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Are Short-sellers Different?

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Abstract

While theoretical models strongly suggest that short-sales are mainly driven by private information, recent empirical evidence of has been rather mixed. This paper contributes to the discussion by looking at various potential motives to sell short and compares these with regular buys and sales with regards to variation in the information contents and timing of short-sales. We find that short-sellers have different private information than regular buyers and sellers, which seems to have a longer life-time, being related to previous buying pressure. The information advantage of short-sellers seems originating from skilled analysis of publicly available data rather than corporate insider information. Short-sales provide an important stabilizing role by providing liquidity in periods of uninformed buying pressure. Overall, we find that short-sales are driven by multiple trade motives, which sets short-sellers apart from regular buyers and sellers.

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1 Introduction and Motivation

Throughout the financial economics literature, short-sellers are associated with market participants who keep prices in line with fundamentals (see, e.g., Harrison and Kreps (1978)).[1] In particular, they move down prices that previous buying pressure has moved above fundamental value. This characterization rests upon the understanding that investors who sell short face the same environment and transaction costs than buyers. In reality, however, short-sales are more difficult to implement than regular buy and sell transactions due to additional costs and regulatory difficulties (see D'Avolio (2002)).[2] This asymmetry in costs between short and long transactions motivates the argument that short-sales should carry more information than long transactions (Diamond and Verrecchia (1987)) and is reflected in the different information characteristics of short sales as compared to long transactions, as we find in our empirical analysis. At the same time, the more difficult it is to sell short, the less efficient the price process should be, which we also find in our empirical results. We therefore investigate whether short-selling restrictions affect price efficiency.

While short-sellers therefore seem to improve the flow of price-relevant information into prices, it is less clear whether short-sellers have better access to private insider information, than public investors. In that case, short-selling activity would be a negative contribution to financial markets as it imposes adverse selection costs on financial markets. Alternatively, if short-sellers merely express a view about fundamental values, there remains a chance that they are wrong, in which case they would impose no adverse selection costs to their counter parties. By comparing

[1] The SEC defines a short-sale as "any sale of a security which the seller does not own or any sale which is consummated by the delivery of a security borrowed by, or for the account of, the seller" (SEC (1999)).

[2] The so-called "tick test" laid out in Rule 10a-1 of the Securities Exchange Act of 1934 provides that a stock can only be sold short "at a price above the immediately preceding reported price or at the last sale price if it is higher than the last different reported price" (SEC (2006)). Transactions that are always exempt from these short-selling restrictions are typically trades by market makers (SEC (2003)).

and contrasting short-sales with regular buy and sale transactions, this study helps putting short-sellers into perspective relative to the investor community who derive their private information from either insider information or from skilled analysis of public data.

Short-sellers theoretically have two opposing effects on financial markets. On the one hand, they are considered to improve informational efficiency. On the other hand, they may impose adverse selection costs and consume liquidity, depending on their private information sets.[3] Diether, Lee and Werner (2005) find evidence for contrarian trading behavior of short-sellers. For contrarian trading to be profitable, however, short-sellers must be able to differentiate between random price fluctuations and changes in fundamental value. Taking short positions in the former situation would lead to profits while losses would accrue in the latter situation. This implies that contrarian short-sales are likely to be implemented by informed value-traders who exploit private information about fundamental values and the stock-market environment while providing liquidity to the financial markets. The third main research focus of this paper therefore is the effect of short-sales on financial market quality.

This paper uses the recently available intra-day transaction-level short-sale data. In January 2005, a large set of U.S. stocks experienced a provisional suspension of short-selling restrictions while intra-day data of short-sales as part of *Reg SHO*[4], allowing the investigation of the information content of short-sales, the impact of short-sales on market quality, and the interaction of the market environment and short-selling activity. Looking at short-sales on a tick-by-tick basis is not entirely unique to this study. However, most intra-day studies of short-sales

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[3] Informed investors are general considered to consume liquidity, as the private information they exploit loses its value as soon as it is known to the public (Harris (2003, p. 226)). However, traders with private information derived from the analysis of firm-level data, referred to as value traders, also supply liquidity if uninformed traders push prices away from fundamentals (Harris (2003, p. 339)).

[4] As of January 3, 2005, Regulation SHO has been introduced to "exclude designated securities from the operation of the tick test of Rule 10a-1 (see footnote 2) and any short-sale price test rule of any exchange or national securities association for a designated period of time" (SEC (2005)) to "study the impact of relaxing the price tests" (SEC (2006)). Short-selling restrictions are suspended for around 1,000 pilot stocks selected from the Wilshire 3,000 index (SEC (2004)). In addition, short-sales are now masked, i.e., indiscernible from regular sales, which closer corresponds to the trading environment in theoretical models of short-sales. The list of these so-called "pilot" stocks can be downloaded from http://www.nyse.com/regshopilot.

either have a relatively small sample that limits the scope of cross-sectional comparison, or rely on data from non-U.S. markets, with market features not comparable to most empirical studies.[5]

The results of this paper add to the understanding of market quality and are potentially interesting to regulators and other market participants as short-sellers, while being apparently informed, seem to improve price efficiency and financial market liquidity. In addition, as this paper looks at potential sources of private information of short-sellers and thereby addresses academic discussions around the origins and nature of short sellers' private information. In addition, to our knowledge, comparing the microstructure characteristics and informativeness of short-sales with regular transactions is new to this study and likely helps to improve the interpretability, academic relevance, and robustness of our results.

The empirical results show that short-sales appear to be an important source of liquidity, especially during times of short-term buying pressure. Short-sellers seem to be able to distinguish informed from uninformed buying pressure and to mostly provide liquidity to the latter. Therefore, short-sales seem help aligning prices with fundamentals and appear providing short-term liquidity. Compared to regular buyers and sellers, short-sellers information set has a longer life-time, is more firm-specific and increases with illiquidity of the stock of the firm.

The average informed short-seller seems to be a skilled information analyst of the trading environment and the current economic situation. Short-selling restrictions appear to reduce price efficiency, implying that short sales are an important component of efficient financial markets. Also, short-sales done outside the NYSE are less likely to carry information and seem to be driven by hedging motives and inventory management. The remainder of this paper is structured as follows. Section 2 provides a review of the extant literature, and Section 3 develops the main

[5] Aitken, Frino, McCorry, and Swan (1998), for instance, look at intra-day reactions of 150 stocks at the Australian Stock Exchange (ASX). Unlike the NYSE, the ASX is a limit order market that immediately discloses the execution of a short-sale. These features likely affect price discovery and market reaction to short-sales. Boehmer, Jones, and Zhang (2006) use only part of the orderflow (NYSE SuperDOT orders instead of all transactions), while Diether, Lee, and Werner (2006) use only six months of data.

hypotheses this paper intends to address. Section 4 describes the data set, Section 5 the results, while Section 6 concludes.

2 Literature Review

Short-selling and buying transactions are necessary in theory to make prices reflect the consensus view of economic prospects. Short-selling restrictions, however, may lead to upwardly biased prices (Harrison and Kreps (1978); Miller (1977)) and a negative return drift (Diamond and Verrecchia (1987)) and thus make short-selling strategies appear more profitable on paper than reality admits (Géczy, Musto, and Reed (2002); Jones and Lamont (2002); Miller (1977)). Short-sales may even be necessary to offset generally positively biased analyst forecast and to impound private information into prices (Cohen, Diether, and Malloy (2006); Desai, Ramesh, Thiagarajan, and Balachandran (2002); Pownall and Simko (2005)). Regulators typically restrict short-selling activity, however, to limit their perceived destabilizing effect on financial markets.[6] Thus, while theoretically necessary to make prices efficient, short-sales are restricted in practice.

Regulatory restrictions and high cost of short-selling[7] make researchers conclude that short-sales contain price-relevant negative information (Diamond and Verrecchia (1987)), which Aitken, et al. (1998) empirically confirm when looking at the price reaction to the publication of short sales. Short-selling restrictions may therefore only be relevant when mispricing already exists (Ofek, et al. (2004)). In practice, however, short-selling activity may actually be dominated by uninformed trades (Daske, Richardson, and Tuna (2005)) due to tax-related trading, hedging options traders, dividend capture strategies (Senchack and Starks (1993)), convertible and index arbitrage (Brent, Morse, and Stice (1990)), and merger arbitrage (Reed (2003)). As a result, some empirical studies find no or only weak evidence for short-sales to contain private information

[6] See Finnerty (2005) and Shkilko (2007) for discussions of "manipulative" and "predatory" short-selling.
[7] See D'Avolio (2002) for a detailed description of the stock lending market.

(Brent, et al. (1990); Daske, et al. (2005); Richardson (2003)).[8] Other empirical studies conclude, however, that short-sales contain private information about future returns.[9] Shorting demand, for instance, is identified as a driver of negative returns during periods with weak public news flow (Cohen, et al. (2006)). Short-sales therefore seem to be based on a multitude of trade motives, which may or may not exploit private information.

If short-sellers are informed, the next question one may ask is what kind of information they exploit. Some empirical studies suggest that informed short sellers derive their private information from financial data (Dechow, et al. (2001)), which cannot confirm using accrual data. As financial statements are low frequency data, this suggests that informed short-sellers may use information that is updated more frequently. The contrarian trading behavior of short sellers makes past returns a likely source of private information (see also Desai et al. (2002)). Finally, as corporate insiders are particularly well informed investors (see, e.g., Lakonishok and Lee (2001)), it is likely that informed short-sellers also exploit insider information (Diether, et al. (2005, 2006)). The relationship between short-selling activity and future stock returns is stronger if there are no exchange-traded stock-options (Christophe et al. (2004)), if institutional ownership is larger (D'Avolio (2002)), and if analyst coverage of the stock is low (Pownall and Simko (2005)). This evidence suggests that short-sellers possess private information that other sophisticated investors, such as institutional traders, also exploit.

The various ways to capture the activity and information contents of short-sales may be the cause that some studies find while other studies fail to find evidence for short-sales to be

[8] Most of these studies look at the combination of short-selling activity and subsequent returns around information events. This assumes that short-sellers know in advance not only the content but also the timing of the surprise, which is typically available only to corporate insiders. Attributing these two pieces of private information to all short-sellers therefore is a strong an assumption as Francis, et al. (2005) point out. This narrow focus of the research design may be among the reasons that so few studies find evidence for private information to be used by short-sellers as this empirical set-up only tests the use of insider information by short-sellers.

[9] Asquith, Pathak, and Ritter (2005), Desai, et al. (2002), Géczy, et al. (2002), Jones and Lamont (2002), and Ofek, Richardson, and Whitelaw (2004) find a significant relationship between rebate rates, the interest paid for borrowing stocks, and subsequent monthly returns. Boehmer, et al. (2006), Dechow, Hutton, Meulbroek, and Sloan (2001), Diether, et al. (2005), Francis, Venkatachalam, and Zhang (2005), Senchack and Starks (1993) confirm the relationship of short-selling activity and information contents of trades over shorter horizons.

informed. Widely used measures are *short interest*, the level of borrowed stock, and the *rebate rate*, the "interest rate" paid on the borrowed.[10] The negative relationship between stock options and these measures of short-selling activity is commonly attributed to the existence of informed traders who prefer using the options market (Christophe, et al. (2004)). Alternatively, this relationship may also be due to uninformed short-selling from options traders. As rebate rates also reflect supply conditions the stock lending market (Cohen, et al. (2006)) it appears that these measures are noisy in capturing the activity and information content of short-sales.

Unlike most previous studies, we directly measure the information content and the trading activity of short-sales. This allows looking at the different motivations to sell short, the impact on market quality of the individual trade motivation, and the likely information set used by informed short-sellers. This paper therefore adds to the existing literature by studying trade motivations that are behind observed short-sales, the information content of short-sales and its potential sources and the impact of short-sales on market quality.

