	–5.14**	28.63	48.89***
Singapore	–2.85***	–9.46	10.97***	–8.33***	–41.24***	8.24
South Africa	–0.40	49.87	23.93	–3.31*	75.44	166.48
South Korea	–3.62***	–13.47**	–19.19**	–8.88**	4.55	–30.67***
Spain	–1.24	–19.04***	–19.44*	–7.03**	–25.07	–5.71
Switzerland	–2.13**	–34.01	39.54	–5.99**	–70.18	81.32
Taiwan	–2.44*	–5.76	–7.79*	–5.42	–14.96	–16.03***
United Kingdom	–0.55	3.77	22.51	–2.07*	–28.04	–45.74
United States	–1.05**	0.23	0.11	–1.61	–7.05	–11.11*
Average coeff.	–1.72	–18.19	2.91	–4.61	–39.31	25.41
# Negative/Total	18/18	13/18	8/18	18/18	12/18	8/18
# Negative & significant at 10%	13	5	5	14	5	5

Table 6. Short-selling activity ahead of news

This table presents the results from the panel regressions predicting one-day and five-day returns on the news days with the prior short-selling activity within each country:

$$r_{i,t:t+n} = \alpha + \beta DTCR_{i,t-n} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-n}$ is the number of shares on loan divided the trading volume in stock i on day $t - n$, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects. Day t in the regression is a tangible news day (see Figure 1 and Section 3 for the definition of tangible news). The regressions use *DTCR* variables lagged by one, five, or 20 trading days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t}$			Dependent variable: $r_{i,t:t+5}$		
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-5}$ coeff.	$DTCR_{i,t-20}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-5}$ coeff.	$DTCR_{i,t-20}$ coeff.
Australia	6.18	13.14	–0.64**	–10.98	18.06***	–3.84***
Canada	–0.54	–1.22	–0.55	–0.42	–3.18	–2.63
Finland	–4.22	–0.68	6.27	1.53	–1.11	3.46
Germany	–18.56**	–9.40**	8.90	–37.14	–15.42***	–3.47
Hong Kong	–13.15***	–1.88**	–12.34	–22.34***	–0.07	–17.59
Japan	0.94	–0.14	–0.62	0.30	0.02	0.36
Malaysia	–4.00	–2.52	–0.08	8.78	–1.69	–3.00
Mexico	19.08***	15.68***	–0.72***	5.91	–33.36	–4.66***
New Zealand	0.93	–16.23***	–4.04	–22.09	–22.41	–28.27
Poland	–8.18	–5.16**	–1.96	–17.29	–11.72	–16.46
Singapore	4.44	–10.53**	–9.56***	–18.74**	–11.73***	–6.81
South Africa	–1.25	6.51***	3.02***	46.93	7.44***	3.87***
South Korea	–4.12	–3.30	–2.05	–18.61***	–9.34	–7.93
Spain	–5.81	–1.67	–2.03	–8.16	–14.50*	–9.72
Switzerland	–2.72	0.96	5.18***	–22.79***	1.04	2.91
Taiwan	–1.25	–5.17**	–0.08	–3.38	–16.14**	–0.91
United Kingdom	–0.98	1.24	0.04	–0.64	–1.66	–0.16
United States	6.25	–1.12	36.64	6.58	–3.34	33.89
Average coeff.	–1.50	–1.19	1.41	–6.25	–6.62	–3.39
# Negative/Total	12/18	13/18	12/18	12/18	14/18	13/18
# Negative & significant at 10%	2	6	3	4	4	2

Table 7. Predictive power of short-selling activity ahead of news vs. all other days

