Do prices reveal the presence of informed trading?☆

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First Version: November 2011
This Version: June 28, 2013

Abstract

Using a comprehensive sample of trades by Schedule 13D filers, who possess valuable private information when they accumulate stocks of targeted companies, this paper studies whether several measures of adverse selection reveal the presence of informed trading. The evidence suggests that when Schedule 13D filers accumulate shares, both high-frequency and low-frequency measures of stock liquidity and adverse selection indicate higher stock liquidity and lower adverse selection, even though prices are positively affected. We document three channels that help explain this phenomenon: (a) informed traders select times of higher liquidity when they trade, (b) liquidity increases in response to informed traders' trades, (c) informed traders use limit orders.

Keywords: Informed Trading, Liquidity, Adverse Selection, Activist Shareholders

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☆We thank Azi Ben-Rephael, Terry Hendershott, Gur Huberman, Wei Jiang, Robert Korajczyk (AFA discussant), Norman Schuerhoff, and, especially, Yakov Amihud and Larry Glosten for many helpful comments. We also thank seminar participants at the University of Illinois at Urbana-Champaign, Copenhagen Business School, Tsinghua University, Columbia University, and participants at the AFA 2013 Annual Meeting and IDC Summer Conference for their helpful comments and suggestions. Virginia Jiang, Xinran Li, Urvi Maru, Hana Na, Shan Qiao, Sofiya Teplitskaya, and Tong Tong provided excellent research assistance.

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Introduction

An extensive body of theory suggests that stock liquidity, as measured by the spread between the bid and ask quotes and by the price impact of trades, should be informative about the magnitude of asymmetric information between market participants (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987; Admati and Pfleiderer, 1988). For example, in his seminal contribution, Kyle (1985) shows how an informed trader hides his private information and optimally accumulates shares at a rate inversely proportional to his price impact,[3] Kyle's lambda, which measures the dollar change in price due to a dollar change in order flow. In the cross-section stocks with more informed trading relative to noise trading experience larger price impact. Specifically, the theory predicts that Kyle's lambda, which can be estimated from a regression of price change on order flow, should be higher for stocks with more informed trading (relative to noise trading).

Following that literature there have been many attempts to measure trading costs empirically, and to decompose such costs into different components such as a adverse selection, order processing cost, and inventory cost (e.g., early papers include Glosten, 1987; Glosten and Harris, 1988; Stoll, 1989; Hasbrouck, 1991a; Amihud, 2002). An extensive empirical literature relies on adverse selection measures assuming they capture information asymmetry (e.g., Barclay and Hendershott, 2004; Vega, 2006; Duarte et al., 2008; Bharath et al., 2009; Kelly and Ljungqvist, 2011). Most of these measures rely on some empirical estimate of price impact and its persistence to identify the amount of private information in trades. While there is an obvious endogeneity issue with this approach (since we do not actually know if the trades are informed), it is natural to think that such price impact measures correlate positively with the informational motivation of trades. For example, in their well-known survey of the micro-structure literature, Biais,

[3]The informed trader's optimal trading strategy is to trade as a linear function of the difference between his signal and the current price, at a rate inversely proportional to his price impact, and that increases as maturity approaches so that all the information eventually makes it into prices. Unconditionally, the expected trading rate of the informed trader is constant (in his own filtration).

Glosten, and Spatt (2005) describe the empirical relation between adverse selection and effective spread, denoted by a price impact measure λ, as follows: "As the informational motivation of trades becomes relatively more important, λ goes up." (page 232).

But, do these empirical measures of adverse selection actually capture information asymmetry?

To really test this one would want to separate informed from uninformed trades ex-ante and test their impact on price changes. Unfortunately, since we generally do not know the traders' information sets, this is hard to do in practice. As a result, it is often assumed that some types of investors are informed. For example, Boulatov et al. (2009) use the institutional order flow as a proxy for informed trading.

In this paper, we use a novel data set of trades by investors we can identify as having substantial private information to study whether proposed liquidity measures reveal the presence of informed trading. Specifically, we exploit a disclosure requirement to identify trades that rely on valuable private information. Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors to file with the SEC within 10 days of acquiring more than 5% of any class of securities of a publicly traded company if they have an interest in influencing the management of the company. In particular, Item 5(c) of Schedule 13D requires the filer to "... describe any transactions in the class of securities reported on that were effected during the past sixty days or since the most recent filing of Schedule 13D, whichever is less." Thus, Schedule 13D filings reveal the date and price at which all trades by the Schedule 13D filer were executed during the 60 days that precede the filing date.[4]

We hand collect a comprehensive sample of trades from the Schedule 13D filings. We view this sample as an interesting laboratory to study the liquidity and the price impact of informed trades. First, an average Schedule 13D filing in our sample is characterized by a positive and significant market reaction upon announcement. For example, the

[4]As we explain in Section 3, our sample includes original Schedule 13D filings only, i.e., amendments to previously submitted filings are excluded from the sample.

cumulative return in excess of the market is about 6% in the (t-10,t+1) window around the filing date and about 3% in the (t-1,t+1) window around the filing date. Second, we calculate several measures of profits made by Schedule 13D filers and show that these profits are economically significant. For example, an average Schedule 13D filer gains $0.8 million on a $22 million stake in a $293 million market cap company. To summarize, the evidence implies that Schedule 13D filers' information is valuable. Therefore, we can classify the pre-announcement trades by Schedule 13D filers as informed trades. It is also important to realize that, by its very nature, the information held by Schedule 13D filers is likely to qualify as 'private information.'[5]

Our main empirical result is that standard measures of adverse selection and stock liquidity *do not* reveal the presence of informed traders. Instead, we find that standard measures of adverse selection and liquidity measures suggest that adverse selection is lower and a stock is more liquid when there is significant informed trading in that stock. Specifically, we find that several measures of adverse selection are lower on days on which Schedule 13D filers trade. For example, on an average day when Schedule 13D filers trade, the measured price impact is almost 30% lower relative to the sample average. Similarly to the high-frequency measures, the low-frequency measures of stock liquidity suggest that liquidity is higher when Schedule 13D filers trade. For example, Amihud's illiquidity measure decreases by almost 10% when Schedule 13D filers accumulate their position. Importantly, we show that days when Schedule 13D filers trade are characterized by positive and significant market-adjusted returns, which suggests that informed trades do impact prices. Liquidity measures, however, fail to detect that price impact.

To summarize, the evidence constitutes a serious challenge to the argument that

[5]Collin-Dufresne and Fos (2013) develop a theoretical model in which activist shareholders can expend effort and change firm value. In that model the market price depends on the market maker's estimate of the activist's share-ownership, since the latter determines the effort level of the informed trader, and hence the liquidation value of the firm. This model shows that a significant part of the valuable private information pertains to the activist's own holdings, which by definition is information known only to him.

standard measures of stock price liquidity, and in particular of the adverse selection component, capture the presence of informed trading (at least not trading based on the long-lived type of information that Schedule 13D filers hold).

We consider three possible mechanisms that could explain this result.

First, and consistent with the the theoretical model presented in Collin-Dufresne and Fos (2012), Schedule 13D filers might *select* the time at which they trade and step in when the market and/or the target stock happen to be liquid.

Second, Schedule 13D filers might *attract* additional uninformed volume. In this case, informed traders also trade when the stock is more liquid. But the difference is that the informed trades are causing the increase in liquidity.

Third, standard liquidity measures are based on models that assume that informed traders mostly demand immediacy, i.e., use market orders. Schedule 13D filers, however, possess relatively long-lived information and therefore might place limit orders instead (e.g. Kaniel and Liu, 2006). Thus, informed investors with long-lived information might improve stock liquidity (and receive the spread rather than pay it).

We perform several tests that indicate that all three mechanisms contribute to our findings.

For a sub-sample of trades where we can identify the individual 'time-stamped' trades, we find clear evidence that Schedule 13D use limit orders. Further, we find that before their ownership crosses the 5% threshold Schedule 13D are more likely to use limit orders than after, when they have only ten days left to trade.

We construct a more general proxy for usage of market orders (based on their average buy price relative to the VWAP) and show that when insiders are more likely to use market orders the impact of their trading on measures of adverse selection measures is less negative.