3 Testable Hypotheses

As short-sales can be informed or uninformed, the first research question is whether short-sales carry private information and if so, whether they use public or private information to generate their information advantage. The distribution of profits of short-sales, for instance, should be symmetrically distributed around zero if short-sales are completely uninformed; if short-sales carry private information one would expect more mass over the positive orthant, however. Looking at the distributional properties of short-sales relative to regular transactions allows

[10] Monthly short interest is used by Asquith, et al. (2005), Brent, et al. (1990), Dechow, et al. (2001), Desai, et al. (2002), Francis, et al. (2005), Pownall and Simko (2005), Richardson (2003), and Senchack and Starks (1993). Weekly short interest is used by Cohen, et al. (2006) while Géczy, et al. (2002) use daily short interest. The rebate rate is used by Cohen, et al. (2006), D'Avolio (2002), Géczy, et al. (2002), Jones and Lamont (2002), Ofek, et al. (2004), and Reed (2003). Amongst the rare cases where short-selling activity is measured on a high-frequency basis are Aitken, et al. (1998), Boehmer, et al. (2006), Christophe, Ferri, and Angel (2004), Daske, et al. (2005), and Diether, et al. (2005, 2006).

getting a first impression of whether informed short-sellers are likely to use the same set of private information than informed traders that use regular buy and sale transactions.

The second research question investigates the public source of private information further to identify whether they use market-wide or stock-specific information. Short-sellers with private information should be more active around price-relevant information events, such as earnings announcements. If short-sellers have insider information, they should know the timing, the direction, and the size of the surprise component of public announcements and anticipate the price reaction to the public announcement accordingly. An informed trader does not necessarily need to have insider information, however. Kim and Verrecchia (1994, 1997) model a trader who receives only public information but is particularly fast and skilled in correctly interpreting these data in terms of likely future price moves. Therefore, short-sellers who on average do not take positions before price-relevant news announcements but rather react quickly to the publication of important information are likely to be – on average – skilled information analysts.

The next question is whether short-sellers exploit public data that refer to only a single stock, whether they use public data that apply to many stocks at once, or whether they rely on a mixture of both.[11] Comparing short-sales with regular buys and sales can thereby help putting the information structure of short-sales into perspective. If short-sellers possess more value-relevant firm-specific information, the activity and information contents of short-sales should be less strongly related to market-wide movements than regular buys and sales. The relationship between the information contents of short-sales and firm-level characteristics, market conditions, and trading characteristics further allows characterizing the information environment of short-sales.

The third research question is about whether short-sales are a positive or negative contribution to the financial markets by affecting price efficiency and financial market liquidity.

[11] Private information about systematic return factors that apply to many stocks at once feature in the theoretical models by, for instance, Admati (1984), Hughes, Liu, and Liu (2005), and Subrahmanyam (1991).

If short-sellers actively take positions based on their private information, e.g., derived from insider information, they should consume liquidity (Harris (2003, p. 226)). Short-sellers supply liquidity, however, if they rather react to changes in the trading activity of uninformed momentum traders. In addition, short-selling activity may be destabilizing to financial markets if it is based on insider information and therefore the public investor rightly associates short-selling activity with adverse selection potentially resulting in large drops in liquidity and price levels. Alternatively, if short-sellers merely express a view, potentially one that is based on the analysis of public information, adverse selection costs associated with short-sales may be less severe, as short-sellers merely make an, albeit educated, guess regarding fundamental values, which includes the possibility that they could be wrong and thereby impose no adverse selection costs to their counter party. We therefore test whether short-sellers supply or demand liquidity and whether the removal of short-selling restrictions affects stock-price volatility. If they consume liquidity, they may be more destabilizing on average. If prices become less volatile after the removal of short-selling restrictions, one could conclude that they improve financial market stability.

4 Data Definition and Construction

The data covers the time period between January 2005 and December 2005. All variables are expressed in daily frequency. Daily stock returns, closing stock-prices, the number of shares outstanding and four-digit SIC codes are from CRSP. Firm size is measured by the market capitalization defined as the product of the shares outstanding and the closing stock price. Stock-level volatility is defined as squared daily returns while market-level volatility is captured by the new methodology VIX index.[12] Momentum returns are the cumulative daily returns over the past five trading days and tick size is measured by the inverse of the stock-price. Industry

[12] The new methodology VIX index is downloaded from the website of the CBOE: http://www.cboe.com/micro/vix/introduction.aspx.

classification is based on the 48 -industries, which are condensed to 19 industry groups. The one-month Treasury bill rate as the risk-free rate and the Fama and French (1993)-factors (SMB, HML, and the return on the market in excess of the risk-free rate) are retrieved from the Fama-French database on WRDS. Daily abnormal stock returns are calculated as the residual of a regression of daily stock returns in excess to the risk-free rate on the three -factors. Market-adjusted stock returns are calculated as the residual of a regression of daily excess stock returns on market excess returns.

Non-missing COMPUSTAT data are winsorized at the first top and bottom percentile and missing items are set to zero. These data are used to calculate the book-to-market ratio, defined as the sum of common equity (item 60), investment tax credits (item 208), and deferred taxes (item 74) less the total value of preferred shares (items 56, 130, and 175) divided by firm size. Research and development (hereafter R&D) expenses are calculated as the ratio of research and development expenses (item 46) to total sales (item 12). Capital expenditures (hereafter Capex) are defined as the ratio of capital expenditures (item 128) to total sales.

Quarterly earnings announcement dates are downloaded from I/B/E/S. Post announcement returns are alternatively calculated as the cumulative sum of daily stock returns, daily market-adjusted returns, or daily abnormal returns during the five days following and including the announcement day.

Intra-day TAQ data are used to calculate daily stock-level bid-ask spreads as the time-weighted daily average of the intra-day NBBO percentage spread. The trade direction for each transaction is inferred using the Lee and Ready (1991)-algorithm, which matches trades with quotes posted at least five seconds before the trade is executed. Daily share order-imbalance is the net of all shares bought and sold on a particular day. Standardized inventory is calculated as the share order-imbalance multiplied by minus one and normalized to a stock-level mean of zero and standard deviation of one. Dollar order-imbalance is calculated as the residual from a regression of the daily U.S. dollar volume sold short scaled by firm size on the net of daily U.S. dollar volume bought and sold also scaled by firm size.

The TAQ Reg SHO data set provides, for NYSE-listed stocks, the timing, price, and share volume of short-sales together with an indicator showing whether a particular transaction is exempt from short-selling restrictions.[13] The daily U.S. dollar volume sold short is calculated as the daily sum of the product of the transaction price and the number of shares sold short. Short turnover is calculated as the ratio of U.S. dollar volume sold short to firm size. Matching regular TAQ data with TAQ Reg SHO by the time-stamp, allows identifying the exchange where a particular batch of stocks has been sold short. We simplify the trade-venue information to trades done on the NYSE, *NYSE trades*, and *Off-NYSE trades*.[14] The list of pilot stocks that are permanently exempt from short-selling restrictions as part of Reg SHO is available on the NYSE web site.[15]

To be included in the CRSP-sample, a stock needs to be ordinary common stock of a U.S. firm with main listing on the NYSE that is not a trust, a closed-end fund, or a REIT. The TAQ-sample excludes data with the time-stamp earlier than 9:30 AM or later than 4:00 PM. In addition, price, quote, and volume data that are out of sequence, with special settlement conditions, that are corrected, negative, or that lead to bid-ask spreads that are negative, above five U.S. dollars, or larger than 40 percent of the quote mid-point are excluded. To be included in the final sample, each daily stock-level observation is required to have TAQ and CRSP data and

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[13] Trades identified as being exempt from short-selling restrictions may sometimes contain a non-exempt portion, which the data set does not allow to disentangle. Note that these trades do not refer to short-sales of pilot stocks. Trades that are only temporarily exempt from short-selling restrictions are referred to as "exempt trades".

[14] The (known) trade direction of short-sales is superimposed on the direction inferred from the -algorithm. It turns out that the Lee and Ready (1991)-algorithm has a tendency to classify short-sales as buys. This is likely the result of short-sellers to sometimes set their quotes a whisker above the quote mid-point to induce an up-tick, which improves the likelihood of their order getting executed. By superimposing the known trade direction of short-sales on the data-set where the trade-direction is inferred using the Lee and Ready (1991)-algorithm, we correct for this problem. Alternatively, Ellis, Michaely, and O'Hara (2000) improve the Lee-and-Ready algorithm for Nasdaq data by using the tick-rule for all trades that do not exactly hit the bid or ask quote. Whether this adjustment also works for hybrid markets, such as the NYSE, is not clear, however.

[15] See: http://www.nyse.com/regulation/memberorganizations/regsho.shtml.

to be in COMPUSTAT. The resulting data set has daily observations for 1,485 individual stocks. Market averages of bid-ask spreads, momentum-returns, order-imbalance, turnover, and information content of short-sales are calculated as the market capitalization-weighted average across the intersection of the CRSP-sample and TAQ-sample.

The information content of short-sales is captured by a direct measure of the adverse selection loss of the counter-party to the short-seller. In the absence of private information, this measure should be zero on average. Presuming that the counter-party of a short-sale has, on average, all publicly available information, this is a trade-based measure of the information content of a short-sale transaction on a high frequency basis. Hasbrouck and Sofianos (1993) and Huang and Stoll (1996), for instance, use a similar measure to capture adverse selection losses. The latter use the difference of the quote mid-point at the time of the transaction and the transaction price some time later. Hasbrouck and Sofianos (1993) or Huang and Stoll (1996) use the scaled difference of the transaction price and the quote mid-point over a fixed time interval to improve the comparability over unequally spaced transaction times. We use a measure based on Naik and Yadav (2003), who replace transaction prices by the quote mid-point and thereby address trade-price related problems due to the bid-ask bounce:[16]

$$IA_t = D_t \left(M_T - M_t \right) / M_t \,, \tag{1}$$

where D_t is the trade direction and M_t and M_T are the quote mid-points when the trade is submitted at time t and a later point in time, T. Taking the daily trade size-weighted average, this measure is fairly robust as it consists of many data-points and allows the inclusion of trade size as an additional information-related variable. Following Bessembinder and Kaufman (1997), quotes in effect five seconds before the reference trade are used.[17]

[16] See Lease, Masulis, and Page (1991) for empirical biases that can arise from the bid-ask bounce.
[17] This paper makes use of time intervals of 15, 30, and 60 minutes, and one up to ten trading days matched with the reference transaction by the second.

Employing a return measure, which *IA* represents, to capture the information contents of short sales has also been employed by Boehmer et al. (2006). The advantage of our method is that it looks at shorter time horizons from intra-day to one week, whereas consider a monthly horizon. This allows us to investigate the information characteristics of short sales more closely, which we find to differ most substantially from regular transactions intraday. In addition, using a stock-level variable allows us to construct further stock-level measures of the information characteristics of short sales, such as the level of information derived from market-wide and stock-specific information.

Summary statistics are shown in Table 2. The numbers in the column *Obs.* of capital expenditure, R&D expenses, and block-ownership are much lower than the numbers of the other stock-level data as the summary statistics only use unique observations. As balance sheet data are typically updated once every fiscal year, there are only between 1,000 and 2,000 unique observations of these data items. Likewise, as the market-environment variables are the cross-sectional averages of the daily realization of the respective stock-level variables, there are only 252 individual observations for each of the market-level data series, which corresponds to the number of trading days. The sample contains over 5,000 post-announcement return observations, suggesting that there are four earnings announcements for almost all stocks in the sample. Average raw announcement returns are positive but drop to zero when adjusted for the three -factors. The average monthly momentum returns are also positive. The large difference between means and medians of share order-imbalance, bid-ask spreads, firm size, capital expenditure, research and development expenses, and block-ownership suggest that these data are fairly skewed.

More importantly, the information characteristics of short sales therefore appear to be different from the information characteristics of regular transactions. This surprising characteristic is investigated more in-depth in the subsequent sections. The data reveal that short-sellers make losses intra-day, which is different to average *IA*-values calculated across buy and sell transactions over intra-day horizons (see Table 2).

