Stealthy Shorts:
Informed Liquidity Supply[*]

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Abstract

Short sellers are widely known to be informed, which would typically suggest that they demand liquidity. We obtain comprehensive transaction-level data to decompose daily short volume into liquidity-demanding and liquidity-supplying components. Contrary to conventional wisdom, we show that the most informed short sellers are actually liquidity suppliers, not liquidity demanders. They are particularly informative about future returns on news days and trade on prominent cross-sectional return anomalies. Our analysis suggests that market making and opportunistic risk-bearing are unlikely to explain these findings. Instead, our results align with recent market microstructure theory, pointing to the strategic liquidity provision by informed traders.

Keywords: Short sales, liquidity supply, informed trading, asset pricing
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1 Introduction

There is a long-standing paradox in the short selling literature: Short sellers, despite being widely recognized as informed investors, are also associated with improved market liquidity.[1] This puzzle arises because, in the standard microstructure literature, market makers react to the presence of informed trading by widening bid-ask spreads to protect against adverse selection, thereby reducing liquidity (Glosten and Milgrom, 1985, and Kyle, 1985). This raises an important question: How can short sellers, as a whole, simultaneously be informed and contribute positively to liquidity?

The natural explanation for this paradox is that there are two types of short sellers. One type are the informed short sellers who use market orders and demand liquidity to quickly act on their informational advantage. The other type are the (voluntary) market makers who place uninformed limit orders, thereby supplying liquidity (Boehmer, Jones, and Zhang, 2008, and Comerton-Forde, Jones, and Putniņš, 2016).

In this paper, we shed light on the informational advantage of short sellers and examine which short trades are more informative about future returns— those that demand liquidity or those that supply it. Surprisingly, as we will show, we find that liquidity-supplying short sellers are actually more informed than the liquidity-demanding short sellers: a result that contradicts much of the existing literature in this area.

One of the main challenges in separating short sellers into liquidity demanders and liquidity suppliers is the limited granularity of commonly used short sale data, which is available at the stock level on a daily basis and does not distinguish between different motives of the short seller. These aggregated measures potentially mask the heterogeneous effects of different types of short sales on return predictability. To overcome this challenge, we (1)

[1] There is substantial evidence that short sellers are informed traders. High levels of short-selling activity are associated with predictably low future returns and improved price efficiency (see, for example, Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; Rapach, Ringgenberg, and Zhou, 2016; and Saffi and Sigurdsson, 2011). At the same time, short selling is also positively related to market liquidity, with restrictions on short sales generally resulting in decreased liquidity (see, for example, Beber and Pagano, 2013, and Bris, Goetzmann, and Zhu, 2007).

obtain comprehensive transaction-level short sale data from each of the twelve main U.S. equity exchanges over a five-year period from 2014 to 2018, and (2) employ a three-step matching algorithm to link each short sale trade to the prevailing market quotes. By using trade and quote prices (Lee and Ready, 1991), we decompose the short-sale volume based on whether the short seller supplies or demands liquidity and analyze the potentially different predictability of returns from these two components. This analysis provides insights into which type of short selling is most informed and at which time horizon. By disaggregating the standard daily short-sale measure, we can better understand the trading strategies of short sellers and how their informational advantage contributes to the efficient incorporation of information into stock prices.

We begin our analysis by replicating a well-documented pattern in the cross section of stock returns: stocks with a high short sale volume relative to their total trading volume underperform those with a low short volume ratio (Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; and Rapach, Ringgenberg, and Zhou, 2016). More importantly, when we decompose this ratio into liquidity-supplying short volume ratio (LSS) and liquidity-demanding short volume ratio (LDS), we uncover interesting heterogeneous patterns. Contrary to conventional wisdom, our portfolio analysis shows that only LSS negatively predicts future equity returns. In particular, stocks in the highest LSS quintile underperform those in the lowest quintile by a risk-adjusted return of 38 basis points over a 21-day holding period. In contrast, the predictive power of LDS over the same holding period is much weaker, at just 12 basis points, which is statistically indistinguishable from zero and driven entirely by the return on the day after portfolio formation. In cross-sectional regressions, we show that the return predictability associated with LSS is not subsumed when controlling for other well-known short-selling metrics and standard return predictors. This suggests that liquidity-supplying short sales contain unique information about future stock returns. In additional tests, we find that our documented predictability is neither concentrated in stocks with specific characteristics, nor driven by particular time periods or samples of stocks, and it holds for various alternative holding periods. Overall, our results indicate strong predictability of future returns from liquidity-supplying short sales, while such predictability is absent for liquidity-demanding short sales over holding periods longer than one day. These findings suggest that liquidity-supplying short sales may represent informed trading by short sellers with relatively long-lived information.

In addition to informed trading, the return predictability associated with liquidity-supplying short sales might partly reflect compensation for voluntary market making or opportunistic risk bearing (Diether, Lee, and Werner, 2009). To explore this possibility, we use a decomposition method, similar to that of Boehmer, Jones, Zhang, and Zhang (2021), to separate the variation in LSS into proxies for these two components and a residual component. Our findings show that only the residual component drives the predictive power of LSS for future returns, while the market-making and risk-bearing components do not predict cross-sectional stock returns in a statistically significant way.

We shed further light on the nature of the return predictability and its link to the informational advantage inherent in liquidity-supplying short sales. First, we use a framework similar to Engelberg, Reed, and Ringgenberg (2012), and examine the predictive power of LSS for stock returns around firm-specific news release days. If the predictive ability of liquidity-supplying short sales stems from an informational advantage, LSS should particularly predict returns on days when news is released and information is incorporated into stock prices. Consistent with this hypothesis, we find that liquidity-supplying short sales are particularly informative about future returns on news days compared to non-news days. Additionally, we demonstrate that this increased predictive power is exclusively present in the residual component of LSS, further supporting the notion that liquidity-supplying shorts are, on average, informed about company fundamentals.

As a second empirical exercise, we study whether liquidity-supplying shorts use their informational advantage and trade on long-term information embedded in cross-sectional equity anomalies. We follow Wang, Yan, and Zheng (2020) in analyzing over- and undervaluation ranks of stocks in portfolios sorted on short volume ratio. We find that liquidity-supplying shorts react to information embedded in anomalies by shorting overvalued stocks more than undervalued ones. The same is not true for liquidity-demanding shorting flows. Overall, our findings indicate that informed short sellers capitalize on longer-term price decreases by supplying rather than taking liquidity out of the market.

Our findings contribute to several important strands of literature. First, we add to the extensive body of research on the role of short sellers as informed traders. While previous studies have documented that short-selling activity predicts lower future returns and reflects valuable information about firm fundamentals (see, for example, Aitken, Frino, McCorry, and Swan, 1998; Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; Christophe, Ferri, and Hsieh, 2010; Dechow, Hutton, Meulbroek, and Sloan, 2001; Desai, Ramesh, Thiagarajan, and Balachandran, 2002; Deshmukh, Gamble, and Howe, 2015; and Rapach, Ringgenberg, and Zhou, 2016), these studies typically rely on aggregated short-sale measures, which mask the different strategies short sellers employ to leverage their informational advantage. By disaggregating short-sale activity into liquidity-supplying and liquidity-demanding components, our paper advances the understanding of how informed short sellers operate and how their trades contribute to the efficient incorporation of information into stock prices. This distinction is crucial for evaluating whether informed short sellers are inherently detrimental to market liquidity or if they can simultaneously enhance liquidity through their trading activities. The study closest to ours is Comerton-Forde, Jones, and Putniņš (2016), who also differentiate between short sales that provide liquidity and short sales that demand liquidity. However, while their work focuses on intraday trading and the role of short sellers in stabilizing markets at high frequency, we study longer-term return predictability and show that liquidity-supplying short sales are particularly informative about future stock returns over holding periods longer than one day. This suggests that informed short sellers play a key role in price efficiency, without necessarily compromising market liquidity.

Second, our research engages with the microstructure literature on the interaction between informed trading and liquidity provision. Traditional models, such as those proposed by Glosten and Milgrom (1985) and Kyle (1985), suggest that informed traders typically demand liquidity, leading to wider bid-ask spreads and reduced market liquidity. However, our findings align with more recent theoretical work (see, for example, Goettler, Parlour, and Rajan, 2008; Hollifield, Miller, and Sandås, 2004; Kaniel and Liu, 2006; and Seppi and Kumar, 1994), which posits that informed traders may strategically supply liquidity, particularly when their information is long-lived and there is no immediate need for trade execution. This perspective is supported by empirical studies that show informed traders, such as insiders, often use limit orders or time their trades to minimize market impact and avoid revealing their informational advantage (Ahern, 2020; Akey, Grégoire, and Martineau, 2022; Collin-Dufresne and Fos, 2015; and Kacperczyk and Pagnotta, 2019). However, these studies typically focus on specific events or small subsets of trades. In contrast, our study examines short sales, which account for approximately 45% of total trading volume, and we find that only liquidity-supplying shorts predict future returns. This broader and more comprehensive evidence sheds light on the mechanisms through which information is efficiently incorporated into stock prices: Informed traders can improve market efficiency by strategically supplying liquidity rather than simply demanding it.

The remainder of the paper is organized as follows. Section 2 details the data sources, describes our methodology for decomposing short volume into liquidity-supplying and liquidity-demanding components, and provides summary statistics. In Section 3, we present our main empirical findings. Section 4 explores the underlying mechanisms behind the results documented in Section 3. Section 5 concludes.

2 Data

This section introduces our sample and provides descriptive statistics. In Section 2.1, we outline our sample of intraday time-stamped short sale transactions reported on U.S. equity exchanges. Section 2.2 details the methodology used to classify short sales as either seller-initiated or buyer-initiated. Finally, Section 2.3 presents the corresponding descriptive statistics.

2.1 Sample construction

We use the NYSE Trade and Quote (TAQ) dataset, which provides comprehensive transaction level data for trades and quotes on the U.S. equity market. However, the TAQ data does not include flags to identify short sales, presenting a significant limitation for understanding short selling activities at intraday level. To address this gap, we obtain proprietary short sale information at the transaction level from each of the three largest exchange groups in the U.S., viz. the NYSE, Nasdaq, and CBOE (which acquired BATS Global Markets in 2017). By the end of our sample period, the twelve exchanges comprising the NYSE, Nasdaq, and CBOE collectively accounted for approximately 97% of the exchange trading volume in U.S. equity markets.[2] The short selling data includes the ticker symbol, exchange code, trade price, trade size, sales conditions (exempt or non-exempt from the price test of SEC's Regulation SHO), and a timestamp at second or millisecond level. We use these variables to match every single short-sale transaction with the corresponding trade in the TAQ data. Following Hu, Jones, and Zhang (2021), we include non-exempt short sales during regular market hours (9:30 am to 4:00 pm). These data allow us to identify transactions of opening short sale trades, but we do not observe when short positions are reversed or closed. Our

[2]The remaining trading volume takes place at the Investors Exchange (IEX), which was approved by the SEC as an official exchange in mid 2016. More detailed trade volume information for each exchange is available at https://www.cboe.com/us/equities/market_share/market. The twelve exchanges include NYSE, NYSE Arca, NYSE National, NYSE Chicago, NYSE Amerian, Nasdaq, Nasdaq BX, Nasdaq PSX, BZX, EDGX, BYX, and EDGA.

dataset covers a sample period from 2014 to 2018.[3]

We complement our transaction-level data with daily stock returns, share prices, shares outstanding and other stock characteristics from the Center for Research in Security Prices (CRSP). We merge the short volume data with the CRSP database by mapping ticker symbols to PERMNOs. Additionally, to ensure that our findings are distinct from those using other short sale metrics previously introduced in the literature, we incorporate two robust predictors of cross-sectional stock returns as control variables in our analyses: active utilization, measured as the ratio of shares on loan to shares available for loans (Boehmer, Huszar, Wang, Zhang, and Zhang, 2021, and Saffi and Sigurdsson, 2011), and the shorting fee (Drechsler and Drechsler, 2021, and Engelberg, Evans, Leonard, Reed, and Ringgenberg, 2022) from IHS Markit. We also account for different stock-day measures of liquidity from Intraday Indicators (IID) by WRDS.[4] Furthermore, we collect stock level accounting information from Compustat and the "Open Source Asset Pricing" database of Chen and Zimmermann (2022). Lastly, we also merge our stock level short volume information with news releases information from RavenPack Analytics (RPA) database. Our sample includes common stocks (share codes 10 and 11) listed on the NYSE, Nasdaq, and AMEX (exchange codes 1, 2, and 3). We exclude stocks with non-positive book-to-market ratios. Lastly, we exclude stocks below the 10th NYSE market capitalization percentile, and stocks with a price below $1 at the end of the previous month. These sample restrictions help alleviate concerns that our results are driven by illiquid microcaps.[5] More details on variable definitions are provided in Appendix A.

[3]Note that the transaction-level short sales are published in monthly files with a publication lag of around two weeks. As such, market participants are not able to observe and trade on these data immediately. Hence, the observed predictability in this paper should be interpreted as a measure of informational content of short sales rather than as real-time information for a trading strategy.

[4]WRDS IID provides stock level variables at daily frequency such as liquidity spreads, intraday volatility, Kyle's Lambda, and market open to close measures of volume and return, calculated using NYSE TAQ data.

[5]Our main results remain robust across various adjustments in sample construction.

2.2 Identification of liquidity-demanding and liquidity-supplying short sales

The objective of our paper is to examine the dynamics and the informational content of two distinct types of short sales: liquidity-demanding short sales and liquidity-supplying short sales. To this end, we first match each short sale transaction to the corresponding observation in the TAQ data, using all transaction details observable in both data sets. In particular, we employ the WRDS Consolidated Trades (WCT) database, which contains not only all equity trades but also the best available national bid and offer (NBBO) prices at the time of each transaction.[6] We employ a three-step matching procedure to link every short-sale transaction to a TAQ trade and to determine the prevailing NBBO quote, as detailed in Appendix B.

