Short Covering[*]

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ABSTRACT

We construct novel, *direct* measures of net and gross short covering to examine when short sellers exit positions. We find that idiosyncratic limits to arbitrage, such as adverse stock price movements, volatility, and equity lending fees, are associated with significantly higher position closures. In contrast, we find little evidence that aggregate limits to arbitrage, including VIX, funding liquidity, and market liquidity, affect short covering. Short covering predicts future returns in the wrong direction, but only if it is induced by limits to arbitrage, consistent with the hypothesis that short sellers are forced to exit too early. It is also associated with lower price efficiency, higher future anomaly returns, and better performance of other informed traders. These results show that firm-level limits to arbitrage are important determinants of trading behavior and future returns.

JEL classification: G12, G14

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Short sellers are archetypical "arbitrageurs" that trade against overpricing. A large literature finds evidence that short sellers are skilled at identifying and correcting overpricing and are significant contributors to market quality.[1] As early as Friedman (1953; and Fama (1965), short selling has been argued to play a central role in understanding financial economics. This importance has been supported by recent evidence that overpricing is the dominant form of mispricing in the financial market in terms of both magnitude (Stambaugh, Yu, and Yuan 2012), persistence (i.e., horizon) and systematic importance (Dong et al. 2022, 2024). Beyond market efficiency implications, overpricing also leads to real inefficiencies where capital in society is overinvested in overhyped business theses (Sharpe and Alexander 1990). Yet, despite the importance of short selling for asset prices and market quality, there is almost no research to date on short covering in U.S. equities.[2] While it is well-established that the opening of short positions is associated with lower future stock returns, we know little about the closing of short positions. Consequently, a number of important questions remain unanswered. Are short sellers skilled at timing their covering decisions? How important are limits to arbitrage in influencing short sellers to close out positions? And finally, if covering decisions are significantly affected by limits to arbitrage, do resulting position closures affect asset prices? These questions are important unconditionally but maybe more so in recent years as the rise of social media/fintech, which allows easy coordination of noise traders, has made short covering an even more relevant topic.

[1] For work showing short sellers are skilled, see Senchack and Starks (1993), Aitken, Frino, McCorry, and Swan (1998), Dechow, Hutton, Meulbroek, and Sloan (2001), Jones and Lamont (2002), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), Christophe, Ferri, and Angel (2004), Boehmer, Jones, and Zhang (2008), Engelberg, Reed, and Ringgenberg (2008), and Cohen, Diether, and Malloy (2009). For work on the relation between short selling and market quality, see Saffi and Siggurdson (2011) and Boehmer and Wu (2013).
[2] To the best of our knowledge, only two papers specifically examine short covering: Takahashi and Xu (2016) and Boehmer, Duong, and Huszar (2018). Both examine short covering using a sample of publicly disclosed short positions in the Japanese stock market. We discuss the relation between our results and the existing literature in greater detail in Section I.

In this paper, we present the first empirical examination of short covering transactions for a broad sample of U.S. equities. Standard databases of short volume and short interest do not contain information on the closing of short positions. However, it is possible to estimate short covering using a simple, intuitive identity:

$$Short\ Interest_t = Short\ Interest_{t-1} + Short\ Volume_{t-1:t} - Short\ Covering_{t-1:t}. \quad (1)$$

The identity relies on the fact that the quantity of open short positions at any point in time (short interest) must equal the quantity of open short positions in the prior period plus new short positions (short volume) minus closed short positions (short covering).[3]

Our analysis uses daily equity lending data from Markit to construct novel measures of gross and net position closures by short sellers. The Markit data is distinct in that it allows us to track the total quantity of borrowed shares each day (i.e., the stock of positions) as well as the quantity of new shares borrowed each day and the quantity of borrowed shares returned each day (i.e., the flow). We show that the quantity of borrowed shares returned each day correlates highly with short covering as calculated in equation (1).[4] Accordingly, we then use the quantity of borrowed shares returned each day as one measure of closed positions, which we term *gross covering*. This number measures how many shares short sellers covered each date in a particular stock.

In addition, we also construct a measure of *net covering*, which we define as the total decrease in open short positions each day. Intuitively, *gross covering* allows us to study whether *any* short seller closed a position while *net covering* allows us to examine whether short sellers,

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[3] We are not the only paper to make this point. Diether, Lee, and Werner (2009) note that short covering must be mechanically linked to short interest and short volume, but they do not actually calculate a measure of short covering.

[4] Specifically, we use the NYSE TAQ short volume data combined with Computstat short interest data to construct estimates of short covering from equation (1) and find that this measure is strongly correlated with the quantity of shares returned.

as a group, decreased their positions. Our analysis is the first to use both measures to develop a more complete picture on the determinants and implications of short covering.

To date, there is surprisingly little research on short covering, despite its potential importance for price efficiency and the allocation of capital in the economy. For example, consider the well-known recent case of GameStop, the first of the so-called "meme" stocks whose stock price increased in early 2021 from less than $18 per share to an intra-day high of $483 per share. Most observers attribute the price increase to buying by small retail investors active on Reddit and other social media boards, and many of the participants on Reddit discussed pushing up GameStop's stock price to inflict losses on short sellers and force them to cover. As Figure 1 illustrates, our short covering measure shows that a large wave of short covering did coincide with GameStop's stock price increase.[5] While this appears consistent with the idea that price increases cause short sellers to exit their position, short covering also increases earlier before the Gamestop price spike which complicates the interpretation. Following the GameStop saga, there has been surge in research interest in short covering, where researchers predominantly use change in short interest as an indirect proxy of short covering. This proxy is simply not a conceptually correct measure of short covering. As we later will show, it has, in some cases, an abysmally low correlation (e.g., -13%) with the true short covering activity, suggesting substantially different information is embedded in the true short covering measures. Thus, without a direct measure, many research conclusions can be misleading in the first place.[6] In other words, there is no comprehensive evidence on the determinants and asset pricing implications of *true* short covering. We attempt to fill this gap in knowledge.

[5] Melvin Capital, a hedge fund that shorted GameStop and was targeted by Reddit posters, suffered a 53% loss in January largely because trading conditions induced it to close its GameStop position at a large loss.
[6] For example, a recent SEC report argues that the GameStop saga is not caused by short squeeze but by retail buying sentiment.

[FIGURE 1 ABOUT HERE]

We begin by examining how different possible limits to arbitrage impact short covering in our sample of approximately 6,000 U.S. stocks over the 2007–2016 period. Our measures include those that are idiosyncratic in nature, such as equity lending fees, bid-ask spreads, and stock-specific returns and volatility, as well as those that are systematic, such as intermediary funding liquidity, aggregate liquidity, VIX, and market volatility.

We find that many idiosyncratic limits to arbitrage affect short seller behavior. Short covering increases significantly when equity lending fees are high. Perhaps more surprisingly, it is not only direct trading costs that influence short sellers. Past stock returns and volatility are both strongly positively related to short covering. By contrast, none of the proxies for potential systematic limits to arbitrage, which many theories suggest should represent important determinants of arbitrageur trading, have an impact on short covering. Moreover, our findings hold for both the gross and net covering measures, which means that the effect of idiosyncratic limits to arbitrage is not limited to individual short sellers but also works for them as a group. In other words, when some short sellers cover their positions in response to higher equity loan fees, losses due to stock price increases, or higher volatility, other investors do not replace them (at least not fully).

The above findings are consistent with the hypothesis that our proxies for idiosyncratic limits to arbitrage induce short sellers to cover their positions. However, they do not answer the crucial question of *why* short sellers do so. Are short sellers "forced" to cover, for example by mounting losses as in the GameStop saga? Or do they exit their positions because the stocks no longer offer them attractive risk-adjusted returns? To infer short sellers' possible motivations, we next study whether short covering predicts future returns.

We sort stocks in our sample by their level of short covering in the previous month. An equal-weighted (value-weighted) portfolio that buys stocks with low net short covering and shorts stocks with high net short covering has a one-month abnormal return of 0.76% (0.49%), with a *t*-statistic of 4.33 (2.65).[7] These findings suggest that short sellers, on average, cover at the wrong time. The stocks continue earning low returns after short sellers exit their positions, indicating that short sellers closed too soon. This finding is surprising in light of prior work showing short sellers are skilled arbitrageurs, who tend to open short positions in stocks that subsequently underperform.

We further explore the role of limits to arbitrage by splitting position closures into *induced* and *uninduced*, where induced closures are the predicted level of short covering based on changes in our limits to arbitrage proxies. If limits to arbitrage induce short sellers to close out positions, it could explain why short covering predicts negative future returns. The data support this hypothesis: a long-short equal-weighted (value-weighted) portfolio based on induced covering has an abnormal return of 1.1% (0.71%). By contrast, portfolios sorted on uninduced covering do not exhibit any spread in returns. We confirm these results in a regression setting – induced covering strongly forecasts returns whereas there is no relation between uninduced covering and returns. The findings suggest that short sellers are skilled at closing their positions when facing no constraints, exiting when the stock price has fully corrected. However, when short sellers are induced to close because of limits to arbitrage, they exit their positions too early.

We also find that short covering has important implications for stock price efficiency. Both gross and net covering are negatively related to a variety of measures for how efficiently stock prices reflect information. As with our previous tests, this relation holds even when we

[7] The results are similar if we use gross covering instead of net covering.

include firm fixed effects, meaning that a given stock's price efficiency is lower when short sellers are covering their trades.

Overall, our results show that various idiosyncratic limits to arbitrage influence short seller trading activities. For equity loan fees, which represent a direct cost of holding a short position, this may not be overly surprising. However, other stock-specific factors should matter only if investors are capital constrained (either directly or indirectly due to agency concerns or internal risk management) and imperfectly diversified. The fact that short sellers strongly respond to adverse stock price changes or increased volatility by reducing positions indicates that they, even as a group, have limited risk-bearing capacity. Consistent with this hypothesis, when short sellers are induced to cover by idiosyncratic limits to arbitrage, the affected stocks have negative expected returns, indicating that short sellers are foregoing profits by exiting (and thus presumably doing so involuntarily).

This last result has two important, related implications. First, although they are a sophisticated investor group on average, short sellers sometimes trade in a non-optimal manner that both hurts their returns and does not push prices towards fair value. Among other things, our findings suggest short squeezes are not just a theoretical concept; they can and do occur. We find that stock price increases are associated with more short covering, and if this generates price pressure, it could cause a cycle of more price increases and more short covering. Furthermore, if short sellers truly are a sophisticated group, they will foresee this possibility and be less aggressive initially when taking positions.[8] In our context, this logic can perhaps explain why short interest remains low for most stocks, despite the apparent absence of binding short sale

[8] Shleifer and Vishny (1997) develop a formal model in which such a mechanism limits the effectiveness of arbitrage.

constraints. Second, our findings provide the first evidence that induced covering predicts lower future returns. This indicates that idiosyncratic limits to arbitrage can impact expected returns.[9]

Our work is related to, but distinct from, several existing papers on short selling. There is little existing empirical evidence on the closing decisions of short sellers. It is important to distinguish a popular concept, short squeeze, from our short covering concept. Using a database of equity loans from one lender over an 18-month period, D'Avolio (2002) shows that on average 2% of equity loans are forced to close each month as a result of share-loan recalls. However, D'Avolio (2002) documents *hard* recalls in which a short seller is obliged to return borrowed shares to the lender. It is possible that soft recalls, situations in which changes to market conditions make a short position undesirable, occur much more frequently. Put differently, while hard recalls are rare, our paper provides novel evidence that soft recalls are much more common. "Forced" short covering represents 30% to 40% of the total short covering variation.