5 Analysis of Short-sales

This section initially characterizes the information content of short-sales in general and around firm-specific information events in particular. Subsequently, we look at whether short-sellers' private information is based on market-wide and stock-specific insights and what the relative importance of each of these pieces of information is. Finally, we evaluate whether short-sales are a positive or negative contribution to financial markets by looking at the impact of short sales on liquidity and how the partial suspension of shorts-selling restrictions affected price efficiency.

5.1 General Information Characteristics of Short-sales

Figure 1 and Table 2 provide the empirical distribution and summary statistics of *IA* for short sales, regular sales, and buys estimated over several horizons. *IA* should be evenly distributed around zero if short-sales are completely uninformed. It turns out that *IA* of short sales, buys and regular sales is roughly symmetrically distributed around zero with slightly more weight in the positive half of the distribution (see Panels A and B in Figure 1), which is consistent with the positive means and medians of *IA* over the same horizons (see Table 2), indicating that traders, whether they use short sales or regular transactions, have some private information on average. The shape of the *IA* distribution of short sales differs from the shape of regular sales and buys, however. Looking at the different horizons over which *IA* is estimated, we observe that the *IA* distribution of short-sales remains fairly symmetrically shaped which is not the case for the *IA* distribution of regular sales and buys. The distribution of intraday *IA* of regular sales and buys is positively skewed while *IA* of short-sales is negatively (see also Table 2). This suggests that these trades carry more short-term information than short sales do.

Over longer horizons, however, we observe that the *IA* distribution has fatter tails demonstrated by the substantially larger kurtosis statistics (see Table 2) as compared to short sales, suggesting that large positive and negative *IA* is more common for short sales than with regular sales and buys. This in turn suggests that these transactions carry less information over longer horizons than short sales as the mass of their *IA* distribution is more strongly centered around zero as for short sales, which is also suggested by the mean and median values shown in Table 2. Furthermore, the annualized mean values show that the information contents of short sales rises until levels off at the horizon of five days, whereas the information contents of regular sales and buys decreases steadily the longer the *IA* horizon, which suggests that the information horizon of short-sellers is typically several days long whereas the information horizon of regular transactions is much shorter.

The characteristics of short-sellers' private information therefore seems to be different from the information set regular traders have, which is also supported by the highly significant Wilcoxon Rank Sum statistic to test the null hypothesis of equality in medians between short-sales and the regular buys and sales.[18] While making larger gains over longer horizons, short-sellers seem to lose intraday, which is contrary to the finding of and potentially reflects the difference in market structure between the ASX and the NYSE. In addition, the pattern of *IA* suggests that although short-sellers typically turn over their positive quicker then long-only investors[19], informed short-sellers hold their positions for at least one trading session. This seems reasonable given the additional complications in establishing short positions (see D'Avolio (2002)) that may inhibit quick intra-day turnover.

[18] We also run a paired observation t-test. As the distribution of the difference between *IA* of short-sales and *IA* of regular buys and sales calculated over the same horizon is highly non-normal, a non-parametric test, such as the Wilcoxon Rank Sum test, seems more appropriate.

[19] The life time of the average short position is about 37 days while the average long position has a lifetime of about 1.2 years (Boehmer, et al. (2006)).

Panel A of Table 2 further shows that the difference in the level of private information between short-sellers and regular traders depends on liquidity, the systematic risk of the firm, and the firm-size. In particular, for short-horizons, short-sellers appear to be less informed than regular traders the larger the systematic risk (measured by the market beta), the higher the book-to-market value, and the higher the tick-size, and the lower the liquidity and the firm size. Some of these factors may reflect the difficulty that short-sellers have to quickly exploit their private information (e.g., liquidity, firm-size, and tick-size) which puts them at a disadvantage relative to regular traders. The fact that this relationship mostly reverts if one increases the *IA* horizon suggests that short-sellers may not be simply less skilled than the other traders but may exploit their information differently, which in addition may have a different life-span as compared to regular traders.

Furthermore, the negative intra-day *IA* means that, on average, short-sellers do not seem to precipitate price declines, as this would result in a positive intra-day *IA* suggesting that destabilizing short-sellers as modeled by Shiloh (2007) are only a minority. Short-sellers seem to benefit from a price reversal, which is even more surprising given that the overall average stock returns over the sample period are positive (see Panel C of Table 2). This suggests some preliminary evidence that short-sellers possess some skill to time their trades. Large surprises, however, do not seem to be anticipated more often by short sellers as it is by regular traders, as the average *IA* for transactions one or two standard deviations away from the firm-level mean is, if anything, slightly smaller for short sales (see Table 2). This issue is further investigated in the following section.

Looking at the different trade types, it appears that their information characteristics differ substantially. Looking at Table 3, Off-NYSE trades seem to have a lower level of information content consistent with the “cream-skimming” by Bessembinder and Kaufman (1997). Exempt trades seem have a comparatively low level of information content, are relatively large, and have a low trading frequency. It therefore seems that these trades are mainly used for inventory management or hedging purposes. Trades with similar characteristics also seem to be more likely to be routed to exchanges other than the NYSE, suggesting that *Off-NYSE* short-sales more likely to be used for inventory management and hedging. Non-pilot stocks have a larger variation in the information content of short-sales. Table 3 also shows that only the difference in *IA* in information contents of short-sales between pilot and non-pilot stocks is statistically significant. This demonstrates the strong impact of the up-tick rule on the informational efficiency of markets and the ability of short-sellers to exploit their private information. This suggests that that prices of non-pilot stocks are less efficient, which is going to be investigated in Section 5.4.2.

5.2 Is Short-sellers Private Information Stock-specific or Market-wide?

Although we fail to find evidence for insider information in the information contents of short-sales, our results point at one potentially important source of information advantage: public information. As this information can be specific to an individual firm (e.g., earnings announcements) or apply to many firms (e.g., the release of economic data), we continue with an analysis of the relative importance of private information that is security specific versus private information that is based on market-wide factors.

As a first step in this investigation, we relate short-volume to market-wide returns and returns that are specific to the individual stock. The strength of this relationship is meant to give a first impression on how much trading of short sellers is related to stock-specific or market-wide information. For this purpose, we regress short volume on returns on the market and stock-specific returns.[20] Results in Panel A of Table 4 show that short-volume is significantly related to stock-specific returns but not to market-wide returns. This relationship seems to apply only to trades that are not exempt from short-selling restrictions and are done on the NYSE. As these two

[20] The results presented here are based on stock-specific returns calculated using the Fama-French three factor model. Using only the market factor, adding the momentum factor, or using equally-weighted instead of value-weighted market returns does not affect the results.

transaction types arguably carry most of the information, one can conclude that this regression captures the information contents of short sales.

It therefore seems that short-sellers do possess information relating to individual firms rather than information that relates to the market as a whole. However, the fact that this relationship is strongest when the coefficients are aggregated on a value-weighted basis as compared to equally-weighted averaging suggests that short sales in large stocks carry most information. These stocks tent to issue more information to the market-place than smaller firms, suggesting that short sellers are simply reacting to public information – of which there is more for larger firms – rather than exploiting insider knowledge which would suggest that the relationship between short volume and returns should be at least equally pronounced with smaller firms.[21] Finally, this relationship between returns and volume cannot be found for regular buys and sales, suggesting that short-sellers have a different information set as compared to the other market participants.

Inducing the importance of market-wide information relative to firm-specific one as a source to private information from a market-model may be fairly noisy due to the importance of mechanical market-wide trading strategies that typically do not use private information.[22] In addition, using total returns as a proxy for the information contents of short sales is fairly imprecise. We therefore use a two-step procedure where market-wide trading volume is first separated from the security-specific volume. The volume attributable to these different sources of information is subsequently related to the information contents of each trade to determine the

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[21] Similarly, lagging either short volume or returns (results not shown but available on request) shows that the strength of this relationship declines as the lags increase. This is further evidence that short sellers react to – rather than successfully forecast – value-relevant information. Also, the effect is much weaker if short-volume is measured in units of USD – rather than the number of trades as in Panel A of Table 4 – which shows that there is considerable noise in the measurement of informed short-volume, which we attempt to address with the subsequent statistical test.

[22] These trades, also referred to as program trades, "encompass a range of portfolio- trading strategies involving the purchase or sale of a basket of at least 15 stocks with a total value of $1 million or more" (NYSE (2007a)). Based on weekly data, the mean fraction of program trades to all regular buys and sales on the NYSE is 29% using the current method of volume reporting that accounts for short-selling activity (NYSE (2007b)).

importance of each source of information to informed trader. Therefore, the following intra-day regression for every day and stock individually:

$$Volume_{i,d} = \theta_{i,0} + \theta_{i,1} MVolume_d + \omega_{i,d}, \tag{2}$$

where $Volume_{i,d}$ is the trading volume in stock i during one-minute interval d and $MVolume_d$ is the market average volume during the same one-minute interval. Security-specific and market-wide volume is calculated as $\left(\hat{\theta}_{i,0} + \hat{\omega}_{i,0}\right)$ and $\left(\hat{\theta}_{i,1} MVolume_d\right)$, respectively. The estimated security-specific and market-wide volume is then scaled by total daily stock-level volume, which results in the relative importance of market-wide and stock-level trading activity. These ratios are then related to the information content of the same transactions during the corresponding intra-day interval:

$$\begin{aligned} IA_{i,d} &= \alpha_{i,1} + \psi_{i,1}\left(\frac{\hat{\theta}_{i,1}\mathrm{MVolume}_d}{Volume_{i,d}}\right) + \tau_{i,d}, \\ IA_{i,d} &= \alpha_{i,2} + \lambda_{i,1}\left(\frac{\hat{\theta}_{i,0} + \hat{\omega}_{i,d}}{Volume_{i,d}}\right) + \nu_{i,d}, \end{aligned} \tag{3}$$

where $IA_{i,d}$ is the information content of either short-sales, regular sales, or regular buys in stock i during one-minute interval d. The estimated daily stock-level intercepts $\alpha_{i,1}$ and $\alpha_{i,2}$ are the information content attributed to security-specific and market-wide trading, respectively.

Results in Panels B of Table 4 show that around two thirds of the information content of short-sales can be attributable to security-specific short-selling.[23] Panel B of Table 4 shows that the typical (median) short-sale transaction makes \$11 over five days from market-wide short-selling and \$26 from security-specific short-selling, while the median transaction size is about \$14,000 (see Table 2). Thus, private information based on market-wide factors generates a return

[23] Results are robust to the definition of volume and the time horizon. Using equally-weighted instead of market value-weighted market averages or using equally-weighted instead of trade size-weighted one-minute interval averages or the intra-interval sum does not materially affect the results. Using trade sized-weighted *IA* is more consistent with the definition of *IA* and therefore presented here. Using intraday volume scaled by total daily volume instead of dollar volume or turnover does not affect the results, either.

of 7.9 basis points and private information based on stock-level factors a generates a return over five days 18.6 basis points over the same horizon; this corresponds to an annual return of 4.0% and 9.7%, respectively.

Both sources of information therefore generate a reasonable return to informed investors. It also appears that there is little variation in the relative importance of security-specific or market-wide information across firm-characteristics (results not reported but available on request). However, there is considerable variation in the relative importance of security-specific short-selling across trade-types (see Panel C of Table 4). Between two thirds and four fifths of the information content of short-sales of pilot stocks are security-specific, while the other trade-types (trades routed on and off the NYSE, non-pilot stocks, exempt trades, and non-exempt trades) show a relative importance of security-specific short-sales similar to the overall sample shown in Panel B of Table 4. This shows again that short-sellers in pilot stocks can react more quickly to stock-level changes in the trading environment whereby informed short-sellers do not seem to discriminate between trading venue.