The classification of each short sale transaction relies on inferring the trade direction by comparing the trade price of the short sale to the NBBO quoted prices at the intraday level. We apply the Lee and Ready (1991) algorithm, which integrates both the quote and the tick tests to determine the direction for each trade at the prevailing midpoint quote. Short sale transactions below the prevailing midpoint quote are categorized as short seller-initiated, while those above it are classified as buyer-initiated. For the remaining short trades executed at the midquote, we apply the tick test and classify a short trade as seller-initiated (buyer-initiated) if the trade price is below (above) the preceding trade price. Using INET order data and a subsample of Nasdaq stocks, Chakrabarty, Moulton, and Shkilko (2012) compare the true percentage of short sales that are either seller- or buyer-initiated to the corresponding percentages based on the Lee and Ready (1991) algorithm. Importantly for our analysis, they find that misclassification rates for short sales are indistinguishable from zero at the daily stock level. Throughout this paper, we will refer to buyer-initiated short

[6] Based on correspondence with WRDS, the WCT dataset contains the complete NBBO, as suggested by Holden and Jacobsen (2014). The WCT database is also used in, for example, Barber, Huang, Jorion, Odean, and Schwarz (2023).

sales as liquidity-supplying and seller-initiated short sales as liquidity-demanding.

In the final step, we aggregate short sale transactions into three daily stock level measures of short selling activity. In line with the literature (see, for example, Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; and Wang, Yan, and Zheng, 2020), we define $ShortingFlow$ as the daily number of shares sold short divided by the total number of shares traded for a stock during the same day. In addition, we introduce two novel metrics critical for our analysis: the liquidity-supplying short volume ratio (LSS) and the liquidity-demanding short volume ratio (LDS). LSS is calculated as the daily number of liquidity-supplying shares sold short for a stock divided by its daily total trading volume, whereas LDS represents the daily number of liquidity-demanding shares sold short for a stock divided by its total trading volume. The total trading volume is the total daily trading volume on the three major U.S. exchanges in our sample.

2.3 Summary statistics

Panel A of Table 1 presents daily stock level summary statistics of the short sale data and other stock characteristics. We present the time-series averages of the cross-sectional mean, standard deviation, 10th percentile, median, and 90th percentile of the variables.

On average, short selling represents 45.5% of total trading volume in our sample. This magnitude of shorting flow is significantly larger compared to that in earlier samples (see, for example, Diether, Lee, and Werner, 2009) but comparable to estimates reported in recent studies (see, for example, Reed, Samadi, and Sokobin, 2020, and Wang, Yan, and Zheng, 2020). After we apply the trade classification algorithm to our short sale data, we find that liquidity-supplying (21.4%) and liquidity-demanding shorts (22.5%) contribute almost equally to the overall trading volume.[7] Studies that use more limited and less recent data report somewhat larger shares of liquidity-supplying short sales (see, for example, Chakrabarty,

[7]The difference between the sum of the two components and the $ShortingFlow$ is due to unsigned short-sale transactions identified as neither liquidity-demanding nor liquidity-supplying (e.g., in cases of a crossed or locked market).

Moulton, and Shkilko, 2012, and Comerton-Forde, Jones, and Putniņš, 2016). For instance, for a sample of 200 Nasdaq-listed stocks during two months in 2005, Chakrabarty, Moulton, and Shkilko (2012) find that 43.3% of short sales are seller-initiated or liquidity-demanding. This difference decreases for a sample in 2008, in which the share of short sales executed at the ask price (39.8%) is similar to that executed at the bid price (35.9%) (Comerton-Forde, Jones, and Putniņš, 2016). Overall, recent data indicate that short sales have gained significant importance over the years, with both buyer- and seller-initiated shorts being equally important.

In Figure 1 we plot the 5-day moving average of short selling volume as a percentage of total volume over time. Additionally, we break down this ratio by the three major exchange groups (NYSE, Nasdaq, and CBOE) and the two types of short sales, as determined by our classification algorithm. We observe that shorting flow varies over time, ranging between approximately 37% and 49%. There is significant fragmentation in short selling across multiple trading venues, aligning with the fragmentation of total exchange traded volume previously reported in the U.S. equity market (Chen and Duffie, 2021; Haslag and Ringgenberg, 2023; and O'Hara and Ye, 2011). This distribution of short volume across the exchange groups highlights the importance of the comprehensive data collection and matching process for our analysis. The balanced distribution of liquidity-supplying short sales (LSS) and liquidity-demanding short sales (LDS) is consistent across each exchange group.[8]

Panel B of Table 1 shows correlations between different short selling activity measures and other stock and firm characteristics. We take the natural log of skewed variables, compute contemporaneous cross-sectional Pearson correlations each day and report their time-series averages. Despite a positive correlation of 0.307 between LSS and LDS, a significant share of

[8] We find no significant difference in the intraday distribution of LSS and LDS using 30-minutes trading intervals between 9:30 am and 4:00 pm. In Figure A2 in the Appendix, we find that both liquidity-supplying and liquidity-demanding shorting follow a U-shape over the course of the trading day, similar to the patterns observed by Hu, Jones, and Zhang (2021) in the CBOE exchange. The short-sale ratios relative to total volume in each 30-minutes interval are stable over the trading day and similar in magnitude to the average daily short sale ratios.

the cross-sectional variation remains unexplained. This suggests that other factors likely play a role in influencing the dynamics of the two type of short sales. Consistent with previous work (see, for example, Boehmer and Wu, 2013, and Diether, Lee, and Werner, 2009), we observe that short selling activity is on average contrarian: Higher contemporaneous and past week's return coincide with higher short selling activity. Such contrarian trading has been at least partly attributed to short sellers' role as liquidity providers (Comerton-Forde, Jones, and Putniņš, 2016). Our decomposition of shorting flow into LSS and LDS confirms this interpretation. The positive correlation between contemporaneous returns and short selling activity is only present for liquidity-supplying short sales, whereas liquidity-demanding short sales coincide with lower returns. A similar pattern emerges when we consider order imbalance as a proxy for stock specific buying pressure. Liquidity-supplying short sales increase with buying pressure relative to liquidity-demanding short sales. Diether, Lee, and Werner (2009) discuss the role of short sellers as, so called, opportunistic risk bearers by trading in periods and stocks with elevated uncertainty. In this case, we expect short selling activity to correlate positively with intraday volatility and spreads. While the aggregate shorting flow does not show correlations consistent with this view, we again observe striking differences between those liquidity-supplying and liquidity-demanding short sales. LSS correlates positively with intraday volatility ($IntraVol$) and realized spread (RS), whereas the correlations of LDS with these two variables has the opposite sign. Liquidity-supplying short sales seem to step in to provide additional risk bearing capacity for stocks of elevated uncertainty. Taken together, short sellers tend to supply rather than demand liquidity in cases of high uncertainty.

Except for market capitalization, LSS and LDS exhibit similar correlations with other stock characteristics in our sample. For instance, both liquidity-supplying and liquidity-demanding short volumes correlate positively with utilization and shorting fees. This positive relationship aligns with the notion that utilization and shorting fees are equilibrium outcome variables that increase with heightened shorting demand. The correlations with $Size$ suggest that short sellers are more likely to demand liquidity rather than to supply it for bigger stocks.

3 Empirical results

There is ample evidence in the literature (see, for example, Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Boehmer and Wu, 2013; Diether, Lee, and Werner, 2009; and Engelberg, Reed, and Ringgenberg, 2012) that short selling activity predicts future negative returns. The literature implicitly treats informed short sales as liquidity-demanding (see, for example, Comerton-Forde, Jones, and Putniņš, 2016). Intuitively, liquidity-demanding short sales are likely to arise from informed traders, potentially those with short lived information. On the other hand, while liquidity-supplying short sales would arise from market makers providing liquidity, it is also possible that these short sales come from other informed traders with longer lived information and no need for immediacy (Boehmer, Jones, Wu, and Zhang, 2020). The previous literature's aggregation of these two categories masks the potentially heterogeneous impact of these short sales on predictability of returns. Our classification of short sales into LDS and LSS allows us to analyze the potentially different predictability of returns from these two components. This analysis provides insights into which type of short selling is most informed and at which time horizon. By disaggregating the data, we can better understand the trading strategies of short sellers and how their informational advantage contributes to the efficient incorporation of information into stock prices.

3.1 Portfolio sorts

We start by examining the predictive ability of daily LSS and LDS by following the methodology of Boehmer, Jones, and Zhang (2008). Specifically, we form quintile portfolios each day $t-1$ based on that day's short volume ratio. We hold these portfolios for 21 days from day t to day $t+20$. We use the overlapping portfolio approach of Jegadeesh and Titman

(1993) to calculate overlapping period returns. The portfolios are value-weighted based on the market capitalization at the end of day $t-1$. We calculate alphas from CAPM and a 6-factor model that includes the five factors of Fama and French (2015) and the momentum factor.

We report cumulative 6-factor alphas for spread portfolios formed based on sorts of LDS or LSS for future horizons varying from 1 to 21 days in Figure 2. Consistent with prior literature (see, for example, Boehmer, Jones, and Zhang, 2008 and Engelberg, Reed, and Ringgenberg, 2012), we find that both LDS and LSS significantly and negatively predict next day t return, with daily 6-factor alphas of around 0.10%. Increasing the holding period, we find that the predictive power of LDS weakens, with no statistically significant predictability after 7 days. In contrast, we find that LSS is a strong negative predictor of future equity returns across all holding periods between 1 and 21 days. For a 21-day holding period, the spread portfolio based on LSS has a cumulative 6-factor alpha of almost 0.40%. Thus, this figure documents a striking empirical pattern: liquidity-supplying shorts negatively predict future equity returns, whereas liquidity-demanding shorts do not, at least for horizons of more than a week.

We present returns and alphas on quintile portfolios and the spread portfolio for a horizon of 21 days in Table 2. Panels A, B, and C sort on total $ShortingFlow$, LSS, and LDS, respectively. Panel A shows that heavily shorted stocks underperform lightly shorted stocks. This finding is robust whether we look at raw returns or risk-adjusted returns and is statistically significant with t-statistics ranging between -2.32 and -2.66. Consistent with prior literature (see, for example, Boehmer, Jones, and Zhang, 2008), we find that the performance difference between portfolios 5 and 1 is primarily driven by the outperformance of quintile 1 rather than by the underperformance of quintile 5.

Our analysis allows us to study the impact of these two kinds of short sales separately. Panel B for sorts on LSS shows that both returns and alphas decrease monotonically as one moves from quintile 1 to quintile 5. The spread portfolio has a return of -0.50% (t-statistic

$= -2.78$) and a 6-factor alpha of -0.38% (t-statistic $= -3.32$). The equivalent numbers in Panel C for sorts on LDS are -0.18% and -0.12% (both statistically insignificant). In fact, none of the quintile portfolios yield a statistically significant 6-factor alpha in Panel C. Panel D of Table 2 shows the difference in returns to the spread portfolio for sorts on LSS and LDS. We find that the spread portfolio has economically and statistically significantly lower returns for sorts on LSS versus sorts on LDS. For example, the 6-factor alpha difference is -0.26% (t-statistic $= -2.72$). These results suggest that the predictability of the short volume ratio, documented in the prior literature, is mostly driven by short trades that provide liquidity rather than demand it.

At first glance, our results might seem at odds with those of Comerton-Forde, Jones, and Putniņš (2016) who find that LDS trades are followed by low returns while LSS trades are not. However, it is important to note that Comerton-Forde, Jones, and Putniņš (2016) conduct their analysis at intraday frequency while our focus is on lower frequency returns. It is also worth mentioning that Figure 2 does show that both LDS and LSS predict the next day return negatively, which provides partial support to the findings of Comerton-Forde, Jones, and Putniņš (2016).

3.2 Cross-sectional regressions

While portfolio sorts are useful for gauging the economic importance of predictability, they do not allow us to control for potential confounding effects from other variables. Accordingly, we next employ Fama and MacBeth (1973) regressions to assess the predictive power of LSS and LDS in a multivariate setting. Following Boehmer, Jones, and Zhang (2008) and Engelberg, Reed, and Ringgenberg (2012), on each day $t-1$, we run the following cross-sectional regression:

$$R_{i,t:t+20} = \gamma_{0,t-1} + \gamma_{1,t-1} LSS_{i,t-1} + \gamma_{2,t-1} LDS_{i,t-1} + \gamma'_{3,t-1} X_{i,t-1} + \varepsilon_{i,t:t+20}, \tag{1}$$

where $R_{i,t:t+20}$ is the cumulative return from day t to day $t+20$ and $X_{i,t-1}$ represents control variables measured with the latest available data as of day $t-1$. The control variables include order imbalance, realized spread, price impact, intraday volatility, Amihud illiquidity, active utilization, shorting fees, market beta, log size, book-to-market ratio, idiosyncratic volatility, and past returns. To conform to the value-weighted portfolio sorts from the previous section, the regressions are value-weighted using market capitalization of day $t-1$. We use Newey and West (1987) adjusted standard errors with 21 lags to adjust for serial correlation in the time series of the slope coefficients. In some specifications, we use panel regressions with firm and time fixed effects, with value-weighted observations and clustered standard errors. All independent variables are cross-sectionally standardized each day by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation.

