Shorting at close range: a tale of two types*

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11 March 2012

Abstract

We examine stock returns, order flow, and market conditions in the minutes before, during, and after recent short sales on the NYSE and Nasdaq. We find two very distinct types of short sales: those that provide liquidity, and those that demand it. Shorts that supply liquidity do so when spreads are unusually wide. These short sellers are also strongly contrarian, stepping in to initiate or increase a short position after fairly sharp share price rises over the past hour or so, and they tend to face greater adverse selection than other liquidity suppliers. In contrast, shorts that demand liquidity tend to be short-term momentum traders. However, there is no evidence that liquidity-demanding short sellers are any different from other liquidity demanders. Overall, liquidity-providing short sales are important contributors to stock market quality, and regulators and policymakers should keep these salutary effects in mind.

JEL classification: G14, G19

Keywords: short selling, information content, market quality, high-frequency trading

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* We thank the Australian Research Council (ARC Linkage Project LP0455536) and the Paul Woolley Centre for Capital Market Dysfunctionality for funding. We thank the Securities Industry Research Centre of Asia-Pacific and Reuters for providing access to data used in this study. We are grateful for the comments of Henk Berkman, Veljko Fotak, Bruce Grundy, Larry Harris, Terry Hendershott, Albert Menkveld, Erik Theissen, Andriy Shkilko, Josef Zechner, and seminar participants at the Paul Woolley Centre for Capital Market Dysfunctionality 2009 annual conference, the European Finance Association 2010 annual conference, the Financial Management Association 2010 European conference, the Financial Management Association 2010 annual meeting, the IX Madrid Finance Workshop, the Institut Louis Bachelier market microstructure conference, the University of Technology Sydney market microstructure conference, the American Finance Association 2012 annual meeting, the Hanken School of Economics, University of Warwick, Vienna Graduate School of Finance, the Stockholm School of Economics / Stockholm Institute for Financial Research, Hong Kong University and the University of Western Australia. This paper succeeds one by Comerton-Forde and Putniņš entitled "Short selling: information or manipulation?"

1. Introduction

Short sellers are at the center of an intense debate that is in progress between regulators, politicians, the media and academics. The key questions in this debate concern the role of short sellers in stock markets and elsewhere. In particular, do short sellers improve market efficiency? Do short sellers destabilize stock prices in any way? Do short sellers improve or worsen market quality?

On one side of the debate, industry observers, issuers, and much of the popular media argue that short sellers employ abusive trading strategies, damage investor confidence and market quality, and amplify price declines.[1] Company directors, shareholders and the media have even gone so far as to blame short sellers for the sharp price declines or collapses of companies such as Bear Stearns, Halifax Bank of Scotland, Lehman Brothers and Merrill Lynch.[2] Regulators have responded with a frenzy of new rules to limit or discourage some short sales. For example, within one week of Lehman's collapse in September 2008, the U.S. Securities and Exchange Commission instituted an emergency ban on short sales in all financial stocks, stating that "unbridled short selling is contributing to the recent, sudden price declines in the securities of financial institutions unrelated to true price valuation".[3]

On the other hand, most academic research argues that short sellers are relatively informed, improve market efficiency, and generally stabilize share prices by identifying and then leaning against overvalued stocks.[4] This view is not unanimous, and some studies argue that short sellers might have incentives to follow manipulative or predatory trading strategies (e.g., Gerard and Nanda, 1993; Brunnermeier and Pedersen, 2005; Goldstein and Guembel, 2008).

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[1] For examples see "There's a Better Way to Prevent 'Bear Raids'" by R. Pozen and Y. Bar-Yam, The Wall Street Journal, 18 November 2008, "Anatomy of the Morgan Stanley Panic" by S. Pulliam et al., The Wall Street Journal, 24 November 2008.

[2] For example, Richard Fuld Jr., the former CEO of Lehman Brothers, during hearings on the bankruptcy filing by Lehman Brothers and bailout of AIG alleged that a host of factors including naked short selling attacks followed by false rumors contributed to both the collapse of Bear Stearns and Lehman Brothers (http://oversight.house.gov/documents/20081006125839.pdf).

[3] SEC press release 2008-211 (http://www.sec.gov/news/press/2008/2008-211.htm).

[4] See, for example, Dechow et al. (2001), Abreu and Brunnermeier (2002), Alexander and Peterson (2008), Boehmer, Jones, and Zhang. (2008), Boehmer and Wu (2010) and Diether, Lee and Werner (2009).

We contribute to this debate in two ways. First, we examine the behavior of short sellers and stock prices at a very fine time scale. We do this using trade-level information on all short sales executed on the NYSE and Nasdaq during the first eight months of 2008 for a sample of 350 stocks. Second, we highlight the fact that there are two very distinct types of short sales: those that provide liquidity, and those that demand it. The heterogeneity we find suggests that researchers, regulators, and market participants should not view short sellers as monolithic.

Much of the existing literature on short sales analyzes the association between various measures of shorting activity and stock returns, typically at horizons of days, weeks, or months. Our main contribution to this literature is to take a fine-toothed comb and analyze the behavior of stock returns, order flow, and market conditions in the minutes before, during, and after a typical short sale. The high level of granularity in our analysis is important in understanding the behavior of short sellers, particularly in light of the evidence that many short sellers employ high-frequency trading strategies.[5]

On the second question, we find that more aggressive, seller-initiated short sales that demand liquidity are quite distinct from passive, liquidity-supplying, buyer-initiated shorting. Shorts that supply liquidity do so when spreads are unusually wide. These short sellers are also strongly contrarian, stepping in to initiate or increase a short position after fairly sharp share price rises over the past hour or so. In contrast, shorts that demand liquidity are not contrarian on average. Especially in smaller stocks, these aggressive short sellers tend to be momentum traders, as their shorting activity tends to follow a price decline over the previous 24 hours. In addition, we find that aggressive short sales have significantly bigger price impacts at short horizons.

We find that in the intraday trenches, liquidity-supplying short sales are clearly a stabilizing force in stock markets. The evidence strongly indicates that they help to narrow spreads, limit price spikes, and provide liquidity at important times. These results

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[5] For example, Jones (2012) finds that 'in-and-out shorting' (short selling and covering the position before the end of the day as in the first scenario) represented about 5% of total daily volume (and a much bigger, but unknown, fraction of short selling activity) in the early 1930s. It is reasonable to expect this fraction to be higher in today's markets given the increases in automation, algorithmic trading, statistical arbitrage and turnover. The argument that short sellers employ rapid trading strategies is also consistent with the finding of Diether, Lee and Werner (2009) that short sales represent on average 23.9% of NYSE and 31.3% of Nasdaq volume.

provide an insight why restrictions imposed on short selling harm market quality (Boehmer, Jones, and Zhang, 2010a). We also find that aggressive order flow from short sellers is not very different from aggressive order flow that originates from long sellers. Based on our close-in examination of the data, the evidence provides no particular reason for regulators to target short sellers over other sellers.

2. Related literature

There are strong theoretical reasons to expect short sellers to contribute to the informativeness of prices. Diamond and Verrecchia (1987) model short sellers as rational and informed traders that take advantage of mispricings, and note that market participants do not short sell for liquidity reasons because they do not have use of the sale proceeds, though they may use short sales to hedge other risks. Theory also predicts that prices diverge from fundamental values when short selling is constrained (e.g., Miller, 1977; Duffie, Garleanu, and Pedersen, 2002; Hong, Scheinkman, and Xiong, 2006). This prediction is supported by empirical evidence that finds overpricing is reduced when short selling constraints are relaxed (e.g., Danielsen and Sorescu, 2001; Jones and Lamont, 2002; Cohen, Diether, and Malloy, 2007). In a similar vein, Saffi and Sigurdsson (2011) find that stocks with tighter short-sale constraints have lower price efficiency.

Evidence on the relation between short selling and future returns is not uniform, but is increasingly moving towards the consensus that short sellers predict future returns. This trend is particularly true in the more recent work that uses data on short flows.

2.1. Granularity and the informativeness of short sales

Several empirical studies use monthly short interest data (total outstanding short positions for each stock, measured in shares, at a particular point in time each month) and find mixed results on the informativeness of short sales. For example, Brent, Morse, and Stice (1990) and Lamont and Stein (2004) find that short interest is positively related to past returns but does not predict future returns in cross-section or time-series. Asquith, Pathak, and Ritter (2005) find return predictability only in the smallest stocks and report that the effect is stronger in stocks with low institutional ownership. In contrast, Desai, Ramesh, Thiagarajan, and Balachandran (2002) find that high short interest predicts negative returns in Nasdaq stocks, and Dechow, Hutton, Meulbroek, and Sloan (2001) find that short sellers target firms that are overpriced according to fundamental ratios. Boehmer, Huszár, and Jordan (2010) find that low short interest predicts high future returns, but the relationship between high short interest and future returns is much weaker.

Some recent studies use more granular data. Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009) construct portfolios of stocks with high and low daily short-sale flows. They measure the informativeness of short sales by comparing the risk-adjusted performance of the portfolios over the next five to 20 trading days. Heavily shorted stocks underperform lightly shorted stocks over the following month, and Boehmer, Jones and Zhang (2008) find that institutional non-program short sales are the most informative. Diether, Lee, and Werner (2009) find that short sellers increase their trading following positive returns and they correctly predict future negative returns. Christophe, Ferri, and Angel (2004) and Boehmer, Jones, and Zhang (2010b) find that daily flows of short sales are concentrated prior to disappointing earnings announcements, which suggests short sellers have access to private information. Engelberg, Reed, and Ringgenberg (2012) and Fox, Glosten, and Tetlock (2010) find that short sellers trade around negative news releases. All of these papers aggregate shorting flow to the daily level; none of them focus on intraday returns, spreads, or trading behavior.

Only a few papers employ intraday data to study short sales. For example, Boehmer and Wu (2010) find that high-frequency informational efficiency of prices improves with greater daily shorting flow. Aromi and Caglio (2008) examine September 2008 data on stock returns and short sale order imbalances at five-minute intervals, and they conclude that on average, episodes of extreme negative returns are not the result of short selling activity. Boehmer, Jones, and Zhang (2010a) use intraday data to measure market quality and the aggressiveness of short sellers around the 2008 temporary ban on shorting U.S. financial stocks.

2.2. Short selling and manipulation

Manipulation, which in the context of short sales is an effort to profit by driving share prices below fundamental value, could also conceivably account for the relationship between short sales and future returns. However, evidence on the involvement of short sellers in market manipulation or predatory trading is scarce. Goldstein and Geumbel (2008) show that aggressive short selling may depress a company's share price and distort the company's investment decision, thereby harming fundamentals and allowing the short sellers to cover their positions at depressed prices. Brunnermeier and Pedersen (2005), Carlin, Lobo, and Viswanathan (2007) and Attari, Mello, and Ruckes (2005) model predatory trading involving sellers (including short sellers) profitably exploiting investors that have a need to exit long positions, or undercapitalized arbitrageurs. Such trading leads to negative return reversals.