This table presents the results from the panel regressions predicting future one-day and five-day market-adjusted returns with the prior short-selling activity measure, *DTCR*, within each country:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_2 News_{i,t} + \beta_3 DTCR_{i,t-1} \times News_{i,t} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock *i* from day *t* to day *t* + *n*, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock *i* on day *t*–1, $News_{i,t}$ is a dummy variable equal to 1 if stock *i* has a tangible news story on day *t*, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock *i* on day *t*–1, and $Year\ FE_t$ denotes calendar-year fixed effects (see Figure 1 and Section 3 for the definition of tangible news). The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t}$		Dependent variable: $r_{i,t:t+5}$	
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times News_{i,t}$	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times News_{i,t}$
Australia	–0.01	6.14	–1.37**	–9.75
Canada	–2.00***	3.03	–4.80	–7.66
Finland	0.38	–0.75	0.05	0.21
Germany	–0.81	0.13	–2.24	–1.24
Hong Kong	–0.76*	0.19	–1.04*	0.61
Japan	–0.95**	–1.34	–0.74	–5.68
Malaysia	–0.69*	–1.53	–1.20	2.91
Mexico	–0.32	1.65	–0.08	2.31
New Zealand	–0.43*	–19.52*	–1.30**	–32.76
Poland	–0.48*	–12.43***	–2.67***	–19.08***
Singapore	–1.08	3.86	–2.36	9.63
South Africa	–0.86***	3.38	–0.71	–2.52
South Korea	–0.30**	1.69*	–1.12**	1.93
Spain	–0.85**	–3.55	–1.48**	10.46
Switzerland	–0.48	18.94***	–1.29*	7.08
Taiwan	0.41*	6.03	0.60	20.59
United Kingdom	–1.06***	1.32	–2.41*	–21.23
United States	–0.84	15.57***	–0.29	15.70
Average coeff.	–0.62	1.27	–1.36	–1.58
# Negative/Total	16/18	6/18	16/18	8/18
# Negative & significant at 10%	10	2	8	1

Table 8. Short-selling activity ahead of different types of news

This table presents the results from the panel regressions predicting one-day and five-day returns on the news days with the prior short-selling activity for different types of news within each country:

$$r_{i,t:t+n} = \alpha + \beta DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock i on day t–1, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects. Day t in the regression is either an informative, tangible, or earnings news day (see Figure 1 and Section 3 for the definition of different news types). The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Informative news		Tangible news		Earnings news	
	$r_{i,t}$	$r_{i,t:t+5}$	$r_{i,t}$	$r_{i,t:t+5}$	$r_{i,t}$	$r_{i,t:t+5}$
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.
Australia	2.20	–5.62	6.18	18.06***	–76.38*	–71.70
Canada	–0.78	–1.15	–0.54	–3.18	–0.51	–0.96
Finland	–1.33	–2.45	–4.22	–1.11	–3.42	–2.42
Germany	–6.91**	–4.41	–18.56**	–15.42***	–5.12	–3.66
Hong Kong	–11.06***	–18.29***	–13.15***	–0.07	–14.21***	–25.70***
Japan	0.96	0.46	0.94	0.02	1.75	1.48
Malaysia	–2.99*	4.21	–4.00	–1.69	–4.15	9.11
Mexico	4.76*	26.75**	19.08***	–33.36	43.63***	15.21
New Zealand	–1.24	6.80	0.93	–22.41	–0.47	–23.22
Poland	–2.89	–10.37	–8.18	–11.72	–17.34	–64.75*
Singapore	2.13	–10.01	4.44	–11.73***	7.45	–15.49*
South Africa	–1.74	0.51	–1.25	7.44***	8.63	39.96
South Korea	–1.26	–10.43***	–4.12	–9.34	–1.01	–15.69***
Spain	–1.34	1.41	–5.81	–14.50*	–7.16	–14.81
Switzerland	–1.58	–24.57***	–2.72	1.04	–2.49	–21.49***
Taiwan	–1.81	–5.13	–1.25	–16.14**	–4.33*	–11.89*
United Kingdom	–0.20	–0.01	–0.98	–1.66	5.20	5.18
United States	0.16	0.17	6.25	–3.34	7.13	8.53
Average coeff.	–1.38	–2.90	–1.50	–6.25	–3.49	–10.68
# Negative/Total	13/18	11/18	12/18	14/18	12/18	12/18
# Negative & significant at 10%	3	3	2	4	3	6

