# The Loud Silence of Suppressed Short-Sale Demand

## 1. Introduction

Short sale is an important market mechanism for bad news to be incorporated into asset prices in an efficient and effective way. However, the constraint on short sale is ubiquitous, and its influence on asset pricing is highly controversial. Miller (1977) argues that due to the short-sale constraint, pessimistic investors could not reveal their negative information, leading to overvaluation of asset prices. Diamond and Verrecchia (1987) argue that the constraint inhibits the price discovery process, especially to bad news. Despite the beneficial roles of short sales suggested by academic studies, regulatory bodies widely ban short-sales in financial crashes (Boehmer et al. 2013).

Empirical evidence is mixed regarding the influence of short-sale on asset pricing, largely due to difficulties of finding unambiguous, publicly available, continuous measures of the short-sale constraint available for a large cross-section of stocks. The first set of measures concerns regulatory changes on short sales, such as the removal of short-sale bans (Chang et al. 2007; Chang et al. 2014) and the temporary imposition of bans (Boehmer et al. 2013). Such eligibility changes are often contaminated by endogeneity or concurrent market-wide regime shift. Regulation SHO pilot program, which is the waiver of uptick test for a subset of stocks (Diether et al. 2009a), is free from endogeneity issues. However, uptick test is a relatively minor dimension of short-sale constraint. Furthermore, Regulation SHO has been effective from May 2005 to August 2006 and was no longer available later on. The second measure of short-sale constraint is short-sale rebate rate. Although it is a direct and unambiguous measure of the constraint, such information is only available in proprietary data (D'Avolio 2002) or in the 1920s~30s (Jones & Lamont 2002). The third measure is the supply of security lending, which is either available only in proprietary data (Cohen et al. 2007) or roughly proxied by institutional ownership (Chen et al. 2002). The fourth measure is the alternative channel for investors to express negative opinions, such as the availability of stock options (Figlewski & Webb 1993) and dual-listed shares shortable in another market. However, stock options are often nonexistent in emerging markets. The last measure is based on revealed short-sale activities, such as monthly short interest (Figlewski 1981) in U.S. and daily short volume in the Chinese market (Chang et al. 2014). Such panel data is publicly available. Yet, a high short-sale volume or interest does not imply less binding short-sale constraint. So far, no existing measures provide a continuous and unambiguous measure of short-sale constraint covering a wide spectrum of stocks.

In this study, we innovatively propose the suppressed short-sale demand as a new measure of short-sale constraint and explore its influence on asset pricing including stock returns and pricing efficiency. We are able to estimate the potentially suppressed short-sale demand owning to the special institutional setting of the Chinese securities market, in which only stocks on a whitelist are eligible for short-sales, and the daily stock-level short-sale volume data are publicly available. On each day, we utilize the cross-section data of shortable stocks and estimate a hedonic model similar to Diether et al. (2009b) to explain revealed short-sale volume. We implicitly assume that shortable stocks are free from shorts-sale constraints and thus, the revealed short-sale volume equals the short-sale demand. Then, we apply the estimated model coefficients out-of-sample to non-shortable stocks and estimate the daily stock-level short-sale demand, which is fully suppressed by regulation as these stocks are ineligible for short sales. We argue that stocks with higher suppressed short-sale demand suffer from stronger short-sale constraint.

We first validate the empirical approach used to estimate suppressed short-sale demand. We divide shortable stocks, which have revealed short-sale volume data available, into two stratified subsamples: one sample is used for the in-sample estimation, and the other is used for the out-of-sample validation. Results show that the performance of the hedonic model is rather decent: whereas the average of the actual short-sale turnover is 1.004% per day, the average of the estimated short-sale turnover is 1.016%, with a difference that is economically insignificant. Furthermore, the correlation between actual and estimated short-sale turnover is reasonably high, with a Pearson correlation of 0.66, and a Spearman correlation of 0.73.

We then examine the return predictive power of suppressed short-sale demand. Results show that suppressed short-sale demand positively predicts one-day-ahead returns but negatively predicts two-day-ahead or one-week-ahead returns. The evidence supports Miller (1977)'s overvaluation theory: as a higher short-sale demand is suppressed and thus a greater amount of negative news is refrained from being incorporated into asset prices, stocks are temporarily overvalued and subsequently underperform by a greater amount. In comparison, we find that the revealed short-sale turnover has no predictive power of future returns, which suggests that the negative information manifested by revealed short sales has been fully incorporated into assets prices.

Cohen et al. (2007) argue that the negative return predictive power of short-sale demand concentrates among firms with less public information flow. Accordingly, we adopt six measures of information environment and find consistent evidence: the suppressed short-sale demand has stronger return predictive power for firms with lower analyst coverage, non-big-4 auditor, opaque, lower fund ownership, smaller firm size, and higher idiosyncratic volatility.

We continue to examine the relation between suppressed short-sale demand and pricing efficiency. We first adopt the price delay measure of Hou and Moskowitz (2005) and Boehmer and Wu (2013) to measure pricing efficiency, and then examine the influence of daily, stock-level short-sale suppressed demand and revealed turnover on one-month-ahead delay measures. We find strong evidence that the revealed short-sale turnover reduces price delay, whereas the suppressed short-sale demand adds to price delay. We further find that the positive relation between suppressed short-sale demand and price delay concentrates among opaque firms with low analyst coverage, low fund ownership, and/or high idiosyncratic volatility. Furtheremore, we utilize the regular information disclosure of earnings announcement events to examine the influence of short-sale demand on post-earnings-announcement-drift (PEAD). We find no obvious change in short-sale turnover prior to earning announcements, suggesting that Chinse short-sellers do not possess superior or inside information. For the subset of firms with very negative unexpected earnings, we do find some evidence that a higher short-sale demand being suppressed is associated with a stronger

PEAD. Overall, the evidence is consistent with the argument of Diamond and Verrecchia (1987) that short-sale constraint reduces pricing efficiency.

This study contributes to the literature from three perspectives. First, we propose a new measure of the short-sale constraint, which is based on publicly available data, continuous, and measurable for a large cross-section of stocks. This new measure is less ambiguous due to the special institutional setting of the Chinese securities market, but can be conveniently extended to other developed market as well. Second, the Chinese market grows to be the largest emerging market and attracts heavy attention of international investors. This market per se is worthy of future extensive investigation. Third, the Chinese market is featured with various market frictions, and the influence of short-sale constraint is arguably more pronounced than in developed markets. This makes the Chinese market an ideal laboratory to test the influence of short-sale constraints on asset pricing, which has rich and general implications for developed markets.

## 2. Literature review and hypotheses development

### *2.1. Short-sale constraint and asset pricing*

The seminal study of Miller (1977) predicts that due to the short-sale constraint, pessimistic investors could not reveal their negative information, leading to overvaluation of asset prices. Boehme et al. (2006) find that stocks with short sale-constraint and high divergence of opinions tend to underperform, suggesting overvaluation of such stocks. However, Diether et al. (2009a) use regulation-SHO data and find no significant difference in return and volatility after the up-tick test is temporarily waived for the pilot stocks. Several event studies (such as the study of Chang et al. (2007) in the Hong Kong market, and Chang et al. (2014) in the Chinese market) find negative stock returns upon lifting of short-sale bans, supporting Miller (1977)'s overvaluation hypothesis.

Another stream of research investigates the influence of short-sale on the pricing discovery process. The theoretical work of Diamond and Verrecchia (1987) posits that constraining short-sellers inhibits the price discovery process, especially to bad news. Bris et al. (2007) examine 46 major equity markets and find supporting evidence that the short-sale practice promotes pricing efficiency, especially in response to negative news. Boehmer and Wu (2013) utilize Regulation-SHO data and find that greater short-selling flow improves intraday pricing efficiency and reduces post-earnings-announcement-drift. Chang et al. (2014) also find enhanced pricing efficiency associated with greater short-sale flows in the Chinese market.

Prior studies suggest that short-sellers might possess superior information. Christophe et al. (2004) examine the short-sale activities in the scenario of earnings announcement and find that abnormal short-sale activities before announcement predict post-earnings announcement returns, suggesting short-sellers as informed traders. Similarly, Christophe et al. (2010) document abnormal short-sale activities before analyst downgrades. Short-sellers might possess superior capability of analyzing information. Boehmer and Wu (2013) further find intensified short-sale activities following negative earnings surprise, which attenuate post-earnings announcement drift. The findings support the argument that short-sellers exploit the overpricing and promote pricing efficiency.  Diether et al. (2009b) utilize Regulation-SHO data and find that short-sellers exploit short-term overreaction to good news and intensified short-sale activities negatively predict future returns.

Literature debates on how short sales influence stock returns volatility and stock-price crash risk. Bris et al. (2007) find that banning short-sale reduces negative skewness using international data, and Chang et al. (2007) find banning short-sale reduces both volatility and negative skewness in the Hong Kong market. However, Chang et al. (2014) find that Chinese short-sellers are short-term contrarians and their trades actually reduce return volatility. Furthermore, Kim et al. (2017) find that intensified short-sale activities are associated with lower stock-price crash risk in the Chinese market, consistent with the theoretic model of Hong and Stein (2003).

Despite the controversial role of short-sale in influencing return moments, short-sales are widely banned in market crashes. Beber and Pagano (2013) examine the influence of global short-sales bans in the 2007 – 2009 subprime crisis and conclude that banning short-sales fails to support price, and the ban reduces liquidity and slows price discovery. Boehmer et al. (2013) investigate the 2008 short-sale ban in the U.S. market and find degrading market quality in terms of spread, price impact, and intraday volatility. Thus, short-sale ban seems to impede the efficiency of negative news to be manifested in prices.

### *2.2. Measuring short-sale constraint*

Overall, prior literature supports Miller (1977)'s overvaluation hypothesis and Diamond and Verrecchia (1987)'s price discovery hypothesis. However, a careful examination of prior studies reveals that most evidence comes from event studies, such as the lift or re-impose of bans in Hong Kong or China that are endogenous events and suffer from self-selection problems. Regulation-SHO pilot program in the U.S. does not involve endogeneity issues, but Diether et al. (2009a) suggest that the effect of tick test on the market is attributable to "distortions in order flow created by the price tests themselves" instead of constraints on short-selling brought about by the up-tick rule.

Empirical studies based on continuous panel data commonly use monthly short-sale interest (Figlewski 1981; Boehme et al. 2006) to measure short-sale constraint, assuming that a high level of short interest indicates a greater extent of short-sale constraint, which is highly debatable. Another commonly used measure of short-sale constraint is borrowing fees of stock loans (Geczy et al. 2002; Jones & Lamont 2002), but such data are often proprietary and not publicly available for a large scale of stocks. Institutional ownership, as a rough measure of the supply of security lending, is also used to measure short-sale constraint (E.g., Berkman et al. 2009). Another stream of literature (E.g., Boehmer & Wu 2013) examines the determinants and influence of short-sale flows. However, a greater trading flow does not translate to a lower extent of short-sale constraint. Whereas early studies mix the shorting supply and demand, Cohen et al. (2007) utilize proprietary data and design a unique identification method to disentangle short-sale demand from supply. They find that increased short-sale demand is associated with negative future returns, supporting the overvaluation hypothesis. Till now, no prior studies are able to measure the quantity of short-sale demand that is curtailed due to the short-sale constraint.

