# Short Traders and Short Investors

JESSE BLOCHER*, PETER HASLAG*, AND CHI ZHANG**

**ABSTRACT**

We now know a great deal about short sellers. For example, they are informed and correct overpricing. However, the literature measures short selling as both a constraint (i.e. loan fees) and through trading activity (volume or trades). With a new measure of short selling activity, we show that short-selling constraints and activity capture two distinct groups of short sellers. The first group, "short *traders*," pay very low stock loan fees (i.e. are unconstrained), have a short investment horizon and lower risk tolerance. The second group, "short *investors*," pay very high loan fees (i.e. are more constrained), have a longer horizon, and a higher risk tolerance. While both types of short sellers are informed, they incorporate different types of information. Short traders trade in a matter of days to include short lived information (i.e. events) while short investors include more long-lived information (i.e. firm fundamentals).

Keywords: Securities Lending, Short Selling, Limits to Arbitrage, Anomalies
JEL: G12, G14, G23

First Version: November 18, 2017

Current version: March 8, 2018

*Assistant Professor of Finance, Owen Graduate School of Management, Vanderbilt University, 401 21st Avenue South, Nashville, TN 37203. **Assistant Professor of Finance, Manning School of Business, University of Massachusetts Lowell, MA 01854. This research was supported by the Vanderbilt's Financial Markets Research Center. This work was conducted in part using the resources of the Advanced Computing Center for Research and Education at Vanderbilt University, Nashville, TN and Wharton Research Data Services, The Wharton School, University of Pennsylvania. The authors can be contacted via email at jesse.blocher@owen.vanderbilt.edu, peter.haslag@owen.vanderbilt.edu and Chi_Zhang1@uml.edu.

# Short Traders and Short Investors


**ABSTRACT**

We now know a great deal about short sellers. For example, they are informed and correct overpricing. However, the literature measures short selling as both a constraint (i.e. loan fees) and through trading activity (volume or trades). With a new measure of short selling activity, we show that short-selling constraints and activity capture two distinct groups of short sellers. The first group, "short *traders*," pay very low stock loan fees (i.e. are unconstrained), have a short investment horizon and lower risk tolerance. The second group, "short *investors*," pay very high loan fees (i.e. are more constrained), have a longer horizon, and a higher risk tolerance. While both types of short sellers are informed, they incorporate different types of information. Short traders trade in a matter of days to include short lived information (i.e. events) while short investors include more long-lived information (i.e. firm fundamentals).



Keywords: Securities Lending, Short Selling, Limits to Arbitrage, Anomalies
JEL: G12, G14, G23

Current version: March 8, 2017

There is a large literature, dating back to Miller (1977), that has shown how short selling constraints predict negative stock returns (e.g., Asquith and Meulbroek (1996), Asquith, Pathak, and Ritter (2005), Nagel (2005), Boehme, Danielsen, and Sorescu (2006)). The framework is simple: given a distribution of investors with varying beliefs, short constraints inhibit the most pessimistic investors from participating in financial markets, and therefore, on average, the stock is overpriced compared to the unconstrained alternative. Miller (1977) showed this graphically, and Blocher, Reed, and Van Wesep (2013) showed it in a more rigorous supply and demand framework. Moreover, Blocher and Zhang (2017) have recently shown that short constraints are quite persistent, on average lasting 9 months. Taken together, long-lived short-selling constraint periods convey significant negative information about a firm.

There is also a literature showing that short selling *activity*, defined as trades or trading volume labeled as short sales, predicts negative returns (e.g., Diether, Lee, and Werner (2009), Boehmer, Jones, and Zhang (2008)). Moreover, Christophe, Ferri, and Angel (2004) show that short selling activity prior to earnings announcements is closely linked to post-announcement returns. Christophe, Ferri, and Hsieh (2010) find increased abnormal short activity prior to analyst downgrades and show that this activity is related to post-downgrade returns. Engelberg, Reed, and Ringgenberg (2012) investigate short trade volume around news events and find short sellers do not necessarily anticipate news, but short sellers are able to process the information better, resulting in a stronger negative relationship between short selling and future returns concurrent with negative news. Overall, this literature on short selling activity has made two main points. First, it shows that short selling activity predicts negative returns over short horizons, consistent with the (longer horizon) literature on short selling constraints. Second, it further clarifies how short sellers are informed traders by focusing on short seller behavior around informative events.

While clearly related, the precise relationship between these two literatures has not been investigated. Indeed, some suggest that the only difference between these two literatures is time scale (monthly vs daily). This may be true: tautologically, substantial cumulative short selling activity (i.e. trades) is a necessary condition for a short selling constraint to bind. Thus, the negative returns documented in both of these literatures could be due to two measured effects (short selling constraints and short selling trades/volume), both of which proxy for the same underlying phenomenon (negative information/beliefs among a segment of investors). This is our null hypothesis.

Our alternative hypothesis, for which we find ample evidence, is that the two measurements (activity and constraints) are capturing two different behaviors. The short selling literature typically measures constraints as stock loan fees that fall above the 90$^{th}$ percentile threshold (e.g. Blocher, Reed, and Van Wesep (2013)). This means that borrowing shares of a constrained stock is very expensive. At such high fees, basic economics dictates that few transactions should take place, and therefore short selling activity should be low when a stock is short constrained. In fact, this is the very definition of the word 'constrained.' Our alternative hypothesis then states that short selling *activity* should only effectively generate short-horizon stock price reductions when short selling is unconstrained. Additionally, when a stock is short constrained, positive stock returns should not predict short activity due to the constraints on that activity. As a result, our alternative hypothesis is that the two measurements of short selling identify separate and distinct behavior.

The primary obstacle to investigating the interaction of short selling constraints and short selling activity has been data availability. Boehmer, Jones, and Zhang (2008), Christophe, Ferri, and Angel (2004), Christophe, Ferri, and Hsieh (2010) all use proprietary data and limited length (often approximately a year of data). Diether, Lee, and Werner (2009) and Engelberg, Reed, and Ringgenberg (2012) use trade data from Regulation SHO, but this data is only available from January 2005 – June 2007.[1] Since short selling constraints are measured at a monthly frequency, the short time period for Regulation SHO limits the sample to 30 observations per firm for short selling constraints, making statistical inference difficult.

We overcome this obstacle by developing a new measure of short selling activity using existing, known data. Specifically, we measure short selling activity as the daily change in shares demanded for stock loans using the daily stock loan demand data from Markit. Our measure is a net short selling activity measure, since daily demand is an aggregation of new stock loans plus existing stock loans minus closed stock loans. This netting effect contrasts with short selling activity measures in the literature, which simply identify short trades and cannot identify

[1] Reg SHO data is also available after 2010 through FINRA but must be hand-collected across exchanges. This newer set of short volume data also no longer predicts negative returns as in Diether, Lee, and Werner (2009). We discuss this in depth in our Data section.

covering trades. Delineating between net shorting-selling and net covering activity should strengthen the economic intuition of our tests.[2] To validate our new measure, we show that it replicates both of the main results in Diether, Lee, and Werner (2009). That is, our new measure shows that positive stock returns predict short selling activity and short selling activity predicts negative returns, all at a horizon of five days.

We begin our analysis by simply considering observation frequency. How often do we observe that a stock is short constrained and also experiencing significant short selling activity? Very rarely. This combination represents only 1.8% of our entire sample. For comparison, 7.7% of our sample is short constrained and 20% of our sample has high (net) short selling activity. This simple, univariate evidence supports our primary hypothesis that activity and constraints are capturing separate phenomena.

Rather than focus on short selling measures, however, our primary contribution is to provide evidence that there exist two distinct short selling strategies: we call them "short *traders*" and "short *investors*." We will characterize them more fully, but to start with, short investors buy and hold riskier short positions in short constrained stocks (i.e. stocks with very high loan fees), while short traders take short term positions in low-risk, unconstrained stocks (i.e. stocks with low loan fees, typically less than 100 bps annualized). These two strategies are correlated with the two short selling measures just described.[3]

To provide robust evidence, we turn to a multivariate, panel specification. We divide our sample into three groups defined by varying persistence of short selling constraints following Blocher and Zhang (2017): persistently constrained (or constrained), transiently constrained (or transient), and unconstrained. When we subdivide the sample into these constraint-based groups, positive returns only predict short selling activity for the unconstrained group (and in the overall sample). In addition, short activity predicts negative returns only among unconstrained stocks.

[2] Blocher and Ringgenberg (2018) show that covering often happens soon after shorting, such that high short volume may be offset by (unobserved) covering transactions. Thus, a net measure will capture the aggregate effect, similar to order imbalances, for example. In addition, intraday short volume transactions (captured by the Reg SHO data) contain much uninformative short selling, for example ETF arbitrage trades and other algorithmic arbitrage trades.

[3] For expositional purposes, we will continue to call these two strategies "short traders" and "short investors" but it need not be the case that they are literally distinct market participants. We contend only that they are distinct short selling strategies, and therefore a single participant could employ either (or both) based on varying market conditions. We cannot identify individuals behind the strategies.

To provide further evidence that short traders and short investors are different, we show that these two groups have different risk tolerances. Short investors have higher risk tolerances: short constrained stocks have volatility ranging from 63-72% annualized. Unconstrained stocks targeted by short traders have a more standard volatility, approximately 40-41% annualized on average. Short selling risk (Engelberg, Reed, and Ringgenberg (2017)) is an order of magnitude higher among short constrained stocks compared to unconstrained stocks. Therefore, short investors target stocks that are substantially riskier than most other stocks.

Short investors and short traders also have different investment horizons. This is predictable based on the existing literature, but we show it rigorously in a multivariate specification. We find that the negative relationship between short activity and returns weakens with increasing investment holding period (from one week to three months). In contrast, the negative relationship between short selling constraints and subsequent strengthens with increasing investment holding period.

To study short sellers' differing information sets, we study activity around analyst downgrades and earnings announcements. First, when considering downgrades we find some evidence of high short activity ahead of analyst downgrades, but only among unconstrained stocks. Among both constrained and unconstrained stocks, we find covering activity from T+3 to T+10 after the event, but among constrained stocks, it is substantially higher. Simultaneously, the largest negative event returns are among constrained stocks, almost 50% higher than the other groups (-3.6% vs -1.9%, daily).

These combined results around analyst downgrades are consistent with informed short sellers, but with two different meanings of 'informed.' Short investors, who have short positions in constrained stocks, have taken their position long before the downgrade and therefore likely formed their negative viewpoint using the firm's fundamentals (e.g. Dechow et al. (2001)) or other long-lived information. In this case, the downgrade is simply the analyst (and perhaps other stock owners) catching up to what the short investor already knew prior to the event. After the news is (more) public, the short investor covers his position. In contrast, short traders trade on short-term information in unconstrained stocks ahead of analyst downgrades. This is consistent with Christophe, Ferri, and Hsieh (2010), who claim that trading ahead of analyst downgrades is a kind of 'leakage' where analysts tip off traders who then trade just ahead of the event. They also cover their short-horizon trade after the event. Thus, short investors and short traders are operating with two different information sets and two different groups of stocks, but both profit off of their information advantage ahead of analyst downgrades.