Table 3 reports the results. Consistent with portfolio level analyses, we find that LSS has statistically significant negative predictive power for the 21-day-ahead cumulative return while this is not the case for LDS. The slope coefficient on LSS is -0.18 (t-statistic $= -3.27$). Note that the independent variables in regressions are cross-sectionally standardized. An increase in LSS from the 10th to the 90th percentile, equivalent to a 2.56 standard deviation increase in a standard normal distribution, predicts a return difference of $-0.18 \times 2.56 = -0.46\%$ over the next 21 days. This finding aligns closely with our portfolio sort results in Table 2.[9] In contrast to LSS, the slope coefficient of LDS at -0.08 is economically small and statistically insignificant. When we include both LSS and LDS in specification (3), we find that LSS remains a significant negative predictor for future returns, whereas LDS coefficient remains insignificant and turns even slightly positive.

Our results remain robust after the inclusion of several control variables, as is shown in specification (4) (we omit the coefficients on control variables for brevity). In panel regressions, following Engelberg, Reed, and Ringgenberg (2012), with time-fixed effects (column 5) and time plus firm-fixed effects (column 6), we find that the coefficient on LSS remains

[9]We choose the 10th and 90th percentiles of the LSS distribution as they correspond to the medians of the top and bottom quintile portfolios from Section 3.1.

largely unchanged while the coefficient on LDS is positive. The regressions in column (6) that include stock fixed effects show that our result is not merely due to cross-sectional differences across stocks but arises also when LSS changes over time for a stock. Notably, the coefficient estimates on LSS are virtually identical in all specifications that we explore. In summary, the stock level regressions lend further support to the fact that the negative predictability from short sales is primarily due to liquidity-supplying short sales.

3.3 Cross-sectional differences in predictability

In an effort to identify whether our results are being driven by previously known results in the literature, we explore whether the return predictability from LSS is concentrated in stocks with certain stock characteristics. On day $t-1$, we compute tercile ranks for each of the following conditioning variables: size, illiquidity, one-day return, one-week return, realized spread, price impact, intraday volatility, and order imbalance.[10] Subsequently, for each day $t-1$, we run the following cross-sectional regression:

$$\begin{aligned} R_{i,t:t+20} &= \gamma_{0,t-1} + \gamma_{1,t-1} LSS_{i,t-1} + \gamma_{1,mid,t-1} LSS_{i,t-1} \times Mid_{i,t-1} \\ &\quad + \gamma_{1,high,t-1} LSS_{i,t-1} \times High_{i,t-1} + \gamma_{2,t-1} LDS_{i,t-1} \\ &\quad + \gamma_{2,mid,t-1} LDS_{i,t-1} \times Mid_{i,t-1} + \gamma_{2,high,t-1} LDS_{i,t-1} \times High_{i,t-1} \\ &\quad + Mid_{i,t-1} + High_{i,t-1} + \gamma'_{3,t-1} X_{i,t-1} + \varepsilon_{i,t:t+20}, \end{aligned} \tag{2}$$

where $Mid_{i,t-1}$ and $High_{i,t-1}$ denote the mid and high tercile indicator variables on day $t-1$ for stock i given a conditioning characteristic. $\gamma_{1,t-1}$ and $\gamma_{2,t-1}$ are the coefficients on LSS and LDS, respectively, for stocks in the low tercile. The coefficients on the tercile interactions can be interpreted as the differences in predictability between stocks in low and mid/high terciles. All regressions include the same control variables as those in column (4)

[10] In unreported results, we also test whether liquidity-supplying short sales are particularly informative about future returns in case of larger retail buying pressure, which may be perceived as likely uninformed. Our findings indicate that the predictive power of LSS does not vary with changes in retail order imbalance.

of Table 3.[11]

The results presented in Table 4 show that none of the interaction terms for any of the stock characteristic are statistically significant at the 5% level. This implies that predictability from LSS does not differ for stocks with different characteristics. For ease of interpretation, we provide the sum of the coefficients and their interaction with $High$ in the last two rows of this table. These coefficients show the predictability for the sub-sample of stocks in the $High$ tercile. We find that across all characteristics, predictability from LSS is negative and statistically significant while this is not the case for LDS.[12]

3.4 Robustness checks

We examine the robustness of results from Section 3.2 by various sample splits in Table 5. The two columns under the heading "Univariate" show the regression coefficients of LSS and LDS when the variables are used as single predictors in two separate regressions (as in columns (1) and (2) of Table 3). The two columns below the heading "Bivariate" show the regression coefficients of LSS and LDS when used jointly as predictors in one regression (as shown in column (3) of Table 3). The columns under the heading "With controls" show the regression coefficients of LSS and LDS when we augment the regression with additional control variables (as shown in column (4) of Table 3).

Different rows of Table 5 show results for different samples. Row (1) shows the baseline regression results from Table 3. Row (2) uses the sample period from 2014 to June 2016. Row (3) uses the sample period from July 2016 to 2018. Row (4) removes stocks below \$5 or below the 20th size NYSE percentile. Row (5) uses all stocks (without price or micro-cap filter). Row (6) covers a sample of the largest 500 stocks based on market capitalization.

[11] When including the tercile indicators based on the conditioning stock characteristic, we omit the corresponding continuous version of that variable.

[12] One exception is the interaction with $Size$. We find that, for this stock characteristic, the coefficient on LDS is negative and statistically significant, while the coefficient on $LDS \times High$ is positive and statistically significant. This suggests that small stocks do show negative predictability of returns following LDS while large stocks do not.

Rows (7) to (9) considers different horizons of future returns as dependent variable. Row (10) uses the 5-day average of LSS and LDS at day t as main independent variable.

We find that, with hardly any exceptions, the coefficient on LSS is negative and statistically significant while that on LDS is statistically insignificantly different from zero.[13] The results are similar across two sub-samples (rows (2) and (3)); for different filters on stocks (rows (4) to (6)); and for different horizons of future returns (rows (7) to (9)). Row (9) in particular shows that the predictability extends to 40 days. Thus our results are not driven by either specific time periods or specific sample of stocks or by particular calculations of variables.

Overall, the results of this section show a strong predictability of future returns from liquidity-supplying short sales but the absence of such predictability from liquidity-demanding short sales. These results suggest that liquidity-supplying short sales may represent informed trading from investors with relatively long lived information.

4 What explains the return predictability?

The evidence reported in Section 3 indicates that liquidity-supplying short sales negatively predict long term equity returns. Moreover, we do not find such predictive power for liquidity-demanding short sales. In this section we discuss and test three hypotheses to explain our results.

The first hypothesis builds on previous work and the general perception that short sellers are informed (Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Christophe, Ferri, and Angel, 2004; Christophe, Ferri, and Hsieh, 2010; Desai, Krishnamurthy, and Venkataraman, 2006; Diether, Lee, and Werner, 2009; Figlewski, 1981; and Senchack and Starks, 1993). Some informed traders may find it optimal under certain con-

[13]The coefficient on LSS is statistically insignificant in row (3) while the coefficient on LDS is statistically significant in row (2); both in univariate regressions.

ditions to submit limit orders and supply liquidity (Ahern, 2020; Chakravarty and Holden, 1995; Garriott and Riordan, 2024; O'Hara, 2015; and Seppi and Kumar, 1994). They may prefer limit orders to trade based on fundamental news, especially if these are long-lived (Collin-Dufresne and Fos, 2015, and Kaniel and Liu, 2006). As short sellers became more profitable trading on long-term information that is gradually incorporated into prices (Wang, Yan, and Zheng, 2020), the return predictability based on LSS is consistent with informed trading.

Besides the informed trading hypothesis, there are two alternative mechanisms that could also explain the reported return predictability: market making and opportunistic risk-bearing. Diether, Lee, and Werner (2009) show that short-selling activity correlates positively with contemporaneous returns. Comerton-Forde, Jones, and Putniņš (2016) find that this contrarian trading at daily horizon is driven by buyer-initiated short sales. These findings are consistent with short sellers stepping in to serve as market makers. When stock prices rise following a sequence of buy orders, market makers reduce their long positions and may even shift to short positions to continue providing liquidity. This surge in selling activity caters to buyers willing to pay for the immediacy. As the buying pressure subsides, the stock prices are likely to revert and compensate short sellers for their market-making activity.

The third hypothesis to explain the results is that short sellers are opportunistic risk-bearers (Diether, Lee, and Werner, 2009). For stocks and periods with a higher price uncertainty, they increase their activity to opportunistically supply liquidity. Once the heightened uncertainty is resolved, the stock price is expected to revert to its long-term level, thus providing a return to the short seller for bearing this risk. In the next subsections, we run a number of empirical exercises to shed light on which of the three non-mutually exclusive hypotheses most likely apply to liquidity-supplying short sales.

4.1 The role of market making and opportunistic risk bearing

To test whether the return predictability based on LSS can be at least partly attributed to short sellers' compensation for market making activity and/or opportunistic risk bearing, we adopt an approach similar to that of Boehmer, Jones, Zhang, and Zhang (2021) to our hypotheses. In the first stage, we decompose LSS, into three components using cross-sectional regressions for each day $t-1$:

$$LSS_{i,t-1} = \underbrace{\beta_{t-1} R_{i,t-1} + \gamma_{t-1} OIB_{i,t-1}}_{\substack{\text{voluntary} \\ \text{market making } (mm)}} + \underbrace{\delta_{t-1} IntraVol_{i,t-1}}_{\substack{\text{opportunistic} \\ \text{risk bearing } (rb)}} + \underbrace{\alpha_{t-1} + \varepsilon_{i,t-1}}_{\text{residual } (res)}. \quad (3)$$

For each day $t-1$, we estimate the exposure of LSS to daily return, Ret, order imbalance, OIB, and intraday volatility, $IntraVol$. Then, we calculate the following three components of LSS for each day $t-1$ using the cross-sectional regression coefficients of day $t-1$ from the first stage:

$$\begin{aligned} LSS_{mm,i,t-1} &= \beta_{t-1} R_{i,t-1} + \gamma_{t-1} OIB_{i,t-1} \\ LSS_{rb,i,t-1} &= \delta_{t-1} IntraVol_{i,t-1} \\ LSS_{res,i,t-1} &= \alpha_{t-1} + \varepsilon_{i,t-1}. \end{aligned} \quad (4)$$

Motivated by the model and the empirical evidence of Comerton-Forde, Jones, and Putniņš (2016), we label the variation of LSS that relates to stock's return and order imbalance as the market making component of LSS (LSS_{mm}). Similar to Diether, Lee, and Werner (2009), we denote the variation of liquidity-supplying short selling associated with a stock's intraday volatility as the risk bearing component of LSS (LSS_{rb}). The remaining variation, LSS_{res}, potentially contains other relevant information about future returns reflected in liquidity-supplying short sales.

We report the results of the decomposition from equation (3) in Panel A of Table 6.

Coefficients on all of the three explanatory variables are positive and highly economically and statistically significant at all conventional levels. These results are consistent with our expectations and the cross-correlations reported in Panel B of Table 1. Liquidity-supplying short selling is contrarian and increases with stronger buying pressure. Moreover, LSS also increases with heightening stock level uncertainty as proxied by intraday volatility. In sum, LSS contains variation that can be explained by both market making activity and opportunistic risk bearing.

In the second stage, we employ Fama and MacBeth (1973) regressions of equation (1) to predict the 21-day ahead stock returns using the three components of LSS. As in Section 3.2, we use Newey and West (1987) adjusted standard errors with 21 lags to adjust for serial correlation in the time series of the slope coefficients and weight observations by the stock's market capitalization at day $t-1$. We include the three components of LSS in different specifications and report the estimates in Panel B of Table 6. All independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation.

In column (1), we find that the coefficient on LSS_{res} is negative at -0.18 (t-statistic $= -3.75$). There is remarkable similarity in the coefficient on LSS_{res} in Table 6 and the coefficient on LSS in Table 3. Column (1) shows that the coefficient on LSS_{mm} is -0.04 (t-statistic $= -1.37$). Hence, we cannot reject the null hypothesis that the market making component of LSS does not contribute significantly to the predictive power of liquidity-supplying short sales. In column (2), we use the opportunistic risk-bearing component of LSS to predict cross-sectional stock returns and find similar results: the coefficient on LSS_{rb} is -0.06 (t-statistic $= -1.14$). Results change only slightly when we add all three components in column (3). In the last specification, next to the three components, we also add our remaining control variables. The residual component, LSS_{res}, remains the only economically and statistically significant component of LSS when predicting future stock returns.

In sum, we find that market making activity and opportunistic risk bearing of liquidity-supplying short sales explain a significant part of the cross-sectional variation in LSS. However, neither of these two components contain significant predictive power for stock returns. The predictability of returns is entirely driven by the residual component, consistent with the hypothesis that liquidity-supplying short sales contain material information about future stock prices.

4.2 Liquidity provision and news

In this section, we further explore the predictive power of LSS in the cross-section of stock returns. In particular, we ask whether the return predictability shown in Section 3 arises from the informational advantage and skill of liquidity-supplying short sellers in identifying mispriced stocks. To address this question, we employ a framework akin to that of Engelberg, Reed, and Ringgenberg (2012). The rationale behind our test is as follows: if the predictive ability of liquidity-supplying short sales is indeed due to an informational advantage, characterized by trading in overpriced stocks and avoiding underpriced ones, then this mispricing should be corrected upon the release of news. In other words, LSS should particularly predict returns on days with news releases.[14]

To test this hypothesis, we compile a sample of news events using RavenPack Analytics (RPA) database and study the short selling patterns around public news releases. The RPA database contains a comprehensive sample of firm specific news stories from thousands of news sources, such as Dow Jones Newswires, the Wall Street Journal, Barron's as well as other leading financial websites. To identify important news events specific to a given firm, we require both the *Relevance* and *Event Relevance* measure to be above 70 (out of 100).[15] Moreover, we consider only news events with *Event Similarity Day* score above 90

[14] Boehmer, Jones, Wu, and Zhang (2020) and Jank, Roling, and Smajlbegovic (2021) use a similar setting to better understand the informational content of short sales and how it varies around news events and earnings announcement days.

