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DOCUMENTO DE TRABAJO N° 116

Febrero de 2022

Citar como:
Gargano, Antonio, Juan Sotes-Paladino y Patrick Verwijmeren (2022). Short of Capital: Stock Market Implications of Short Sellers' Losses. *Documento de trabajo RedNIE N°116*.

Short of capital: Stock Market Implications of Short Sellers' Losses*

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January, 2021

We provide evidence that losses constrain short sellers but not the transmission of information to prices. Using unique data on U.S. equity lending, we document a negative impact of the mark-to-market losses of a stock's short sellers, but no impact of their gains, on the future shorting of the stock. Consistent with funding and institutional constraints limiting short selling, we further show that the effect is highly asymmetric across different loss levels and stronger among stocks facing higher margin requirements. However, loss-making short selling has no predictive power for returns, suggesting a low impact of these constraints on the transmission of short sellers information to prices.

Keywords: Short Selling, Margin Constraints, Limits to Arbitrage, Informed Trading.

JEL Classification: G12, G14

*We are grateful to Laura Andreu (discussant), Peter Brooke, James Brugler, Si Cheng (discussant), Darwin Choi (discussant), Carole Comerton-Forde, Zhi Da, Ross Garon, Luis Goncalves-Pinto, Choi Jaewon (discussant), Griffin Wenxi Jiang, Yoon Kang Lee, Junye Li, Bryan Lim, Dmitriy Muravyev, Melissa Porras Prado, Alberto Rossi, Ronnie Sadka, Pedro Saffi, Andriy Shkilko (discussant), Esad Smajlbegovic, Kumar Venkataraman, Ingrid Werner, Jianfeng Yu and Zhuo Zhong for comments and suggestions. The paper has also benefited from comments made at presentations at the the 2019 SFS Cavalcade Asia-Pacific, 2019 ABFER, CEPR and CUHK First Annual Symposium in Financial Economics, the 2019 Chinese International Conference in Finance, the 2019 FMA Europe Annual Meeting, the 27th Finance Forum, the 2019 SECHI Annual Meeting, and seminars at Point72 Asset Management, ESSEC Business School in Singapore, the University of Chile, the University of New South Wales, University of Sydney and University of Technology Sydney. We acknowledge support from the Faculty Research Grant funded by the University of Melbourne. All errors are our own. This paper was previously titled "The Profits and Losses of Short Sellers."

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1 Introduction

Short sellers are widely regarded as informed traders in the academic literature. However, an ex-ante information advantage need not always translate into ex-post outperformance. Indeed, dedicated-short bias funds suffered hefty losses during recent bull markets according to press reports.[1] This observation raises the question of whether and how mark-to-market losses impair the ability of short sellers to trade and transmit their information to prices. In this paper, we take this question to the data by building on recent theory of the potential links between trading losses and the activity and pricing implications of sophisticated investors.

As long as a trading opportunity is profitable enough, a textbook short seller has access to sufficient capital to exploit it. In practice, however, short sellers face several funding and institutional constraints that could render profits relevant for their activity. First, they must post the proceeds from their sales along with additional cash in margin accounts that are marked to market. Second, institutional short sellers are usually bound by risk management practices and portfolio constraints that effectively limit the maximum allowable losses on their positions. Third, institutional short sellers can also experience capital withdrawals by their investors following poor performance on their trades. With limited access to capital, these constraints could lead mark-to-market losses to limit short selling and the transmission of relevant information to prices.

Lack of detailed data on short-selling losses has prevented an in-depth examination of these implications. We overcome this limitation by using a novel dataset on the mark-to-market profits that equity short sellers experience on their positions. For approximately 4,000 U.S. stocks between 2011 and 2017, our dataset contains *direct* information on the *distribution* of cumulative returns on the short positions in each stock at daily frequency. These data allow us to have a disaggregated view on the different levels of gains and losses that short sellers experience on approximately 98% of the U.S. stock market.

We start our analysis by characterizing short-selling profits in both the overall stock market and the cross section of stocks. Aggregating across stocks, the mark-to-market net-of-fees performance of short selling in our sample amounts to a loss of 5.1% of the value of all short positions. Although

[1] "How to lose 93% of your money... and be happy about it." *The Wall Street Journal*, January 12 of 2018.

economically significant, these aggregate losses are not inconsistent with short sellers being informed. In fact, when we disaggregate our analysis by firm and stock characteristics, we find that short sellers experience positive and sizable net-of-fees gains on the most heavily shorted stocks, on small-caps, on value stocks, and on stocks of firms subject to higher information asymmetry, even during the strong bull market of 2011–2017.

We next examine the relation between the performance of short selling and the subsequent shorting activity in a stock. The existence of such a relation is not obvious from prior empirical studies, which distinguish among profiting from short-term overvaluation (Diether et al., 2009), exploiting the continuation of stock underperformance (Lamont and Stein, 2004; Curtis and Fargher, 2014), and hedging (Brent et al., 1990) as drivers of short selling. Accounting for recent stock performance, none of these motives assigns a role to the mark-to-market profits of short sellers in explaining subsequent changes in their positions. To understand why such a role can exist, consider two stocks, A and B, for which short sellers are experiencing average mark-to-market losses and gains of 15%, respectively. In presence of funding and institutional constraints, cross-sectional differences in future short selling can emerge between these stocks that cannot be identified from their returns. Indeed, assume that over the following month both stocks experience a price increase of 10%. The return pushes short sellers of A into deep losses and trigger constraints such as additional margin calls that can render (some of) them unable to sustain their positions. By contrast, it leaves short sellers of B in positive mark-to-market profits territory and their positions likely to be unaffected. Disentangling this channel from other drivers of short selling is key to the ongoing debate on the role of short sellers in financial markets, as the destabilizing effect often associated with momentum-driven shorting (Diether et al., 2009) is clearly absent when changes in short selling are driven by margin calls or other capital restrictions.[2]

Since funding and institutional constraints do not bind when short sellers experience gains, we first hypothesize that, controlling for past returns, there is an asymmetric relationship between the short-selling activity in a stock and the mark-to-market profits of its current short sellers, whereby losses have a negative and larger (in absolute value) impact than gains. In line with this hypothesis, we find that short-selling losses have a statistically and economically significant negative relation with

[2]With the stated goal of maintaining market stability, several regulators across European and Asian countries temporarily banned short selling at the outset of the COVID-19 pandemic (Della Corte et al., 2020; Ostroff, 2020).

future short interest, whereas we find no effect of gains. We further find that a one-standard deviation increase in losses is associated with a drop of 6.5% of the mean short interest, revealing a similar economic relevance as the effect of past returns (momentum) on future shorting.

We further hypothesize that funding and institutional constraints are particularly tight when short sellers incur large losses. Brunnermeier and Pedersen (2009) show that higher margins or losses on existing short positions can lead arbitrageurs to reduce their positions in response to binding capital constraints ("funding liquidity risk"). In their model, the effect of speculators' capital on their positions is highly nonlinear, as a marginal change in capital has a small effect when speculators are far from, but a large effect when they are close to their constraints. Similarly, large losses are more likely to increase the size of a short position of an institutional investor beyond the maximum allowed by a portfolio weight constraint. To the extent that these constraints bind, the profit sensitivity of short selling should be highly asymmetric across different levels of losses, with larger losses having a disproportionally greater (negative) impact.

We find support for this prediction. First, short selling falls more after large losses than after small losses. Second, for medium (20%) to low (10%) thresholds separating large from small losses, only losses above the threshold have a statistically significant impact on future short selling. The effect is such that an increase in losses from 0 to 10% has no effect on short interest, while the same increase from 20% to 30% leads to a reduction in short interest as high as 8.6% of its sample mean. Lastly, gains have no significant impact on future short selling regardless of their size. Overall, these findings are consistent with a situation in which, as losses—but not gains—build up, short sellers' funding and institutional constraints become binding, forcing some of them to exit their positions.

We perform additional tests to disentangle the effect of short-selling frictions that operate at the stock level from those more likely to operate at the portfolio level, and discuss the plausibility of an alternative explanation for our findings. If stock-level frictions like margin requirements were a main constraint facing short sellers, the negative reaction of short selling to losses should be more pronounced among stocks with higher margins. Prime brokers typically impose additional ("special") margins on stocks with a history of high volatility or low liquidity to mitigate the risk of large losses to which these types of stocks expose them (Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2018).[3] The

[3]We employ proprietary information from a large prime broker to confirm these relations.

short sellers of these stocks could then face tighter funding constraints and their shorting activity be curbed to a greater extent. In line with this implication, we find that the effect of losses on short selling is substantially larger among stocks with higher volatility and lower liquidity. Second, stock-level losses might affect short selling only by worsening arbitrageurs' portfolio performance and increasing outflow risk (Shleifer and Vishny, 1997). We compute losses on the portfolio of the representative short seller and test whether these losses weaken, or even subsume, the effect of stock-level short-selling losses on future shorting. We find that stock-level frictions remain a significant determinant of short selling once we control for the effect of portfolio-level constraints. Lastly, we consider whether a "learning" channel, according to which losses prompt short sellers to revise down the profitability of their trades and trim their positions accordingly, can explain our findings. We argue that several of our results, including the significance of short-selling losses for future shorting when controlling for past returns, are inconsistent with this explanation.

It is an open question whether the covering of short positions following losses hurts the transmission of information to prices. Several studies have documented that short-sale limitations, including most notably outright bans, are detrimental for liquidity and price discovery (Bris et al., 2007; Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Boehmer et al., 2013; Jain et al., 2013). However, funding and institutional constraints such as margin requirements are fundamentally different from constraints such as short-selling bans. Unlike outright bans, margins do not prevent traders from establishing a short position, and unlike both shorting bans and restrictions, margins do not affect all short sellers in a stock but only those who suffer losses. These features make it unclear whether and how funding and institutional constraints should affect the transmission of short sellers' information to prices. On the one hand, they can have a detrimental effect on this transmission if, as studied by Liu and Longstaff (2004), short sellers are informed but suffer potentially large losses before fully profiting from their information. On the other hand, loss-related constraints should not impair the transmission of information to prices if short sellers are heterogeneously informed, so that losses belong predominantly to the lesser-informed sellers. If so, only the gain-making component of short selling should have explanatory power for stock returns, and conditioning on short-selling gains should improve the cross-sectional ability of short interest to predict returns.

We take this implication to the data in the last part of our analysis. In Fama-MacBeth regressions that control for past returns and other determinants, the power of short interest to predict future stock underperformance at one- to three-month horizons significantly increases with the fraction of short positions in the stock running gains (FRG). In double-sorted portfolios that first condition on short interest, stocks with higher FRG consistently underperform. Moreover, short interest has no predictive power among stocks in which all short sellers are experiencing losses. Consequently, the hedge portfolio that buys high-FRG stocks and shorts low-FRG stocks, among those most heavily shorted, returns value-weighted average four-factor alphas of -8.4% per annum over the subsequent three months. Altogether, these findings are consistent with loss-making short selling being uninformative about future returns and imply that, even when funding and institutional constraints are pervasive and economically significant—as evidenced by the sensitivity of short selling to large losses, the short selling they limit is relatively uninformed.

Our findings contribute to several strands of the literature. First, they contribute to the literature on the limits to arbitrage, and more precisely to the strand emphasizing the role of capital requirements and margin constraints. Shleifer and Vishny (1997) is the first paper to posit that the ability of arbitrageurs to correct mispricing is constrained by the risk of fund withdrawals in response to trading losses. In deriving the optimal strategy of a risk-averse investor in an arbitrage opportunity whose short leg must be collateralized, Liu and Longstaff (2004) show that temporary losses might force the investor to close the position before being able to profit from it. Gromb and Vayanos (2002) study the welfare implications of margin requirements that limit the role of arbitrageurs. In Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2018) lenders endogenously vary margins according to asset illiquidity and volatility to protect themselves against default after extreme price increases. We provide empirical evidence on the extent to which these funding constraints bind. Our findings suggest that, as predicted by these models, the constraints can force short sellers to close their positions after losses. Perhaps more surprisingly, our analysis also indicates that the shorting activity most affected by these frictions is relatively uninformed, thus less likely to reflect arbitrage trades. This is in line with Geczy et al. (2002), who find that short-selling constraints have a limited impact on well-accepted arbitrage portfolios such as size, book-to-market, or momentum.