Allen and Gale (1992) and Aggarwal and Wu (2006) present theoretical and empirical evidence of 'pump-and-dump' manipulation. This type of manipulation involves taking a position in a stock, inflating the price with techniques such as wash trades or rumor mongering, at the same time attracting liquidity to the stock, and finally reversing the original position at a profitable price. Although the documented evidence of this strategy involves stock price inflation (profiting from long initial positions) it is not difficult to imagine a similar strategy involving initially short selling the stock and then manipulating the price downwards. Such trading strategies, commonly known as 'bear raids', were widespread in the 1930s and prompted the introduction of the 'uptick rule' in the United States during the Great Depression. Anecdotal evidence suggests such strategies have been used recently by market manipulators exploiting the environment of fear and uncertainty to profit from attacks on vulnerable companies.[6]

Three recent papers empirically examine short selling in relation to particular manipulative or abusive trading strategies. Shkilko, Van Ness, and Van Ness (2009) examine stocks that experience large negative intraday price moves followed by a reversal before the end of the day. They find aggressive short sales during the price decline period (though long sellers are even more aggressive than short sellers), and they suggest that short sellers may occasionally engage in predatory trading. Fotak, Raman, and Yadav (2009) investigate the effects of naked short selling on markets using the level of fails to deliver during settlement as a proxy for naked short selling. They find that naked short sellers have positive effects on market quality, such as reducing price error and volatility. They also examine the levels of naked short selling surrounding four high profile cases of financial firms that experienced dramatic stock price declines during 2008. Fotak, Raman,

[6] For examples see "There's a Better Way to Prevent 'Bear Raids'" by R. Pozen and Y. Bar-Yam, The Wall Street Journal, 18 November 2008; "One way to stop bear raids" by G. Soros, The Wall Street Journal, 23 March 2009; and "Blame the bear raids" by T. Brennan, CNBC, 20 March 2008.

and Yadav (2009) conclude that the level of naked short selling prior to the price declines was too low to reasonably 'cause' the price declines and naked short selling only become abnormally heavy *after* the price declines, not *before*. Blocher, Engelberg, and Reed (2009) examine whether fund managers holding short positions manipulate prices down with short selling on the last trading day of the year. They find increased levels of short selling in the last hour of the last trading day of the year for stocks that have large short interest. The short selling is accompanied by poor returns and subsequent reversals at the beginning of the year. All of these results are consistent with end of year manipulation by fund managers holding short positions.

2.3. Liquidity demand vs. liquidity supply

Traditional models, such as Glosten and Milgrom (1985), assume that dealers supply liquidity, and all other investors demand liquidity. In modern limit order markets, each individual trader can choose whether to supply liquidity via a limit order, or demand liquidity by submitting a marketable order. In Foucault, Kadan, and Kandel (2005), for example, patient investors are more likely to submit limit orders, while impatient investors are more likely to submit market orders. In order submission models with adverse selection, such as Glosten (1994), better informed investors use market orders, while uninformed investors are more likely to employ limit orders. Thus, any observed difference in liquidity demand vs. supply between short sellers and long sellers would indicate differences in patience or informedness.

Hollifield, Miller, Sandas, and Slive (2006) give investors private values, and they also allow investors to differ in their cost of submitting an order. In their model, investors with smaller order submission costs would be more sensitive to order book conditions: they would submit limit orders when the book is relatively empty, and use marketable orders when the book is relatively full. In contrast, investors with larger order submission costs would be on the sidelines more often. Empirically, if one group (short sellers or long sellers) is more likely to supply liquidity when spreads are wide, and also more likely to demand liquidity when spreads are narrow, that would indicate smaller order submission costs for that group.

Alternatively, and perhaps more intuitively, one can think of investors as having different costs, ability, or speed in monitoring the state of the market, as in Foucault, Roell, and Sandas (2003). Those with better monitoring ability are more likely to be the first to submit limit orders when the book is relatively empty, and they are more likely to be the first to identify and take liquidity from an attractive sitting limit order.

3. Data and summary statistics

In the U.S., the SEC requires a broker-dealer to mark a short sale when the order is sent to a trading venue. Short sale orders are not publicly disclosed as such, but for audit and compliance purposes exchanges are required to track all short sale orders. Thus we are able to obtain data from the respective exchanges on all short sales executed at the NYSE or Nasdaq from January 1, 2008 through August 31, 2008 for a sample of 350 stocks. Sample stocks are selected by sorting all NYSE-listed common stocks (Center for Research in Securities Prices (CRSP) share codes 10 and 11) into deciles based on their market capitalization as of 31 December 2007 and then randomly sampling 35 stocks from each size decile.

We couple the short sales data with all trades and quotes during the same period, obtained from the Thomson Reuters Tick History database maintained by the Securities Industry Research Centre of Asia-Pacific.[7,8] We add company level variables, including book-to-market ratio, market capitalization, number of shares on issue, and short interest from the CRSP database, Compustat and Thomson Reuters Datastream.

< TABLE 1 HERE >

Table 1 reports summary statistics about the number, volume and size of short sales relative to non-short sales on the two exchanges, as well as for the pooled sample. There are more than 103 million short sales in these 350 stocks over the eight-month

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[7] Similar to the TAQ database, the Reuters database is a record of the consolidated tape.

[8] We match short sales to trades by exchange, symbol, date, price, size and time. We first look for exact matches, down to the second. To correct for small differences in the timestamps recorded in each of the databases, we then look for matches where time stamps differ by one second, and finally we look for matches with two-second timestamp differences. For our sample, 98.2% of the short sales match to trades and we discard the remaining 1.8%.

sample period, and almost 170 million long sales. About 60% of the short sales in these NYSE-listed stocks take place on the NYSE, with the remaining 40% executing on Nasdaq.

Short sales constitute 40.2% and 39.2% of total dollar volume on the NYSE and Nasdaq, respectively. Shorting is a similar fraction of the overall number of reported trades on those two venues. For about a quarter of the stocks in our sample, shorting actually accounts for a majority of the trading activity. The proportion of short selling has been increasing over time. Boehmer, Jones, and Zhang (2008) find that short selling represents about 13% of volume in their 2001-2005 sample, and Diether, Lee, and Werner (2009) report that short selling represents an average of 24% of share volume on the NYSE in 2005. Note that our sample ends before the SEC ban on short selling in financial stocks and is thus unaffected by that regulatory change. Boehmer, Jones, and Zhang (2010a) show that shorting activity in affected stocks is reduced by about two-thirds during the ban.

On the NYSE, short sales and long sales are distributed quite similarly. The mean size of a short sale is \$6,581, while the mean size of a long sale is \$6,754. The quartile points are also virtually identical. The 25th percentile is \$1,710 for short sales vs. \$1,721 for long sales, the medians are \$3,046 vs. \$3,065, and the 75th percentiles are \$4,928 for short sales vs. \$4,953 for long sales. The similarity in distribution makes sense if short sellers and long sellers use similar order-splitting algorithms, as both types of sellers could be expected to have similar incentives to blend in and not telegraph their order flow. Short sales on Nasdaq have a very similar distribution to the short sales and long sales on the NYSE, with a mean size of \$6,551. Long sales on Nasdaq tend to be somewhat smaller, with a mean size of \$5,860.

< TABLE 2 HERE >

Table 2 reports how average short selling activity varies with firm characteristics. In Panel A, we sort stock-days into quintiles based on both size and book-to-market ratios. There are only very modest patterns across these two characteristics. Shorting is a bit more prevalent in small stocks (41.2% of dollar volume) than it is in the largest cap quintile (38.0% of dollar volume). On average, short sales account for 36.5% of dollar volume for the lowest book-to-market firm quintile vs. 41.3% of dollar volume for the highest book-to-market firm quintile. This is notable, because it runs counter to the evidence in Dechow, Hutton, Meulbroek and Sloan (2001), which indicates that short sellers tend to concentrate their activity in low book-to-market stocks.

In Panel B, we sort into quintiles based on share price and short interest at the end of the previous month, where short interest is calculated as a fraction of shares outstanding. The pace of shorting activity does not appear to be related to share price. Not surprisingly, the shorting flow measure used here (shorting as a fraction of overall trading volume) is positively correlated with short interest (short positions outstanding at a given point in time), which is a stock measure. But it is worth noting that there is still substantial shorting activity even in the stocks with the smallest short interest. Short sales account for 34.2% of dollar volume for the low short interest quintile, compared to 43.4% of dollar volume for the high short interest quintile.

< TABLE 3 HERE >

Table 3 reports the aggressiveness of executed short and non-short sell orders relative to the prevailing quotes. Short sales and long sales display similar aggressiveness, indicating nothing unusual about shorting activity relative to other selling. About 40% of sales occur at the best ask quote (and thus are liquidity-supplying limit sell orders), about 35% are at the best bid quote (indicating that they are liquidity-demanding market sell orders), and about one-sixth execute between the best bid and best ask quotes. A small fraction (3.8% to 4.2%) execute at prices above the ask quote, and a similar number (3.7% to 3.9%) execute at prices below the bid quote. Short sales and long sales are virtually identical in terms of aggressiveness, indicating that long sellers and short sellers are similarly patient.

When we partition the sample by market cap, the most notable result is that there are relatively few executions within the quotes for the largest cap quintile. Only about 13% of sales (long or short) take place between the quotes, while the corresponding figure is more than 20% for most of the other size quintiles. This is probably due to the fact that the inside spread in most large-cap stocks is usually equal to the minimum tick of one cent. Finally, when we compare sell orders executed on the NYSE and the Nasdaq, there are only very small differences in the distribution of executions relative to the prevailing quotes, and no discernible cross-exchange differences in the aggressiveness of short sales.

4. Two types of short sales

The heart of the paper is a comparison at close range of the dynamics and characteristics of aggressive (seller-initiated) vs. passive (buyer-initiated) short sales. We assign short sales to one of these two categories based on the transaction price compared to the midpoint between the prevailing bid and ask price at the time of the trade.[9] Short sales that take place below the prevailing midpoint are considered seller-initiated, while short sales that take place above the prevailing midpoint are considered buyer-initiated. We use the Lee and Ready (1991) method to assign trades that are at the prevailing midpoint.[10] As a practical matter, during our sample period the quoted spread on most U.S. stocks is the minimum tick of one cent most of the time. In most cases, then, trades are at either at the prevailing bid or the prevailing ask, and short sales at the bid are considered seller-initiated, while short sales at the ask are buyer-initiated. Note that we will often refer to seller-initiated shorts as aggressive or liquidity-demanding, while buyer-initiated shorts are often referred to passive or liquidity-supplying, because in an electronic limit order book market, these trades result from a marketable buy order trading with a standing (non-marketable) limit order to short sell.

For comparison, we use the same methods to partition long sales into buyer-initiated and seller-initiated. Thus we have four different types of order flow that lead to transactions: buyer-initiated trades involving a long seller (BIL), seller-initiated trades involving a long seller (SIL), buyer-initiated trades involving a short seller (BIS), and seller-initiated trades involving a short seller (SIS).

It is important to emphasize that our partition is based on trade-level data; a particular seller might find her individual trades in more than one of our categories. For example, some high-frequency traders move back and forth rapidly between long sales and short sales. Menkveld (2011) provides evidence on one such high-frequency market-

[9] The prevailing bid and ask are taken from the most recent consolidated quote with a time-stamp prior to that of the transaction.