[15] *Event Relevance* provides information on the prominence of an event within a news story whereas *Relevance* focuses on how strongly related the entity is to the underlying news story. Our empirical results

(up to 365 days), thereby requiring at least 90 days since a similar event was detected in the past. Following Reed, Samadi, and Sokobin (2020), we remove (1) news stories relating to trading and market activity, such as "technical-analysis," "stock-prices," and "insider-trading," and (2) news in the categories "revenues" and "investor-relations" to avoid a large overlap with earnings news announcements days. Furthermore, we augment the news sample with earnings announcement dates from IBES if not already included in the RPA database. We define a stock-day news indicator variable ($News$) as one if a news event occurred on that day for a particular firm. Following Engelberg, Reed, and Ringgenberg (2012), if a news story is released after 4:00 pm, then we define the following trading day as the event day.

We then extend the Fama and MacBeth (1973) regressions of Section 3.2 by including the news indicator variable and interaction terms with our two short-selling measures, LDS and LSS. We report the results in Table 7. As a starting point, column (1) simply replicates the bivariate regression of 21-day ahead returns on LSS and LDS from column (3) of Table 3. Column (2) shows that, while the coefficient on $News$ indicator variable is small and insignificant, the coefficient on the interaction term, $LSS \times News$, is relatively large (-0.17), and statistically significant with a t-statistic of -2.64. In the same specification, the coefficient on LSS by itself is -0.12 (t-statistic $= -2.81$). Thus, the predictive power of LSS more than doubles on news days. In contrast, the coefficient on the $LDS \times News$ is 0.09 and not statistically different from zero. These results suggest that the return predictability of LSS stems from the informational advantage of liquidity-supplying short sellers, with their predictive power being most pronounced on days when information is released and embedded into stock prices.

Next, to study whether the increased predictability of LSS depends on content of news, we decompose the $News$ indicator variable into three distinct components: positive news, neutral news, and negative news. Specifically, following the approach of Engelberg, Reed, and Ringgenberg (2012), we define $PosNews$ and $NegNews$ as indicator variables that take

are robust to restricting both relevance scores to 90 or even 100.

the value of one when news occurs and the firm's return falls within the highest and lowest quintiles, respectively, of all event-returns for that day. $NeutNews$ is assigned a value of one when news occurs but the firm's return is neither in the top nor the bottom quintile.[16]

The last two columns of Table 7 show the results of regressions where we interact LSS and LDS with these news sentiment indicator variables. Column (3), for instance, suggests that the predictive ability seen before for LSS is driven most strongly by negative news events (coefficient on $LSS \times NegNews$ is -0.27 with a t-statistic of -3.71), and, to a lesser extent, by neutral news events (coefficient on $LSS \times NeutNews$ is -0.17 with a t-statistic of -2.29). The magnitude of these coefficients suggests that the LSS predictability more than triples on days with negative news events. The coefficients are similar in column (4) where we include additional control variables. We also find in Table 7 that the coefficient on $LSS \times PosNews$ is positive, unlike the coefficients on interactions with $NeutNews$ and $NegNews$, but statistically indistinguishable from zero (t-statistic of 1.33 in column (4)). It is also worth noting that the predictive power of LDS, as opposed to LSS, does not differ across news content types, and is not statistically significant for any type of news content.

At a broad level, the analysis in this section shows that liquidity-supplying short sales are particularly informative about future returns on news days relative to non-news days. This is also consistent with Engelberg, Reed, and Ringgenberg (2012) who find that short sales (the sum of liquidity-demanding and liquidity-supplying short sales in their setting) have more predictive power for returns on news days. At a more detailed level, this section shows that the liquidity-supplying short sales are most informative in the presence of negative or neutral news relative to positive news.

[16]This approach, as highlighted by Engelberg, Reed, and Ringgenberg (2012) and Reed, Samadi, and Sokobin (2020), offers an advantage over sentiment scores based on positive and negative word counts because it incorporates information relative to the market's prior expectations.

4.3 News and short sellers' motivation

Section 4.1 shows that the residual component of liquidity-supplying shorts is the most informative about future returns. Section 4.2 shows predictive content of liquidity-supplying shorts is the highest around news days, and especially so around negative news days. In this section, we combine the liquidity-supplying short sale decomposition, i.e., market-making (LSS_{mm}), risk-bearing (LSS_{rb}), and residual (LSS_{res}) from Table 6 with the news decomposition from Table 7. The goal is to evaluate how short sellers' motivation might shed light on the source of their informational advantage

Table 8 reports the results. As a starting point, column (1) simply replicates column (3) of Table 6, where we see that the residual component drives the vast majority of LSS's predictability. In column (2), we add the interaction terms, and we see that the residual component of LSS drives the vast majority of predictability on news days. In particular, the coefficient on $LSS_{res} \times News$ is -0.23, and it is strongly statistically significant (t-statistic $= -3.02$), unlike all of the other news interactions. In terms of magnitude, comparing the coefficient of -0.11 on the standalone version of LSS_{res} to the effect of $LSS_{res} \times News$ shows that future returns are roughly three times as large on news days than on non-news days. In other words, like previous results, short sellers' information advantage while supplying liquidity accrues mostly on news days, and it seems that the residual component of their liquidity provision is the key driver of that advantage. Together, these findings further support informed trading as the most plausible explanation for the return predictability associated with LSS.

Columns (3) and (4) show a finer-grained decomposition in which news is split into positive, neutral, and negative news. There are a large number of interaction variables, but the baseline effect of LSS_{res} is far stronger than that of LSS_{mm} and LSS_{rb}. When looking at the interaction terms involving LSS_{res}, negative and neutral news are more negative than those with positive news. To give a sense for the magnitude, we see the coefficient estimate in column (3) for $LSS_{res} \times NegNews$ is -0.25 (t-statistic $= -3.32$). The magnitude of the coefficient on $LSS_{res} \times NeutNews$ is similar, as is the statistical significance, but the magnitude and significance of the coefficient on $LSS_{res} \times PosNews$ is much lower.

In general, we see very little statistical significance for coefficients on the market making component or on the risk bearing component of liquidity-supplying short sales. Thus, the residual component of the liquidity-supplying short sales drives most of the results, providing further evidence that the return predictability result is likely due to informed trading by liquidity-supplying short sellers.

On the other hand, we notice that $LSS_{rb} \times PosNews$ has a statistically significant coefficient estimate in both columns (3) and (4). Since LSS_{rb} has no effect on future returns in the models without interactions in columns (1) and (2), we suspect that the positive effect in the last two columns comes from a stronger influence of outliers because of the finer disaggregation and the resulting reliance on a smaller number of observations for each category in models (3) and (4).

We next explore how the volume of liquidity-supplying short sales varies around news days. Our empirical approach follows Engelberg, Reed, and Ringgenberg (2012). Specifically, we run a series of panel regressions with stock and day fixed effects, where the dependent variable is one of the components of LSS. The independent variable takes the value of one if a news story occurs and zero otherwise. Across the specifications, we vary the timing of the dependent variable relative to the news event to examine short-volume changes around news. For example, -1 indicates the change in LSS observed one day prior to the news event. Lastly, we follow Engelberg, Reed, and Ringgenberg (2012) and include two lags of daily returns as control variables in all regression specifications. We plot the coefficient estimates on the news indicator variables from these regressions as bars in Figure 3. In Panel A, we limit the sample to negative news announcements, and in Panel B, we limit the sample to positive news announcements.

We first focus on the residual component of liquidity-supplying short sales as dependent variable. Panel A shows a statistically significant increase of LSS_{res} a few days before the release of negative news, peaking on the day of the event. This evidence indicates that liquidity-supplying short sellers exhibit some anticipation of negative news events, although the economic magnitude is relatively small compared to the cross-sectional standard deviation of LSS. When we consider positive news separately in Panel B, we find evidence that the ratio of liquidity-supplying short sales to other trades is small in the days leading up to a news event. While we would expect that informed short sellers open fewer short positions ahead of (or on the day of) positive news releases, interestingly, we find that the residual component of LSS increases on the day of the positive event. This finding is consistent with our results in Table 7 and Table 8 that LSS_{res} exhibits the weakest return predictability on positive news days compared to the remaining news days in our sample.

Next, we study the dynamics of the market-making component of LSS around news days. For both negative and positive news events, this component remains quite stable before and after news days. However, there is a striking effect on the day of the announcement of news. For negative news days, there is significantly less market-making activity by short sellers, whereas we observe the opposite for positive news days. This finding is consistent with LSS_{mm} capturing the contrarian trading by short sellers. On days with positive news, short sellers step in and sell when buying pressure is high. On the contrary, in case of negative news, when there is overall more selling than buying pressure, we observe significantly less informal market making by short sellers.[17]

Overall, our results support the interpretation that the return predictability based on liquidity-supplying short sales reflects the informational advantage held by short sellers over other market participants. The return predictability is particularly pronounced (1) on days when fundamental information is disclosed to the market and (2) when we exclude the

[17]We also study the opportunistic risk-bearing component of liquidity-supplying short sales, LSS_{rb}, around both negative and positive news days. There is no significant variation in LSS_{rb} between day -5 to day 5 surrounding the event dates. For the sake of clarity, we have omitted these results from Figure 3. However, they are available in Appendix Figure A1 for interested readers.

market-making and risk-bearing components from our short-selling measure.

4.4 Short sellers and cross-sectional return anomalies

Our results so far indicate that the predictive power of short sales for the cross section of equity returns stems from informed liquidity provision by short sellers. Moreover, the graphical representation of the return predictability for varying holdings periods in Figure 2 suggests that these short sales trade on information that is slowly incorporated into stock prices. To further shed light on the nature of the information that short sellers exploit, we study to what extent liquidity-supplying short sales trade on long term information embedded in cross-sectional equity anomalies.

To this end, we examine 10 prominent anomaly variables that the previous literature has found to be related to the cross-section of stock returns. These anomaly variables, derived from accounting, price and/or trading data, contain valuable long run information on the underlying. If liquidity-supplying short sellers are informed investors who understand the return predictability based on these anomalies, then we expect these short sellers to sell stocks in the short leg of these anomalies and to avoid stocks that are in the long leg.

We follow the procedure of Wang, Yan, and Zheng (2020) in testing this hypothesis. Each anomaly variable is signed, based on prior literature, such that the future mean returns increase in the signed characteristic. We sort all stocks in our sample into deciles based on each signed anomaly variable. We follow previous literature in forming the rebalancing and holding frequencies. For anomalies constructed using annual Compustat data, we form portfolios at the end of each June in year y by using accounting data from the fiscal year ending in calendar year $y-1$. Furthermore, we hold the portfolio from July of year y to June of year $y+1$. For anomalies constructed using quarterly Compustat data (such as those using ROE), we form portfolios at the end of quarter q using data from the fiscal quarter ending in calendar quarter $q-1$ and hold the portfolio over calendar quarter $q+1$. Lastly, for anomalies constructed using monthly CRSP data, we form portfolios every month m and hold the portfolio for the next month $m+1$. Using this portfolio formation procedure, for each stock-month and for each anomaly, we calculate the decile rank for that stock based on its corresponding portfolio assignment. Next, for each day t, we sort stocks into quintiles based on either LSS or LDS. For each shorting quintile and for each anomaly, we subsequently compute the average anomaly decile rank at the end of the previous month. Since decile 10 (1) of each anomaly represents the long (short) leg, we expect the average rank of the high shorting quintile to be significantly lower than the average rank of the low shorting quintile.

We show the results in Panel A of Table 9. We find that the average anomaly rank of the LSS quintile 5 is lower than that of the LSS quintile 1 for all anomalies. For instance, for the anomaly based on Net Stock Issues, the average rank of quintile 1 and 5 of LSS portfolios is 7.07 and 6.11, respectively. This means that stocks where liquidity-supplying short sales are high (quintile 5) are also more likely to be stocks that tilt towards the stocks that have low Net Stock Issues and thus overpriced. The difference in these ranks is -0.96 with a t-statistic of -11.67 calculated using Newey and West (1987) errors with 60 lags. In fact, the difference in average anomaly ranks between the LSS quintiles 5 and 1 is negative and statistically significant across all anomalies. The average difference across all anomalies is -0.72 (t-statistic $= -23.65$).

Panel A also shows that difference in average anomaly ranks between the LDS quintiles 5 and 1 is negative and statistically significant for 9 out of 10 anomalies between the high and low LDS quintile. In the last column of Panel A, we compute the difference-in-differences between LSS and LDS and find that the LSS spread in average anomaly rank is larger than the LDS spread. Among the 10 anomalies, 8 anomalies exhibit statistically significant differences at the five percent level.

It may appear odd that we find significant differences in average anomaly rank even for LDS quintiles given the absence of our earlier evidence regarding long term predictability from LDS. Note, however, that LDS and LSS are cross-sectionally correlated with a correlation of 0.307 (see Table 1). To decipher the pure effect of LSS and LDS, we make one modification to the above procedure. Specifically, we orthognalize LDS each day t by cross-sectionally regressing $LDS_{i,t}$ on $LSS_{i,t}$ and taking the residuals. We call this residuals $LDS^{\perp}$; by construction they are purged of the effect of LSS. We construct a similar orthognalized version of LSS by cross-sectionally regressing $LSS_{i,t}$ on $LDS_{i,t}$ and calling the residuals $LSS^{\perp}$. Panel B of Table 9 shows the results using $LSS^{\perp}$ and $LDS^{\perp}$ as sorting variables. Comparing Panels A and B, we find similar results for LSS and its orthogonalized counterpart $LSS^{\perp}$. The results are, however, markedly different for LDS and $LDS^{\perp}$. Only one anomaly shows a negative spread between quinitles 1 and 5 of $LDS^{\perp}$ that is also statistically significant. The average difference across all anomalies for $LDS^{\perp}$ is only -0.02 (t-statistic $= -0.73$). We conclude that liquidity-supplying shorting flows are reactive to information embedded in anomalies in the sense that they short more of stocks deemed as overvalued than stocks deemed as undervalued. The same is not case for liquidity-demanding shorting flows.