Our study fills the gap. Owning to the special design in China, we are able to take advantage of the dual-layer short-sale practice. In the Chinese market, only a subset of stocks on a white-list is eligible for short-sales. Assuming such stocks are free from short-sale constraints and their short-sale demands are fully revealed by short-sale flows, we utilize stock characteristics of such eligible stocks to estimate a cross-sectional hedonic model of short-sale demand. We then apply the estimated model to non-shortable stocks to estimate the short-sale demand that is fully suppressed by regulation. We then examine how such suppressed short-sale demand influence asset pricing in terms of returns and pricing efficiency.

The suppressed short-sale demand has three advantages to measure short-sale constraint. First, different from short interests or short flows, our suppressed short-sale demand measure is an unambiguous measure of short-sale constraint, with a stronger suppressed demand indicating more stringent shorting constraint. Second, different from short-sale bans, our short-sale demand measure successfully captures the stock-varying short-sale constraint. Third, our measure does not rely on proprietary data and is available for a large scale of stocks, especially those with binding constraints, making replication and extension of this study feasible for a broad set of stocks.

### *2.3. Hypothesis*

Short-sale is an important mechanism for bad-news to be incorporated into stock prices. Thus, a higher suppressed short-sale demand is associated with delayed revelation of bad news and temporary overvaluation (Miller 1977), which implies lower future returns. We thus derive the first hypothesis regarding the cross-sectional of stock returns:

*H1: Other things being equal, a higher suppressed short-sale demand is associated with lower future returns.*

Cohen et al. (2007) suggest that the influence of short-sale demand on asset pricing is more pronounced among firms with less public information flow. Accordingly, we predict the influence of suppressed short-sale demand to be stronger for firms with less information flow, which is a stronger version of H1:

*H2: The negative association between suppressed short-sale demands and future stock returns concentrates among firms with less public information flow.*

Short-sale has been considered an important trading mechanism for negative news to be manifested in prices. Therefore, we expect suppressing short-sale demand to impede price discovery, especially in response to negative information. We thus derive the third hypothesis regarding the pricing efficiency:

*H3: other things being equal, a higher suppressed short-sale demand is associated with lower future pricing efficiency.*

## 3. Suppressed short-sale demand

### *3.1. Data*

As the pilot reform that lifted bans on short-sales for a subset of stocks in the Chinese market began in 31 March 2010, our data period spans 1 April 2010 to 31 December 2015. The list of stocks eligible for short-sale and margin-purchase expanded from 90 stocks to around 900 stocks as of the end of 2015, comprising around one-third of the number of A-shares in the mainboard and over two-thirds of the total market capitalization. Readers may refer to Chang et al. (2014) for institutional details. Daily short-sale and margin-purchase data for shortable firms are retrieved from WIND. Daily stock trading data, financial data, and analyst forecasts are obtained from CSMAR data base provided by GuoTaiAn.

*3.2. Estimation process*

On each trading day *t*, we estimate the below model by regressing stock-level short-sale turnover on a range of stock characteristics using a cross-section of stocks that are eligible for short-sale and/margin purchase.

$$short_t = r_{-5:-1} + r_t + \sigma_t + \sigma_{-5:-1} + to_{-5:-1} + lmv_{t-1} + bm_{t-1} + ivol_{t-1} + lev_{t-1} + roa_{t-1}\,. \qquad (1)$$

All variables in Model (1) are measured at the stock level. In particular, $short_t$ is the short-sale turnover for each stock on day *t*, defined as daily short-sale volume in shares scaled by total trading volume in shares. Variable $r_{-5:-1}$ is the cumulative returns in the previous five trading days, and $r_t$ is the contemporaneous return on day *t*. Variable $\sigma_t$ is the difference between high and low prices scaled by high price, and $\sigma_{-5:-1}$ is the average daily $\sigma$ in the previous five trading days. Variable $to_{-5:-1}$ is the average share turnover in the previous five trading days. We also include additional firm-characteristics such as log firm capitalization (*lmv*) on day *t-1*, book-to-market ratio (*bm*), idiosyncratic volatility (*ivol*), leverage ratio (*lev*), and ROA (return on asset). On each day, for each stock, we run a market model by regressing daily stock returns on value-weighted market index using all A-shares in a window of the previous 250 trading days, and *ivol* is the square root of variance of residuals in the market model. Days in July and December are matched to the financial statement data as of the end of the previous year, and days in January to June are matched to the financial statement data at the end of the previous two years. The book-value of equity (CSMAR item A003000000) is then matched to the contemporaneous December-end total market value to calculate *bm* ratio. Leverage is defined as long-term debt (A002206000 or A002200000) plus long term debt matured in one year (A002125000) scaled by the sum of long-term and book value of equity. ROA is profit scaled by total assets (A001000000) at the end of the previous year, whereas profit is the sum of net income (B002000000), financial expenses (B001211000), tax expenses (B002100000), and depreciation (D000103000).

Model (1) follows the essence of Table 3 of Diether et al. (2009b), which adopts a panel regression with day and stock fixed effect. To identify the appropriate model, we estimate three versions of models (1) and (2). In version A of the model, we include only $r_{-5:-5}$ and $r_t$ as explanatory variables. In version B, we add $\sigma_t$, $\sigma_{-5:-1}$, and $to_{-5:-1}$, as additional explanatory variables. Thus, we include all low-frequency explanatory variables in Diether et al. (2009b) in Version B.[1] Finally, as Diether et al. (2009b) adopt the panel regression with the control of firm- and trading day-fixed effects and we estimate the cross-sectional model every day, we also include extra stock characteristics including firm size and book-to-market ratio (Fama &

[1] Diether et al. (2009b) also use high-frequency measures including concurrent bid-ask spread ($spread_t$), concurrent order imbalance ($oimb_t$), and historical order imbalance ($oimb_{-5:-1}$). Diether et al. (2009b) also include the past short-sale turnover ($short_{-5:-1}$) as a control. We intend to apply the estimation model to non-shortable stocks, which do not have past short-sale turnover available. Thus, we drop this control variable.

French 1992), idiosyncratic volatility (Ang et al. 2006), leverage (George & Hwang 2010), and profitability (Lewellen 2015).

After we estimate the loadings of stock characteristics using the cross-section of shortable firms according to Model (1), we then apply the coefficients to non-shortable stocks to obtain the expected short-sale turnover (*Eshort*), which is suppressed short-sale demand that is not revealed in the market.

The suppressed margin-purchase demand is estimated in a similar way. On each trading day, we estimate the below cross-sectional regression using the observations of marginable firms:

$$Margin_t = r_{-5:-1} + r_t + \sigma_t + \sigma_{-5:-1} + to_{-5:-1} + lmv_{t-1} + bm_{t-1} + ivol_{t-1} + lev_{t-1} + roa_{t-1}. \qquad (2)$$

The estimated coefficient on each day is then applied to non-marginable firms in order to estimate the suppressed margin demand (*Emargin*).

*3.3. Suppressed demands*

Following the estimation process discussed in Section 3.1, we estimate Models (1) and (2) using the cross-section data of eligible firms on each day, and then apply the estimated coefficients to the sample of ineligible firms to estimate the suppressed demand. We alternatively estimate three versions of Models (1) and (2) with varying subset of explanatory variables. To reduce the influence of outliers, we winsorize all variables in Models (1) and (2) by their respective 1-st and 99-th percentiles in the full sample. We report the summary statistics on the variables used in Models (1) and (2) in Panel A of Table 1. The average daily short-sale turnover is only 1.00% from 2010 to 2015, which is slightly higher than an early

Chinese study by Chang et al. (2014), suggesting a quick development in the short-sale market. However, the magnitude is still much lower than its U.S. counterparty, which is as high as 23.89% reported by Diether et al. (2009b).

Table 2 reports the average of daily estimated coefficients of stock characteristics, and *t*-statistics are calculated using Newey-West standard errors with six lags (Goyal & Santa-Clara 2003). We include an expanded set of explanatory variables from model A to C. Throughout columns 1, 3, and 5, we find that realized short-sale turnover tends to be higher when the past return is lower and the concurrent return is higher. Such finding suggests that short-sellers seem to be momentum traders who expect past trend to continue and increase their position in a temporary price bounce. In comparison, throughout columns 2, 4, and 6, we intensified margin-purchase activities when the concurrent return is lower, suggesting margin-buyers as very short-run contrarian traders. Our findings are consistent with the evidence documented in Chang et al. (2014). It is worth-noting that although we only include past and concurrent returns as explanatory variables, Model A has an average R-square of 4.21% in explaining the cross-section of realized short-sale turnover, and an average R-square of 3.12% in explaining realized margin-purchase turnover.

While we gradually expand the set of explanatory variables, the R-square substantially improves. In the complete model C, the average R-square is as high as 28.54% for short-sale turnover, and 13.85% for margin-purchase turnover. Furthermore, realized short-sale turnover tends to be higher in the case of lower return volatility, lower past aggregate share turnover, bigger firm size, lower book-to-market ratio, lower idiosyncratic volatility, and higher leverage. Due to the high R-square of Model C, subsequent results are based on model C only.

We then apply the estimated coefficients to non-shortable/marginable firms to obtain the estimate short-sale or margin-purchase demand that are suppressed by regulation. Table 1 reports the summary statistics. Panel A is reported for the subsample of eligible firms for which *short*/*margin* are realized turnovers, and Panel B is reported for the subsample of ineligible firms for which *Eshort* or *Emargin* are estimated suppressed short-sale or margin-purchase demands. Estimated demands are winsorized at the 1-st and 99$^{th}$ percentiles in the full sample. Whereas the average realized short-sale turnover is 1.00% per day for shortable firms, the average estimated demand is only 0.17% for non-shortable firms. Further comparison reveals that firms that are eligible for short-sale tend to have a higher market capitalization and lower idiosyncratic volatility,[2] which partially explains why the estimated demand is on average lower than realized turnovers. The average magnitude of estimated margin-purchase demand (13.25%) is slightly lower than that of realized margin-purchase turnover (16.37%).

*3.4. Validation of estimated demand*

As discussed in Section 3.3, the estimated short-sale demand for non-shortable firms is much lower than the realized short-sale turnover for shortable firms. As the hedonic model adopted

[2] Firms eligible for short-sale and margin-purchase are constituent stocks in expanded sets of stock indices. The list was gradually expanded to include around 900 firms at the end of 2015. Eligible firms must be big enough, have sufficiently high turnover and sufficiently low return volatility.

to estimate suppressed short-sale demand is critical in this study, we intend to validate the hedonic model in this section.

To validate the estimated short-sale demand, we divide the estimation sample of shortable/marginable firms into two stratified groups. One group is used for the in-sample estimation, and the other group is used for out-of-the-sample evaluation. In particular, on each day, we rank firms that are eligible for short-sale and/or margin-purchase by their past 5-day returns[3] and sequentially number the observations. We use firms with odd numbers to estimate the coefficients of the three alternative versions of Models (1) and (2), and then apply the estimated coefficients to firms with even numbers as out-of-the-sample tests. Note that firms used for out-of-sample tests now have both realized short-sale turnover and estimated short-sale demand, and the realized turnover becomes a natural benchmark for us to evaluate the precision of the estimate demand. If our cross-sectional hedonic model is appropriate and precise, then the estimated short-sale demand should have similar magnitude to the realized short-sale turnover, and the correlation between estimated demand and realized turnover should be reasonably high.