[10] Chakrabarty, Moulton, and Shkilko (2012) use Nasdaq order book data to show that the Lee-Ready algorithm misclassifies 21% to 31% of short sales. This adds noise to our estimates and reduces statistical power, but should not introduce bias.

maker, who switches from a long position to a short position many times in a single day. Along the same lines, a large institutional order – sometimes called the parent order – is likely to be broken up and executed in many small pieces via child orders. Algorithms typically submit (and often cancel and resubmit at different prices) these child orders over time, and typically they use a mix of limit orders and marketable orders. Thus, a single seller would in part supply liquidity and in part demand liquidity. However, impatient or better informed sellers would still be expected to use more marketable orders.

4.1. Effective spreads, realized spreads, and price impacts

We begin by examining whether market conditions are associated with the likelihood of these four different transaction types. In particular, we focus on the variation in liquidity over time, to see whether long and short sales of various types are more or less likely to take place when spreads are relatively wide. To do this, we calculate the effective half-spread associated with a transaction in stock i at time t (ES_{it}) as the distance, in basis points, between the transaction price and the prevailing quote midpoint.

< TABLE 4 HERE >

Table 4 has the mean effective spreads for each transaction type, partitioned by market-cap quintile as well as pooled across all stocks. Comparing the two buy trade types, we find that effective spreads for buyer-initiated short sales (BIS) average 6.03 basis points for the whole sample vs. 5.74 basis points for buyer-initiated long sales (BIL), and this difference is statistically distinguishable from zero. There are similar results for each of the market-cap quintiles: compared to long sellers that supply liquidity, short sellers that supply liquidity do so at wider average effective spreads.

Turning to seller-initiated trades, we find the reverse result. Short-sellers that demand liquidity (SIS) do so at average effective spreads which are narrower than average effective spreads for liquidity-demanding long sellers (SIL). For example, using the pooled sample, the average spreads are 5.89 basis points for SIL and 5.55 basis points for SIS, and the average spreads in the largest market-cap quintile are 1.85 basis points for seller-initiated longs vs. 1.79 basis points for seller-initiated shorts.

There are several possible econometric explanations for these findings. It could be that our four trade types tend to concentrate in different stocks. It could be that short sellers and long sellers trade at different times in the same stocks. To sort out these explanations, we estimate the following fixed-effect panel regression on the 270 million trades in our sample:

$$ES_{it} = \mu_i + \beta_1 D_{it}^{BIL} + \beta_2 D_{it}^{BIS} + \beta_3 D_{it}^{SIL} + \beta_4 D_{it}^{NYSE} + \varepsilon_{it}$$

where there are fixed effects for each stock, indicator variables for each transaction in stock i at time t if the transaction is associated with a buyer-initiated long sale (BIL), buyer-initiated short sale (BIS), or a seller-initiated short sale (SIL), and an indicator variable for trades executed on the NYSE. The omitted transaction type is a seller-initiated short sale (SIS), so all indicator variables reflect the differential effective spread compared to a seller-initiated short sale on Nasdaq. We estimate the model on the pooled sample as well as on five market-cap quintiles, and in each case we report standard errors that are clustered by date.

< TABLE 5 HERE >

The results are in Panel A of Table 5. The fixed-effect regression results match up with the overall means from the earlier table, confirming that the effects are not the result of short sellers and long sellers concentrating their activity in different stocks. For a given stock, average effective spreads are narrowest when seller-initiated short sales take place. In the pooled sample, buyer-initiated long sales take place at effective spreads that are 0.07 basis points wider on average, buyer-initiated short sales average 0.19 basis points wider, and seller-initiated long sales average 0.16 basis points wider. The results for BIS, BIL and SIL are statistically significant. The results are broadly similar across the market-cap quintiles, though the BIL coefficients are statistically indistinguishable from zero for two of the quintiles. Overall these results indicate that liquidity-demanding shorts (SIS) tend to act when spreads are unusually narrow.[11]

One other econometric possibility is that these four transaction types – BIL, BIS, SIL, and SIS – differ in the distribution of trade size. For example, if seller-initiated long sales (SIL) are larger than seller-initiated short sales (the omitted SIS category in the

[11] We find very similar results for seller-initiated short sales across share price quintiles.

regression), this could account for the observed positive coefficient on the SIL dummy. Given that Table 1 showed that short sales and long sales have a very similar distribution of sizes, we do not expect this to account for the effective spread differences. However, to investigate this, we estimate a variant of equation (1) that includes a linear and a quadratic term for the dollar volume of the trade. We also include 1/price in the regression to control for differences caused by price level and tick size. The results are in Panel B of Table 5. The trade size coefficients capture important variation in effective spreads, but the coefficients on the trade type dummies are virtually unchanged. Thus, trade size does not explain the observed differences between aggressive short sellers and other seller types. Similarly, 1/price is also highly significant but does not change the significance of the trade type coefficients.

Aggressive short sellers tend to pull the trigger when effective spreads are unusually narrow. What induces a passive short seller to trade? Wide spreads help. As noted above, short sellers that supply liquidity do so when effective spreads are an average of 0.19 basis points wider, compared to spreads when short sellers demand liquidity. And in some of the market-cap quintiles, passive long sellers and passive short sellers are different. Particularly for quintiles 2 and 3, when a short seller provides liquidity, spreads are statistically wider than when a long seller provides liquidity. For example, in quintile three, spreads are 0.243 – 0.096 = 0.15 basis points wider for buyer-initiated short sellers (BIS) compared to buyer-initiated long sellers (BIL). This indicates that liquidity-supplying short sellers are more sensitive to order book conditions and tend to supply liquidity when there is more spread to capture.

Together, these results indicate that, on average, short sellers are more sensitive to time-varying liquidity conditions. In the framework of Foucault, Roell, and Sandas (2003), this means short sellers have better monitoring ability than long sellers. As a practical matter, this probably means that short sellers on average have invested more in trading infrastructure. As a result, they are faster to respond to changing order book conditions, and they are better able to monitor previously placed orders. In contrast, long sellers are less sensitive to the spread that they are paying. This implies that long sellers are somewhat less sophisticated on average in terms of being able to monitor time-varying order book conditions. Our guess is that many long sellers also have access to advanced algorithms and technology, giving them the ability to monitor liquidity conditions and access liquidity quickly, but some long sellers, including retail investors, do not have access to these capabilities. As a result, these investors cannot adjust their order submission strategies in the same way to short-run changes in market conditions, and these long sellers affect the overall averages. Comparing algorithmic traders to non-algorithmic traders on the Deutsche Borse, Hendershott and Riordan (2012a) find similar results on sensitivity to order book conditions, lending support to our interpretation that short sellers are disproportionately algorithmic traders.

Do passive short sellers (BIS) actually capture more spread than passive long sellers (BIL)? It could be that passive short sellers face greater adverse selection and are not able to pocket the wider effective spreads. To investigate this possibility, we measure five-minute realized spreads for the four types of trades. Realized spreads are defined for buys as the transaction price minus the quote midpoint five minutes later, and are defined analogously for sells. Realized spreads are a proxy for liquidity supplier profits under the assumption that these liquidity suppliers hold onto their position for five minutes and are then able to unwind at the then-prevailing midpoint. Realized spreads can be equivalently defined as the effective spread less the five-minute price impact, so if realized spreads do not match up with effective spreads, it must be due to differences in the magnitude of adverse price moves following a transaction.

Average realized spreads are also in Table 4 for both the pooled sample and the five market-cap quintiles. In the pooled sample, realized spreads for passive short sellers and passive long sellers are very similar. Short sellers that supply liquidity (BIS) earn 1.82 basis points vs. 1.75 basis points for long sellers supplying liquidity (BIL), and this difference is not statistically significant. However, there is some cross-sectional heterogeneity in this result. In the smallest-cap quintile, passive short sellers earn smaller realized spreads than passive long sellers (3.96 vs. 4.55 basis points). By the accounting identity that relates effective and realized spreads, this means that buyer-initiated shorts face larger adverse price moves on average in this quintile, with five-minute price impacts 10.75 basis points vs. 9.03 bps for long sellers who supply liquidity, and this difference is statistically significant. Thus, at least in the small-cap quintile, passive short sellers are relatively more willing to step in when conditions are more adverse, indicating that these short sellers are adding to overall market quality. In large-caps, on the other hand, there are no statistically reliable differences in price impacts or realized spreads between buyer-initiated shorts (BIS) and buyer-initiated long sellers (BIL). In these two quintiles, the BIS vs. BIL differences are only marginally statistically significant.

The realized spread results can also be viewed through the lens of the theoretical models mentioned earlier. According to Foucault, Kadan, and Kandel (2005), smaller realized spreads indicate that passive short sellers are more patient. Hollifield, Miller, Sandas, and Slive (2006) would say that passive short sellers have a smaller order submission cost than passive long sellers. And Walrasian auction models such as the one in Nagel (2011) would conclude that, all else equal, passive short sellers are less risk averse than passive long sellers. Whatever the exact terminology, the evidence is consistent with a distinct comparative advantage for this set of short sellers in supplying liquidity.

We can also use price impacts to understand the relative trading behavior of liquidity demanders. In the pooled sample, five-minute price impacts associated with long sellers (SIL) are 4.15 basis points, and this is statistically indistinguishable from the comparable number of 3.98 bps for liquidity-demanding short sellers. Again, the only significant difference is in the smallest quintile, where five-minute price impacts are greater for long sellers (9.80 basis points) than for liquidity-demanding short sellers (8.54 basis points). Thus, if anything, aggressive short sellers push share prices down less than their long counterparts.

While we are discussing realized spreads, it is worth noting how small they are in general. Across all stocks in our sample and all four trade types, realized spreads average only about 1.8 basis points, or about one-half cent on a typical $30 stock. In fact, realized spreads are less than one basis point in the largest-cap quintile.[12] Note that these are gross realized spreads that do not take into account rebates paid to liquidity suppliers. During our sample period, the NYSE did not pay these rebates, while Nasdaq rebates were 0.28 cents per share for high-volume liquidity suppliers, which amounts to about one additional basis point on a typical $30 stock. Even though realized spreads do not directly measure trading revenue earned by liquidity suppliers, these results indicate that supplying liquidity is a very competitive business during our sample period.

[12] This differs from Hendershott and Riordan (2012b), who find that liquidity supply on Nasdaq by high-frequency traders during 2008-2009 actually loses money excluding rebates.

In sum, our evidence so far indicates that compared to passive long sellers, passive short sellers are more willing to step in and supply liquidity in adverse market conditions, and short sellers demanding liquidity are not very different from long sellers that demand liquidity. In the next section, we investigate price behavior just prior to a trade in order to further characterize the behavior of our four types of sellers.

4.2. Stock returns just before and after various types of sales

There is some prior evidence that short sellers are contrarian, taking short positions in stocks that have experienced recent stock price increases. For example, Diether, Lee, and Werner (2009) use daily data on shorting activity from 2005 and find that short sales increase the day after a share price rise. In this section, we investigate whether this is also true at finer time intervals. We also examine whether aggressive short sellers and passive short sellers are similarly contrarian, and we compare short sellers to long sellers to see if they are qualitatively similar.