Arguably the closest study to ours is Boehmer et al. (2018), who examine short covering using Japanese data from 2008 to 2010 and find that short sellers cover efficiently and in anticipation of future positive returns. They do not specifically explore limits to arbitrage, which is the focus of our paper. Our results suggest that short covering decisions are more likely to be affected by limits to arbitrage in the U.S. market, perhaps due to differences in the structure of securities lending between Japan and the U.S.[10]

[9] It is possible that idiosyncratic limits to arbitrage affect expected returns because they prevent arbitrageurs from correcting mispricing or because they are priced sources of risk. While this is an important distinction, exploring it is beyond the scope of this paper. There is some extant evidence consistent with the finding that idiosyncratic limits to arbitrage affect returns (e.g., idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang, 2009).

[10] U.S. equity lending markets are over-the-counter whereas Japan has an equity lending exchange. As a consequence, Japanese short sellers may be less likely to experience loan recalls or loan fee increases that compel them to close their positions early.

We know of only two other papers that investigate short covering transactions in *any* context. Takahashi et al. (2016) also examine Japanese data on 108 short selling and covering trades around Nikkei 225 index deletions and conclude that individual investors play a prominent role in Japanese short selling markets. Diether (2011) uses a proprietary database of equity loan transactions from a mutual fund to see the opening and closing of a sub-sample of short transactions, which allows him to study the profitability of certain strategies. Our tests focus on a different aspect of short transactions: instead of trading strategies of short sellers, we specifically study the determinants of covering across all U.S. equities and the resulting implications for asset prices.

Finally, our work is related to several papers on limits to arbitrage and short selling. While many of these papers find that high equity lending fees are associated with greater mispricing (e.g., Jones and Lamont, 2002, and Geczy et al., 2002), we are the first to show that short covering responds to time-varying stock and lending-market conditions. Engelberg, Reed, and Ringgenberg (2018) ague that short sellers are sensitive to equity lending fee risk, but they do not examine how various limits to arbitrage affect short seller decisions to close out positions. Our paper provides the first evidence that other time-varying limits to arbitrage (such as volatility or margin calls) affect the exit decisions of short sellers. We also contribute to the literature on short selling and market quality. Saffi et al. (2011) and Boehmer et al. (2013) both find that short sellers are associated with improvements in market quality and efficiency. We examine the complement to their results, showing that price efficiency degrades when short sellers are forced to cover their positions.

Taking all of our findings together, the overall picture emerges: real-world arbitrage is risky and costly, and conditions in the stock and equity lending markets strongly influence short seller's decision to maintain a position. When conditions move against short sellers, they tend to close their positions too early, resulting in more mispricing and worse price efficiency.

The remainder of this paper proceeds as follows: Section I describes the data and the construction of our key measures of short seller behavior. Section II shows our analysis of the determinants of short covering. Section III examines the relation between short covering and future returns, and Section IV presents additional tests, including on price efficiency. Section V concludes.

I. Data

We examine two measures of short covering. The first is *GrossCover*, which we construct as a direct measure of the closing of short positions by short sellers. It is intended to capture to what extent short sellers are covering positions, irrespective of whether they are being replaced by new investors. The second is *NetCover*, which we define as the net decrease in short interest. It is intended to capture the covering of positions by short sellers as a group (i.e., including both existing and new short sellers). In what follows, we discuss our data and the construction of our short covering measures in greater detail.

A. Gross Short Covering

To construct a direct measure of gross short covering, we use information about short positions from Markit, a leading provider of data in the equity loan market. The Markit data aggregates and distributes information regarding equity loan positions at the daily frequency. The database contains a number of statistics summarizing transactions in the equity loan market at the stock-day level. In particular, it collects data on new equity loans, closed equity loans, and outstanding equity loans for each stock and date. Using the variables in the Markit data, we construct a measure of Short Covering for each stock and date, which we call *GrossCover*. Formally, we define:

$$GrossCover_{i,t} = BO\ On\ Loan\ quantity\ removed_{i,t} + BO\ On\ Loan\ quantity\ decrease_{i,t}, \quad (1)$$

where *BO On Loan quantity removed*$_{i,t}$ tracks the reduction in open loans in stock *i* on day *t* from beneficial owners (BO) who remove shares from their equity loan supply and *BO On Loan quantity decrease*$_{i,t}$ tracks the reduction in shares on loan from lenders whose loan balance in stock *i* on day *t* decreases. The sum of these variables measures the total decrease in the number of shares on loan on a particular date for a given stock (without taking into account newly established short positions). Both variables are scaled by total shares outstanding. We sum up the daily *GrossCover* values to get a monthly measure for each firm.

Markit also provides gross short covering information recorded from the broker side, which includes the decrease in borrowed shares for brokers with zero borrowed shares (as a result of short covering) and the decrease in borrowed shares for brokers whose loan balance falls as a result of short covering. The sum of these two quantities is an alternative way to generate the *GrossCover* measure, which provides a way to cross-validate this measure. We verify that *GrossCover* measures calculated based on the information from the beneficial owner and broker sides are similar, and our results throughout the paper remain the same using the broker-based *GrossCover* measure.

B. Net Short Covering

Over any given period, short interest can change for two reasons: opening of new short positions (i.e., *ShortVolume*) and closing of existing short positions (i.e., *GrossCover*). When the former is lower than the latter, short interest decreases (and vice versa). We construct a net short covering measure that focuses on situations when closed short positions exceed newly opened short positions. More specifically, we define *NetCover* as follows:

$$NetCover_{i,t} = -\Delta Short_{i,t} \text{ } if \text{ } \Delta Short_{i,t} < 0; \text{ } Otherwise \text{ } NetCover_{i,t} = 0, \tag{2}$$

where $Short_{i,t}$ is the short interest at the end of month t, measured as loan quantity in Markit (shares sold short in a stock on a given date) scaled by total shares outstanding, and $\Delta Short_{i,t} = Short_{i,t} - Short_{i,t-1}$, which is the change in short interest over month t.

In summary, *GrossCover* and *NetCover* measure the gross and net activity for short position closures, respectively. For completeness, we also examine our main results using the total change in short interest, $\Delta Short_{i,t}$.

C. Gross and Net Short Volume

In some of our specifications, we include as control variables the gross and net activity for short position increases. *GrossVolume* directly captures the numbers of newly shorted shares. Formally, we definite it as:

$$GrossVolume_{i,t} = BO\ On\ Loan\ quantity\ add_{i,t} + BO\ On\ Loan\ quantity\ new_{i,t} \\ + BO\ On\ Loan\ quantity\ increase_{i,t}, \tag{3}$$

where $BO\_On\_Loan\_quantity\_add_{i,t}$ and $BO\_On\_Loan\_quantity\_new_{i,t}$ measure the increase in the number of shares on loan from lenders who just start lending shares (of stock i on day t), and $BO\_On\_Loan\_quantity\_increase_{i,t}$ measures the increase in the number of shares on loan from lenders who have existing loan balances (in stock i at the start of day t). We sum up the daily *GrossVolume* to get a monthly measure for our main tests.

Net short volume (*NetVolume*) is defined similarly as net short covering, focusing on the states of the world when newly opened short positions exceed existing short position closures. Specifically, we compute *NetVolume* as:

$$NetVolume_{i,t} = \Delta Short_{i,t} \text{ if } \Delta Short_{i,t} > 0; \text{ Otherwise } NetVolume_{i,t} = 0. \quad (4)$$

D. Firm- and Market-Level Determinants of Limits to Short Arbitrage

To measure the effect of firm-level characteristics, we construct various firm-level variables that are potentially related to limits to arbitrage using data from the Center for Research in Security Prices (CRSP), Compustat, the New York Stock Exchange (NYSE) Trade and Quote (TAQ) database, the 13F institutional ownership database, and Markit. We keep only common U.S. stocks (CRSP share codes 10 and 11) and drop any observations with a current or lagged stock price less than $5. We add the second screen because margin requirements for short sales typically change below this level.

From CRSP and Compustat, we add one-month return (*Ret*), 6-month momentum (*Mom6m*), 12-month momentum (*Mom12m*), return volatility (*RetVol*), market capitalization (*MktCap*), and book-to-market ratio (*BM*). We compute 6-month (12-month) momentum as the cumulative return from month *t–6* to *t–2* (*t–12* to *t–2*). Return volatility is calculated as the standard deviation of daily returns over a month. We also add the stock-level mispricing measure (*Misp*) from Stambaugh, Yu, and Yuan (2015) and the inverse of price efficiency (*PriceDelay*), using the Delay1 measure in Hou and Moskowitz (2005). Higher values of *PriceDelay* indicate greater price delays, which suggests worse price efficiency. We also examine the degree to which returns follow a random walk using variance ratios (*VarRatio*), which are the bias-corrected variance ratios calculated using 2-day, 4-day, and 8-day horizons with overlapping observations (Lo and MacKinlay, 1988). From TAQ, we compute the effective spread (*Spread*), which is defined as each trade price divided by the most recent quote midpoint, computed for each trade each day, then averaged daily, and again averaged to get a monthly measure.

We obtain borrowing costs (*Fee*) from Markit. Equity borrowing cost is the daily average of the indicative fee over a month.

We further consider several measures of aggregate market conditions that are potentially related to limits to arbitrage. They include VIX_t, which is the Volatility Index from the Chicago Board Options Exchange (CBOE) at the end of month *t*; $FundingLiq_t$, which is a monthly measure of funding liquidity for primary dealers from He, Kelly, and Manela (2017);[11] $MktLiq_t$, which is the aggregate market liquidity level for month *t* provided by Pastor and Stambaugh (2003). *Recession* is a recession indicator variable that takes the value one during recession months as defined by the National Bureau of Economic Research (NBER). We winsorize *Short*, *ΔShort*, at the top and bottom 1%. Since *GrossCover*, *GrossVolume*, *NetCover*, and *NetVolume* are bounded at 0, we winsorize them only on one side.

E. Summary Statistics

Table 1 provides summary statistics for the variables used in our analyses. In general, our sample appears to be representative. The short interest measures (*Short*) exhibit similar summary statistics as those reported in the previous literature (e.g., Hong, Kubik, and Fishman, 2012). The stocks in the sample are actively shorted, with a mean (median) short interest of 4.1% (2.1%). Furthermore, short sellers frequently enter (average monthly gross volume is 1.41%) and exit (average monthly gross cover is 1.39%) their positions. The lending fee is low for a large majority of stocks, suggesting they are easy to borrow. The stocks also exhibit high liquidity,

[11] We thank Asaf Manela for providing this data on his website.

with a mean (median) effective spread of 0.55% (0.11%), and are relatively large, with a mean (median) market capitalization of $5.7B ($0.8B).

[TABLE 1 ABOUT HERE]

Table 2 provides the cross-correlations for the main short seller variables that we study. The correlation between *GrossCover* and *NetCover* is 41%, indicating that the trading behavior of existing and new short sellers is related. Interestingly, *GrossCover* is highly correlated with *GrossVolume* with a correlation efficient of 82%, which shows that the divergence in short sellers' actions is very high with a comparable number of short sellers entering and exiting positions in a given stock at any point in time. In contrast, *NetCover* and *NetVolume* are negatively correlated, with a correlation coefficient of –21%, consistent with the construction of these two measures. Finally, *ΔShort* exhibits a relatively low correlation with *GrossCover* and *GrossVolume* (–13% and 16%, respectively), while its correlation with *NetCover* and *NetVolume* is high (–77% and 79%, respectively), suggesting that the gross measures are more likely than the net ones to contain different information from the traditional change in short interest. Since *GrossCover, GrossVolume, NetCover*, and *NetVolume* are all highly skewed, we use log transformations of these variables in our regression tests.