Table 3 reports the verification results. Panel A reports summary statistics of the real short-sale turnover (*short*) and estimated short-sale demands (*Eshort*), where the superscript A, B, or C denotes the three alternative versions of Model (1). A rough comparison between realized short turnover and estimated short demands suggests that our estimation is quite

[3] As past return is the only variable adopted by Diether et al. (2009b) to forecast future short-sale turnover in the benchmark model, we use past return as the primary ranking variable.

decent. In samples used for out-of-the-sample test, the estimation errors seem to be only minor: whereas as the mean of the realized short-sale turnover is 1.004%, the estimated short-sale demands are on average 1.000%, 1.001%, and 1.016% according to version A, B, and C, respectively. Panel B of Table 3 reports the correlation. Among the three versions of estimated short-sale demands, version C produces the highest correlation with the realized short-sale turnover, with a Pearson correlation of 0.66 and a Spearman correlation of 0.73.[4] This further justifies the choice of Version C of Model (1) with the full set of stock characteristics in the estimation. The estimated margin-purchase demands also perform well, with similar magnitude and high correlation with the realized margin-purchase demand. To keep consistency, we also apply the full set of stock characteristics for Model (2). Unreported robustness checks reveal that splitting the estimation sample by alternative ranking variables produces essentially the same validation results.

## 4. The influence of constrained short-sale demand

### *4.1. Future stock returns*

We next explore how suppressing short-sale demand influences future stock returns. In the univariate test, we form quintile portfolios on each day by firms' daily turnovers or suppressed demands and observe portfolio returns in one-day ahead, two-day ahead, and one-week ahead (Diether et al. 2009b). Panel A of Table 4 reports abnormal returns on portfolios

[4] One can always add additional stock characteristics into Models (1) and (2) to improve the precision of the estimation, such as the high-frequency microstructure variables suggested by Diether et al. (2009b). We argue that the current model performs reasonably well, and the variables are easy to obtain and the model results are easily replicatable.

ranked by realized or suppressed short-sale turnovers. The results show that firms with higher realized turnovers tend to have lower future returns. For example, for the quintile with highest short-sale turnovers, we observe -0.023% returns on day *t*+1, another -0.027% return on day *t*+2, and a cumulative return of -0.104% from day *t*+2 to *t*+6. The evidence suggests that short-sale trades contain negative firm-specific information, which is gradually incorporated into stock prices and thus predicts future returns. In comparison, portfolios ranked by suppressed short-sale demand show a stronger return predictive power. For the quintile with highest suppressed short-sale demand, the abnormal return on day *t*+2 is -0.055%, and a cumulative return of .285% from day *t*+2 to *t*+6. Long-short portfolios of buying the quintile with the lowest suppressed short-sale demand and selling the quintile with the highest demand generate 0.096% abnormal return on day *t*+2 and 0.399% from day *t*+2 to *t*+6. The evidence implies that the extent of underreaction to negative information is even severer for firms that are ineligible for short-sales.  We also perform robustness check by forming value-weighted portfolios and find qualitatively similar results.

Panel B of Table 4 reports abnormal returns on portfolios ranked by realized or suppressed margin-purchase turnovers. The results show that firms with lower margin-purchase turnovers under-perform and firms with higher turnovers outperform, suggesting underreaction to positive news contained in margin-purchase trades. In contrast, for portfolios ranked by suppressed margin-purchase demand, return predictive power comes from the low demand quintile. It is likely that firms with low margin-purchase demands overlap those with high short-sale demands. Untabulated correlation analysis shows that the firm-level suppressed short-sale demand (*Eshort*) is negatively correlated with suppressed margin-purchase demand (*Emargin*) with a correlation coefficient of -0.22, which is both statistically and economically significant. To disentangle the joint effect, we orthogonalize *Emargin* with respect to *Eshort* by regressing *Emargin* on *Eshort* and use the residual to replace *Emargin* in the multivariate regression analysis (Cohen et al. 2007).

Next, we follow Diether et al. (2009b) and examine how revealed short-sale turnover influences future stock returns using the panel of daily stock-level data for shotable stocks:

$$r_{t+\tau} = short_t + margin_t + r_{-5:-1} + \sigma_t + to_{-5:-1}, \tag{3}$$

where *short* is the revealed short-sale demand, and *margin* is the orthoganized revealed margin-purchased turnover. The left-hand-side variables are future stock-level abnormal returns on day $t$+1, $t$+2, or $t$+2:$t$+6. Right-hand-side control variables include stock-level abnormal returns in the past five trading days ($r_{-5:-1}$), intra-day high-low-price volatility ($\sigma_t$), and past share turnover ($to_{-5:-1}$). We control for stock- and day-fixed effect. If negative news is gradually incorporated into stock prices, we expect to observe a negative coefficient of *short* in Eq. (3).

More importantly, we use the panel data of non-shortable stocks to examine how expected or suppressed short-sale demand influences future stock returns:

$$r_{t+\tau} = Eshort_t + Emargin_t + r_{-5:-1} + \sigma_t + to_{-5:-1}, \tag{4}$$

and the variable of interest is *Eshort* , which is the fitted short-sale turnover by applying the estimated coefficients from Eq. (1) to non-shortable stocks. Variable *Emargin* is the orthoganized suppressed margin-purchased demand. As predicted by H1, a higher short-sale demand being suppressed indicates concurrent overvaluation and therefore lower future return. Thus, *Eshort* is expected to have a negative coefficient in model (4).

Table 5 reports the multivariate regression results. Columns (1), (3), and (5) report the influence of revealed short-sale and margin-purchase trades as in model (3), and Columns (2), (4), and (6) show the influence of suppressed short-sale and margin-purchase demands as in model (4). Interestingly, the revealed short-sale turnover is insignificantly correlated with 2-day and 1-week ahead returns, showing no underreaction to bad news with the control of margin-purchase turnover. In Sharpe contrast, the suppressed short-sale demand is positively associated with one-day ahead return and negatively associated with two-day and one-week ahead returns. In other words, a higher level of short-sale demand being suppressed is associated with a temporary overvaluation and following reversals, suggesting that the negative information is gradually incorporated into prices. In particular, the coefficient of *Eshort* is -0.092 ($t$ = -23.68) in Column (4). It indicates that a 10% increase in the suppressed short-sale demand as a percentage of daily trading volume is associated with 92 bps drop in stock prices on day $t$+2. This pattern persists into 1-week ahead without reversal. Thus, the evidence supports H1 that suppressed short-sale demand is associated with overvaluation.

Besides, Columns (4) and (6) reveal that suppressed margin-purchase demand is positively associated with two-day and one-week-ahead returns. Margin-purchase arguably facilitates the incorporation of good-news into stock prices. Thus, we expect suppressing margin-purchase to be associated with under-reaction to good news, and therefore, positive future returns. Empirical evidence supports this expectation.

*4.2. Information revelation*

Following Cohen et al. (2007) and Lang et al. (2003), we continue to explore how information environment alters the influence of suppressed short-sale demand on future returns. We measure information environment by six alternative dummy variables. The first variable is the number of analyst following, orthoganized with respect to firm size (Cohen et al. 2007). Dummy *# analyst* equals one if the residual analyst following is higher than sample median and zero otherwise. We add an interaction term between *Eshort* and dummy variable into model (4) and examine the marginal influence of information environment. A higher number of analyst forecast indicates greater public information follow and therefore better information environment. We expect the influence of suppressed short-sale demand to be stronger among firms with lower analyst coverage, and thus a positive coefficient of the interaction term. Other dummy variables including *big4* that equals one if the firms' auditor is a Big Four accounting firm and zero otherwise, *opacity* that equals one if the firms' disclosure score is a C or D and zero for A and B, *fund%* that equals one if the firm's mutual-fund ownership is above the sample median and zero otherwise, *size* that equals one if the firm's market capitalization is above the sample median and zero otherwise, and *ivol* that one if the firm's idiosyncratic volatility is above the sample median and zero otherwise. We expect firms that are not audited by Big4, opaque, with lower fund ownership, small capitalization, or higher idiosyncratic to exhibit a stronger influence of short-sale demand on future returns.

The subsample regression results are reported in Panel B of Table 6. With all six dummy variables that measure information environment, we observe consistently negative coefficient of *Eshort*. Furthermore, the negative predictive power of *Eshort* is stronger for opaque firms or firms with higher idiosyncratic volatility. The effect is weaker for firms with higher analyst following, bid4 auditor, high fund ownership, and large size; however, the positive coefficients of the interaction term has a smaller magnitude than the negative coefficients of *Eshort*, which suggests that the return predictive power of suppressed short-sale demand remains even within the subsample of firms with better information environment. The evidence supports H2 that suppressing short-sale leads to severer temporary overvaluation for firms that have lower-quality information environment.

The subsample analysis utilizing the sample of shortable firms reveals different patterns. Results in Table 5 show that revealed short-sale turnover cannot reliably predict future returns. Panel A of Table 6 future reveals that short-sale turnover negatively predict future returns for the subsample of firms poor information flow, featured by low analyst coverage, non-big-4 auditor, opaque, and high idiosyncratic volatility. For the subsample of firms with good information environment, featured by high analyst coverage, big-4 auditor, high fund ownership, and low idiosyncratic volatility, short-sale turnover actually positively predicts future returns. Hong and Stein (1999) suggest that a low speed of information diffusion leads to more pronounced underreaction and following overshooting. At two-day horizon, it is likely that firms with poor information revelation is still in the underreaction stage whereas firms with smooth information revelation already goes to the reversal stage.

## 5. Pricing efficiency

In this section, we explore whether suppressed short-sale demand impedes pricing efficiency. We examine two efficiency measures: price-delay and the degree of post-earnings-announcement-drift.

### *5.1. Price delays*

We follow Boehmer and Wu (2013) and calculate a low-frequency modified price delay measure (Hou & Moskowitz 2005). We utilize the daily stock returns in each month to run below unrestricted regression:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \sum_{\tau=1}^{5} \delta_{i\tau} r_{m,t-\tau} + \varepsilon_{it}\ , \tag{5}$$

where $r_{it}$ is the daily return on stock *i* in this particular month, $r_{mt}$ is the value-weighted market return of all A-shares, and $r_{m,t-\tau}$ is the lagged market returns in the previous 5 days. We then estimate a second regression that restricts all the coefficients ($\delta_{i\tau}$) of lagged market returns to be zero. Consistent with Boehmer and Wu (2013), we require a minimum of fifteen observations per firm per month. The monthly delay measure is accordingly defined as:

$$delay = 1 - \frac{R^2\left(\text{restricted model}\right)}{R^2\left(\text{unrestricted model}\right)}\ . \tag{6}$$

A higher *delay* suggests a lower pricing efficiency, as a higher proportion of stock return variation is captured by delayed reaction to market-wide information.