However, using two placebo tests that exploit reforms implemented by NASDAQ and NYSE, we show that the limit order mechanism cannot be the sole explanation. Indeed, we find that even in samples where limit orders were not (or less) available to informed traders, there is no significant relation between informed trades and liquidity measures.

Instead, there is very strong statistical evidence that the pattern in abnormal volume observed on (and around) days when insiders trade is not random (both comparing the target firms' abnormal volume to its own past history or to a matched sample of firms). This clearly shows that either 13D filers select the days when they trade based on available liquidity or that their trades generate abnormal patterns in the stock's liquidity.

Consistent with the 'selection mechanism,' we show that Schedule 13D filers trade more aggressively not only when the stock they are purchasing is more liquid, but also when market-wide conditions change. For example, high aggregate volume and low market return positively affect the likelihood of a trade by Schedule 13D filers on a given day.

Overall, we conclude that Schedule 13D filers are likely (a) to trade when stock liquidity is high for exogenous as well as for endogenous reasons, and (b) when feasible, to use limit orders, which leads to an inverse relation between standard empirical measures of adverse selection and the informational motivation of trades.

The rest of the paper is organized as follows. Section 1 discusses related literature. Section 2 provides an overview of the institutional background. Section 3 describes the data. The magnitude of information asymmetry is analyzed in Section 4. Section 5 shows that when Schedule 13D filers trade, stock prices increase. Section 6 describes liquidity measures used in the analysis. Section 7 presents the main evidence on the effect of informed trading on liquidity measures. Section 8 studies mechanisms that are consistent with the inverse relation between adverse selection measures and informed trading. Finally, Section 9 concludes.

1. Related Literature

This paper is related to several strands of literatures.

First, this paper contributes to the empirical literature that relies on liquidity measures as a proxy for information asymmetry (e.g, Barclay and Hendershott, 2004; Vega, 2006; Duarte et al., 2008; Bharath et al., 2009; Kelly and Ljungqvist, 2011). Our evidence suggests that empirical measures of information asymmetry might not reveal the presence of informed traders. Therefore, empirical researchers should be cautious when relying on a liquidity measure as a proxy for information asymmetry.

Second, our paper is related to the large literature on the estimation of the asymmetric information component of transaction costs (e.g., Easley and O'Hara, 1987; Glosten and Harris, 1988; Stoll, 1989; Hasbrouck, 1991a; Lin et al., 1995). In contrast to this literature, our paper does not rely on time-series properties of stock prices to identify informed trades, but uses well-identified trades executed by informed traders to study the impact of asymmetric information on stock price liquidity measures.

Third, our paper is related to the empirical literature that studies the impact of informed trading on the stock liquidity. One strand of this literature studies the impact of share repurchases on stock liquidity and finds mixed results (Barclay and Smith, 1988; Singh et al., 1994; Franz et al., 1995; Miller and McConnell, 1995; Brockman and Chung, 2001; Ginglinger and Hamon, 2007). Another strand of this literature studies the impact of insider trading on stock liquidity.[6] While some studies conclude that insider trading impairs stock liquidity (Bettis et al., 2000; Cheng et al., 2006), others show that there is no significant effect of insider trading on stock liquidity (Chung and Charoenwong, 1998; Charoenwong and Chung, 2000; Cao et al., 2004). Our papers differs from this literature in that it uses trades by investors we can identify as having significant private information, as traders make substantial profits and their trades constitute a significant fraction of the stock's daily volume. Instead, in the extant insider trading literature it is often not clear that the trades are based on substantial private information. Share

[6]Whether trades by corporate insiders contain valuable information is an empirical question. For example, Lakonishok and Lee (2001) show that very little market movement is observed when insiders trade and when they report their trades to the SEC. Recently, Cohen et al. (2012) decompose insider trading into routine (i.e., uninformed) and opportunistic (i.e., informed) and show that only the opportunistic trades yield positive abnormal return. However, even in that case the dollar profits realized by the insiders are trivial.

repurchases, for example, can be motivated not only by private information, but also by liquidity needs (excess cash leads to higher stock repurchases), investment policy (deterioration in investment opportunities leads to higher payouts), and compensation policy (repurchasing shares in anticipation of option expirations). In addition, (legal) insider trading usually constitute only a very small fraction of the daily stock trading activity.

One notable exception is the paper by Cornell and Sirri (1992), which our study is closely related to. Cornell and Sirri (1992) present a clinical study of one case of illegal insider trading during Anheuser-Busch's 1982 tender offer for Campbell Taggar, for which they obtained ex-post court records to identify trades by corporate insiders and their tippees. They find that surprisingly liquidity increases when there is active informed trading. Our findings are consistent with their case study, but uses a comprehensive data-set of trades by legal 'insiders.'

Fourth, in a recent paper, Obizhaeva (2011) provides evidence on selection bias in liquidity estimates. Obizhaeva shows that liquidity is lower than what is usually measured, especially in high volume markets, because traders employ price-dependent strategies and often choose not to execute their orders entirely. Related, our results point to another distinct selection bias in liquidity measures due to the endogenous timing of the trading strategies of informed investors.

Finally, the paper contributes to the corporate governance literature by showing how activist shareholders benefit from liquid stock markets. Kyle and Vila (1991), Bolton and von Thadden (1998), and Maug (1998) predict that greater liquidity trading facilitates monitoring and shareholder activism. While recent empirical papers show that stock liquidity facilitates hedge fund activism and proxy contests (Brav et al., 2008; Klein and Zur, 2009; Fos, 2012), this paper provides direct evidence on the magnitude of these profits. Importantly, in this paper we show that trading strategies of activist shareholders depend on stock liquidity. That is, we provide the micro-level data to support the conjecture that higher stock liquidity benefits activist shareholders who actively intervene in corporate governance.

2. Institutional Background

In this section we summarize the institutional background and describe what information we exploit in then empirical tests. Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors to file with the SEC within 10 days of acquiring more than 5% of any class of securities of a publicly traded company if they have an interest in influencing the management of the company.[7]

Item 5(c) of Schedule 13D requires the filer to "... describe any transactions in the class of securities reported on that were effected during the past sixty days or since the most recent filing of Schedule 13D, whichever is less." Importantly, we restrict our sample to original Schedule 13D filings only, i.e., amendments to previously submitted filings are excluded from the sample (this maximizes the 'asymmetric information' content of the trades by the informed trader). Thus, our Schedule 13D filings reveal the date and price for all transactions by the Schedule 13D filer that were executed during sixty days that precede the filing date. Figure 1 presents a typical time line of a Schedule 13 filing. See Appendix A for a description of a case study.

[Insert Figure 1 here]

For each event we extract the following information from the Schedule 13D filings: CUSIP of the underlying security, date of every transaction, transaction type (purchase or sell), transaction size, and transaction price. In addition, we extract filing date, event date (date of crossing the 5% threshold), and the beneficial ownership of the Schedule 13D filer at the filing date. In the vast majority of cases transaction data are reported at

[7] In general, an investor who has an interest in influencing the management of the company is required to file Schedule 13D in the following cases: (i) an investor's position exceeds the legal threshold of 5%, (ii) a group of investors decides to act as a legal group and the ownership of the group exceeds the legal threshold of 5%, and (iii) an investor's previously established position changes by more than 1% of stocks outstanding, either positive or negative.

daily frequency. If the transaction data are at higher-than-daily frequency, we aggregate it to the daily level. Specifically, for every day we calculate the total change in stock ownership and the average purchase price. The average price is the quantity-weighted average of transaction prices.

3. Sample Description

3.1. Data Sources

Data are compiled from several sources. Stock returns, volume, and prices come from the Center for Research in Security Prices (CRSP). Intraday transactions data (trades and quotes) come from the Trade and Quote (TAQ) database. Data on trades by Schedule 13D filers come from a unique hand-collected database, described next.