To do this, we take our four types of executed order flow – BIS, SIS, BIL, and SIL – and for each stock we aggregate each type of order flow over five-minute intervals. Since U.S. stock markets are open for 6½ hours a day, from 9:30am to 4:00pm, there are 78 five-minute intervals each day. For calculating five-minute returns, we use the midquote that is in effect at the end of each five-minute interval. In our plots, the overnight return period from the 4:00pm close to the 9:30am open on the next trading day is considered a separate five-minute interval.

We then examine cumulative stock returns up to one day before and after transactions of various types using an event study methodology. The results are in Figure 1. We show average cumulative stock returns pooled over all stocks and five-minute intervals, weighted either by the dollar volume of the particular sale type (Panel A) or by the number of trades of the relevant sale type (Panel B). Dollar volume weighting is dominated by trading in large-cap stocks, so the equal-weighting in Panel B gives more influence to trades in smaller-cap names. Figure 1 Panel C shows the results for each weighting scheme for each of the five market-cap quintiles.

< FIGURE 1 HERE >

The results for price moves leading up to a sale are quite revealing. Not much happens to prices before a long sale. For SIL and BIL, average returns are generally close to zero up to one trading day (78 five-minute periods) before the relevant sale. Aggressive short sales (SIS) tend to be momentum traders, particularly in the smallest two market-cap quintiles. For example, when short sales are equal weighted, the average return over the 24 hours prior to an aggressive short sale is -0.43% for the smallest quintile and -0.32% for the next-smallest quintile. Standard errors clustered by stock and by date confirm that these average returns are statistically different from the returns prior to the other three transaction categories. There are benign and not-so-benign explanations for this result, and we discuss this in more detail later in the paper.

The strongest regularity is for short sales that provide liquidity. Looking at the pooled dollar-volume weighted results in Panel A of Figure 1, average share prices rise a full 10 basis points in the 100 minutes (from five-minute period -20 to period 0) prior to a buyer-initiated short sale (BIS). If anything, the effect is even steeper as we get closer to event time zero. This result is not limited to large-cap stocks; the share price rise is statistically significant and of very similar magnitude in four out of the five market-cap quintiles. Passive short-sellers are sharply contrarian, responding by adding sell-side liquidity following a sharp price rise in the previous few minutes. It is important to emphasize the magnitude of this result. On a typical $30 stock, 10 basis points means an increase of $0.03 in the quote midpoint, averaged across every short sale that takes place at the ask. Thus, it seems clear that short sellers that supply liquidity react very differently than other types of sellers.[13]

Interestingly, this price rise is permanent, not temporary. In fact, there is a further price rise that represents the immediate price impact of the buyer-initiated order flow. Looking out further after the passive short sale, prices remain more or less flat. There is no further upward drift and no downward price reversal, consistent with markets that efficiently incorporate trade-related information. This is to be expected given the competitive nature of market-making and high-frequency trading during the 2008 sample

[13] This result could also arise somewhat mechanically. Suppose for illustration that market-makers are the only liquidity providers and the only short sellers, and they begin a given period with a long inventory position. A sequence of buys comes along. Prices rise, and market-makers reduce their long position. If there are enough buys in the sequence, eventually the market-makers must go short to provide liquidity. In this situation, the data would record a price rise before these short sales, but this would simply be the result of ordinary market-making behavior in response to persistent buyer-initiated order flow.

period. The pooled results indicate that three of the four sale types – BIS, BIL, and SIL – do not show appreciable drift in the midpoint following the trade. Prices continue to erode slightly following aggressive short sales (SIS), as average quote midpoints drift down an additional 2 basis points or so over the 24 hours following these liquidity-demanding short sales, but this additional decline is not statistically significant.

When we disaggregate the results by market-cap quintile, we find that the results are far from uniform in the cross-section. Passive shorts demonstrate distinctive contrarian behavior most strongly in large-cap stocks, particularly quintiles 4 and 5. They are not at all contrarian for stocks in quintile 2, and they are not as contrarian as passive long sellers in the smallest-cap quintile. In the large-cap quintiles, the contrarian results are more dramatic under dollar volume-weighting, which means that the effect is driven by large trades and/or by stocks with high share prices. In results not reported, we sort stocks into quintiles based on share price, and for the high-price quintiles we continue to find the same effect. This implies that trade size is driving the result; with large trades more contrarian than small trades. Thus, both the extensive and intensive margins matter for a passive short seller. A sharp short-term price rise not only makes it more likely that a short seller will provide liquidity, but a passive short seller on average trades a larger amount in this situation.

The graphs also suggest that price impacts are bigger in magnitude when a short seller is involved. Compared to a seller-initiated long sale (SIL), for example, prices fall further following a seller-initiated short sale (SIS). To determine whether the patterns in the graphs are statistically significant, we turn to a panel regression approach that measures share price moves immediately following the four sale types.

For a time horizon *k* following a trade in stock *i* at time *t*, we regress the cumulative post-trade midpoint return $r_{t,t+k}$ (the subscript *i* is suppressed) on indicator variables for BIL, BIS, and SIL transaction types, and possible fixed effects:

$$r_{t,t+k} = \mu_i + \gamma_t + \beta_1 D_{it}^{BIL} + \beta_2 D_{it}^{BIS} + \beta_3 D_{it}^{SIL} + \varepsilon_{it},$$

where Model 1 has an intercept and no fixed effect, Model 2 has a stock fixed effect, and Model 3 has a fixed effect for each five-minute interval. The time dummies in Model 3 take out the average return across all sample stocks for that interval. Thus, this model is equivalent to using excess returns vs. the market as the dependent variable, thereby accounting for relative rather than raw stock price behavior. As in earlier regressions, the omitted category is aggressive shorting (SIS), so that the intercept in Model 1 is the average value for liquidity-demanding short sales (SIS), and the coefficients on indicator variables measure the incremental effect relative to the SIS case. Standard errors are clustered by stock and by date. We examine post-trade time horizons of five minutes, 30 minutes, two hours, and 24 hours. The five-minute and 30-minute horizons are common in empirical microstructure work, but we also examine returns up to one day out in order to connect to some of the lower-frequency information content literature. We estimate a version using the entire pooled sample as well as five market-cap quintile subsamples.[14] We also estimate the models where each trade is weighted by dollar volume and where each trade is equal weighted. The results for these alternative weights are very similar. We focus on the dollar volume-weighted results because these better reflect liquidity suppliers' aggregate dollar losses to better-informed traders.

< TABLE 6 HERE >

We start with the pooled results in Panel A of Table 6. At the five-minute horizon, we cannot statistically distinguish between the price impact of a seller-initiated short sale (2.37 basis points on average, based on Model 1) and the price impact of a seller-initiated long sale (2.37 – 0.16 = 2.21 basis points). This result holds in Panel B across all five market-cap quintiles, and we see the same lack of significant difference between SIS and SIL trades at longer horizons. Aggressive short sellers and aggressive long sellers have virtually the same average price impact.[15] At first glance, this might seem incompatible with results by others showing that short sellers have superior information. However, those results are at longer horizons, with holding periods measured in weeks or months. The results here simply indicate that if this group of short sellers is indeed better informed,

[14] Note that because all trades are grouped into five-minute intervals, the return period depends on a trade's location within such an interval. For example, if a trade takes place at 10:32:00am, the five-minute post-trade midpoint return would be measured from 10:30am to 10:35am. The same five-minute return would be used for any trade in that stock that occurs between 10:30:00am and 10:34:59am inclusive. Also, except for the 24 hour time horizon, the time horizons count only time when the market is open. For example, for a trade that takes place at 3:31pm, the two-hour return would be calculated from 3:30pm to 11:00am the next trading day.

[15] In fact, Model 3 shows that price impacts are actually *smaller* when it is a short seller that demands liquidity. Market-adjusted prices actually move down 0.70 basis points further for SIL trades compared to similar trades involving a short seller. This difference is significant at the 1% level.

they possess long-lived information that takes more than one day to be impounded into prices.

In contrast, for buyer-initiated trades the price impact is statistically different when a short seller is on the other side. At a five-minute horizon, a passive short sale (BIS) faces an adverse price impact of -2.37 + 6.40 = 4.03 basis points, while a long seller providing liquidity (BIL) experiences an adverse price impact of only -2.37 + 4.93 = 2.56 basis points. This result is also present in Model 2 with stock fixed effects, which rules out the possibility that passive short sellers are simply concentrated in stocks with less adverse selection. This suggests that short sellers who supply liquidity are willing to face greater adverse selection risk, at least compared to similar long sellers. This is consistent with our earlier evidence that passive short sellers tend to step in after a sharp price rise. That sharp pre-trade price rise suggests an unfavorable information environment for providing liquidity on the ask side, and the evidence here bears that out.[16] The pooled result is driven mainly by large-cap stocks: BIL and BIS five-minute price impacts are statistically distinguishable only for the top two market-cap quintiles.

4.3 The joint evolution of long and short sales over time

Up to now, we have conditioned on the single occurrence of a certain type of trade. However, we know that order flow is persistent, and our different order flow types may themselves persist and may induce persistence in other types of order flow.

To investigate the dynamic relationships among our four sale types and between order flow and returns, we adapt the Hasbrouck (1991) vector autoregressive framework to our order flow partition. We classify trades into four categories (SIS, SIL, BIS, and BIL) to create order flow variables x_{it}^{SIS}, x_{it}^{SIL}, and so on, measured in number of shares. For each stock over the whole sample period, we estimate the following system:

$$x_t^{BIL} = \mu^{BIL} + \sum_{i=1}^{10} \phi_i^r r_{t-i} + \sum_{i=1}^{10} \phi_i^{BIL} x_{t-i}^{BIL} + \sum_{i=1}^{10} \phi_i^{BIS} x_{t-i}^{BIS} + \sum_{i=1}^{10} \phi_i^{SIL} x_{t-i}^{SIL} + \sum_{i=1}^{10} \phi_i^{SIS} x_{t-i}^{SIS} + \varepsilon_t^{BIL}$$

[16] Interestingly, this difference between BIS and BIL is fairly short-lived. At the 30-minute horizon, price impacts associated with the two types of trades differ by only 0.66 basis points on average using Model 1. This price impact difference is only about one standard error and thus is not significant. Models 2 and 3 yield the same statistical inference.

$$x_t^{BIS} = \mu^{BIS} + \sum_{i=1}^{10} \theta_i^r r_{t-i} + \sum_{i=1}^{10} \theta_i^{BIL} x_{t-i}^{BIL} + \sum_{i=1}^{10} \theta_i^{BIS} x_{t-i}^{BIS} + \sum_{i=1}^{10} \theta_i^{SIL} x_{t-i}^{SIL} + \sum_{i=1}^{10} \theta_i^{SIS} x_{t-i}^{SIS} + \varepsilon_t^{BIS}$$

$$x_t^{SIL} = \mu^{SIL} + \sum_{i=1}^{10} \lambda_i^r r_{t-i} + \sum_{i=1}^{10} \lambda_i^{BIL} x_{t-i}^{BIL} + \sum_{i=1}^{10} \lambda_i^{BIS} x_{t-i}^{BIS} + \sum_{i=1}^{10} \lambda_i^{SIL} x_{t-i}^{SIL} + \sum_{i=1}^{10} \lambda_i^{SIS} x_{t-i}^{SIS} + \varepsilon_t^{SIL}$$

$$x_t^{SIS} = \mu^{SIS} + \sum_{i=1}^{10} \beta_i^r r_{t-i} + \sum_{i=1}^{10} \beta_i^{BIL} x_{t-i}^{BIL} + \sum_{i=1}^{10} \beta_i^{BIS} x_{t-i}^{BIS} + \sum_{i=1}^{10} \beta_i^{SIL} x_{t-i}^{SIL} + \sum_{i=1}^{10} \beta_i^{SIS} x_{t-i}^{SIS} + \varepsilon_t^{SIS}$$

$$r_t = \mu + \sum_{i=1}^{10} \gamma_i^r r_{t-i} + \sum_{i=0}^{10} \gamma_i^{BIL} x_{t-i}^{BIL} + \sum_{i=0}^{10} \gamma_i^{BIS} x_{t-i}^{BIS} + \sum_{i=0}^{10} \gamma_i^{SIL} x_{t-i}^{SIL} + \sum_{i=0}^{10} \gamma_i^{SIS} x_{t-i}^{SIS} + \varepsilon_t^r ,$$

where t indexes trades and individual stock subscripts are suppressed.[17] Therefore, for each trade t, one of $\{x_{it}^{SIS}, x_{it}^{SIL}, x_{it}^{BIS}, x_{it}^{BIL}\}$ will be equal to the volume of the trade and the others will be zero.[18] r_t is the log-midquote change subsequent to the t^{th} trade.