Second, we complement the literature on the motivation of short sellers and their reaction to past returns. Besides the exploitation of short-term overvaluation or return momentum, recent studies have examined the past performance of short sellers, inferred from past stock returns, as a determinant of short-selling activity (Savor and Gamboa-Cavazos, 2014; von Beschwitz and Massa, 2017; Boehmer et al., 2018). For each stock and date in our sample we examine both the level and the entire distribution of short-selling profits based on the actual price at which short positions are established. This allows us to test, as predicted by limits of arbitrage theories, whether the different *levels* of gains and losses that the short sellers of a stock experience have an asymmetric impact on their shorting activity in the stock.

Third, we contribute to the literature on the information content of short selling. Diamond and Verrecchia (1987) develop a theoretical model in which the costs associated with short selling squeeze liquidity traders out of the order flow, making short orders more informative than the population of regular sell orders. Several studies find empirical support for this prediction. At the aggregate stock market level, Rapach et al. (2016) exploit monthly data over a 42-year period to show that short interest is a strong predictor of the stock market returns. In the cross-section, the informativeness of short sales has been documented at the intraday (e.g., Aitken et al., 1998), daily (e.g., Boehmer et al., 2008) and monthly (e.g., Desai et al., 2002) frequencies. We take advantage of our unique data on the *distribution* of profits across a stock's short positions to shed more light on these empirical findings. In particular, we show that the power of short selling to predict returns is driven by the component experiencing gains, consistent with gains-making short sellers being relatively more informed.[4]

The rest of the paper is organized as follows. Section 2 develops our testable hypotheses. Section 3 describes our dataset and presents summary statistics. Section 4 characterizes the profits to equity short selling in the aggregate market and in the cross-section. Section 5 turns to the relation between future short interest and past losses and gains. Section 6 documents the information content of the losses and gains of short sellers about future returns. Section 7 concludes.

[4]Engelberg et al. (2012) and Boehmer et al. (2017) show that the predictive power of short interest improves, respectively, on days with public news, and in countries with mild forms of short-sale restrictions, better market quality, and more developed markets.

2 Hypotheses Development

Prior studies emphasize two motivations for speculative short selling. According to the first, "valuation-based" motive, short sellers trade to profit from stock overvaluation and subsequent price correction to fundamental value. For example, Diether et al. (2009) find that short selling increases following positive returns, consistent with short sellers trading against overvaluation driven by short-term overreaction. According to the second, "momentum-based" motive, short sellers bet on the continuation of stock underperformance in the recent past (see Lamont and Stein, 2004 and Curtis and Fargher, 2014). The main driver of short selling under both views is the stock's recent performance.[5] The literature also considers short selling for non-speculative purposes, such as convertible arbitrage, dividend-related tax arbitrage or index arbitrage (see Brent et al., 1990). None of these motivations assigns a role, after accounting for past returns, to the mark-to-market profits of short sellers.

In practice, short sellers face several funding and institutional constraints that could render profits relevant for their shorting activity. First, they must borrow the security they short. To limit their counterparty credit risk, lenders require short sellers to post the proceeds from the sale along with additional cash in a margin account.[6] Since this account is marked to market, short sellers that incur losses have to put in additional capital to maintain their trades. Mark-to-market losses could then lead short sellers to cover their positions. Indeed, in deriving the optimal strategy of a risk-averse investor in an arbitrage opportunity whose short leg must be collateralized, Liu and Longstaff (2004) show that temporary losses might force the investor to close the position before being able to profit from it. Similarly, Brunnermeier and Pedersen (2009) present a model in which, over the life of a trade, higher margins or losses on existing short positions can make capital constraints bind ("funding liquidity risk") and induce arbitrageurs to reduce their positions. Second, investment mandates typically require institutional short sellers (e.g., hedge funds) to adhere to risk management practices such as Value-at-Risk (VaR) and portfolio weight constraints that effectively limit the maximum allowable loss on a particular position. Third, institutional short sellers that act as agents for owners of capital

[5] Diether et al. (2009) argue that short sellers could also act as voluntary providers of liquidity or of additional risk-bearing capacity in periods of elevated uncertainty. For example, short sellers can provide liquidity when liquidity-motivated buying pressure drives prices up.

[6] In the U.S., Regulation T (Sec. 220.12 (c)) requires short sellers to deposit 150% of the value of the short position in a margin account. Some prime brokers offer hedge funds offshore investment facilities in less restrictive jurisdictions, allowing them to reduce (but not eliminate) the effective margin requirements on their short positions (Ang et al., 2011).

might be additionally forced to close their positions prematurely according to Shleifer and Vishny (1997) if poor portfolio performance leads to fund outflows. Since none of these constraints binds when short sellers experience gains, we hypothesize that:

Hypothesis 1 (H1): *Controlling for past returns, there is an asymmetric relationship between the short-selling activity in a stock and the mark-to-market profits of its current short sellers, whereby losses have a negative and larger (in absolute value) impact than gains.*

Funding and institutional constraints should be particularly tight when short sellers incur large losses. For instance, in Brunnermeier and Pedersen (2009) the effect of speculators' capital on their positions is highly nonlinear, with a marginal change in capital having a small effect when speculators are far from their constraints, but a large effect when they are close to their constraints. Similarly, large losses are more likely to increase the size of a short position of an institutional investor beyond the maximum allowed by a portfolio weight constraint. Hence, the profit sensitivity of short selling that we consider in Hypothesis **H1** should differ not only between gains and losses, but also across different levels of losses, motivating our next hypothesis:

Hypothesis 2 (H2): *Larger losses on the short positions of a stock have a disproportionally greater (negative) impact on the stock's short selling.*

Importantly, we note that the stock pricing implications of these "loss-related" constraints depend on whether the short sellers they constrain are informed or uninformed. In Diamond and Verrecchia (1987), short-selling restrictions and outright prohibitions can negatively affect the speed of transmission of information to prices. Their theoretical prediction has found empirical support in the analyses of Bris et al. (2007), Saffi and Sigurdsson (2011), Boehmer and Wu (2013), and Beber and Pagano (2013).[7] However, loss-related constraints are fundamentally different. First, unlike outright bans, they do not prevent traders from establishing a short position. Second, unlike both shorting bans and restrictions, they do not affect all short sellers in a stock but only those suffering losses.

These observations make it unclear whether and how loss-related constraints should affect the

[7] More recently, Engelberg et al. (2018) show that the dynamic risks associated with the variation in shorting fees over time result in significant limits to arbitrage.

transmission of short sellers' information to prices. They can have a detrimental effect on this transmission if, as studied by Liu and Longstaff (2004), short sellers are informed but suffer potentially large losses before fully profiting from their information. In this case, conditioning on the profits (gains or losses) of short sellers should not enhance the well-documented predictive power of short interest in the cross-section. In contrast, loss-related constraints should have no detrimental effect on the transmission of information to prices when the short selling they restrict is relatively uninformed. This would be the case if short sellers are heterogeneously informed (Boehmer et al., 2008), so that the lesser-informed sellers on average lose money on their trades with better-informed investors. If so, only the gain-making component of short selling should have explanatory power for stock returns, and conditioning on short-selling gains should improve the cross-sectional ability of short interest to predict returns. We contrast these opposing views by testing the following hypothesis:

Hypothesis 3 (H3): *The predictive power of short interest in the cross-section does not vary with the profits of short sellers.*

Accordingly, we interpret a lack of evidence against this null (or evidence of a negative relation between short sellers' gains and the predictive power of short interest) as supporting the first view that loss-constrained short sellers are informed. By contrast, we interpret an empirical rejection of this null as supporting the second view that loss-constrained short sellers are relatively uninformed.

3 Data and Summary Statistics

In this section we describe our data, key variables and summary statistics.

3.1 Short-Selling Profits Dataset

We use a novel dataset on the profits of short sellers from IHS Markit, a leading industry financial data provider. IHS Markit collects transaction-level information on the securities lending market—an over-the-counter (OTC) market—directly from a variety of participants. These include prime brokers, custodians, asset managers and hedge funds, who together account, according to Markit, for about 90% of the securities lending market in developed countries. We focus on the U.S. market, for which their database covers a broad cross-section of 4,000 stocks for a total of approximately 5.7 million stock-day observations over the period spanned between January 2011 and December 2017.

From this database we observe, for each stock i and day t, the full distribution of gross-of-fees mark-to-market (cumulated) returns being experienced by the short sellers of i from the start date of their transactions (the initiation date for new transactions and the original start date for renewing transactions) until t.[8] These returns are tabulated over 19 bins. Each of the bins, which we denote by $bin_{i,t}^{\lfloor n \rfloor}$ ($n = 1, \dots, 19$), represents the fraction of shares on loan for stock i whose cumulated returns fall in the nth return interval—with left and right boundaries '$\lfloor$' and '$\rfloor$'—at time t. The first 10 intervals ($n = 1, \dots, 10$) correspond to the negative domain of the distribution and are defined as follows: $(-\infty, -100\%]$, $(-100\%, -75\%]$, $(-75\%, -50\%]$, $(-50\%, -40\%]$, $(-40\%, -30\%]$, $(-30\%, -20\%]$, $(-20\%, -15\%]$, $(-15\%, -10\%]$, $(-10\%, -5\%]$, and $(-5\%, 0\%]$. The remaining 9 intervals ($n = 11, \dots, 19$) cover the positive domain of the distribution in a specular fashion, from $(0\%, 5\%]$ for $n = 11$ to $(75\%, 100\%]$ for $n = 19$. Additionally, we observe the weighted average (with weights given by the number of shorted shares) mark-to-market *dollar* profit per share shorted of the stock, $\$PnL$, where a negative profit corresponds to a *loss* and a positive profit to a *gain*.

As an example, we illustrate an instance of the data in Figure 1, which depicts the distribution of mark-to-market returns to the short positions in Herbalife Nutrition as of October 31, 2017. Consistent with a large and positive year-to-date stock return of 50.2%, approximately 70% of the shares on loan were experiencing losses. Still, a non-negligible fraction of short sellers (30%) were experiencing gains in the 0 to 10% range, with most of them located in the $(5\%, 10\%]$-gains interval.[9]

Based on the different return bins, we capture the mean level of profits of a stock's short sellers by computing the weighted average gross cumulated return, PnL, as:

$$PnL_{i,t} = \sum_{n=1}^{N} bin_{i,t}^{\lfloor n \rfloor} \times \frac{\lfloor n + n \rfloor}{2} = bin_{i,t}^{(-100,-75]} \times (-87.5) + bin_{i,t}^{(-75,-50]} \times (-62.5) + \dots + bin_{i,t}^{(50,75]} \times 62.5 + bin_{i,t}^{(75,100]} \times 87.5. \tag{1}$$

[8] Since U.S. equity short sellers need to borrow the stocks they sell, IHS Markit infers short-selling activity from transactions in the stock lending market. To determine the date on which the initial short was placed with the broker, IHS Markit uses $T - 3$ from the stock lending start date assuming a 3-day settlement, unless the stock is experiencing relatively high borrowing costs, in which case they use same-day pricing assuming high demand to short the stock.

[9] Herbalife's stock price on October 31 was not a historical maximum.

We further compute the total fraction of shares shorted running gains, FRG, as

$$FRG_{i,t} = \sum_{n=11}^{19} bin_{i,t}^{\lfloor n \rfloor} = bin_{i,t}^{(0,5]} + \ldots + bin_{i,t}^{(75,100]}, \tag{2}$$

from which the total fraction of shares shorted experiencing losses is simply $FRL = 1 - FRG$. FRG (FRL) allows us to separate the short positions in a given stock into different groups depending on their profitability.

There are limitations to our data. First, short-selling activity is inferred from transactions in the stock lending market, which excludes any short selling that is initiated and covered within the day ("in-and-out shorting"). As such, we capture the profits of short-selling activity other than intraday shorting. Because stock borrowing constraints and firm fundamentals should play only a minor (if any) role in intraday shorting, we believe that this limitation should not invalidate our analysis. Second, we do not observe the identity of short sellers or their motives. This implies that we cannot perfectly distinguish speculative short selling, more likely to act on fundamental information, from non-speculative activity (e.g., shorting in response to hedging needs). We examine informed versus uninformed activity in more detail in Section 6.

3.2 Auxiliary Data Sources

We use the stock's CUSIP identifier in our short-selling profits database to merge it with an array of standard datasets. We obtain information on the stock borrowing and lending activity from the Markit Securities Finance Buyside Analytics Datafeed. We obtain stock market prices and other stock characteristics data from CRSP and compute various financial accounting ratios using information from COMPUSTAT. Finally, we collect information on special margin requirements on U.S. stocks from a large stockbroker. We drop stocks with market capitalization below $10 million or prices below $1.