3.2. The Sample of Schedule 13D Filings with Information on Trades

The sample of trades by Schedule 13D filers is constructed as follows. First, using an automatic search script, we identify 19,026 Schedule 13D filings from 1994 to 2010. The scripts identifies *all* Schedule 13D filings that appear on EDGAR. Next, we check the sample of 19,026 filings manually and identify events with information on trades. Since the trading characteristics of ordinary equities might differ from those of other assets, we retain only assets whose CRSP share codes are 10 or 11, i.e., we discard certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and REITs. We exclude stocks whose prices are below $1 and above $1,000. Moreover, we exclude events that involve derivatives, such as options, warrants, and swaps. Finally, we exclude Schedule 13D/A filings (i.e., amendments to previously submitted filings) that are mistakenly classified as original Schedule 13D filings.

The final sample is the universe of all Schedule 13D filings that satisfy the above criteria from 1994 to 2010 and consists of 3,126 events. Importantly, our top-down approach guarantees that the sample contains *all* Schedule 13D filings with information on trades. Figure 2 presents the time distribution of the Schedule 13D filings with information on trades in common stocks during 1994-2010. During the sample period, on average 184 events take place each year. Importantly, the sample covers a 17-year period, during which several changes in microstructure took place. These changes allow testing several hypotheses related to informed trading (see Section 8 for further details).

[Insert Figure 2 here]

Next, we examine the trading strategy of Schedule 13D filers. The trading strategy is described using the following three measures: (1) the probability that a Schedule 13D filer trades at least one share on a given day, (2) the percentage of outstanding shares traded by Schedule 13D filers, and (3) the probability of trading with a Schedule 13D filer. Each measure of the trading activity is calculated at daily frequency. Figure 3 presents the cross-event average of each measure for the sixty days prior to the filing date, plotted as a function of the distance to the filing date.

[Insert Figure 3 here]

For every distance to the filing date, the probability that a Schedule 13D filer trades at least one share is the number of filings with a non-zero trade by the filer divided by the total number of Schedule 13D filings in the sample. Figure 3 indicates that the probability that a Schedule 13D filer trades at least one share on a given day is approximately 25% and it reaches a 50% level ten days prior to the filing date.

To further understand the trading strategy of Schedule 13D filers, we calculate the percentage of outstanding shares traded by Schedule 13D filers. For every distance to the filing date, the percentage of outstanding shares traded by Schedule 13D filers is the ratio of the number of shares traded by the Schedule 13D filer to the number of total shares outstanding. Figure 3 suggests that a Schedule 13D filer gradually increases the percentage of outstanding shares purchased on every trading day. Closer to the filing date Schedule 13D filers trade more aggressively. For example, the average percentage of outstanding shares purchased on every trading day by the Schedule 13D filers increases from 0.03%-0.05% to 0.15%-0.20% closer to the filing date.

Finally, we observe that the probability of trading with a Schedule 13D filer co-moves with the percentage of outstanding shares purchased by Schedule 13D filers. For every distance to the filing date, the probability of trading with Schedule 13D filer is the cross-event average of the number of shares traded by the filer divided by the security's volume from CRSP. If no trade is reported on a given day by the filer, the percentage of outstanding shares traded by the filer is set to zero. The probability of facing an informed trader in a transaction increases dramatically from 5% to 10%-15% level when approaching the filing date.

Summary statistics of trading strategies adopted by Schedule 13D filers are reported in Table 1. Columns (1) and (4) report summary statistics of all reported trades. The average (median) stock ownership on the filing date is 7.51% (6.11%). The average (median) filer purchases 3.8% (2.8%) of outstanding shares during sixty-day period prior to the filing date. It corresponds to an average (median) purchase of 899.692 (298,807) shares at average (median) cost of $16.4 ($2.5) million. On days with non-zero informed volume the filer purchases 0.5% (0.2%) of outstanding shares.

[Insert Table 1 here]

The summary statistics of trades executed by Schedule 13D filers during the pre event date period are reported in columns (2) and (5) and the summary statistics of trades during the post event date period are reported in columns (3) and (6). The event date is the day when the filer's ownership exceeds the 5% threshold. The evidence suggests that Schedule 13D filers trade more aggressively in the post-event period (i.e., between the event date and the filing date). For example, the average (median) increase in the ownership per trading day with non-zero informed volume is 0.8% (0.3%) during the post-event period compared with 0.3% (0.2%) during the pre-event period. Similarly, the average (median) percentage of trading days with informed trades increases from 29.7% (24.2%) during the pre-event period to 45.5% (40.0%) during the post-event period.

To summarize, the evidence suggests that (1) Schedule 13D filers do not trade every day (but rather every two or three days), (2) when they trade, they trade a relatively large fraction of the daily volume (around one quarter of the daily volume), (3) Schedule 13D filers trade more aggressively closer to the filing date. We note that these findings are at odds with what one might have expected based on a standard Kyle (1985) insider trading model, where the insider is expected to trade continuously, and at a constant rate as he approaches maturity.[8] To further illustrate our data, we present in Appendix A a specific case study of one Schedule 13D filer.

4. Are Schedule 13D filers informed?

At the core of this study is the following assumption: Schedule 13D filers possess valuable information on the underlying securities when they trade in the pre-announcement period. We use two approaches to assess the extent of the filer's private information. First, we use short-term announcement event-day returns upon Schedule 13D filing. The short-term announcement event-day returns summarize the market's perception of the value created by Schedule 13D filers. Second, we use profits made by Schedule 13D filers on purchasing stocks at the pre-announcement prices.

Note that Schedule 13D filers trade on long-lived information that, by its very nature, is not likely to be available to other market participants.

In most cases, these activist share-holders know they can increase the value of the firm they invest in by their own effort (e.g., shareholder activism). Their effort level is, of course, conditional on their achieving a large stake in the firm. It is their very actions and share-holdership that constitutes the 'private' information in many cases. Only when they reach the 5% threshold, does the information, due to the disclosure

[8] Of course, there are several features that distinguish the activist setup from a standard Kyle (1985) setup. Most notably, unlike in Kyle's model, for an activist share-holder (a) the terminal date is endogenous (ten days after his holdings hit 5%), (b) the liquidation value paid out at that time is endogenous, and (c) risk-aversion may play a role. Some of the theoretical implications are discussed further in Collin-Dufresne and Fos (2013).

requirement, become public. We can measure the extent to which the market believes their future actions have value over and above what is already in prices by looking at announcement returns. This also allows us to measure the private information content of their trades.

4.1. Announcement Returns

Panel A in Figure 5 plots the average buy-and-hold return, in excess of the buy-and-hold return on the value-weighed NYSE/AMEX/NASDAQ index from CRSP, from sixty days prior to the filing date to forty days afterward. The sample includes data from the 1994 to 2010 sample period. There is a run-up of about 3% between sixty days to one day prior to the filing date. The two-day jump in excess return observed at the filing date is around 2.5%. After that the excess return remains positive and the post-filing 'drift' cumulates to a total of 9%.[9] Thus, the short-term announcement event-day returns suggest that Schedule 13D filers indeed possess valuable private information during the pre-announcement period.

[Insert Figure 5 here]

Next, we test whether the positive announcement date abnormal return is statistically significant. Panel B in Figure 5 plots the daily abnormal return, calculated as the average daily return in excess of the value-weighted market return. In addition, we plot 1% confidence bounds to test whether the abnormal return is statistically different from zero. The evidence suggests that the filing date abnormal return is positive and statistically significant, indicating that Schedule 13D filers possess valuable information. To further test the magnitude of the filing date announcement return, we regress average

[9] The evidence is consistent with Brav et al. (2008) and Klein and Zur (2009), who report significant positive stock reaction to announcement of hedge fund activism, where the announcement is triggered by Schedule 13D filings. There are two main differences between our samples. First, we consider all Schedule 13D filings while Brav et al. (2008) and Klein and Zur (2009) consider only filings by hedge funds. Second, a Schedule 13D filing is required to have information on trades in order to be included in our sample. That is, we restrict our sample to cases in which the Schedule 13D filer actively accumulate shares and crosses the 5% threshold.

daily return in excess of the value-weighted market return on indicators of (t-2,t+2), (t-1,t), or t, where t is the filing date.