Second, we look at negative earnings surprises. We find no evidence of short selling ahead of the event either in the pooled sample or any subsamples.[4] After the negative earnings surprise, we find that short investors engage in substantial covering: net covering volume divided by total volume is 22% cumulatively from day 3 to day 10 post-event. Unconstrained stocks show a smaller amount of net short selling after an earnings surprise, which may be trading to capture the well-documented post-earnings announcement drift phenomenon. When considering announcement returns, the magnitudes are similar across samples. Overall, we interpret these findings as short investors covering their positions, at least in part, after negative information has been revealed about firm fundamentals.

To summarize, these results around information and risk indicates two different sets of short sellers. On the one hand, short investors gather fundamental information about firms, and are willing to pay high fees and maintain a riskier position over extended periods of time. These short sellers are identified with measures of short selling constraints. On the other hand, short traders identify shorter duration deviations in stock price or trade around events such as downgrades and earnings announcements. They pay lower fees, have shorter holding periods, and are only informed about short-run movements in stock prices.

We further solidify these findings by investigating price efficiency using the Delay measure in Hou and Moskowitz (2005). We confirm the findings in Boehmer and Wu (2013), who show that short selling activity measures help improve price efficiency. However, we further show that this effect disappears when stocks are short constrained. This is unsurprising given that the Delay measure is a short-term (weekly) measure of price efficiency and short activity impacts prices over that horizon. It is also possible that short investors also help price efficiency over longer horizons, but to show this, a long-term measure of price efficiency needs to be developed. We leave this for future research.

Ljungqvist and Qian (2016) help illustrate the difference between activity and constraint and its relationship to traders and investors. Short selling campaigns receive tremendous amounts

[4] Indeed, we find mostly covering activity ahead of negative earnings surprises. However, we find similar covering activity before all earnings announcements, regardless of outcome, so this can be explained by risk aversion in the light of expected information disclosure. If there is a positive earnings surprise, a short seller would face significant losses due to a possible margin call.

of attention in the business press and these campaigns can persist for months, and even years Typically, after the short seller establishes her position, she publicly argues that the firm has, for example, fundamental flaws with the business strategy, misleading disclosures or outright fraud.[5] These features capture the idea of a long-horizon short investor and are likely to overlap with a constrained stock. At the other end of the spectrum, there is ample academic research showing that short sellers take advantage of short-term mispricing due to liquidity shocks. These short traders are aptly characterized by activity and short-lived information.

Overall, our results are intuitive. The literature investigating short selling activity (trades, volume, etc.) has always used a pooled sample. Therefore, it stands to reason that the documented effects exist primarily among unconstrained stocks, which make up the vast majority of observations in any given panel data set (at any frequency). In contrast, the literature on short selling constraints has always focused on the tail of the distribution, either directly (Asquith, Pathak, and Ritter (2005)) or indirectly by using indicator variables to identify expensive stocks (Blocher, Reed, and Van Wesep (2013)). Either approach to measuring constraints ends up investigating just 10% of the sample. One can, in simple terms, quantify our contribution as showing definitively that these two samples have minimal overlap, and that the market participants identified by each measure have distinct information sets and risk tolerances.

## II. Hypothesis Development, Data, and Measurements

We have briefly delineated our hypotheses in the introduction, but we develop them more fully in this first section. Second, we describe our data set and then detail how we measure short selling activity and short selling constraints.

### A. *Hypothesis Development*

It is true that absent large shifts in supply, some amount of short selling volume must precede the existence of a short selling constraint (as measured by high stock loan prices).[6] However, this alone does not justify a hypothesis that short selling volume and short selling

[5] And firms fight back, see Lamont (2012).

[6] Cohen, Diether, and Malloy (2007)showed that stock loan supply is not important in predicting stock returns, Blocher and Zhang (2016) show that stock loan supply is slow moving as stocks become expensive to borrow.

constraints are both measuring the same underlying phenomenon. The timing does not align for them to be measuring the same thing at a monthly frequency.

The results in the literature (e.g., Diether, Lee, and Werner (2009)) use relatively high frequency measures of short selling volume (e.g., five days) and measure returns over an equally short period. Boehmer, Jones, and Zhang (2008), however, predict returns for 20 trading days with five days of trading volume. If short volume only predicts returns for the subsequent 20 trading days, and short selling constraints, measured monthly, predict the subsequent month's return, then the only way for both short volume and short constraints to be measuring the same latent phenomenon is if they are concurrent in time. Said differently, there must be some measurable short trading volume happening while a stock is 'constrained' as typically measured.

Our alternative hypothesis is simply that short selling activity and short selling constraints measure two separate and independent effects. This could mean two different things. First, it could mean that short activity predicts negative returns, but that the state of short constraints is irrelevant. In this case, there is overlap between the two, but it is randomly distributed – i.e. they are not measuring the same thing. We call this the "independence" hypothesis. Second, "two effects" could mean two non-intersecting events. Event 1 is that short activity predicts negative returns and stocks are not constrained, and Event 2 is that when stocks are constrained, short activity does not predict negative returns. We call this the "disjoint" hypothesis.

To illustrate, we provide two examples in Figure 1 and Figure 2. Figure 1 plots various measures related to stock pricing and short selling for Home Away, an online portal for vacation rentals, founded in 2005 in Austin, TX, and purchased by Expedia in November 2015. Their initial public offering was in June 2011. As frequently happens with IPOs (Geczy, Musto, and Reed (2002)), they start off already short constrained due to the combination of low institutional ownership (i.e. low stock loan supply) and the lockup period for insiders. The lockup expired in December 2011, however, and the stock remains persistently short constrained until January 2013, over a year later.

Of note is the two patterns in short constraints, which are a function of lending fees (and hence stock loan demand, or short interest, and stock loan supply) and short activity, which is a measure of day-to-day short selling (measured by changes in stock loan quantity). Short constraint is measure with the orange line and divides the time series into two periods. The early period is constrained, the later period is not. The reason for this is clear in Panel B and C, which plots the lending fee (Panel B) and supply and demand (Panel C). Lending fees are quite high during the constraint period (by definition) and supply and demand in Panel C reflect that, which shares demanded matching (and sometimes exceeding) available supply.[7] After January 2013, however, supply increases substantially, while demand drops, as is reflected in loan fees.

Panels D and E shows short selling activity. In Panel E, the dark red series shows the raw measure of short selling activity, defined as the change in quantity demanded (daily short interest) divided by total daily volume. The black line is a 42-day moving average to smooth the noise. We choose 42 days because that is the same horizon as the short constraint measure. In Panel D in green is an indicator for high short selling activity. This measure is generated from the upper quintile of short activity, defined as change in short interest divided by total daily volume, ranked each day. The purple series in Panel D is an indicator for high covering activity, which is measure the same, but the bottom quintile.

The most fundamental observation is that short selling activity (Panel E, as well as the green and purple series in Panel D), is largely unaffected by short constraints (Panel B and C). What is abundantly clear is that short selling and short covering are closely related to each other, and that short selling activity is a noisy process.

To show that this is not anomalous or simply related to a profitable, new technology firm, we present another example in Figure 2. Here, we show the same set of plots for Barnes and Noble, a bricks-and-mortar book retailer under intense competitive pressure from Amazon.com. Early in the time series, they are not short constrained at all, yet there is still significant short selling (and covering). There is a brief uptick in lending fees in December 2008, which turns on our constraint indicator, but it reverses quickly.

Panel C shows that short demand (in grey) starts steadily growing in December 2007and peaks in October 2009, when our short constraint indicator (in orange) turns on. During this time, supply and demand are relatively close to each other, as reflected in the relatively high lending fees (Panel B). After May 2013, they diverge again, with supply greatly exceeding demand, and loan fees declining to general collateral levels.

[7] This may seem odd, but it is possible because of A. measurement error and B. our data provider does not cover 100% of the market, so actual supply may exceed our measure of it.

Again, however, Panel D and E both show that short selling activity appears consistently noisy throughout the entire time series. There is no material difference between when a stock is hard to borrow versus when it is not. Short selling and covering continue to mirror each other, both showing up substantially both within periods of short constraint and unconstraint.

Visually, this is evidence for our "independence" hypothesis. Clearly, it would seem that short selling is not materially constricted during periods of high loan fees. However, the question remains about return predictability: are the results in the literature showing that short selling activity predicts negative returns isolated to situations of constraint or unconstraint? To answer this question, we need a more rigorous analysis.

### B. *Data*

The timeframe for this study is June 2006 to September 2016, with a daily frequency. We begin with the ordinary common shares (SHRCD of 10 or 11) of all firms in the Center for Research in Security Prices (CRSP), and focus on stocks that had a median stock price above five dollars. We compute market capitalization and book-to-market groups using the NYSE breakpoints from Ken French's website. We compute the market-to-book ratio as in Daniel and Titman (2006), with market values taken from CRSP as of the end of December in the firm's fiscal year.

Our primary securities lending dataset is for the North American equity loan market from Markit (formerly Data Explorers), which includes data from 125 large custodians and 32 prime brokers in the securities lending industry. The data coverage is quite large, accounting for about 80% of U.S. equities, and 85% of the securities lending market. This dataset provides detailed information on each stock's demand, supply, and lending fees in the equity lending market.

The Markit dataset also contains two important borrowing cost variables. The first is borrowing cost variable is the Daily Cost to Borrow Score (DCBS). The DCBS is a 1-10 integer categorization that describes how expensive a stock is to borrow, with 1 being the cheapest and 10 being the most expensive. The scores are computed by Markit for each stock-day and are based on actual lending fees that they receive from securities dealers but are not allowed to re-distribute. The second is indicative lending fees, which we use to compute short selling risk.

We compute two risk measures. The first is volatility, which is compute daily for the trailing 252 days, and then annualized. The second is the short selling risk measure of Engelberg, Reed, and Ringgenberg (2017), which is also computed daily from 252 day trailing data. Rather than use the predicted value from their regression, however, we use the simple unconditional measure of risk based on historical loan fee variance. Engelberg, Reed, and Ringgenberg (2017) show in their appendix that it is more parsimonious and leads to the same inference.

Our analyst downgrades data comes from Institutional Brokers' Estimate System (I/B/E/S), using the I/B/E/S Recommendations Detail File over the period July 2006 to September 2016. Following Christophe, Ferri, and Hsieh (2010) and Mikhail, Walther, and Willis (2004), we restrict our sample based on the following criteria. First, during the sample period, the stock price has to be at least $5 on the downgrade date. Second, there are no other downgrades in the preceding week and no quarterly earnings announcement in the preceding or following week. Third, we exclude downgrades that transitioning from "Strong Buy" to "Buy". Fourth, we only include the downgrades that the time difference between current recommendation and prior recommendation is within 365 days. Finally, we require non-missing information of share price, total shares outstanding, volume, and stock return during our sample period. In case a downgrade occurs on a non-trading day, the next closest trading day will be coded as though it were the downgrade day.