[TABLE 2 ABOUT HERE]

II. Determinants of Short Covering

A. Regression Framework

Traders do not hold positions forever, but rather they strategically choose when to enter and exit positions (Harrison and Kreps, 1978). In this section, we examine the determinants of short covering, with a special focus on the impact of limits to arbitrage. Our baseline regression specification takes the following form:

$$Covering_{i,t} = \alpha + \beta_1 Id\_Limits_{i,t-1} + \beta_2 Sys\_Limits_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}, \quad (5)$$

where *Covering* is either *GrossCover* or *NetCover*. The first measure explores whether limits to arbitrage cause any short sellers to exit, while the latter measure tests whether short sellers, as a group, reduce their positions. For independent variables, we use lagged values (i.e., the variables are measured at *t–1*) to reduce concerns about reverse causality. Our results are similar if we instead examine the contemporaneous relation (i.e., with variables measured at time *t*).

Id_Limits contains a set of firm-specific limits to arbitrage motivated by the existing literature. We include the lagged return, $Ret_{i,t-1}$, because higher returns lead to losses for short sellers, which can induce them to cover their positions because of capital constraints, internal risk management, or margin calls.[12] We also use six- and 12-month momentum, measured by cumulative returns $Ret_{i,t-2:t-6}$ and $Ret_{i,t-2:t-12}$, respectively, to capture losses over longer horizons, which may impact short sellers differently (Shleifer and Vishny, 1997). Next, we add *RetVol*, which is a trailing measure of daily stock-specific return volatility. Higher volatility is a potential limit to arbitrage that forces short sellers to exit (Pontiff, 2006). For example, when evaluating their positions, capital-constrained short sellers will anticipate the possibility of future losses, which are more likely for high-volatility stocks.

Borrowing fee, $Fees_{i,t-1}$, represent the direct cost of holding a short position, which is an obvious impediment for short sellers. If fees go up, this lowers the expected future profitability of the short position and can thus induce short sellers to exit (Engelberg et al., 2018). We include

[12] Short sellers may be especially sensitive to losses from a particular position since shorting a stock is fundamentally different from buying it in that, *ceteris paribus*, an adverse price movement increases a portfolio's exposure to that stock. Consider a portfolio with a long position representing 20% of its net value. A price decline of 50% will reduce that long position to 11% of the portfolio's new net value. Now, consider a portfolio with a short position equal to 20% of its net value. If the price of the stock rises by 50%, the short position will grow to 33% of the portfolio's new net value.

the bid-ask spread as a measure of stock liquidity (Amihud and Mendelson, 1986), which can limit short sellers' ability to easily enter or exit a position. Finally, we examine the role of the existing short interest, *Short*. This is an important control for a number of reasons. First, mechanically there will be more short covering when there are more shares sold short. Second, if short sellers have limited risk-bearing capacity, a larger short position can lead to more position closures. Third, short interest is an equilibrium outcome that reflects the level of limits to arbitrage affecting the stock.

Sys_Limits contains a set of market-wide (i.e., systematic) limits to arbitrage motivated by the existing literature. We include the Chicago Board Options Exchange Volatility Index (*VIX)*, which is a forward-looking measure of expected market volatility. [13] Market-wide volatility can represent a limit to arbitrage if such higher volatility leads to a reduction in leverage available to arbitrageurs (e.g., Ang, Gorovyy, and van Inwegen, 2011, and Nagel, 2012). We also include *Funding Liquidity* from He, Kelly, and Manela (2017) and *Market Liquidity* from Pastor and Stambaugh (2003), both of which have been proposed as important aggregate limits to arbitrage. When intermediary capital is constrained, arbitrageurs can face funding constraints (He, Kelly, and Manela, 2017). If market liquidity dries up, arbitrageurs will find it harder to get in and out of positions easily (Shleifer and Vishny, 1997). As our final aggregate-level measure, we add a recession indicator since limits to arbitrage may depend on economic conditions.

As controls, we include the stock's book-to-market ratio, *BM,* and market capitalization, *MktCap*, which previous literature suggests can be related to the level of limits to arbitrage

[13] Results are similar if we instead use realized market return volatility.

(Baker and Wurgler, 2006). We also add stock, time, and industry fixed effects.[14] These fixed effects absorb unobserved characteristics that do not vary across stocks, time, and industry, respectively.[15] We cluster standard errors by stock and time to account for time-series and cross-sectional dependence.

B. Short Covering and Limits to Arbitrage

We present the results on the determinants of short covering in Table 3. Column (1) studies the relation between idiosyncratic limits to arbitrage and gross short covering (i.e., covering by short sellers with an existing position in the stock). The coefficient on borrowing fee, *Fee*, is positive and statistically significant (*t*-statistic = 3.16), consistent with the intuitive hypothesis that (individual) short sellers cover when the costs of maintaining their positions are higher. The relation between the effective spread, *Spread*, and gross covering is negative and significant (*t*-statistic = –6.53), suggesting that short sellers are more likely to exit a position (which involves making a trade) when liquidity is higher, and in line with the argument that liquidity conditions shape the optimal trading strategy of informed investors (Collin-Dufresne and Fos, 2015, 2016). Market capitalization, another potential proxy for liquidity, is strongly positively related to short covering (*t*-statistic = 15.14). Together, these results show that firm-specific trading frictions influence short sellers.

[TABLE 3 ABOUT HERE]

More surprisingly, the loadings of short covering on past returns are positive for all horizons and statistically significant except at the shortest horizon. These findings indicate that losses induce short sellers to exist their positions, consistent with the presence of capital

[14] We exclude year-month fixed effects when including the Systematic Risk Measures as that would induce collinearity. We use year fixed effects instead in these specifications.

[15] We include industry fixed effects together with stock fixed effects because the industries a firm operates in occasionally change. All our findings remain the same if we exclude industry fixed effects from specifications with stock fixed effects.

constraints. The relation is stronger if losses are accumulated over a longer horizon, as argued by Shleifer and Vishny (1997). The coefficient estimate on return volatility, *RetVol*, is also significantly positive (*t*-statistic = 13.85), suggesting that holding costs (Pontiff, 1996) or precautionary motives lead short sellers to scale back their investments.

Even if limits to arbitrage cause existing short sellers to close positions, there may be no impact on prices if new short sellers step in. This potential mechanism is especially plausible for limits to arbitrage that do not involve direct trading frictions, such as capital constraints. However, all of the above results remain when we use net covering, which captures the exit trades of existing investors net of short sales by new investors, as our dependent variable in Column (3). In other words, idiosyncratic limits to arbitrage do not influence only individual short sellers but also short sellers as a group, with existing and potential traders both included. The role of past losses actually becomes stronger, with positive and significant coefficients over all three horizons. Last month's returns are especially important, with a coefficient estimate of 0.318 and a *t*-statistic of 7.45 (compared with 0.036 and 1.03 for gross covering). By contrast, liquidity factors have less impact (while remaining significant) compared to their effect on *GrossCover*, which is an expected result. Higher liquidity makes it easier to cover positions, but it also makes it easier to open positions, so existing short sellers who cover are more likely to be replaced by new short sellers.

Higher prior-month short interest, *Short*, is strongly related to both gross and net covering. However, it is difficult to interpret what the coefficient estimates mean because short interest is mechanically related to short covering. Only existing positions can be covered, so short covering cannot be high for stocks with low prior short interest.[16] This mechanical relation

[16] We find that the strong negative relation between *Short* and cover variables remain strong in subsamples of high- and low-*Short* short, but this does not resolve the issue.

very likely explains the extremely high levels of statistical significance for *Short* coefficients. The positive coefficients are also consistent with the hypothesis that short sellers do not want to or cannot maintain their positions over longer horizons (perhaps due limits on available shares or risk management considerations), but given the mechanical-relation issue we cannot say much more on this question.

In Columns (2) and (4), we add market-wide limits to arbitrage to our specification. Their inclusion does not affect any of the results for idiosyncratic limits to arbitrage, which stay essentially the same. More importantly, we find that most of our aggregate proxies do not exhibit a statistically significant relation with short covering. Coefficient estimates on implied market volatility, funding liquidity for primary dealers, and aggregate market liquidity are not statistically significant for either *GrossCover* or *NetCover*. The *Recession* dummy estimate is statistically significant (*t*-statistic = 3.31) for *NetCover* (but not *GrossCover*), showing there is more short covering for short sellers as a group in recessions. This is consistent with the limits-to-arbitrage argument, as various financial frictions are likely higher in recessions (Dong, Kang, and Peress, 2020; Dong, Li, Rapach, and Zhou, 2022). Overall, though, the results suggest that aggregate limits to arbitrage do not have a strong impact on short covering, contrary to many theories that stress their importance for risk premia and asset prices.

Our findings above provide several new facts about short sellers and, more generally, arbitrageurs. The evidence shows that various idiosyncratic limits to arbitrage, ranging from direct costs to limited risk-bearing capacity, affect short covering. By contrast, systematic limits to arbitrage mostly do not have a significant effect. Importantly, the inclusion of stock fixed effects means our results are not driven by unobserved differences across stocks, but rather they reflect how limits to arbitrage impact within-stock short covering.

C. Potential Omitted Variable Impact

While we use lagged independent variables to assuage concerns about reverse causality, it remains possible that an omitted variable that jointly affects limits to arbitrage and short covering influences our findings. To address this issue, we apply the omitted variable test developed in Oster (2019). The key parameter of this test, denoted by "Delta," measures how important an omitted variable needs to be (in percentage terms) relative to the control variables in order to render the parameter of interest (the treatment effect) insignificant. For example, an absolute value of Delta of one means that the omitted variable has to be 100% as important as the observable variables to overturn the significant finding on the treatment effect. The higher the absolute value of Delta, the smaller the likelihood of an omitted variable having a significant effect. An absolute value of Delta higher than one strongly suggests that the parameter of interest is unlikely to be fully explained by an omitted variable.

Table A1 in the appendix reports Delta estimates for the regression coefficients in Columns (1) and (3) of Table 3. The results show that Deltas are higher than one in absolute value for almost all the significant coefficients in Table 3 using *GrossCover* as the dependent variable. The sole exception is *Spread,* in which case the value of Delta is still high (0.68). The Deltas for the significant coefficients in Table 3 with *NetCover* are mostly below one in absolute value, except for $Ret_{i,t-1,}$ (for which Delta is 1.86). The findings suggest that an omitted variable likely cannot drive our conclusions for all the significant coefficients in the case of *GrossCover* and for Ret_{t-1} in the case of *NetCover*. Importantly, this test only explores the *potential* impact of an omitted variable and provides no evidence either for or against the existence of such an issue.

III. Short Covering and Post-Event Returns

The results in the previous section show that various proxies for idiosyncratic limits to arbitrage are positively related to both gross and net short seller covering. The interpretation of this finding depends crucially on future stock returns. If a stock affected by limits to arbitrage increases in value after short sellers cover, we cannot conclusively attribute their trades to any other motive than portfolio return maximization. However, if such a stock experiences negative returns after short sellers exit their positions, we can propose with at least a degree of confidence that their actions reflect some constraint (or behavioral bias). By covering in this situation, short sellers are forgoing gains they would otherwise capture when the stock price falls in the future. Thus, we next examine the performance of stocks after short sellers close their positions.