5.3 Short-sales around Stock-specific Information Events

To investigate whether short-sellers possess private firm-specific information, we look at the information contents of short-selling around the publication of earnings announcements. In particular, we regress the information contents of short sales, buys and regular sales on a dummy variable that is one indicates when the particular *IA* value refers to a short sale and zero otherwise:

$$
\begin{aligned}
IA_{i,t} &= \beta_0 + \beta_1 ShortDummy_{i,t} + \varepsilon_{i,t} \\
IA_{i,t} &= \beta_0 + \beta_1 ShortDummy_{i,t} + \beta_2 \left(ShortDummy_{i,t} \times PilotDummy \right) + \varepsilon_{i,t} \\
IA_{i,t} &= \beta_0 + \beta_1 ShortDummy_{i,t} + \beta_2 \left(ShortDummy_{i,t} \times PilotDummy \right) + \beta_3 NYSEVOL + \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

whereby *ShortDummy* is a dummy being one if $IA_{i,t}$ refers to short sales and zero otherwise. *PilotDummy* is a dummy if stock *i* is a pilot stock and zero otherwise. *NYSEVOL* is the short volume traded on the NYSE standardized using the non-parametric method of normal scores.

Results presented in Panel A of Table 5 show that short sales traded on the announcement date are not particularly informed, if anything the *IA* loading is negative, suggesting that over a short horizon, short sellers lose money on these dates, which is similar to the regular trading dates. The intercept, which subsumes the information contents of regular transactions is positive intraday, suggesting that among the regular buyers and sellers, there are some traders that make consistent profits in these periods. Looking at longer return horizon, we can see that the information content is higher on average with non-pilot stocks, suggesting that prices in these stocks are informationally less efficient. Also, above average volume on the NYSE is significantly positive for longer horizons suggesting that the long-term informed short sales are mainly done on the NYSE. A similar picture emerges a day prior to the announcement, though the low explanatory power of the regressions may flag caution in interpreting too much into these results.

The weakness of the results could be related to the fact that short-sellers only care about one particular type of earnings announcement: negative surprises. We therefore group the volume of short-sales, regular buys and sales into buckets based on the cross-sectional rank of the size of the earnings surprise. Results in Panel B of Table 5 show that transaction volumes in short-sales are somewhat higher concurrent to negative surprises but not much different to normal volume prior to the announcement. This is in contrast to the volume of regular buys and sales, where the volume significantly elevated even prior to the announcement. Our results therefore suggest that short-sellers, similar to traders using regular transactions, are not using insider information around earnings announcements. If anything, they seem to be analyzing public information on the day of the announcement to derive their private information for informed sales in line with the skilled information analyst in Kim and Verrecchia (1994, 1997).

Unlike regular sale transactions, short-selling activity is above average also on days of positive announcement surprises. This suggests that short-sellers provide liquidity when positive information is released. As Table 2 shows that short-sellers have private information on average, this suggests that – while not relying on insider information and while supplying liquidity during positive news events – informed short-sellers have other sources of private information apart from firm-specific insider information. Our results therefore suggest that short-sellers supply liquidity to the market – which allows them to earn the bid-ask spread – while additionally focusing on long-term gains rather than short term gains that arise from temporary price pressures that are unrelated to fundamental value.

5.4 Are Short-sellers a Positive or Negative Contribution to Financial Markets?

Thus far, we found that short-sellers, while exploiting private information, do not rely on insider information as a basis of their trades. Rather, it seems that they use public information, both firm-specific and market-wide, as a basis of their trades. The patters of information contents of short sellers exhibited in Table 2 shows that the private information short-sellers use is most useful for return horizons of at least five days. All these evidence suggests that short-sellers are *value traders* as defined by , unlike regular buyers and sellers, as they seem to sacrifice short-term gain to profit over the longer term. We further investigate this first impression by looking at how short-sellers affect financial market liquidity, followed by a study of short-sellers impact on financial market liquidity.

5.4.1 Short-sales and Financial Market Liquidity

One of the prominent features of value traders as defined by is that they supply liquidity at times when uninformed buying or selling pressure moves prices away from fundamentals. It is therefore further investigated whether short-sellers absorb buying pressure and thus provide short-term liquidity by estimating a regression of short-selling volume on the level of liquidity providers' inventory of the previous day and some control variables:

$$ShortVolume_{i,t} = \beta_{i,0} + \beta_2 Inventory_{i,t-1} + \varepsilon_{i,t}, \tag{6.a}$$

$$ShortVolume_{i,t} = \sum_{j=1}^{5} \gamma_j InventoryDummy_{j,i,t-1} + \varepsilon_{i,t}, \tag{6.b}$$

$$ShortVolume_{i,t} = \sum_{j=1}^{5} \gamma_j InventoryDummy_{j,i,t-1} + \sum_{k=1}^{6} \delta_k TradeTypeDummy_{k,i,t} + \varepsilon_{i,t}, \tag{6.c}$$

$$\begin{aligned} ShortVolume_{i,t} = \sum_{j=1}^{5} \gamma_j InventoryDummy_{j,i,t-1} + \\ \vartheta\left(FutureReturn_{i,t} \times InventorySizeDummy_{5,i,t-1}\right) + \varepsilon_{i,t}, \end{aligned} \tag{6.d}$$

where $ShortVolume_{i,t}$ represents the U.S. dollar volume sold short on day t of stock i scaled by the yearly average trading volume and normalized to a mean of zero and standard deviation of one. $Inventory_{i,t-1}$ is the level of liquidity providers' inventories in stock i on the previous day. $InventoryDummy_{j,i,t-1}$ is a dummy variable that is equal to one if market maker's inventory level of stock i at date $t-1$ is in inventory-size group j and zero otherwise. Inventory-size groups are defined as the stock-level inventory quintiles. $TradeTypeDummy_{k,i,t}$ is a dummy variable that is equal to one if the short-volume data of stock i on day t refers to trade-type k and zero otherwise.[24] $FutureReturn_{i,t}$ is the return investors earn from holding stock i from day t over the next month.

If short-sellers provide liquidity in response to buying pressure, one could expect to find a negative regression coefficient on inventory, showing that shorts sellers sell more when

[24] To avoid co-linearity problems in regression (2.d), short-volume data sets of each of the six trade-types are stacked on top of each other. These daily stock-level trade-types are calculated (1) across trades routed to the NYSE, (2) across trades routed off the NYSE, (3) across trades that are exempt from short-selling restrictions, (4) across trades that are not exempt from short-selling restrictions, (5) across trades of pilot stocks, and (6) across trades of non-pilot stocks. Trades of non-pilot stocks are the base level.

inventory-levels of liquidity providers fall.[25] The negative relationship between the level of inventory and short volume (see Table 6) confirms the expectation that, consistently across trade-type, short-sellers step in to provide additional liquidity when inventory levels of liquidity providers are low. As presented in Table 6, the relationship between inventory and exempt trades is comparatively weak. This indicates that changes in orderflow of exempt trades are less strongly related to fluctuations in inventory than changes in orderflow of the other trade-types. It is likely that these trades are mostly routed to trading venues other than the NYSE as short-selling activity outside the NYSE seems also to be hardly affected by the level of liquidity providers' inventory positions. This is consistent with the "cream-skimming" hypothesis put forward by Bessembinder and Kaufman (1997) as trades that are exempt and routed to alternative trading venues have a lower level of information content (see Table 3).

Looking at the absolute size of the regression coefficient and the R-square, it appears that pilot stocks have a slightly stronger relationship with inventory than non-pilot stocks. Considering that non-pilot stocks have a larger variation in the information content of short-sales (see Table 3), these results suggests that prices of non-pilot stocks are less efficient (see the next section for a formal test of this issue). It therefore seems that short-selling restrictions reduce the effectiveness of short-sellers to provide liquidity to uninformed traders and to impound private information into prices. Next to reducing price efficiency, short-selling restrictions could therefore raise the costs of trading, which may even affect the costs of capital.

The positive loading on average volume is as expected showing that short-sellers tend to provide more liquidity in actively traded securities, which typically are also more efficiently priced. Short-sales in stocks that are less heavily traded and less efficiently priced are thus likely to carry more insider-related idiosyncratic private information, consistent with who find that

[25] This regression has been estimated in U.S. dollar terms and units of shares, which alternatively have been used as is or scaled by the total trading volume, defined as the sum of short sales, long buys, and regular sales. As results are very similar, only figures where un-scaled U.S. dollar volume is used are reported.

insider trades in small firms carry more information than insider trades in stocks of larger firms. This implies that -type short-sellers who provide liquidity to uninformed buying pressure are relatively more important the larger the firm becomes. Therefore, short-sales seem to be based on several trade motives. Table 6 shows that lower levels of inventory make short-sellers trading more. This further confirms the hypothesis that short-sellers provide liquidity to the market when liquidity providers see their inventory move away from their average level.

Looking more closely at the coefficients, it appears that the relationship between short-selling activity and inventory is U-shaped. Consistent with orderflow models of information dissemination (see, e.g., Lyons (2001)), very high selling pressure may indicate that fundamental values have changed downward while intermediate level selling pressure constitutes mostly uninformed orderflow that short-sellers help accommodate. To ascertain this conjecture, regression (6.b) is estimated by including future changes in asset value as additional explanatory variable next to inventory and average trading volume. Future changes in asset value, approximated by the log-difference of the concurrent stock price and the stock price in one month are considered to capture changes in fundamental value. A one-month interval is chosen to ensure all value-relevant price-signals that short-sellers may trade on are fully reflected in prices. In addition, a longer return interval helps to avoid concurrent uninformed price-pressure to affect the proxy of changes in fundamental value.

If fundamental values are indeed revised downward on days with the largest inventory, one should see a negative coefficient on the interaction of the inventory dummy for inventory size group 5 and future changes in asset value. Average monthly CRSP returns are positive[26] and short-selling volume associated with size group 5 is lower than the average volume associated

[26] Mean monthly returns in 2005 of the data sample are 0.6% with a t-statistic of 9.6 for a test of zero mean. To be consistent with the measure of future change in asset value, returns unadjusted for dividends are used.

with inventor size group 1 (see Table 6). This implies that a negative association between short volume and changes in fundamental value are not necessarily a foregone conclusion.

Results in Table 6 show a significantly negative regression coefficient on future changes in asset value. Thus, the information-related advantage of informed short-sellers appears to rest on an understanding of the trading environment, which allows these traders to react to buying pressure to profitably provide additional liquidity. In addition, as information about value-relevant fundamentals is typically revealed over a time horizon longer than one day (e.g., see Keim and Madhavan (1995)) informed short-sellers also seem to have private information about fundamentals which may help differentiate between informed and uninformed orderflow. They therefore differentiate informed from uninformed buying pressure and avoid trading when fundamental values rise while they seem to increase their positions when fundamental values fall.

5.4.2 Short-sales Price Efficiency

To investigate directly how short-sales affect price efficiency, we calculate various measures of price efficiency for the pilot sample and the non-pilot stocks individually. We therefore conduct a variance-ratio test following using a set of sampling frequencies to subdivide our year of data. The number that the resulting ratio deviates from unity can be interpreted as the return auto-correlation. Table 7 shows that the random walk hypothesis cannot be rejected for neither of pilot nor non-pilot stocks. We do find, however, that pilot stocks tend to have a negative auto-correlation, which is reflected in the mean-reverting price behavior that short-sellers exploit. As points out, asset prices where prices are quoted with bid and ask spreads should, if they are efficient, experience negative serial auto-correlation. This market set-up also applies to stocks, it follows from this that one should expect efficiently prices stocks to have some negative serial auto-correlation. As we find negative auto-correlation only for pilot stocks, one could interpret this as some evidence for pilot stocks being more efficiently priced than non-pilot stocks that do not exhibit negative auto-correlation on average.

Therefore, while we fail to find strong direct evidence for stock prices to be more efficient when short-selling restrictions are revoked; our results provide some tentative evidence that pilot stocks may be priced more efficiently than non-pilot stocks. We do find strong evidence, however, that short-sellers provide liquidity to the market, which in itself is a positive contribution by short-sellers and therefore implies that, overall, stock-markets benefit from short-selling.