For each equation, we estimate coefficients on 10 lags of each variable. In addition to the 10 lags, midquote returns are also determined by contemporaneous order flow. A separate estimation is performed for each stock using the entire eight-month sample. Impulse responses are then calculated for a shock to each of the order flow types, holding all other types of volume equal to their unconditional means. To make the impulse responses comparable across order flow types, the magnitude of each volume shock is set equal to the standard deviation of unanticipated buyer-initiated long (BIL) volume. We report the equal-weighted average impulse response up to 20 trades ahead, where the averaging is across all stocks in a given size quintile.

< FIGURE 2 HERE >

Figure 2 contains the results for the cumulative return response to various kinds of volume shocks. Midpoints adjust fully to a trade innovation within approximately 10 trades. This partial adjustment is consistent with the effects of discreteness, as well as the standard practice of reporting multiple trades to the consolidated tape when a single

[17] There is no separate overnight return in this analysis. The overnight return (adjusted for distributions) is included as part of the return from the last trade for the day to the first trade of the following day.

[18] An exception occurs for the small number of trades that are made up partly from short volume and partly from long volume. Such trades arise when one order executes simultaneously against two or more orders and a single trade is recorded on the tape. If, for example, a market buy order for 500 shares executes against a 200 share long sale and a 300 share short sale and is recorded as a single trade, then the volume variables would take the values $x_{it}^{BIL} = 200$ and $x_{it}^{BIS} = 300$.

marketable order interacts with multiple standing limit orders of smaller size. To confirm this, we also conduct the VAR in calendar time (results available on request), and we find that quote midpoints fully adjust to order flow innovations within one minute, consistent with market efficiency.

The price impacts are generally quite symmetric. To be precise, the price impact for a buyer-initiated short sale (BIS) is similar in magnitude to the price impact for a seller-initiated short sale (SIS), and the price impact for a buyer-initiated long sale (BIL) is similar in magnitude to the price impact for a seller-initiated long sale (SIL). Most interesting is that price impacts associated with long sales tend to be smaller than price impacts associated with short sales. The relative gap between long sale and short sale price impacts is widest for large stocks. In fact, for the large cap-quintile, the price impacts associated with short sales are about twice as large as the price impacts associated with similarly-sized long sales. The difference cannot be attributed to trade size. As noted earlier, long sales and short sales have very similar trade size distributions. Instead, it appears that short sellers tend to trade at times when information asymmetries are more severe. This is true for short sellers that demand liquidity as well as short sellers that supply liquidity. This result is consistent with recent empirical evidence that shorting is concentrated around news events which give rise to higher information asymmetries (e.g., Engelberg, Reed, and Ringgenberg (2012), Fox, Glosten, and Tetlock (2010), Christophe, Ferri, and Angel (2004), Boehmer, Jones, and Zhang (2010b)).

< FIGURE 3 HERE >

Figure 3 shows the cumulative response of each type of volume to its own shock, as inferred from the estimated VAR. All four types of volume are persistent, and for the three small-cap quintiles, there are no discernible differences in persistence across order-flow types. The results for the two large-cap quintiles are different, as long sales are considerably less persistent than short sales for this group. We conjecture that the order flow persistence arises from working a large parent order via a sequence of child orders. It could also be the case that multiple traders receive similar signals about valuation and tend to trade in the same direction at approximately the same time. The difference in persistence could arise from differences in average parent order size. Long sale parent orders are likely to be smaller on average, because the long sale categories mix large institutional parent orders and small individual orders, while shorting tends to be dominated by institutions. The institutional long sales would generate persistence, but long sales by individuals would not, and on average at the trade level, long sales would appear less persistent.

We also use the VAR to examine cross-volume effects. For each volume type, the cross effects are virtually zero and therefore are not reported.

5. Concluding discussion

In this paper, we take a magnifying glass to short sales and characterize what happens just prior to, at the same time as, and just after a short sale on the Nasdaq or NYSE during the first two-thirds of 2008. We partition by order aggressiveness, distinguishing more aggressive seller-initiated short sales from buyer-initiated shorting. We find that these two types of shorting are quite distinct. Shorts that supply liquidity step in when spreads are unusually wide. They are also strongly contrarian, stepping in to short sell after fairly sharp share price rises over the past hour or so. They face greater adverse selection when they do step in, as prices tend to move up more following a passive short sale compared to times when a long seller is providing liquidity to a buyer-initiated trade. Thus, it appears that liquidity-supplying short sellers are serving a vital function as contributors to market quality. They seem to be the liquidity suppliers on the margin, stepping in when others are unwilling to do so on the same terms.

Who are these short sellers who provide liquidity? We suspect many are high-frequency traders who make markets algorithmically, including firms like Getco, Knight, and a number of large hedge funds[19], as well as the market-making operations at many large broker-dealers. These liquidity suppliers may be formal, registered market-makers, or they may simply provide liquidity informally.

Given that liquidity-supplying short sellers are a stabilizing influence and provide important market quality benefits at the margin, our results suggest that regulators and policymakers should encourage these particular market participants. In particular, rules

[19] One of the common strategies employed by high frequency trading firms is electronic market making. Like traditional market makers this involves the firms posting two-sided quotes, however, they typically enter and exit positions over very short time horizons.

targeting short sellers should take care not to undermine this particular shorting function. For instance, a complete ban or short selling would make it impossible for many of these participants to provide liquidity, and the evidence in Boehmer, Jones, and Zhang (2010a) indicates that the 2008 temporary U.S. ban on short selling in financial stocks severely damaged market quality in those stocks. In contrast, the SEC's more recent regulatory efforts are more carefully crafted. In early 2010, the SEC adopted rules that prohibit short sellers from demanding liquidity in a stock once it has fallen at least 10% in one trading day.[20] However, short sellers that supply liquidity are unaffected. Our results suggest that these restrictions are unlikely to damage market quality.[21]

In contrast, shorts that demand liquidity are not contrarian on average, and actually these aggressive short sellers tilt slightly toward momentum trading. However, aggressive short sales are not very different from aggressive long sales in terms of price impacts at short horizons. In fact, if anything, liquidity-demanding short sellers have smaller price impacts than liquidity-demanding long sellers in small-cap stocks.

The slight tilt toward momentum trading by liquidity-demanding short sellers is the only piece of evidence that warrants a closer look. It could be that aggressive short sellers possess important negative information about fundamentals or future order flow, and this information is simply revealed over the short-term. A potentially less benign alternative is that aggressive short sellers are actually driving prices down by their continued selling activity. However, we do not see any evidence of this in the VAR analysis. Aggressive shorting is persistent, but no more so than any of the other types of trading that we identify. There is nothing to indicate that seller-initiated shorting follows any sort of unusual pattern. To say it another way, the results point away from "bear raid" types of explanations.

It is important to note that these are average results, cumulated over eight months of trading and across a large number of stocks. It is possible that this aggregation masks some interesting heterogeneity across stocks or over time. Seller behavior might be different around certain corporate events. It might differ near the open or the close of the

[20] SEC filing 34-61595, adopted February 26, 2010, effective date May 10, 2010 and compliance date 28 February 2011.

[21] A Credit Suisse research report analyzing the introduction of this rule reports that the rule was triggered 2,700 times during its first two months of existence. The report argues that the rule has not had any adverse impact on liquidity and that the effect on prices has been positive.

market, and it might be somewhat different for stocks that are in financial distress. In future work, we intend to investigate some of these data subsets to see whether the aggregate findings are broadly applicable. We also remain somewhat puzzled by the price impact differences between long sales and short sales in the VAR, and we are currently trying to shed more light on these differences.

In sum, the paper identifies an important heterogeneity among short sales. Short sales that provide liquidity are qualitatively very different from short sales that demand liquidity. While there is no evidence that liquidity-demanding short sellers are any different from other liquidity demanders, there is strong evidence that liquidity-providing short sales have salutary effects on share prices and stock market quality. The evidence emphasizes that short sales are not a homogeneous category of trades that can be condemned in blanket fashion.

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Table 1
Summary statistics

This table reports summary statistics on the number, volume and size of short sales relative to non-short sales executed on the NYSE (Panel A), Nasdaq (Panel B) and the pooled sample consisting of NYSE and Nasdaq trades. *25%*, *50%* and *75%* refer to distribution quartiles, *n* refers to the total number of short sales and non-short sales in the sample. To calculate daily number of trades, dollar volume per stock and short proportion, we first sum the number of trades and dollar volume and calculate the short proportion for each stock-day and then calculate the mean and quartiles for the stock-days in the sample. To calculate short and non-short trade sizes, we first find the mean (median) short and non-short trade sizes for each stock-day and then calculate the mean (quartiles) for the stock-days in the sample.

	Daily number of short sales per stock	Shorting share of trades	Daily dollar volume of short sales per stock ($'000)	Shorting share of dollar volume	Size of a short sale ($)	Size of non-short sale ($)
Panel A: NYSE trades						
Mean	1,123	38.0%	11,047	40.0%	6,580	6,754
25%	268	29.2%	939	30.2%	1,710	1,721
50%	682	38.2%	3,280	40.7%	3,046	3,065
75%	1,449	47.7%	10,659	50.9%	4,927	4,953
n					60,848,720	94,090,063
Panel B: Nasdaq trades						
Mean	788	38.6%	8,940	39.1%	6,587	5,892
25%	105	31.1%	354	30.8%	1,767	1,704
50%	318	39.6%	1,524	40.1%	3,171	3,039
75%	866	47.8%	6,443	49.0%	5,102	4,884
n					42,675,697	75,503,593
Panel C: Pooled sample						
Mean	1,911	39.2%	19,988	38.7%	6,602	6,414
25%	390	31.4%	1,380	30.0%	1,713	1,700
50%	1,016	40.3%	4,925	39.6%	3,057	3,026
75%	2,325	48.9%	17,371	48.8%	4,960	4,889
n					103,524,417	169,593,656

Table 2
Dollar volume of short sales

This table reports mean daily dollar volumes ($ ‘000s) of short sales per stock and the percentage of total daily dollar volume per stock made up by short sales. The dollar volumes and percentages are reported for stocks grouped in quintiles of four variables: book-to-market ratio (*B/M*); market capitalization (*Size*); closing price (*Price*); and the open short interest as a percentage of total shares on issue (S*hort Interest*). *Pooled* indicates results not grouped by quintiles of the corresponding variable.