A. Portfolio Analysis

Our main test in Table 4 is based on standard calendar-time portfolio analysis. We sort stocks into monthly decile portfolios based on the previous month's *GrossCover* or *NetCover*. We then compute the Fama-French four-factor alpha for each (equal-weighted or value-weighted) portfolio. The *Low* (*High*) portfolio comprises stocks in the lowest (highest) short covering decile.

[TABLE 4 ABOUT HERE]

We find that short covering is strongly negatively associated with future returns. The highest-decile portfolio based on *GrossCover* suffers a negative equal-weighted abnormal return of –0.29% (*t*-statistic = –2.15), while the lowest-decile portfolio enjoys a positive abnormal return of 0.34% (*t*-statistic = 2.06). The performance differential between *High* and *Low* portfolios is –0.63% (*t*-statistic = –2.96), an economically meaningful magnitude of –7.56% on annualized basis. Furthermore, the abnormal return is lowest for *High* portfolio, highest for *Low* portfolio, and the relation across portfolios is almost fully monotonic. The results are even stronger for *NetCover*. The highest-decile (lowest-decile) portfolio has a return of –0.41% (0.35%), with a *t*-statistic of –3.08 (2.65), and the associated long-short portfolio return is –0.76% (*t*-statistic = –4.33).

When we use value-weighted returns, the results remain very similar. *High* portfolio underperforms *Low* portfolio by 0.53% (t-statistic = –2.66) based on *GrossCover* sorts and by 0.49% (t-statistic = –2.65) based on *NetCover* sorts. The evidence thus clearly shows that short sellers, both individually and as a group, do not exit their positions optimally. The stocks with most short covering are the ones with the worst subsequent returns, meaning short sellers missed out on future profits. Assuming short sellers on average correctly evaluate the expected returns for the stocks they target (as most previous research indicates), these findings support the hypothesis that limits to arbitrage influence short covering. Moreover, to the extent that short seller trades impact prices, the resulting covering may push prices further away from fundamental value, providing an example of destabilizing arbitrageur trading. Finally, the resulting upward pressure and mounting losses for remaining short sellers can force more covering (in other words, a short squeeze).[17]

B. Induced vs. Uninduced Position Closures

Short sellers close their positions for a variety of reasons and not just due to the limits of arbitrage. If short sellers are indeed skilled, only those positions that are covered because of

[17] In Table A3, we sort stocks into terciles first based on *Short* and then on *Covering*. Consistent with our intuition that short covering cannot be high if there is no short interest, we find that the high-minus-low short covering return spread is particularly strong for the portfolios with the highest short interest. However, when we average the high-minus-low return spread across low, medium, and high short interest portfolios, we still obtain a significant return differential. Therefore, the short covering findings remain even when controlling for short interest.

limits to arbitrage should be associated with future negative returns.[18] We explore this hypothesis by estimating such "induced" covering.

We start with Equation (5), our specification for relating limits to arbitrage to short covering. We omit the systematic limits to arbitrage variables, since they have little effect on either *GrossCover* or *NetCover*.[19] We then use the remaining coefficient estimates to generate predicted short covering. Finally, we define the predicted short covering value as *Induced* covering and the residual as *Uninduced* covering. The *Induced* measure is the amount of covering we would expect given the limits to arbitrage (lending fee, liquidity, past losses, return volatility) for a given stock and date. The *Uninduced* measure is the portion of short covering that is not due to variation in limits to arbitrage and thus captures voluntary position closures.

Figure 2 presents a decomposition of short covering into its *Induced* and *Uninduced* components. The proportion of total variation explained by induced covering is based on the within-R^2 of the regressions in Columns (1) and (3) of Table 3. The rest of the variation is attributed to uninduced covering. The figure shows that approximately 40% and 30% of the gross and net covering activities, respectively, are driven by induced covering. In other words, while D'Avolio (2002) finds that forced recalls are relatively rate, our results indicate that soft recalls (when stock-level conditions induce short sellers to close their position) are quite common. Therefore, a significant proportion of short covering activity is likely linked to limits to arbitrage.

[FIGURE 2 ABOUT HERE]

In Table 5, we construct calendar-time portfolios separately for induced and uncovering measures. The principal take-away is that only induced covering predicts future returns, while

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[18] It is possible that short sellers are skilled at entering new positions, as prior research demonstrates, but not at exiting them.

[19] Our results stay the same if we include them.

there is no relation for uninduced covering. Compared to results in Table 4 based on total short covering, portfolios sorted on *Induced* are significantly stronger both in terms of economic magnitude and statistical significance. For example, the long-short *High-Low* portfolio based on induced gross (net) covering suffers a negative equal-weighted abnormal return of –0.75% (–1.1%), with a t-statistic of –3.62 (–4.56), compared to –0.63% (–0.76%) when based on total short covering. Results are the same for value-weighted portfolios. In contrast, there is no return spread between *High* and *Low* for any of the portfolios based on uninduced covering. These results show that short sellers cover too early only when their trades are driven by limits to arbitrage, further illustrating these constraints' importance for short seller activity and their influence on prices.[20]

[TABLE 5 ABOUT HERE]

C. Regression Analysis

As further evidence, we examine the impact of induced covering using regression analysis. Our specification is:

$$AbnRet_{i,t} = \alpha + \beta_1 Covering_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t+1}, \tag{6}$$

where $AbnRet_{i,t}$ is a stock's raw return minus the return of the matching Fama-French 5-by-5 size and book-to-market portfolio. We use the same covering measures as in Table 3 and also add other short selling variables as controls. As before, the regressions include time (month-year)

[20] For completeness, we report in Table A2 in the appendix the portfolio analysis for *ΔShort* (the change in the short interest). *Low* portfolio (now implying high levels of short covering) suffers negative abnormal returns only for the *Induced* measure, consistent with our previous results. *High* portfolio (associated with short sellers increasing their positions) by contrast has a negative abnormal return only for the *Uninduced* measure, consistent with the previous literature that finds short sellers establish positions in stocks with low subsequent returns.

and stock fixed effects. This ensures that we focus on return predictability that is related to the variation in short covering not due to unobserved stock and time characteristics.

We report the results in Table 6. Columns (1) and (3) show that *GrossCover* and *NetCover* both negatively predict returns (*t*-statistics = –9.49 and –5.64, respectively), consistent with the portfolio analysis above. In Column (2), *GrossCover* is still negatively associated with future returns (*t*-statistic = –4.04) even after controlling for *GrossVolume*, a measure of increases in short positions. *GrossVolume* also significantly negatively predicts returns, suggesting that when short sellers initiate new positions, their trading correctly predicts future returns. In contrast, for position closures their trading activity is, on average, "wrong," in that short sellers forgo future profits by exiting.

[TABLE 6 ABOUT HERE]

Columns (4) through (6) add in the logarithm of *Short* (short interest ratio) itself as a return predictor. The estimates show that the level of short interest, the current holdings of short sellers as a group, exhibits significant negative relation with future returns, with *t*-statistics ranging from –4.57 to –7.34. But its inclusion does not subsume the return predictability of either short covering or short volume measures. Therefore, we conclude that both trading and holdings decisions of short sellers contain independent information about subsequent returns.

In Table 7, we include induced and uninduced covering measures in the same regression, with each variable standardized by its standard deviation. The results show that induced gross and net covering measures exhibit significant predictive power for subsequent returns, while uninduced covering measures do not. A one-standard-deviation increase in induced *GrossCover* (*NetCover*) is associated with 1.42% (0.96%) lower returns in the subsequent month, with a *t*-statistic of –9.85 (–6.12), which represents a meaningful economic effect.

[TABLE 7 ABOUT HERE]

Overall, this section provides additional evidence that short sellers are sometimes induced to cover their positions by (idiosyncratic) limits to arbitrage, confirming their importance in determining asset prices.

D. Long-Horizon Return Predictability

Finally, we examine the implications of short covering for long-horizon stock returns. One potential concern regarding our main return predictability finding is that short covering generates a temporary price pressure, which is then followed by a short-term return reversal as compensation for liquidity provision (Nagel, 2012). In other words, the negative abnormal returns for stocks with high levels of (induced) short covering do not represent foregone short-seller profits, but are simply a cost short sellers need to bear to exit their positions.

We test this conjecture by replacing the dependent variable in the return predictability regression in equation (6) with cumulative abnormal returns over longer horizons. Figure 3 plots the resulting regression coefficients, showing that the cumulative returns following short covering keep decreasing with no return reversal over the next 10 months. This finding is consistent with the hypothesis that short covering is associated with forgone profits due to limits to arbitrage, and it does not support the temporary price pressure interpretation.

[FIGURE 3 ABOUT HERE]

IV. Additional Analysis

In the preceding section, we show that short sellers cover too early when faced with limits to arbitrage. Here we investigate the broader implications of short covering. We first examine market quality and stock mispricing after short sellers close their positions. Consistent with existing evidence that market quality improves when short sellers trade, we find that price efficiency and mispricing get worse after short sellers are inducted to exit a position. Next, we examine the relation between hedge trading and short covering. We find that premature short covering enables hedge fund sellers of their long positions to become more informed, again in line with the literature.

A. Price Efficiency and Market Quality

We first investigate the price efficiency and market quality implications of short covering. Arbitrageurs, and short sellers in specific, have been linked to better price efficiency and market quality (Saffi and Sigurdsson, 2011). If short sellers face constraints in maintaining their positions, then this may adversely affect price formation.

To measure price efficiency, we use the mispricing measure (*MISP*) from Stambaugh, Yu, and Yuan (2015), the price delay (*Price Delay*) measure from Hou and Moskowitz (2004), and the variance ratio. Each of these has been established in the literature as a measure of price inefficiency – as each gets larger, it indicates more mispricing. Each is also computed using very different input data and thus should provide different views of price efficiency and market quality.

We then estimate the following specification:

$$Price\ Efficiency_{i,t} = \alpha + \beta_1 Covering_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where the dependent variable is one of three price efficiency measures just described. We use the same fixed effects and standard error clustering as in our past specifications. Control variables include all the independent variables in Column (1) of Table 3 (except ret_t as it is closely related to the mispricing level at the end of the period *t*).

We provide the results in Table 8. Both *GrossCover* and *NetCover* are positively related to *MISP*, *Price Delay*, and the variance ratio with coefficient estimates that are highly statistically significant, with the exception of the relation between *Price Delay* and *GrossCover.* Interestingly, the covering variables, as well as lending fee and market capitalization, always exhibit the same relation with price efficiency measures, while for other variables, such as momentum, volatility, and short interest ratio, the direction flips depending on the measure. The results provide strong evidence that short covering has a negative impact on price efficiency and market quality. Thus, the results complement existing evidence – while previous studies find that price efficiency is increasing in short seller trading, our findings show it is also decreasing when short sellers exit the market. While this finding is intuitive, it provides an important data point that supports prior results using an entirely new test.

[TABLE 8 ABOUT HERE]

B. Anomaly Returns

Anomaly returns present another test of potential deterioration in market efficiency. Intuitively, one explanation for anomalies in stock returns is that they reflect mispricing (Mclean and Pontiff, 2016), and such mispricing is largely driven by overpriced stocks that comprise the short leg of various test portfolios (Stambaugh, Yu, and Yuan 2012, 2015; Dong, Li, Rapach, and Zhou, 2022). If short covering over a period is contemporaneously associated with more mispricing, especially overvaluation as suggested by our earlier tests, then anomalies should enjoy a larger return in the subsequent period as stock prices of overpriced stocks correct.