[Insert Table 2 here]

Table 2 reports the results, suggesting a significant positive abnormal return around the filing date. For example, the filing date abnormal return is 1.12% and is highly statistically significant. The three-day abnormal return, reported in column (2), is 2.4% (0.8% times 3) and is highly statistically significant as well. Overall, the evidence strongly supports the assumption that Schedule 13D filers possess valuable information on the underlying securities when they trade in the pre-announcement period.[10]

4.2. Profits

We calculate three measures of profits. First, we calculate Schedule 13D filers' profits from purchasing shares at the pre-announcement prices:

$$Trading\ Profit = \mathbf{q}'(p_{post} - \mathbf{p}), \tag{1}$$

where $\mathbf{q}$ is the vector of trades (purchases are positive and sales are negative) during the sixty-day period, p_{post} is the post-announcement price, and $\mathbf{p}$ is the vector of transaction prices. The post-announcement price is the average stock price during the week that follows the Schedule 13D filing.

If Schedule 13D filers indeed own valuable private information, they would be expected to purchase shares at a discount relative to the post-announcement price. Of course, by purchasing securities schedule 13D filers may also push up prices. Thus their cumulative profits also depend on the price impact of their trades. If price impact is large, then we expect realized profits of informed traders to be lower than if price impact

[10]As we show in Appendix C, there is no evidence of reversal in the buy-and-hold return during 120 days period after the filing sate.

is low. Thus the trading profits of Schedule 13D filers depend both on the value of their private information and on the stock price liquidity.

Second, we calculate the total profit realized by informed investors:

$$Total\ Profit = Trading\ Profit + (p_{post} - p_0)w_0, \tag{2}$$

where p_0 is the price of the first transaction and w_0 is the initial ownership, which is established before the sixty-day period. This measure assumes that a Schedule 13D filer purchases the initial stake at the price of the first transaction. This assumption is most likely to cause a downward bias in estimated total profits.

Finally, we report the total value created for the shareholders of a company that experience a Schedule 13D filing:

$$Value\ Created = (p_{post} - p_0)SHOUT, \tag{3}$$

where $SHOUT$ is the number of shares outstanding.

Table 3 presents the distribution of trading profits. We split the sample into five market cap quantiles and report average profit measures for every quantile. The evidence suggests that informed traders make significant profits. For example, a Schedule 13D filer who acquires a \$22 million stake in a \$293 million market cap company (i.e., 7.51% stake, which is the average stake size in our sample) expects to benefit \$0.8 million. This can be further broken down into a \$0.4 million profit on trades during the sixty-day period and a \$0.4 million profit on the initial ownership, purchased prior to the sixty-day window.

[Insert Table 3 here]

The evidence also suggests that the main beneficiaries are shareholders who own shares on the announcement date. For example, shareholders of companies in the fifth market cap quantile gain \$33 million during an average event whereas the Schedule 13D filer gains $1.8 million. Therefore, while Schedule 13D filers benefit from uninformed traders who sell their shares during the pre-announcement period, they create significant value for all other shareholders by deciding to file Schedule 13D and to intervene in a company's governance.

5. Price Impact of Informed Trades

The evidence in Section 4 strongly supports the assumption that Schedule 13D filers possess valuable information on the underlying securities when they trade in the pre-announcement period. Next we show that trades by Schedule 13D filers affect prices. First, note from Figure 5 that stock prices increase closer to the filing date. Moreover, Figure 3 shows that Schedule 13D filers trade more aggressively closer to the filing date. This suggests that trades by Schedule 13D filers affect prices and specifically, that when Schedule 13D filers buy stocks, their prices appreciate and get closer to the post-filing date level.

Second, we compare the market-adjusted returns and the daily turnover during the sixty-day disclosure period and the sixty-day period during the previous year. Panel A in Table 4 suggests that the market-adjusted returns and the daily turnover are higher during the sixty-day disclosure period. The changes are not only statistically but also economically significant. For example, the average market adjusted return increases from zero to 0.09%.

[Insert Table 4 here]

Third, Panel B in Table 4 shows that market-adjusted returns and daily turnover are higher on days when Schedule 13D filers trade. For example, the average market-adjusted return is 0.64% on days when Schedule 13D filers trade and -0.04% on days when Schedule 13-D filer do not trade. In that sense the adverse selection risk seems worse on days when they trade.

Overall, the evidence indicates that on days when Schedule 13D filers trade prices move up. In addition, days with trades by Schedule 13D filers are characterized by high daily turnover. Next we study whether liquidity measures reveal the presence of informed trading.

6. Liquidity Measures

We use six measures of stock liquidity that rely on high-frequency data: the Kyle lambda, the effective spread, the realized spread, price impact, the cumulative impulse response, and the trade-related component of the variance of changes in the efficient price. The cumulative impulse response and the trade-related component of the variance of changes in the efficient price are calculated using the Hasbrouck (1991a,b) framework. In addition, we use three low-frequency measures of stock liquidity: the Amihud (2002) illiquidity, the daily bid-ask spread, and the probability of informed trade ("*pin*") introduced by Easley et al. (1996).

We categorize these measures as follows: (1) measures that intend to capture the adverse selection cost (Kyle lambda, price impact, cumulative impulse response, the trade-related component of variance of changes in the efficient price, Amihud illiquidity, and *pin*), (2) measures that intend to capture the non-informational component of spreads such as order handling costs, inventory costs, or market power (realized spread), and (3) other measures (effective spread and daily bid-ask spread).

In Appendix B we define these measures, explain how they are constructed, and provide descriptive summary statistics.

7. Do Liquidity Measures Reveal the Presence of Informed Trading?

The evidence reported in Section 4 suggests that Schedule 13D filers indeed possess valuable private information and benefit from trading with uninformed traders. Thus, we can confidently argue that there is a substantial amount of asymmetric information in Schedule 13D trades. Moreover, the evidence reported in Section 5 indicates that, on days when Schedule 13D filers trade, prices move up. Therefore, it is an ideal environment for testing whether liquidity measures capture the increase in the information asymmetry between market participants. In this section we test whether standard liquidity measures, described in Section 6, indicate the presence of informed trading.

We begin the analysis by considering the sixty-day disclosure period and testing whether liquidity measures during this period differ from liquidity measures during the same calendar window in the year prior to the filing date. Table 5 presents the results. The evidence reported in column (3) suggests that none of the adverse selection measures indicate the presence of informed traders during the sixty-day disclosure period. Instead, four out of six measures indicate lower adverse selection. For example, *pin* is more than 9% lower during the sixty-day disclosure period.[11] Therefore, the evidence presented in Table 5 constitutes a major challenge to the argument that these adverse selection measures detect informed trades. Not only do none of the six measures of adverse selection increase when intensive informed trading is taking place, but instead four out of six measures are significantly lower when informed trading is taking place.

[Insert Table 5 here]

Other liquidity measures as well as the realized spread indicate higher stock liquidity and higher competition among liquidity providers. This evidence is consistent with liquidity being high when informed trading takes place. We will return to the discussion of this result in the next section.

Next, we adopt a "diff-in-diff" approach. For each stock, we find a matched stock. The matched stock is selected from the same industry (Fama and French, 1997), same exchange, same size (market cap), and same low frequency volatility (annual return volatility). Then we test whether the change in liquidity measures for event stocks was different from the change in liquidity measures for matched stocks. The main purpose of using this approach is to make sure that time-series changes in liquidity measures do

[11]Related to our results, evidence in Aktas et al. (2007) suggests that *pin* is lower before merger and acquisition announcements.

not confound the results. Columns (4)-(7) in Table 5 reports the results. Column (7) reports diff-in-diff estimates and suggests that *relative* to the matched sample, adverse selection is lower and stock liquidity is higher during the disclosure period. For example, the average change in λ for event (matched) stocks is -3.3274 (1.2514), implying that the diff-in-diff estimate is -4.5788. While some diff-in-diff estimates are not statistically significant, none of the measures indicate either higher adverse selection or lower liquidity during the sixty-day period. Reduction in statistical significance of the differences in liquidity measures indicates that Schedule 13D filers are more likely to trade when aggregate liquidity is high. We will return to discussion of this result in Section 8.