Summary statistics for our dataset are in Table I. Short selling activity has a slightly negative mean implying that we observe slightly more net covering of short positions over our sample. Approximately 7.7% of the firm-days are persistently constrained in the pooled sample. That is, 7.7% of firm-day observations have experienced higher fees to borrow the stock over the last 42 trading days. Approximately 74.3% of firm-days in the sample are unconstrained, which is to say they have had low stock loan fees for the past 42 days. The remainder, Transient, represents firm-days that have had at least one day over the past 42 days in which it was expensive to borrow the stock. These observations make up the remaining 18% of the sample.

### C. *Measures of Activity and Constraints*

We measure daily short selling activity as the change in daily shares lent, divided by volume. By definition, our measure omits trades that are covered intraday. This is because our measure derives from loan data, and shorts that are covered within the same day do not require a stock loan. Intraday shorts will show up in exchange-provided trade data such as Regulation SHO, but cannot be differentiated and so must be included. Diether (2016) can identify intraday vs multi-day trades and chooses to omit the former, so we conclude that missing this information is not important.[8]

Because our measure is a net measure, we can also capture net covering activity (i.e. changes where short interest is decreasing on net). Therefore, to sharpen our analysis we create an asymmetric measure of activity where we split activity into short activity and cover activity. Thus, our primary Short Activity measure is a weakly positive variable and helps differentiate the effects of shorting activity and cover activity. This way, a reported coefficient must be due to increasing or decreasing net short selling activity, and is in no way related to covering. For econometric reasons, we include the mirror-image variable that includes only net covering observations with net short selling activity zeroed out.

We measure short constraint following the PERSIST measure of Blocher and Zhang (2017), but at a daily level. Starting with daily data, we create an indicator for days where stock lending fees were high, DCBS > 1, the 90$^{th}$ percentile of lending fees. We then take a moving average of the indicator over the previous 42 trading days.[9] If the moving average is exactly equal to one then this implies that the stock has been persistently expensive to borrow and we therefore label it as CONST for constrained. To contrast our constrained variable, we classify stocks as being unconstrained (UNCONST) when the trailing moving average equals zero. We drop all stock-month observations where more than 50% of DCBS observations are missing, and in practice this filter eliminates few observations, since DCBS is populated quite consistently. All days with the trailing moving average between 0 and 1 we label as Transient (TRANS), since they are transiently or temporarily short constrained.

We start with a simple calibration exercise since our measure of short activity is new to the literature.[10] What we show is that cumulative short activity predicts short selling constraints, as just defined. Recall that the constraint measure is based on loan fees, and high loan fees certainly inhibit short selling, and almost certainly result from high demand. Separately, our measure is based on changes in daily short interest, or loans demanded, so the link between the

[8] See Blocher and Ringgenberg (2018) for more discussion and comparison of the two datasets.
[9] For the majority of our tests we will utilize forty two trading days which amounts to two months. This helps us maintain a consistent definition as Blocher and Zhang (2017), who use two months of daily observations.
[10] In addition, we also replicate Diether, Lee, and Werner (2009) from July 2006 to June 2007, which is the one year that Reg SHO and our sample overlap. We show that our measure broadly replicates their findings, when moved to the later period. Their original measurement period was January – December 2005. Results available upon request.

two need not be mechanical. Rather, we are clearly showing that our measure is not picking up noise or some other unobserved variable.

The calibration is in Table II. We find a positive and significant relationship between lagged (not contemporaneous) activity and constraints. The empirical regression asks how activity today predicts becoming constrained in the next two months in a linear probability model with a dependent variable taking the value of one if the stock is constrained forty-two trading days ahead. Because our definition of constraint relies on a high lending fee for the previous forty-two trading days, we use the indicator forty-two days in the future to avoid conflating the two. Hence, we run the following regression

$$Persist_{i,t+42} = \beta_1 Short\ Activity_{i,t} + \delta\ Controls_{i,t} + \tau_t + \theta_i + \varepsilon_{i,t+42}$$

for stock *i* on day *t*. We include controls for stock characteristics capturing liquidity, trading, and return moments, as well as firm and day fixed effects. Moreover, we double cluster standard errors along the firm and day dimensions. We find that more activity leads to a greater likelihood of becoming constrained. In an economic sense, we see that a one standard deviation increase in shorting activity leads to a 0.2% increase in the likelihood of becoming constrained. Recall that the unconditional probability of becoming persistently constrained is about eight percent, so this is a relative increase of around 3%. Note further that we are measuring a single day's impact of a measure spanning the subsequent 42 days. We also see that times of greater trading activity and slightly higher volatility are associated with an increased likelihood of becoming constrained. On the whole, this validates our measure of short selling activity because we can show that constraints are preceded by large amounts of activity.[11]

### III. Short Activity versus Short Constraints

In this first results section, we focus on the two primary measures of short selling in the literature: activity (i.e. short volume or trades) and constraints (i.e. high cost to short). As initial evidence, we present a simple frequency table in Table III. The first item to note is that 74.3% of the sample is in the unconstrained category, which is consistent with past literature. We separate activity into quintiles on a daily basis so each grouping of activity represents 20% of the sample, as seen by the last column (Total) in Panel B.

[11] In unreported results, we repeat this analysis with various measures of aggregated short activity and find stronger results. We include this single specification for brevity since this is a simple calibration exercise.

Only 1.8% is both Highest Short Activity and Constrained. Overall, this analysis shows that the important difference in the data is by column, when sorted by short selling constraint. The sorts into Activity do not generate any meaningful pattern. For example, if short selling activity and short selling constraints were both measuring the same phenomenon, we would expect an overweighting of observations in the upper left corner of the table, where both are present. This previews our results that the two measures are separate phenomena, but seems to provide more backup for the "independence" hypothesis rather than the "disjoint" hypothesis.

We begin by testing whether high returns lead to short selling activity, and then whether short selling activity predicts negative returns, similar to the setup in Diether, Lee, and Werner (2009). We then split our analysis into subsets based on the varying degrees of short selling constraints leading into the test. This is then a test of our two hypotheses. If we find results only where the stock is short constrained, then we conclude that the null hypothesis is correct: both measures identify the same underlying phenomena. If we only find results among unconstrained stocks, then we conclude that the "disjoint" hypothesis is correct: constraints and activity measure two distinct, separate phenomena. If we find a relationship in all cases, then that supports the "independence" hypothesis.

Next, we turn to a multivariate setting. Here, we investigate whether high short selling activity follows positive returns among constrained or unconstrained stocks. The first set of results are in Table IV, where we test whether past returns predict short selling activity. In this table, we use our baselin measure of Short Activity, which is the change in daily shares demanded, scaled by volume. Recall that we winsorize the measure at zero, meaning that every negative number is set to zero. The reason for doing so is that we want to isolate our measure only to identifying net short selling activity. Negative changes in daily short interest indicate net covering activity, which adds noise or possibly a spurious correlation.[12]

The primary variable of interest is Past Return [-5,-1], which is the cumulative raw return over the five days previous to day *t*. It is positive and significant in every specification except (5), the subsample of constrained stocks (CONST). There, the t-statistic is 1.24. This compares to the unconstrained sample, which has a t-statistic of 33.22. Hence, the lack of a result stems from

[12] Specifically, net covering activity (a more negative number) might relate to positive returns, thus creating a negative coefficient that has nothing to do with net short selling. We want to measure when a more positive number (more short selling activity) relates to negative returns.

both economic and statistical significance. Model (1) and (2) are baseline specifications using the entire sample, which give a positive and significant coefficient on Past Return, consistent with Diether, Lee, and Werner (2009).

Next, we investigate the variation in how short activity predicts negative returns. To better understand whether activity is always predictive of future returns, we again split our sample into constraint subsets. There is reason to believe that activity might be even more predictive during times of constraint because establishing positions when the cost is high might be more informative about future returns. On the other hand, the relatively low level of activity in constrained stocks may not add any additional information.

The primary results are in Table V. The dependent variable is the cumulative raw return from day $t$+2. The primary explanatory variable of interest is Short Activity, as described above. Models (1) and (2) show the main result present in the literature in the pooled sample. Short selling activity predicts negative returns. In model (3), we subsample to include only unconstrained stocks (UNCONST) and find virtually identical results, though with slightly less economic and statistical significance. Transient stocks show a slightly larger economic effect but statistically weaker. Finally, for constrained stocks, we find the coefficient shows no significant predictability from activity. In untabulated results, we find very similar effects looking at a window from days $t+2$ to $t+5$ and for Fama-French 25 portfolio adjusted returns.

Taking the short-selling activity and return predictability together, it appears that among constrained stocks, the relationship between returns and activity are suppressed. A high cost to borrow may inhibit a trader's ability to express an opinion through short selling. Similarly, the types of information which generate this short-term predictability may no longer be profitable after high borrowing costs. Thus, our multivariate results primarily back up our "disjoint" hypothesis, that short activity and short constraints are distinct and non-overlapping.

## IV. Short Traders versus Short Investors

Having established that the two measures of short selling in the literature (activity and constraints) are identifying two different phenomena, we now attempt to better characterize the differences. We will do this by drawing contrasts in three areas: risk, investment horizon (holding period) and information set.

It is clear that short selling is risky (e.g., Engelberg, Reed, and Ringgenberg (2017)). However, Engelberg, Reed, and Ringgenberg (2017) focus primarily on longer holding periods and their results use a monthly frequency. This strongly implies that they are only analyzing short sellers who end up constrained, not those measured with short selling activity measures. Taken together, this would imply that the benefits to information gathering (e.g. in Boehmer, Jones, and Zhang (2008), etc.) do not pair with the risks faced by short sellers in Engelberg, Reed, and Ringgenberg (2017), but this relationship is as of yet untested. We do so.

Second, there is a clear distinction between the literature on short selling activity and short selling constraints with regards to investment horizon (or holding period, observation frequency, etc.). Measures of short activity (trading volume) are higher frequency and use shorter holding periods, while measures of short constraints (loan fees) are lower frequency and use longer holding periods. We will attempt to be more thorough in measuring the precise time horizon over which each measure retains its predictability of future negative returns.

Third, we know that short sellers are informed, but this is a broad term. Boehmer, Jones, and Zhang (2008) show that short sellers are primarily institutional investors, a group typically seen as sophisticated. Christophe, Ferri, and Hsieh (2010) and Christophe, Ferri, and Angel (2004) show that short sellers anticipate analyst downgrades and earnings announcements, respectively. Dechow et al. (2001) show that high short interest is associated with firms having weak fundamentals (e.g. book-to-market). These are all ways of describing short sellers as informed, but are they describing the same groups of short sellers? We begin to address this question here.[13]

Our goal in this section is to better characterize what we have shown are two distinct groups of market participants, each measured by one of the two short selling measures. We call the first group short traders, who we claim are measured by short activity, and we call the second group short investors, who we claim are measured by short constraints.

---

[13] Engelberg, Reed, and Ringgenberg (2012) test whether shorts are informed about news events, but we do not test this event.