Panel A: Size and book-to-market quintiles

	Size					
B/M	Small	2	3	4	Big	Pooled
Low	841	1,854	8,135	20,585	72,910	31,314
	40.5%	40.9%	42.0%	37.3%	36.0%	36.5%
2	811	2,615	7,233	13,825	52,410	17,430
	43.3%	38.8%	40.6%	37.8%	41.0%	39.9%
3	596	2,993	8,567	17,616	54,965	17,154
	41.7%	41.4%	39.8%	39.3%	36.5%	37.6%
4	542	2,293	5,844	16,505	69,951	17,251
	40.5%	41.2%	42.2%	42.6%	38.9%	39.5%
High	1,252	2,980	7,056	18,055	221,123	15,558
	41.1%	40.3%	41.2%	42.7%	41.0%	41.3%
Pooled	902	2,591	7,464	16,625	71,470	19,730
	41.2%	40.7%	41.0%	39.3%	38.0%	38.5%

Panel B: Price and short interest quintiles

	Short Interest					
Price	Low	2	3	4	High	Pooled
Low	2,968	1,713	997	2,037	6,208	3,213
	36.6%	38.8%	41.6%	42.0%	39.8%	39.6%
2	39,685	11,500	3,386	3,314	7,032	8,478
	29.8%	41.3%	38.5%	39.5%	42.3%	35.2%
3	7,535	46,467	4,159	25,145	6,793	21,168
	35.4%	41.6%	38.5%	45.0%	45.5%	42.0%
4	44,926	27,865	22,891	16,107	10,289	25,703
	35.8%	40.3%	38.7%	43.5%	45.0%	38.8%
High	45,657	40,680	39,876	45,787	16,166	39,838
	34.2%	38.5%	41.9%	37.6%	46.0%	37.3%
Pooled	31,382	31,790	13,126	14,031	8,366	19,730
	34.2%	40.3%	40.3%	41.4%	43.4%	38.5%

Table 3
Order aggressiveness

This table reports the aggressiveness of executed short and non-short sale orders relative to the prevailing quotes. Size quintiles are calculated using market capitalization.

		NYSE		Nasdaq		Pooled	
		Non-short sales	Short sales	Non-short sales	Short sales	Non-short sales	Short sales
Panel A: Pooled							
	Behind-the-ask limit order	4.0%	4.1%	3.8%	4.2%	3.9%	4.2%
	At-the-ask limit order	40.8%	39.9%	39.9%	39.5%	40.4%	39.8%
	Within the quotes	15.5%	15.6%	17.2%	17.8%	16.3%	16.5%
	At-the-bid market order	35.8%	36.6%	35.2%	34.8%	35.5%	35.9%
	Below-the-bid market order	3.9%	3.7%	3.9%	3.7%	3.9%	3.7%
Panel B: By size quintile							
	Behind-the-ask limit order	2.0%	2.3%	1.9%	2.3%	2.0%	2.3%
	At-the-ask limit order	41.1%	39.3%	39.0%	37.0%	40.3%	38.6%
Small	Within the quotes	20.1%	20.3%	22.3%	23.3%	20.9%	21.2%
	At-the-bid market order	34.8%	36.3%	34.7%	35.4%	34.8%	36.0%
	Below-the-bid market order	2.0%	1.8%	2.1%	1.9%	2.1%	1.8%
	Behind-the-ask limit order	2.0%	2.2%	1.9%	2.2%	2.0%	2.2%
	At-the-ask limit order	41.0%	39.1%	38.5%	37.2%	40.1%	38.5%
2	Within the quotes	19.4%	19.2%	23.3%	23.9%	20.8%	20.7%
	At-the-bid market order	35.5%	37.7%	34.2%	34.8%	35.1%	36.8%
	Below-the-bid market order	2.1%	1.8%	2.1%	1.8%	2.1%	1.8%
	Behind-the-ask limit order	2.6%	2.6%	2.5%	2.7%	2.5%	2.7%
	At-the-ask limit order	41.2%	39.7%	39.5%	38.5%	40.5%	39.2%
3	Within the quotes	18.0%	17.5%	20.3%	20.9%	18.9%	18.7%
	At-the-bid market order	35.7%	37.9%	35.1%	35.6%	35.4%	37.0%
	Below-the-bid market order	2.6%	2.3%	2.6%	2.3%	2.6%	2.3%
	Behind-the-ask limit order	3.3%	3.6%	3.2%	3.6%	3.3%	3.6%
	At-the-ask limit order	38.4%	37.4%	36.5%	36.0%	37.6%	36.9%
4	Within the quotes	20.2%	20.2%	24.2%	24.3%	21.8%	21.7%
	At-the-bid market order	34.7%	35.6%	32.8%	32.9%	33.9%	34.5%
	Below-the-bid market order	3.4%	3.3%	3.4%	3.2%	3.4%	3.2%
	Behind-the-ask limit order	5.1%	5.4%	4.5%	5.0%	4.8%	5.2%
	At-the-ask limit order	41.6%	41.4%	41.2%	41.2%	41.4%	41.3%
Big	Within the quotes	11.9%	11.9%	13.8%	14.2%	12.8%	12.9%
	At-the-bid market order	36.4%	36.5%	36.0%	35.2%	36.2%	35.9%
	Below-the-bid market order	5.0%	4.8%	4.5%	4.4%	4.8%	4.6%

Table 4
Mean spreads and price impacts

This table reports means of effective half-spreads, five-minute midquote price impacts, and five-minute realized spreads, measured in basis points. Trades are classified into four groups: buyer initiated trades with long sell side (BIL), buyer initiated short sales (BIS), seller initiated long sales (SIL) and seller initiated short sales (SIS). Means of the three variables for each trade type are calculated in three steps: (i) a simple average across trades in each stock-day, (ii) a simple average of the stock-day means on each date to produce a time-series, and (ii) a simple mean across dates in the time-series. Prior to calculating means the variables are winsorised within each stock at the 1^{st} and 99^{th} percentile for price impact and realized spread and the 99^{th} percentile for effective spreads. Standard errors are reported in parentheses.

		BIL	BIS	SIL	SIS
Panel A: Pooled					
	Effective spread	5.74	6.03	5.89	5.55
		(0.05)	(0.05)	(0.05)	(0.05)
	Price impact	4.17	4.46	4.15	3.98
		(0.20)	(0.21)	(0.19)	(0.19)
	Realized spread	1.75	1.82	1.93	1.75
		(0.19)	(0.21)	(0.20)	(0.20)
Panel B: By size quintile					
	Effective spread	13.17	13.98	13.48	12.50
		(0.12)	(0.14)	(0.12)	(0.13)
Small	Price impact	9.03	10.75	9.80	8.54
		(0.28)	(0.36)	(0.31)	(0.34)
	Realized spread	4.55	3.96	4.07	4.42
		(0.28)	(0.34)	(0.32)	(0.34)
	Effective spread	6.50	6.87	6.69	6.45
		(0.06)	(0.07)	(0.06)	(0.06)
Q2	Price impact	5.18	5.39	4.82	4.99
		(0.24)	(0.26)	(0.22)	(0.24)
	Realized spread	1.49	1.69	2.07	1.63
		(0.23)	(0.25)	(0.22)	(0.24)
	Effective spread	4.27	4.45	4.38	4.22
		(0.04)	(0.04)	(0.04)	(0.04)
Q3	Price impact	3.20	3.16	2.93	2.91
		(0.21)	(0.21)	(0.19)	(0.19)
	Realized spread	1.18	1.42	1.58	1.44
		(0.20)	(0.20)	(0.20)	(0.19)
	Effective spread	2.86	2.99	2.93	2.81
		(0.03)	(0.02)	(0.03)	(0.02)
Q4	Price impact	2.15	2.00	1.95	2.10
		(0.18)	(0.18)	(0.17)	(0.17)
	Realized spread	0.79	1.09	1.08	0.78
		(0.17)	(0.18)	(0.18)	(0.17)
	Effective spread	1.82	1.87	1.85	1.79
		(0.02)	(0.02)	(0.02)	(0.02)
Big	Price impact	1.20	1.01	1.14	1.36
		(0.16)	(0.17)	(0.16)	(0.15)
	Realized spread	0.70	0.94	0.80	0.49
		(0.16)	(0.17)	(0.17)	(0.16)

Table 5
Effective spread regressions

This table reports trade-level regression estimates where the dependent variable is effective half-spread measured in basis points. *D_BIL*, *D_BIS*, and *D_SIL* are dummy variables for buyer initiated trades with long sell side, buyer initiated short sales, and seller initiated long sales, respectively (short seller initiated trades are the base case). *D_NYSE* is a dummy variable for trades executed on the NYSE (Nasdaq is the base case). *dVol* and *Price* are the dollar volume and price of the trade, respectively. Regressions include fixed effects for each stock. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered by date. T-statistics are reported in parentheses.

		By size quintile				
	Pooled	Small	Q2	Q3	Q4	Big
Panel A: Model 1						
Intercept	9.789***	24.395***	9.698***	2.448***	2.194***	1.750***
	(39.40)	(9.63)	(38.23)	(35.13)	(30.37)	(40.64)
D_BIL	0.067**	-0.046	0.137**	0.096***	0.025	0.068**
	(2.40)	(-0.69)	(2.54)	(3.27)	(0.98)	(2.23)
D_BIS	0.193***	0.645***	0.484***	0.243***	0.173***	0.117***
	(12.45)	(10.41)	(9.84)	(12.08)	(15.24)	(6.24)
D_SIL	0.156***	0.404***	0.368***	0.214***	0.121***	0.109***
	(4.88)	(5.34)	(6.40)	(4.82)	(4.22)	(3.55)
D_NYSE	0.151***	0.399***	0.079	0.181***	0.163***	0.134***
	(5.79)	(6.21)	(1.46)	(3.67)	(6.86)	(5.32)
Panel B: Model 2						
Intercept	0.907	-5.002	3.001***	-0.573	0.498***	0.630***
	(0.67)	(-1.22)	(3.59)	(-0.80)	(3.99)	(3.35)
D_BIL	0.052*	0.082	0.072	0.057*	0.030	0.066**
	(1.87)	(1.37)	(1.32)	(1.74)	(1.19)	(2.17)
D_BIS	0.186***	0.783***	0.454***	0.207***	0.180***	0.117***
	(11.89)	(12.09)	(9.61)	(8.56)	(15.89)	(6.22)
D_SIL	0.145***	0.488***	0.317***	0.194***	0.126***	0.107***
	(4.59)	(7.98)	(5.76)	(4.36)	(4.42)	(3.46)
D_NYSE	0.194***	0.473***	0.271***	0.228***	0.178***	0.145***
	(6.95)	(7.78)	(5.51)	(4.36)	(7.38)	(5.51)
dVol	0.019***	0.969***	0.364***	0.192***	0.069***	0.012***
	(11.19)	(5.51)	(9.90)	(8.87)	(12.13)	(8.14)
$dVol^2$	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.91)	(-4.25)	(-8.23)	(-7.77)	(-5.07)	(-5.03)
1/Price	66.969***	96.165***	49.017***	65.722***	47.698***	39.904***
	(6.54)	(7.25)	(7.73)	(4.06)	(22.43)	(6.85)