The evidence in Section 3 suggests that Schedule 13D filers trade on average only on 14 days during the sixty-day disclosure period. Motivated by this evidence, we next test how liquidity measures behave on days when Schedule 13D filers trade compared to days when they do not trade, during the disclosure period. That is, we perform a within-sixty-day period comparison of liquidity measures, which allows for arbitrary differences in levels of liquidity measures between sixty-day period events. Table 6 presents the results.[12] The evidence suggests that all liquidity measures indicate higher adverse selection and higher stock liquidity on days with trades by Schedule 13D filers. For example, the average λ is 14.33 on days with informed trades and 20.16 on days with no informed trades. That is, it is almost 30% lower on days with informed trades.

[Insert Table 6 here]

Next, we explore the "diff-in-diff" approach and test whether the difference in liquidity measures is significant relative to the difference in liquidity measures for matched stocks. Column (5) in Table 6 indicates that λ, the realized spread, and the effective spread of event stocks decrease more than those measures of matched stocks. The only exception is the price impact component of the effective spread, which

[12]This approach does not allow us to study lower frequency measures. This is because the estimation of these measures requires a time series of a certain length, and cannot be performed on adjacent days. For example, it is typically suggested to estimate the *pin* measure over at least a one month horizon.

decreases for both event and matched stocks. Thus, measured adverse selection and stock illiquidity are lower not only *when* informed trading trading takes place, but also *relative* to stocks with similar characteristics.

Robustness Tests

To check the robustness of our findings, we adopt the regression methodology used in Hendershott et al. (2011) and estimate the following regression:

$$liq_{it} = \alpha + \gamma itrade_{it} + \eta_i + \epsilon_{it}, \tag{4}$$

where liq_{it} is a measure of liquidity for company i on day t, $itrade_{it}$ is an indicator that is +1 on a day with trades by Schedule 13D filers and zero else, and η_i are event fixed effects. The sample is restricted to the $(t-60, t)$ period around the filing date. Event fixed effects absorb differences in levels of liquidity measures between events. Therefore, the estimated coefficients exploit only the within-event variation in liquidity measures.

Panel A in Table 7 reports the results. Odd columns report results for unmatched measures and even columns report results for matched measures. The results are consistent with the evidence reported in Table 6, suggesting *lower* adverse selection and *higher* stock liquidity on days with trades by Schedule 13D filers. For example, λ decreases by 3.4855, which is an 18% reduction relative to the $(t-60, t)$ period around the filing date. Since all cross-sectional variation in liquidity measures is captured by the event fixed effects, the evidence implies that stocks appear more liquid *when* Schedule 13D filers trade. When matched measures of stock liquidity are used, results are almost unchanged, indicating that adverse selection and liquidity on days with Schedule 13D trading is lower than for matched stocks. The only exception is the price impact component of the effective spread, which remains negative but loses statistical significance.[13]

[13] A significant part of Schedule 13D trading takes place during the (t-30,t) period. To verify that the results are not driven by the (t-60,t-31) period, we report in Panel E results in the sub-samples of trading days from the (t-30,t) period. There is no significant change in the results in this sub-sample.

[Insert Table 7 here]

Crisis vs. Non-crisis Period

Almost 25% of events in the sample take place during the financial crisis. Since the financial crisis period was characterized by a higher trading volume and volatility, we want to test whether adverse selection and liquidity measures reveal the presence of informed trading in the pre-crisis period (i.e., pre-2007 period). To perform the test, we restrict our sample to the pre-crisis period. Panel B in Table 7 reports the results. The evidence suggests that results are not affected by removing financial crisis period from the sample.

Order vs. Quote Driven Markets

In our sample, 62% of companies are listed on the NASDAQ and 29% are listed on the NYSE (the remaining 9% are listed on the AMEX). To test whether adverse selection and liquidity measures perform differently across NASDAQ and NYSE market structures, we split the sample into NASDAQ and NYSE listed stocks.[14] Panels C and D in Table 7 report the results. The evidence suggests that the results are stronger for the sample of NASDAQ-listed stocks. All measures gain additional economic significance in the NASDAQ sample. For example, the difference in matched-adjusted price impact on days with and without informed trading (column (4)) increases from insignificant -0.0003 (Panel A) to -0.0009 (Pane C), which is significant at the 1% level. For stocks listed on the NYSE (Panel D), the coefficient of *itrade* remains significant in λ and *cumir* regressions. While for all other measures the coefficient of *itrade* is insignificant, those measures still fail to reveal the presence of informed trading.

To summarize, the evidence constitutes a major challenge to the idea that empirical measures of adverse selection reveal the presence of informed trading. Instead, we find

[14]Garfinkel and Nimalendran (2003) suggest that there is a difference in the degree of anonymity between NASDAQ and NYSE market structures. Specifically, they find evidence that is consistent with less anonymity on the NYSE specialist system compared to the NASDAQ dealer system. After Reg NMS was implemented, however, Post-Reg NMS US exchanges have become more similar in structures and trading mechanisms.

that measured adverse selection is smaller when informed investors trade. Moreover, stock price liquidity measures indicate higher stock liquidity when informed investors trade.

8. Why do Adverse Selection Measures Fail?

In the previous section we show that traditional measures of adverse selection not only do not capture informed trading by Schedule 13D filers, but also often indicate a lower adverse selection cost. We consider three possible mechanisms that could explain this result.

First, schedule 13D traders might *select* the time at which they trade and step in when the market and/or the target stock happen to be liquid. The argument finds support in the theoretical literature. Collin-Dufresne and Fos (2012) present a theoretical model that extends Kyle's model to stochastic noise trader volatility. In their model informed traders trade more aggressively when uninformed order-flow volatility is high, which can lead to a negative correlation between measures of price impact and aggregate execution costs paid by noise traders.

Second, schedule 13D traders might *attract* additional uninformed volume. In this case, informed traders also trade when the stock is more liquid. But the difference is that the informed traders' trades are the cause for the increase in liquidity. For example, there could be uninformed investors facing large liquidity shocks who will elect to trade more in the stock where they experience least price impact[15] or 'falsely informed' value-traders who, as put forth by Cornell and Sirri (1992), might think they are informed based on technical analysis and therefore act as liquidity providers to the insiders' trades.[16]

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[15]One example is mutual funds facing redemptions and seeking to place large trades as suggested in Gantchev and Jotikasthira (2013).

[16]Cornell and Sirri (1992) present a clinical study of one case of illegal insider trading during Anheuser-Busch's 1982 tender offer for Campbell Taggar, for which they obtained ex-post court records to identify trades by corporate insiders and their tippees. They find that surprisingly liquidity increases when there is active informed trading. Our findings are consistent with their case study, but uses a comprehensive data-set of trades by legal informed traders. In addition, there maybe some high frequency traders who

Third, standard liquidity measures are based on models that assume that informed traders mostly demand immediacy, i.e., use market orders. Schedule 13D filers, however, possess relatively long-lived information and therefore might place limit orders instead (e.g., Kaniel and Liu, 2006). Thus, informed investors with long-lived information might improve stock liquidity.

We first present some evidence consistent with all three mechanisms.

Abnormal Volume

We study abnormal trading activity during the sixty-day disclosure period. Figure 6 presents the average percentage of outstanding shares purchased by Schedule 13D filers and the abnormal volume that does not come from Schedule 13D filers. We refer to the abnormal volume that does not come from Schedule 13D filers as "uninformed."

In Panel A, the two series are centered around the event date. In Panel B, the two series are centered around the filing date. The evidence indicates that closer the event date both Schedule 13D trading and uninformed trading activity increase, reaching maxima at the event date. The correlation between two series is 80% during the (t-60,t-1) period and 96% during (t,t+9) period.

[Insert Figure 6 here]

The evidence is consistent with all three mechanisms. The 'selection' mechanism implies that informed investors trade more aggressively when uninformed trading activity is high. That is, they submit more market buy orders when uninformed trading activity is high. Under the 'endogenous volume' mechanism, the positive correlation between Schedule 13D trading and uninformed trading is there because uninformed investors are attracted by the buy orders posted by Schedule 13D filers. The 'limit order' mechanism implies that limit orders placed by Schedule 13D filers are executed when trading activity is high.

might initially provide liquidity for the trades of the 13D filers and ultimately lead to a 'hot-potato' style trading volume (Lyons, 1997).