Lastly, we decompose LSS into three components as before: market making, risk bearing, and the residual. We repeat our analysis by sorting on these components and computing the average anomaly ranks. We show the results in Table 10. For LSS_{res}, we find that the average decile anomaly rank for the high shorting quintile is significantly lower than the average decile anomaly rank for the low shorting quintile for all anomalies. For the LSS_{mm} , we find significant differences for 7 out of 10 anomalies. Lastly for LSS_{rb}, we find significant differences for 8 out of the 10 anomalies. Across 10 anomalies, the average 5$-$1 difference in anomaly ranks is -0.71, -0.16, and -0.45 for LSS_{res}, LSS_{mm}, and LSS_{rb}, respectively. As in the previous sections, we find that the residual component of short selling supply is the most closely aligned with well-known profitability of anomaly strategies.

5 Conclusion

Our research provides significant insights into the role of short sellers in financial markets, particularly in relation to their impact on market liquidity and their informativeness of trades. By distinguishing between liquidity-demanding and liquidity-supplying short sales, we challenge the conventional wisdom that only those demanding liquidity are informed. We show that liquidity-supplying short sellers are, in fact, better at predicting future stock returns, particularly over longer holding periods. Our study aligns with more recent theoretical work that posits a dual role for informed traders, one that includes liquidity provision as a strategy to capitalize on long-lived information.

The fact that the same short sellers both supply liquidity and improve market efficiency adds to an already challenging task for regulators (Edwards, Reed, and Saffi, 2024). This paper shows that short sellers who trade in the direction of their information, which presumably affects prices, are doing so through liquidity-providing trades. Our results, which show they are one and the same, add to the challenge faced by regulators who, especially in times of crisis, want to, on the one hand, prevent negative price movements, and on the other hand, ensure that markets are as liquid as possible.

Appendices

A Variable definitions

Variable	Description
$ShortingFlow$	Shorting flow is the daily stock level short volume divided by total trading volume across the three exchanges (NYSE, Nasdaq, and CBOE).
Liquidity-Demanding Shorting Volume, LDS	Short sales that take place below the prevailing midpoint are considered liquidity-demanding. LDS is defined as the daily sum of liquidity-demanding short volume divided by total trading volume across the three exchanges.
Liquidity-Supplying Shorting Volume, LSS	Short sales that take place above the prevailing midpoint are considered liquidity-supplying. LSS is defined as the daily sum of liquidity-supplying short volume divided by total trading volume across the three exchanges.
$ActiveUtilization$	The percentage of shares lent by custodians relative to the amount held by them in their lendable inventory pool. Data are obtained from Markit.
$ShortingFee$	Shorting Fee is proxied by the indicative fee, which is defined as the expected borrow cost, in fee terms, for a hedge fund on a given day. Data are obtained from Markit.
Illiquidity, ILQ	The average ratio of the daily absolute return to the (dollar) trading volume over the past twelve months, following Amihud (2002). Data are obtained from Open Source Asset Pricing.
Realized Spread, RS	Share weighted percent realized spread: $\sum_{k=1}^{n} w_k \frac{2D_k(P_k - M_{t+5})}{M_k}$, where M_{t+5} is the midpoint 5 minutes later after the kth trade and P_k is the transaction price. w_k is the share weight of each trade. D_k equals $+1(-1)$ if trade k is a buy (sell) following the Lee and Ready (1991) classification algorithm. Data are obtained from the 'Millisecond Intraday Indicators' by WRDS.
Price Impact, PI	Share weighted Percent Price Impact: $\sum_{k=1}^{n} w_k \frac{2D_k(M_{t+5} - M_t)}{M_k}$, where M_{t+5} is the midpoint 5 minutes later after the kth trade and M_k is the midpoint at the kth trade.
$IntraVol$	Trade-based intraday volatility obtained from the 'Millisecond Intraday Indicators' by WRDS.
Order Imbalance, OIB	Total number of buys minus sells scaled by total number of transactions. Buy and sell volumes are classified by the algorithm of Lee and Ready (1991). Data are obtained from the 'Millisecond Intraday Indicators' by WRDS.

Variable	Description
$Beta$	Coefficient of a 60-month rolling window regression of monthly stock returns minus the risk-free rate on market return minus the risk free rate. Data are obtained from Open Source Asset Pricing.
$Size$	Market capitalization (stock price times shares outstanding, in $ billion).
BM	Book-to-Market Ratio following Eugene and French (1992).
$IdioVol$	Standard deviation of residuals obtained from Fama-French three factor regressions using the past month of daily data. Data are obtained from Open Source Asset Pricing.
R_{t-1}	Stock return over the previous day.
$R_{t-5:t-2}$	Stock return over the previous week excluding the previous day.
Net Stock Issues, NS	Growth in number of split-adjusted shares between month $m-18$ and $m-6$. Data are obtained from Open Source Asset Pricing.
Composite Stock Issues, CS	5-year growth in number of split-adjusted shares. Data are obtained from Open Source Asset Pricing.
$Accruals$	Annual change in current total assets (`act`) minus annual change in cash and short-term investements (`che`) minus annual change in current liabilities (`lct`) minus annual change in debt in current liabilities (`dlc`) minus change in income taxes (`txp`). All divided by average total assets (`at`) over this year and last year. Data are obtained from Open Source Asset Pricing.
Net Operating Assets, NOA	Difference between operating assets and operating liabilities, scaled by lagged total assets. Operating assets are total assets (`at`) minus cash- and short-term investments (`che`), operating liabilities are total assets minus long-term debt (`dltt`), minority interest (`mib`), deferred charges (`dc`) and book equity (`ceq`). Data are obtained from Open Source Asset Pricing.
Asset Growth, AG	Annual growth rate of total assets (`at`). Data are obtained from Open Source Asset Pricing.
Investments-to-Assets, IA	One-year change in property, plants and equipment (`ppegt`) plus one year change in inventory (`invt`), scaled by one-year lagged assets (`at`). Data are obtained from Open Source Asset Pricing.
Distress, $Dist$	Distress is proxied by the Failure Probability of Campbell, Hilscher, and Szilagyi (2008). Data are obtained from Open Source Asset Pricing.
Momentum, $R_{m-12:m-2}$	Stock return between months $m-12$ and $m-2$.
Gross Profitability, GP	Revenue (`sale`) minus cost of goods solds (`cogs`), divided by 12 months lagged total assets (`at`). Data are obtained from Open Source Asset Pricing.
Return on Assets, ROA	Quarterly net income (`ibq`) divided by lagged total assets (`atq`). Data are obtained from Open Source Asset Pricing.

B Matching short sale transactions

We match our intraday short sale data with all trades and quotes from the same period using TAQ data. Specifically, we use the WRDS Consolidated Trades (WCT) files, as in Barber, Huang, Jorion, Odean, and Schwarz (2023), which provides us with the NBBO at the time of the trade. We delete trades associated with locked or crossed bid-ask, following Holden and Jacobsen (2014). In the first step, we match short sales to trades by the following grouping variables: exchange, symbol, date, time, price, size. In this step, we look for exact matches with the same ordering and group size. In the second step, we purely match on the remaining short sales to trades by exchange, symbol, date, time, price, size, by the second. In the third step, we look for the most prevailing previous quote at the second-level for the remainder of unmatched short-sales. This procedure allows us to merge quoted data into our short sales data, and subsequently classify short sales into liquidity-supplying. We are able to match 97.5% of the short sales to trades, and discard the remainder.

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Figure 1: Short volume across exchanges

The figure shows the proportion of short volume relative to the total trading volume (5-day moving average) decomposed by exchange, and by LDS and LSS. Variables are defined in Appendix A. The sample period is 2014 to 2018.

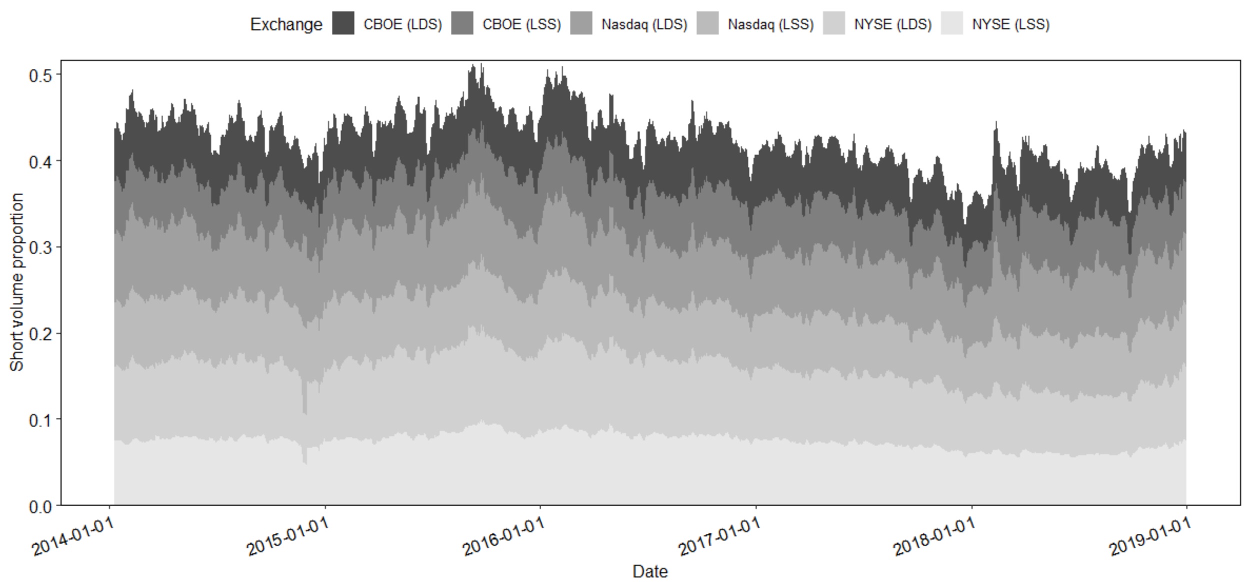


Figure 2: Cumulative six-factor alpha

This figure shows the cumulative six-factor alpha, expressed in percentage terms, for long-short portfolios based on liquidity-demanding (LDS) and liquidity-supplying (LSS) short volume ratios. Variables are defined in Appendix A. The shaded regions represent the 95% confidence intervals for the risk-adjusted return estimates. The sample period is 2014 to 2018.

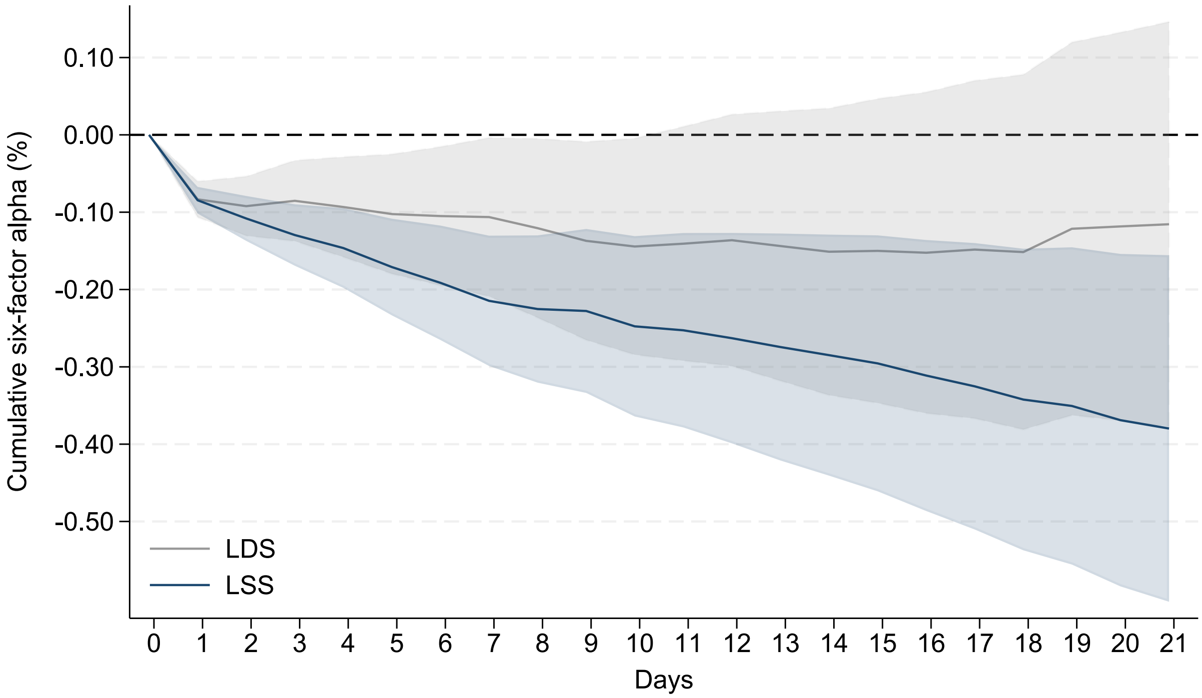
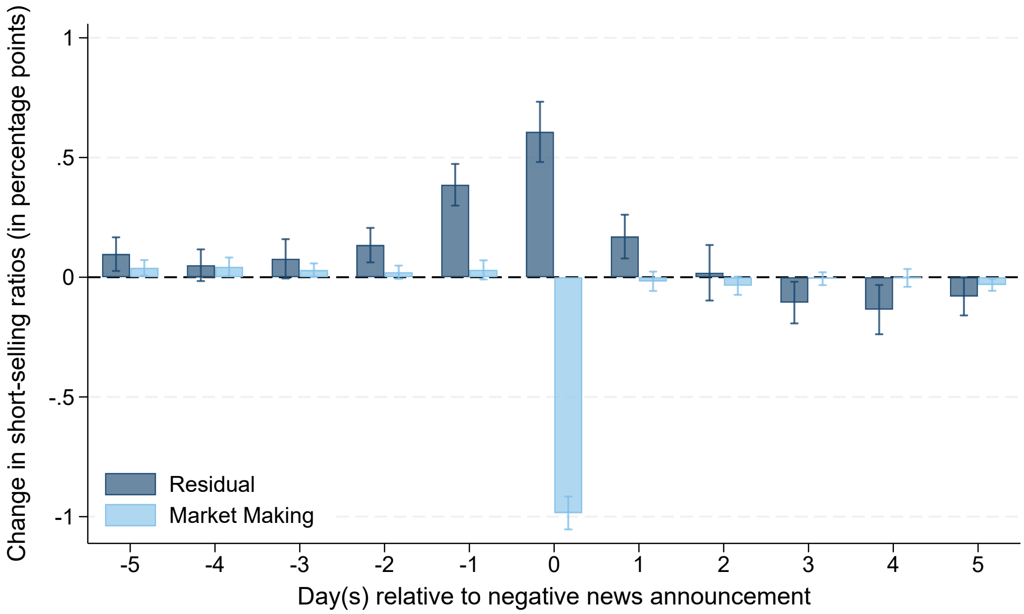