Appendix A: Additional Results

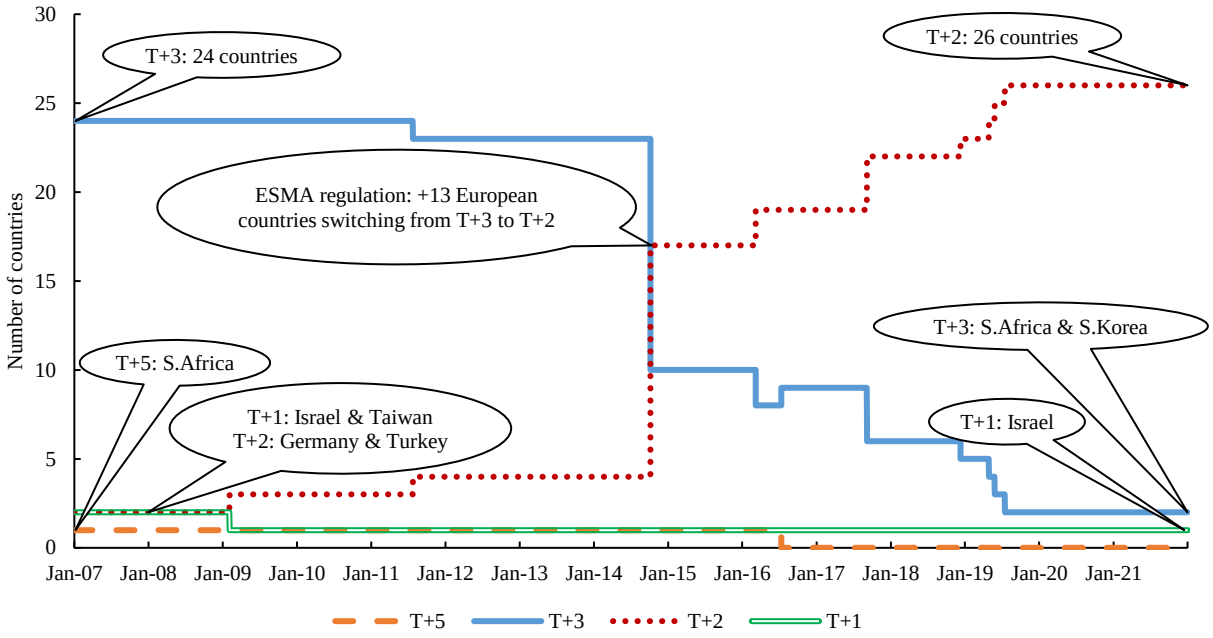

Figure A1. Settlement cycle changes 2007–2021

This figure plots the changes in equity settlement cycles across 29 countries, January 2007–December 2021. The settlement cycle determines the time in business days when a (short) seller must deliver the sold stock to the buyer. Following a trade on day *T*, the (short) seller must deliver the stock to the buyer by the end of day $T + n$.

Table A1. Equity settlement cycles across countries

This table describes the equity settlement cycles adopted across 29 countries of my sample between January 2007 and December 2021. The settlement cycle determines the time in business days when a (short) seller must deliver the sold stock to the buyer. Following a trade on day *T*, the (short) seller must deliver the stock to the buyer by the end of day $T + n$. All information is retrieved from the local regulator and clearinghouse websites.

Country	Settlement cycles
Australia	Before March 7, 2016: $T + 3$. From March 7, 2016: $T + 2$.
Austria	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Belgium	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Brazil	Before May 27, 2019: $T + 3$. From May 27, 2019: $T + 2$.
Canada	Before September 5, 2017: $T + 3$. From September 5, 2017: $T + 2$.
Denmark	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Finland	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
France	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Germany	Entire sample period: $T + 2$.
Hong Kong	Before July 25, 2011: $T + 3$. From July 25, 2011: $T + 2$.
Israel	Entire sample period: $T + 1$.
Italy	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Japan	Before July 16, 2019: $T + 3$. From July 16, 2019: $T + 2$.
Malaysia	Before April 29, 2019: $T + 3$. From April 29, 2019: $T + 2$.
Mexico	Before September 5, 2017: $T + 3$. From September 5, 2017: $T + 2$.
Netherlands	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
New Zealand	Before March 7, 2016: $T + 3$. From March 7, 2016: $T + 2$.
Norway	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Poland	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Singapore	Before December 10, 2018: $T + 3$. From December 10, 2018: $T + 2$.
South Africa	Before July 11, 2016: $T + 5$. From July 11, 2016: $T + 3$.
South Korea	Entire sample period: $T + 3$.
Spain	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Sweden	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Switzerland	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
Taiwan	Before February 2, 2009: $T + 1$. From February 2, 2009: $T + 2$.
Turkey	Entire sample period: $T + 2$.
United Kingdom	Before October 6, 2014: $T + 3$. From October 6, 2014: $T + 2$.
United States	Before September 5, 2017: $T + 3$. From September 5, 2017: $T + 2$.