3.3 Summary Statistics

Panel A of Table 1 presents summary statistics for the different bins of returns to short selling. Overall, 53.3% of the shares of the stock on loan experience losses during our sample period. For the average stock, about 4.1% (=1.89+1.04+1.15+0.40) and 4.4% (=1.75+0.95+0.92+0.12) of the short positions in the sample are characterized by losses and gains, respectively, larger than 30%. Panel B of Table 1 displays summary statistics for the level of profits to short selling in the cross-section. The average share shorted in our sample cumulates negative returns (PnL) and dollar losses ($\$PnL$) of, respectively, 2.1% and \$0.79. Figure 2, which displays the time-series dynamics of the cross-sectional distribution of PnL, indicates that these mean losses are not concentrated on a particular period, but rather characterize the mark-to-market performance of the typical shorted share throughout most of the sample.[10] However, there is substantial cross-sectional variation insofar as the upper and lower deciles of PnL fluctuate around 15% and -20%, respectively.

Panel C of Table 1 displays summary statistics for our equity lending variables. The characteristics of the stocks in our sample are in line with previous studies (e.g., D'Avolio, 2002). In particular, the mean fraction of shares available for lending is 21.6% of the total market capitalization and the mean short interest is 3.9%.[11] The mean borrowing fee is 1.24% per annum while the mean time over which a short position is open is 83 days. Since summary statistics for stock and firm characteristics, displayed in Panel D, are also consistent with prior studies, we conclude that our sample of stocks is comparable with those examined in related literature.

4 A Characterization of Short-Selling Profits

Given that the mark-to-market losses of short sellers play a key role in our hypothesis development, we first characterize the profits to short selling both in the overall stock market and in the cross section of stocks.

[10] Noticeable exceptions are the large mean short-selling profits during the sharp market declines of August-September 2011 and January 2016.

[11] As is standard in the literature (see, e.g., Boehmer et al., 2017), we approximate total open short positions in a stock, or "short interest," by the number of shares of the stock borrowed in the lending market. We follow Richardson et al. (2017) in using the shares borrowed on date $t + 3$ to estimate the short interest at t, except in regressions with returns as dependent variables, in which case we use the shares borrowed on date t to avoid conditioning on an unobservable variable.

4.1 The Overall Profitability of Short Selling

We examine two market-wide measures of mark-to-market profits. The first measure is the equal-weighted cross-sectional average of annualized returns to short selling, $\overline{PnL}_t^{ann}$:

$$\begin{aligned}\overline{PnL}_t^{ann} &= \frac{1}{N_t}\sum_{i=1}^{N_t}[(1+PnL_{i,t})^{1/Tenure_{i,t}}-1]\times 252,\\ &= \frac{1}{N_t}\sum_{i=1}^{N_t}PnL_{i,t}^{ann},\end{aligned} \tag{3}$$

where N_t is the number of stocks in the sample at time t; $Tenure_{i,t}$ is the weighted average number of days over which the positions have been open; and $PnL_{i,t}^{ann}$ is the annualized version of the PnL measure (1) that allows for comparability of returns cumulated over different position durations.

The second measure is the aggregate mark-to-market dollar profits to short selling across stocks relative to the total value of the positions:

$$\$PnL\_to\_Short_t = \frac{\sum_{i=1}^{N_t}\frac{252}{Tenure_{i,t}}\$PnL_{i,t}\times Q\_short_{i,t}}{\sum_{i=1}^{N_t}P_{i,t}\times Q\_short_{i,t}},$$

where $\$PnL_{i,t}$ is the average dollar profit/loss per share shorted described in subsection 3.1; $Q\_short_{i,t}$ is the number of shares shorted; and $P_{i,t}$ is the stock price. Similarly to $\overline{PnL}^{ann}$, we annualize our measure of profits in the numerator of $\$PnL\_to\_Short$ for comparability purposes. In comparison with $\overline{PnL}^{ann}$, $\$PnL\_to\_Short$ is a weighted average of the dollar profits to short selling, with weights proportional to the size of the positions in each stock. We report time-series summary statistics for $\overline{PnL}^{ann}$ and $\$PnL\_to\_Short$ both gross and net of shorting fees in Table 2.[12]

The rows corresponding to $\overline{PnL}^{ann}$ indicate that, on a typical day, a short position in the average stock runs at a loss of 10.5% gross of shorting fees (Panel A), and 11.6% net of fees (Panel B). These losses are not disproportionate by comparison with the strong performance of the overall stock market during our sample period (see Figure 2), when the S&P 500 index returned an average of 15.7% per year over the risk-free rate. The returns to short selling exhibit high dispersion in the time series, but experience negative territory (net of fees) on at least 75% of the days. Returns can be high in positive

[12]Specifically, we follow Diether (2011) in adding the rebate rate $r_t^f - fee_{i,t}$, computed as the difference between the (annualized) risk-free rate r_t^f and the stock borrowing fee $fee_{i,t}$, to the gross profits of short sellers.

payoff days, however, as on 5% of the days the cumulated annualized return to a short positions exceeds 26% and 24% on gross-of-fees and net-of-fees bases.

When aggregating positions across all stocks in the rows corresponding to $\$PnL\_to\_Short$, mark-to-market losses to short selling amount to 4.2% and 5.1% of the aggregate value of the positions on gross-of-fees and net-of-fees bases, respectively. While the dispersions in $\$PnL\_to\_Short$ and $\overline{PnL}^{ann}$ are similar, $\$PnL\_to\_Short$ is positive on a larger fraction of days. Indeed, the gross-of-fees and net-of-fees annualized gains to short selling exceed 2.2% and 1.2% of the value of the positions, respectively, in 25% of the days in our sample.

It is important to note that the aggregate losses to short selling that we document in this section are not inconsistent with short sellers being sophisticated or with particular groups of short sellers outperforming on a risk-adjusted basis, as has been documented by earlier studies. For example, Jank and Smajlbegovic (2017) analyze daily disclosures of large short positions of hedge funds in Europe and report annualized Fama-French three-factor alphas as high as 5.5%. Similarly, Choi et al. (2017) find significant abnormal returns among the short-termed short trades of U.S. hedge funds. Because the portfolios of short sellers typically have negative exposure to the market and other priced factors, an average loss in a bull market period can very well correspond to an outperformance on risk-adjusted bases. Moreover, short sellers could suffer losses in the aggregate yet consistently experience gains across specific firm or stock characteristics. We investigate whether this is the case in the next section.

4.2 The Profitability of Short Selling in the Cross-Section

Economic intuition and prior literature point to several firm and stock characteristics that could affect the cross-sectional dispersion in short-selling profits that we observe in Figure 2. The stock's recent performance has a direct and first-order impact on the cumulated returns to its short positions, as these returns increase (decrease) following negative (positive) stock returns. We measure recent stock performance using the stock's cumulated returns $ret(-t_1, -t_2)$ over the previous $t = t_2 - t_1 + 1$ days, with t equal to one or six months. To the extent that short sellers take advantage of better information (Cohen et al., 2007) or information-processing ability (Engelberg et al., 2012), their profits depend on the economic uncertainty and degree of information asymmetry surrounding a firm. Our proxies for these characteristics are the stock's realized variance ($Variance$, the sum of squared daily returns), the average turnover ($Turnover$), and the average bid-ask spread ($BA\,Spread$) over the previous month (see, e.g., Diether et al., 2009). Because short sellers should require higher gross-of-fee returns on stocks that are more costly to borrow (as theoretically argued, e.g., by Diamond and Verrecchia, 1987), the conditions in the equity lending market, including the cost of borrowing a stock, could also be related to the (gross) profitability of short selling. We thus examine a stock's shares on loan as a measure of borrowing demand ($Short\_Interest$), the number of lendable shares available as a measure of supply ($Supply$), the borrowing fees (Fee) as a measure of short-selling costs, and the weighted average duration of the short positions ($Tenure$). Across firms, other characteristics associated with fundamental value could covary with the profitability of short selling. These include the ratio of market value to book value of assets ($Market\ to\ Book$) and the market capitalization ($Size$).[13]

Table 3 reports the $\overline{PnL}^{ann}$ (Panel A, gross of shorting fees) and $\$PnL\_to\_Short$ (Panel B, net of fees) measures introduced in Section 4.1 across deciles of firm and stock characteristics. As expected, short-selling profits are strongly negatively related with recent stock performance. This is consistent with the cumulated profits on short positions (mechanically) increasing after negative returns, as well as with short sellers profiting from downside momentum among losing stocks. Interestingly, short-selling profits typically increase with a stock's demand for short selling (SI), confirming the negative relation between short interest and future returns documented in the literature (see, e.g., Desai et al., 2002 and Boehmer et al., 2008). Consistent with the notion that short sellers have better information or information-processing ability, short selling is more lucrative under higher information asymmetry (higher $Variance$, $BA\,Spread$ and $Turnover$), as well as among smallcaps (low $Size$). In the Appendix A, we confirm the statistical significance of these relations in multivariate regressions that account for the cross correlation in the data.

From Panel A of Table 3 we see that, despite suffering losses on the average stock (as argued in Section 4.1), short positions consistently experience *gains* on specific stock categories. This is clearly the case for stocks in the low-past return deciles and, more interestingly, for stocks with high

[13]The market value of assets is computed as the sum of the closing stock price (COMPUSTAT item: PRCCQ) multiplied by the common shares (COMPUSTAT item: CSHPRQ), debt in current liability (COMPUSTAT item: DLCQ), long-term debt (COMPUSTAT item: DLTTQ), and preferred stocks (COMPUSTAT item: PSTKQ), minus deferred taxes and investment tax credit (COMPUSTAT item: TXDITCQ).

information asymmetry (high $BA\,Spread$), the highest shorting fees, and the smallest size.

Moreover, when we examine $\$PnL\_to\_Short$ in Panel B, some of the losses reported in Panel A turn into gains even after accounting for shorting fees. For example, the stocks in size deciles 2 to 5 exhibit a negative mean $\overline{PnL}^{ann}$ in Panel A. The reason for this is that $\overline{PnL}^{ann}$ is higher among more heavily shorted stocks. Thus, the large profits that short sellers as a group make on possibly a few heavily shorted stocks can offset some of the losses they incur on potentially many lightly shorted stocks.[14] Short sellers experience sizable net-of-fee gains also on the top half of stocks sorted by bid-ask spread, on the bottom 30% of stocks sorted by market-to-book, as well as on the most heavily shorted stocks. The latter result reveals that the profitability of high-short interest portfolios documented in previous studies is actually exploited by real-life short sellers and translates into positive aggregate profits on their positions in certain stocks.

5 Implications of Short-Selling Profits on Shorting Activity

In this section we examine, following hypotheses **H1** and **H2**, whether and how short selling responds to past performance, and whether this response is asymmetric with respect to gains versus losses.

5.1 Effects of Mark-to-Market Losses and Gains

According to our first hypothesis (**H1**), the mark-to-market profits of a stock's short sellers have a separate effect from past returns on the shorting activity in the stock, whereby differences in the extent to which loss-related constraints bind can lead stocks with similar returns to experience different subsequent shorting. Assessing the level of profits of a stock's short positions is not possible without information on when the positions are established. Thus, an innovation of our data relative to existing ones is that it allows for a quantitative examination of this hypothesis. To this end, we first regress future short interest on short-selling profits, past returns and other control variables following the

[14] A numerical example illustrates this point. Assume short sellers sell 1 share of stock A and 100 shares of stock B, both of which are traded at \$100 per share. After one year, stocks A and B trade at \$110 and \$99, respectively, so the returns and dollar profits per share sold short are: $PnL_A^{ann} = -10\%$, $PnL_B^{ann} = 1\%$, $\$PnL_A = -\$10$, and $\$PnL_B = \$1$. The average PnL across the stocks, $\overline{PnL}^{ann}$, is negative and equals -4.5% (=(-10+1)/2). However, assuming no fees $\$PnL\_to\_Short$ is positive and equals 0.9% $(= (-\$10 \times 1 + \$1 \times 100)/(\$110 \times 1 + \$99 \times 100))$.

specification of Diether et al. (2009) and Curtis and Fargher (2014):

$$SI_{i,t+1} = \beta \times PnL_{i,t} + \gamma' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1}, \tag{4}$$

where $SI_{i,t}$ and $PnL_{i,t}$ are, respectively, short interest and the profit variable defined in Section 3.1 for stock i at time t; $x_{i,t}$ is a vector of firm and stock characteristics that includes past returns and a range of additional control variables[15] (as introduced in Section 4) that have been related to short selling in the prior literature (see, e.g., Reed, 2013); and α_i and τ_t denote, respectively, firm and time fixed effects. We present our estimates in the first column of Table 4.