Short-sale constraints arguably impede the price discovery in response to negative information. To further exploit the potential asymmetry in price adjustment speed, we follow

Boehmer and Wu (2013) and modify the above unrestricted models to isolate negative market returns:

$$r_{it} = \alpha_i + \beta_i r^-_{mt} + \sum_{\tau=1}^{5} \delta_{i\tau} r^-_{m,t-\tau} + \varepsilon_{it} \,, \tag{7}$$

where $r^-_{mt}$ refers to days with negative market returns. We then use the $R^2$ from Eq. (7) in the denominator of Eq. (6) to calculate a modified $delay^-$ measure that captures price adjustment to negative information. We similarly calculate a modified $delay^+$ captures delayed price adjustment to positive information.

We then utilize the panel data of stock-month observations and regress delay measures on the lagged suppressed short-sale demands:

$$delay_t = Eshort_{t-1} + Emargin_{t-1} + lprc_{t-1} + lmv_{t-1} + to_{-5:-1} + DV_{-1} \,, \tag{8}$$

where the variable of interest is *Eshort*. H3 predicts a positive coefficient of *Eshort*, as a greater suppressed short-sale demand will leads to greater price delay. Control variables include orthoganized margin-purchase demand (*Emargin*), log price level (*lprc*), log market capitalization (*lmv*), share turnover (*to*), and lagged dependent variable ($DV_{t-1}$)

Results are reported in Table 7. Columns (1), (3), and (5) show the influence of realized short-sale turnover on price delays, and columns (2), (4), and (6) show the influence of suppressed short-sale demand. Realized short-sale turnover is negatively associated with price delays in all three columns, supporting the proposition that short-sale promotes pricing efficiency (Bris et al. 2007; Chang et al. 2007). More importantly, suppressed short-sale demand is positively associated with future price delays, and coefficient is significantly positive in columns (2) and (6). The evidence supports H3 that suppressing short-sale demand reduces pricing efficiency.

We further examine the influence of suppressed short-sale demand on price delays in subsamples with varying information environment. Similar to Section 4.2, we use six dummy variables to measure public information flows: analyst coverage, big-four auditor, opacity, mutual fund ownership, firm capitalization, and idiosyncratic volatility. We add the interaction terms between short-sale demand and the aforementioned dummy variables into Model (8) to examine how information environment varies the influence of suppressed short-sale demand on price delays.

Results are reported in Table 8. Panel A shows that realized short-sale turnover reduces price delays. The beneficial effect of short-sale activities is stronger among opaque firms but weaker among big firms. Revealed short-sale turnover even adds to price delays for firms with high idiosyncratic volatility. Panel B exhibits that a higher suppressed short-sale demand adds to price delays when the analyst coverage is low or when the fund ownership is high. However, for the subsample of high analyst coverage (column 1), the negative coefficient of interaction term almost offset the positive coefficient of *Eshort*, suggesting negligible influence of suppressed short-sale demand. The evidence lends future support to H3 that when the firm's public information flow is scare, suppressing short-sales further exacerbates the pricing inefficiency. Short-sale is one of several alternative ways to reveal negative information. When the public information is abundant, suppressing short-sale demands does not substantially harm efficiency.  Column (6) of Panel B also shows that the suppressing short-sale demand only influences pricing efficiency for firms with high idiosyncratic volatility, which arguable have higher arbitrage difficulties and higher proportion firm-specific information.

*5.2. Around earnings announcement*

Firms' earnings announcements are important corporate disclosure events. We take advantage of these regular events to explore how suppressing short-sale demand influences pricing efficiency around earnings announcements. We collect all forecasted *EPS* from the analyst forecast datasets of CSMAR. As quarterly earnings are not audited, analysts in the Chinese market only forecast annual earnings. To obtain the consensus analyst forecasts, we retain the most updated forecast per institution in each fiscal year for each stock, and we drop forecasts that are more than one-year old. Then, we follow Mendenhall (2004) and define standardized unexpected earnings (*SUE*) as:

$$SUE_{it} = \frac{Actual_{it} - \overline{Forecast_{it}}}{SD\left(Forecast_{it}\right)}, \tag{9}$$

where $Actual_{it}$ is the actual *EPS* for stock *i* in fiscal year *t*, and $\overline{Forecast_{it}}$ is the average of forecasted *EPS* by unique institutions for stock *i* in fiscal year *t*, and *SD* is the cross-sectional standard deviation of these forecasts. We require each stock-year to have at least two unique forecasts, and set *SD* to \$0.01 if it is zero.

Our samples cover 5320 annual earnings announcement events from 2010 to 2015. Among them, 1607 events belong to firms eligible for short-sale and margin-purchase, and the remaining 3713 are for ineligible firms. In each year, we categorize samples into positive- and negative-*SUE* groups. We then equally divide each group into two subgroups according to the magnitude of *SUEs*. Firms with very (moderately) negative *SUE*s are labeled as -2 (-1), and firms with very (moderately) positive *SUE*s are labeled as +2 (+1). Figure 1 plots the cumulative abnormal returns (*CARs*) around announcements of annual financial statements, and Figures 1a and 1b are for the subsamples of shortable and non-shortable stocks, respectively. Figures 1a shows that for shortable stocks, all four groups seem to experience price run-up prior to earnings announcement. On the announcement day, we observe positive (negative) returns in response to positive (negative) *SUE*s. Table 9 further reveals that for 551 events with very negative *SUE*s, the average announcement abnormal return is -0.51% (*t*=-4.48). We observe monotonically increasing announcement returns when *SUE* gets more positive across four *SUE*-quartiles. However, we observe no obvious post-earnings-announcement-drift at the aggregate level. Figure 1a indicates the existence of post-earnings-announce-drift (PEAD) for positive-*SUE* groups and the mildly negative-*SUE* group, but not for the very negative *SUE* group. Furthermore, returns only drift for one or two days for positive-return groups and quickly reverse. Table 9 reveals that for the quartile with very negative *SUE*s, the average post-announcement returns in the [+1,+5] window is 0.02% (*t*=1.07), which is neither statistically nor economically significant.

The return pattern seems quite different for non-shortable stocks. In Figure 1b, we observe a common trend of the price run-up before earnings announcement and a common price drop upon announcement regardless of the sign of *SUE*s. Table 9 further reports that the announcement day returns are significantly negative for all four *SUE* quartiles. It seems that the price discovery fails to function for firms that are not shortable or marginable. The PEAD pattern is even noisier and harder to analyze at the aggregate level.

Motivated by Christophe et al. (2004), we check the short-sale activities and suppressed demands before earnings announcement. Figure 2 plots the *CAR*s and short-sale turnover/demands aggregated by trading days around the event window. Figure 2a plots for the most-negative-*SUE* group of shortable stocks, and we observe no discernable pattern in the change of short-sale turnover around earnings announcement. The average daily short-sale turnover fluctuates around 1.1%, with a magnitude comparable to the average short turnover of 1.0% for the full sample as reported in Panel A of Table 1. Interestingly, the average short-sale turnover is much higher for shortable firms with the most positive *SUE* group, around 1.8%. Further untabulated correlation analyses reveal that firms with intensified pre-announcement short-sale activities have higher announcement return, and that pre-announcement short-sale turnover has no significant correlation with post-announcement returns. Such evidence suggests that short-sellers in the Chinese market do not possess superior information and cannot reliably predict future returns, which is different from the evidence reported by Christophe et al. (2004) in the U.S. market.

Motivated by Boehmer and Wu (2013), we also check whether short-sellers exploit the under-reaction to information in PEAD and short-sell firms with negative announcement returns. Figure 2a provides no obvious support to this hypothesis either, as we discover no reliable increase in short-sale turnover in the post announcement period, and untabulated paired t-statistic show no statically difference in short-sale activities between pre- and post-announcement period. Further untabulated correlation analyses shows that announcement-day short-sale turnover is positively correlated to announcement return, indicating intensified short-sale activities associated with more positive announcement return. Such evidence echoes the short-sale strategies documented in Table 2 that Chinese short-sellers trade against concurrent price run-up, but is inconsistent with the evidence documented in Boehmer and Wu (2013) that U.S. short-sellers exploit underreaction to negative information as implied by PEAD and short-sell firms with negative *SUE*s.

We focus our analyses on whether realized short-sale turnover promotes pricing efficiency by attenuating PEAD, and whether suppressed short-sale demand hinders price discovery by exacerbating PEAD.  Consistent with the framework of Boehmer and Wu (2013), we utilize the panel data of earnings announcement and run below regression:

$$CAR_{it} = DUE_{it} + DUE_{it} \times D\Delta short_{it} + DUE_{it} \times D\Delta margin_{it} + controls\,. \qquad (10)$$

The dependent variable is the post-earnings-announcement abnormal return cumulated from day +1 to day +5, where abnormal returns are estimated from a rolling window market model (as discussed in Section 3.1). On the right-hand-side, *DUE* is the decile ranking of SUEs, and *DΔshort* is the decile ranking of changes in daily short-sale turnover from [−5, −1] to [+1, +5] around earnings announcement events. The interaction term between *DUE* and *DΔshort* captures the marginal effect of short-sale activities on PEAD. We similarly define a decile ranking variable based on the change of margin-purchase activities (*DΔmargin*). Whereas we examine the influence of realized short-sale turnover for the subsample of shortable firms, we also examine the influence of suppressed short-sale demand for the subsample of non-shortable firms.

Table 10 reports the regression results. Columns (1) and (2) are reported for realized short-sale turnover, and columns (3) and (4) are reported for suppressed short-sale demands. Following Boehmer and Wu (2013), we focus on the most-negative SUE quartile. The results seem rather consistent: whereas realized short-sale demand shows no discernable influence on PEAD, constraining short-sale demand significantly add to the extent of PEAD. The coefficient of *SUE*×*DΔshort* is significantly positive when *DΔshort* is measured for suppressed short-sale demand, indicating that for firms with greater short-sale demand that are suppressed by regulation, PEAD tends to be more severe. Such evidence lends further support to Hypothesis 3 that suppressed short-sale demand destroys pricing efficiency.

## 6. Conclusion

Utilizing the special institutional setting in the Chinese securities market, we innovatively propose suppressed short-sale demand as a new measure of short-sale constraint. We employ the revealed short-sale volume of shortable stocks to estimate the suppressed short-sale demand for non-shortable stocks. A higher short-sale demand being suppressed indicates a more binding short-sale constraint. Consistent with (Miller 1977)'s overvaluation theory, we find that suppressed short-sale demand negatively predicts future returns, and such relation concentrates among firms with poor information environment. Consistent with Diamond and Verrecchia (1987), we find that a higher suppressed short-sale demand is associated with lower pricing efficiency.