To test this conjecture, we focus on the anomalies from Jensen, Kelly, and Pedersen (2022). Our sample covers the post-publication period, which is when return patterns for most anomalies attenuate (Mclean and Pontiff, 2016). We focus on the anomalies that remain significant with a t-value greater than 1.64 during our sample period. This results in 70 anomalies out of the 153 anomalies from Jensen *et al.* (2022). We then run the following cross-sectional regression for each anomaly:

$$Ret_{i,t+1} = a_i + b_i * Rank_{i,t} * GrossCover_{i,t} + c_i * Rank_{i,t} + d_i * GrossCover_{i,t} + \varepsilon_{i,t+1}, \quad (8)$$

where $Rank_{i,t}$ is the decile rank of stock i in month t based on a given anomaly's signal. Every anomaly is signed so that its $Rank$ is positively associated with future returns. Given anomalies are based on a cross-sectional relation, we focus on *GrossCover* only as *NetCover* mainly captures the cross-sectional variation of a different subset of the full cross section each month.

Figure 4 plots the histogram of the coefficient b_i for the 70 individual anomalies. The coefficients are grouped into 19 bins. The x-axis shows coefficient magnitude and the y-axis the fraction of coefficients in each bin as a percentage out of the total number (70) of coefficients. The estimated b_i coefficient is positive for a large majority of anomalies, suggesting that $Rank$ predicts future returns more strongly when short covering is high. Put differently, anomaly returns are higher following months with high levels of short covering.

Table 9 illustrates this short covering effect in more detail. On average, the anomalies deliver a Fama-French four-factor alpha of 41 bps per month over the sample period. The average c_i coefficient, which measures the magnitude of the anomaly return when *GrossCover* equals 0, is 2.60 with a t-statistic of 9.54. The average b_i coefficient across anomalies is 0.45 with a t-statistic of 3.69. The standard deviation of *GrossCover* is 1.5, while a bottom-to-top decile change (from 10th percentile to 90th percentile) in *GrossCover* is 3.5. Therefore, a one-standard-deviation change in *GrossCover* increases the magnitude of anomaly returns by 26% (0.45×1.5/2.6), and a bottom-to-top decile change in *GrossCover* increases anomaly returns by 61% (0.45×3.5/2.6).

[TABLE 9 ABOUT HERE]

Overall, these findings support the hypothesis that greater short covering is associated with more mispricing, which results in larger future anomaly returns.

C. Hedge Fund Trading

Another way to assess the effect of short covering on mispricing is to examine the performance of hedge fund trades conditional on short covering. Hedge funds represent informed investors (Jiao, Massa, and Zhang, 2016; Chen, Da, and Huang, 2018). Dong, Liu, Shen, and Wang (2021) theoretically and empirically demonstrate that the selling decisions of institutions are less affected by the limits to arbitrage that constrain short selling (e.g., lending fees, recalls, and margin call risk). Therefore, we expect that when short sellers close their positions prematurely due to limits to arbitrage, this might leave more opportunities for other types of informed traders, such as hedge funds, which are less subject to the same set of limits to arbitrage.

To test this hypothesis, we regress $AbnRet_t$ on the most recent available hedge fund trades, $HFTrade_{t-1}$, as well as the interaction term $HFTrade_{t-1} \times Covering_{t-1}$. We identify hedge fund trading activity using the classification in Agarwal, Jiang, Tang, and Yang (2013), which combines the information in the 13F institutional holdings data and hedge fund names data from a union of five major hedge fund databases. A 13F-filing institution is classified as a hedge fund if its major business is sponsoring/managing hedge funds according to the information revealed from a range of sources, including the institution's own websites, SEC filings, industry directories and publications, and news article searches. Our final sample consists of 1,565 unique hedge funds. $HFTrade_t$ is defined as the change in the current-quarter hedge-fund ownership of a stock relative to the stock's average hedge-fund ownership over the past four quarters, scaled by the average.

Table 10 reports the results. Columns (1) and (3) confirm that hedge fund trading is informative, with a significant positive relation between *HFTrade* and subsequent returns. The coefficient estimates on the interaction $HFTrade_{t-1} \times Covering_{t-1}$ are positive for both covering measures, indicating that *HFTrade* is more strongly associated with future returns when there is high short covering. This interaction effect is, however, only statistically significant for *GrossCover* (*t*-statistic = 2.68).

Focusing on *GrossCover,* we decompose *HFTrade* into buy and sell measures. Specifically, $HFBuy=HFTrade$ if $HFTrade>0$ and otherwise $HFBuy=0$, and $HFSell=HFTrade$ if $HFTrade<=0$ and otherwise $HFSell=0$. We interact these buy and sell measures separately with *GrossCover* by including two interaction terms $HFBuy_{i,t-1} \times GrossCover_{i,t-1}$ and $HFSell_{i,t-1} \times GrossCover_{i,t-1}$. Column (2) shows that only the *HFsell* interaction term is significant. Therefore, the result suggests that the interaction effect in Column (1) is driven by the interaction of short covering and hedge fund sales. In other words, short covering is associated with more informative hedge-fund sales, as hedge fund sellers take advantage of the mispricing associated with premature covering of short sellers.

[TABLE 10 ABOUT HERE]

V. Conclusion

Short sellers are important participants in capital markets, yet little is known about the determinants of their covering behavior. We fill the gap in the existing literature by providing new evidence on the covering activity of short sellers using a large panel of U.S. equities over a ten-year period. Using daily equity lending data, we examine the flow and stock of open short positions, and we use this to construct novel measures of position closures. We then examine the determinants and implications of position closures.

Interestingly, we show that many idiosyncratic limits to arbitrage, ranging from direct costs to potential capital constraints, cause short sellers to exit their positions. By contrast, most systematic limits to arbitrage, which are often highlighted as important in models of financial frictions, do not. Perhaps more importantly, we find that idiosyncratic limits to arbitrage are related to expected returns. Specifically, our results show that when short sellers are induced to cover their positions, subsequent returns are negative, implying a premature exit. Furthermore, such situations are associated with greater mispricing and worse price efficiency. Overall, our findings highlight the importance of idiosyncratic limits to arbitrage. Not only can they hinder the activities of informed investors, but to the extent that induced covering pushes up stock prices, they can also lead to destabilizing arbitrageur trades.

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Figure 1: GameStop Episode

This figure plots the dynamics of the GameStop stock price and NetCover measure over a six-week period centered on the day GameStop achieved its peak stock price (Jan 27, 2021). NetCover is defined as NetCover = –ΔShort if ΔShort<0; otherwise NetCover = 0.

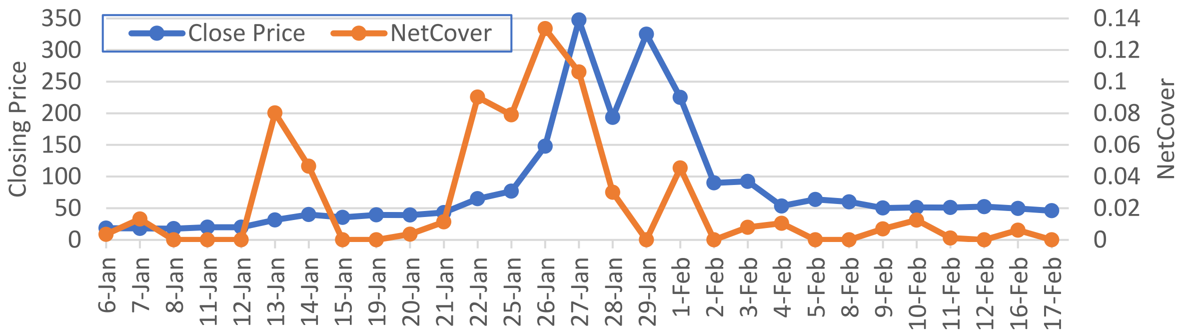


Figure 2: Induced and Uninduced Covering

This figure plots the decomposition of the total variance of the *GrossCover* and *NetCover*. The fraction of the total variation explained by induced cover is defined as the within R^2 of the regression of *GrossCover* (*NetCover*) on limits to arbitrage variables in Column 1 (3) of Table 3. The remaining variation is defined as the variation explained by uninduced covering.

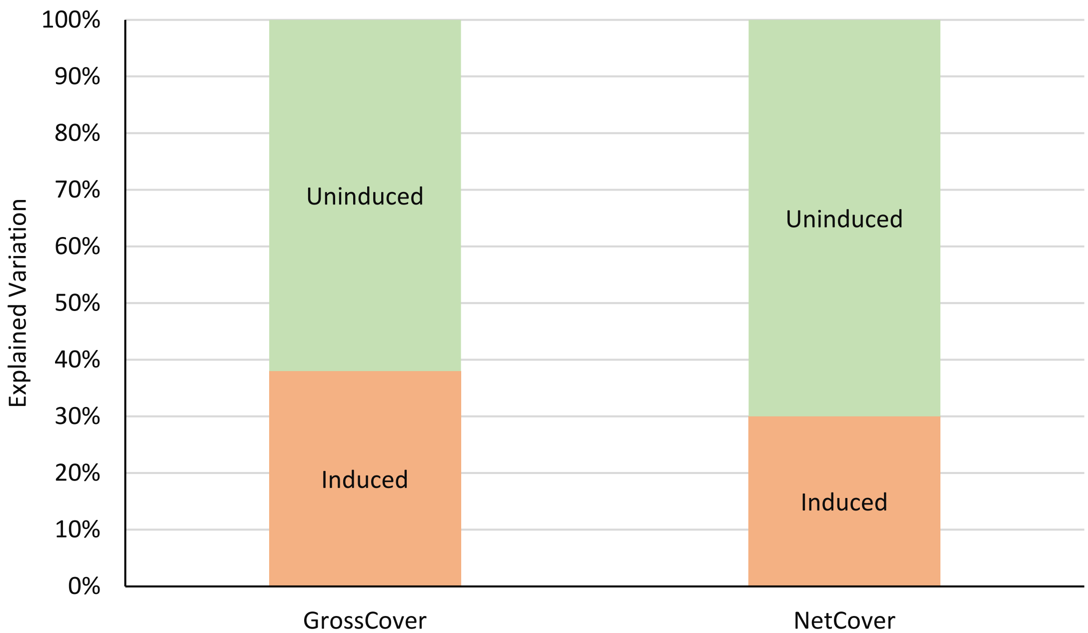
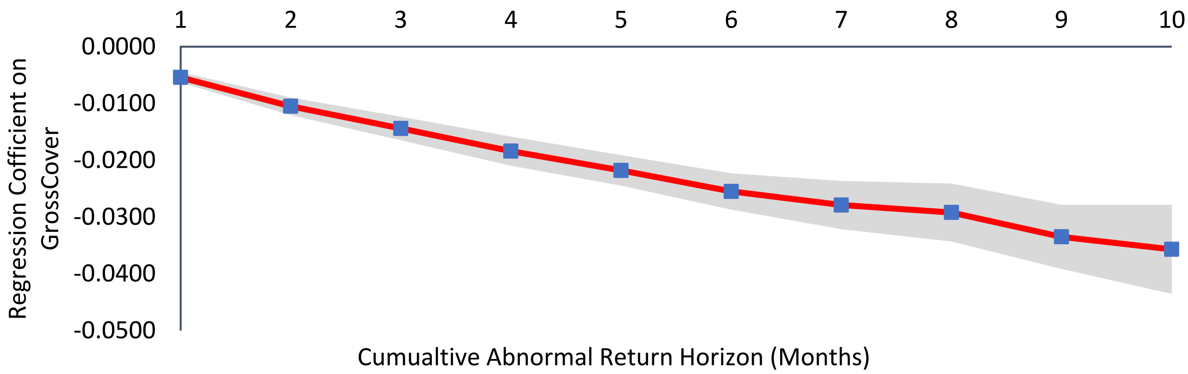