Figure 3: Components of LSS around news event days

This figure shows the change of the residual and the liquidity-supplying component of LSS in percentage points around firm-specific news events. Each bar is based on a panel regression with stock and day fixed effects. The dependent variable is one of the daily components of LSS and the independent variable of interest is an indicator variable that takes the value one if a news story occurs and zero otherwise. In each regression we vary the timing of the dependent variable relative to the news event to examine short-volume changes around news. For example, $t-1$ indicates that the dependent variable is observed one day prior to the news event. To control for the response of short sellers to past returns, we include five day lags of daily returns (where the lags are relative to the timing of the dependent variable). In Panel A and Panel B we examine changes in components of LSS around negative and positive news events, respectively. We define a news event as negative (positive) if the announcement day return is in the bottom (top) quintile of returns on a given day, respectively. The sample period is 2014 to 2018.

Panel A



Panel B

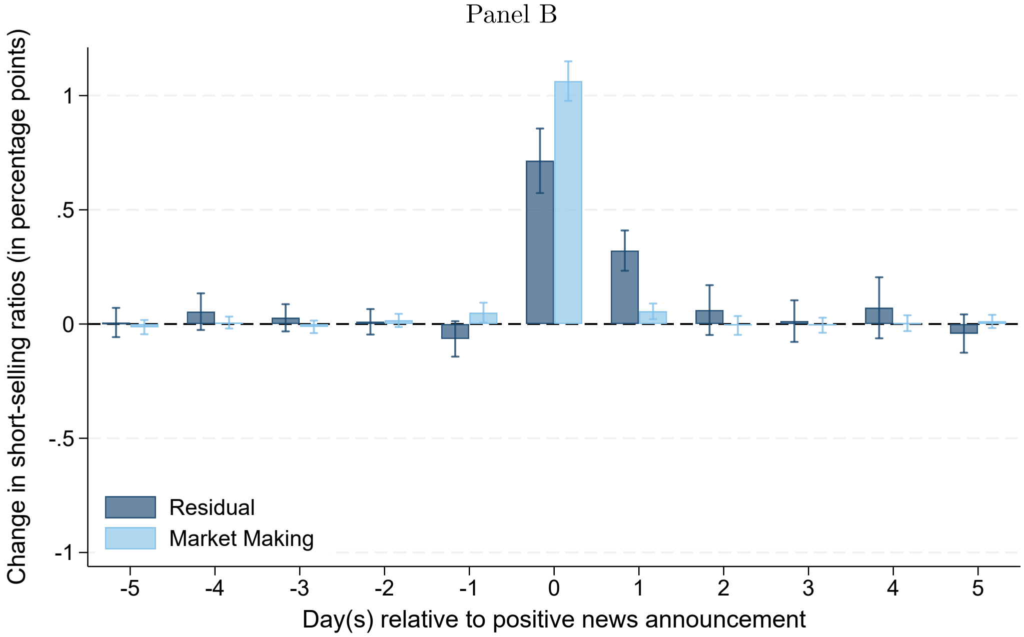


Table 1: Summary statistics

This table reports the time-series average of the cross-sectional mean, standard deviation, 10/90th percentile, median, and average number of firms (N) of each variable. Short volume data is obtained from NYSE, Nasdaq, and CBOE. *Shortingflow* is the ratio of daily short volume to daily total volume. *LDS* and *LSS* are the corresponding ratios using liquidity-demanding and liquidity-supplying short volumes. The direction of short trades are inferred from the algorithm of Lee and Ready (1991). The remaining variables are defined in Appendix A. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than $1 and market capitalization above the 10th NYSE size percentile at end of day $t-1$. The sample period is 2014 to 2018.

Panel A: Descriptives

	Mean	Std Dev	10th	Median	90th	N
Short sales						
ShortingFlow	0.455	0.119	0.302	0.455	0.610	1,939
LDS	0.225	0.072	0.135	0.224	0.314	1,939
LSS	0.214	0.071	0.128	0.210	0.306	1,939
ActiveUtilization	13.900	18.841	0.744	6.554	35.763	1,934
ShortingFee	0.742	2.512	0.354	0.361	0.599	1,934
Liquidity						
ILQ	0.006	0.089	0.000	0.001	0.008	1,939
RS	3.857	13.242	−3.018	1.645	12.113	1,914
PI	10.364	14.189	1.002	6.836	23.431	1,914
IntraVol	1.515	8.072	0.028	0.277	2.586	1,914
OIB	−0.009	0.135	−0.161	−0.008	0.141	1,915
Other characteristics						
Beta	1.175	0.640	0.446	1.096	1.957	1,938
Size	10.9	35.6	5.0	2.2	21.7	1,939
BM	0.515	0.385	0.131	0.433	0.951	1,940
IdioVol	1.487	1.003	0.654	1.203	2.631	1,940
R_t	0.028	2.089	−1.798	0.019	1.834	1,940
$R_{t-4:t-1}$	0.112	4.186	−3.771	0.073	3.956	1,939

Panel B: Correlations

	ShortingFlow	*LSS*	*LDS*
ShortingFlow	1.000	0.802	0.803
LSS	0.802	1.000	0.307
LDS	0.803	0.307	1.000
Ret_t	0.026	0.088	−0.042
$Ret_{t-4:t-1}$	0.050	0.061	0.023
OIB	−0.054	0.156	−0.239
IntraVol	−0.060	0.034	−0.117
RS	−0.067	0.005	−0.105
PI	−0.008	0.057	−0.057
ActiveUtilization	0.350	0.302	0.253
ShortingFee	0.113	0.090	0.089
ILQ	−0.112	−0.021	−0.166
Beta	0.063	0.054	0.041
Size	0.038	−0.032	0.104
BM	−0.041	−0.028	−0.047
IdioVol	0.110	0.108	0.066

Table 2: Returns to portfolios sorted on shorting flow

At the end of each day $t-1$, we sort stocks into five portfolios based on their $ShortingFlow$, LSS, or LDS, and hold these portfolios from day t to day $t+20$. We then calculate overlapping period returns of these portfolios and report the performance numbers in this table. The columns labeled Raw, CAPM, and FF6 report the average raw returns, CAPM alphas, and Fama-French-Carhart six-factor alphas, respectively. We also report the performance of long-short 5−1 portfolio. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than \$1 and market capitalization above the 10th NYSE size percentile at the end of day $t-1$. Newey and West (1987) robust t-statistics are reported in parentheses. The sample period is 2014 to 2018.

	Panel A: $ShortingFlow$			Panel B: LSS			Panel C: LDS		
	Raw	CAPM	FF6	Raw	CAPM	FF6	Raw	CAPM	FF6
1	0.99	0.27	0.22	1.00	0.29	0.25	0.84	0.13	0.12
	(1.99)	(3.35)	(3.10)	(2.04)	(3.76)	(3.56)	(1.71)	(1.56)	(1.56)
2	0.85	0.10	0.06	0.88	0.13	0.08	0.85	0.11	0.07
	(1.65)	(1.83)	(1.27)	(1.70)	(2.32)	(1.91)	(1.67)	(2.01)	(1.47)
3	0.79	0.03	0.03	0.76	0.00	−0.00	0.82	0.07	0.06
	(1.53)	(0.79)	(0.74)	(1.46)	(0.04)	(−0.11)	(1.59)	(1.74)	(1.54)
4	0.71	−0.05	0.01	0.67	−0.09	−0.03	0.78	0.01	0.05
	(1.35)	(−0.71)	(0.15)	(1.28)	(−1.23)	(−0.55)	(1.48)	(0.18)	(1.02)
5	0.52	−0.25	−0.10	0.50	−0.28	−0.13	0.66	−0.12	0.01
	(0.95)	(−1.77)	(−1.16)	(0.91)	(−2.09)	(−1.67)	(1.22)	(−0.96)	(0.11)
5−1	−0.46	−0.53	−0.32	−0.50	−0.57	−0.38	−0.18	−0.24	−0.12
	(−2.32)	(−2.66)	(−2.49)	(−2.78)	(−3.24)	(−3.32)	(−1.08)	(−1.50)	(−0.87)
				Panel D: $LSS - LDS$					
5−1				−0.32	−0.33	−0.26			
				(−3.00)	(−3.03)	(−2.72)			

Table 3: Regressions of future returns on short volume

We run regressions where the dependent variable is 21-day-ahead cumulative return (from day t to day $t+20$) and the independent variables (measured at day $t-1$) are LSS, LDS, and other control variables. The control variables are ILQ, $ActiveUtilization$, $ShortingFee$, RS, PI, $IntraVol$, $Beta$, $\log(Size)$, BM, $IdioVol$, R_{t-1}, $R_{t-5:t-2}$, and OIB. All variables are defined in Appendix A. All independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than $1 and market capitalization above the 10th NYSE size percentile at the end of day t. Columns (1)-(4) estimates are based on value-weighted Fama and MacBeth (1973) cross-sectional regressions, where we value-weight based on $Size$ of day $t-1$. t-statistics (in parentheses) are computed using Newey and West (1987) standard errors with 21 lags. Column (5) estimates are based on OLS regressions with day fixed effects and t-statistics are computed with standard errors clustered by day. Column (6) includes time and stock fixed effects and t-statistics are computed with standard errors clustered by day and stock. We omit the intercept and coefficients of control variables. The sample includes 2,385,741 observations from 2014 to 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
LSS	−0.18	—	−0.19	−0.19	−0.18	−0.18
	(−3.27)		(−4.08)	(−4.29)	(−9.51)	(−3.95)
LDS	—	−0.08	0.02	0.01	0.07	0.09
		(−1.46)	(0.39)	(0.41)	(3.29)	(2.27)
Controls	No	No	No	Yes	Yes	Yes
Method	FMB	FMB	FMB	FMB	OLS	OLS
Time FE	—	—	—	—	Yes	Yes
Stock FE	—	—	—	—	No	Yes
R^2	0.57	0.61	1.06	13.12	22.42	25.76

Table 4: Return predictability across different stock characteristics

We run Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is 21-day-ahead cumulative return (from day t to day $t+20$) and the independent variables (measured at day $t-1$) are LSS, LDS, and other control variables as in column (4) of Table 3, except that we include interactions of LSS and LDS with tercile indicator variables based on stock characteristics (shown in each column). All variables are defined in Appendix A. Except for indicator variables, all independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than \$1 and market capitalization above the 10th NYSE size percentile at the end of day $t-1$. t-statistics (in parentheses) are computed using Newey and West (1987) standard errors with 21 lags. We omit the intercept and coefficients on control variables. The last two rows present the sum of the coefficients on LSS or LDS and their interaction with High tercile indicator variable. The sample includes 2,385,741 observations from 2014 to 2018.