Table A2. News classification

This table describes the news type classification adopted in the paper. The leftmost column shows the news type name used in the paper, the middle column shows corresponding news groups in RavenPack, and the rightmost column provides examples of typical headlines for a specific RavenPack news group. The news sample analyzed in the paper only considers news about companies (*ENTITY_TYPE = "COMP"*) that is specifically relevant to it (*RELEVANCE = 100*) and that is based on factual data rather than on expert opinions or forecasts (*FACT_level = "fact"*). The news sample covers 29 countries from January 2007 to December 2021.

News type in the paper	Corresponding RavenPack news group	A typical news headline for the group
All news	Any of the 50 available groups	
Informative news	Any of the 50 available groups except:	
	• "stock-prices"	The company's share price rise (drop) from a previous level makes headlines
	• "technical-analysis"	The price of the entity is considered overbought (oversold) and becoming overvalued (undervalued)
	• "order-imbalances"	An exchange reports an excess of buy (sell) orders for the company's stock during a market open/close auction
Tangible news	Any of the following six groups:	
	• "earnings"	The company announces earnings that exceed (miss) forecasts or benchmarks for the period
	• "revenues"	The company announces revenues that exceed (miss) forecasts or benchmarks for the period
	• "analyst-ratings"	The company's stock is upgraded (downgraded)
	• "price-targets"	The entity's projected price target remains unchanged (is upgraded/downgraded)
	• "stock-picks"	The company's stock is seen as a buy (sell) or given a positive (negative) recommendation
	• "credit-ratings"	The entity's credit/bond rating remains unchanged (is upgraded/downgraded)
Earnings news	Group "earnings"	See above

Table A3. Effect of news on abnormal volatility

This table presents the results from the contemporaneous panel regressions of the abnormal stock return volatility measure, $|r_{i,t}|$, on the news indicator dummy within each country:

$$|r_{i,t}| = \alpha + \beta NewsDummy_{i,t} + Stock\ FE_i + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $|r_{i,t}|$ is the absolute value of stock i's return in excess of the local value-weighted market return on day t, $NewsDummy_{i,t}$ is a dummy variable equal to 1 if stock i has an informative or tangible news story on day t, and $Stock\ FE_i$ and $Year\ FE_t$ denote stock and calendar-year fixed effects, respectively (see Figure 1 and Section 3 for the definition of informative and tangible news). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in percentage points. The sample period is January 2007–December 2021.

	Informative news		Tangible news	
	NewsDummy coeff.	Adj. R^2	*NewsDummy* coeff.	Adj. R^2
Australia	0.79^{***}	14.97%	0.96^{***}	14.95%
Austria	0.35^{***}	10.67%	0.42^{***}	10.71%
Belgium	0.40^{***}	10.19%	0.55^{***}	10.15%
Brazil	0.35^{***}	7.58%	0.38^{***}	7.56%
Canada	0.42^{***}	16.43%	0.49^{***}	16.30%
Denmark	0.49^{***}	10.40%	0.70^{***}	10.66%
Finland	0.41^{***}	8.91%	0.59^{***}	9.16%
France	0.45^{***}	11.41%	0.61^{***}	11.35%
Germany	0.45^{***}	12.06%	0.51^{***}	11.82%
Hong Kong	0.46^{***}	10.10%	0.55^{***}	10.10%
Israel	0.38^{***}	10.18%	0.46^{***}	10.05%
Italy	0.35^{***}	6.33%	0.42^{***}	6.26%
Japan	0.68^{***}	10.60%	0.85^{***}	10.76%
Malaysia	0.34^{***}	13.26%	0.41^{***}	13.26%
Mexico	0.22^{***}	6.67%	0.23^{***}	6.62%
Netherlands	0.40^{***}	10.23%	0.57^{***}	10.38%
New Zealand	0.43^{***}	10.62%	0.55^{***}	10.76%
Norway	0.47^{***}	11.63%	0.63^{***}	11.48%
Poland	0.36^{***}	7.78%	0.40^{***}	7.77%
Singapore	0.38^{***}	15.03%	0.47^{***}	15.04%
South Africa	0.36^{***}	13.33%	0.53^{***}	13.40%
South Korea	0.29^{***}	5.65%	0.37^{***}	5.63%
Spain	0.29^{***}	9.80%	0.34^{***}	9.60%
Sweden	0.55^{***}	11.59%	0.77^{***}	11.54%
Switzerland	0.33^{***}	11.12%	0.43^{***}	10.96%
Taiwan	0.20^{***}	8.02%	0.21^{***}	8.02%
Turkey	0.26^{***}	5.46%	0.28^{***}	5.45%
United Kingdom	0.50^{***}	11.52%	0.59^{***}	11.32%
United States	0.69^{***}	10.54%	0.98^{***}	11.51%
Average outside the United States	0.41	10.41%	0.51	10.40%