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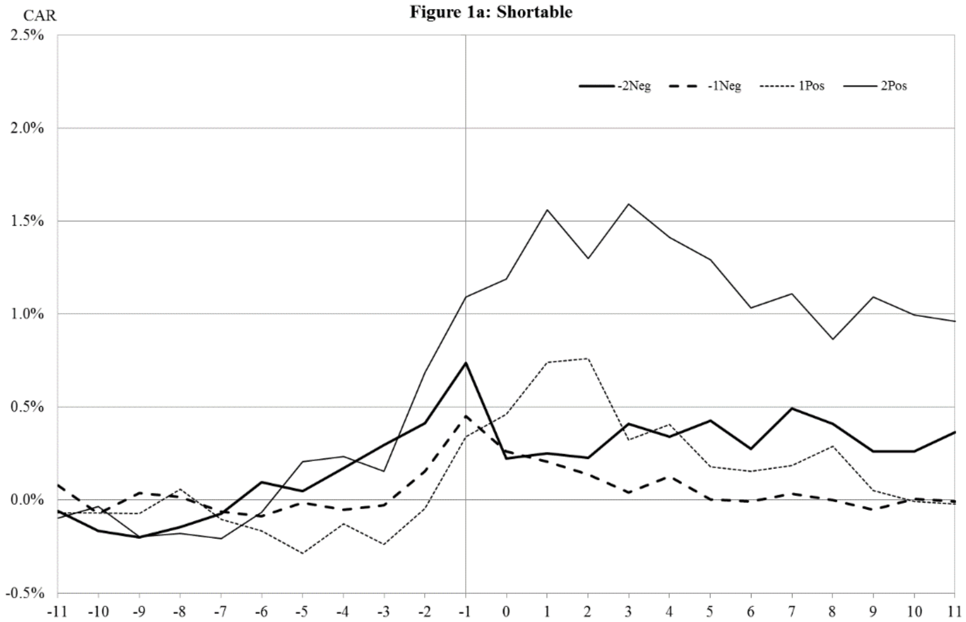
## Figures and Tables

### Figure 1. CARs around earnings announcements

We categorize earnings announcement events into four groups by the sign and magnitude of standardized unexpected earnings (*SUE*s) from very negative (-2) and moderately negative (-1) to moderately positive (+1) and very positive (+2). We plot the cumulative abnormal returns (*CAR*s) in [-11,+11] trading days' window around announcements for each *SUE*-groups and for shortable and non-shortable stocks, respectively.



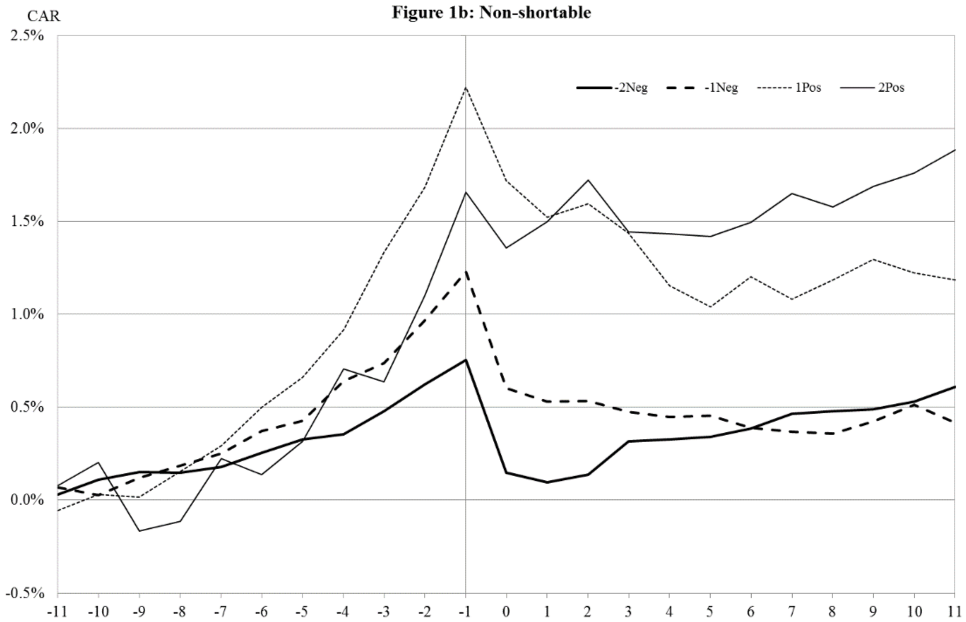
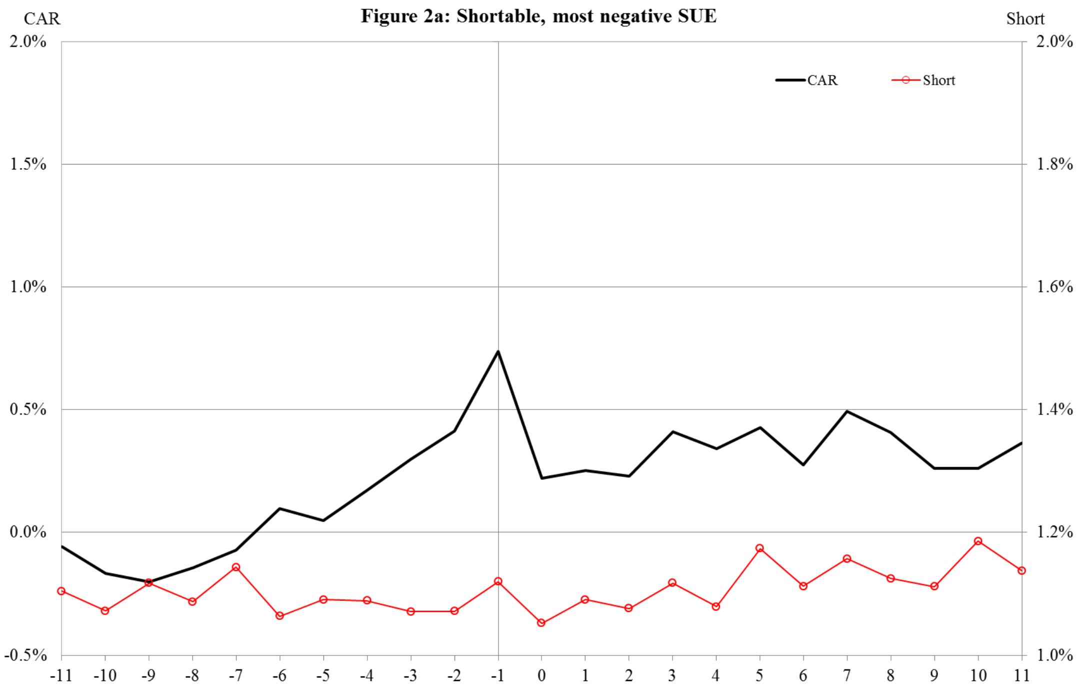
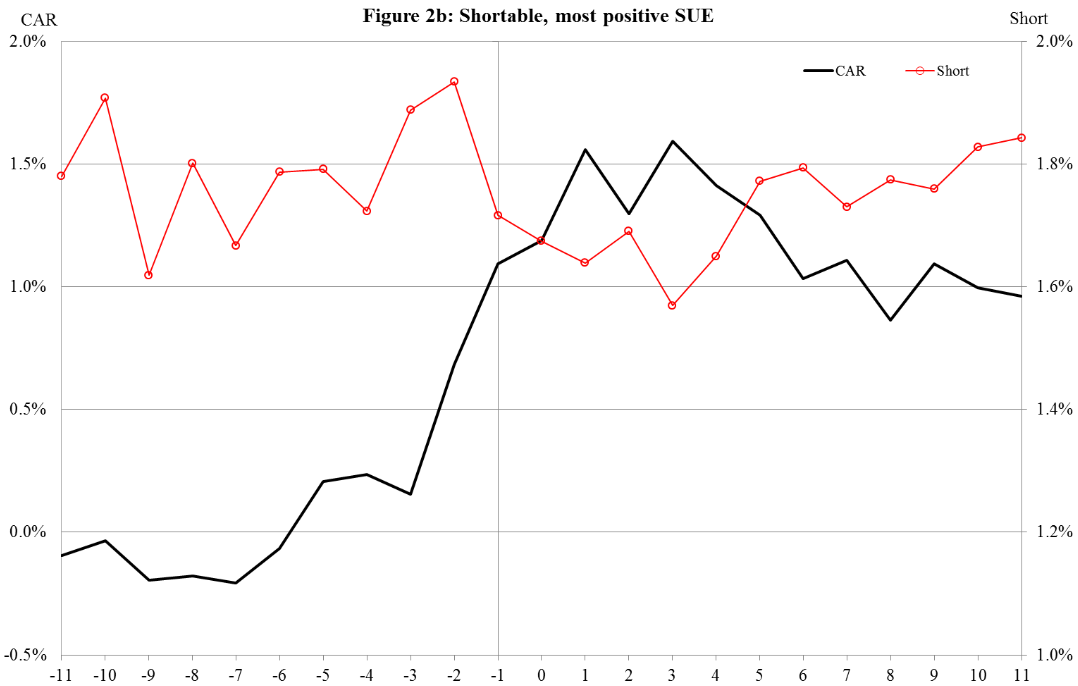



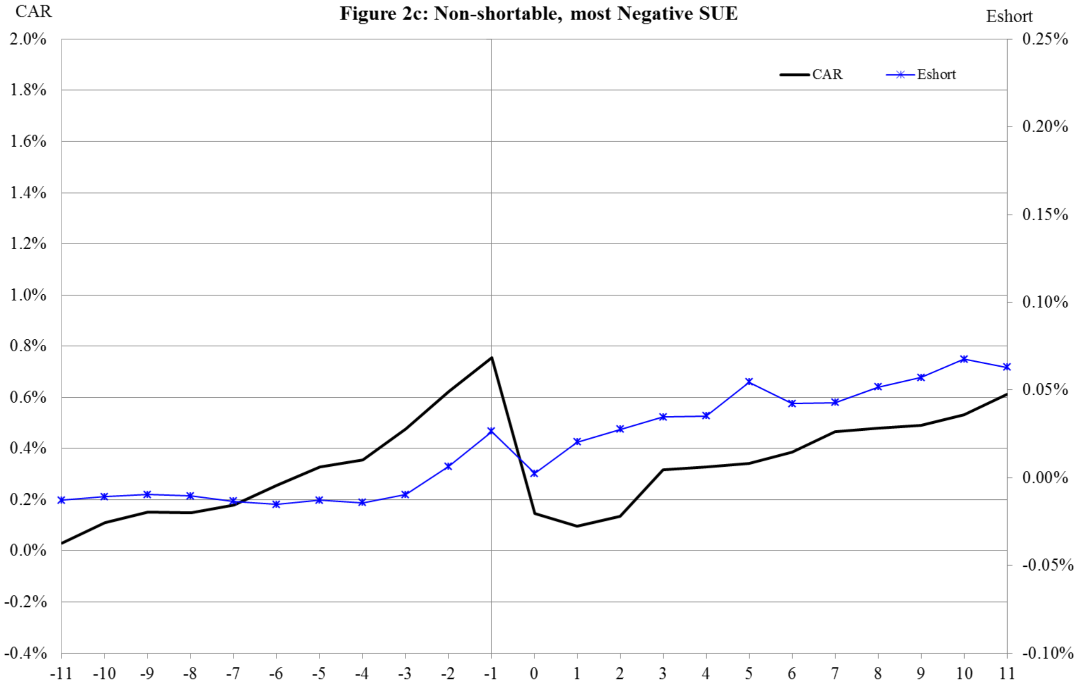
**Figure 2. Short-sale activities around earnings announcements**

We categorize earnings announcement events into four groups by the sign and magnitude of standardized unexpected earnings (*SUE*s) from most negative (-2) and moderately negative (-1) to moderately positive (+1) and most positive (+2). We plot the cumulative abnormal returns (*CAR*s) and average short-sale turnovers in [-11,+11] trading days' window around announcements for the most negative and most positive *SUE*-groups. For non-shortable firms, we plot the CARs and the estimated short-sale turnovers.