Pre vs. Post Event Date Periods

Next, we exploit the nature of the disclosure requirement, which imposes very specific constraints on trading strategy of Schedule 13D filers. As we discussed in Section 2, Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors to file with the SEC within 10 days of acquiring more than 5% of any class of securities of a publicly traded company if they have an interest in influencing the management of the company. The day when the ownership crosses the 5% threshold is the event date. Thus, before the event date the binding constraint is the ownership (and not time). In contrast, after the event date, a Schedule 13D filer has up to 10 days to file with the SEC and therefore is time-constrained.

To test whether the relation between informed trading and liquidity measures changes after the event date, we estimate the following regression:

$$liq_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 postevent_{it} + \gamma_3 itrade_{it} * postevent_{it} + \eta_i + \epsilon_{it}, \qquad (5)$$

where liq_{it} is a measure of liquidity for company i on day t, $itrade_{it}$ indicates days on which Schedule 13D filers trade, $postevent_{it}$ indicates trading days between the event date and the day before the filing date, and η_i are event fixed effects. The analysis is based on daily observations from 60 days before the filing date to the filing date. Table 8 presents the results.[17]

[Insert Table 8 here]

Coefficients of *itrade* suggest that on days when Schedule 13D filers trade during the pre event date period the adverse selection measures are lower and stock liquidity is higher (relative to days when Schedule 13D filers do not trade during the pre event date period). Coefficients of *postevent* show that adverse selection measures are lower and stock liquidity is higher on days when Schedule 13D filers do not trade during the

[17] We obtain similar results when use matched-stock adjusted measures of liquidity.

post event date period (relative to days when Schedule 13D filers do not trade during the pre event date period). This suggests that Schedule 13D filers select to cross the 5% ownership threshold at times when stock liquidity is higher.
The interaction term indicates that the trade-related component of variance of changes in the efficient price increases significantly on days with informed trading during the post event date period, relative to days with informed trading during the pre event date period. λ, the realized spread, and the effective spread increase as well, though the change is not statistically significant.

We also test whether liquidity measures on days when Schedule 13D filers trade during the post event period are different from liquidity measures on days when Schedule 13D filers do not trade. That is, we test whether $\gamma_1 + \gamma_3 = 0$. F-tests suggest that the null is rejected for λ and *cumir* and indicate that the adverse selection is lower when Schedule 13D filers trade during the post event date period. The null is not rejected when other measures of stock liquidity are concerned. Lower economic and statistical significance of *itrade* coefficients during the post event date period is consistent with the 'selection' and the 'limit order' mechanisms being less likely to operate during the post event date period.

Buy-Sell Order Imbalance

In addition to the liquidity measures, we study the relation between informed trading and order imbalance. Order imbalance is the difference in proportion of buy- and sell-initiated trades. Results are reported in column (7) of Table 8. The coefficient of *itrade* indicates that the order imbalance is lower on days with informed trading, indicating either an abnormal selling pressure or usage of buy limit orders by Schedule 13D filers. For example, during the pre event date period, the order imbalance on days with informed trading is more than 4% lower relative to days without informed trading. The interaction term indicates that order imbalance is higher on days with informed trading in the post event date period relative to days with informed trading in the pre event date period. This result is consistent with Schedule 13D filers having less flexibility to select days and to use limit orders once their information becomes short-lived. The evidence, however, seems less consistent with the 'falsely informed noise traders' mechanism: if the causality goes from informed trading to noise trading, one would expect a similar relation between informed trading and stock liquidity measures (including order imbalance) before and after the event date.

Overall, the evidence presented above is broadly consistent with the three proposed explanations. We next provide evidence to discriminate between them.

8.1. Limit Orders

In this section we provide evidence consistent with informed traders using both limit and market orders. Standard measures of adverse selection are based on the assumption that informed traders are using market orders. Schedule 13D filers, however, possess relatively long-lived information and therefore might place limit buy orders instead (e.g. Kaniel and Liu, 2006). Thus, informed investors with a long-lived information might improve stock liquidity.

Rule 13d-1(a) of the 1934 Securities Exchange Act does not require investors to disclose what type of orders they use. We use two approaches to overcome the lack of this information.

Direct Evidence on Limit Orders

First, we match transaction data disclosed in Schedule 13D filings with TAQ data and then test whether these trades are categorized as buy or sell orders by the Lee and Ready (1991) algorithm. The main idea behind this exercise is that if purchase transactions are classified as buy- (sell-) initiated transactions, the Schedule 13D filers are likely to use market (limit) orders. Therefore, we can use transactions that have a unique match with TAQ data to infer whether Schedule 13D filers are using limit orders.

In general, Schedule 13D requires disclosure at daily level and not at transaction level. Therefore, our sample of 292,551 Schedule 13D transactions consists of both aggregated (to daily level) transaction data and of specific transactions. We match transaction data with TAQ data on the following dimensions: transaction date, transaction price, and transaction quantity. The matching procedure leaves us with 108,706 transactions, or 37% of the sample, which suggests that very often Schedule 13D filers disclose aggregated transaction data. Next, we require a Schedule 13D transaction to have a unique match to TAQ data.[18] The matching procedure leaves us with 12,576 trades that have a unique match to the TAQ data.[19]

Figure 7 presents the distribution of these trades during a trading date. The Figure indicates that Schedule 13D filers are more likely to trade in the beginning and at the end of the trading date. This trading pattern is consistent with Schedule 13D filers trading when intraday trading activity is high, i.e., in the beginning and at the end of the trading day (e.g., Jain and Joh, 1988).

[Insert Figure 7 here]

Using sample of 12,576 transactions that have a unique match with TAQ data, we study whether these trades are categorized as buy or sell orders by the Lee and Ready (1991) algorithm. The evidence suggests that only 52.8% of purchase transactions are classified as buy initiated transactions by the Lee and Ready (1991) algorithm, implying that Schedule 13D filers often use limit orders. In addition, it suggests that Schedule 13D filers often receive and do not pay the trading costs.

Next, we compare the percentage of trades classified as buy initiated transactions by the Lee and Ready (1991) algorithm before and after the event date. The evidence suggests that more trades are classified as buy initiated transactions *after* the event date: the percentage of trades are classified as buy initiated transactions increases from

[18] The match on date, quantity, and price is not unique because Schedule 13D filers do not disclose the exact timing of each transaction.

[19] There is one final concern, however, about the quality of the match. While reported 12,576 trades have unique match to TAQ data on transaction date, transaction price, and transaction quantity, it is possible that Schedule 13D filers report aggregated information about a series of transactions and that aggregated 'transaction' has a unique match to the TAQ data. To mitigate this concern, we restricted the sample to the filings in which Schedule 13D filers disclose at least five transaction on a given day. Our assumption is that in these cases Schedule 13D filers are likely to disclose information on true and not aggregated traders. There is almost no change in results, suggesting that the matching procedure is very likely to generate sample of trades which have a unique match to the TAQ data.

51.5% before the event date to 56.3% after the event date. It indicates that Schedule 13D filers are less likely to use limit orders after the event date.[20]

Proxy for Market Order Usage

Second, we develop a proxy for usage of market orders. We start from calculating two versions of the volume-weighted average transaction price for every trading day: (1) using all transactions (*vwap*), and (2) using buy-initiated transactions (*vwap_buy*). Then, we augment the data with the average price Schedule 13D filers pay (hand-collected from Schedule 13D filings). Finally, we hypothesize that if the average price paid by a Schedule 13D filer is above *vwap_buy*, the filer is likely to use market orders.[21]

To support the validity of the proxy, we test whether the effect of informed trading on order imbalance and excess stock returns depends on the order type. If our proxy for usage of market orders is correct, we should find a positive effect on order imbalance and on excess returns when market orders are concerned. To test the hypothesis, we estimate the following regression:

$$y_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 itrade_{it} * above\_vwap\_buy_{it} + \eta_i + \epsilon_{it}, \tag{6}$$

where y_{it} is either order imbalance or excess stock return for company i on day t, $itrade_{it}$ indicates days on which Schedule 13D filers trade, $above\_vwap\_buy_{it}$ indicates trading days when Schedule 13D filers are likely to use market orders, and η_i are event fixed effects. The analysis is based on daily observations from 60 days before the filing date to the filing date. Table 9 presents the results.