Figure 3: Cumulative Abnormal Returns Over Time

This figure reports the coefficients from the return predictability regressions over various horizons. The dependent variable is the cumulative abnormal returns over horizons ranging from 1 to 10 months. The abnormal returns are the characteristic-adjusted returns, measured as the stock's raw return minus the return of the matching Fama-French 5-by-5 size and book-to-market portfolio. *GrossCover* is the log of the *GrossCover* defined in Table 1. *NetCover* is the log of the *NetCover* defined in Table 1. All regressions include stock, month, and industry fixed effects. *t*-statistics, calculated using standard errors clustered by stock and date, are shown below the estimates in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: GrossCover and Post-Formation Returns



Panel B: NetCover and Post-Formation Returns

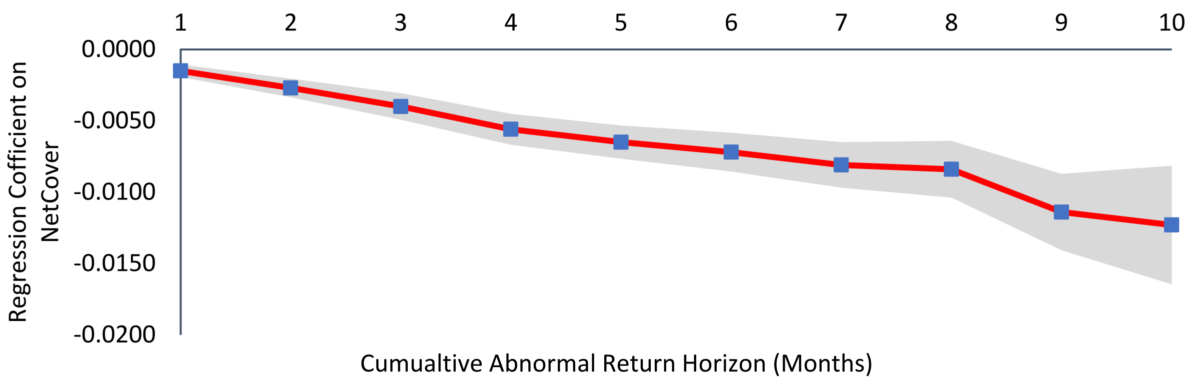


Figure 4: Short Covering and Anomalies

This figure plots the histogram of the coefficient b for the 70 individual anomalies, where b_i for each anomaly i is the coefficient estimate on the interaction term ($Rank \times GrossCover$) in the following cross-sectional regression:

$$Ret_{i,t+1} = a_i + b_i * Rank_{i,t} * GrossCover_{i,t} + c_i * Rank_{i,t} + d_i * GrossCover_{i,t} + \varepsilon_{i,t+1}$$

$$+d_i * GrossCover_{i,t} + \varepsilon_{i,t+1}$$

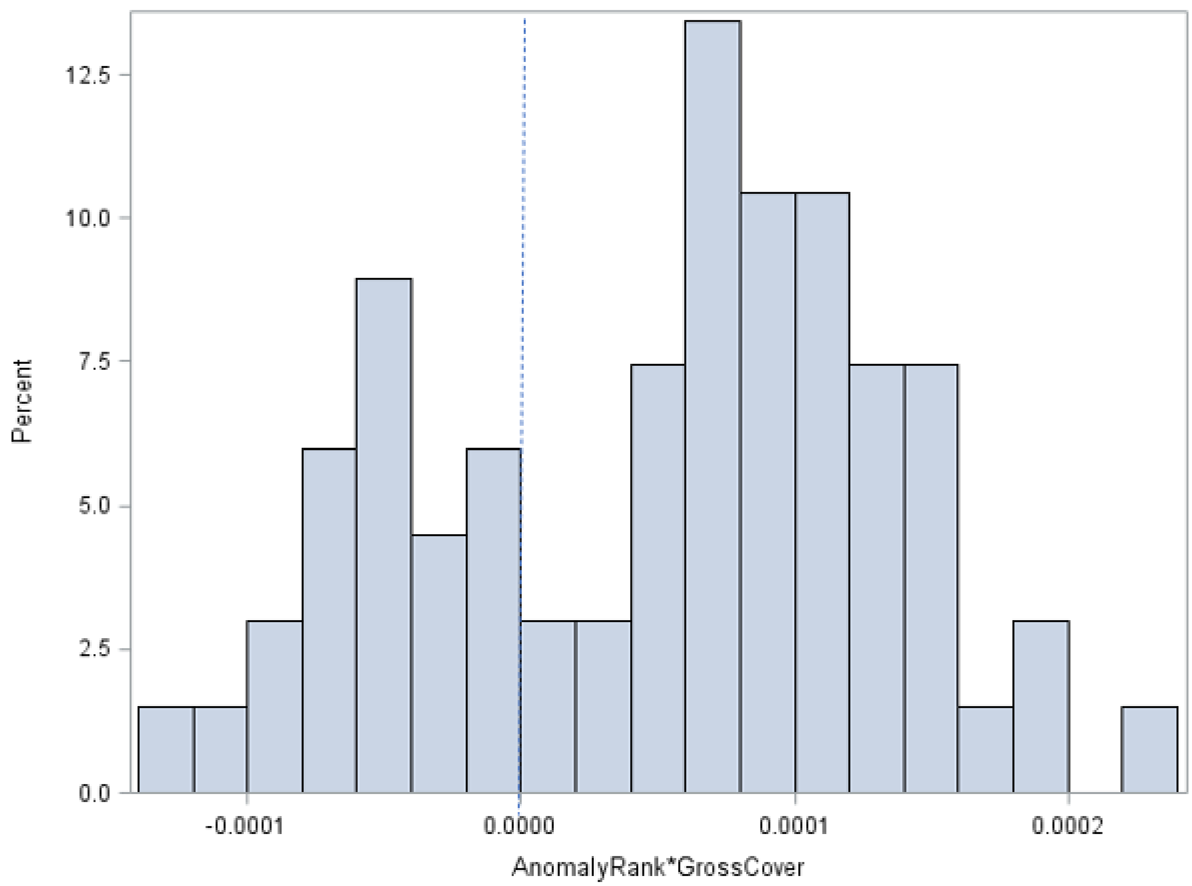


Table 1: Summary Statistics

This table displays summary statistics of monthly variables used in our tests. *GrossCover* is the existing short positions closed, divided by shares outstanding (i.e., short covering in percentage terms). *GrossVolume* is the new short positions opened, divided by shares outstanding (short volume in percentage terms). *ΔShort* is the change in *Short*, where *Short* is the short interest ratio, defined as short interest divided by shares outstanding (in percentage points). *NetCover* is defined *as NetCover = –ΔShort* if *ΔShort<0*; otherwise *NetCover = 0*. *NetVolume* is defined as *NetVolume = ΔShort* if *ΔShort>0*; otherwise *NetVolume = 0*. *Mom6m* is the cumulative return from month *t–6* to *t–2*. *Mom12m* is cumulative return from month *t–12* to *t–2*. *RetVol* is the daily return volatility, measured over the previous month. *Fee* is the equity lending fee for a stock, measured as the average daily expected borrowing cost. *Spread* is the effective bid-ask spread computed from TAQ. *MktCap* is the market value (in USD MM). *BM* is the book-to-market ratio. *MISP* is the mispricing score from Stambaugh, Yu, and Yuan (2013). *PriceDelay* is the price delay measure from Hou and Moskowitz (2005). *VarRatio* is the bias-corrected variance ratio calculated using 2-day, 4-day, and 8-day horizons with overlapping observations.

Variable	**N**	**Mean**	**P1**	**P50**	**P99**	**Std**
GrossCover	316,643	1.39	0.00	0.90	6.69	1.49
GrossVolume	316,731	1.41	0.00	0.89	7.09	1.55
NetCover	399,937	0.33	0.00	0.00	4.15	0.72
NetVolume	364,077	0.38	0.00	0.00	4.34	0.79
Short	369,510	4.11	0.00	2.05	21.37	5.10
ΔShort	364,077	0.02	-4.25	0.00	4.34	1.21
Mom6m	383,886	0.07	-0.54	0.04	1.11	0.38
Mom12m	398,489	0.15	-0.65	0.09	1.98	0.62
RetVol	395,006	0.02	0.00	0.02	0.09	0.02
Fee	377,015	1.31%	0.26%	0.38%	18.45%	4.76%
Spread	363,533	0.55	0.01	0.11	7.97	1.94
MktCap	399,922	5711	22	811	99,525	22,665
BM	393,985	0.57	-0.27	0.49	2.22	0.59
MISP	328,641	50.15	22.91	49.83	80.94	12.85
PriceDelay	279,216	0.58	0.21	0.58	0.97	0.18
VarRatio	364,583	86.18	0.31	1.06	3.17	51125.99

Table 2: Correlations

This table reports cross-correlations for the main short selling variables considered in our tests. *GrossCover* is the existing short positions closed, divided by shares outstanding. *GrossVolume* is the new short positions opened, divided by shares outstanding. *ΔShort* is the change in *Shor*t, where *Short* is the short interest ratio, defined as short interest divided by shares outstanding. *NetCover* is defined *as NetCover* = $-\Delta Short$ if $\Delta Short<0$; otherwise *NetCover* = 0. *NetVolume* is defined as *NetVolume* = *ΔShort* if $\Delta Short>0$; otherwise *NetVolume* = 0. *t*-statistics are shown below the estimates in parentheses.