The positive and strongly statistically significant coefficient estimate for PnL provides evidence of a separate effect of short-selling profits from past stock returns on the shorting activity in a stock. The point estimate of β implies not only that short interest is lower following losses (a negative value of PnL) than following gains (a positive value of PnL), but also that the effect is economically significant, as a one-standard deviation increase in PnL raises short interest by 6.2% of its sample mean. By comparison, a one-standard deviation decrease in past three-month stock returns raises short interest by 9% of its sample mean, so the effect of PnL on short interest is in the same order of magnitude as the effect of past returns.

Having established a role for short sellers' profits in affecting future short selling we next examine whether, following hypothesis **H1**, this effect follows primarily from a negative sensitivity of short selling to losses rather than from a positive sensitivity to gains. To this aim, we split PnL into loss (defined as $-min(0, PnL)$) and gain (defined as $max(0, PnL)$) variables, and regress future short interest on each of these variables and the set of controls in Eq. (4):

$$SI_{i,t+1} = \beta_1 \times Loss_{i,t} + \beta_2 \times Gain_{i,t} + \gamma' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1} \tag{5}$$

Our estimates, presented in column (2) of Table 4, highlight a clearly asymmetric effect of losses versus gains on short selling that validates hypothesis **H1**. First, the mark-to-market losses of short sellers show a strongly negative association with future short interest. The effect is economically

[15] We include Variance, BA spread, Turnover, Supply, Fee, Tenure, Market-to-Book, Size, Profitability and Leverage.

large, as a one-standard deviation increase in prior losses is associated to a reduction of 6.5% in short interest relative to its sample mean. Second, the mark-to-market gains of short sellers have no discernible impact on future short interest, as the coefficient for *Gains* is statistically insignificant. The estimated coefficients for the control variables across columns (1) and (2) imply that longer-term returns are negatively correlated with short-selling activity, supporting the findings of Lamont and Stein (2004) and Curtis and Fargher (2014) that short sellers follow momentum strategies.

Overall, the statistical and economic significance of PnL in Eq. (4) and $Loss$ in Eq. (5), when simultaneously controlling for past returns, indicates that short sellers' profits affect their shorting activity through a distinct channel from momentum trading or the adjustment of short positions to the information short sellers learn from past prices. We delve deeper into the difference between constraints and learning in Section 5.3.3.

5.2 Nonlinearities in the Relation between Profits and Short Selling

Following hypothesis **H2**, if the asymmetric response of short selling to losses versus gains is driven by loss-related (funding and institutional) constraints facing short sellers, we should expect the loss sensitivity of short sellers' positions to increase with their mark-to-market losses. To test this hypothesis, we estimate piecewise linear regressions that differentiate between losses and gains that are smaller or larger than a threshold τ%:

$$SI_{i,t+1} = \lambda_1 Loss_{i,t}^{[\tau,\infty)} + \lambda_2 Loss_{i,t}^{[0,\tau)} + \gamma_1 Gain_{i,t}^{(0,\tau]} + \gamma_2 Gain_{i,t}^{(\tau,100]} + \beta' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1}, \tag{6}$$

for $\tau \in \{50, 30, 20, 10\}$. In (6), $Loss_{i,t}^{[\tau,\infty)}$ is equal to $-PnL_{i,t}$ if $PnL_{i,t} \leq -\tau$ and zero otherwise; $Loss_{i,t}^{[0,\tau)}$ is equal to $-PnL_{i,t}$ if $-\tau < PnL_{i,t} \leq 0$ and zero otherwise; $Gain_{i,t}^{(0,\tau]}$ is equal to $PnL_{i,t}$ if $\tau \geq PnL_{i,t} > 0$ and zero otherwise; $Gain_{i,t}^{(\tau,100]}$ is equal to $PnL_{i,t}$ if $PnL_{i,t} > \tau$ and zero otherwise; $x_{i,t}$ is the vector of firm and stock characteristics that we employ in Table 4, and α_i and τ_t are firm and time fixed effects, respectively. We include both losses and gains of different magnitude to rule out the possibility that the insignificance of gains in the regression models above is the result of model misspecification (e.g., opposite signs for small and large gains). We report our regression estimates in Table 5.

Our results suggest that constraints bind more following larger losses and support hypothesis **H2**. First, comparing point estimates, the negative sensitivity of short selling to large losses is greater (in absolute value) than to small losses across all threshold specifications. This is more evident when the kink in the piecewise specification (6) is set to 20%, but it also holds for both larger and smaller kinks. Second, for medium (20%) to small (10%) thresholds τ only losses above the threshold have a statistically significant impact on future short selling. Indeed, while $Loss_{i,t}^{[\tau,\infty)}$ is significant at least at the 1% level across columns of Table 5, $Loss_{i,t}^{[0,\tau)}$ is statistically insignificant in the third and fourth columns. The effect is such that an increase in losses from 0 to 10% has no effect on short interest, while the same increase from 20% to 30% leads to a reduction in short interest as high as 8.6% of its sample mean. Third, and in line with the results of Table 4, gains have no significant impact on future short selling regardless of their size, indicating that our results above are not an artifact of imposing a linear relationship between gains and short selling.

Together with our findings in the previous section, these results provide evidence that the accumulation of losses results in some short sellers exiting their trades.

5.3 Additional Analysis

So far, our analysis of the relation between short-selling losses and shorting activity has not distinguished among the different funding and institutional frictions that are consistent with such relation. We next look deeper into the potentially separate effect of these constraints, with emphasis in distinguishing between the type of frictions that operate at the stock level (margin requirements, VaR and position limits) from those that are more likely to operate at the portfolio level (fund withdrawals in response to poor performance). We further discuss the possibility that a third channel unrelated to these frictions, namely the learning of short selling from their own performance, explains our findings of Sections 5.1 and 5.2.

5.3.1 Margin Requirements and the Reaction of Short Selling to Losses

A potential source of differences in margin requirements across stocks is the possibility that stockbrokers impose "special" margins, in addition to the standard margins required by regulation T, on certain stocks. Special margins aim to reduce the counterparty risk that equity lenders face. According to Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2018), they should be particularly valuable among stocks with a history of high volatility or low liquidity, whose price can change dramatically over a short period. Short sellers of these stocks should then face tighter margin requirements and their ability to short sell should be further curbed. Equivalently, we expect the asymmetric effect of short selling losses versus gains of hypothesis **H1** to be more prevalent among more volatile and illiquid stocks.

To investigate this hypothesis we first confirm empirically the positive relationship between margin requirements and stock volatility ($Variance$) and illiquidity (*BA Spread*) hypothesized by Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2018) using proprietary information from a large prime broker (we report our analysis and results in Appendix B). We then split our sample of stocks in two based on their values of either $Variance$ or *BA Spread* ("Low" and "High" columns) and repeat the analysis from the second column of Table 4 on each of these subsamples. We report our estimates in Table 6.

In line with hypothesis **H1**, the results highlight the role of margin requirements in limiting short selling. First, while the short selling in stocks of both above- and below-median volatility react to losses and do not respond to gains, point estimates of the effect are 68% larger for the subsample of high-volatility stocks ($\beta_1 = -0.016$, with a t-statistic of -6.11), compared to the subsample of low-volatility stocks ($\beta_1 = -0.01$, with a t-statistic of -2.74). Second, short selling in stocks with above-median illiquidity (high *BA spread*) reacts significantly negatively to past losses ($\beta_1 = -0.016$, with a t-statistic of -5.95), while short selling in stocks with below-median illiquidity is insensitive to both losses and gains.[16]

5.3.2 Aggregate versus Stock-Level Losses

It is possible that the effect of stock-level losses on short selling further reflects the more general effect of outflow risk on arbitrage first suggested by Shleifer and Vishny (1997), according to which institutional short sellers who suffer outflows triggered by losses at their overall portfolio level are forced to close

[16]In Table 4 short selling responds significantly positively to past gains among stocks with high bid-ask spreads. We note that the asymmetry in impacts of losses versus gains underlying hypothesis **H1** is still present in economic terms: in the comparison of magnitudes of point estimates, the coefficient on losses is about 1.5 times the coefficient on gains.

their positions. Even though we observe short positions at the stock- but not the portfolio-level, we can approximate the portfolio of the representative short seller in our sample by computing, at each point in time, the aggregate portfolio of all short-selling positions across stocks. Adding the losses and gains on this portfolio as controls for the portfolio-level profits of the representative short seller, we can then reestimate equation (5) to test for the importance of stock-level versus portfolio-level profits on short selling in the cross-section.[17] We present the results of this analysis in Table 7.

Regardless of the weighting methods used in the aggregation of short positions, two results are evident. First, even with an arguably noisy proxy for the portfolio level performance of short sellers, we find that portfolio-level losses matter for the shorting activity in a stock. The estimates in the first and third columns, where only aggregate short-selling profits are considered, indicate that the asymmetric effect of losses versus gains on equity shorting of hypothesis **H1** is present even when these are measured at the overall portfolio level.

Second, controlling for portfolio-level short-selling profits, stock-level losses—but not gains—keep a strong and significantly negative relation to future shorting. If portfolio-level constraints subsumed the role of stock-level funding and institutional constraints on future shorting, we would expect the results in section 5.1 to weaken, or even disappear, once we control for short sellers' performance at the portfolio level in the second and fourth columns. In contrast with this implication, we find that the coefficients for both *Loss* and *Gain* and their statistical significance remain virtually unchanged relative to Table 4.

5.3.3 Short Seller's Learning

In a realistic context in which short sellers face uncertainty about stock returns, one could argue that a separate channel between short-selling profits and the shorting activity in a stock could exist regardless of whether short sellers face financial constraints or not. According to this "learning channel," short sellers would learn about the (unobservable) true profitability of their trades from their (observed) past performance, with their updated beliefs being an increasing function of their short-selling profits. Under this logic, losses would prompt short sellers to revise down the profitability of their trades and trim their positions accordingly, similarly to what we find in our foregoing analysis.

[17] We remove time-fixed effects since they absorb the variation in aggregate short-selling gains and losses.

Notwithstanding the plausibility of the learning channel, we offer several reasons why it cannot fully account for our findings. First, the cumulated performance on a short position contains no additional information about the stock's prospects over the stock's past returns in the same period. Thus, any learning effect of short-selling profits on future shorting in our analysis of sections 5.1 and 5.2 should be directly captured by the stock's past returns over different horizons that we add as controls in our regressions, leaving short-selling profits (both losses and gains) to reflect the effect of other, unrelated, determinants.

Second, a standard learning argument would predict that gains also should matter for the inference of short sellers about the profitability of their trades, but also gains. Moreover, there is no reason to expect asymmetries in the relation between short-selling profits and future shorting as the effect of gains on that inference, in standard learning models, is symmetric to the effect of losses. The insignificant effect of shorting gains on future short selling, and the highly asymmetric relation between short-selling performance and shorting activity that our analysis above uncovers, is strongly at odds with this type of explanation of our findings.

Finally, the learning argument also requires that short sellers learn more slowly, thus change their positions less dramatically, in stocks with more volatile returns, whose signal-to-noise is lower. Once again, this implication goes in the opposite direction to our findings in Section 5.3.1, which indicate that the effect of losses on future shorting is much stronger among the higher return volatility stocks.

6 The Information in Gains and Losses about Future Returns

Following hypothesis **H3**, we assess the relative information content of loss-making versus profitable short positions. Our proxies for the fractions of short positions in a stock experiencing losses and gains are the FRL and FRG variables defined in Section 3. If loss-making positions are as informative as profitable positions we should observe, for a *given* level of short interest, that the predictive power of short interest on the stock's future returns should not increase with FRG (equivalently, decrease with FRL).[18] We test this hypothesis using multivariate regressions to control for well-known cross-sectional return determinants, and calendar-time portfolios to assess the economic significance of our

[18] Given that $FRL = 1 - FRG$, we can focus our test on FRG only. All results can be interpreted as applying equivalently (although with the opposite sign) to FRL.

findings.