	$Size$	ILQ	R_t	$R_{t-5:t-1}$	RS	PI	$IntraVol$	OIB
LSS	−0.13	−0.22	−0.21	−0.19	−0.19	−0.20	−0.21	−0.20
	(−3.65)	(−3.90)	(−3.77)	(−3.25)	(−3.92)	(−3.53)	(−3.59)	(−3.34)
$LSS \times Mid$	0.07	0.13	−0.00	0.03	−0.03	0.05	0.05	−0.06
	(1.85)	(1.95)	(−0.06)	(0.70)	(−1.04)	(1.06)	(0.90)	(−1.50)
$LSS \times High$	−0.08	0.08	0.08	−0.00	0.08	0.05	0.08	0.04
	(−1.38)	(1.32)	(1.78)	(−0.01)	(1.81)	(0.83)	(0.98)	(0.71)
LDS	−0.13	0.04	0.00	−0.02	−0.01	0.06	0.06	0.03
	(−3.11)	(0.72)	(0.08)	(−0.39)	(−0.15)	(0.86)	(0.98)	(0.51)
$LDS \times Mid$	−0.01	−0.18	0.02	0.04	0.09	−0.13	−0.20	0.02
	(−0.40)	(−2.80)	(0.47)	(0.75)	(2.31)	(−1.79)	(−2.99)	(0.46)
$LDS \times High$	0.18	−0.11	0.00	0.05	−0.06	−0.14	−0.13	0.03
	(2.46)	(−1.57)	(0.02)	(1.00)	(−1.07)	(−1.66)	(−1.53)	(0.46)
$LSS + LSS \times High$	−0.22	−0.13	−0.13	−0.19	−0.11	−0.15	−0.14	−0.16
	(−4.10)	(−4.44)	(−2.70)	(−3.88)	(−2.71)	(−4.57)	(−3.51)	(−3.56)
$LDS + LDS \times High$	0.06	−0.07	0.00	0.03	−0.07	−0.09	−0.07	0.05
	(0.91)	(−1.88)	(0.10)	(0.62)	(−1.55)	(−1.75)	(−1.43)	(1.20)

Table 5: Return predictability across different samples

We run Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is 21-day-ahead cumulative return (from day t to day $t+20$) and the independent variables (measured at day $t-1$) are LSS, LDS, and other control variables as in Table 3. The two columns under the heading "Univariate" show the regression coefficients of LSS and LDS when the variables are used as single predictors in two separate regressions (as in columns (1) and (2) of Table 3). The two columns below the heading "Bivariate" show the regression coefficients of LSS and LDS when used jointly as predictors in one regression (as in column (3) of Table 3). The columns below "With controls" show the regression coefficients of LSS and LDS when we augment the regression with additional control variables (as in column (4) of Table 3). All variables are defined in Appendix A. All independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation. Different rows use different samples. Row (1) shows the baseline regression results from Table 3. The baseline sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than \$1 and market capitalization above the 10th NYSE size percentile at the end of day $t-1$ and the sample period is from 2014 to 2018. Row (2) uses the sample period from 2014 to June 2016. Row (3) uses the sample period from July 2016 to 2018. Row (4) uses the removes stocks below \$5 or below the 20th size NYSE percentile. Row (5) uses all stocks (without without price or micro-cap filter). Row (6) uses a sample of the largest 500 stocks based on market capitalization. Rows (7) to (9) considers different horizons of future returns as dependent variable. Row (10) uses the 5-day average of LSS and LDS at day $t-1$ as main dependent variable. t-statistics (in parentheses) are computed using Newey and West (1987) standard errors with 21 lags.

		Univariate		Bivariate		With controls	
		LSS	LDS	LSS	LDS	LSS	LDS
(1)	Baseline	−0.18	−0.08	−0.19	0.02	−0.19	0.01
		(−3.27)	(−1.46)	(−4.08)	(0.39)	(−4.29)	(0.41)
(2)	First-half	−0.22	−0.14	−0.20	−0.04	−0.15	−0.04
		(−3.32)	(−2.78)	(−2.86)	(−0.84)	(−1.98)	(−0.86)
(3)	Second-half	−0.15	−0.02	−0.19	0.08	−0.23	0.07
		(−1.61)	(−0.21)	(−2.92)	(1.05)	(−5.10)	(1.29)
(4)	No <\$5 or 20% micro	−0.17	−0.07	−0.18	0.02	−0.18	0.01
		(−3.18)	(−1.39)	(−4.06)	(0.42)	(−4.23)	(0.40)
(5)	No exclusions	−0.24	−0.11	−0.25	0.03	−0.25	0.03
		(−3.25)	(−1.34)	(−4.04)	(0.44)	(−4.43)	(0.50)
(6)	Largest 500	−0.15	−0.04	−0.18	0.06	−0.19	0.04
		(−2.92)	(−0.77)	(−3.96)	(1.16)	(−3.99)	(1.06)
(7)	$R_{t:t+4}$	−0.05	−0.01	−0.06	0.01	−0.05	0.02
		(−3.08)	(−0.76)	(−3.86)	(0.87)	(−3.61)	(1.17)
(8)	$R_{t+5:t+20}$	−0.09	−0.03	−0.11	0.03	−0.11	0.03
		(−2.13)	(−0.64)	(−3.02)	(0.80)	(−3.25)	(1.02)
(9)	$R_{t:t+39}$	−0.26	−0.13	−0.27	0.01	−0.24	0.00
		(−3.41)	(−1.86)	(−3.97)	(0.16)	(−4.38)	(0.08)
(10)	5-day average of X	−0.19	−0.07	−0.25	0.09	−0.21	0.05
		(−1.77)	(−0.65)	(−2.83)	(1.01)	(−3.00)	(0.88)

Table 6: Decomposing LSS volume

We first regress LSS_{t-1} on contemporaneous return (Ret_{t-1}), order imbalance (OIB_{t-1}), and intraday volatility ($IntraVol_{t-1}$). We then use the fitted values of this regression to define market-making component (LSS_{mm}), risk-bearing component (LSS_{rb}), and denote the residual as LSS_{res}. Panel B reports descriptive statistics on these components. Panel C uses these components in Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is 21-day-ahead cumulative return (from day t to day $t + 20$) as in Table 3. The control variables in column (4) in Panel C are the same as those in column (5) of Table 3 except that we do not include the variables used in the first-stage regression, namely Ret, OIB, and $IntraVol$. All variables are defined in Appendix A. All independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than \$1 and market capitalization above the 10th NYSE size percentile at the end of day $t-1$ and the sample period is from 2014 to 2018. t-statistics (in parentheses) are computed using Newey and West (1987) standard errors with 21 lags. The sample includes 2,385,741 observations from 2014 to 2018.

Panel A: First stage regression				
	Ret	OIB	$IntraVol$	R^2
Slope	33.58	17.69	0.09	9.72
	(22.34)	(92.72)	(6.76)	

Panel B: Future return predictability				
	(1)	(2)	(3)	(4)
LSS_{res}	−0.18	−0.18	−0.18	−0.17
	(−3.35)	(−3.35)	(−3.35)	(−4.36)
LSS_{mm}	−0.04	—	−0.04	1.04
	(−1.37)		(−1.37)	(0.46)
LSS_{rb}	—	−0.06	−0.06	−0.01
		(−1.14)	(−1.22)	(−0.26)
Controls	No	No	No	Yes
R^2	1.07	0.70	1.19	11.33

Table 7: Relation between future returns, short volume, and news

We run Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is 21-day-ahead cumulative return (from day t to day $t+20$) and the independent variables (measured at day $t-1$) are LSS, LDS, and other control variables as in Table 3, except that we include interactions of LSS and LDS with news indicator variables. $News$ is an indicator variable equal to 1 if a firm-specific news event occurs on day t, and 0 otherwise. $PosNews$, $NeutNews$, and $NegNews$ are indicator variables equal to 1 for firm-specific news event days, if the announcement day t return falls into the top, middle three, and bottom quintile of daily returns, respectively; and 0 otherwise. All other variables are defined in Appendix A. Except for indicator variables, all independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than \$1 and market capitalization above the 10th NYSE size percentile at the end of day $t-1$. t-statistics (in parentheses) are computed using Newey and West (1987) standard errors with 21 lags. We omit the intercept and coefficients on control variables. The sample includes 2,324,138 observations from 2014 to 2018.

	(1)	(2)	(3)	(4)
LSS	−0.19	−0.12	−0.12	−0.07
	(−3.91)	(−2.81)	(−2.81)	(−2.20)
LDS	0.02	0.00	0.00	−0.00
	(0.38)	(0.04)	(0.04)	(−0.11)
$LSS \times News$	—	−0.17	—	—
		(−2.64)		
$LDS \times News$	—	0.09	—	—
		(1.09)		
$News$	—	0.08	—	—
		(0.81)		
$LSS \times PosNews$	—	—	0.14	0.09
			(1.86)	(1.33)
$LSS \times NeutNews$	—	—	−0.17	−0.16
			(−2.29)	(−2.50)
$LSS \times NegNews$	—	—	−0.27	−0.24
			(−3.71)	(−3.10)
$LDS \times PosNews$	—	—	0.01	0.02
			(0.14)	(0.21)
$LDS \times NeutNews$	—	—	0.14	0.14
			(1.57)	(2.00)
$LDS \times NegNews$	—	—	0.09	0.12
			(1.33)	(1.71)
Controls	No	No	No	Yes
R^2	1.04	2.37	6.27	16.61

Table 8: Relation between future returns, components of LSS volume, and news

We run Fama and MacBeth (1973) cross-sectional regressions where the dependent variable is 21-day-ahead cumulative return (from day t to day $t+20$) and the independent variables (measured at day $t-1$) are components of LSS from Table 6, news indicator variables from Table 7, and other control variables from Table 6. All other variables are defined in Appendix A. Except for indicator variables, all independent variables are cross-sectionally standardized each day by subtracting the cross-sectional and dividing by cross-sectional standard deviation. The sample contains common stocks listed on the NYSE, AMEX, and NASDASQ with price greater than \$1 and market capitalization above the 10th NYSE size percentile at the end of day $t-1$. t-statistics (in parentheses) are computed using Newey and West (1987) standard errors with 21 lags. We omit the intercept and coefficients on control variables. The sample includes 2,324,138 observations from 2014 to 2018.

	(1)	(2)	(3)	(4)
LSS_{res}	−0.19	−0.11	−0.11	−0.08
	(−3.94)	(−2.43)	(−2.43)	(−2.64)
LSS_{mm}	−0.03	−0.05	−0.05	2.49
	(−1.12)	(−1.93)	(−1.93)	(1.52)
LSS_{rb}	−0.07	−0.06	−0.06	−0.02
	(−1.32)	(−1.40)	(−1.40)	(−0.40)
$LSS_{res} \times News$	—	−0.23	—	—
		(−3.02)		
$LSS_{mm} \times News$	—	0.06	—	—
		(1.04)		
$LSS_{rb} \times News$	—	0.39	—	—
		(0.84)		
$News$	—	0.04	—	—
		(0.37)		
$LSS_{res} \times PosNews$	—	—	0.07	0.03
			(0.76)	(0.35)
$LSS_{res} \times NeutNews$	—	—	−0.25	−0.24
			(−2.98)	(−3.34)
$LSS_{res} \times NegNews$	—	—	−0.25	−0.24
			(−3.32)	(−3.20)
$LSS_{mm} \times PosNews$	—	—	0.10	0.12
			(1.28)	(1.60)
$LSS_{mm} \times NeutNews$	—	—	0.13	0.11
			(2.05)	(2.09)
$LSS_{mm} \times NegNews$	—	—	−0.08	−0.03
			(−0.94)	(−0.40)
$LSS_{rb} \times PosNews$	—	—	2.43	2.15
			(2.54)	(2.81)
$LSS_{rb} \times NeutNews$	—	—	0.70	0.51
			(1.04)	(1.28)
$LSS_{rb} \times NegNews$	—	—	0.28	0.15
			(0.27)	(0.18)
Controls	No	No	No	Yes
R^2	1.61	3.32	7.76	16.39

Table 9: Anomalies and short volume

Each month, we assign decile ranks to stocks based on an anomaly. All variables are defined in Appendix A. Decile 1 (10) is the group of stocks associated with lower (higher) future returns. On each trading day of the subsequent month, we independently sort stocks into quintiles based on LSS and LDS. This tables presents the average rank of quintiles 1, 5, and the difference between 5 and 1. We report Newey and West (1987) adjusted (using 60 lags) t-statistics for the differences in parentheses. Panel A uses unorthognalized LSS and LDS while Panel B uses orthognalized $LSS^{\perp}$ and $LDS^{\perp}$. $LSS^{\perp}$ is the residual from cross-sectional regression each day of LSS on LDS. $LDS^{\perp}$ is the residual from cross-sectional regression each day of LDS on LSS. The sample periods is 2014 to 2018.