## A. *Short traders and short investors have different risk tolerances*

A key differentiating characteristic among market participants is risk aversion. Thus, it is natural to ask if these two groups of investors, short traders and short investors, have different tolerances for risk.

Risk in short selling has two dimensions, both important. One is the stock volatility, a standard measure for any investor. However, volatility should loom even larger for short sellers due to the inherent leverage in their position. If the price goes against them (i.e. up), then they will be required to put up more collateral for their stock loan. This is directly analogous to a leveraged long position, where margin calls can force liquidation at an inopportune time. The second dimension of risk for short sellers is lending fee variance, or short selling risk, as coined by Engelberg, Reed, and Ringgenberg (2017). This is, very simply, the risk that lending fees, which are set daily, may rise over the course of holding a short position, making it gradually more expensive to hold.

Our goal is to measure the riskiness of positions taken by short investors versus short traders. First, we look at some simple univariate statistics in Table VI. Panel A shows results for short selling risk, and it is clear that the Constrained stocks have short selling risk that is an order of magnitude higher than any other category. In the bottom row (ignoring Short Activity), short selling risk is 352 among Constrained stocks but just 25.0 among Unconstrained stocks. This pattern holds regardless of short selling activity. In Panel B, we see the same pattern in Volatility. The Total row shows that Volatility among Constrained stocks is 66.8%, but among Unconstrained stocks it is just 40.5%.

Next, we test these differences in a multivariate setting. We set up the test from the perspective of a short seller, ex ante, sizing up the risk of a possible short position. Specifically, we test if trailing measure of risk predict short selling constraints (short investor perspective) or higher short selling activity (short trader perspective).

Table VII shows the results. Models 1-3 investigate the risk tolerance of short investors because it uses a leading measure of persistent constraints. Models 4-6 investigate the risk tolerance of short traders, because it uses a leading measure of short activity. The results are striking, though not surprising given what we know already. There is a positive and significant relationship between both volatility and short selling risk and subsequent constraints in models 1-3. Put differently, stocks that are high risk are likely to become constrained. This implies that a short investor considering a position in a stock already somewhat constrained should already know that this is a risky stock and therefore a risky position. Since constraints are often persistent, we add in a lagged constraint indicator, CONST and interact it with our risk measures. The interaction coefficient is positive and significant for short selling risk. This shows that stocks that have been constrained and continue to be constrained are even riskier to short, and that short investors must, therefore, have a very high risk tolerance.

The story is almost the opposite among short traders. The relationship between short selling risk and future short activity is weak and becomes statistically insignificant once we account for a firm already being constrained. Interestingly, the relationship between volatility and future short selling activity remains positive and significant. This is understandable if we conceive of short traders as short-term traders engaging in short horizon (less than 5 days) arbitrage trades. A very volatile stock presents more opportunities. Though, it is a bit surprising given the volatility may make short-term arbitrage trades harder to execute profitably.

### B. *Investment Horizon*

Next, we consider the investment horizon of short traders and short investors. There is a distinction in the literature, where studies of short activity focus on short horizons and studies on short constraints focus on long horizons. A notable exception is Boehmer, Jones, and Zhang (2008), who measure short selling activity over a week and measure returns over the subsequent month.

Our results are in Table VIII. We measure short activity (and short covering) over a week and vary the dependent variable from one week (Model 1) up to three months (Model 5). Our results show that short traders and short investors have two distinct investment horizons. Short activity only predicts negative returns at the one or two week horizon. Model 8 shows some predictability at the one month horizon for Fama and French adjusted returns only. In contrast, constraints only predict returns at the two or three month horizon, as seen in Models 4 and 5 (Raw Returns) and Models 9 and 10 (Fama and French adjusted returns).

### C. *Short traders and short investors have different information sets*

To investigate varying information sets, we analyze analyst downgrades as in Christophe, Ferri, and Hsieh (2010) and negative earnings announcements as in Christophe, Ferri, and Angel

(2004). Christophe, Ferri, and Hsieh (2010) find that short sellers anticipate downgrades by trading ahead of them, and test whether this result is due to 'tipping' or instead due to fundamental analysis of publicly available information. They conclude that their result is due to tipping – i.e. analysts somehow communicate to other market participants that new information is forthcoming. Christophe, Ferri, and Angel (2004) find that short sellers trade in anticipation of earnings announcements, and that more activity is associated with larger (negative) post-announcement returns.

We revisit these two results in light of our finding that short sellers are not a uniform group. Specifically, we split the two samples (Analyst Downgrades and Earnings Announcements) into our three main groupings by short selling constraints: constrained, unconstrained, and transient (neither). Then, we separately investigate both stock returns and short selling activity around the events within each of these categories.

The results for returns around analyst downgrades are in Table IX. The most important result in this table is the event day return, identified in the row marked Time (0). In Model 3, the event return is -3.57%, which is a large, daily return for Constrained stocks. This is almost double the event day return of -1.89% among Unconstrained stocks (in Model 2). This difference is statistically significant (results available upon request). The rest of the table shows an expected pattern, with some positive results ahead of the downgrade, and negative results on the event day and afterwards, all consistent with newly revealed negative information, with some drift.

Table X Shows the same specification, but now with short activity instead of returns. We show raw short activity but have similar results for Fama-French adjusted short activity, available upon request. In the unconstrained sample (Model 2), we see some short selling ahead of the event (Time -10, -3), a small amount on event day itself, followed by covering activity. This combined with the previous table's result is what Christophe, Ferri, and Hsieh (2010) found.

Among constrained stocks (Model 4), there is no detectable short selling at all, before or during the event. The only result is both before and after the event, where a negative and significant coefficient indicates net covering activity at times (-3, -10) and (3,10). The covering ahead of the event is hard to explain, but it is also only marginally significant, statistically, with a t-statistic of -1.88. The post-event covering is much more robust. This stands to reason if the short seller's negative information has now been revealed publicly and he or she is closing the position at a profit. The lack of short selling among constrained stocks is intuitive since short constrained stocks are, by definition, difficult to short sell.

It also has implications for how we view short sellers' information. Christophe, Ferri, and Hsieh (2010) claimed that they had evidence that their result indicated that there was 'tipping' of some sort happening ahead of analyst downgrades, and this is what it meant for short sellers to be 'informed' ahead of analyst downgrades. We concur, but our results complete the picture. Instead of rejecting the hypothesis of short sellers using publicly available firm fundamentals, our results are consistent with short investors trading on that type of long-lived information and the analyst downgrade revealing it clearly to the public. Dechow et al. (2001) has shown that short sellers do, in fact, use fundamental information to inform their trades. Our results show that constrained stocks have the largest return response, but without any short activity ahead of time. This is consistent with longer-lived negative beliefs about a stock with positions in place before the 21-day symmetric window around analyst downgrades. The analyst downgrade clearly reveals the negative information already obtained (or perhaps processed using publicly available information) by the short investor.

We find more evidence of this when we consider returns and active around negative earnings surprises in Table XI and Table XII, respectively. Table XI shows that there is a similar return result regardless of subsample. We interpret the weaker statistical significance among the Constrained sample to be a function of the significantly smaller sample size compared to the other subsamples. We measure this using the bottom quintile of earnings surprises using analyst expectations (SUE3) but find very similar results with other specifications.[14]

Table XII shows the results for short activity. The results in the pooled sample (Model 1) and Unconstrained sample (Model 2) are similar. Both show covering in almost every time period. There are two explanations for this, one for the pre-event behavior and one for post-event behavior. Ahead of the event, we see net covering activity, which exists regardless of earnings surprise grouping: there is net covering behavior ahead of earnings announcements (results available upon request). We attribute this behavior to risk aversion – short sellers know there is an information event coming, but if they are wrong, they could possibly face a costly short

[14] We use the SUE1 and SUE2 specifications, which use a seasonally-adjusted random walk model. SUE2 additionally adjusts for extraordinary items. We also use strictly negative surprises rather than bottom quintile surprises. The results are all similar.

squeeze as the price goes up and they are forced to cover due to a margin call. The post-even behavior is easier to explain: once the firm has missed earnings, and the stock has gone down, many shorts will cover their position and capture the return from their position.

We interpret this result as short investors using fundamental information. They have already established their very costly short position and have held it for a while. The very fact that the stock is expensive to borrow is itself a signal to owners that they may want to sell (Blocher and Zhang (2017)). There is also some covering in advance for the same reason as among the unconstrained sample: risk aversion. There is very little activity right around the event, however. Since we know there is still a substantial return response, this must be attributable to current owners selling the stock rather than short sellers. After the event, there is substantial covering activity. This stands to reason given that the stock has recently corrected downward: many shorts may now view it as fairly priced and want to liquidate their position to move to another investment. We do not find evidence of short trading ahead of earnings announcements in any sample (Christophe, Ferri, and Angel (2004)).

As a final test, we consider price efficiency. Using the Delay measure in Hou and Moskowitz (2005) as the dependent variable, we show that short activity increases price efficiency (lowers Delay) as already shown in the literature (Boehmer and Wu (2013)). This is shown in Table XIII, row 3, where the coefficient on Short Activity is negative and significant. However, we further show that short constrained stocks are associated with worse price efficiency (higher delay), as shown by the positive and significant coefficient on the Constraint indicator. In Model 5, when we interact the two, the interaction term is not significant, meaning that the two effectively cancel each other out. When stocks are constrained, short activity does not impact price efficiency, and vice versa.

These results are, due to the definition of Delay, isolated to short-term price efficiency. Diamond and Verrecchia (1987) show that constrained stocks likely will exhibit delays in incorporating negative information. If those delays last as long as the constraints, which can last many months, then a weekly measure of price efficiency is not sufficient to capture the effect. To determine if short constrained stocks also contribute to price efficiency, a new, long-term measure of price efficiency needs to be developed. This non-trivial task we leave to future research.

## V. Conclusion

The literature on short selling has robustly shown that short sellers are informed and help correct overpricing. We have shown that these results show up in different ways among two distinct groups of short sellers, which we have termed short investors and short traders.

Short investors face short constraints. These positions are higher risk, measured both in terms of the stock volatility and the loan fee variance (short selling risk). These positions are also likely higher reward, since they are associated with greater negative returns around analyst downgrades, for instance. The returns to a short sale are hard to quantify, however, so conclusions around the profitability of short investors is mostly conjecture with indirect evidence. Short investors are informed in the sense that they incorporate long-lived information into prices, such as firm fundamental information. It is possible that they are superior information processors, obtaining public information and distilling out the pertinent portions to come to their bearish stance. We do not test this directly, but it is consistent with our results.

Short traders, in contrast, face no short constraints. These positions are shorter horizon and lower risk, as measured by short selling risk. Short selling risk is mitigated because of the shorter holding period. Short traders are also informed, but informed about short-lived information such as analyst downgrades or post-earnings announcement drift. They quickly enter the trade, capture the event return, and cover their position.

Overall, the distinction between activity and constraints, and moreover that of short investors versus short traders, has important implications for future research on short selling. The distinction highlights the process of correcting overpricing and informed short selling in two very different scenarios: short constrained versus not. In summary, distinguishing between short selling activity and constraints helps clarify how and why short selling contributes information to stock prices.