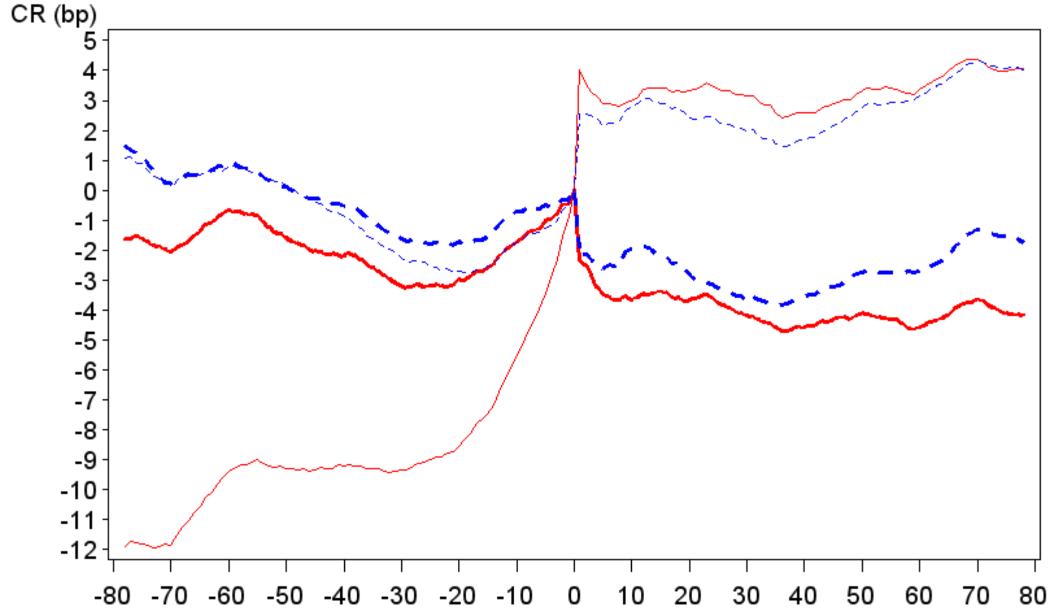
Table 6
Cumulative returns following trades

This table reports interval-level regression estimates, where the dependent variable is cumulative return (CR) measured in basis points over various length periods forward in time. Each trade is weighted by dollar volume. *D_BIL*, *D_BIS*, and *D_SIL* are dummy variables for buyer initiated trades with long sell side, buyer initiated short sales, and seller initiated long sales, respectively (short seller initiated trades are the base case). *Small* to *Big* are size quintiles measured by average market capitalization. Model 1 does not have fixed effects, Model 2 includes fixed effects on stocks and Model 3 includes fixed effects on five-minute intervals. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered by stock and by date.

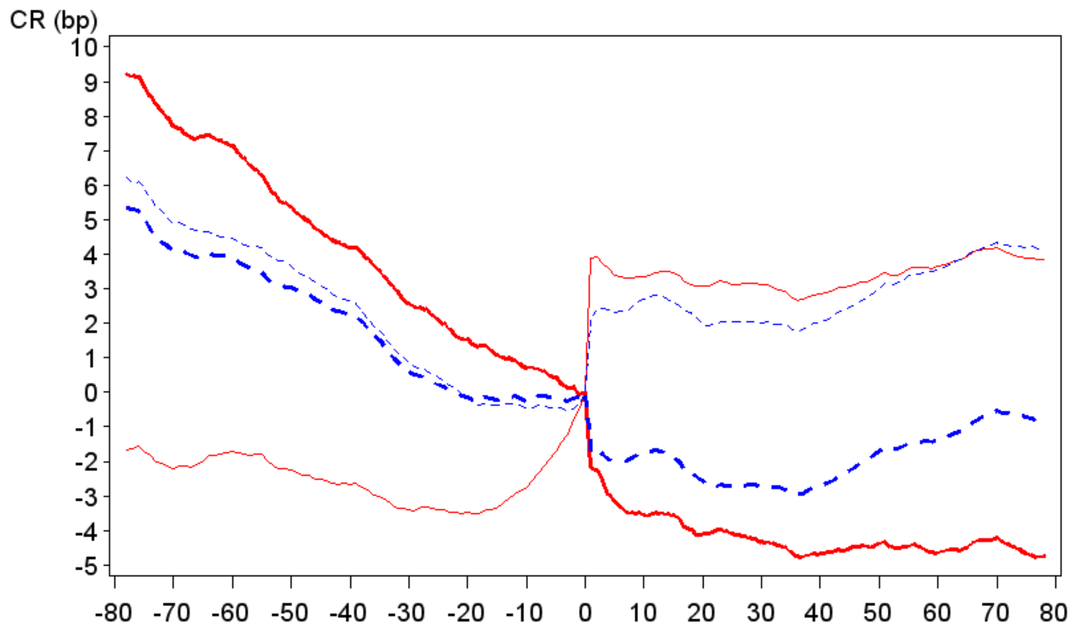
		5 mins			30 mins			2 hours			24 hours		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Panel A: Pooled													
	Intercept	-2.37***			-3.55*			-3.59			-4.13		
	D_BIL	4.93***	5.00***	2.62***	5.80***	5.89***	3.73***	6.04***	6.31***	4.49***	8.18***	8.54***	6.63***
	D_BIS	6.40***	6.38***	4.65***	6.46***	6.47***	4.83***	7.09***	7.08***	5.12***	8.25***	8.23***	5.84***
	D_SIL	0.16	0.24	-0.70***	1.04*	1.12**	0.21	0.46	0.71	0.73	2.40	2.79	2.80
Panel B: By size quintile													
Small	Intercept	-8.06***			-7.67**			-11.85			-23.41		
	D_BIL	18.92***	19.00***	11.04***	18.67***	18.77***	10.06***	20.01***	20.62***	10.27***	22.66**	22.61*	8.66
	D_BIS	19.99***	19.94***	13.05***	20.09***	20.15***	12.90***	20.20***	20.60***	12.56***	17.64***	18.35***	9.90***
	D_SIL	0.12	0.19	-1.20	-2.51	-2.46	-3.47***	-3.06	-2.56	-4.14	-5.65	-5.58	-9.14*
2	Intercept	-5.85***			-10.1***			-13.69**			-27.39**		
	D_BIL	13.77***	13.71***	8.24***	17.54***	17.54***	10.23***	18.55***	19.03***	9.04***	25.68***	26.41***	11.10***
	D_BIS	14.33***	14.22***	7.82***	16.34***	16.22***	9.38***	17.55***	17.37***	9.20***	20.32***	19.63***	10.80***
	D_SIL	0.50	0.55	-1.49***	3.32**	3.39**	0.41	3.70	4.17	-1.02	8.85	9.63	-0.54
3	Intercept	-3.27***			-4.31**			-5.84			-10.07		
	D_BIL	7.47***	7.31***	3.92***	8.39***	8.19***	4.78***	8.71***	8.51***	5.03***	15.87***	15.29***	10.62***
	D_BIS	8.79***	8.76***	5.75***	8.34***	8.30***	5.93***	8.44***	8.41***	5.54***	10.27***	10.03***	6.57***
	D_SIL	0.29	0.16	-1.21*	1.31	1.12	-0.55	1.74	1.47	0.21	6.82**	6.17*	4.32**
4	Intercept	-2.85***			-4.96**			-10.20			-17.21		
	D_BIL	5.28***	5.36***	3.19***	6.26***	6.49***	3.73***	6.90***	7.60***	4.84***	11.38***	12.54***	7.69***
	D_BIS	7.12***	7.08***	5.27***	7.41***	7.45***	5.58***	7.64***	7.84***	5.54***	8.71***	9.07***	6.54***
	D_SIL	1.52	1.61	0.11	1.98*	2.07**	0.34	2.16	2.34	1.40	5.61	5.88	3.56
Big	Intercept	-1.98***			-2.89			-1.46			0.39		
	D_BIL	4.14***	4.23***	1.96***	4.89***	4.99***	3.11***	4.87***	5.22***	3.54***	5.67*	6.27**	4.69**
	D_BIS	5.55***	5.54***	3.79***	5.54***	5.55***	3.91***	6.27***	6.24***	4.29***	7.33***	7.33***	4.80***
	D_SIL	-0.18	-0.09	-0.88***	0.73	0.85	0.07	-0.25	0.18	0.22	0.84	1.62	1.63

Figure 1. Average cumulative raw log midquote returns (CR) for short sales (solid red line) that are buyer initiated (light weight line) and seller initiated (heavy weight line) and non-short sales (all trades other than those in which the sell side is short – dashed blue line) that are buyer initiated and seller initiated. The horizontal axis measures the number of five-minute intervals from the trade (which takes place in interval zero). 78 intervals equals a whole trading day, i.e., for a trade at 13:05 on Wednesday, the cumulative return to interval 78 is the return from 13:05 on Wednesday to 13:05 on Thursday. In Panel A trades are weighted by their dollar volume, in Panel B trades are equal weighted, and Panel C provides separate results for the five market-cap quintiles.