	1	5	5−1		1	5	5−1		5−1	
Panel A: Using unorthognalized LSS and LDS										
	LSS				LDS				$LSS-LDS$	
Net Stock Issues	7.07	6.11	−0.96	(−11.67)	6.71	6.42	−0.29	(−2.69)	−0.67	(−8.83)
Comp. Equity Issues	6.90	5.99	−0.90	(−10.37)	6.54	6.17	−0.37	(−3.91)	−0.53	(−12.50)
Accruals	5.72	5.62	−0.10	(−1.94)	5.73	5.69	−0.04	(−0.95)	−0.05	(−1.44)
Net Operating Assets	5.77	5.49	−0.27	(−3.51)	5.78	5.68	−0.11	(−1.48)	−0.16	(−3.49)
Asset Growth	5.75	5.40	−0.35	(−4.83)	5.69	5.55	−0.15	(−2.29)	−0.20	(−3.02)
Investments-to-Assets	5.91	5.23	−0.68	(−11.90)	5.93	5.30	−0.63	(−10.72)	−0.05	(−0.69)
Distress	8.33	6.66	−1.67	(−24.38)	8.06	6.97	−1.09	(−9.60)	−0.58	(−7.76)
Momentum	6.15	5.40	-0.75	(−8.17)	6.02	5.53	-0.49	(−5.84)	-0.26	(−5.36)
Gross Profitability	5.86	5.37	−0.49	(−9.05)	5.73	5.40	−0.34	(−4.47)	−0.15	(−3.52)
Return on Assets	7.04	5.96	−1.08	(−12.09)	6.82	6.12	−0.69	(−6.44)	−0.39	(−6.84)
Average	6.45	5.72	−0.72	(−23.65)	6.30	5.88	−0.42	(−9.44)	(−0.31)	(−10.66)
Panel B: Using orthognalized $LSS^{\perp}$ and $LDS^{\perp}$										
	$LSS^{\perp}$				$LDS^{\perp}$				$LSS^{\perp}-LDS^{\perp}$	
Net Stock Issues	6.99	6.09	−0.90	(−14.65)	6.32	6.61	0.29	(3.78)	−1.19	(−10.71)
Comp. Equity Issues	6.86	6.06	−0.80	(−15.51)	6.25	6.41	0.15	(2.73)	−0.95	(−17.07)
Accruals	5.68	5.56	−0.11	(−2.37)	5.63	5.69	0.06	(1.50)	−0.17	(−2.42)
Net Operating Assets	5.77	5.55	−0.22	(−3.62)	5.76	5.77	0.01	(0.22)	−0.23	(−2.73)
Asset Growth	5.73	5.40	−0.33	(−5.38)	5.60	5.60	−0.00	(−0.01)	−0.33	(−3.16)
Investments-to-Assets	5.79	5.35	−0.44	(−7.35)	5.78	5.43	−0.35	(−6.28)	−0.09	(−0.88)
Distress	8.07	6.77	−1.30	(−22.88)	7.47	7.31	−0.15	(−1.61)	−1.15	(−9.22)
Momentum	6.10	5.53	−0.57	(−8.27)	5.88	5.76	−0.12	(−1.93)	−0.45	(−5.30)
Gross Profitability	5.80	5.45	−0.35	(−9.11)	5.61	5.50	−0.10	(−1.62)	−0.24	(−3.52)
Return on Assets	6.90	6.03	−0.87	(−15.34)	6.41	6.38	−0.03	(−0.40)	−0.84	(−10.93)
Average	6.37	5.78	−0.59	(−26.32)	6.07	6.05	−0.02	(−0.73)	−0.57	(−12.69)

Table 10: Anomalies and components of LSS volume

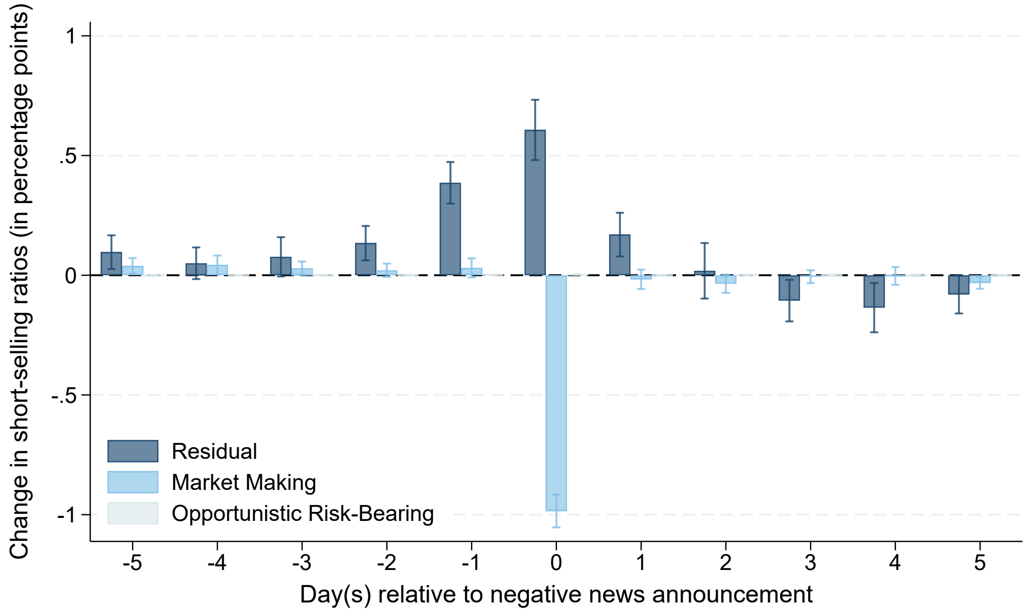
Each month, we rank stocks into ten deciles based on an anomaly. All variables are defined in Appendix A. Decile 1 (10) is the group of stocks associated with lower (higher) future returns. On each trading day in the subsequent month, we independently sort stocks into quintiles based on LSS_{res}, LSS_{mm}, or LSS_{rb} from Table 6 in ascending order. This table presents the average rank (from 1 to 10) of each anomaly for quintiles 1, 5, and the difference between 5 and 1. We report Newey-West adjusted (using 60 lags) t-statistics for the differences in parentheses. The sample periods is 2014 to 2018.

	1	5	5−1		1	5	5−1		1	5	5−1	
	LSS_{res}				LSS_{mm}				LSS_{rb}			
Net Stock Issues	7.03	6.13	−0.89	(−10.83)	6.65	6.21	−0.43	(−13.44)	6.63	5.70	−0.93	(−5.11)
Comp. Equity Issues	6.89	5.99	−0.90	(−10.42)	6.43	6.39	−0.05	(−1.18)	6.33	5.77	−0.56	(−4.54)
Accruals	5.73	5.62	−0.11	(−2.30)	5.60	5.71	0.11	(4.04)	5.68	5.32	−0.36	(−4.36)
Net Operating Assets	5.76	5.49	−0.27	(−3.66)	5.74	5.63	−0.11	(−4.23)	6.15	5.97	−0.18	(−4.07)
Asset Growth	5.74	5.41	−0.33	(−4.88)	5.68	5.46	−0.22	(−8.23)	5.64	5.51	−0.12	(−2.73)
Investments-to-Assets	5.89	5.23	−0.66	(−12.46)	5.68	5.46	−0.22	(−8.40)	5.73	5.70	−0.03	(−1.12)
Distress	8.31	6.69	−1.62	(−24.28)	7.56	7.17	−0.39	(−7.89)	7.70	6.18	−1.52	(−5.07)
Momentum	6.15	5.38	−0.77	(−8.87)	5.85	5.84	−0.01	(−0.26)	5.87	5.78	−0.09	(−1.10)
Gross Profitability	5.84	5.36	−0.48	(−9.07)	5.65	5.57	−0.07	(−1.83)	5.62	5.54	−0.08	(−3.16)
Return on Assets	7.03	5.95	−1.07	(−11.82)	6.51	6.29	−0.22	(−4.42)	6.48	5.80	−0.68	(−5.00)
Average	6.43	5.72	−0.71	(−23.07)	6.13	5.97	−0.16	(−8.17)	6.18	5.73	−0.45	(−5.01)

Figure A1: Components of LSS around news event days including risk-bearing component

This figure shows the change of the residual, the market-making component, and the risk-bearing component of LSS in percentage points around firm-specific news events. Each bar is based on a panel regression with stock and day fixed effects. The dependent variable is one of the daily components of LSS and the independent variable of interest is an indicator variable that takes the value one if a news story occurs and zero otherwise. In each regression we vary the timing of the dependent variable relative to the news event to examine short-volume changes around news. For example, $t-1$ indicates that the dependent variable is observed 1 day prior to the news event. To control for the response of short sellers to past returns, we include five day lags of daily returns (where the lags are relative to the timing of the dependent variable). In Panel A and Panel B we examine changes in components of LSS around negative and positive news events, respectively. We define a news event as negative (positive) if the announcement day return is in the bottom (top) quintile of returns on a given day, respectively. The sample period is 2014 to 2018.

Panel A



Panel B

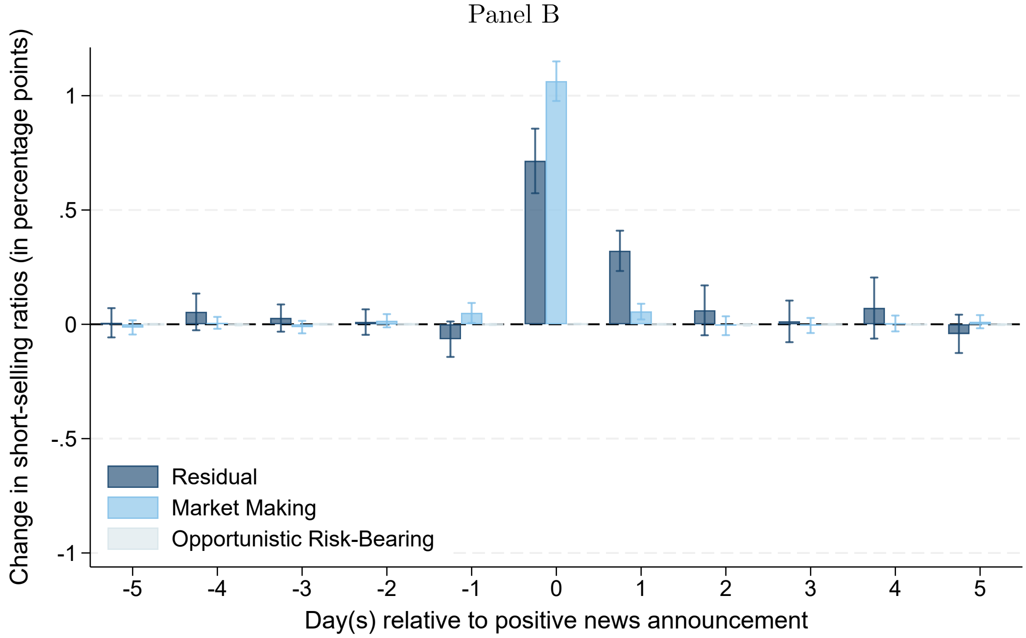


Figure A2: Intraday short volume

This figure shows the percentage of liquidity-demanding and liquidity-supplying short-selling volume within 30-minute intervals as a proportion of the total daily short-selling volume (Panel A) and as a proportion of the trading volume within the same 30-minute interval (Panel B). White bars represent the volume of liquidity-demanding shorts (LDS), while striped bars indicate liquidity-supplying shorts (LSS). The sample period is 2014 to 2018.

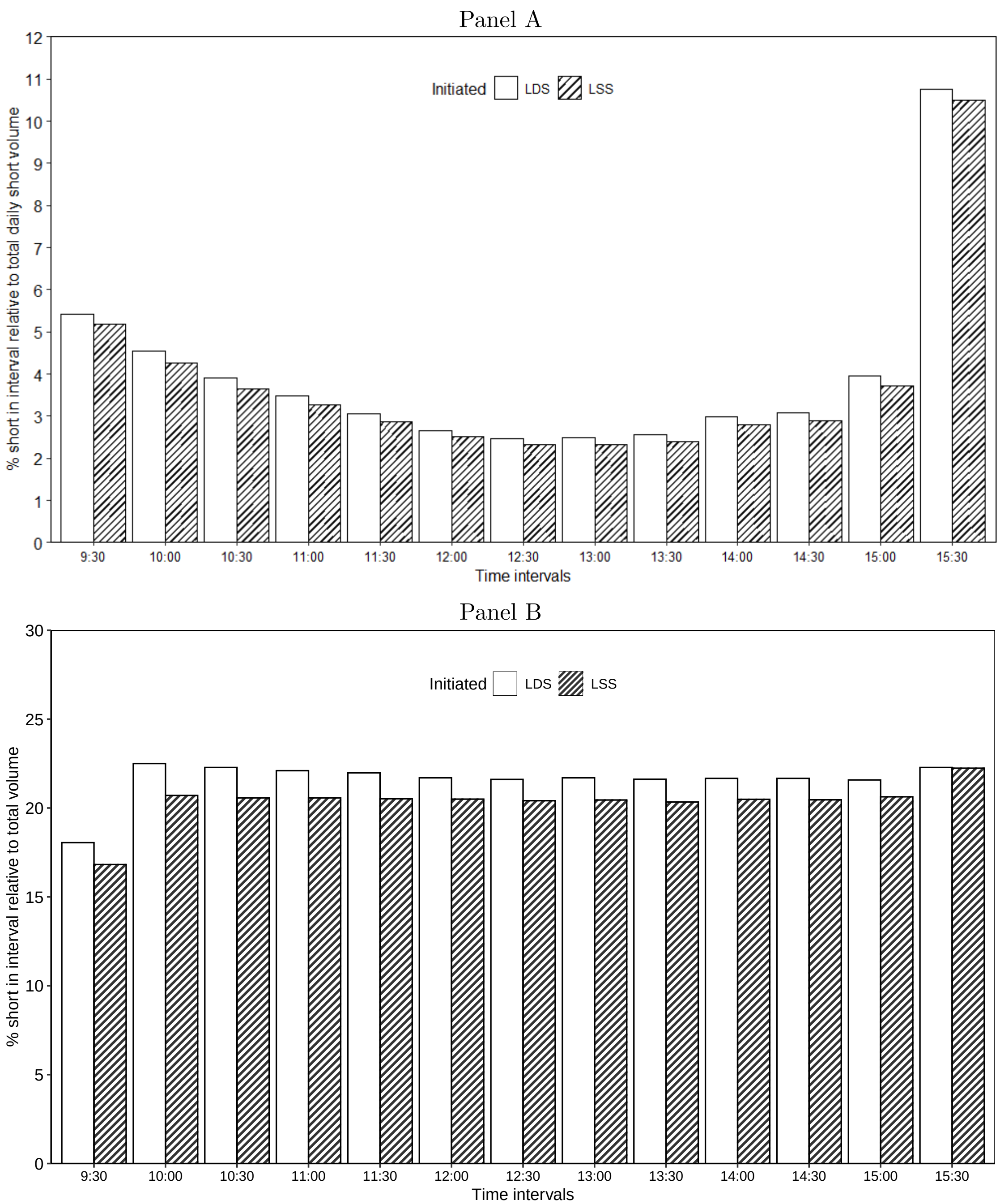


Figure A3: Predictability of future returns from Intraday short volume

The figure shows Fama and MacBeth (1973) coefficients estimated from the regression of future 21-day return on intra-day short volume. The error bars denote the 95% confidence intervals. White bars represent the volume of liquidity-demanding shorts (LDS), while striped bars indicate liquidity-supplying shorts (LSS). The sample period is 2014 to 2018.