## Figure 2c: Non-shortable, most Negative SUE




## Figure 2d: Non-shortable, most positive SUE

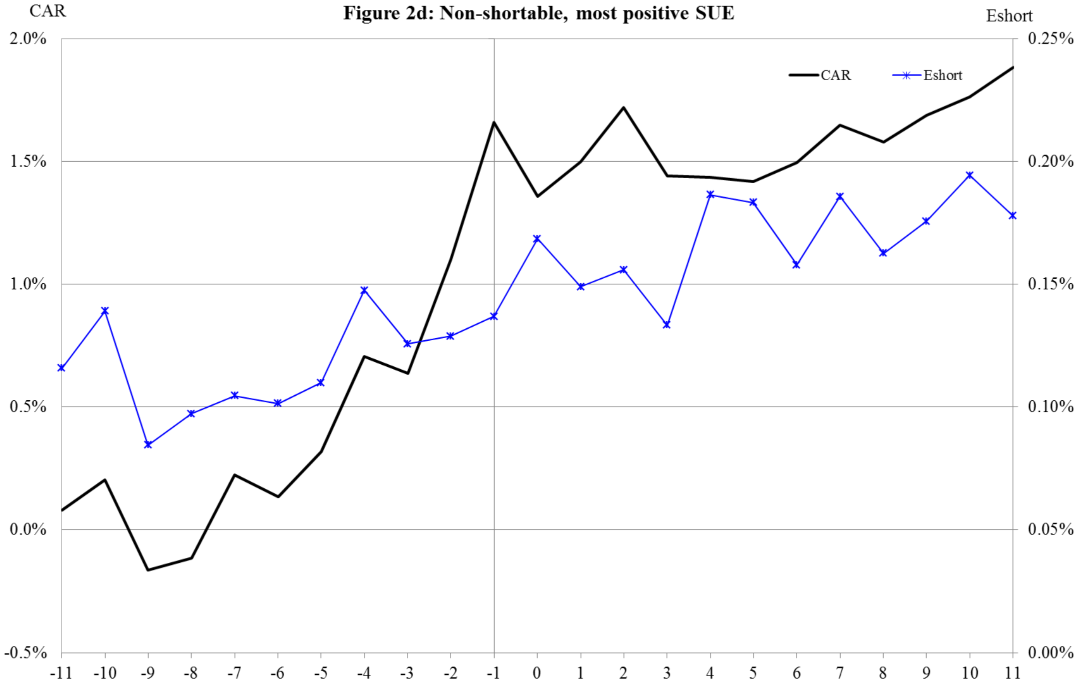


**Table 1. Summary statistics.**

This table reports summary statistics of firm-day variables for the subsample of shortable and non-shortable firms, respectively. Data period covers 2010.04 to 2015.12. In Panel A, realized short-sale turnover ($short_t$) is daily short-sale volume in shares scaled by shares outstanding, and realized margin-purchase turnover is defined similarly. In Panel B, *Eshort* and *Eshort* are estimated short-sale and margin-purchase demands, respectively. Control variables include $r_t$ (current-day abnormal return), $r_{-5:-1}$ (cumulative abnormal returns during the previous five trading days), $\sigma_t$ (current-day high-low price ratio), $to_{-5:-1}$ (average share turnover the previous five trading days), $lmv_{t-1}$ (log market value of tradable shares on the previous day), $bm_{t-1}$ (book-to-market ratio), $ivol_{t-1}$ (idiosyncratic volatility), $lev_{t-1}$ (debt-to-asset ratio), and $roa_{t-1}$ (return on asset).

| | n | mean | std. dev. | max | Q3 | median | Q1 | min |
|---|---|---|---|---|---|---|---|---|
| *Panel A: For the sample of shortable firms* | | | | | | | | |
| $short_t$ | 600,774 | 1.00% | 1.51% | 7.21% | 1.37% | 0.31% | 0.01% | 0.00% |
| $margin_t$ | 600,774 | 16.37% | 8.51% | 37.82% | 22.26% | 16.70% | 10.12% | 0.24% |
| $r_t$ | 588,733 | 0.00% | 2.40% | 8.74% | 0.98% | -0.20% | -1.25% | -6.37% |
| $r_{-5:-1}$ | 588,733 | -0.03% | 5.33% | 18.25% | 2.36% | -0.36% | -2.86% | -14.85% |
| $\sigma_t$ | 600,774 | 4.03% | 2.48% | 12.08% | 5.07% | 3.30% | 2.24% | 0.91% |
| $to_{-5:-1}$ | 600,604 | 2.30% | 2.38% | 15.69% | 3.06% | 1.49% | 0.70% | 0.14% |
| $lmv_{t-1}$ | 600,740 | 16.45 | 0.98 | 18.59 | 17.05 | 16.34 | 15.74 | 13.40 |
| $bm_{t-1}$ | 599,991 | 0.53 | 0.49 | 2.67 | 0.65 | 0.37 | 0.21 | -0.01 |
| $ivol_{t-1}$ | 588,733 | 2.18% | 0.71% | 4.40% | 2.64% | 2.10% | 1.64% | 0.97% |
| $lev_{t-1}$ | 600,025 | 0.20 | 0.19 | 0.74 | 0.31 | 0.15 | 0.02 | 0.00 |
| $roa_{t-1}$ | 600,025 | 10.87% | 8.57% | 39.17% | 14.91% | 9.13% | 4.82% | -13.30% |
| | n | mean | std. dev. | max | Q3 | median | Q1 | min |
| *Panel B: For the sample of nonshortable firms* | | | | | | | | |
| $Eshort_t$ | 1,997,635 | 0.17% | 0.74% | 2.64% | 0.49% | 0.04% | -0.15% | -1.58% |
| $Emargin_t$ | 2,003,431 | 13.25% | 8.07% | 28.18% | 20.10% | 13.89% | 6.05% | 0.18% |
| $r_t$ | 2,011,619 | 0.02% | 2.41% | 8.74% | 1.03% | -0.15% | -1.25% | -6.37% |
| $r_{-5:-1}$ | 2,011,619 | 0.04% | 5.43% | 18.25% | 2.57% | -0.24% | -2.88% | -14.85% |
| $\sigma_t$ | 2,283,286 | 4.04% | 2.32% | 12.08% | 5.02% | 3.41% | 2.38% | 0.91% |
| $to_{-5:-1}$ | 2,277,839 | 2.85% | 2.98% | 15.69% | 3.65% | 1.81% | 0.89% | 0.14% |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $lmv_{t-1}$ | 2,282,194 | 14.81 | 0.83 | 18.59 | 15.34 | 14.78 | 14.25 | 13.09 |
| $bm_{t-1}$ | 2,135,817 | 0.51 | 0.48 | 2.67 | 0.64 | 0.37 | 0.21 | -0.01 |
| $ivol_{t-1}$ | 2,011,619 | 2.26% | 0.62% | 4.40% | 2.60% | 2.19% | 1.84% | 0.97% |
| $lev_{t-1}$ | 2,135,935 | 0.13 | 0.17 | 0.74 | 0.20 | 0.04 | 0.00 | 0.00 |
| $roa_{t-1}$ | 2,135,952 | 7.66% | 7.07% | 39.17% | 10.49% | 6.94% | 3.95% | -13.30% |

**Table 2. Average estimated coefficients in the hedonic model.**

On each trading day, we utilize the cross-section of shortable and marginable firms to regress short-sale turnover and margin-purchase turnover on a set of explanatory variables:

$$short_t = r_{-5:-1} + r_t + \sigma_t + \sigma_{-5:-1} + tv_{-5:-1} + lmv_{t-1} + bm_{t-1} + ivol_{t-1} + lev_{t-1} + roa_{t-1}. \quad (1)$$

$$margin_t = r_{-5:-1} + r_t + \sigma_t + \sigma_{-5:-1} + tv_{-5:-1} + lmv_{t-1} + bm_{t-1} + ivol_{t-1} + lev_{t-1} + roa_{t-1}. \quad (2)$$

Variable $short_t$ is realized short-sale turnover in % on day *t*., defined as short-sale volume in shares scaled by shares outstanding, and $margin_t$ is realized margin-purchase turnover in %. Control variables include $r_{-5:-1}$ (cumulative stock returns during the previous five trading days), $r_t$ (current-day stock return), $\sigma_t$ (intraday high-low price ratio), $\sigma_{-5:-1}$ (average intraday high-low price ratio in previous five trading days ), $to_{-5:-1}$ (average share turnover the previous five trading days), $lmv_{t-1}$ (log market value of tradable shares on previous day), $bm_{t-1}$ (book-to-market ratio), $ivol_{t-1}$ (idiosyncratic volatility), $lev_{t-1}$ (debt-to-asset ratio), and $roa_{t-1}$ (return on asset). Sample period spans 2010.04 to 2015.12. This table reports the time-series average of the daily coefficient estimates, with Newey-West corrected *t*-statistics reported in the brackets. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

| | *Model A* | | *Model B* | | *Model C* | |
|---|---|---|---|---|---|---|
| | $short_t$ [1] | $margin_t$ [2] | $short_t$ [3] | $margin_t$ [4] | $short_t$ [5] | $margin_t$ [6] |
| *Intercept* | 0.863*** | 11.496*** | 0.844*** | 11.822*** | -7.470*** | 32.279*** |
| | [19.29] | [21.35] | [12.02] | [20.48] | [-14.7] | [26.17] |
| $r_{-5:-1}$ | -0.790*** | -1.239** | -0.276* | -0.636 | -0.954*** | -0.643 |
| | [-4.33] | [-1.98] | [-1.76] | [-0.96] | [-6.87] | [-1.16] |
| $r_t$ | 5.641*** | -21.862*** | 4.700*** | -16.028*** | 5.461*** | -18.151*** |
| | [14.76] | [-16.2] | [13.46] | [-11.9] | [15.98] | [-14.0] |
| $\sigma_t$ | | | 4.050*** | -18.352*** | 4.343*** | -16.274*** |
| | | | [8.55] | [-13.3] | [10.46] | [-11.8] |
| $\sigma_{-5:-1}$ | | | 6.017*** | -12.659*** | 4.081*** | 1.923 |
| | | | [5.45] | [-3.92] | [4.20] | [0.69] |
| $to_{5:-1}$ | | | -17.356*** | 49.024*** | -7.195*** | 19.335*** |
| | | | [-13.8] | [12.00] | [-5.43] | [8.35] |
| $lmv_{t-1}$ | | | | | 0.506*** | -1.102*** |
| | | | | | [14.63] | [-21.1] |
| $bm_{t-1}$ | | | | | 0.119*** | -0.304*** |
| | | | | | [8.02] | [-6.80] |
| $ivol_{t-1}$ | | | | | -4.523*** | -93.428*** |
| | | | | | [-3.33] | [-17.3] |
| $lev_{t-1}$ | | | | | -0.227*** | 0.059 |
| | | | | | [-13.2] | [0.77] |
| $roa_{t-1}$ | | | | | 0.024 | -2.565*** |
| | | | | | [0.44] | [-9.87] |
| n | 431 | 430 | 431 | 430 | 422 | 421 |
| R2 | 4.21% | 3.12% | 10.68% | 6.81% | 28.54% | 13.85% |