6.1 Cross-sectional Regressions

Following Boehmer et al. (2008), we run daily Fama-MacBeth return regressions of the form:

$$ar_{i,t+h} = \alpha + \beta SI_{i,t} + \gamma FRG_{i,t} + \delta\Big(SI_{i,t} \times FRG_{i,t}\Big) + \theta' x_{i,t} + \epsilon_{i,t+h}, \tag{7}$$

where $ar_{i,t+h}$ is the factor-adjusted future return of stock i cumulated over h days, $SI_{i,t}$ is the short interest in stock i at time t, $FRG_{i,t}$ is the fraction of short positions in stock i running gains at time t, and x is a vector of control variables, as described below. We consider predictive horizons of one to six months ($h = 21, 42, 63$ or 126 days). We compute factor-adjusted returns following the approach in Boehmer et al. (2017), according to which the betas for each of the k factors in the model (where rf is the risk-free rate of return):

$$E(r_{i,t}) - rf_t = \beta_i^{(1)} E(F_{1,t}) + ... + \beta_i^{(k)} E(F_{k,t})$$

are computed quarterly using daily data from the previous quarter, with the requirement that there are at least 21 non-missing daily observations. We compute abnormal returns as the difference between the raw returns and the model-implied returns for the corresponding period, using the estimated betas for the previous quarter:

$$ar_{i,t} = r_{i,t} - \Big(rf_t + \hat{\beta}^{(1)}_{i,q(t)-1} F_{1,t} + ... + \hat{\beta}^{(k)}_{i,q(t)-1} F_{k,t}\Big).$$

Given the impact of cross-sectional momentum both on the profits of short sellers (as documented in Section 3) and on future stock returns, we choose the Fama-French-Carhart four-factor model specification to compute abnormal returns and include past stock returns over different horizons in our set of controls, The other controls we include follow from previous studies (Boehmer et al., 2008; Diether et al., 2009), and comprise the average bid-ask spread over the previous month; the average turnover over the previous month; the average stock volatility over the previous month; the (log) market capitalization; and the (log) market-to-book ratio. We adjust standard errors using the Newey and West (1987) correction for autocorrelation, with a number of lags equal to the length of the holding period. We report our results in Table 8.

Our estimates of β are strongly negative across predictive horizons, ranging from -0.035 (one month) to -0.226 (six months), and are statistically significant at the 1% level or better in all cases. Consistent with Aitken et al. (1998), Asquith et al. (2005), and Boehmer et al. (2008), among others, short interest is highly informative about future returns in our sample, and its predictive power extends over several months after portfolio formation.

Our main coefficient of interest in Equation (7) is δ, the one associated to the interaction term between short interest and FRG. Following hypothesis **H3**, if short positions running losses are at least as informed as those running gains, we expect δ to be insignificant (or even positive) in our regressions. Against hypothesis **H3**, δ is negative and significant over one- to three-month horizons. In the first to third columns, δ equals -0.037, -0.078 and -0.087, respectively, and is significant at the 5% or 10% level. Especially for the one- and two-month predictive horizons, the incremental predictive power conveyed by FRG over short interest is highly economically significant. When FRG equals 0, a one-standard deviation increase in short interest is associated with a decrease of 1.98% and 1.93%, respectively, in annual four-factor alphas at one- and two-month predictive horizons. When FRG rises to 1, the effect of short interest on future returns doubles, as a one-standard deviation increase is now associated with a decrease of 4.08% and 4.13%, respectively, in annual four-factor alphas over the same horizons. The results indicate that short interest predicts even lower future abnormal returns as the fraction of short sellers running gains increases.

A possible interpretation of our findings is that the fraction of short positions running gains captures the relatively better-informed component of a stock's short selling. The timing decisions of short sellers to enter their positions could respond to different motivations (e.g., speculative versus hedging) or levels of information across short sellers. If so, we can expect short positions incurring losses, consistent with a poorer timing decision, to be on average less informative about future returns than those running gains. The significantly negative estimated coefficient of FRG (γ) on 3-month ahead abnormal returns in Table 8 supports this interpretation. In the next subsection we provide additional evidence for this interpretation across portfolio sorts.

6.2 Calendar Portfolios

To assess whether conditioning on FRG affects the economic value of the signal contained in short interest we employ the conditional double sorting procedure that is standard in the literature (see Asquith et al., 2005). To this aim, on each day t we first allocate stocks into quintiles based on the level of short interest. Within these groupings, we allocate all stocks with *no* short selling making gains, $FRG = 0$, into a first sub-group. This is the subset of stocks, within each short-interest group, that contains only loss-making short sellers. We allocate the remaining stocks into four sub-groups (from low to high) conditional on FRG, for a total of twenty five portfolios. We then compute the (annualized) average return to each value-weighted (VW) buy-and-hold portfolio for a K-day holding period. Given the lack of effects at the six-month horizon that we report in the previous section, we limit our analysis to holding periods of 21, 42 and 63 days. We repeat this portfolio sorting approach each day, giving rise to a series of K overlapping portfolios at any given point in time. We then regress the returns on these portfolios on the four Fama-French-Carhart factors, and use Newey and West (1987) standard errors to correct for autocorrelation, with a number of lags equal to the length of the holding period. We present our results in Table 9. Consistent with our regression results, short interest predicts negative and sizable abnormal returns among the most heavily shorted stocks. Within the top two quintiles (Q4 and Q5) of short interest, alphas are negative and highly statistically significant across most FRG bins and all predictive horizons.

Notably, the future abnormal returns of heavily shorted stocks fall with FRG, leading to a large and significant difference between the top and bottom FRG bins. Within the top short-interest quintile (Q5), the one-, two- and three-month ahead VW average abnormal returns for the top FRG bins are, respectively, -6.13%, -6.60% and -7.93% per annum. The corresponding VW average abnormal returns for the bottom FRG bins are -1.70%, -0.37% and 0.20% per annum, and are statistically insignificant at conventional levels in all cases. This pattern results in economically large average spreads in abnormal returns between high- and low-FRG stocks of, respectively, -4.61%, -6.08% and -8.42% per annum.

Importantly, loss-making short selling (FRG=0) contains no predictive power for returns in the cross-section. The short positions in the stocks in this group are all experiencing mark-to-market losses, many of which are large enough to potentially hit funding or institutional constraints and trigger subsequent covering.[19] The lack of information about future stock performance in these positions alleviates concerns about a detrimental effect of loss-related constraints on the transmission of information to prices.

In line with the intuition that the fraction of short positions experiencing gains captures informed short selling, high-FRG stocks can underperform even among mildly shorted stocks. Indeed, the average abnormal returns to the stock in the fifth bins of FRG ($Q4$) are negative and significant not only for the high short interest quintiles (Q5) across all holding horizons, but also for medium short interest quintiles (Q3 and Q4) for holding horizons of two to three months. Since prior literature (e.g. Boehmer et al., 2008) finds no significant predictive power of short selling among lightly shorted stocks, this result contributes novel evidence of information in short selling.

Summing up, our findings in this section are consistent with heterogeneity in information across short sellers and with mark-to-market gains proxying for the informativeness of their positions. When considered jointly with our results from the previous section, these findings indicate that the short sellers more likely to be constrained to close their positions (i.e., those incurring losses) are also less likely to be informed. Thus, while loss-related constraints seem pervasive and economically significant (Section 5), the short positions they affect might reflect the trades of predominantly uninformed investors rather than the bets of informed arbitrageurs.

7 Conclusions

Using a unique dataset on the distribution of the mark-to-market profits of short sellers in the U.S. equity market over the period 2011-2017, we provide evidence that losses (i) feed back into future shorting activity but (ii) the short selling most affected by these losses is also the relatively lesser informed.

Consistent with the economic relevance of stock-level funding and institutional constraints on short selling, we find a significantly negative relation between the losses, but not the gains of short

[19] In unreported analysis, we verify that the short sellers in the bottom (FRG=0) bin experience the largest mean losses among FRG bins, across all short interest quintiles. These short sellers also suffer the most extreme losses (i.e., the 5th percentile of PnL corresponding to the FRG=0 bin is the smallest across all FRG bins). Results are available from the authors upon request.

sellers and future short interest. This relation is particularly evident among stocks experiencing larger short-selling losses, and among stocks likely subject to higher margin requirements. An important implication of our findings is that, without accounting for the effect of losses, the role of momentum on short selling strategies and their negative impact on financial market stability could be overstated.

If the short sellers that incur losses are relatively well-informed, loss-related constraints could hinder the transmission of information to stock prices. On the contrary, we find that loss-making short selling contains no predictive power for returns in the cross-section. Moreover, we find that short interest predicts substantially lower future abnormal returns as the fraction of short selling experiencing gains increases, consistent with the gain-making subset of short sellers being more informed. We conclude that even though short sellers are affected by stock-level funding and institutional constraints, concerns about the role of these constraints as limits to arbitrage might be unwarranted as they limit predominantly lesser-informed short sellers.

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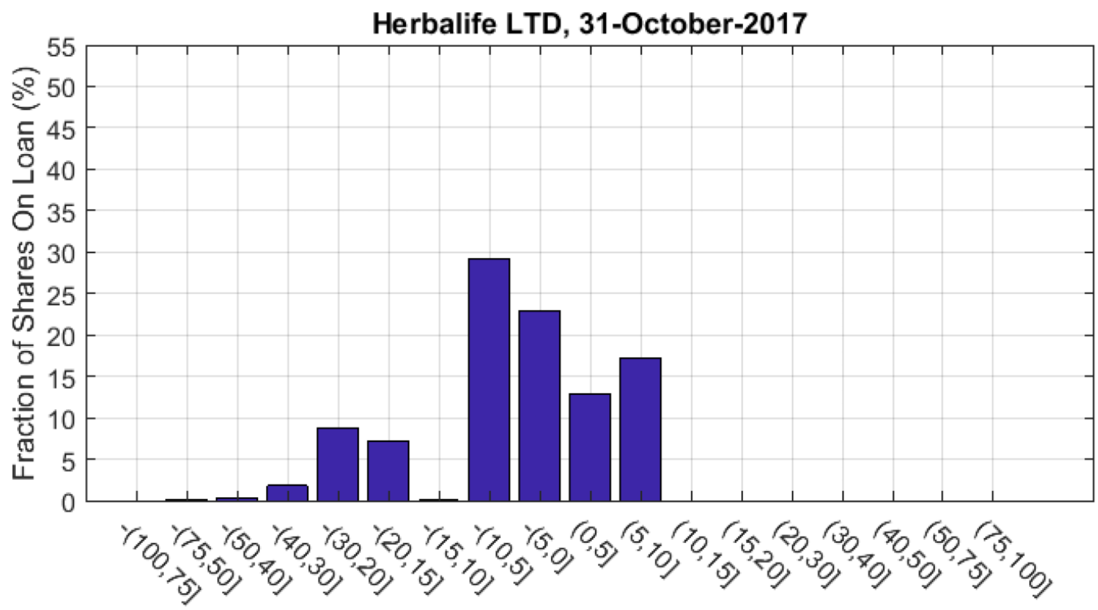
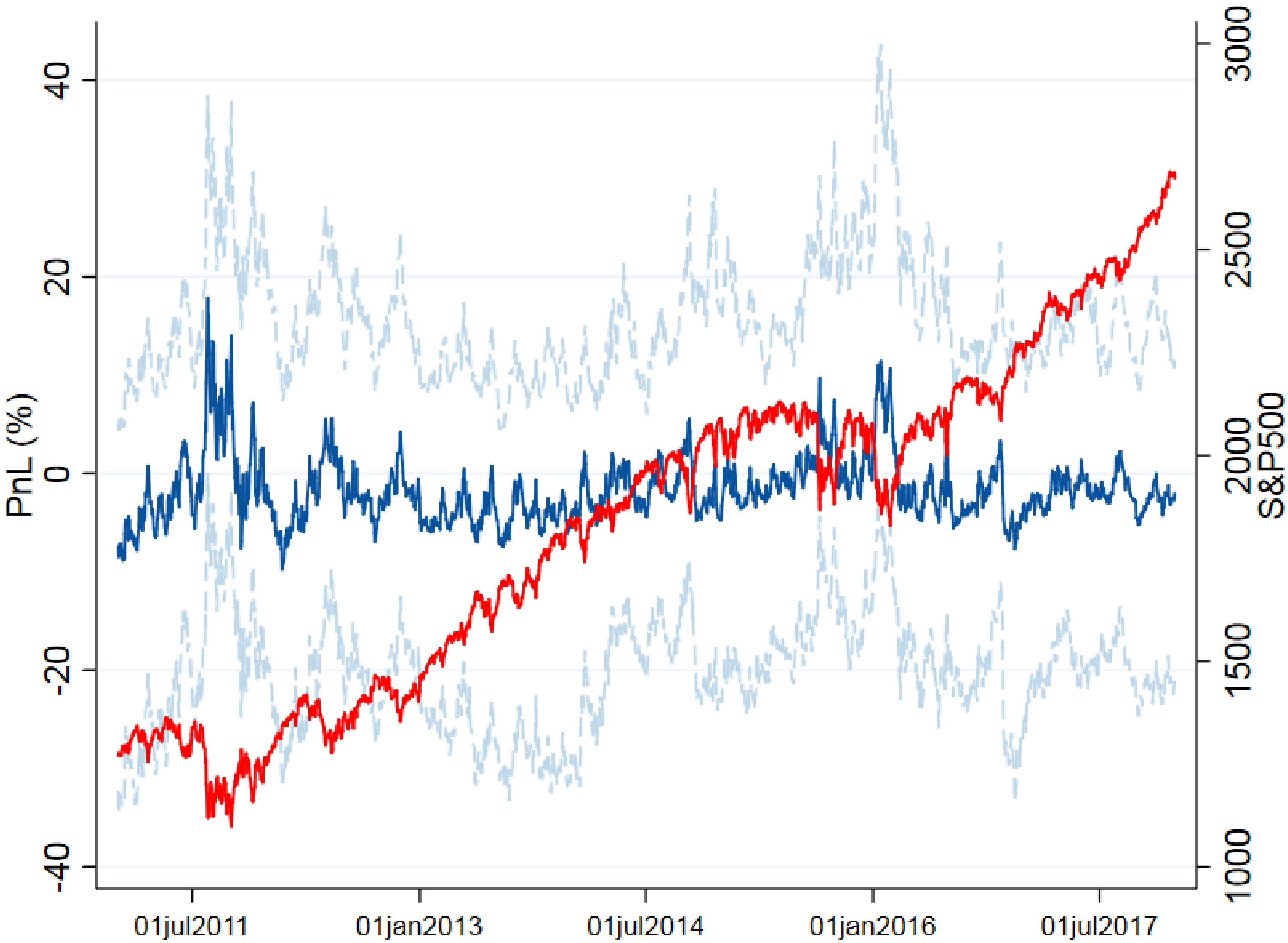
Figure 1: The Distribution of Short-Selling Profits in Herbalife