## References


Asquith, Paul, and Lisa Meulbroek, 1996, An empirical investigation of short interest, *Unpublished working paper*.

Asquith, Paul, Parag A Pathak, and Jay R Ritter, 2005, Short interest, institutional ownership, and stock returns, *J. Financ. Econ.* 78, 243–276.

Blocher, Jesse, Adam V Reed, and Edward D Van Wesep, 2013, Connecting two markets: An equilibrium framework for shorts, longs, and stock loans, *J. Financ. Econ.* 108, 302–322.

Blocher, Jesse, and Chi Zhang, 2016, Supply Side Short-Selling Constraints: Who is Buying When Shorts are Selling? *SSRN Working Paper*, 1–44.

Blocher, Jesse, and Chi Zhang, 2017, Short Constraints are Persistent Constraints, *SSRN Working Paper*, 1–39.

Blocher, Jesse, and Matthew C Ringgenberg, 2018, Short Covering, *SSRN Working Paper*, 1–36.

Boehme, Rodney, Bartley Danielsen, and Sorin M Sorescu, 2006, Short-Sale Constraints, Differences of Opinion, and Overvaluation, *Journal of Financial and Quantitative Analysis* 41, 455–487.

Boehmer, Ekkehart, and Julie Wu, 2013, Short Selling and the Price Discovery Process, *Rev. Financ. Stud.* 26, 287–322.

Boehmer, Ekkehart, Charles M Jones, and Xiaoyan Zhang, 2008, Which Shorts Are Informed? *J. Finance* 63, 491–527.

Christophe, Stephen E, Michael G Ferri, and James J Angel, 2004, Short-Selling Prior to Earnings Announcements, *J. Finance* 59, 1845–1876.

Christophe, Stephen E, Michael G Ferri, and Jim Hsieh, 2010, Informed trading before analyst downgrades: Evidence from short sellers, *J. Financ. Econ.* 95, 85–106.

Cohen, Lauren, Karl B Diether, and Christopher J Malloy, 2007, Supply and Demand Shifts in the Shorting Market, *J. Finance* 62, 2061–2096.

Daniel, Kent D, and Sheridan Titman, 2006, Market Reactions to Tangible and Intangible Information, *J. Finance* 61, 1605–1643.

Dechow, Patricia M, Amy P Hutton, Lisa Meulbroek, and Richard G Sloan, 2001, Short-sellers, fundamental analysis, and stock returns, *J. Financ. Econ.* 61, 77–106.

Diamond, Douglas, and Robert E Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *J. Financ. Econ.* 18, 277–311.

Diether, Karl B, 2016, Short it Again, *Unpublished working paper*, 1–35.

Diether, Karl B, Kuan-Hui Lee, and Ingrid M Werner, 2009, Short-sale strategies and return predictability, *Rev. Financ. Stud.* 22, 575–607.

Engelberg, Joseph E, Adam V Reed, and Matthew C Ringgenberg, 2012, How are shorts informed? *J. Financ. Econ.* 105, 260–278.

Engelberg, Joseph E, Adam V Reed, and Matthew C Ringgenberg, 2017, Short Selling Risk, *The Journal of Finance*.

Geczy, Christopher C, David K Musto, and Adam V Reed, 2002, Stocks are special too: An analysis of the equity lending market, *J. Financ. Econ.* 66, 241–269.

Hou, Kewei, and Tobias J Moskowitz, 2005, Market Frictions, Price Delay, and the Cross-Section of Expected Returns, *Rev. Financ. Stud.* 18, 981–1020.

Lamont, Owen A, 2012, Go Down Fighting: Short Sellers vs. Firms, *Review of Asset Pricing Studies* 2, 1–30.

Ljungqvist, Alexander, and Wenlan Qian, 2016, How Constraining Are Limits to Arbitrage? *Rev. Financ. Stud.* 29, 1975–2028.

Mikhail, Michael B, Beverly R Walther, and Richard H Willis, 2004, Do security analysts exhibit persistent differences in stock picking ability? *J. Financ. Econ.* 74, 67–91.

Miller, Edward, 1977, Risk, Uncertainty, and Divergence of Opinion, *J. Finance* 32, 1151–1168.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *J. Financ. Econ.* 78, 277–309.

WRDS Research Macros, 2017. Wharton Research Data Services, The Wharton School, University of Pennsylvania, wrds.wharton.upenn.edu.

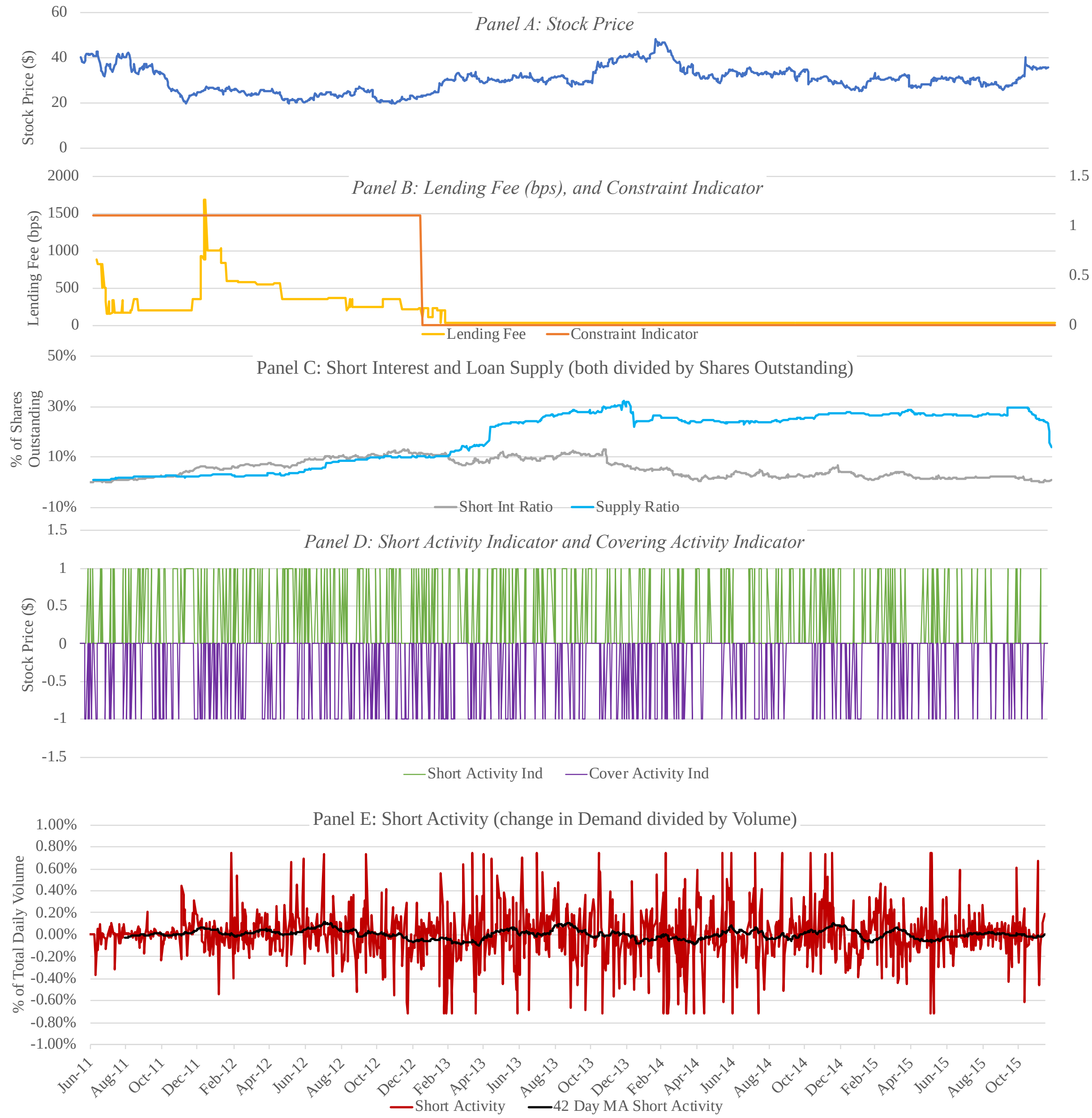


**Figure 1: Example of the intersection of short selling constraints and short selling activity.** Plotted are various metrics for Home Away (NASDAQ:AWAY) from its IPO in June 2011 until they were bought by Expedia in November 2015. Home Away is a portal for short term rental properties, similar to AirBnB. Panel A shows the stock price. Panel B plots lending fees (in bps) with the short selling constraint indicator. Panel C plots the level of daily short interest (grey) and total loan supply (light blue), both divided by shares outstanding. Panel D plots indicators for short activity (green) and covering activity (purple). Panel E plots raw short activity (change in demand, divided by total daily volume, in red) and its 42-day moving average (black). The constraint indicator is 1 when the DCBS > 1 for 42 days. High short activity indicator is top quintile of activity, grouped daily, high covering activity is bottom quintile of activity, grouped daily.