**Table 3. Verification of estimated short-sale or margin-purchase demand**

On each day, we rank shortable firms by their past 5-day returns and sequentially number them. We use firms with odd numbers for in-sample estimation of coefficients of three alternative hedonic models, and apply estimate coefficients to firms with even numbers as out-of-the-sample tests. Sample period spans 2010.04 to 2015.12. Panel A reports summary statistics of the real short-sale/margin-purchase turnover and estimated demands by three alternative models, and Panel B reports correlation coefficients with Pearson correlation in the left triangle and Spearman correlation in the right triangle. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

*Panel A: Summary statistics*

| | n | mean | std. dev. | max | Q3 | median | Q1 | min |
|---|---|---|---|---|---|---|---|---|
| *Short* | 300,000 | 1.004% | 1.52% | 7.21% | 1.37% | 0.31% | 0.01% | 0.00% |
| $E^A$*Short* | 299,818 | 1.000% | 0.63% | 5.53% | 1.40% | 1.08% | 0.59% | -2.12% |
| $E^B$*Short* | 299,818 | 1.001% | 0.75% | 9.77% | 1.50% | 1.05% | 0.40% | -4.81% |
| $E^C$*Short* | 293,851 | 1.016% | 1.07% | 9.20% | 1.56% | 0.81% | 0.11% | -5.75% |
| *Margin* | 300,000 | 16.374% | 8.51% | 37.82% | 22.27% | 16.70% | 10.13% | 0.24% |
| $E^A$*Margin* | 299,876 | 16.384% | 6.28% | 34.77% | 21.34% | 17.83% | 13.07% | -5.33% |
| $E^B$*Margin* | 299,876 | 16.391% | 6.38% | 37.86% | 21.34% | 17.79% | 12.84% | -8.23% |
| $E^C$*Margin* | 293,907 | 16.315% | 6.56% | 34.95% | 21.35% | 17.59% | 12.47% | -11.54% |

*Panel B: Correlation*

| | *Short* | $E^A$*Short* | $E^B$*Short* | $E^C$*Short* | *Margin* | $E^A$*Margin* | $E^B$*Margin* | $E^C$*Margin* |
|---|---|---|---|---|---|---|---|---|
| *Short* | | 0.53*** | 0.58*** | 0.73*** | -0.06*** | -0.06*** | -0.08*** | -0.12*** |
| $E^A$*Short* | 0.40*** | | 0.85*** | 0.64*** | -0.02*** | -0.11*** | -0.10*** | -0.09*** |
| $E^B$*Short* | 0.46*** | 0.85*** | | 0.74*** | -0.05*** | -0.09*** | -0.13*** | -0.12*** |
| $E^C$*Short* | 0.66*** | 0.59*** | 0.69*** | | -0.09*** | -0.08*** | -0.11*** | -0.17*** |
| *Margin* | -0.07*** | -0.01*** | -0.04*** | -0.07*** | | 0.71*** | 0.72*** | 0.73*** |
| $E^A$*Margin* | 0.00 | -0.01*** | -0.01*** | 0.00 | 0.73*** | | 0.97*** | 0.94*** |
| $E^B$*Margin* | -0.02*** | -0.01*** | -0.05*** | -0.03*** | 0.74*** | 0.98*** | | 0.97*** |
| $E^C$*Margin* | -0.06*** | -0.01*** | -0.04*** | -0.09*** | 0.75*** | 0.96*** | 0.97*** | |

**Table 4. Daily *short*/*margin* portfolios**

This table reports future abnormal returns (in %) on equally-weighted portfolios ranked by past revealed short-sale or margin-purchase turnover (*short*$_t$ and *margin*$_t$) or estimated suppressed short-sale or margin-purchase demand (*Eshort*$_t$ and *Emargin*$_t$). Sample period spans 2010.04 to 2015.12. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

| | Rank by revealed turnover | | | Rank by suppressed demand | | |
|---|---|---|---|---|---|---|
| | $r_{t+1}$ | $r_{t+2}$ | $r_{t+2:+6}$ | $r_{t+1}$ | $r_{t+2}$ | $r_{t+2:+6}$ |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| *Panel A: Rank by short-sale turnover or demand* | | | | | | |
| Low | 0.04 | 0.012 | -0.001 | 0.025 | 0.041 | 0.108 |
| | *[1.22]* | *[0.38]* | *[-0.01]* | [0.72] | [1.15] | [0.71] |
| 2 | -0.003 | 0.003 | -0.06 | 0.043 | 0.053 | 0.168 |
| | *[-0.11]* | *[0.12]* | *[-0.58]* | *[1.33]* | *[1.63]* | *[1.20]* |
| 3 | -0.011 | -0.004 | -0.023 | 0.031 | 0.034 | 0.11 |
| | *[-0.52]* | *[-0.19]* | *[-0.27]* | *[1.01]* | *[1.08]* | *[0.82]* |
| 4 | -0.025 | -0.015 | -0.107* | 0.014 | 0 | -0.036 |
| | *[-1.32]* | *[-0.99]* | *[-1.75]* | *[0.47]* | *[-0.01]* | *[-0.28]* |
| High | -0.023* | -0.027* | -0.104* | -0.002 | -0.055** | -0.285*** |
| | *[-1.66]* | *[-1.92]* | *[-1.89]* | *[-0.08]* | *[-2.09]* | *[-2.58]* |
| Low - High | 0.063* | 0.048 | 0.132 | 0.029 | 0.096*** | 0.399*** |
| | *[1.77]* | *[1.31]* | *[0.88]* | *[1.58]* | *[5.11]* | *[5.37]* |
| *Panel B: Rank by margin-purchase turnover or demand* | | | | | | |
| Low | 0.036* | -0.005 | -0.135* | -0.01 | -0.091*** | -0.508*** |
| | *[1.77]* | *[-0.30]* | *[-1.94]* | *[-0.30]* | *[-2.94]* | *[-3.99]* |
| 2 | -0.037** | -0.025 | -0.097 | -0.001 | 0.001 | -0.052 |
| | *[-2.44]* | *[-1.64]* | *[-1.45]* | *[-0.05]* | *[0.02]* | *[-0.40]* |
| 3 | -0.021 | -0.014 | -0.086 | 0.03 | 0.039 | 0.126 |
| | *[-1.23]* | *[-0.81]* | *[-1.19]* | *[0.97]* | *[1.25]* | *[0.95]* |
| 4 | 0.009 | 0.007 | 0.03 | 0.052 | 0.066** | 0.267* |
| | *[0.49]* | *[0.39]* | *[0.38]* | *[1.64]* | *[2.07]* | *[1.96]* |
| High | 0.043* | 0.037* | 0.148* | 0.04 | 0.061* | 0.212 |
| | *[1.88]* | *[1.69]* | *[1.68]* | *[1.18]* | *[1.83]* | *[1.52]* |
| Low - High | 0 | -0.040** | -0.272*** | -0.048** | -0.158*** | -0.731*** |
| | *[-0.01]* | *[-2.35]* | *[-4.08]* | *[-1.99]* | *[-7.82]* | *[-10.00]* |

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**Table 5. Suppressed short-sale demand and future returns**

We use the panel data and regress future stock abnormal returns on past short-sale and margin-purchase revealed turnover or suppressed demand. Sample period spans 2010.04 to 2015.12. For regressions on revealed turnovers, we use daily observations of shortable/marginable stocks. For regressions on suppressed demands, we use daily observations of non-shortable/non-marginable stocks. Control variables include $r_{-5:-1}$ (cumulative abnormal returns during the previous five trading days), $\sigma_t$ (intraday high-low price ratio), and $to_{-5:-1}$ (average share turnover the previous five trading days). We control for stock- and day-fixed effects. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

| | $r_{t+1}$ | | $r_{t+2}$ | | $r_{t+2:+6}$ | |
|---|---|---|---|---|---|---|
| | Revealed | Suppressed | Revealed | Suppressed | Revealed | Suppressed |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| $short_t$ | -0.004 | 0.030*** | 0.003 | -0.092*** | 0.006 | -0.461*** |
| | [-1.28] | [7.82] | [0.95] | [-23.68] | [0.87] | [-52.28] |
| $margin_t$ | -0.005*** | 0.001 | 0.001 | 0.028*** | 0.020*** | 0.127*** |
| | [-8.25] | [1.17] | [1.31] | [30.52] | [14.95] | [60.77] |
| $r_{-5:-1}$ | -0.004*** | -0.009*** | 0.001 | -0.005*** | 0.012*** | -0.005*** |
| | [-6.48] | [-26.16] | [1.16] | [-15.05] | [8.55] | [-6.53] |
| $\sigma_t$ | -0.039*** | -0.048*** | -0.017*** | -0.023*** | -0.091*** | -0.086*** |
| | [-20.61] | [-47.69] | [-9.18] | [-23.06] | [-20.89] | [-37.71] |
| $to_{5:-1}$ | -0.036*** | -0.047*** | -0.038*** | -0.051*** | -0.192*** | -0.236*** |
| | [-16.95] | [-50.84] | [-17.84] | [-54.95] | [-39.49] | [-111.83] |
| N | 588,733 | 1,997,615 | 588,733 | 1,997,595 | 588,727 | 1,997,521 |
| $R^2$ | 7.37% | 13.12% | 7.32% | 12.68% | 8.55% | 17.06% |

**Table 6. Subsample analysis of future returns**

We use the panel data and regress future stock returns on past short-sale and margin-purchase suppressed demand interacted with dummy variables. Sample period spans 2010.04 to 2015.12. Dummy variables include *#analyst* (0/1 for low/high number of analysts following), *big4* (1 for big-four auditor and 0 otherwise), *opacity* (1 for transparent scores of C or D, and 0 otherwise), *fund%* (0/1 for low/high fund ownership), *size* (0/1 for small/big firm capitalization), and *ivol* (0/1 for low/high idiosyncratic volatility). We control for stock- and day-fixed effects. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

| | *# analyst* | *big4* | *opacity* | *fund%* | *size* | *ivol* |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| $Eshort_t$ | -0.100*** | -0.094*** | -0.090*** | -0.099*** | -0.094*** | -0.074*** |
| | [-22.58] | [-23.81] | [-22.56] | [-20.75] | [-19.57] | [-15.59] |
| $Emargin_t$ | 0.029*** | 0.028*** | 0.028*** | 0.028*** | 0.029*** | 0.028*** |
| | [30.90] | [30.53] | [30.20] | [29.67] | [30.60] | [29.78] |
| $Eshort_t$*Dummy | 0.023*** | 0.050*** | -0.015* | 0.011** | 0.009* | -0.031*** |
| | [4.74] | [3.70] | [-1.89] | [2.18] | [1.74] | [-6.63] |
| $Emargin_t$*Dummy | -0.002*** | -0.001 | 0.001 | 0.001*** | -0.002*** | 0.000 |
| | [-4.88] | [-0.53] | [1.17] | [2.61] | [-3.24] | [-1.11] |
| $r_{-5:-1}$ | -0.005*** | -0.005*** | -0.005*** | -0.005*** | -0.005*** | -0.005*** |
| | [-14.79] | [-14.82] | [-14.80] | [-15.03] | [-14.96] | [-15.15] |
| $\sigma_t$ | -0.024*** | -0.023*** | -0.023*** | -0.023*** | -0.023*** | -0.023*** |
| | [-23.20] | [-23.08] | [-23.16] | [-22.91] | [-23.18] | [-22.91] |
| $tv_{5:-1}$ | -0.051*** | -0.051*** | -0.051*** | -0.051*** | -0.051*** | -0.051*** |
| | [-54.70] | [-54.87] | [-54.79] | [-55.02] | [-54.74] | [-55.12] |
| N | 1,988,332 | 1,988,332 | 1,988,332 | 1,997,595 | 1,997,595 | 1,997,595 |
| $R^2$ | 12.687% | 12.685% | 12.685% | 12.679% | 12.679% | 12.680% |