This Figure displays the distribution of profits (in %) on the short positions in Herbalife as of October 31 of 2017. Each bar denotes the fraction of shares on loan experiencing a cumulated return in its associated interval, as displayed on the x-axis.

Figure 2: Evolution of Short-Selling Profits over Time



This figure displays the evolution of the average profits of all shares on loan, PnL (left axis), and the S&P 500 index (red solid line, right axis) over our sample period. PnL is computed as:

$$PnL_{i,t} = \sum_{n=1}^{N} bin_{i,t}^{\lfloor n \rfloor} \times \frac{\lfloor n+n \rfloor}{2} = bin_{i,t}^{(-100,-75]} \times (-87.5) + bin_{i,t}^{(-75,-50]} \times (-62.5) + \cdots + bin_{i,t}^{(50,75]} \times 62.5 + bin_{i,t}^{(75,100]} \times 87.5,$$

where $bin_{i,t}^{(x,y]}$ denotes the fraction of shares on loan in stock i experiencing a *cumulated* returns in the $(x\%, y\%]$ interval on day t. The blue solid line, lower dashed line and upper dashed line represent, respectively, the cross-sectional mean, the 10th, and 90th percentiles of PnL.

Table 1: Summary Statistics

	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
	Panel A: Cumulated Return Bins (%)						
$(-100, -75]$	0.40	0.04	0.91	0.00	0.00	0.47	1.82
$(-75, -50]$	1.15	0.55	1.78	0.00	0.03	1.66	4.04
$(-50, -40]$	1.04	0.75	1.22	0.00	0.16	1.54	3.01
$(-40, -30]$	1.89	1.62	1.63	0.00	0.62	2.79	4.73
$(-30, -20]$	3.87	3.76	2.41	0.26	2.08	5.34	7.79
$(-20, -15]$	3.56	3.56	1.82	0.70	2.41	4.61	6.23
$(-15, -10]$	5.98	6.04	2.29	2.14	4.66	7.34	9.31
$(-10, -5]$	11.24	11.50	3.38	5.51	9.17	13.46	16.18
$(-5, 0]$	23.85	22.59	9.68	10.33	16.64	30.25	40.89
$(0, 5]$	21.64	21.02	6.93	11.70	16.68	26.10	33.50
$(5, 10]$	9.70	9.81	3.16	4.43	7.94	11.49	14.47
$(10, 15]$	5.10	5.13	2.88	0.54	2.92	6.98	9.71
$(15, 20]$	3.09	2.71	2.42	0.00	1.11	4.69	7.48
$(20, 30]$	3.46	2.31	3.66	0.00	0.46	5.38	10.81
$(30, 40]$	1.75	0.58	2.60	0.00	0.00	2.55	7.28
$(40, 50]$	0.95	0.03	1.93	0.00	0.00	1.07	4.80
$(50, 75]$	0.92	0.00	2.58	0.00	0.00	0.38	5.22
$(75, 100]$	0.12	0.00	0.78	0.00	0.00	0.00	0.45
Fraction Running Losses	53.29	55.08	11.89	30.75	46.64	61.13	69.98
Fraction Running Gains	46.73	44.93	11.89	30.02	38.89	53.38	69.25
	Panel B: Gains and Losses						
PnL (%)	-2.10	-1.71	11.34	-20.39	-7.23	3.36	15.24
$Pnl	-0.79	-0.26	4.26	-6.80	-1.79	0.83	3.79

[Continues on the next page]

	Panel C: Equity Lending Market						
Supply (%)	21.61	23.00	10.56	2.102	13.83	29.63	36.97
Short Interest (%)	3.916	1.856	5.231	0.144	0.759	4.833	15.09
Utilization (%)	16.23	8.134	19.89	0.491	3.126	21.06	63.78
Tenure (days)	82.66	65.38	69.57	13.83	37.44	106.7	208.6
Fee (% per annum)	1.244	0.375	3.677	0.373	0.375	0.464	5.041
	Panel D: Stock and Fundamental Characteristics						
Return (% per month)	1.075	0.433	10.69	-61.39	-18.48	19.41	64.65
Bid-Ask Spread (%)	0.148	0.0693	0.232	0.0141	0.0326	0.159	0.552
Market Equity ($m)	6,847	1,377	21,552	170.3	480.3	4,319	28,588
Assets (Log)	7.725	7.714	1.572	7.002	7.385	8.047	8.483
Market To Book (Log)	1.480	0.894	2.042	0.123	0.441	1.714	4.734
Leverage (%)	29.60	27.55	25.25	21.25	22.14	35.39	45.04
Profitability (%)	1.639	1.859	4.443	-0.885	1.127	2.387	3.312

This table presents summary statistics for the main variables in our analysis. Panel A displays summary statistics relative to the cumulated return bins (in percentage). For each variable in this panel we first compute the time-series average at the individual stock level. We then report the mean, median, standard deviation, the 5th, 25th, 50th and 95th percentile of the resulting cross-sectional distribution. Each *bin* denotes the fraction of shares on loan experiencing a *cumulated* returns in the $(x\%, y\%]$ interval, $Fraction\ Running\ Losses$ is the total fraction of shares on loan experiencing losses (i.e. the sum of all negative bins), and $Fraction\ Running\ Gains$ is the total fraction of shares on loan experiencing gains (i.e. the sum of all positive bins). In the remaining panels, for each variable we first compute daily cross-sectional summary statistics: mean, median, standard deviation, the 5th, 25th, 50th and 95th percentile. We then report the time-series mean of each statistic. Panel B displays summary statistics related to the level of short-selling profits. PnL, is the weighted average gross-of-fees cumulated return (in %) of the shares on loan, and $\$PnL$, is the weighted average dollar profits of the shares on loan. Panel C displays summary statistics relative to equity lending variables. *Supply* is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, $Short\ Interest$ is the total quantity of shares loaned out as a percentage of shares outstanding, $Utilization$ is the quantity of shares loaned out as a percentage of active shares available to be borrowed, $Tenure$ is the weighted average number of days over which the short positions have been open, and Fee is the borrowing fee (in % per annum). Panel D displays summary statistics relative to stock and fundamental characteristics. $Return$ is the stock return expressed in percentage per month, $Bid-AskSpread$ is the bid-ask spread as percentage of mid-price, $MarketEquity$ is the market value of equity in millions, $Assets$ is the (log) of total asset, $MarketToBook$ is the (log) ratio of the market value of assets and the book value of assets, $Leverage$ is the ratio of total debt and the market value of assets, and $Profitability$ is the ratio of operating income before depreciation and total assets.

Table 2: Aggregate Short-Selling Profits

	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
			Panel A: Gross				
$\overline{PnL}^{ann}$	-0.105	-0.134	0.208	-0.383	-0.249	0.001	0.266
$\$PnL\_to\_Short$	-0.042	-0.066	0.162	-0.239	-0.145	0.022	0.255
			Panel B: Net				
$\overline{PnL}^{ann}$	-0.116	-0.144	0.206	-0.393	-0.258	-0.011	0.248
$\$PnL\_to\_Short$	-0.051	-0.075	0.162	-0.248	-0.156	0.012	0.244

This table displays time-series summary statistics of the aggregate short-selling profits. $\overline{PnL}_t^{ann}$ is the equal-weighted average annualized cumulated return across all stocks,

$$\overline{PnL}_t^{ann} = \frac{1}{N_t}\sum_{i=1}^{N_t} PnL_{i,t}^{ann},$$

where $PnL_{i,t}^{ann}$ is the annualized PnL and equals, for a weighted average number of days $Tenure_{i,t}$ over which the positions have been open, $[(1+PnL_{i,t})^{1/Tenure_{i,t}} - 1] \times 252$; and N_t is the number of stocks in the sample at time t. Its net version is computed by adding $r_t^f - fee_{i,t}$ where r_t^f and $fee_{i,t}$ denote the risk-free rate and the borrowing fee, both in annualized terms. $\$PnL\_to\_Short_t$ is the ratio of aggregate dollar profits to size across all short positions:

$$\$PnL\_to\_Short_t = \frac{\sum_{i=1}^{N_t} \frac{252}{Tenure_{i,t}} \$PnL_{i,t} \times Q\_short_{i,t}}{\sum_{i=1}^{N_t} P_{i,t} \times Q\_short_{i,t}},$$

where $\$PnL_{i,t}$ is the average dollar profit per share; $Q\_short_{i,t}$ is the number of shares shorted; $P_{i,t}$ is the stock price. Its net version is computed by adding $P_{i,t} \times Q\_short_{i,t}(r_t^f - fee_{i,t})$ to the numerator.

Table 3: Short-Selling Profits in the Cross-Section

Panel A: $\overline{PnL}^{ann}$ (gross of fees, in % per annum)

Q	1M Ret	6M Ret	Variance	BA Spread	Turnover	SI	Supply	Fee	Tenure	Mkt Book	Size
1	58.31	43.58	-13.53	-15.84	-5.61	-11.66	-3.60	-12.89	-16.94	-1.10	13.63
2	21.89	17.01	-12.55	-14.79	-7.33	-14.07	-6.49	-26.28	-11.63	-2.35	-6.82
3	9.20	6.72	-11.90	-15.01	-9.71	-13.56	-11.12	11.13	-10.39	-1.61	-10.80
4	0.73	-0.42	-11.70	-13.97	-10.77	-12.75	-10.71	-20.71	-10.01	-5.24	-10.85
5	-6.39	-6.59	-11.23	-12.34	-11.71	-11.37	-11.91	-16.41	-9.86	-7.72	-13.85
6	-12.96	-12.20	-10.88	-11.17	-12.15	-11.34	-11.88	-6.21	-9.73	-9.73	-14.07
7	-20.22	-17.88	-9.46	-9.40	-11.80	-10.62	-12.30	-13.21	-9.85	-12.04	-14.95
8	-28.50	-25.03	-8.23	-7.01	-12.33	-9.22	-12.59	-9.51	-9.36	-13.15	-16.23
9	-41.02	-35.36	-6.23	-3.74	-11.37	-7.74	-12.61	-5.97	-8.41	-14.81	-15.79
10	-82.39	-69.01	-5.44	2.19	-8.36	-2.67	-11.94	3.09	-8.89	-29.90	-15.52

Panel B: $\$PnL\_to\_Short$ (net of fees, in % per annum)