Table A4. Predicting future market-adjusted returns on informative news days

This table presents the results from the panel regressions predicting five-day and 20-day market-adjusted returns after positive and negative news days with the short-selling activity on the news days within each country:

$$r_{i,t:t+n} = \alpha + \beta DTCR_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock i on day t–1, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects. Day t–1 in the regression is a day with at least one informative news story (see Figure 1 and Section 3 for the definition of informative news). News days are classified as positive or negative based on the market-adjusted returns on those days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Predicting returns after positive news		Predicting returns after negative news	
	$r_{i,t:t+5}$	$r_{i,t:t+20}$	$r_{i,t:t+5}$	$r_{i,t:t+20}$
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1}$ coeff.
Australia	–3.38***	–7.97***	–5.32	32.90
Canada	0.40	5.64	–0.48	–1.32
Finland	–1.06	–30.07	9.27	–9.67
Germany	–34.52	–82.94**	1.37	28.82
Hong Kong	–41.89*	–52.67	–16.07***	–32.64***
Japan	0.88	–2.97	2.31	–1.69
Malaysia	–9.43	–22.19*	–7.63*	–31.49**
Mexico	–9.83	–29.35*	95.22	284.63
New Zealand	–44.16**	–59.26**	–4.53**	–4.52
Poland	–10.53**	20.80*	–5.15	26.30
Singapore	–11.81**	–26.52	5.13	–11.05
South Africa	–0.59	40.47	5.19	7.10
South Korea	–8.56*	2.99	–17.22***	–27.34*
Spain	3.95	4.49	–10.35	–7.98
Switzerland	–33.85	–105.40	19.36	–18.56
Taiwan	–7.98*	–12.22	–13.95***	–19.91***
United Kingdom	–8.53	–15.02	4.07	–1.87
United States	1.01	–0.94	–4.72	–16.13**
Average coeff.	–12.22	–20.73	3.14	10.87
# Negative/Total	14/18	13/18	10/18	13/18
# Negative & significant at 10%	7	5	5	5

Table A5. Predictive power of short-selling activity on informative news vs. non-news days