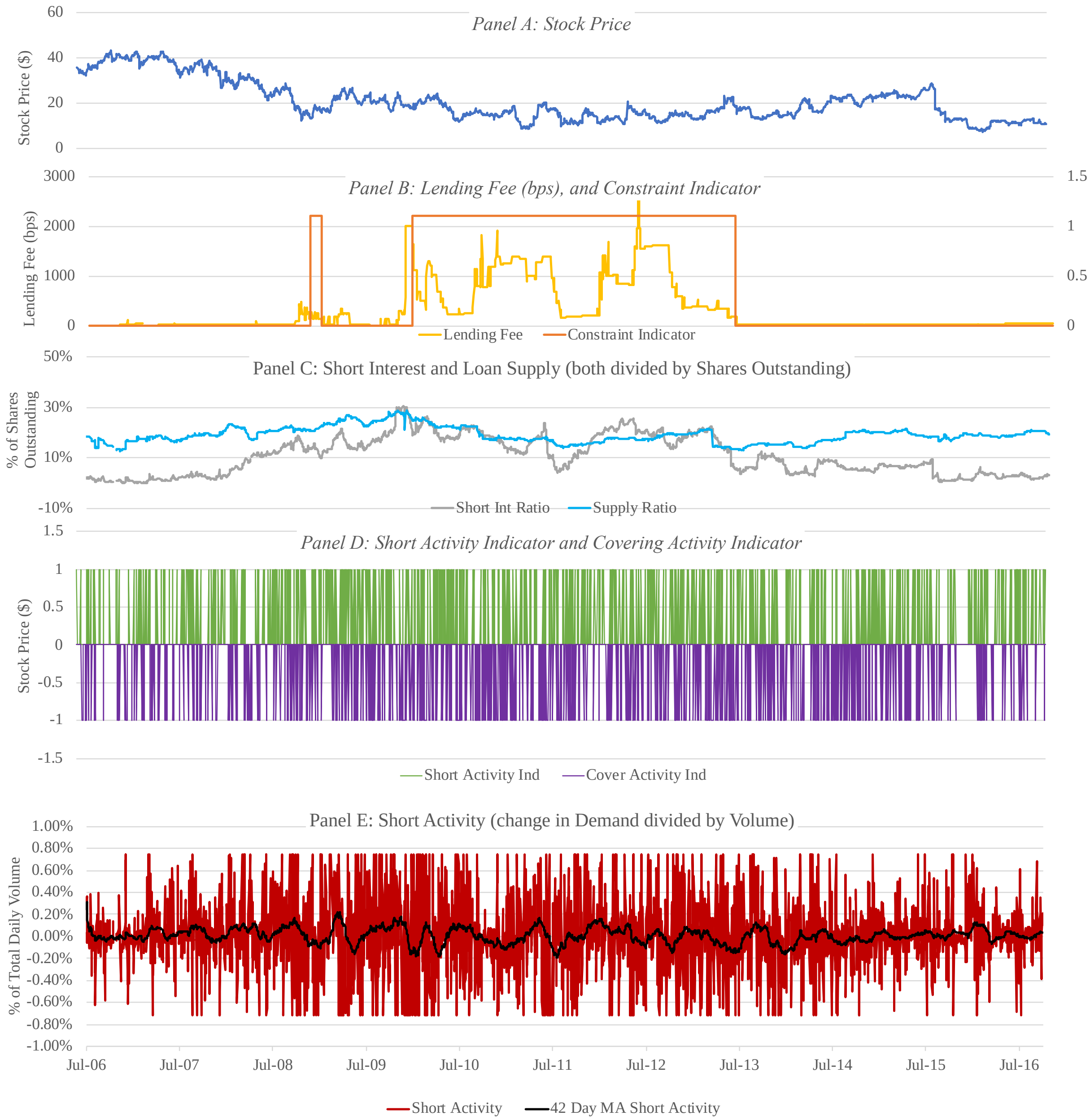


**Figure 2: A second example of short constraints and short selling activity.**
Plotted are various metrics for Barnes and Noble (NYSE:BKS) from July 2006 until the end of our sample in September 2016. Barnes and Noble is a nationwide bricks and mortar bookseller under intense pressure from online competition. Panel A shows the stock price. Panel B plots lending fees (in bps) with the short selling constraint indicator. Panel C plots the level of daily short interest (grey) and total loan supply (light blue), both divided by shares outstanding. Panel D plots indicators for short activity (green) and covering activity (purple). Panel E plots raw short activity (change in demand, divided by total daily volume, in red) and its 42-day moving average (black). The constraint indicator is 1 when the DCBS > 1 for 42 days. High short activity indicator is top quintile of activity, grouped daily, high covering activity is bottom quintile of activity, grouped daily.

**Table I**
**Summary statistics**

Data is daily from June 2006 to September 2016. Short activity is computed as the change in daily short interest divided by total daily volume. We further separate out activity by computing an asymmetric measure which takes the value of short activity if it is positive and zero otherwise. Cover activity takes the opposite position and is negative if we observe net short cover activity and zero otherwise. Spread is the bid-ask difference divided by the midpoint. Order Imbalance Plus is an asymmetric order imbalances measure computed from TAQ, where negative numbers are set to zero. High – Low is the intraday high price minus the intraday low price. Turnover is monthly share volume divided by end-of-month shares outstanding. Raw returns are from CRSP, and Volatility and Short Selling Risk are computed over the trailing 12 months with daily returns, annualized. Adjusted returns are daily returns less the matched 25-portfolio Fama-French portfolio return. Constraint (CONST) is an indicator set to 1 if the past 42 days all had a Daily Cost to Borrow Score (DCBS) greater than 1, Unconstrained (UNCONST) is the same, except DCBS = 1 for 42 days. Transient (TRANS) an indicator for the remaining, in between, set of observations.

| | N Obs | Mean | Std. Dev. | Min. | 25% | Median | 75% | Max. |
|---|---|---|---|---|---|---|---|---|
| Short Activity | 6,850,821 | -0.002 | 0.245 | -1.0 | -0.094 | 0.000 | 0.089 | 1.0 |
| Short Activity (Asym) | 6,850,821 | 0.081 | 0.159 | 0.0 | 0.0 | 0.0 | 0.089 | 1.0 |
| Cover Activity (Asym) | 6,850,821 | -0.084 | 0.160 | -1.0 | -0.094 | 0.0 | 0.0 | 0.0 |
| Return Trailing MA | 6,851,859 | 0.282 | 7.457 | -92.9 | -2.7 | 0.2 | 3.048 | 1100.0 |
| Bid-Ask Spread | 6,851,859 | 0.007 | 0.047 | 0.0 | 0.001 | 0.0 | 0.0 | 7.8 |
| Order Imbalance Plus | 6,851,859 | 24.4 | 259.9 | 0.0 | 0.0 | 0.0 | 12.6 | 139,409 |
| High - Low | 6,851,859 | 0.051 | 0.117 | 0.0 | 0.016 | 0.0 | 0.0 | 1.0 |
| Turnover Trailing MA | 6,851,859 | 9.9 | 16.0 | 0.0 | 3.6 | 6.7 | 11.9 | 5,526 |
| Return[t+2,t+5] | 6,847,538 | 0.226 | 6.6 | -97.3 | -2.40 | 0.135 | 2.68 | 1,094 |
| Return[t+2] | 6,851,859 | 0.058 | 3.4 | -94.2 | -1.2 | 0.0 | 1.2 | 825 |
| Short Selling Risk (trailing) | 5,385,994 | 52.3 | 234.8 | 0.0 | 3.0 | 6.5 | 16.0 | 13,364 |
| Volatility (trailing) | 5,182,372 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1 |
| Adj. Return[t+2, t+5] | 5,513,192 | 0.075 | 5.7 | -89.9 | -2.2 | -0.1 | 2.1 | 1,095 |
| Adj. Return[t+2] | 5,733,099 | 0.000 | 0.029 | -0.9 | 0.0 | 0.0 | 0.010 | 4.8 |
| Constraint (CONST) | 6,851,859 | 0.077 | 0.266 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Transient (TRANS) | 6,851,859 | 0.180 | 0.384 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Unconstrained (UNCONST | 6,851,859 | 0.743 | 0.437 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |

**Table II**

**Calibration of short activity measure**

Data is daily from June 2006 to December 2015. The dependent variable is the Constraint measure (CONST) at day T+42, which captures future constraints over days T+1 to T+42. Short Activity is measured as the change in daily short interest divided by total daily volume, with all negative values set to zero, thus isolating only positive changes in short interest. Cover Activity is the same but sets positive values to zero. CONST is the constraint indicator, measured over the trailing 42 days. Return is the current day's event return. Spread is the effective spread computed from intraday data. Order Imbalance is measured as the number of buys less sells scaled by the number of trades where trades are signed using Lee and Ready (1991) with a zero second delay. High – Low price is the high minus low intra-day price. Turnover is daily volume divided by shares outstanding. We include firm and day FE, with standard errors clustered by firm and day. T-statistics are displayed in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | CONSTRAINT measure at T+42 | | | | | |
| Short Activity | 0.023*** | 0.025*** | 0.013*** | 0.034*** | 0.036*** | 0.014*** |
| | (15.54) | (16.54) | (17.19) | (17.07) | (18.04) | (15.66) |
| Cover Activity | | | | -0.036*** | -0.037*** | -0.003*** |
| | | | | (-17.47) | (-18.30) | (-3.88) |
| CONST | | | 0.660*** | | | 0.660*** |
| | | | (99.37) | | | (99.35) |
| Past Return [-5,-1] | | -0.000 | -0.000*** | | -0.000 | -0.000*** |
| | | (-1.42) | (-4.61) | | (-1.12) | (-4.58) |
| Return | | 0.015** | -0.004 | | 0.017*** | -0.004 |
| | | (2.35) | (-0.94) | | (2.65) | (-0.90) |
| Eff. Spread | | 0.051** | 0.003 | | 0.049* | 0.003 |
| | | (1.99) | (0.27) | | (1.95) | (0.26) |
| Order Imbalance | | -0.000 | -0.000 | | -0.000 | -0.000 |
| | | (-0.70) | (-0.19) | | (-0.53) | (-0.17) |
| High - Low Price | | 0.046*** | 0.020*** | | 0.048*** | 0.020*** |
| | | (3.20) | (3.40) | | (3.31) | (3.42) |
| Turnover | | 0.001*** | 0.001*** | | 0.001*** | 0.001*** |
| | | (4.83) | (4.99) | | (4.84) | (4.99) |
| Ln(Price) | | -0.057*** | -0.018*** | | -0.057*** | -0.018*** |
| | | (-13.08) | (-10.83) | | (-13.10) | (-10.83) |
| Observations | 6,795,348 | 6,795,348 | 6,795,348 | 6,795,348 | 6,795,348 | 6,795,348 |
| R-squared | 0.448 | 0.460 | 0.697 | 0.448 | 0.461 | 0.697 |

**Table III**

**Frequency diagram of activity measure versus constraint measure**

Data is daily from June 2006 to September 2016. Short Activity is measured as the change in daily short interest divided by total daily volume. Short (and Cover) activity is divided into quintiles, daily. Constrained is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained is defined as being cheap-to-borrow (DCBS=1) in the past 42 days. Transient is the remaining sample that is neither. Panel A lists simple counts of firm-day observations. Panel B reports percentages of the entire sample of 6,850,621 observations.