Q	1M Ret	6M Ret	Variance	BA Spread	Turnover	SI	Supply	Fee	Tenure	Mkt Book	Size
1	66.15	65.14	-11.64	-10.51	-4.72	-8.37	1.91	-7.56	-8.64	9.62	63.47
2	24.34	24.02	-10.25	-7.60	-8.03	-10.16	2.12	-17.59	-6.03	8.53	29.72
3	11.23	10.39	-8.97	-6.54	-9.92	-10.62	-1.70	11.97	-5.13	3.49	18.28
4	3.03	2.12	-7.81	-3.78	-10.09	-10.30	-3.45	-9.22	-4.21	-1.72	10.82
5	-3.26	-3.82	-6.29	-0.08	-9.72	-8.83	-6.33	-7.67	-3.99	-2.46	3.73
6	-8.72	-8.68	-5.06	2.85	-9.21	-8.29	-6.00	0.84	-4.24	-4.23	-0.45
7	-14.45	-13.37	-3.17	6.13	-7.73	-7.87	-5.29	-1.12	-4.67	-6.43	-4.29
8	-20.64	-18.68	-0.50	13.48	-6.26	-6.09	-6.38	-2.01	-4.63	-7.84	-6.32
9	-28.39	-25.09	5.07	20.59	-3.56	-4.25	-6.51	1.12	-4.62	-7.49	-7.37
10	-45.55	-39.51	21.92	33.93	7.12	1.10	-5.78	6.05	-5.53	-14.46	-10.86

Each day we split the stocks in our sample into ten decile portfolios sorted along each variable in the column headings (e.g., "Variance") and compute the average of $\overline{PnL}^{ann}$ across stocks and $\$PnL\_to\_Short$, as defined in Table 2, within each portfolio. The table presents the time-series mean for each decile. $1M$ *Ret* is the past 1-month return, $6M$ *Ret* is the past 6-month return, $Variance$ is realized variance (the sum of squared daily returns) over the previous month, *BA Spread* is the average BA spread (i.e. $\frac{Ask_{price}-Bid_{price}}{0.5*(Ask_{price}+Bid_{price})}$) over the previous month, $Turnover$ is the average turnover over the previous moth, SI is the total quantity of shares loaned out as a percentage of shares outstanding, *Supply* is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, Fee is the borrowing fee, $Tenure$ is the weighted average number of days over which the short positions have been open, *Mkt Book* is the (log) ratio of the market value of assets and the book value of assets, *Size* is the (log) product of the price and the number of shares outstanding.

Table 4: Short-Selling Reaction to Losses and Gains

	(1)	(2)
PnL	0.0094***	
	(3.981)	
Loss		-0.0127***
		(-5.316)
Gain		0.0021
		(0.594)
ret(-1,-5)	0.0023	0.0005
	(1.015)	(0.227)
ret(-6,-21)	-0.0049***	-0.0058***
	(-2.998)	(-3.497)
ret(-22,-63)	-0.0114***	-0.0117***
	(-10.575)	(-10.784)
ret(-64,-126)	-0.0079***	-0.0080***
	(-10.272)	(-10.376)
Other Controls	YES	YES
Firm FE	YES	YES
Time FE	YES	YES
R-Square	0.76	0.77
N	4,078,471	4,078,471

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following fixed-effects (FE) panel regressions:

$$SI_{i,t+1} = \beta \times PnL_{i,t} + \gamma' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1}, \qquad (Column\ 1)$$

and

$$SI_{i,t+1} = \beta_1 \times Loss_{i,t} + \beta_2 \times Gain_{i,t} + \gamma' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1} \qquad (Column\ 2)$$

where SI is the total quantity of shares loaned out as a percentage of shares outstanding; PnL is the weighted average cumulated return of the shares on loan defined in Eq. (1), $Loss$ is defined as $-min(0, PnL)$, Gain is defined as $max(0, PnL)$, and a_i and τ_t denote stock and time fixed-effects, respectively. The set of controls (x) include the stock returns cumulated over the previous five days, the previous month excluding the first five days, the previous three months excluding the first month and the previous six months excluding the first three months, $Variance$ is realized variance, $BA\ Spread$ is the average BA spread and $Turnover$ is the average turnover, all three measures computed over the previous moth, $Supply$ is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, Fee is the borrowing fee, $Tenure$ is the (log) weighted average number of days over which the short positions have been open, $Mkt\ Book$ is the (log) ratio of market value to book value of assets, $Size$ is the (log) product of the price and the number of shares outstanding, $Profitability$ is the ratio of operating income before depreciation and total assets, $Leverage$ is the ratio of total debt and the market value of assets. t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 5: Short-Selling Reaction to Large versus Small Losses and Gains

	(1) τ=50%	(2) τ=30%	(3) τ=20%	(4) τ=10%
$Loss^{[\tau,\infty)}_{i,t}$	-0.0153***	-0.0167***	-0.0146***	-0.0127***
	(-5.664)	(-6.562)	(-5.768)	(-5.081)
$Loss^{[0,\tau)}_{i,t}$	-0.0119***	-0.0067**	-0.0021	-0.0006
	(-4.431)	(-2.316)	(-0.709)	(-0.190)
$Gain^{(0,\tau]}_{i,t}$	0.0022	0.0020	0.0027	-0.0024
	(0.614)	(0.572)	(0.746)	(-0.585)
$Gain^{(\tau,100]}_{i,t}$	0.0013	0.0029	0.0031	0.0030
	(0.243)	(0.685)	(0.808)	(0.827)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
R-Square	0.74	0.74	0.74	0.74
N	4,078,469	4,078,469	4,078,469	4,078,469

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following fixed-effects (FE) panel regression:

$$SI_{i,t+1} = \lambda_1 Loss^{[\tau,\infty)}_{i,t} + \lambda_2 Loss^{[0,\tau)}_{i,t} + \gamma_1 Gain^{(0,\tau]}_{i,t} + \gamma_2 Gain^{(\tau,100]}_{i,t} + \beta' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1},$$

for the four values of τ: 50%,30%,20%,10% reported in columns (1) to (4) respectively. SI is the total quantity of shares loaned out as a percentage of shares outstanding; $Loss^{[\tau,\infty)}_{i,t}$ is equal to $-PnL_{i,t}$ if $PnL_{i,t} \leq -\tau$ and zero otherwise; $Loss^{[0,\tau)}_{i,t}$ is equal to $-PnL_{i,t}$ if $-\tau < PnL_{i,t} \leq 0$ and zero otherwise; $Gain^{(0,\tau]}_{i,t}$ is equal to $PnL_{i,t}$ if $\tau \geq PnL_{i,t} > 0$ and zero otherwise; $Gain^{(\tau,100]}_{i,t}$ is equal to $PnL_{i,t}$ if $PnL_{i,t} > \tau$ and zero otherwise; a_i and τ_t denote stock and time fixed-effects respectively. The set of controls (x) include the stock returns cumulated over the previous five days, the previous month excluding the first five days, the previous three months excluding the first month and the previous six months excluding the first three months, $Variance$ is realized variance, *BA Spread* is the average BA spread and $Turnover$ is the average turnover, all three measures computed over the previous moth, *Supply* is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, Fee is the borrowing fee, $Tenure$ is the (log) weighted average number of days over which the short positions have been open, *Mkt Book* is the (log) ratio of market value to book value of assets, $Size$ is the (log) product of the price and the number of shares outstanding, $Profitability$ is the ratio of operating income before depreciation and total assets, $Leverage$ is the ratio of total debt and the market value of assets. t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 6: Short-Selling Reaction and Margin Requirements

	Variance		BA Spread	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Loss	-0.0097***	-0.0163***	-0.0057	-0.0157***
	(-2.744)	(-6.114)	(-1.399)	(-5.951)
Gain	-0.0008	-0.0014	-0.0077	0.0104***
	(-0.159)	(-0.361)	(-1.341)	(2.641)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
R-Square	0.70	0.75	0.76	0.78
N	1,890,539	2,187,886	2,133,180	1,945,259

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following fixed-effects (FE) panel regressions:

$$SI_{i,t+1} = \beta_1 \times Loss_{i,t} + \beta_2 \times Gain_{i,t} + \gamma' x_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t+1}$$

where SI is the total quantity of shares loaned out as a percentage of shares outstanding; $Loss$ is defined as $-min(0, PnL)$, Gain is defined as $max(0, PnL)$, and a_i and τ_t denote stock and time fixed-effects respectively. We split our sample of stocks in two based on their values of either $Variance$ or $BA\ Spread$ ("Low" and "High" columns). The set of controls (x) include the stock returns cumulated over the previous five days, the previous month excluding the first five days, the previous three months excluding the first month and the previous six months excluding the first three months, $Variance$ is realized variance, $BA\ Spread$ is the average BA spread and $Turnover$ is the average turnover, all three measures computed over the previous moth, $Supply$ is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, Fee is the borrowing fee, $Tenure$ is the (log) weighted average number of days over which the short positions have been open, $Mkt\ Book$ is the (log) ratio of market value to book value of assets, $Size$ is the (log) product of the price and the number of shares outstanding, $Profitability$ is the ratio of operating income before depreciation and total assets, $Leverage$ is the ratio of total debt and the market value of assets. t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 7: Short-Selling Reaction to Aggregate Losses and Gains

	Short-Weighted		Value-Weighted	
	(1)	(2)	(3)	(4)
$Loss_{port}$	-0.0545***	-0.0511***	-0.0256**	-0.0211*
	(-6.414)	(-6.100)	(-1.984)	(-1.660)
$Gain_{port}$	-0.0010	0.0025	0.0283*	0.0331**
	(-0.086)	(0.209)	(1.839)	(2.118)
Loss		-0.0143***		-0.0158***
		(-5.537)		(-6.067)
Gain		0.0016		0.0020
		(0.421)		(0.546)
ret(-1,-5)	-0.0018	0.0053*	-0.0035*	0.0044
	(-0.948)	(1.818)	(-1.859)	(1.505)
ret(-6,-21)	-0.0076***	-0.0029	-0.0093***	-0.0039*
	(-5.352)	(-1.459)	(-6.390)	(-1.943)
ret(-22,-63)	-0.0133***	-0.0108***	-0.0141***	-0.0112***
	(-12.037)	(-8.814)	(-12.584)	(-9.137)
ret(-64,-126)	-0.0089***	-0.0078***	-0.0095***	-0.0082***
	(-10.364)	(-9.287)	(-10.842)	(-9.659)
Other Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
R-Square	0.73	0.73	0.73	0.73
N	4080137	4078469	4080137	4078469

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following fixed-effects (FE) panel regression:

$$SI_{i,t+1} = \beta_1 \times Loss_{i,t} + \beta_2 \times Gain_{i,t} + \delta_1 \times Loss_{port,t} + \delta_2 \times Gain_{port,t} + \gamma' x_{i,t} + \alpha_i + \epsilon_{i,t+1}$$

where SI is the total quantity of shares loaned out as a percentage of shares outstanding; PnL is the weighted average cumulated return of the shares on loan defined in Eq. (1); $Loss$ is defined as $-min(0, PnL)$; Gain is defined as $max(0, PnL)$; and a_i denote a stock fixed-effect. The set of controls (x) includes the stock returns cumulated over the previous five days, the previous month excluding the first five days, the previous three months excluding the first month, and the previous six months excluding the first three months; the realized variance ($Variance$), the average BA spread ($BA\ Spread$), and the average turnover ($Turnover$), all three measures computed over the previous moth; the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding ($Supply$); the borrowing fee (Fee); the (log) weighted average number of days over which the short positions have been open ($Tenure$); the (log) ratio of market value to book value of assets ($Mkt\ Book$); the (log) product of the price and the number of shares outstanding ($Size$), the ratio of operating income before depreciation and total assets ($Profitability$); and the ratio of total debt and the market value of assets ($Leverage$). t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 8: Gain-Making Short Selling and Abnormal Returns

	Abnormal Returns			
	21 days	**42 days**	**63 days**	**126 days**
Short Interest	-0.035***	-0.068***	-0.120***	-0.226***
	(-2.782)	(-2.917)	(-3.710)	(-3.743)
Fraction Running Gains	-0.002	-0.003	-0.007**	-0.008
(FRG)	(-1.136)	(-1.399)	(-2.073)	(-1.275)
Short Interest × FRG	-0.037**	-0.078**	-0.087*	-0.130
	(-2.196)	(-2.514)	(-1.842)	(-1.307)
Controls	YES	YES	YES	YES
avg. R-square	0.037	0.038	0.037	0.036