Variable	GrossCover	GrossVolume	NetCover	NetVolume	ΔShort
GrossCover	1.00				
GrossVolume	0.82	1.00			
	(0.00)				
NetCover	0.41	0.22	1.00		
	(0.00)	(0.00)			
NetVolume	0.24	0.47	-0.21	1.00	
	(0.00)	(0.00)	(0.00)		
ΔShort	-0.13	0.16	-0.77	0.79	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	

Table 3: Determinants of Short Covering

This table reports the regression results for determinants of short covering. The dependent variables are *GrossCover*, defined as the log of the *GrossCover* from Table 1, and *NetCover*, defined as the log of the *NetCover* from Table 1. *Short* is the log of the short interest ratio. *Ret* is the monthly return. *Mom6m* is the cumulative return from *t–6* to *t–2*. *Mom12m* is the cumulative return from t–12 to t–2. *RetVol* is the daily return volatility measured over the previous month. *Fee* is the equity lending fee for a stock, measured as the average daily expected borrowing cost. *Spread* is the effective bid-ask spread computed from TAQ. *MktCap* is the market value (in USF MM). BM is the book-to-market ratio. *VIX* is the market implied volatility index. *FundingLiq* is a monthly measure of funding liquidity for primary dealers from He, Kelly, and Manela (2017). *MktLiq* is the aggregate market liquidity level from Pastor and Stambaugh (2003). *Recession* is a recession indicator variable, where recession month is defined by the NBER. All regressions include stock, month-year, and industry fixed effects, except those with time-series market level variables (*VIX, FundLiq, MktLiq, Recession*), in which case we use year fixed effects. *t*-statistics, calculated using standard errors clustered by firm and date, are shown below the estimates in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	$GrossCover_{i,t}$		$NetCover_{i,t}$	
	(1)	(2)	(3)	(4)
$Short_{i,t-1}$	**0.488*** **	**0.490*** **	**0.817*** **	**0.816*** **
	(78.05)	**(74.60)**	**(123.10)**	**(99.61)**
$Ret_{i,t-1}$	0.0362	0.0463	**0.318*** **	**0.301*** **
	(1.03)	(1.35)	**(7.45)**	**(5.45)**
$Mom6m_{i,t-1}$	**0.0179** **	**0.0383*** **	**0.0679*** **	**0.0671** **
	(2.31)	**(3.19)**	**(3.85)**	**(2.24)**
$Mom12m_{i,t-1}$	**0.0150*** **	**0.0152** **	**0.0281*** **	0.0268
	(2.82)	**(2.57)**	**(2.87)**	(1.43)
$RetVol_{i,t-1}$	**5.665*** **	**5.231*** **	**0.836** **	**1.045***
	(13.85)	**(12.94)**	**(2.02)**	**(1.93)**
$Fee_{i,t-1}$	**0.382*** **	**0.397*** **	**0.268** **	**0.290** **
	(3.16)	**(3.34)**	**(2.30)**	**(2.26)**
$Spread_{i,t-1}$	**-0.0462*** **	**-0.0453*** **	**-0.00676***	-0.00542
	(-6.53)	**(-6.18)**	**(-1.68)**	(-0.85)
$BM_{i,t-1}$	-0.0137	**-0.0175***	-0.00876	-0.00960
	(-1.49)	**(-1.74)**	(-0.77)	(-0.90)
$MktCap_{i,t-1}$	**0.188*** **	**0.189*** **	**0.0250***	**0.0347***
	(15.14)	**(14.93)**	**(1.97)**	**(2.07)**
VIX_{t-1}		-0.000686		0.00582
		(-0.22)		(1.66)
$FundingLiq_{t-1}$		-3.891		5.679
		(-0.92)		(1.62)
$MktLiq_{t-1}$		-0.317		-0.153
		(-1.38)		(-1.14)
$Recession_{t-1}$		0.0201		**0.167*** **
		(0.24)		**(3.31)**
Month-Year FE	Yes	No	Yes	No
Year FE	No	Yes	No	Yes
Stock FE	Yes	Yes	Yes	Yes
N	240,615	240,615	138,851	138,852
Adj. R^2	0.807	0.801	0.572	0.568

Table 4: Portfolio Sorts for GrossCover and NetCover

This table presents Fama-French four-factor alphas for monthly calendar-time equal-weighted and value-weighted portfolios sorted by $X_{i,t-1}$, where X = *GrossCover* or *NetCover*. *t*-statistics are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Equal-Weighted		**Value-Weighted**	
	GrossCover	**NetCover**	**GrossCover**	**NetCover**
Low	0.0034**	0.0035***	0.0027***	0.003**
	(2.06)	(2.65)	(2.78)	(2.47)
2	0.0023*	0.0005	0.0019**	0.0009
	(1.91)	(0.38)	(2.12)	(0.83)
3	0.0024**	0.0009	0.0015*	0.0014
	(2.24)	(0.9)	(1.91)	(1.36)
4	0.0014*	0.0016*	-0.0004	0.0001
	(1.71)	(1.71)	(-0.42)	(0.06)
5	0.0003	0.0008	0.0001	0.0004
	(0.35)	(0.88)	(0.12)	(0.24)
6	0.0004	0.0013	0.0009	-0.0013
	(0.55)	(1.32)	(0.9)	(-0.96)
7	0.0002	-0.0013	0.0006	0.0009
	(0.26)	(-1.36)	(0.51)	(0.57)
8	-0.0001	-0.0009	-0.0019*	-0.0015
	(-0.11)	(-0.92)	(-1.73)	(-1)
9	-0.0008	-0.0009	-0.0014	-0.0001
	(-1.03)	(-0.82)	(-1.09)	(-0.07)
High	-0.0029**	-0.0041***	-0.0028*	-0.0019
	(-2.15)	(-3.08)	(-1.7)	(-1.18)
High-Low	**-0.0063*** **	**-0.0076*** **	**-0.0053*** **	**-0.0049*** **
	(-2.96)	**(-4.33)**	**(-2.66)**	**(-2.65)**

Table 5: Portfolio Sorts for Induced vs. Uninduced Covering

This table presents the Fama-French four-factor alphas for monthly calendar-time equal-weighted (Panel A) and value-weighted (Panel B) portfolios. Sorts are based on $X_{i,t-1}$, where X = *GrossCover* or *NetCover*. We consider two versions of $X_{i,t-1}$: "Induced" and "Uninduced," which represent the predicted and residual components of $X_{i,t-1}$, respectively, using the regressions in Columns (1) and (3) of Table 3, where all the firm-level determinants are included (market-level determinants are excluded) and all determinants are measured at *t–2*. *t*-statistics are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Equal-Weighted Portfolios

	GrossCover		NetCover	
	Induced	Uninduced	Induced	Uninduced
Low	0.0041**	0.0008	0.0047***	0.0016
	(2.55)	(0.62)	(2.81)	(1.32)
2	0.0016	0.0021***	0.0026**	-0.0003
	(1.19)	(2.77)	(1.99)	(-0.28)
3	0.0023**	0.0011	-0.0002	0.0004
	(2.12)	(1.53)	(-0.16)	(0.3)
4	0.0019**	0.001	0.003***	-0.0002
	(2.35)	(1.17)	(2.85)	(-0.12)
5	-0.0001	-0.0001	0.0008	-0.0002
	(-0.17)	(-0.19)	(0.83)	(-0.11)
6	0.0012	0.0004	0.0011	0.0009
	(1.56)	(0.62)	(1.12)	(0.64)
7	0.0002	0.0009	0.0005	-0.0016
	(0.24)	(1.33)	(0.53)	(-1.15)
8	0.0000	0.0001	-0.0011	-0.0004
	(-0.02)	(0.08)	(-1.14)	(-0.29)
9	-0.0005	0.0013	-0.0013	0.0022
	(-0.5)	(1.57)	(-1.13)	(1.49)
High	-0.0034**	-0.0003	-0.0063***	0.0012
	(-2.53)	(-0.25)	(-3.68)	(0.68)
High-Low	**-0.0075***	-0.001	**-0.011***	-0.0004
	(-3.62)	(-0.69)	**(-4.56)**	(-0.2)

Table 5 (continued) **Panel B: Value-Weighted Portfolios**

	GrossCover		NetCover	
	Induced	Uninduced	Induced	Uninduced
Low	0.0028**	0.0019*	0.0026***	0.0042**
	(2.51)	(1.86)	(2.03)	(2.5)
2	0.0018*	0.0002	0.0001	-0.0026
	(1.73)	(0.26)	(0.11)	(-1.36)
3	0.0009	0.0008	-0.0003	0.0003
	(1.04)	(0.81)	(-0.22)	(0.19)
4	0.0005	0.001	0.0021*	-0.0029*
	(0.66)	(1.17)	(1.78)	(-1.78)
5	0	0.0004	-0.0011	0.0033**
	(-0.02)	(0.4)	(-0.91)	(1.98)
6	0.0005	-0.0009	-0.0006	-0.0019
	(0.47)	(-0.98)	(-0.47)	(-1.06)
7	0.0018**	0.0013	-0.0014	-0.0011
	(2.02)	(1.16)	(-0.92)	(-0.52)
8	0.0000	-0.0015	0.0001	-0.004*
	(-1.44)	(-1.25)	(0.04)	(-1.86)
9	-0.0011	-0.0004	0.001	0.0043*
	(-0.91)	(-0.36)	(0.65)	(1.93)
High	-0.0043***	0.002*	-0.0045***	0.0033*
	(-2.79)	(1.75)	(-2.62)	(1.77)
High-Low	**-0.0071*****	0.0002	**-0.0071*****	-0.0009
	(-3.18)	(0.11)	**(-2.95)**	(-0.36)

Table 6: Return Predictability Regression

This table reports the coefficient estimates for a return predictability regression. The dependent variable is *AbnRet*, the characteristic-adjusted abnormal return measured as the stock's raw return minus the return of the matching Fama-French 5-by-5 book-to-market and size portfolio. *GrossCover* is the log of the *GrossCover* defined in Table 1. *GrossVolume* is the log of the *GrossVolume* defined in Table 1. *NetCover* is the log of the *NetCover* defined in Table 1. *Short* is the log of the short interest ratio. All regressions include stock, month-year, and industry fixed effects. *t*-statistics, calculated using standard errors clustered by stock and date, are shown below the estimates in parentheses. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$GrossCover_{i,t-1}$	**-0.00536*** **	**-0.00256*** **		**-0.00322*** **	**-0.00197*** **	
	(-9.49)	**(-4.04)**		**(-6.63)**	**(-3.27)**	
$GrossVolume_{i,t-1}$		-0.00450***			-0.00297***	
		(-7.31)			(-4.50)	
$NetCover_{i,t-1}$			**-0.00153*** **			**-0.000580** **
			(-5.64)			**(-2.42)**
$Short_{i,t-1}$				-0.00373***	-0.00323***	-0.00235***
				(-7.34)	(-6.94)	(-4.57)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
N	256,136	252,168	151,754	251,755	249,013	151,754
Adj. R^2	0.008	0.008	0.014	0.009	0.009	0.015

Table 7: Return Predictability Regression for Induced vs. Uninduced Cover

This table reports the coefficient estimates for a return predictability regression, focusing on induced and uninduced short covering. The dependent variable is *AbnRet*, the characteristic-adjusted abnormal return measured as the stock's raw return minus the return of the matching Fama-French 5-by-5 book-to-market and size portfolio. X = *GrossCover* or *NetCover*. We include two versions of $X_{i,t-1}$: "Induced" and "Uninduced," which represent the predicted and residual components of $X_{i,t-1}$, respectively, using the regressions in Columns (1) and (3) of Table 3, where all the firm-level determinants are included (market-level determinants are excluded) and all determinants are measured at *t–2*. Regressions include stock, month-year, and industry fixed effects. *t*-statistics, calculated using standard errors clustered by firm and date, are shown below the estimates in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Induced $GrossCover_{i,t-1}$	**-0.0142*****	
	(-9.85)	
Uninduced $GrossCover_{i,t-1}$	-0.000459	
	(-0.86)	
Induced $NetCover_{i,t-1}$		**-0.00962*****
		(-6.12)
Uninduced $NetCover_{i,t-1}$		0.000111
		(0.23)
Month-Year FE	Yes	Yes
Stock FE	Yes	Yes
N	191,388	55,370
Adj. R^2	0.01	0.02