This table presents the results from the panel regressions predicting future five-day and 20-day market-adjusted returns with the short-selling activity measure, *DTCR*, within each country:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_1 PosNews_{i,t-1} + \beta_2 NegNews_{i,t-1} + \beta_4 DTCR_{i,t-1} \times PosNews_{i,t-1} + \beta_5 DTCR_{i,t-1} \times NegNews_{i,t-1} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock i from day t to day $t + n$, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock i on day t–1, $PosNews_{i,t-1}$ ($NegNews_{i,t-1}$) is a dummy variable equal to 1 if stock i has a positive (negative) informative news story on day t–1, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock i on day t–1, and $Year\ FE_t$ denotes calendar-year fixed effects (see Figure 1 and Section 3 for the definition of informative news). News days are classified as positive or negative based on the market-adjusted returns on those days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t:t+5}$			Dependent variable: $r_{i,t:t+20}$		
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times PosNews_{i,t-1}$	$DTCR_{i,t-1} \times NegNews_{i,t-1}$	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times PosNews_{i,t-1}$	$DTCR_{i,t-1} \times NegNews_{i,t-1}$
Australia	–1.30**	–2.61**	–3.43	–3.45***	–5.22***	35.52*
Canada	–1.13**	1.52	0.72	–2.35*	7.95	0.98
Finland	–1.20	–2.67	3.58	–6.80**	–32.02	–20.95
Germany	–1.30**	–30.94	6.64	–5.00***	–64.20*	42.77
Hong Kong	–2.71***	–30.65	–12.84***	–5.31**	–28.37	–25.20***
Japan	–1.16***	2.51	3.34	–4.08***	1.17	0.95
Malaysia	–1.32*	–9.34	–6.82**	–2.68**	–20.88	–31.28**
Mexico	–1.29	–4.42	98.66	–1.82	–18.18	328.52
New Zealand	–2.14	–49.18***	–2.55	–3.77	–48.13*	–0.34
Poland	–3.13***	–6.04	–1.18	–5.22**	28.09*	33.00
Singapore	–2.83***	–9.67	8.28*	–8.35***	–16.93	–2.06
South Africa	–0.40	6.55	14.69	–3.33*	41.90	22.08
South Korea	–3.61**	–4.19**	–12.80***	–8.92**	11.13	–16.22
Spain	–1.61	5.18*	–8.95	–7.28**	10.86	–1.45
Switzerland	–2.12**	–44.34	21.58	–5.97**	–71.68	15.08
Taiwan	–2.39*	–5.33	–10.11**	–5.35	–11.73	–19.96***
United Kingdom	–0.55	–5.36	4.60	–2.11*	–8.52	–0.13
United States	–1.24**	2.13	–3.48	–1.60	0.43	–15.76**
Average coeff.	–1.75	–10.38	5.55	–4.63	–12.46	19.20
# Negative/Total	18/18	13/18	9/18	18/18	11/18	10/18
# Negative & significant at 10%	12	3	2	14	3	4

Table A6. Predictive power of shorting ahead of news vs. on the news vs. on all other days

This table presents the results from the panel regressions predicting future one-day and five-day market-adjusted returns with the prior short-selling activity measure, *DTCR*, within each country:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_2 PosNews_{i,t-1} + \beta_3 NegNews_{i,t-1} + \beta_4 News_{i,t} + \beta_5 DTCR_{i,t-1} \times PosNews_{i,t-1} + \beta_6 DTCR_{i,t-1} \times NegNews_{i,t-1} + \beta_7 DTCR_{i,t-1} \times News_{i,t} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock *i* from day *t* to day *t* + *n*, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock *i* on day *t*–1, $PosNews_{i,t-1}$ ($NegNews_{i,t-1}$) is a dummy variable equal to 1 if stock *i* has a positive (negative) tangible news story on day *t*–1, $News_{i,t}$ is a dummy variable equal to 1 if stock *i* has a tangible news story on day *t*, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock *i* on day *t*–1, and $Year\ FE_t$ denotes calendar-year fixed effects (see Figure 1 and Section 3 for the definition of tangible news). News days are classified as positive or negative based on the market-adjusted returns on those days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t:t+5}$			
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times PosNews_{i,t-1}$	$DTCR_{i,t-1} \times NegNews_{i,t-1}$	$DTCR_{i,t-1} \times News_{i,t}$
Australia	–1.37**	–55.88	2.31	–9.61
Canada	–4.56	–26.98***	8.03	–6.74
Finland	–0.06	15.44	37.68*	–0.62
Germany	–2.20	0.66	–7.75	0.07
Hong Kong	–1.12*	4.17	1.52	–0.27
Japan	–0.78	11.88	–9.72	–6.52
Malaysia	–1.22	–0.90	15.93	0.68
Mexico	–0.08	–27.34*	4.07	2.32
New Zealand	–1.28**	–71.21***	–41.39	–23.83
Poland	–2.66***	–69.01	2.46	–20.93**
Singapore	–1.91	–19.55*	–2.96	11.90*
South Africa	–0.71	–214.75***	105.47	–2.59
South Korea	–1.20**	2.57	5.26	1.29
Spain	–1.45**	–12.45	–12.76	12.66*
Switzerland	–1.29*	–43.84**	62.64	6.96
Taiwan	0.53	20.62	21.42	16.18
United Kingdom	–1.94	–38.31	–6.13***	–19.76
United States	–0.35	15.47	1.84	15.17
Average coeff.	–1.31	–28.30	10.44	–1.31
# Negative/Total	17/18	11/18	6/18	9/18
# Negative & significant at 10%	7	6	1	1