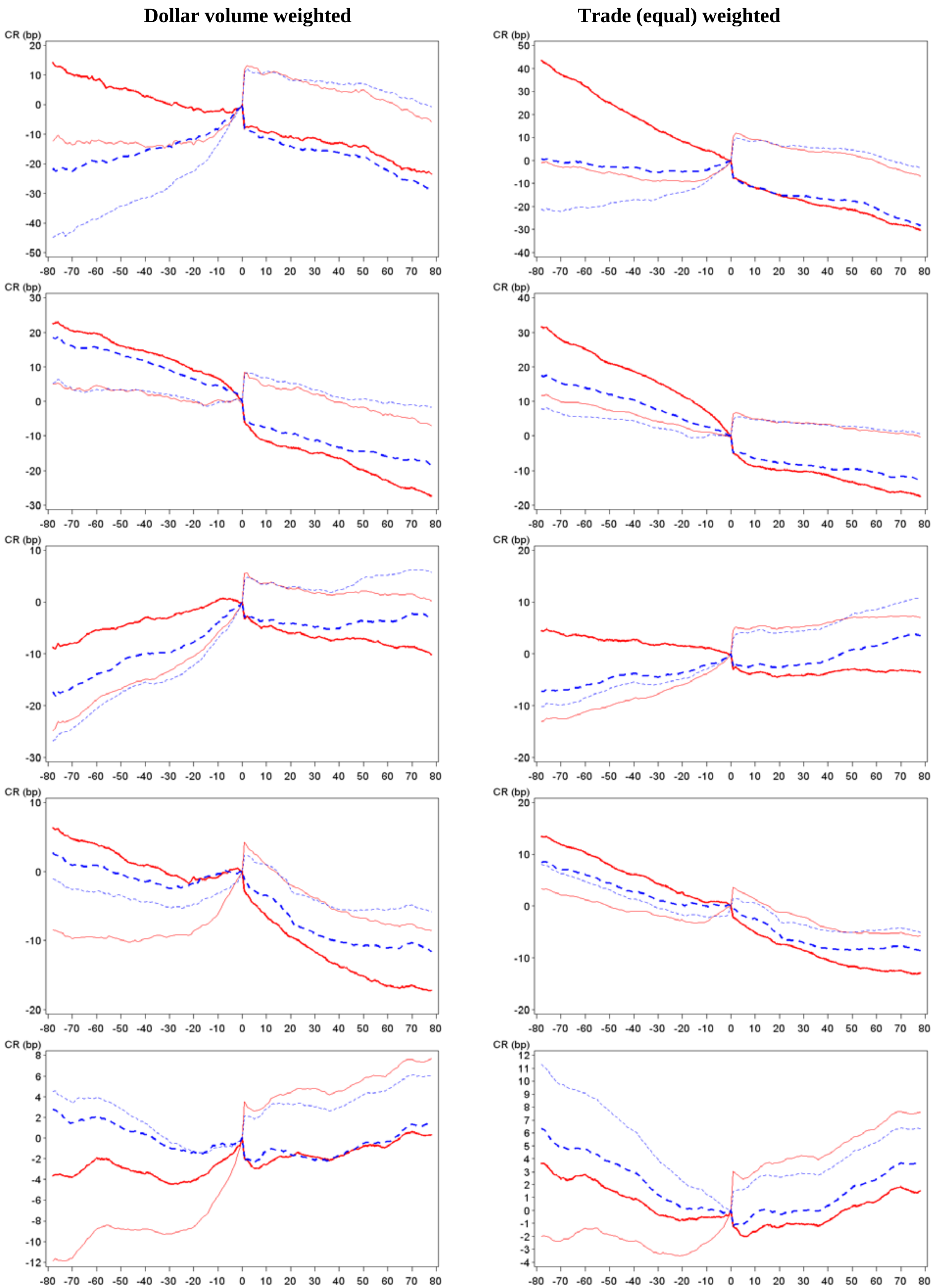
Panel A: Dollar volume weighted



Panel B: Trade (equal) weighted



Panel C. Results for each market-cap quintile, with the smallest quintile at the top.



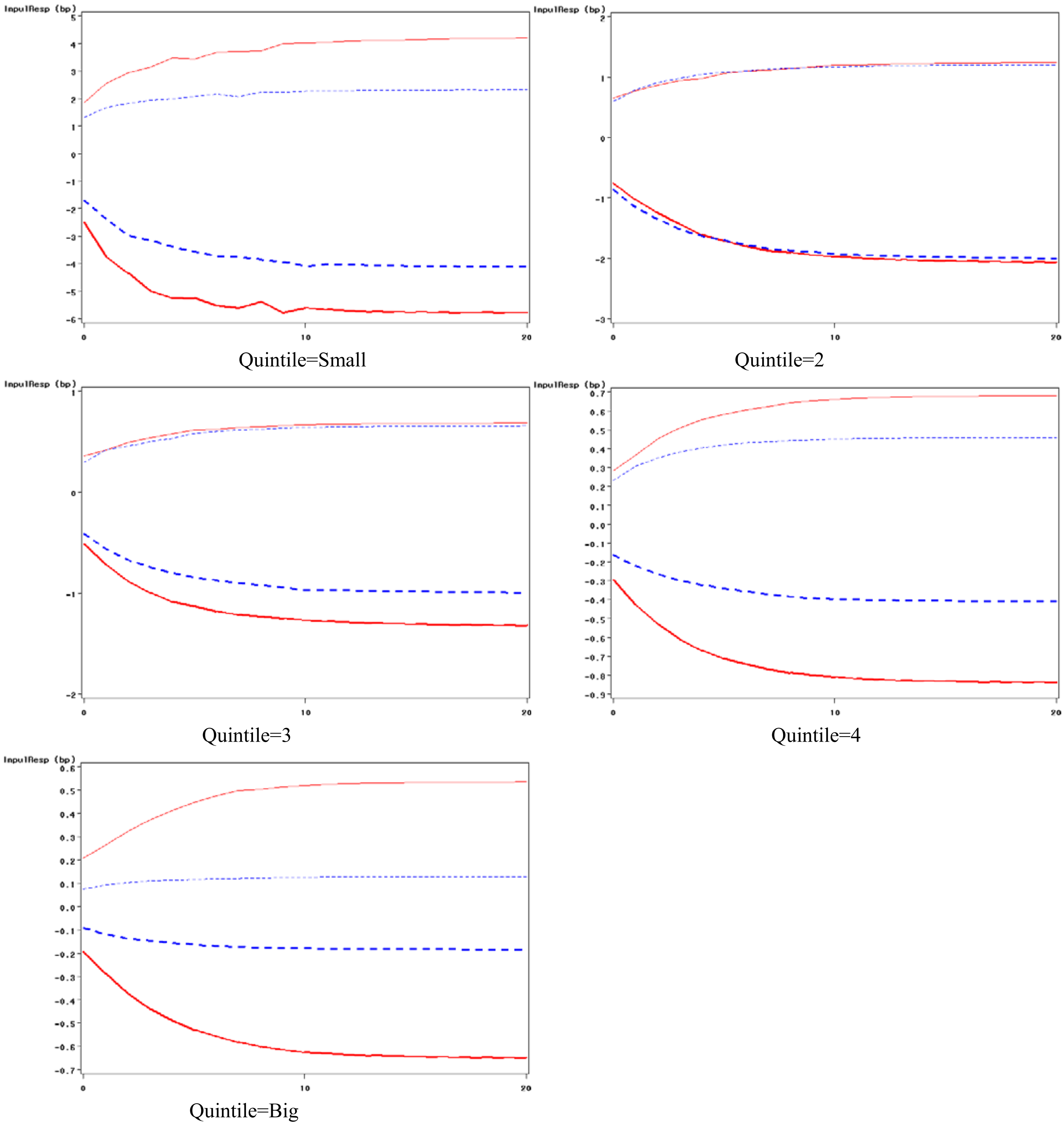


Figure 2. Cumulative return response to volume shocks, estimated from a VAR model. Solid red (dashed blue) lines represent shocks to short (long) volume, with heavyweight (lightweight) lines for seller initiated (buyer initiated) volume. The horizontal axis measures the number of trades from the shock (which takes place at t=0). The VAR coefficients and impulse response are estimated separately for each stock and then the estimates averaged across stocks within size quintiles (measured by market capitalization). The magnitude of each volume shock is equal to the standard deviation of unanticipated buyer-initiated long volume.

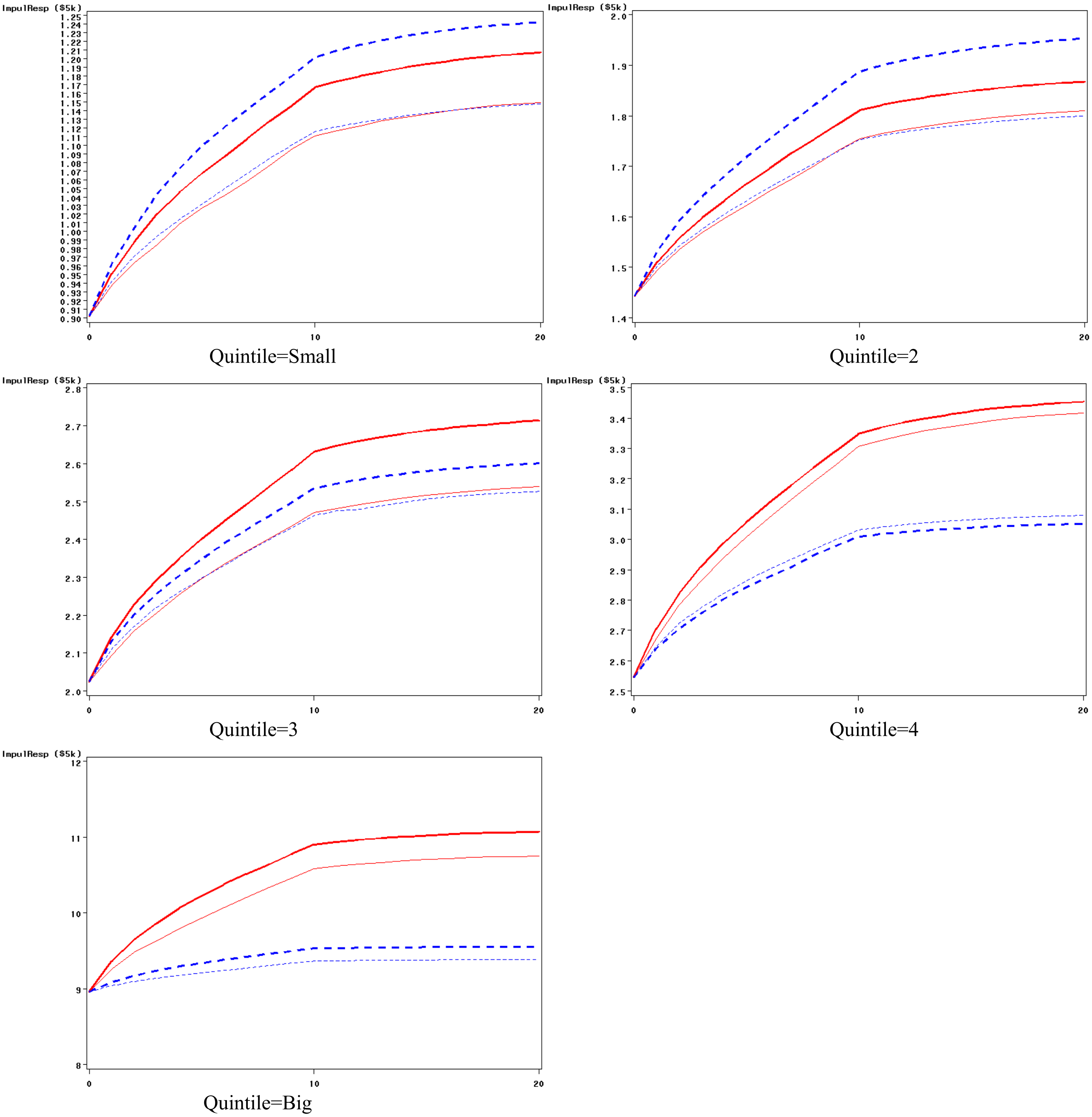


Figure 3. Cumulative dollar volume response to same volume type shock, estimated from a VAR model. Solid red (dashed blue) lines represent shocks to short (long) volume, with heavyweight (lightweight) lines for seller initiated (buyer initiated) volume. The horizontal axis measures the number of trades from the shock (which takes place at t=0). The VAR coefficients and impulse response are estimated separately for each stock and then the estimates averaged across stocks within size quintiles (measured by market capitalization). The magnitude of each volume shock is equal to the standard deviation of unanticipated buyer-initiated long volume.