6 Conclusion

This paper looks at short-sales, investigates the information content and trade motivation behind informed short-sales and compares these with regular buys and sales. Short-sales appear to be an important source of liquidity during times of uninformed buying pressure. This appears to make short-sales unprofitable intra-day as prices, pushed up by uninformed trading pressure, temporarily move against short-sellers' positions. The reversal of prices provides short-sellers with a reasonable return for their liquidity service. To implement this strategy of informed liquidity provision, informed short-sellers seem to rely on both, their understanding of the market environment and private information about fundamental values.

Short-sellers exploit negative earnings surprises, which they typically do not seem to anticipate, however. Rather, short-sellers appear to react to the public announcement of negative surprises, suggesting that the typical short-seller does not have insider information but rather appears to be a -type skilled information analyst. Short-selling constraints seem to affect the price efficiency, though it appears that prices – even with short-selling restrictions – are fairly efficiently priced. Further, investors are more likely to be exposed to informed short-sales when trading on the NYSE while short-sales on alternative trading venues are more likely to be used for inventory management and hedging purposes.

Public investors may find the results interesting that trading on exchanges other than the NYSE, the avoidance of short-term momentum strategies, and the reduction of trading activity during periods of low liquidity may protect them from adverse selection losses associated with exposure to informed short-sellers. Informed short-sellers seem not to use corporate insider information but rather appear to provide liquidity, which may be an interesting finding for regulators. Thus, short-sales are a net positive contribution to the financial markets, as they improve price efficiency and provide liquidity that keeps prices from diverging too much from fundamentals.

Among the limitations of this study is the short time horizon, although the large number of daily and intra-daily observations that are used imply sufficient statistical validity of the empirical results. It would be interesting to investigate further in future research one of the main issues looked at in this paper, i.e., the contribution of short-selling restrictions to price efficiency and financial market stability. In particular, looking at short-selling trading patters in pilot and non-pilot stocks during market downturns could improve the understanding about the benefits and costs of short-selling restrictions.

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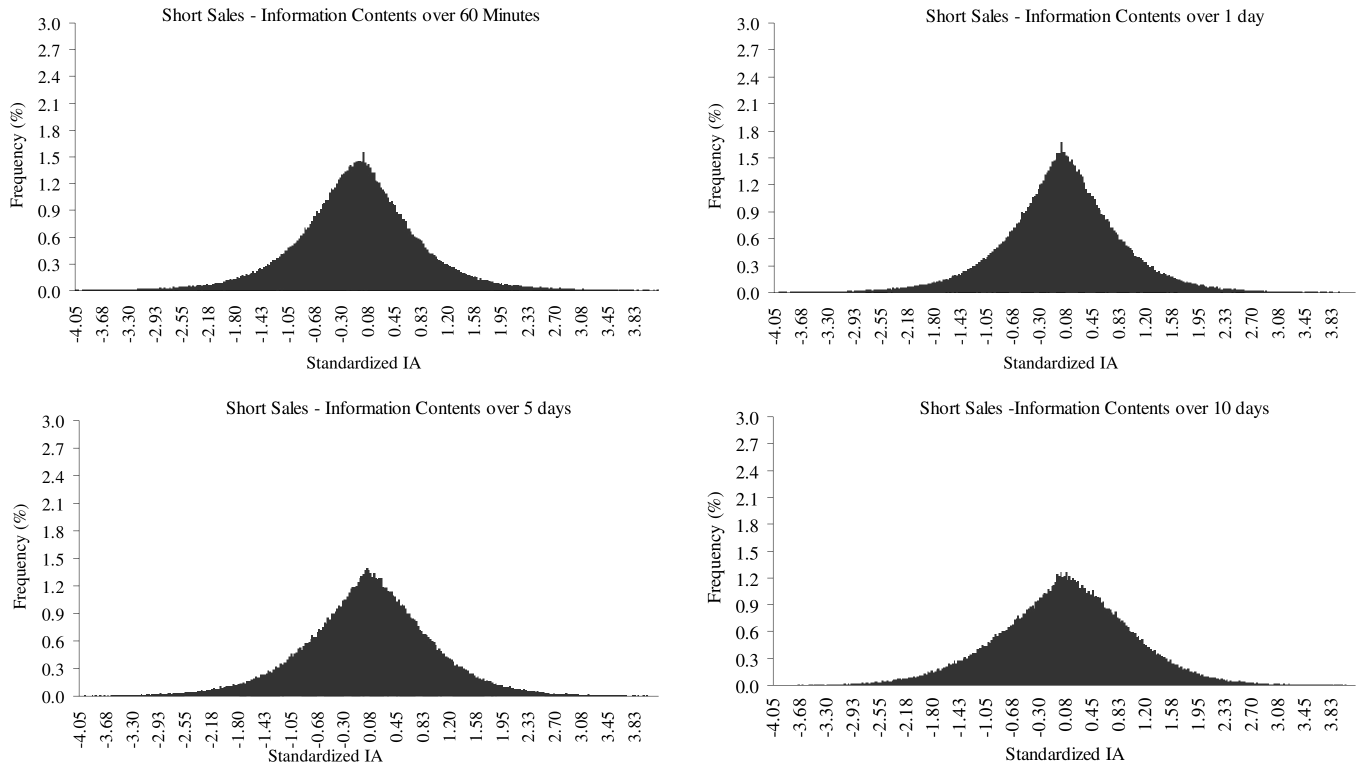
Figure 1 – Distribution of Information Content of Short-sales

This figure shows the empirical distribution of the information content of short-sales normalized for each firm individually over various horizons. Panel A shows the distribution of short sales and Panel B shows the distribution of regular sales and buys

Panel A –Distribution of Information Content of Short-sales



Panel B –Distribution of Information Content of Regular Sales and Buys

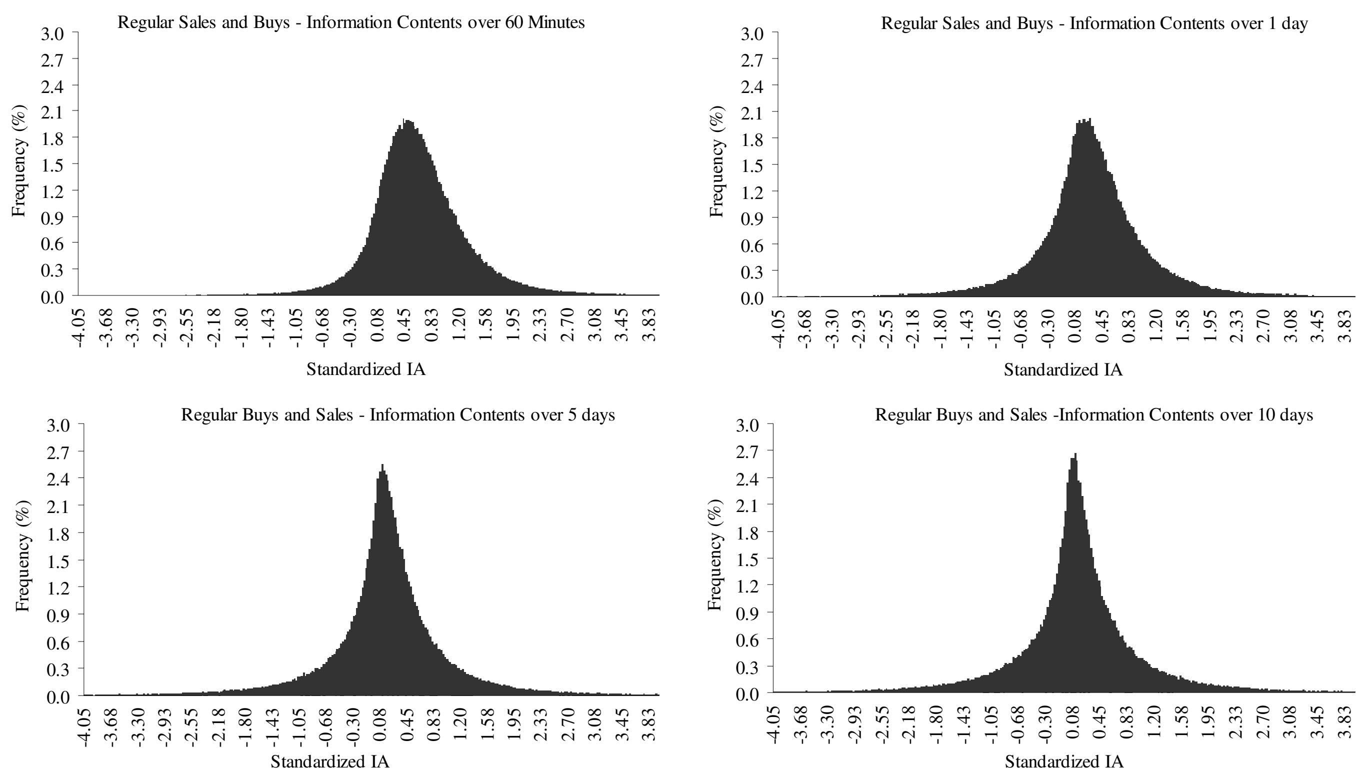


Table 1 – Summary Statistics Explanatory Variables

This table lists the names of the variables used in this paper in column *Variable Name* and the definition used to construct the respective variable in the column *Definition*.

Variable	Definition
Abnormal returns	The residual from a regression of daily stock returns in excess of the risk-free rate on daily market excess returns and the SMB and HML factor returns during the time-period covered by this study.
Announcement surprise	The cumulative post-announcement returns during the five days that follow the announcement including the announcement day.
AvVolume	The yearly average of total daily dollar trading volume of a particular stock.
Beta	The stock-level beta calculated using the Fama and French (1992) methodology.
Bid-ask spread	The daily time-weighted average of the intra-day difference between the BBO quotes scaled by the quote-mid point.
BTM	The sum of common equity, investment tax credits, and deferred taxes less the total value of preferred shares divided by firm size.
Dollar imbalance	The residual from a stock-level regression of dollar imbalance on *Turnover*.
Dollar volume	The daily sum of the $ trade volume in the stocks of a particular firm.
Firm size	The daily market capitalization measured as the product of total shares outstanding and the closing stock price.
FutureReturn	The return in a particular stock over the next month and is calculated as the first difference of the logarithm of the stock price today and the logarithm of the last valid stock price observation exactly one month later than today.
IA	The daily trade size-weighted average of the difference between the quote mid-point right before a transaction and the quote mid-point some minutes or trading days later scaled by the first quote mid-point.
$IA_{i,d}$	The *Trade size-weighted mean* (or the *Sum*) of IA of all short-sales (or buys or regular sales) during one-minute intra-day interval *d*. *IA* is multiplied by the trade size and thus expressed in dollars if Dollar Volume is used on the right hand side of the regression in Panels B and C in Table 4.
Inventory	The level of inventory of liquidity providers a particular stock. This is approximated by the net daily number of shares bought and sold multiplied by minus the closing stock price and is normalized for each stock individually to a mean of zero and a variance of one.
$InventoryDummy_j$	A dummy variable that is equal to one if the level of inventory in a particular stock is in inventory-size group *j* and zero otherwise. Inventory size Groups 1 to 5 are defined as the five inventory quintiles evaluated on the individual stock-level with Group 1 being the lowest inventory.
Market-adjusted returns	The residual from a regression of daily stock returns in excess of the risk-free rate on daily market excess returns.
Market-adjusted short volume	The standardized stock-level short-selling volume less the market value-weighted average standardized relative short-selling volume of that day.
MIA	The market value-weighted average *IA*.
Momentum returns	The compounded daily returns over the past five days.
$MVolume_d$	The market value-weighted average of the *Trade size-weighted mean* (or *Sum*) of the volume sold short, bought, or regularly sold during one-minute intra-day interval *d*.
Post-announcement returns	Captured alternatively by *Raw Returns* or *Abnormal Returns*, which are calculated as the residual from a regression of stock returns in excess of the risk-free rate on market excess returns and the SMB and HML factor returns.
Raw returns	Daily stock returns.
Relative Volume	The ratio of short *Dollar Volume* to total daily dollar trading volume.
Returns (cumul.) around announcements	The cumulative return during the five days that follow quarterly earnings announcements.
Share order-imbalance	The net number of shares bought and sold during a particular day.
ShortVolume	The dollar volume sold short scaled by the total trading volume on that day.
Tick size	The inverse of the daily stock price.
Trade-type	This variable specifies the short-sale data set considered, which comprises either *All trades*, only *NYSE trades*, only short-sales routed *Off-NYSE*, only short-sales that are *Exempt* from short-selling restrictions, only short-sales that are *Non-exempt* from short-selling restrictions, short-sales of stocks that are part of the Reg SHO *Pilot* sample, and short-sales of stocks that are not part of the pilot sample (referred to as *Non-pilot*).
$TradeTypeDummy_k$	A dummy variable that is one if the short-volume data of a particular stock refer to trade-type *k* and zero otherwise.
Turnover	Defined as *Dollar volume* scaled by the daily market capitalization of a firm.
Volume	The US-Dollar value traded during a day.
$Volume_{i,d}$	The trade size-weighted mean of the volume sold short, bought or sold (measured alternatively by *Dollar Volume*, *Relative Volume*, or *Turnover*) in stock *i* during one-minute intra-day interval *d*.