Table A7. Predictive power of short-selling activity ahead of earnings news vs. all other days

This table presents the results from the panel regressions predicting future one-day and five-day market-adjusted returns with the prior short-selling activity measure, *DTCR*, within each country:

$$r_{i,t:t+n} = \alpha + \beta_1 DTCR_{i,t-1} + \beta_2 News_{i,t} + \beta_3 DTCR_{i,t-1} \times News_{i,t} + \boldsymbol{\gamma X_{i,t-1}} + Year\ FE_t + \varepsilon_{i,t:t+n},$$

where $r_{i,t:t+n}$ is the cumulative market-adjusted return for stock *i* from day *t* to day *t* + *n*, $DTCR_{i,t-1}$ is the number of shares on loan divided the trading volume in stock *i* on day *t*–1, $News_{i,t}$ is a dummy variable equal to 1 if stock *i* has an earnings news story on day *t*, $\boldsymbol{X_{i,t-1}}$ is a set of the stock-level control variables measured for stock *i* on day *t*–1, and $Year\ FE_t$ denotes calendar-year fixed effects (see Figure 1 and Section 3 for the definition of earnings news). News days are classified as positive or negative based on the market-adjusted returns on those days. The number of shares on loan in *DTCR* is adjusted for the settlement cycle to reflect short-selling activities associated with these loans (see Section 2.2 for details). Stock-level control variables include the natural logarithm of the market capitalization (in millions of USD) at the end of the previous month (*MCap*), the natural logarithm of the book-to-market ratio at the end of the previous month (*BM*), the previous one-month cumulative return (*RET1M*), the previous six-month cumulative return with one month skipped (*RET6M*), the average daily return standard deviation from the previous month (*RETVol*), the average daily turnover from the previous month (*Turnover*), and the percentage of zero-return days in the previous month (*PctZero*). *DTCR* is standardized to have a mean of zero and a standard deviation of one within each country-year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, derived from the standard errors clustered at the stock-year level. All coefficient estimates are in basis points.

Country	Dependent variable: $r_{i,t}$		Dependent variable: $r_{i,t:t+5}$	
	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times News_{i,t}$	$DTCR_{i,t-1}$ coeff.	$DTCR_{i,t-1} \times News_{i,t}$
Australia	0.00	–75.10*	–1.37**	–70.21
Canada	–1.95***	–0.76	–4.95	3.37
Finland	0.39	–9.87	0.01	12.71
Germany	–0.81	–0.36	–2.30	2.39
Hong Kong	–0.76*	0.19	–0.98	0.02
Japan	–0.90**	–11.32**	–0.61	–29.44**
Malaysia	–0.70*	0.12	–1.22	11.48
Mexico	–0.29	3.38	–0.03	3.65
New Zealand	–0.44*	–4.96	–1.32**	–1.28
Poland	–0.48*	–13.45***	–2.65***	–22.63**
Singapore	–0.89	0.81	–2.01	4.49
South Africa	–0.86***	2.71	–0.70	–5.20
South Korea	–0.30**	2.52**	–1.13**	3.18
Spain	–0.86**	–3.46	–1.49**	11.52*
Switzerland	–0.47	41.37	–1.29*	20.16
Taiwan	0.42*	12.25	0.68	37.67
United Kingdom	–1.05***	–0.05	–2.41*	–24.20
United States	–0.85	16.31***	–0.30	17.66
Average coeff.	–0.60	–2.20	–1.34	–1.37
# Negative/Total	15/18	9/18	16/18	6/18
# Negative & significant at 10%	10	3	7	2