[20] What do these numbers tell us about how often 13D filers use limit orders? This depends on the accuracy of the Lee-Ready algorithm. Suppose for example that 70% of the trades are correctly classified by the LR algorithm (Cornell and Sirri (2001) report such numbers). Then if we measure 56.3% buy orders, this would imply 13D filers are using limit orders in 34.25% of cases. Instead 51.5% of measured buy orders, would imply they use limit orders in 46.25% of cases.

[21] Indeed, recall that prices tend to go up on days when Schedule 13D filers trade. Thus to pay a higher price than *vwap_buy* by posting limit orders would require the investor to post all (or most) of his limit orders towards the end of the day at prices exceeding the *vwap*, which would be an extraordinarily poorly designed limit order strategy.

[Insert Table 9 here]

The results support the validity of our proxy for usage of market orders. The negative and significant coefficient of *itrade* suggests that when Schedule 13D filers trade, order imbalance is more negative. On days when the average price paid by Schedule 13D filers is higher than *vwap_buy*, however, order imbalance increases. This is consistent with usage of market orders by the filers. The F-test suggests that the effect on order imbalance is not only higher relative to days when the market orders are not likely to be used, but is also positive and significant.

When we analyze excess stock returns, we find that prices appreciate more when Schedule 13D filers are likely to use market orders. While on a typical trading day with informed trading the excess returns are 0.52%, when Schedule 13D filers are likely to use market orders the excess returns increase by an additional 0.21% to 0.73%. Overall, when our proxy indicates usage of market orders by Schedule 13D filers, informed trades have a positive and significant impact on order imbalance and excess stock returns. It suggests that our proxy for usage of market orders by Schedule 13D filers is likely to be valid.

An additional piece of evidence to support the validity of the proxy comes from matched trades. Specifically, we separate 12,576 trades that have a unique match to the TAQ data into two groups: (1) trades executed on days when Schedule 13D filers' average transaction price was above *vwap_buy* and (2) trades executed on days when Schedule 13D filers' average transaction price was below *vwap_buy*. If our proxy is correct, there should be more trades classified as buy-initiated in the first group. The evidence suggests that 60% of purchase transactions in the first group are classified as buy initiated transactions by the Lee and Ready (1991) algorithm. Importantly, the difference in proportion of trades classified as buy initiated between the two groups is highly significant (t-stat of the difference is 10.44). Therefore, more transactions are classified as buy initiated when Schedule 13D traders are likely to use market orders.

After we establish a proxy for usage of market orders, we test how the relation between informed trading and liquidity measures is affected by the order type used by the informed trader. To perform the test, we estimate the following regression:

$$liq_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 itrade_{it} * above\_vwap\_buy_{it} + \eta_i + \epsilon_{it}, \tag{7}$$

where liq_{it} is a measure of liquidity for company i on day t, $itrade_{it}$ indicates days on which Schedule 13D filers trade, $above\_vwap\_buy_{it}$ indicates trading days when Schedule 13D filers are likely to use market orders, and η_i are event fixed effects. The analysis is based on daily observations from 60 days before the filing date to the filing date. Table 10 presents the results. Panel A presents estimates of the basic specification (4). In Panel B we augment the basic specification with the interaction between *itrade* and $above\_vwap\_buy_{it}$.

[Insert Table 10 here]

The analysis shows interesting differences between high-frequency measures. Specifically, the measures that are typically classified as adverse selection measures (*pimpact*, *cumir*, and $trade - related$) tend to be higher on days when insiders are more likely to use market orders relative to when they use limit orders as indicated by the positive sign of the coefficient on the interaction term. Instead, other measures of liquidity such as *rspread* and *espread* tend to be lower when insiders are more likely to use market orders, which is consistent with the selection mechanism, i.e., that 13D filers use limit orders when liquidity is high. This table seems to suggests that these different measures are not always perfectly correlated and may indeed pick up different elements of the spread (note however, that the coefficient on the λ-measure is always negative and more so when 13D filers are more likely to use market orders).

Overall, the evidence suggests that Schedule 13D filers use both market and limit orders when they accumulate shares in targeted companies, and that by using limit orders they tend to lower measured adverse selection.

8.2. Selection

In this section we provide evidence to support the 'selection' mechanism. We start from analyzing the likelihood of observing the abnormal volume around the event date.

ABNORMAL VOLUME

Figure 6 suggests that informed investors trade more aggressively when uninformed trading activity is high. To differentiate between the 'limit order,' 'selection,' and 'endogenous' volume mechanisms, we ask how likely is it that the observed volume around the event date is randomly drawn from the empirical distribution of the volume. Specifically, for each firm we calculate the empirical probability of drawing a volume less than or equal to that observed on the event date. Under the null of firm event-date volumes being independently and randomly distributed, the distribution of these probabilities across firms should be uniform on the [0,1] interval. If, however, Schedule 13D filers select to trade when volume is high, p-values should be higher than under the null.

[Insert Table 11 here]

Table 11 reports the results. Columns (1) and (2) report mean and standard deviation of a random variable with [0,1] uniform distribution. Columns (3) and (4) report mean and standard deviation of p-values from the empirical distribution of daily volume of target stocks. The evidence suggests that the observed volume is typically higher than under the null. For example, during $(t-4,t)$ period around the event date the average p-value is 75%, indicating that in 75% of cases a average volume over a five-day period will be lower than $(t-4,t)$ volume observed prior to the event date. Importantly, the hypothesis of the average p-value being less than 50% (null hypothesis) is rejected at any confidence level, indicating the observed volume is not drawn randomly. Consistent with the trading strategy of Schedule 13D filers, columns (3) suggests the volume is 'more abnormal' closer to the event date. When we consider the net volume (i.e., total volume net of that due to 13D purchases) in columns (5) and (6), we find that the volume is still more abnormal closer to the event date, though the trend is weaker relative to the trend for total volume.

The fact that the volume of target stocks is abnormally high is consistent with both the selection and endogenous volume mechanisms. Therefore, we next study the volume of *matched* stocks. Columns (7) and (8) report the results. The evidence indicates that Schedule 13D filers are likely to trade when liquidity of matched stocks is high. Since trading target stocks is not likely to cause an increase in volume of matched stocks, the result for matched stocks clearly supports the 'selection' mechanism.

Placebo Sample

Next, we perform two placebo tests that show that the main result of the paper holds when usage of limit orders by informed investors was severely limited. The first test exploits the fact that in 1997 the NASDAQ was required to implement a reform, which required that public investors be allowed to supply liquidity by placing limit orders, thereby competing with NASDAQ dealers (Biais et al., 2005). Prior to this it was almost impossible for non dealers to use limit orders. If the 'selection' mechanism operates, the main results of the paper should hold during the pre-reform period. If, in contrast, only the 'limit order' mechanism operates, the main result of the paper should not hold during the pre-reform period. To perform the test, we estimate the following regression:

$$itrade_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 before_t + \gamma_3 itrade_{it} * before_t + \eta_i + \epsilon_{it}, \qquad (8)$$

where *itrade* indicates days on which Schedule 13D filers trade, $before$ indicates the placebo period, and η_i are event fixed effects. Panel A in Table 12 reports the results. None of the interaction coefficients are statistically significant and the F-test indicates that the relation between adverse selection and liquidity measures was overall negative or insignificant in the placebo sample. Since the measures are statistically significantly more negative (when 13D filers trade) in the second half of the sample, we conclude that limit orders contribute significantly to the negative relation we find in the later part of the sample between informed trading and measures of adverse selection. However, the pre-1997 results also suggest that limit orders are not the sole explanation for our finding. Specifically, we still find that on the NASDAQ pre-1997 measured adverse selection tends to be lower (if not always statistically significantly so) on days when informed trade than when they do not (relative to matched firms).