Table 2 – Sample Summary Statistics

This table shows summary statistics of the data used in this study. Panel A reports the number of *Observations*, the *Mean* and *Median* values and the first and third quartile (*Q1* and *Q3*) of the *IA*, dollar volume, and turnover data used in this study. The statistics are based on firm-level means. The columns *Data Type* and *Variable* indicate the broad area the respective variable refers to and the variable name, respectively. Appended to the variable names in parentheses are the units of measurement, whereby *10,000 $* and *bp* denote ten thousand dollars and basis points, respectively. *Skew* and *Kurt* is the mean of the firm-level skewness and kurtosis values. *IA* measures the information content of *Short-sales* or of *Other Trades*, defined as the value-weighted average of long buys and sales not classified as shorts by firms that also have short sales data on the particular date. The columns *% positive*, *% > 1 σ*, and *% > 2 σ* denote the mean percentage of firm-level *IA* observations that are positive, more than 1 standard deviation and more than 2 standard deviations above the firm-level mean-*IA*, respectively. The column *Annualized* shows the *IA* values calculated over at least one day annualized to make the measure better comparable across horizons assuming a 250 day-count. The column *P-val* shows the *p*-value of a non-parametric two-sided Kruskal-Wallis test of equality in medians between the short-sales *IA* and the *IA* of regular buys and sales estimated over the same horizon. Panel B shows the Mean and Median difference (in basis points) between *IA* of short sales and the *IA* of regular buys and sales (which are grouped together) by *Quintiles* (with 1 being the smallest and 5 the largest group) based on *Firm size*, *Beta*, *Book-to-Market*, the *Bid-ask spread*, *Tick-size*, *Volume*, and the *Number of trades*. *Volume* and the *Number of trades* are calculated over the sum of short-sales, and regular buys and sales. Panel C shows the number of observations (*Obs.*), the *Mean* and *Median* values and the first and third quartile (*Q1* and *Q3*) of the explanatory variables used in this study. The columns *Data Type* and *Variable* indicate the broad area the respective variable refers to and the variable name, respectively. Appended to the variable names in parentheses are the units of measurement, whereby *10,000 $*, *billion $*, *%*, and *bp* denote ten thousand dollars, billion dollars, percentages, and basis points, respectively. See Table 1 for variable definitions

Panel A – Measures of Information Contents

Data Type	Variable	Observations	Mean	Q1	Median	Q3	% positive	% > 1σ	% > 2σ	Skew	Kurt	Annualized	P-val
Short sales data	IA over 15 minutes (bp)	457,567	-4.99	-5.82	-3.14	-1.71	36.76	8.91	2.10	-27.93	1,569.17		0.00
	IA over 30 minutes (bp)	457,567	-4.56	-5.60	-2.82	-1.22	41.30	10.12	2.27	-16.54	1,075.77		0.00
	IA over 60 minutes (bp)	457,567	-3.95	-5.55	-2.45	-0.65	44.54	11.14	2.40	-10.23	716.20		0.00
	IA over 1 day (bp)	427,908	-0.61	-8.52	-0.85	6.51	49.95	10.68	2.05	39.97	1,771.24	-1.5%	0.00
	IA over 2 days (bp)	412,335	2.46	-14.13	0.64	14.50	50.31	11.50	2.18	26.80	914.31	3.1%	0.00
	IA over 3 days (bp)	397,872	5.53	-18.74	2.89	23.21	50.61	11.99	2.26	20.89	647.08	4.7%	0.00
	IA over 4 days (bp)	381,364	12.74	-20.98	7.79	35.01	51.72	12.33	2.27	14.43	482.96	8.3%	0.00
	IA over 5 days (bp)	368,281	19.15	-22.09	11.68	48.31	52.35	12.60	2.32	11.97	387.83	10.0%	0.00
	IA over 6 days (bp)	353,202	22.57	-26.48	12.86	57.09	52.13	12.83	2.42	12.15	321.49	9.8%	0.00
	IA over 7 days (bp)	329,182	26.56	-32.21	14.14	67.27	52.18	13.18	2.42	11.64	270.25	9.9%	0.00
	IA over 8 days (bp)	305,632	27.88	-37.28	14.41	75.03	52.29	13.31	2.37	8.83	233.13	9.1%	0.00
	IA over 9 days (bp)	282,032	30.58	-43.73	15.96	86.69	52.67	13.59	2.29	4.71	198.46	8.9%	0.00
	IA over 10 days (bp)	258,116	35.92	-48.02	19.52	98.04	52.89	13.88	2.32	4.13	171.49	9.4%	0.00
	Dollar volume (10,000 $)	457,567	1.99	0.87	1.41	2.49							
	Turnover (bp)	457,567	0.12	0.04	0.08	0.13							
Regular buys and sales	IA over 15 minutes (bp)	457,488	13.31	6.40	9.65	15.02	94.06	10.74	3.32	162.38	1,459.55		
	IA over 30 minutes (bp)	457,488	13.14	6.29	9.60	14.69	91.59	10.89	3.24	129.48	1,298.57		
	IA over 60 minutes (bp)	457,488	12.86	6.10	9.25	14.39	87.87	10.82	3.12	101.57	1,277.44		
	IA over 1 day (bp)	427,846	11.54	4.77	7.72	13.28	70.34	9.09	2.49	37.45	1,827.00	33.4%	
	IA over 2 days (bp)	412,276	11.55	4.32	7.62	13.74	66.96	8.75	2.56	22.86	1,631.50	15.5%	
	IA over 3 days (bp)	397,812	11.65	3.84	7.58	14.04	65.28	8.62	2.57	24.23	1,550.19	10.2%	
	IA over 4 days (bp)	381,306	12.33	4.05	8.08	14.87	64.46	8.79	2.65	26.76	1,385.03	8.0%	
	IA over 5 days (bp)	368,225	12.66	3.68	8.11	15.79	63.73	8.76	2.70	18.42	1,298.07	6.5%	
	IA over 6 days (bp)	352,749	12.32	3.27	7.85	15.96	62.90	8.95	2.75	12.99	1,214.50	5.3%	
	IA over 7 days (bp)	328,756	12.64	2.95	8.16	16.68	62.34	9.06	2.83	17.95	1,114.74	4.6%	
	IA over 8 days (bp)	305,236	12.26	2.72	8.02	16.68	61.53	9.08	2.81	13.88	1,059.49	3.9%	
	IA over 9 days (bp)	281,674	12.63	2.20	8.13	17.54	61.41	9.16	2.82	13.39	1,004.84	3.6%	
	IA over 10 days (bp)	257,790	13.12	1.91	8.53	18.53	61.17	9.36	2.93	9.58	943.05	3.3%	
	Dollar volume (10,000 $)	457,138	1.32	0.69	1.07	1.70							
	Turnover (bp)	457,138	0.10	0.03	0.06	0.11							

(continued)

Table 2 – Sample Summary Statistics (continued)

Panel B – Information Contents and Firm Characteristics

		IA of short sales less IA of regular buys and sales over									
		60 minutes		1 day		3 days		5 days		10 days	
Group	Decile	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Firm size	1	-32.4	-22.5	-24.6	-16.6	-16.9	-9.7	-1.5	8.0	20.5	36.2
	2	-16.4	-13.9	-13.1	-9.9	-9.6	-6.7	3.0	6.8	11.9	21.2
	3	-11.2	-9.9	-7.5	-6.6	-1.4	-3.1	9.4	7.0	22.5	18.0
	4	-8.0	-7.2	-6.0	-5.5	-2.7	-4.6	4.3	2.3	12.5	9.4
	5	-4.7	-4.3	-1.3	-1.0	1.8	-1.4	8.5	7.0	18.6	13.4
Beta	1	-12.6	-9.1	-8.2	-6.1	-2.8	-4.7	7.5	4.8	20.6	12.0
	2	-12.8	-9.5	-7.8	-7.1	-1.5	-5.4	11.4	4.9	27.7	12.8
	3	-11.4	-8.7	-8.6	-7.0	-5.3	-5.3	3.3	2.6	14.2	13.0
	4	-17.8	-12.3	-14.4	-8.8	-10.4	-4.2	0.3	11.2	9.0	35.6
	5	-18.6	-11.4	-13.7	-7.1	-8.8	-4.1	1.4	9.5	14.2	25.8
Book-to-Market	1	-11.4	-8.1	-6.9	-4.9	2.8	0.0	15.8	11.6	34.2	27.0
	2	-10.9	-8.4	-7.0	-5.5	-2.0	-4.5	8.3	5.1	23.3	19.2
	3	-12.6	-9.7	-10.6	-7.5	-7.3	-4.9	0.8	5.8	9.6	13.8
	4	-15.1	-10.8	-12.0	-8.2	-10.6	-8.4	-1.0	3.3	3.4	11.1
	5	-22.6	-13.5	-15.7	-9.8	-11.4	-6.4	0.1	4.6	14.8	20.2
Bid-ask	1	-5.0	-4.7	-1.1	-1.9	3.7	-1.4	12.8	6.1	23.1	10.5
	2	-7.5	-7.2	-5.0	-4.3	-0.2	-2.3	5.6	4.4	11.5	10.4
	3	-10.7	-9.7	-7.5	-6.8	-4.6	-4.6	4.7	6.7	13.4	17.4
	4	-15.9	-14.0	-12.7	-10.2	-9.0	-7.8	3.4	6.9	11.4	22.8
	5	-33.4	-23.8	-26.1	-18.1	-18.7	-11.3	-3.0	6.4	26.7	40.3
Tick-size	1	-7.1	-6.3	-1.7	-5.3	7.9	-6.2	22.0	2.9	46.6	11.5
	2	-9.4	-8.0	-7.9	-5.6	-5.6	-4.5	1.7	3.3	6.5	8.0
	3	-11.5	-9.5	-9.2	-6.2	-7.8	-4.2	0.1	6.8	5.7	16.2
	4	-15.3	-11.9	-12.1	-7.7	-9.3	-4.6	-1.7	7.2	3.7	21.6
	5	-29.3	-19.0	-21.5	-12.3	-13.8	-4.3	1.5	13.1	22.4	45.1
Volume	1	-30.4	-21.0	-22.3	-14.3	-14.6	-7.0	-1.3	10.8	21.4	37.7
	2	-15.5	-12.2	-12.1	-8.5	-7.0	-4.2	2.7	7.4	13.1	25.5
	3	-11.6	-9.3	-8.5	-6.3	-6.3	-3.4	4.7	6.9	8.7	14.0
	4	-8.9	-7.2	-6.8	-5.6	-1.6	-4.4	5.5	3.9	12.3	3.7
	5	-6.2	-5.0	-2.7	-3.1	1.0	-5.6	12.0	3.0	30.0	14.4
Number of Trades	1	-29.4	-19.1	-19.2	-11.8	-7.3	-3.6	7.9	12.6	34.1	36.3
	2	-16.1	-12.3	-13.4	-8.4	-8.7	-4.2	1.9	5.2	14.9	20.2
	3	-12.1	-9.7	-9.5	-6.9	-5.1	-4.9	4.8	6.9	9.5	18.5
	4	-9.2	-7.4	-7.7	-5.3	-5.5	-3.5	4.6	4.7	15.0	10.1
	5	-5.8	-4.6	-2.8	-2.9	-1.9	-7.9	5.0	1.4	14.1	9.3