*Panel A: Observation Counts*

| | Constrained | Transient | Unconstrained | Total |
|---|---|---|---|---|
| Highest Short Activity | 124,175 | 240,275 | 1,008,102 | 1,372,552 |
| High Short Activity | 89,434 | 231,902 | 1,052,842 | 1,374,178 |
| Normal Activity | 92,836 | 286,273 | 981,405 | 1,360,514 |
| High Cover Activity | 88,880 | 231,912 | 1,053,873 | 1,374,665 |
| Highest Cover Activity | 130,853 | 244,862 | 992,997 | 1,368,712 |
| Total | 526,178 | 1,235,224 | 5,089,219 | 6,850,621 |

*Panel B: Percentages of Total Observations*

| | Constrained | Transient | Unconstrained | Total |
|---|---|---|---|---|
| Highest Short Activity | 1.8% | 3.5% | 14.7% | 20.0% |
| High Short Activity | 1.3% | 3.4% | 15.4% | 20.1% |
| Normal Activity | 1.4% | 4.2% | 14.3% | 19.9% |
| High Cover Activity | 1.3% | 3.4% | 15.4% | 20.1% |
| Highest Cover Activity | 1.9% | 3.6% | 14.5% | 20.0% |
| Total | 7.7% | 18.0% | 74.3% | 100.0% |

**Table IV**

**Positive returns predict short selling activity among unconstrained stocks**

Data is daily from June 2006 to September 2016. The dependent variable is Short Activity. Short Activity is measured as the change in daily short interest divided by total daily volume, winsorized at zero. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS=1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Past Return is the cumulative raw return from day t-5 to t-1. Return is the event day return. Spread is the bid-ask divided by the midpoint. Order Imbalance is number of buy orders less the number of sell orders divided by total orders, truncated at zero. Short Activity [-5, -1] is lagged short activity, cumulative over the 5 days prior. High-Low Prices the intraday high and low price for the stock. Turnover is the average turnover over the five days prior to day t. We include firm and day FE, with standard errors clustered by firm and day. T-statistics are displayed in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Short Activity (divided by Volume) | | | | |
| Past Return [-5. -1] | 0.001*** | 0.001*** | 0.001*** | 0.000*** | 0.000 |
| | (22.23) | (23.29) | (33.22) | (11.66) | (1.24) |
| Return | | -0.053*** | -0.060*** | -0.046*** | -0.046*** |
| | | (-18.08) | (-16.65) | (-10.58) | (-11.07) |
| Spread | | 0.022*** | 0.032*** | 0.022*** | 0.034*** |
| | | (3.81) | (4.43) | (3.92) | (3.53) |
| Order Imbalance | | -0.000*** | -0.000** | -0.000 | -0.000*** |
| | | (-3.11) | (-2.36) | (-1.17) | (-3.43) |
| Log (Price) | | 0.001*** | -0.003*** | 0.008*** | 0.007*** |
| | | (3.04) | (-4.92) | (10.66) | (6.48) |
| High - Low Price | | -0.033*** | -0.029*** | -0.048*** | -0.080*** |
| | | (-10.87) | (-9.37) | (-9.39) | (-5.84) |
| Turnover [-5. -1] | | -0.000*** | 0.000*** | -0.000*** | -0.000** |
| | | (-6.08) | (5.78) | (-3.84) | (-2.50) |
| Subset | ALL | ALL | UNCONST | TRANS | CONST |
| Observations | 6,846,877 | 6,846,877 | 5,087,475 | 1,233,635 | 525,720 |
| R-squared | 0.043 | 0.043 | 0.047 | 0.053 | 0.056 |

## Table V
## Abnormal short activity and overpricing

Data is daily from June 2006 to September 2016. The dependent variable cumulative raw return on day T+2. Short Activity is measured as the change in daily short interest divided by total daily volume, with all negative values set to zero, thus isolating only positive changes in short interest. Cover Activity is the same but sets positive values to zero. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS=1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Return[-5,-1] is the cumulative raw return from day t-5 to t-1. Spread is the bid-ask divided by the midpoint. Order Imbalance is number of buy orders less the number of sell orders divided by total orders, truncated at zero. High-Low Prices the intraday high and low price for the stock. Turnover is the average turnover over the five days prior to day t. We include firm and day FE, with standard errors clustered by firm and day. T-statistics are displayed in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | Return [day 2] | | |
| Short Activity | -0.052*** | -0.045*** | -0.037*** | -0.050* | -0.017 |
| | (-4.75) | (-4.03) | (-3.62) | (-1.85) | (-0.51) |
| Cover Activity | 0.050*** | 0.053*** | 0.039*** | 0.054 | 0.039 |
| | (4.12) | (4.28) | (4.00) | (1.63) | (1.08) |
| Return [-5,-1] | | -0.004*** | -0.004** | -0.007*** | -0.006*** |
| | | (-3.11) | (-2.35) | (-2.92) | (-3.76) |
| Spread | | -0.011 | 0.049 | -0.191 | 0.065 |
| | | (-0.14) | (0.51) | (-1.21) | (0.41) |
| Order Imbalance | | 0.000 | -0.000 | 0.000* | 0.000 |
| | | (1.42) | (-0.07) | (1.66) | (1.13) |
| High - Low Price | | 0.050 | 0.045 | 0.148 | -0.130 |
| | | (1.01) | (1.23) | (0.87) | (-0.69) |
| Turnover [-5,-1] | | -0.000 | 0.000 | -0.000 | 0.000 |
| | | (-0.03) | (0.44) | (-0.58) | (0.74) |
| Log (Price) | | -0.180*** | -0.207*** | -0.324*** | -0.282*** |
| | | (-9.97) | (-11.09) | (-8.79) | (-9.99) |
| Subset | ALL | ALL | UNCONST | TRANSIENT | CONST |
| Observations | 6,846,877 | 6,846,877 | 5,087,475 | 1,233,635 | 525,720 |
| R-squared | 0.21 | 0.211 | 0.257 | 0.203 | 0.132 |

**Table VI**
**Short selling and varying risk tolerances: univariate**

Data is daily from June 2006 to September 2016. Short selling risk (Panel A) is the trailing annual variance in the stock loan fee following Engelberg, Reed, and Ringgenberg (2017). Volatility (Panel B) is computed daily over the trailing year, annualized. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS=1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Pooled is the entire sample across rows, Total is the entire sample across columns. Short (and Cover) activity is divided into quintiles, daily.

*Panel A: Short Selling Risk*

| | Constrained | Transient | Unconstrained | Pooled |
|---|---|---|---|---|
| Highest Short Activity | 359.7 | 56.1 | 24.2 | 56.4 |
| High short Activity | 355.3 | 52.4 | 25.1 | 48.0 |
| Normal Activity | 346.0 | 48.9 | 26.6 | 47.3 |
| High Cover Activity | 343.8 | 50.2 | 25.1 | 46.6 |
| Highest Cover Activity | 351.4 | 55.6 | 24.2 | 57.4 |
| Total | 352.0 | 52.6 | 25.0 | 51.2 |

*Panel B: Volatility*

| | Constrained | Transient | Unconstrained | Pooled |
|---|---|---|---|---|
| Highest Short Activity | 63.7% | 48.0% | 40.2% | 42.9% |
| High short Activity | 68.8% | 47.9% | 40.5% | 42.9% |
| Normal Activity | 72.5% | 48.5% | 41.1% | 44.0% |
| High Cover Activity | 68.5% | 47.6% | 40.4% | 42.8% |
| Highest Cover Activity | 63.5% | 48.1% | 40.2% | 43.1% |
| Total | 66.8% | 48.1% | 40.5% | 43.1% |

**Table VII**
**Short selling and varying risk tolerances: Predictability in a multivariate setting**

Data is daily from June 2006 to September 2016. In models 1-3, the dependent variable is a leading indicator for constrained stocks. Over days t+1 to t+42, every day must have DCBS > 1. In models 4-6, we compute a count of Short Activity daily indicators from day t+1 to t+42, such that it is a categorical variable ranging from 0 to 42. Short selling risk is the trailing annual variance in the stock loan fee following Engelberg, Reed, and Ringgenberg (2017). Volatility is computed daily over the trailing year, annualized. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Short Activity is measured as the change in daily short interest divided by total daily volume, with all negative values set to zero, thus isolating only positive changes in short interest. Cover Activity is the same but sets positive values to zero. Included but not shown for brevity: Return[-5,-1] is the cumulative raw return from day t-5 to t-1. Return is the event day return. Spread is the bid-ask divided by the midpoint. Order Imbalance is number of buy orders less the number of sell orders divided by total orders, truncated at zero. High-Low Prices the intraday high and low price for the stock. Turnover is the average turnover over the five days prior to day t. Ln(Price) is the log of the firm's stock price. We include firm and day FE, with standard errors clustered by firm and day. T-statistics are displayed in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Leading Constraint | | | Leading Activity Count | | |
| Short Selling Risk | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000** | 0.000 |
| | (6.92) | (4.18) | (3.43) | (3.40) | (2.01) | (1.27) |
| Volatility | 1.778*** | 0.407*** | 0.577*** | 18.735*** | 17.121*** | 22.267*** |
| | (7.38) | (4.76) | (6.14) | (6.49) | (6.03) | (6.71) |
| CONST | | 0.694*** | 0.722*** | | 0.815*** | 1.809*** |
| | | (80.30) | (50.24) | | (7.14) | (6.80) |
| SS Risk x CONST | | | 0.000*** | | | 0.000 |
| | | | (3.27) | | | (1.10) |
| Volalitity x CONST | | | -0.959*** | | | -27.101*** |
| | | | (-3.48) | | | (-4.32) |
| Short Activity | 0.021*** | 0.006*** | 0.006*** | 0.990*** | 0.973*** | 0.969*** |
| | (11.13) | (7.32) | (7.11) | (28.39) | (28.27) | (28.25) |
| Cover Activity | -0.023*** | 0.001 | 0.001 | -0.242*** | -0.215*** | -0.211*** |
| | (-12.06) | (1.03) | (1.25) | (-7.53) | (-6.77) | (-6.67) |
| Observations | 4,006,305 | 4,006,305 | 4,006,305 | 3,928,040 | 3,928,040 | 3,928,040 |
| R-squared | 0.444 | 0.708 | 0.708 | 0.539 | 0.540 | 0.540 |

**Table VIII**
**Investment Horizon**

Data is daily from June 2006 to September 2016. The dependent variable is varying lengths of stock return holding period, but all are normalized to be one week average returns for comparability. Models 1-5 are raw returns. Models 6-10 are Fama-French adjusted returns, where the raw holding period return is subtracted from the portfolio-matched Fama-French portfolio holding period return. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Short Activity is measured as the change in daily short interest divided by total daily volume, with all negative values set to zero, thus isolating only positive changes in short interest, aggregated weekly. Cover Activity is the same but sets positive values to zero. Included but not shown for brevity: Weekly Lagged Return is the cumulative raw return from the previous week, matching the dependent variable. Return is the event day return. Spread is the bid-ask divided by the midpoint. Order Imbalance is number of buy orders less the number of sell orders divided by total orders, truncated at zero. High-Low Prices the intraday high and low price for the stock. Turnover is the average turnover over the five days prior to day t. We include firm and day FE, with standard errors clustered by firm and day. T-statistics are displayed in parentheses. Standard errors clustered by firm and month. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | Raw Return Holding Period | | | | | Fama French Adjusted Return Holding Period | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | One Week | Two Week | One Month | Two Month | Three Month | One Week | Two Week | One Month | Two Month | Three Month |
| Weekly Short Activity | -0.001*** | -0.001* | -0.001 | -0.000 | -0.000 | -0.001*** | -0.001*** | -0.001*** | -0.000 | -0.000 |
| | (-2.59) | (-1.87) | (-1.61) | (-0.71) | (-0.15) | (-3.06) | (-2.31) | (-1.73) | (-0.78) | (-0.20) |
| Weekly Cover Activity | 0.002*** | 0.001*** | 0.001 | 0.000 | 0.000 | 0.001*** | 0.001*** | 0.001 | 0.000 | 0.000 |
| | (5.15) | (2.53) | (1.08) | (0.46) | (0.24) | (5.30) | (2.73) | (1.06) | (0.54) | (0.27) |
| CONST | -0.001 | -0.000 | -0.001 | -0.004** | -0.005** | -0.000 | -0.000 | -0.001 | -0.003* | -0.004** |
| | (-0.69) | (-0.61) | (-1.19) | (-1.98) | (-2.55) | (-0.59) | (-0.45) | (-0.83) | (-1.67) | (-2.31) |
| Activity x CONST | 0.000 | 0.000 | 0.000 | -0.000 | 0.002 | 0.000 | 0.000 | 0.000 | -0.001 | 0.002 |
| | (0.57) | (0.22) | (0.32) | (-0.27) | (1.33) | (0.52) | (0.17) | (0.42) | (-0.39) | (1.22) |
| Observations | 1,650,159 | 1,645,868 | 1,637,286 | 1,620,122 | 1,602,966 | 1,650,159 | 1,645,868 | 1,637,286 | 1,620,122 | 1,602,966 |
| R-squared | 0.196 | 0.195 | 0.192 | 0.207 | 0.208 | 0.016 | 0.015 | 0.019 | 0.027 | 0.027 |