This table reports Fama and MacBeth (1973) regression results. We estimate daily regressions of the form

$$ar_{i,t+h} = \alpha + \beta SI_{i,t} + \gamma FRG_{i,t} + \delta\Big(SI_{i,t} \times FRG_{i,t}\Big) + \theta' x_{i,t} + \epsilon_{i,t+h},$$

where $ar_{i,t+h}$ is the factor-adjusted (abnormal) future return of stock i cumulated over $h = 21, 42, 63$ or 126 days, $SI_{i,t}$ is the short interest in stock i at time t, $FRG_{i,t}$ is the fraction of short positions in stock i running gains at time t, and x is a vector of control variables. Abnormal returns are alphas from the Fama-French-Carhart four-factor model, and are calculated as the difference between the raw and the model-implied returns for the corresponding period. Model-implied returns are equal to the risk-free rate plus the sum of the products of the estimated betas from the previous quarter and the current value of the factors. Our set of controls includes: (i) the stock returns cumulated over the previous five days, the previous month excluding the first five days, the previous three months excluding the first month and the previous six months excluding the first three months; (ii) the average bid-ask spread over the previous month; (iii) the average turnover over the previous month; (iv) the average volatility over the previous month; (v) the (log) market equity; and (vi) the (log) market-to-book ratio. We report the time-series mean of the parameter estimates with t-statistics based on adjusted standard error using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 9: Portfolio Abnormal Returns: 4-Factor Model

SI \ FRG	$FRG = 0$	**Q1**	**Q2**	**Q3**	**Q4**	**Q4−FRG=0**
				Panel A: 21 days		
Q1	-0.87	0.29	-0.69	0.38	0.27	1.02
	(-0.64)	(0.40)	(-1.08)	(0.38)	(0.19)	(0.70)
Q2	-2.40*	-1.03	-0.00	-0.51	0.12	2.50
	(-1.79)	(-1.20)	(-0.00)	(-0.54)	(0.07)	(1.60)
Q3	-2.22*	-0.29	-3.06***	-2.36*	-0.47	1.93
	(-1.67)	(-0.34)	(-3.04)	(-1.89)	(-0.29)	(1.20)
Q4	-0.63	-1.45	-0.84	-2.66**	-5.24***	-4.78***
	(-0.41)	(-1.48)	(-0.88)	(-2.00)	(-2.90)	(-2.69)
Q5	-1.70	-4.35***	-3.49***	-4.95***	-6.13***	-4.61**
	(-0.78)	(-3.87)	(-3.24)	(-3.65)	(-3.09)	(-2.30)
				Panel B: 42 days		
Q1	0.36	0.70	-0.12	-0.13	-0.37	-0.58
	(0.33)	(1.15)	(-0.17)	(-0.17)	(-0.29)	(-0.49)
Q2	-1.98	-0.11	0.39	0.38	-1.97	-0.07
	(-1.63)	(-0.13)	(0.55)	(0.45)	(-1.43)	(-0.06)
Q3	-0.53	0.02	-2.92***	-3.05***	-2.62*	-2.02
	(-0.47)	(0.02)	(-3.45)	(-2.87)	(-1.71)	(-1.62)
Q4	1.08	0.22	-1.44*	-3.40**	-4.74***	-5.78***
	(0.79)	(0.25)	(-1.91)	(-2.45)	(-2.70)	(-4.29)
Q5	-0.37	-4.47***	-4.09***	-4.77***	-6.60***	-6.08***
	(-0.15)	(-4.77)	(-4.31)	(-3.79)	(-3.66)	(-3.23)
				Panel C: 63 days		
Q1	0.32	0.93	0.31	-0.58	-0.44	-0.60
	(0.34)	(1.26)	(0.46)	(-0.89)	(-0.39)	(-0.58)
Q2	-0.56	-0.37	-0.05	0.37	-2.09	-1.52
	(-0.48)	(-0.46)	(-0.08)	(0.41)	(-1.43)	(-1.39)
Q3	-0.09	-0.66	-3.17***	-3.11***	-2.70*	-2.59**
	(-0.08)	(-0.88)	(-3.87)	(-3.00)	(-1.72)	(-2.29)
Q4	1.32	0.14	-1.56**	-3.60***	-4.71**	-6.02***
	(1.06)	(0.16)	(-2.09)	(-2.72)	(-2.50)	(-4.78)
Q5	0.20	-4.20***	-4.19***	-5.44***	-7.93***	-8.42***
	(0.10)	(-3.79)	(-4.28)	(-5.06)	(-4.54)	(-5.40)

This table presents (annualized) Fama-French-Carhart four-factor alphas (in percent). We examine value-weighted portfolios formed daily by first sorting into quintiles using the level of short interest (SI) and then sorting into five sub-groups using the fraction of shares on loan running gains (FRG). The first of these sub-groups contains all stocks with *no* short seller making gains, for which $FRG = 0$. The remaining stocks are allocated into 4 equally-sized bins from low to high FRG. Portfolios are rebalanced daily, and are held for a K-day holding period (K=21, 42, and 63 days). The last column in each panel ($Q4-$FRG=0) shows returns to a long-short portfolio where firms with FRG in the top (bottom) bin are assigned to the long (short) portfolio. The reported alphas are the intercept from regressing portfolio returns in excess of the risk-free rate, on the excess market return (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors. t-statistics are based on adjusted standard error using Newey and West (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Internet Appendix to

Short of capital: Stock Market Implications of Short Sellers' Losses

Appendix A Short Sellers' Profits and Stock characteristics

In this Appendix, we present multivariate regression results on the relation between the profits of short sellers and a range of variables. The set of variables we consider include, but is not limited to, the variables examined in Section 4.2. More precisely, we include the stock's cumulated returns $ret(-t_1, -t_2)$ over the previous $t = t_2 - t_1 + 1$ days, with t equal to five days, one month (excluding the first five days), three months (excluding the first month), and six months (excluding the first three months). Our proxies for the level of uncertainty and asymmetric information are the stock's realized variance ($Variance$, the sum of squared daily returns), the average turnover ($Turnover$), and the average bid-ask spread ($BA\ Spread$) over the previous month. We include stock shares on loan as a measure of borrowing demand ($Short\_Interest$), the number of lendable shares available as a measure of supply ($Supply$), borrowing fees (Fee) as a measure of short-selling costs, and the weighted average duration of the short positions ($Tenure$) as a measure of the average number of days over which the positions exist. We consider a set of firm characteristics that are either associated with the cross-section of stock returns or that proxy for a firm's fundamental value, including the ratio of the market value of assets to the book value of asset ($Market\ to\ Book$), market capitalization ($Size$), firm profitability ($Profitability$) and firm leverage ($Leverage$). Lastly, we capture market-wide conditions by including the following proxies for aggregate funding availability and the business cycle (see Richardson et al., 2017): the TED spread (the difference between the 3-month LIBOR rate and the 3-month Treasury rate), the VIX index (the CBOE Volatility Index constructed from the implied volatility on options on the S&P 500) and the Yield spread (the difference between the 10-year Treasury rate and the 3-month T-bill rate). Table A1 presents regressions of contemporaneous PnL on the different sets of variables identified above. The specifications differ depending on whether they exclude firm fixed effects (first specification) or not (second specification), while both include time fixed effects.

Table A1: Variation of PnL in the Cross-Section

	(1)	(2)
Ret(-1,-5)	-0.863***	-0.833***
	(-138.94)	(-133.05)
Ret(-6,-21)	-0.571***	-0.543***
	(-138.52)	(-130.51)
Ret(-22,-63)	-0.294***	-0.273***
	(-82.23)	(-79.29)
Ret(-64,-126)	-0.125***	-0.107***
	(-44.29)	(-42.22)
Variance(-1,-21)	0.030*	-0.013
	(1.77)	(-0.82)
BA spread(-1,-21)	1.654***	-0.391
	(3.88)	(-0.82)
Turnover(-1,-21)	0.272***	0.044
	(3.84)	(0.50)
Short Interest	0.061***	0.063***
	(4.38)	(3.92)
Supply	-0.025***	0.008
	(-4.91)	(0.75)
Fee	0.130***	0.093***
	(7.33)	(4.43)
Tenure	-0.017***	-0.017***
	(-12.07)	(-13.83)
Market to Book	-0.014***	-0.046***
	(-9.62)	(-12.66)
Size	-0.001***	-0.018***
	(-3.93)	(-9.91)
Profitability	-0.111***	-0.041**
	(-9.69)	(-2.54)
Leverage	-0.007**	-0.036***
	(-2.25)	(-5.25)
TED	0.007	0.006
	(0.32)	(0.30)
VIX	0.004***	0.004***
	(8.24)	(8.33)
Yield Spread	0.000	0.000
	(0.02)	(0.04)
R-Square	0.654	0.708
N	3,971,901	3,971,830
Firm FE	NO	YES
Time FE	YES	YES

This Table reports coefficient estimates and associated t-statistics (in parentheses) of panel regressions. The dependent variable is PnL, the weighted average cumulated return of the shares on loan. The set of regressors include the stock returns cumulated over the previous five days, the previous month excluding the first five days, the previous three months excluding the first month, and the previous six months excluding the first three months, $Variance$ is realized variance, $BA\ Spread$ is the average BA spread and $Turnover$ is the average turnover, all three measures computed over the previous month, $Short\ Interest$ is the total quantity of shares loaned out as a percentage of shares outstanding, $Supply$ is the active quantity of shares available to be borrowed expressed as a percentage of shares outstanding, Fee is the borrowing fee, $Tenure$ is the (log) weighted average number of days over which the short positions have been open, $Mkt\ Book$ is the (log) ratio of market value to book value of assets, $Size$ is the (log) product of the price and the number of shares outstanding, $Profitability$ is the ratio of operating income before depreciation and total assets, $Leverage$ is the ratio of total debt and the market value of assets. TED is the TED spread, VIX is the VIX index, and $YieldSpread$ is the difference between the 10-Year and 3-Month treasury constant maturity yields. t-statistics are based on double-clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Appendix B Margin Requirements and Stocks Characteristics

We use proprietary information on the special maintenance margins that a large stockbroker requires for a subset of the stocks in our sample on December 5, 2014. These requirements range from 45% to 100%. We run a cross-sectional regression of the margin requirement for shorting a stock ($Margin$), on the stock's realized variance ($Variance$) and average bid-ask spread ($BA\ Spread$), both computed over the previous month:

$$Margin_i = \alpha + \beta \times Variance_i + \gamma \times BA\ Spread_i + \delta' x_i + \epsilon_i,$$

where x_i is a vector of firm characteristics that include the stock returns cumulated over the previous months, stock turnover, the (log) ratio of market to book value of assets, the (log) market capitalization, short interest and borrowing fee.

Regression estimates, presented in Table A.2, confirm positive relation conjectured by prior studies between margin requirements and recent stock volatility and illiquidity. Across specifications, both β and γ are positive and highly statistically significant, with the corresponding effects being economically meaningful. Without controls, a one-standard deviation increase in the stock's recent variance and bid-ask spreads are associated with 22% and 31% standard-deviation increases, respectively, in margin requirements.[20] With controls, the effects remain statistically and economically significant, with the impact of variance slightly exceeding that of illiquidity. Table A.2 also confirms the intuition that margin requirements are higher among stocks of firms with a higher market-to-book ratio, lower market capitalization and higher borrowing fees.

[20]The standard deviation in margin requirements equals 20% in our sample.

Table A.2: (Special) Margin Requirements

	(1)	(2)
Variance	0.229***	0.178***
	(7.340)	(5.625)
BA spread	0.318***	0.126***
	(6.626)	(2.643)
Return		0.035
		(1.047)
Turnover		-0.085**
		(-2.254)
Market to Book		0.234***
		(6.682)
Size		-0.328***
		(-8.827)
Short Interest		-0.048
		(-1.476)
Fee		0.104***
		(3.151)
Constant	-0.033	-0.024
	(-1.099)	(-0.882)
R-Square	0.18	0.28
N	917	914

This table reports coefficient estimates and associated t-statistics (in parentheses) of the following cross-sectional regression estimated on the 5th of December of 2014

$$Margin_i = \alpha + \beta \times Variance_i + \gamma \times BA\ Spread_i + \delta' x_i + \epsilon_i$$

The dependent variable is the margin requirement for shorting stock i set by a Large Prime Broker. $Variance$ and $BA\ Spread$ are the realized variance and the average bid-ask spread computed over the previous month. The set of controls (x) include the stock returns cumulated over the previous months, Turnover, the (log) ratio of market value to book value of assets, the (log) market capitalization, short Interest and the borrowing fee. All variables are standardized to have zero mean and unit standard deviation. t-statistics are based on robust standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.