**Table 7. Suppressed short-sale demand and price delay**

We use the panel data and regress stock-level monthly delay measures on average short-sale and margin-purchase revealed turnover or suppressed demand in the previous month. Sample period spans 2010.04 to 2015.12. For regressions on revealed turnovers, we use daily observations of shortable/marginable stocks. For regressions on suppressed demands, we use daily observations of non-shortable/non-marginable stocks. Monthly price delays are defined following Boehmer and Wu (2013) (Equation (6)), and $Delay^-$ ($Delay^+$) uses only down (up) market returns in the restricted model. Control variables include $lprc_{t-1}$ (log stock price at the end of the previous month), $lmv_{t-1}$ (log market value of tradable shares at the end of the previous month), $to_{-5:-1}$ (average daily share turnover in the previous month), and $DV_{t-1}$ (the lagged dependent variable). We control for stock- and day-fixed effects. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

| | $Delay_{t+1}$ | | $Delay_{t+1}^-$ | | $Delay_{t+1}^+$ | |
|---|---|---|---|---|---|---|
| | Revealed | Suppressed | Revealed | Suppressed | Revealed | Suppressed |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| $short_t$ | -0.374*** | 0.346** | -1.553*** | 0.196 | -0.802** | 1.222** |
| | [-3.08] | [1.97] | [-3.87] | [0.44] | [-2.42] | [1.97] |
| $margin_t$ | -0.011 | -0.065* | -0.003 | 0.155* | -0.064 | -0.116 |
| | [-0.46] | [-1.82] | [-0.04] | [1.66] | [-1.02] | [-0.96] |
| $lprc_t$ | 0.033*** | 0.032*** | 0.041** | 0.005 | 0.031** | 0.075*** |
| | [6.11] | [10.69] | [2.41] | [0.57] | [2.24] | [8.48] |
| $lmv_t$ | 0.002 | 0.014*** | 0.005 | 0.022*** | 0.005 | 0.023*** |
| | [0.59] | [6.04] | [0.37] | [3.67] | [0.43] | [3.13] |
| $to_t$ | 0.440*** | 0.551*** | 0.038 | 0.995*** | 0.282 | 0.535*** |
| | [5.73] | [14.77] | [0.11] | [8.83] | [1.58] | [5.44] |
| $DV_{t-1}$ | 0.061*** | 0.060*** | 0.114*** | 0.039*** | -0.003 | -0.002 |
| | [10.16] | [17.96] | [6.55] | [4.97] | [-0.38] | [-0.42] |
| N | 28,982 | 95,733 | 4,898 | 22,107 | 15,729 | 38,046 |
| $R^2$ | 32.92% | 30.23% | 36.43% | 29.81% | 25.98% | 27.71% |

**Table 8. Subsample analysis of price delay.**

We use the panel data and regress stock-level monthly delay measures on average short-sale and margin-purchase revealed turnover or suppressed demand in the previous month. Sample period spans 2010.04 to 2015.12. Monthly price delays are defined following Boehmer and Wu (2013) (Equation (6)), and $Delay^-$ ($Delay^+$) uses only down (up) market returns in the restricted model. For regressions on revealed turnovers, we use monthly observations of shortable/marginable stocks. For regressions on suppressed demands, we use monthly observations of non-shortable/non-marginable stocks. Dummy variables include *#analyst* (0/1 for low/high number of analysts following), *big4* (1 for big-four auditor and 0 otherwise), *opacity* (1 for transparent scores of C or D, and 0 otherwise), *fund%* (0/1 for low/high fund ownership), *size* (0/1 for small/big firm capitalization), and *ivol* (0/1 for low/high idiosyncratic volatility). We control for stock- and month-fixed effects. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Coefficients of control variables are suppressed for brevity, including $lprc_{t-1}$ (log stock price at the end of the previous month), $lmv_{t-1}$ (log market value of tradable shares at the end of the previous month), $to_{-5:-1}$ (average daily share turnover in the previous month), and $DV_{t-1}$ (the lagged dependent variable).

| | *# analyst* | *big4* | *opacity* | *fund%* | *size* | *ivol* |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| $Eshort_t$ | 0.659*** | 0.251 | 0.299* | 0.426** | 0.254 | -0.330 |
| | [3.24] | [1.40] | [1.66] | [2.02] | [1.19] | [-1.53] |
| $Emargin_t$ | -0.050 | -0.049 | -0.051 | -0.059 | -0.058 | -0.021 |
| | [-1.32] | [-1.35] | [-1.40] | [-1.61] | [-1.59] | [-0.54] |
| $Eshort_t$*Dummy | -0.734*** | 0.924 | 0.241 | -0.118 | 0.236 | 1.124*** |
| | [-3.34] | [1.56] | [0.64] | [-0.52] | [0.97] | [5.25] |
| $Emargin_t$*Dummy | 0.003 | 0.069 | 0.012 | -0.022 | -0.011 | -0.075*** |
| | [0.13] | [1.13] | [0.33] | [-1.01] | [-0.48] | [-3.50] |
| $lprc_{t-1}$ | 0.031*** | 0.031*** | 0.031*** | 0.032*** | 0.032*** | 0.031*** |
| | [10.31] | [10.43] | [10.41] | [10.68] | [10.66] | [10.60] |
| $lmv_{t-1}$ | 0.015*** | 0.015*** | 0.015*** | 0.014*** | 0.014*** | 0.015*** |
| | [6.32] | [6.43] | [6.36] | [5.89] | [5.77] | [6.37] |
| $tv_{t-1}$ | 0.550*** | 0.552*** | 0.553*** | 0.552*** | 0.550*** | 0.551*** |
| | [14.69] | [14.72] | [14.75] | [14.79] | [14.74] | [14.77] |
| $DV_{t-1}$ | 0.061*** | 0.061*** | 0.061*** | 0.060*** | 0.060*** | 0.060*** |
| | [18.06] | [18.05] | [18.09] | [17.97] | [17.96] | [17.85] |
| N | 95,246 | 95,246 | 95,246 | 95,733 | 95,733 | 95,733 |
| $R^2$ | 30.26% | 30.25% | 30.25% | 30.23% | 30.23% | 30.26% |

**Table 9. Short sales around earnings announcements.**

This table reports the summary statistics of (cumulative) abnormal returns and realized or suppressed short-sale turnovers around earnings announcements. Stocks are categorized into four groups by the sign and magnitude of standardized unexpected earnings (*SUE*), which is the difference between actual EPS and mean analyst forecasts, scaled by the standard deviation of analyst forecasts. Stocks with very (moderately) negative *SUE* are labeled “-2” (“-1”), and stocks with very (moderately) positive *SUE* are labeled “+2” (“+1”). *AR* is the abnormal return on the earnings announcement day, and $CAR_{+1:+5}$ is the cumulative abnormal returns in [+1,+5] trading days after announcements. $Short_t$ is short-sale turnover/demand on earnings announcement, $Short_{+1:+5}$ is average short-sale turnover/demand in [+1,+5] trading days, and $Short_{+1:+5}$-$Short_{-5:-1}$ is the change in average short-sale turnover/demand in five trading days around earnings announcements.

| *SUE* category | *n* | $AR_t$ | $CAR_{+1:+5}$ | $Short_t$ | $Short_{+1:+5}$ | $Short_{+1:+5}$-$Short_{-5:-1}$ |
|---|---|---|---|---|---|---|
| ***Panel A: For the subsample of shortable firms*** | | | | | | |
| -2 | 551 | -0.51% | 0.02% | 1.05% | 1.11% | 0.02% |
| | | [-4.48] | [0.07] | | | [0.84] |
| -1 | 665 | -0.19% | -0.23% | 1.29% | 1.31% | -0.03% |
| | | [-1.69] | [-1.11] | | | [-1.41] |
| +1 | 246 | 0.12% | -0.46% | 1.35% | 1.38% | -0.05% |
| | | [0.67] | [-1.68] | | | [-1.08] |
| +2 | 145 | 0.09% | -0.53% | 1.67% | 1.66% | -0.15% |
| | | [0.38] | [-1.23] | | | [-2.66] |
| ***Panel B: For the subsample of non-shortable firms*** | | | | | | |
| -2 | 1486 | -0.60% | 0.27% | 0.00% | 0.04% | 0.04% |
| | | [-7.70] | [2.00] | | | [6.22] |
| -1 | 1455 | -0.62% | -0.11% | 0.06% | 0.09% | 0.03% |
| | | [-8.02] | [-0.73] | | | [5.18] |
| +1 | 473 | -0.49% | -0.34% | 0.12% | 0.12% | 0.01% |
| | | [-3.43] | [-1.42] | | | [1.48] |
| +2 | 299 | -0.30% | -0.01% | 0.17% | 0.16% | 0.04% |
| | | [-1.60] | [-0.02] | | | [2.16] |

**Table 10. Suppressed short-sale demand and PEAD**

We use the panel data and regress event-level post-earnings-announcement-drift (PEAD) on DUE, the decile group of *SUE* ranging from 1 to 10 for stocks with the **most-negative *SUE* quartile**. *SUE* is the difference between actual EPS and mean analyst forecasts, scaled by the standard deviation of analyst forecasts. *DΔshort* is a rank variable that ranges from 1 to 10, higher for stocks with greater change in short-turnover from [-5,-1] to [+1,+5]. Sample period spans 2010.04 to 2015.12. Control variables include $r_{-5:-1}$ (cumulative abnormal returns during the previous five trading days), $to_{-5:-1}$ (average share turnover the previous five trading days), and $ivol_{t-1}$ (idiosyncratic volatility). We control for stock- and day-fixed effects. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

| | Revealed | | Suppressed | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| *DUE* | -0.383 | -0.191 | 0.237 | -0.327 |
| | [-0.76] | [-0.26] | [1.05] | [-1.04] |
| $DUE*D\Delta short_t$ | | 0.050 | | 0.091*** |
| | | [0.83] | | [2.80] |
| $DUE*D\Delta margin_t$ | | -0.095 | | 0.018 |
| | | [-1.53] | | [0.56] |
| $CAR_{-5:-1}$ | 0.066 | 0.090 | -0.003 | -0.003 |
| | [0.60] | [0.81] | [-0.06] | [-0.06] |
| $to_{-5:-1}$ | -0.429 | -0.479 | -0.105 | -0.047 |
| | [-1.26] | [-1.41] | [-0.72] | [-0.33] |
| $ivol_{t-1}$ | -0.336 | -0.357 | -0.502*** | -0.550*** |
| | [-1.05] | [-1.08] | [-3.08] | [-3.43] |
| N | 551 | 550 | 1,486 | 1,475 |
| $R^2$ | 80.41% | 80.47% | 70.29% | 71.37% |