(continued)

Table 2 – Sample Summary Statistics (continued)
Panel B – Summary Statistics of Explanatory Variables

Variable	Obs.	Mean	Std	Skewness	Kurtosis	Q1	Median	Q3
Share order-imbalance (1,000)	347,942	101.50	189.57	4.6	28.4	11.13	37.79	108.90
Inventory (million $)	313,424	-90.79	177.32	-4.7	33.0	-94.46	-26.19	-6.76
Raw returns (cumul.) around announcements (%)	5,332	0.39	3.01	-0.6	5.3	-0.99	0.47	1.76
Market-adjusted returns (cumul.) around announcements (%)	5,332	-0.05	2.90	-0.6	5.7	-1.34	-0.02	1.24
Abnormal returns (cumul.) around announcements (%)	5,332	0.04	2.82	-0.5	5.4	-1.25	0.04	1.26
Bid-ask spread (bp)	347,942	18.87	27.83	5.7	50.1	6.30	10.46	19.59
Momentum returns (bp)	347,942	20.57	94.53	-4.3	72.0	-10.63	19.57	58.78
Dollar order-imbalance (bp)	347,942	0.03	1.61	15.2	548.6	0.00	0.00	0.00
Volatility (bp)	347,942	4.78	11.77	18.5	422.0	1.81	3.14	5.13
Tick size (%)	347,942	5.58	8.39	6.6	60.9	2.29	3.46	5.59
Firm size (billion $)	347,942	7.39	22.70	9.1	112.7	0.71	1.72	5.01
Book value-to-market value (%)	347,942	57.01	47.04	2.9	11.7	29.14	46.88	68.35
Capital expenditures (%)	1,826	6.96	13.16	4.7	25.3	1.51	3.15	6.61
Research and development (%)	1,616	1.37	4.52	11.0	194.1	0.00	0.00	1.01
Block ownership (%)	1,486	6.96	14.13	2.5	6.7	0.00	0.00	7.00
Bid-ask spread (bp)	252	5.45	0.36	0.9	0.7	5.19	5.39	5.63
Momentum returns (bp)	252	24.43	128.50	-0.2	-0.1	-62.32	30.95	114.46
Order-imbalance (bp)	252	0.04	1.29	-0.4	2.1	-0.80	0.02	0.75
Volatility	252	12.81	1.47	0.7	0.2	11.69	12.52	13.65
Turnover (bp)	252	0.02	0.00	4.1	24.6	0.02	0.02	0.03

Table 3 – Sub-samples of Short-selling Activity and Information Content

This table shows the median value of the stock-level mean short-selling *Dollar Volume* and *Average IA of short-sales over 15 minutes* up to *10 trading days* by *Trade-type*. The variable definitions are given in Table 1. The column *Daily Observations* displays the number of daily stock-level observations. *Daily Trades* shows the median number of short-sales done each day. *Dollar Volume* is measured in units of $10,000. The row t-*statistic* shows the *t*-statistic of the difference in mean between each group of trade-types. Thereby, the two-sided independent *t*-tests (assuming unequal variances) for the trade-type groups *Exempt/Non-exempt* and *NYSE trades/Off-NYSE* are calculated for each stock individually and the statistic shown is the mean across the firm-level *t*-values. The *t*-test for the trade-type group *Pilot/Non-pilot* is calculated across all stocks.

				Average IA of short-sales over												
	Daily	Daily	Dollar	Minutes			Days									
Trade-type	Observations	Trades	Volume	15	30	60	1	2	3	4	5	6	7	8	9	10
Exempt	224,008	8.0	4.1	0.35	0.40	-0.07	-3.33	-3.31	-0.93	-0.19	2.03	-5.90	-9.10	-6.51	-6.16	-0.72
Non-exempt	448,837	253.3	1.4	-3.22	-2.85	-2.44	-0.64	0.87	3.10	8.30	11.72	11.06	13.22	12.68	14.13	17.72
t-statistic				-0.81	-0.64	-0.39	0.10	0.13	0.08	0.14	0.16	0.26	0.32	0.29	0.26	0.23
NYSE trades	449,231	268.5	1.4	-3.09	-2.76	-2.41	-0.60	0.71	3.00	8.10	11.62	11.33	12.46	12.37	14.05	17.42
Off-NYSE	255,086	1.7	0.9	-2.72	-2.55	-2.40	-3.37	-2.28	-2.69	2.35	7.38	4.30	6.63	4.15	7.15	7.74
t-statistic				-0.06	-0.11	-0.16	-0.16	-0.12	-0.12	-0.11	-0.07	-0.09	-0.10	-0.08	-0.07	-0.02
Pilot	296,994	417.0	2.0	-2.05	-1.77	-1.50	-0.23	0.64	1.99	4.80	7.78	8.74	9.43	9.97	10.57	12.95
Non-pilot	160,573	137.2	1.0	-5.81	-5.47	-5.15	-2.74	0.44	5.30	12.46	18.57	20.30	25.04	25.63	27.52	35.06
t-statistic				-37.93	-33.10	-26.08	-2.83	-0.88	0.96	2.32	3.30	3.74	4.15	4.16	4.27	4.54
All trades	457,567	274.1	1.4	-3.14	-2.82	-2.45	-0.85	0.64	2.89	7.79	11.68	12.86	14.14	14.41	15.96	19.52

Table 4 – Market-wide and Security-specific Short-sales

This table compares the information content of short-sales based on market-wide signals with short-sales based on security-specific signals. Panel A shows the average regression coefficient and *t*-statistic of a stock-level regression of short volume and the volume of regular buys and sales, measured by the number of trades, on a constant and *Market Returns* and *Stock-specific Returns*. Stock-specific returns are calculated by retaining the residual of a regression of stock returns on a constant and the three Fama-French Factors and the market return is the respective market return factor. The column Weight shows whether the aggregation of the stock-level coefficients is done on an equally-weighted basis (*EW*), or weighted by the average market-value of each stock over the sample period (*VW*).The coefficients are scaled by 100 and the adjusted R^2 is in percentages. The asterisks *, **, and *** denote statistical significance on a 10%, 5%, and 1% level of a two-sided *t*-test. Results in Panels B and C refer to the estimation of the following regressions each day for every stock individually:

$$
\begin{aligned}
Volume_{i,d} &= \theta_{i,0} + \theta_{i,1}\text{MVolume}_d + \omega_{i,d}\,, \\
IA_{i,d} &= \alpha_{i,1} + \psi_{i,1}\left(\frac{\hat{\theta}_{i,1}\text{MVolume}_d}{Volume_{i,d}}\right) + \tau_{i,d}\,, \\
IA_{i,d} &= \alpha_{i,2} + \lambda_{i,1}\left(\frac{\hat{\theta}_{i,0} + \hat{\omega}_{i,d}}{Volume_{i,d}}\right) + \nu_{i,d}\,,
\end{aligned}
$$

whereby the variable definitions are presented in Table 1. Panel B shows the medians of the stock-level median estimates of α_1 and α_2, which are labeled *Security-specific Short-selling* and *Market-wide Short-selling*, respectively. The columns *Relative security-specific short-selling* show the ratio of the absolute value of α_1 to the sum of the absolute values of α_1 and α_2 and the column *Intra-day interval* indicates whether volume and *IA* during one-minute intra-day interval *d* are *Trade size-weighted means* or cumulative *Sums*. Numbers in the two left-most columns of *Relative Volume* and *Turnover* are in basis points and *Dollar Volume* is in dollars. Panel C shows the median information content of short-sales based on *Dollar Volume* of market-wide and security-specific short-selling by *Trade-type*. Values associated with *Relative Volume* are in basis points.

Panel A – Average Relationship of Short-volume with Market-level and Stock-specific Returns

		Market Returns		Stock-specific Returns		
Trade-type	Weight	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Adj. R^2
All Trades	EW	12.51	0.36	28.46 *	1.88	12.0
	VW	44.90	1.10	88.50 ***	3.30	9.6
NYSE trades	EW	11.71	0.18	26.67 **	2.03	11.9
	VW	40.61	1.08	79.50 ***	3.26	9.4
Off-NYSE	EW	0.05	0.08	0.15	0.68	5.4
	VW	0.47	0.61	0.73 *	1.66	4.1
Non-Exempt	EW	11.99	0.35	25.22 *	1.80	11.6
	VW	37.40	1.10	76.18 ***	3.35	9.7
Exempt	EW	-0.24	0.07	1.59	0.34	3.0
	VW	3.68	0.12	4.06	0.42	1.6
Regular buys and sales	EW	-34.71	-0.22	-5.07	0.08	10.6
	VW	-188.47	-0.51	31.46	-0.04	5.0

(continued)

Table 4 – Market-wide and Security-specific Short-sales (continued)

Panel B – Market-wide and Security-specific Short-selling by Return Horizon

		Market-wide Short-selling			Security-specific Short-selling			Relative Security-specific Short-selling		
Intraday Interval	Time Horizon	Dollar Volume	Relative Volume	Turnover	Dollar Volume	Relative Volume	Turnover	Dollar Volume	Relative Volume	Turnover
Trade size-weighted mean	15 minutes	-2.57	-2.01	-1.48	-5.42	-2.59	-2.38	0.68	0.56	0.62
	60 minutes	-1.50	-1.34	-1.06	-3.61	-1.74	-1.70	0.71	0.57	0.62
	1 day	1.91	1.97	2.26	5.28	3.08	2.65	0.73	0.61	0.54
	3 days	5.11	8.13	8.49	12.17	8.33	7.82	0.70	0.51	0.48
	5 days	11.01	16.30	16.22	26.17	16.10	16.37	0.70	0.50	0.50
Sum	15 minutes	-3.66	-3.67	-2.71	-6.31	-4.74	-4.55	0.63	0.56	0.63
	60 minutes	-2.35	-2.64	-1.98	-4.46	-3.52	-3.38	0.66	0.57	0.63
	1 day	2.51	3.31	3.28	5.13	5.02	4.67	0.67	0.60	0.59
	3 days	5.83	9.88	8.76	11.36	11.61	11.74	0.66	0.54	0.57
	5 days	11.77	19.24	17.05	26.69	24.79	23.85	0.69	0.56	0.58