**Table IX**
**Returns around analyst downgrades**

Data is daily from June 2006 to September 2016. The dependent variable is Fama-French abnormal return, which is raw return less the five by five Fama and French matched portfolio return. The independent variables are indicators for the time intervals displayed, and so there is no constant to avoid collinearity nor are there fixed effects. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS=1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Each state is determined at time T-10. T-statistics are displayed in parentheses. Standard errors clustered by firm and month. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Fama-French Abnormal Return | | | |
| Time (-10,-3) | 0.0118*** | 0.0100*** | 0.0225*** | 0.0160*** |
| | (8.474) | (7.960) | (4.097) | (5.143) |
| Time (-2) | 0.0018*** | 0.0012*** | 0.0075*** | 0.0022*** |
| | (5.229) | (3.795) | (3.499) | (2.786) |
| Time (-1) | 0.0009** | 0.0007* | 0.0029 | 0.0015 |
| | (2.198) | (1.690) | (1.034) | (1.504) |
| Time (0) | -0.0213*** | -0.0189*** | -0.0357*** | -0.0273*** |
| | (-24.096) | (-22.664) | (-11.061) | (-18.378) |
| Time (1) | -0.0042*** | -0.0040*** | -0.0034* | -0.0053*** |
| | (-12.241) | (-13.340) | (-1.818) | (-4.516) |
| Time (2) | -0.0005* | -0.0002 | -0.0018 | -0.0011 |
| | (-1.704) | (-0.841) | (-1.260) | (-1.431) |
| Time (3,10) | 0.0006 | 0.0007 | -0.0044 | 0.0019 |
| | (0.740) | (0.904) | (-0.993) | (1.070) |
| Subset | ALL | UNCONST | CONST | TRANS |
| N | 81,791 | 63,718 | 5,153 | 12,920 |
| adj. R-sq | 0.03 | 0.03 | 0.04 | 0.03 |

**Table X**
**Short selling activity around analyst downgrades**

Data is daily from June 2006 to September 2016. The dependent variable, Short Activity, is measured as the change in daily short interest divided by total daily volume. The independent variables are indicators for the time intervals displayed, and so there is no constant to avoid collinearity nor are there fixed effects. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS = 1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Each state is determined at time T-10. T-statistics are displayed in parentheses. Standard errors clustered by firm and month. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Short Activity (Divided by Volume) | | | |
| Time (-10,-3) | 0.0166 | 0.0274*** | -0.0742* | 0.0005 |
| | (1.418) | (2.649) | (-1.884) | (0.021) |
| Time (-2) | 0.0018 | 0.0015 | 0.0062 | 0.0015 |
| | (0.757) | (0.601) | (0.649) | (0.321) |
| Time (-1) | 0.0015 | 0.0019 | -0.0141 | 0.0057 |
| | (0.728) | (0.924) | (-1.460) | (1.044) |
| Time (0) | 0.0039** | 0.0038** | -0.0097 | 0.0098* |
| | (2.128) | (2.104) | (-1.303) | (1.698) |
| Time (1) | 0.0010 | 0.0024 | -0.0077 | -0.0019 |
| | (0.437) | (1.067) | (-0.946) | (-0.282) |
| Time (2) | 0.0014 | 0.0019 | -0.0167 | 0.0063 |
| | (0.584) | (0.817) | (-1.187) | (0.961) |
| Time (3,10) | -0.0457*** | -0.0436*** | -0.1583*** | -0.0104 |
| | (-3.323) | (-3.687) | (-4.140) | (-0.300) |
| Subset | ALL | UNCONST | CONST | TRANS |
| N | 81,789 | 63,716 | 5,153 | 12,920 |
| adj. R-sq | 0.00 | 0.00 | 0.02 | 0.00 |

**Table XI**
**Returns around negative earnings announcements**

Data is daily from June 2006 to September 2016. The dependent variable is Fama-French abnormal return, which is raw return less the five by five Fama and French matched portfolio return. The independent variables are indicators for the time intervals displayed, and so there is no constant to avoid collinearity nor are there fixed effects. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS=1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Each state is determined at time T-10. We measure earnings surprises based on Analyst Estimates (SUE3), but results for other specifications are similar. Only the bottom quintile is used to identify negative earnings surprises. T-statistics are displayed in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Fama-French Abnormal Return | | | |
| Time (-10,-3) | 0.0002 | 0.0012 | -0.0002 | -0.0049 |
| | (0.127) | (0.887) | (-0.023) | (-1.105) |
| Time (-2) | -0.0003 | -0.0004 | 0.0086* | -0.0018 |
| | (-0.505) | (-1.249) | (1.730) | (-0.895) |
| Time (-1) | -0.0002 | -0.0002 | 0.0029 | -0.0012 |
| | (-0.350) | (-0.372) | (0.588) | (-0.790) |
| Time (0) | -0.0169*** | -0.0166*** | -0.0143* | -0.0192*** |
| | (-12.094) | (-12.344) | (-1.708) | (-4.976) |
| Time (1) | -0.0131*** | -0.0141*** | -0.0192** | -0.0060* |
| | (-10.276) | (-12.878) | (-2.264) | (-1.804) |
| Time (2) | -0.0011** | -0.0006 | -0.0043 | -0.0028** |
| | (-2.444) | (-1.370) | (-1.381) | (-2.323) |
| Time (3,10) | 0.0023 | 0.0021 | 0.0051 | 0.0027 |
| | (1.428) | (1.398) | (0.498) | (0.900) |
| Subset | ALL | UNCONST | CONST | TRANS |
| N | 27,691 | 22,345 | 1,156 | 4,190 |
| adj. R-sq | 0.02 | 0.03 | 0.01 | 0.01 |

**Table XII**
**Short selling activity around earnings announcements**

Data is daily from June 2006 to September 2016. The dependent variable, Short Activity, is measured as the change in daily short interest divided by total daily volume. The independent variables are indicators for the time intervals displayed, and so there is no constant to avoid collinearity. Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS = 1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Each state is determined at time T-10. We measure earnings surprises with a rolling seasonal random walk model (SUE1). Only the bottom quintile is used to identify negative earnings surprises. T-statistics are displayed in parentheses. Standard errors clustered by firm and month. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Short Activity (Divided by Volume) | | | |
| Time (-10,-3) | -0.0371*** | -0.0296*** | -0.1321*** | -0.0507** |
| | (-2.987) | (-2.645) | (-2.608) | (-2.043) |
| Time (-2) | -0.0076** | -0.0095*** | -0.0209* | 0.0063 |
| | (-2.545) | (-2.958) | (-1.891) | (0.730) |
| Time (-1) | -0.0096*** | -0.0109*** | -0.0140 | -0.0016 |
| | (-2.906) | (-3.305) | (-1.333) | (-0.165) |
| Time (0) | -0.0024 | -0.0059** | 0.0177 | 0.0106 |
| | (-1.078) | (-2.354) | (1.569) | (1.590) |
| Time (1) | -0.0045** | -0.0062*** | 0.0042 | 0.0022 |
| | (-2.195) | (-2.861) | (0.291) | (0.317) |
| Time (2) | -0.0077*** | -0.0105*** | 0.0411** | -0.0061 |
| | (-2.939) | (-3.786) | (2.381) | (-0.744) |
| Time (3,10) | 0.0726*** | 0.0908*** | -0.2201*** | 0.0562 |
| | (4.708) | (6.514) | (-4.080) | (1.438) |
| Subset | ALL | UNCONST | CONST | TRANS |
| N | 27,691 | 22,345 | 1,156 | 4,190 |
| adj. R-sq | 0.01 | 0.01 | 0.05 | 0.01 |

**Table XIII**
**Price Efficiency, Short Constraints, and Short Activity**

Data is daily from June 2006 to September 2016. The dependent variable, Delay 1 from Hou and Moskowitz (2005). Constrained (CONST) is defined as being expensive-to-borrow (DCBS > 1) for the past 42 days. Unconstrained (UNCONST) is defined as being cheap-to-borrow (DCBS = 1) in the past 42 days. Transient (TRANS) is the remaining sample that is neither. Short Activity is measured as the change in daily short interest divided by total daily volume, with negative values set to zero. Cover Activity is the same, but positive values are set to zero T-statistics are displayed in parentheses. Return[-5,-1] is the cumulative raw return from day t-5 to t-1. Eff Spread is the effective spread computed from intraday TAQ data. Order Imbalance is number of buy orders less the number of sell orders divided by total orders, winsorized at zero. High-Low Prices the intraday high and low price for the stock. Turnover is the average turnover over the five days prior to day t. We include firm and day FE, with standard errors clustered by firm and day. Standard errors clustered by firm and month. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | Delay 1 | | |
| Constrained | 0.032*** | 0.044*** | 0.030*** | 0.021*** | 0.020*** |
| | (6.71) | (8.70) | (6.22) | (4.40) | (4.36) |
| Transient | | 0.025*** | 0.020*** | | |
| | | (11.95) | (9.63) | | |
| Short Activity | | | | -0.015*** | -0.015*** |
| | | | | (-13.34) | (-13.40) |
| Cover Activity | | | | 0.012*** | 0.012*** |
| | | | | (10.94) | (10.91) |
| CONST x Short Activity | | | | | 0.002 |
| | | | | | (0.58) |
| Past Return [-5.-1] | | | 0.001*** | 0.001*** | 0.001*** |
| | | | (12.05) | (11.84) | (11.84) |
| Eff. Spread | | | 0.086*** | 0.088*** | 0.088*** |
| | | | (4.86) | (5.02) | (5.02) |
| Order Imbalance | | | -0.000 | -0.000 | -0.000 |
| | | | (-1.07) | (-1.55) | (-1.55) |
| High - Low Price | | | -0.015* | -0.018** | -0.018** |
| | | | (-1.65) | (-1.99) | (-1.99) |
| MA Turnover [-5.-1] | | | 0.000*** | 0.000*** | 0.000*** |
| | | | (4.79) | (4.54) | (4.54) |
| Ln(Price) | | | -0.031*** | -0.029*** | -0.029*** |
| | | | (-13.71) | (-12.82) | (-12.82) |
| Observations | 7,362,418 | 7,362,418 | 7,362,418 | 6,426,686 | 6,426,686 |
| R-squared | 0.475 | 0.476 | 0.480 | 0.473 | 0.473 |