Table 8: Short Covering and Price Efficiency

This table reports the coefficient estimates for a regression of price efficiency measures on short covering variables (*NetCover* or *GrossCover*) and arbitrage determinants. The dependent variables are: *MISP*, the mispricing score from Stambaugh, Yu, Yuan (2013); *PriceDelay*, the price delay measure from Hou and Moskowitz (2005), and *Abs(VarRatio-1)*, the log of the absolute value of the variance ratio minus 1. *NetCover* is the log of the *NetCover* defined in Table 1. *GrossCover* is the log of the *GrossCover* defined in Table 1. *Short* is the log of the short interest ratio. *Mom6m* is the cumulative return from month *t–6* to *t–2*. *Mom12m* is cumulative return from month *t–12* to *t–2*. *RetVol* is the daily return volatility measured over the previous month. *Fee* is the equity lending fee for a stock, measured as the average daily expected borrowing cost. *Spread* is the effective bid-ask spread computed from TAQ. *MktCap* is the market capitalization (in USD MM). BM is the book-to-market ratio. All regressions include stock, month-year, and industry fixed effects. *t*-statistics, calculated using standard errors clustered by stock and date, are shown below the estimates in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	$MISP_{i,t}$		Price $Delay_{i,t}$		Abs(Var Ratio-1)$_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$GrossCover_{i,t}$	**0.394*** **		0.000965		**0.0312*** **	
	(7.09)		(1.06)		**(7.11)**	
$NetCover_{i,t}$		**0.0808*** **		**0.000979*** **		**0.0127*** **
		(4.37)		**(2.76)**		**(5.07)**
$Short_{i,t}$	0.492***	0.564***	-0.00350***	-0.00345***	-0.0161***	-0.00786**
	(8.33)	(10.21)	(-4.19)	(-4.15)	(-4.97)	(-2.43)
$Mom6m_{i,t}$	-3.460***	-3.406***	0.0136***	0.0151***	-0.00755	-0.00524
	(-6.77)	(-7.37)	(4.93)	(5.21)	(-0.79)	(-0.41)
$Mom12m_{i,t}$	-3.935***	-4.416***	0.00867***	0.00896***	-0.00801	-0.00833
	(-5.76)	(-6.65)	(4.85)	(4.72)	(-1.34)	(-1.05)
$RetVol_{i,t}$	55.21***	64.66***	0.0219	0.0595	-4.766***	-4.869***
	(14.07)	(16.33)	(0.48)	(1.22)	(-9.44)	(-7.71)
$Fee_{i,t}$	6.609***	5.313***	0.131***	0.125***	0.354***	0.240***
	(3.39)	(3.08)	(4.11)	(3.98)	(4.34)	(2.63)
$Spread_{i,t}$	0.0382	-0.0133	0.000821	0.000950	0.00588***	0.00554**
	(1.44)	(-0.48)	(1.33)	(1.53)	(2.67)	(2.29)
$BM_{i,t}$	0.701**	0.721**	0.00241	0.000395	0.00106	0.00802
	(1.98)	(2.51)	(0.88)	(0.15)	(0.14)	(0.76)
$MktCap_{i,t}$	-1.044***	-0.756***	-0.0145***	-0.0154***	-0.0528***	-0.0391***
	(-3.51)	(-2.76)	(-4.65)	(-5.22)	(-4.48)	(-3.04)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
N	274,858	154,138	227,984	128,911	291,488	164,901
Adj. R^2	0.622	0.617	0.487	0.491	0.024	0.028

Table 9: Short Covering and Anomaly Returns

This table summarizes the anomaly returns and their interaction with short covering using the following cross-sectional regression:

$$Ret_{i,t+1} = a_i + b_i * Rank_{i,t} * GrossCover_{i,t} + c_i * Rank_{i,t} + d_i * GrossCover_{i,t} + \varepsilon_{i,t+1}$$

Anomaly alpha is computed based on the Fama-French 4-factor model. *t*-statistics are reported in parentheses.

Number of Anomalies	70
Average Long-Short Monthly Anomaly Alpha	41 bps
	(9.52)
Average Coefficient *b* (x10000) on $Rank * GrossCover$	0.45
	(3.69)
Average Coefficient *c* (x10000) on *Rank*	2.60
	(9.54)

Table 10: Short Covering and Hedge Fund Trading

This table examines the interaction between hedge fund trading and short covering. The dependent variable is *AbnRet*, the characteristic-adjusted abnormal return measured as the stock's raw return minus the return of the matching Fama-French 5-by-5 book-to-market and size portfolio. *HFTrade* is the most recent change in hedge fund holdings of the stock. *HFBuy = HFTrade* if *HFTrade>0*; otherwise *HFBuy = 0*. *HFSell = HFTrade* if *HFTrade<=0*; otherwise *HFSell = 0*. *GrossCover* is the log of the *GrossCover* defined in Table 1. NetCover is the log of the *NetCover* defined in Table 1. All regressions include stock, month-year, and industry fixed effects. *t*-statistics, calculated using standard errors clustered by stock and date, are shown below the estimates in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
$HFTrade_{i,t-1}$	**0.00195*****		**0.00179****
	(3.54)		**(2.36)**
$HFTrade_{i,t-1} \times GrossCover_{i,t-1}$	**0.000650*****		
	(2.68)		
$HFTrade_{i,t-1} \times NetCover_{i,t-1}$			0.000345
			(1.39)
$HFBuy_{i,t-1}$		0.00234***	
		(3.34)	
$HFSell_{i,t-1}$		0.00180	
		(1.46)	
$HFBuy_{i,t-1} \times GrossCover_{i,t-1}$		0.000421	
		(1.39)	
$HFSell_{i,t-1} \times GrossCover_{i,t-1}$		**0.00141****	
		(2.39)	
$GrossCover_{i,t-1}$	-0.00562***	-0.00482***	
	(-8.74)	(-8.13)	
$NetCover_{i,t-1}$			-0.00139***
			(-5.29)
Month-Year FE	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
N	245,851	245,851	145,826
Adj. R^2	0.006	0.006	0.014

Internet Appendix for
"Short Covering"[1]

This Internet Appendix provides additional empirical evidence to supplement the analyses provided in the main text.

[1] Citation format: Blocher, Jesse, Xi Dong, Matthew C. Ringgenberg, and Pavel Savor, Internet Appendix for "Short Covering"

Table A1: Oster Omitted Variable Test

The table shows the results of the test for unobservable selection, using δ of Oster (2019). Oster's δ measures the degree of selection on unobservables relative to observables that would be required to make the estimated beta zero. δ is calculated based on the assumptions that the maximum R^2—the R^2 value that can be obtained if all unobserved variables are included—is one and the true beta is zero. The table reports the δ for each independent variable for our regressions in Table 3. *GrossCover* is the log of the *GrossCover* defined in Table 1. *NetCover* is the log of the *NetCover* defined in Table 1. *Short* is the log of the short interest ratio. *Ret* is the monthly return. *Mom6m* is the cumulative return from *t–6* to *t–2*. *Mom12m* is the cumulative return from t–12 to t–2. *RetVol* is the daily return volatility measured over the previous month. *Fee* is the equity lending fee for a stock, measured as the average daily expected borrowing cost. *Spread* is the effective bid-ask spread computed from TAQ. *MktCap* is the market value (in USF MM).

	(1)	(2)
	$GrossCover_{i,t}$	**$NetCover_{i,t}$**
$Short_{i,t-1}$	1.14	0.46
$Ret_{i,t-1}$	-12.47	1.86
$Mom6m_{i,t-1}$	-3.02	-0.19
$Mom12m_{i,t-1}$	-5.19	-0.13
$RetVol_{i,t-1}$	3.10	0.14
$Fee_{i,t-1}$	-20.53	0.17
$Spread_{i,t-1}$	0.68	0.04
$MktCap_{i,t-1}$	1.96	0.17

Table A2: Portfolio Sorts for Change in Short Interest

This table presents the Fama-French four-factor alphas for monthly calendar-time equal-weighted (Panel A) and value-weighted (Panel B) portfolios. Sorts are based on $X_{i,t-1}$, where X = *ΔShort*. We consider two versions of $X_{i,t-1}$: "Induced" and "Uninduced," which represent the predicted and residual components of $X_{i,t-1}$, respectively, using the regressions in Columns (1) and (3) of Table 3, where all the firm-level determinants are included (market-level determinants are excluded) and all determinants are measured at *t–2*. *t*-statistics are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Equal-Weighted			Value-Weighted		
	Total	Induced	Uninduced	Total	Induced	Uninduced
Low	-0.0023**	-0.0078***	-0.0009	-0.0011	-0.0044**	-0.0002
	(-2.26)	(-4.65)	(-0.85)	(-0.89)	(-2.51)	(-0.18)
2	-0.0009	-0.0014	0.0007	-0.0002	-0.0014	0.0002
	(-1.17)	(-1.37)	(0.86)	(-0.15)	(-1.1)	(0.21)
3	0.0012	-0.0008	0.0016*	-0.0003	-0.0006	0.0002
	(1.38)	(-0.88)	(1.92)	(-0.3)	(-0.54)	(0.16)
4	0.0002	0.0000	0.0009	0.0007	0.0005	0.0003
	(0.2)	(0.02)	(0.93)	(0.78)	(0.43)	(0.35)
5	0.0007	0.0003	0.0014	0.0008	-0.0006	0.0008
	(0.65)	(0.37)	(1.58)	(1.04)	(-0.65)	(0.98)
6	0.0022**	0.0016**	0.0012	0.0011	0.0007	0.0004
	(2.2)	(2.17)	(1.33)	(1.42)	(0.77)	(0.42)
7	0.0028***	0.0016**	0.001	0.0006	0.0002	0.001
	(3.16)	(1.98)	(1.02)	(0.77)	(0.19)	(1.08)
8	-0.0005	0.0019**	0.0003	-0.001	0.0012	-0.0001
	(-0.55)	(2.2)	(0.3)	(-1.07)	(1.52)	(-0.16)
9	-0.0024***	0.0016*	-0.0022***	0.0001	0.0006	-0.0014
	(-2.76)	(1.87)	(-2.68)	(0.12)	(0.95)	(-1.25)
High	-0.0036***	0.003**	-0.0045***	-0.0027**	0.0016	-0.0026**
	(-3.18)	(2.24)	(-3.77)	(-2.22)	(1.4)	(-2.31)
High-Low	-0.0012	**0.0108*****	**-0.0037*****	-0.0016	**0.0061****	-0.0024
	(-1.03)	**(4.53)**	**(-2.75)**	(-1.04)	**(2.45)**	(-1.54)

Table A3: Portfolio Double Sorts on Short Interest and Short Covering

This table reports the Fama-French four-factor alphas for monthly calendar-time portfolios double-sorted on $Short_{i,t-1}$ and $GrossCover_{I,t-1}$. *Short* is the log of the short interest ratio. *GrossCover* is the log of the *GrossCover* defined in Table 1. Panels A and B report the equal- and value-weighed portfolio returns, respectively. *t*-statistics are shown in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Equal-Weighted Portfolio

	GrossCover			
Short	Low	Medium	High	High-Low
Low	0.13*	0.03	0.10	-0.03
	(1.80)	(0.37)	(0.40)	(-0.12)
Medium	0.27*	0.03	-0.05	-0.32
	(1.89)	(0.33)	(-0.39)	(-1.60)
High	0.64**	-0.00	-0.28***	-0.92***
	(2.35)	(-0.00)	(-2.62)	(-3.15)
Avg				**-0.42****
				(-2.57)

Panel B: Value-Weighted Portfolio

	GrossCover			
Short	Low	Medium	High	High-Low
Low	0.13*	0.05	-0.04	-0.17
	(1.79)	(0.64)	(-0.14)	(-0.58)
Medium	0.15	0.03	-0.03	-0.19
	(1.10)	(0.36)	(-0.26)	(-0.92)
High	0.60**	-0.05	-0.26**	-0.86***
	(2.17)	(-0.30)	(-2.48)	(-2.92)
Avg				**-0.40****
				(-2.33)