Panel C – Market-wide and Security-specific Short-selling by Trade-type

		Market-wide Short-selling (Dollar Volume)						Security-specific Short-selling (Dollar Volume)					
Intraday Interval	Time Horizon	NYSE Trades	Off-NYSE	Exempt	Non-exempt	Non-pilot	Pilot Stocks	NYSE Trades	Off-NYSE	Exempt	Non-exempt	Non-pilot	Pilot Stocks
Trade size-weighted mean	15 minutes	-2.57	-2.03	0.45	-2.31	-2.00	-2.41	-4.10	-2.26	0.27	-4.35	-3.77	-4.95
	60 minutes	-1.50	-2.00	0.00	-1.50	-1.33	-1.45	-2.67	-2.25	0.00	-2.85	-2.83	-3.13
	1 day	1.91	-2.00	0.00	0.00	0.49	1.69	-0.31	-2.27	-0.50	0.00	0.00	7.33
	3 days	5.11	-1.08	-0.50	1.82	2.83	4.71	2.00	-2.20	-1.50	2.01	3.00	11.29
	5 days	11.01	7.51	4.11	7.69	5.84	11.36	11.02	8.00	4.49	12.82	10.07	23.66
Sum	15 minutes	-3.66	-2.50	0.53	-2.69	-2.41	-3.78	-4.76	-2.51	0.52	-5.02	-4.04	-6.08
	60 minutes	-2.35	-2.08	0.00	-1.85	-1.58	-2.40	-3.34	-2.51	0.00	-3.49	-3.00	-4.15
	1 day	2.51	-1.50	0.08	0.00	0.05	3.22	-0.25	-2.13	-0.05	0.00	0.00	6.58
	3 days	5.83	-2.00	-0.50	1.04	2.71	4.97	2.13	-2.51	-1.14	1.59	2.50	10.89
	5 days	11.77	7.50	3.15	6.80	6.89	10.39	10.44	7.28	4.00	13.06	10.30	26.43

Table 5 – Informed Trading around Earnings Announcements

This table shows in Panel A the results of regressing *IA* of short sales, regular buys and sales on a set of explanatory variables:

$$IA_{i,t} = \beta_0 + \beta_1 ShortDummy_{i,t} + \varepsilon_{i,t}$$

$$IA_{i,t} = \beta_0 + \beta_1 ShortDummy_{i,t} + \beta_2 \left(ShortDummy_{i,t} \times PilotDummy \right) + \varepsilon_{i,t}$$

$$IA_{i,t} = \beta_0 + \beta_1 ShortDummy_{i,t} + \beta_2 \left(ShortDummy_{i,t} \times PilotDummy \right) + \beta_3 \left(NYSEVOL \times PilotDummy \right) + \varepsilon_{i,t}$$

whereby *ShortDummy* is a dummy being one if $IA_{i,t}$ refers to short sales and zero otherwise. *PilotDummy* is a dummy if stock *i* is a pilot stock and zero otherwise. *NYSEVOL* is the short volume traded on the NYSE standardized using the non-parametric method of normal scores. In the table below, column *Relative to Announcement* shows whether the regression uses observations at the date of the earnings announcement (*Contemporaneous*) or observations *1 day prior* to the announcement. All coefficients are in basis points and the *p*-value associated with the null hypothesis of the coefficient being equal to zero is reported in parentheses underneath. *Panel* B reports the *Mean Volume Relative to the Announcement Day* of Short-sales, regular buys and sales at the quarterly earnings announcement day and one day earlier, indicated by the column headers *0* and *–1*, respectively. The individual rows specify short volume by *Return Quintile* based on abnormal returns. The asterisks *, **, and *** denote significance levels of 10%, 5% and 1% associated with a two-sided t-test of the mean normalized market adjusted volume number in the particular *Return Quintile* being significantly different from zero. Stock-level volume is adjusted for average market trading activity and the normalization is done on a stock-level across all dates.

Panel A – IA around Earnings Announcements

Relative to Announcement	IA Horizon	Intercept	Short Dummy	Pilot X Short Dummy	NYSEVOL x Short Dummy	Adj R^2
Contemporaneous	60 minutes	13.86	-18.26			5.6
		(0.00)	(0.00)			
		13.86	-19.96	2.38		5.6
		(0.00)	(0.00)	(0.39)		
		13.86	-18.29		1.54	5.7
		(0.00)	(0.00)		(0.30)	
	1 day	10.69	-36.69			0.3
		(0.31)	(0.01)			
		10.69	-44.55	11.03		0.3
		(0.31)	(0.05)	(0.64)		
		10.69	-37.54		40.90	0.9
		(0.31)	(0.01)		(0.00)	
	5 days	13.07	-17.01			0.0
		(0.40)	(0.44)			
		13.07	42.12	-82.99		0.4
		(0.40)	(0.20)	(0.02)		
		13.07	-18.47		70.06	0.8
		(0.40)	(0.40)		(0.00)	
1 day prior	60 minutes	10.55	-16.15			8.0
		(0.00)	(0.00)			
		10.55	-22.75	9.15		9.0
		(0.00)	(0.00)	(0.00)		
		10.55	-16.15		-0.24	8.0
		(0.00)	(0.00)		(0.86)	
	1 day	9.95	-26.03			0.2
		(0.40)	(0.12)			
		9.95	-17.28	-12.12		0.2
		(0.40)	(0.50)	(0.65)		
		9.95	-25.81		10.69	0.2
		(0.40)	(0.13)		(0.47)	
	5 days	6.84	-10.95			0.0
		(0.74)	(0.71)			
		6.84	94.32	-145.85		0.8
		(0.74)	(0.04)	(0.00)		
		6.84	-9.27		84.93	0.9
		(0.74)	(0.75)		(0.00)	

(continued)

Table 5 – Informed Trading around Earnings Announcements (continued)

Panel B – Average Volume by Return Group

Return Quintile	Short-sales 0	Short-sales -1	Regular Buys 0	Regular Buys -1	Regular Sales 0	Regular Sales -1
	Market-adjusted Mean Volume Relative to Announcement Day					
-5	0.01	0.00	0.42***	0.05	0.37***	0.1**
-4	0.13***	-0.07*	0.56***	0.05	0.63***	0.07*
-3	0.16***	0.02	0.6***	0.13***	0.6***	0.13***
-2	0.07*	-0.02	0.64***	0.08**	0.66***	0.14***
-1	0.14***	-0.02	0.7***	0.1**	0.68***	0.13***
1	0.1**	0.00	0.62***	0.11***	0.57***	0.13***
2	0.06	-0.05	0.58***	0.05	0.66***	0.06
3	0.02	-0.09**	0.52***	0.00	0.49***	0.04
4	-0.17***	-0.21***	0.19***	-0.15***	0.25***	-0.15***
5	0.08***	-0.03	0.49***	0.05	0.51***	0.08***

Table 6 – Short Sales and Liquidity Providers' Inventory

This table shows the relationship between liquidity providers' inventory and trading activity by short-sellers via estimating the following regression *Specifications*:

$$(1)\ \ \text{ShortVolume}_{i,t} = \beta_{i,0} + \beta_1 \text{Inventory}_{i,t-1} + \varepsilon_{i,t},$$

$$(2)\ \ \text{ShortVolume}_{i,t} = \sum_{j=1}^{5} \gamma_j \text{InventoryDummy}_{j,i,t-1} + \varepsilon_{i,t},$$

$$(3)\ \ \text{ShortVolume}_{i,t} = \sum_{j=1}^{5} \gamma_j \text{InventoryDummy}_{j,i,t-1} + \sum_{k=1}^{6} \delta_k \text{TradeTypeDummy}_{k,i,t} + \varepsilon_{i,t},$$

$$(4)\ \ \text{ShortVolume}_{i,t} = \sum_{j=1}^{5} \gamma_j \text{InventoryDummy}_{j,i,t-1} + \vartheta\left(\text{FutureReturn}_{i,t} \times \text{InventoryDummy}_{5,i,t-1}\right) + \varepsilon_{i,t},$$

whereby *ShortVolume* refers to the volume of short-sales scaled by the average Dollar trading volume of stock *i* during the year normalized to a mean of zero and a standard deviation of one. The variable definitions are given in Table 1. The table below reports the estimated regression coefficients and in parentheses to the right of each coefficient the *p*-value associated with a two-sided *t*-test of the coefficient being equal to zero. As *Specification (4)* excludes the data set that contains data calculated across *All trades*, the base-level trade-type is the sample comprising trades in *Non-pilot* stocks. The R^2 calculated following the derivation by Nagelkerke (1991) is in percentages.

		Short-sale Trade-type													
Specifi-		All trades		NYSE trades		Off-NYSE		Non-exempt		Exempt		Pilot stocks		Non-pilot	
cation	Variable	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value
(1)	Inventory	-0.130	(0.00)	-0.132	(0.00)	-0.048	(0.00)	-0.148	(0.00)	-0.013	(0.00)	-0.177	0.000	-0.083	(0.00)
	R^2	4.69		4.99		7.84		5.47		0.02		8.07		0.79	
(2)	Inventory Group 1	0.283	(0.00)	0.285	(0.00)	0.098	(0.00)	0.313	(0.00)	0.025	(0.00)	0.360	(0.00)	0.206	(0.00)
	Inventory Group 2	-0.006	(0.07)	-0.006	(0.07)	0.008	(0.07)	-0.002	(0.62)	-0.003	(0.57)	-0.001	(0.86)	-0.014	(0.02)
	Inventory Group 3	-0.105	(0.00)	-0.105	(0.00)	-0.037	(0.00)	-0.113	(0.00)	-0.007	(0.16)	-0.125	(0.00)	-0.086	(0.00)
	Inventory Group 4	-0.141	(0.00)	-0.142	(0.00)	-0.044	(0.00)	-0.156	(0.00)	-0.012	(0.01)	-0.171	(0.00)	-0.112	(0.00)
	Inventory Group 5	-0.035	(0.00)	-0.035	(0.00)	-0.028	(0.00)	-0.046	(0.00)	-0.004	(0.45)	-0.069	(0.00)	0.003	(0.60)
	R^2	2.25		2.28		0.26		2.75		0.004		3.60		1.23	
(3)	Inventory Group 1	0.008	(0.02)	0.006	(0.07)	-0.097	(0.00)	0.005	(0.17)	0.284	(0.00)	0.009	(0.01)		
	Inventory Group 2	-0.028	(0.00)												
	Inventory Group 3	-0.038	(0.00)												
	Inventory Group 4	-0.042	(0.00)												
	Inventory Group 5	-0.034	(0.00)												
	R^2	1.00													
(4)	Inventory Group 1	0.283	(0.00)	0.284	(0.00)	0.098	(0.00)	0.311	(0.00)	0.025	(0.00)	0.360	(0.00)	0.204	(0.00)
	Inventory Group 2	-0.006	(0.07)	-0.006	(0.07)	0.008	(0.07)	-0.002	(0.62)	-0.003	(0.57)	-0.001	(0.86)	-0.014	(0.02)
	Inventory Group 3	-0.105	(0.00)	-0.105	(0.00)	-0.037	(0.00)	-0.113	(0.00)	-0.007	(0.16)	-0.125	(0.00)	-0.086	(0.00)
	Inventory Group 4	-0.141	(0.00)	-0.142	(0.00)	-0.044	(0.00)	-0.156	(0.00)	-0.012	(0.01)	-0.171	(0.00)	-0.112	(0.00)
	Inventory Group 5	-0.035	(0.00)	-0.034	(0.00)	-0.027	(0.00)	-0.045	(0.00)	-0.003	(0.61)	-0.066	(0.00)	0.001	(0.82)
	Future Return	-0.566	(0.00)	-0.582	(0.00)	-0.313	(0.00)	-0.641	(0.00)	-0.160	(0.00)	-0.678	(0.00)	-0.478	(0.00)
	R^2	2.61		2.64		0.30		3.20		0.02		3.68		1.84	

Table 7 – Variance Ratio Test for Pilot and Non-pilot Stocks

This table shows the results of conducting a variance-ratio test following on the daily CRSP-returns data on the pilot and non-pilot stocks in our sample. For that purpose, a value-weighted return index for the pilot and non-pilot stocks is calculated, which forms the basis of the test. A ratio of unity indicated no auto-correlation, a ratio below (above) one indicates negative (positive) autocorrelation. The heteroskedasticity consistent test-statistic has been calculated using various *Frequencies*. The column of the normally distributed Test-statistic shows the significance of the deviation of the variance ratio from unity.

	Pilot Stocks		Non-pilot Stocks	
Frequencies	Variance Ratio	Test Statistic	Variance Ratio	Test Statistic
2	0.91	-0.89	1.04	0.35
4	0.81	-1.28	1.01	0.05
8	0.73	-1.22	0.90	-0.45
16	0.67	-1.07	0.92	-0.25