[Insert Table 12 here]

The second placebo test exploits the start of autoquoting on NYSE (Hendershott et al., 2011). Previously, specialists were responsible for manually disseminating the inside quote. This was replaced in early 2003 by a new automated quote system whenever there was a change to the NYSE limit order book. Presumably, the ability of Schedule 13D traders to rely on limit orders must have been enhanced by the reform. Therefore, the 'limit order' mechanism implies weaker results during the pre-reform period. Panel B in Table 12 reports the results. The evidence suggests that the main result of the paper holds during the second placebo period as well, indicating that the 'limit order' mechanism is not the only mechanism that explains the main result.

Market Wide Liquidity Indicators

To further study the 'selection' mechanism, we next show how variations in market-wide and stock-specific conditions affect the trading strategies of Schedule 13D filers. Specifically, we estimate the following regression:

$$itrade_{it} = \alpha + X_{it}\gamma + \eta_i + \epsilon_{it}, \tag{9}$$

where $itrade_{it}$ indicates days on which Schedule 13D filers trade, X_{it} is a vector of observable market-wide and firm-specific characteristics, and η_i are event fixed effects. X_{it} includes the percentage deviation of CRSP volume from its annual average level ($crspvol_t$), market return in excess of the risk-free rate (mkt_t), the average level of the liquidity measures on day t ($liq_t = \frac{1}{n}\sum_{j \neq i} liq_{jt}$), the liquidity measure for the matched stocks ($liqm_{it}$), daily turnover (to_{it}), as well as lagged values of these variables. In addition, X_{it} includes the lead level of the liquidity measure for the matched stocks ($liqm_{it+1}$) and of the daily turnover (to_{it+1}). The matched stock is assigned from the same industry, same exchange, same size, and same low frequency volatility (See Section 7 for further details). The analysis is based on daily observations from 60 days before the filing date to the filing date. Table 13 reports the results.

[Insert Table 13 here]

The evidence in Table 13 suggests that Schedule 13D filers are more likely to trade when aggregate market activity is high (high *crspvol*) and after the market performs poorly (low mkt_{t-1}). When we consider stock-specific characteristics, we find that contemporaneous and lagged turnover (to_{it} and to_{it-1}) negatively affects the likelihood of informed trading in some specifications. In contrast, future turnover is not correlated with the likelihood of informed trading. In addition, neither current, lagged, or lead liquidity of matched stocks has a significant impact on the likelihood of informed trading.[22]

The evidence on daily turnover supports the 'selection' mechanism and suggests that the 'endogenous' volume mechanism is not likely to operate. The positive and significant relation between the lagged and contemporaneous turnover and the likelihood of informed trading is consistent with the 'selection' mechanism. The absence of a significant relation between the future turnover and the likelihood of informed trading suggests that informed trading is not likely to increase trading activity in the targeted stock, at least in the following days.

If the 'selection' mechanism operates, the relation between informed trading and liquidity measures should be weaker if a regression included variables on which informed traders select. To test this hypothesis, we augment regression (4) with market-wide and firm-specific characteristics. Table 14 reports the results. Panel A reports estimates

[22]The result is not in conflict with Schedule 13D filers trading when liquidity of matched stock is high. As Table 11 indicates, volume for matched stocks is uniformly high during the 30-day period before the event date (i.e., on days with and without informed trading).

of the basic specification. In panel B we augment the regression with date fixed effects, which basically controls for any market-wide observable and unobservable stock characteristics. In panel C we augment the regression with the market-wide and stock-specific characteristics used in equation (9). Consistently with the hypothesis, the results show that coefficient of *itrade* is closer to zero in λ, *rspread*, and *espread* regressions. For example, the coefficient of *itrade* in the *rspread* regression changes from -0.0008 to -0.0005 when market-wide and stock-specific characteristics are added to the regression. The only exception is regression with *pimpact*, which is stronger related to informed trading when the regression includes market-wide and stock-specific characteristics. The fact that the coefficients are still negative and statistically significant (albeit weaker) after controlling for our market wide and stock specific liquidity factors indicates that we have not explained all of the effect with 'selection.' Of course, this may be because we are not using sufficiently precise instruments to control for market and stock specific liquidity. It may however also suggests that some of the variation in the liquidity measures is also due to the 'endogenous volume' mechanism.

[Insert Table 14 here]

Directional Liquidity Measures

Next we present the relation between informed trading and directional liquidity measures. Directional liquidity measures are calculated based on either buy- or sell-initiated trades. For example, *pimpact* of buy orders is calculated based on buy-initiated orders only. We consider the directional versions of λ, *pimpact*, and *rspread*.[23] Table 15 reports the results. Panel A presents estimates of the basic specification (4). In Panel B we augment the basic specification with market excess return (*mkt*).

[Insert Table 15 here]

[23]To the best of our knowledge, it is the first time such directional measures are used to detect presence of informed trading.

The evidence reveals that the price impact of buy-initiated transactions, as measured by *pimpact*, is higher on days when informed investors trade. In contrast, the price impact of sell-initiated transactions is smaller on days with informed trading. The asymmetric relation between price impacts based buy- and sell-initiated trades suggests the price impact does reveal that an intensive purchasing of shares is taking place. The evidence is also consistent with market being less liquid on the buy side and more liquid on the sell side. Specifically, the realized spread is lower when buy-initiated transactions are concerned, suggesting that market makers make less money on these transactions. Panel B shows that the results are not affected by controlling for market excess return.

In Panels C and D we repeat the analysis using matched stocks. The evidence clearly shows that there is no relation between directional measures and liquidity measures when matched stocks are concerned. This result indicates that it is possible to use directional measures of adverse selection to identify presence of informed traders.

9. Conclusion

In this paper we exploit a hand-collected data set on stock transactions by Schedule 13D filers. We find substantial evidence that trades by Schedule 13D filers contain valuable information: both announcement returns and profits realized by the filers are substantial. Moveover, we show that when Schedule 13D filers trade, prices tend to move up. We therefore feel warranted to classify pre-filing trades by Schedule 13D filers as informed.

The data set allows us to test whether measures of adverse selection proposed in the literature reveal the presence of informed traders. The evidence suggests that neither high-frequency nor low-frequency measures of stock liquidity indicate the presence of informed traders. Instead, traditional measures of adverse selection exhibit higher liquidity on days when insiders trade. We reconcile this evidence by documenting that insiders make extensive use of limit orders (especially when they have a lot of flexibility i.e., before their holdings cross the 5% threshold), thus contributing to the improvement in the measured 'adverse selection.' Further, we find clear evidence that insiders select to trade on days when liquidity is abnormally high (for example, when the aggregate S&P500 volume is high) and thus measured adverse selection tends to be low.

The main implication of the paper is that standard adverse selection measures are not robust to the ability of informed traders (who are strategic and have relatively long-lived information like 13D filers) to select when and how to trade.

References

Admati, A., Pfleiderer, P., 1988. A theory of intraday patterns: Volume and price variability. The Review of Financial Studies 1 (1), 3–40.

Aktas, N., de Bodt, E., Declerck, F., Van Oppens, H., 2007. The PIN anomaly around M&A announcements. Journal of Financial Markets 10 (2), 169–191.

Amihud, Y., January 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5 (1), 31–56.

Barclay, M., Hendershott, T., 2004. Liquidity externalities and adverse selection: Evidence from trading after hours. The Journal of Finance 59 (2), 681–710.

Barclay, M., Smith, C., 1988. Corporate payout policy: Cash dividends versus open-market repurchases. Journal of Financial Economics 22 (1), 61 – 82.

Bettis, J., Coles, J., Lemmon, M., 2000. Corporate policies restricting trading by insiders. Journal of Financial Economics 57 (2), 191 – 220.

Bharath, S. T., Pasquariello, P., Wu, G., 2009. Does asymmetric information drive capital structure decisions? Review of Financial Studies 22 (8), 3211–3243.

Biais, B., Glosten, L., Spatt, C., 2005. Market microstructure: A survey of microfoundations, empirical results, and policy implications. Journal of Financial Markets 8 (2), 217–264.

Bolton, P., von Thadden, E.-L., February 1998. Blocks, liquidity, and corporate control. The Journal of Finance 53 (1), 1–25.

Boulatov, A., Hendershott, T., Livdan, D., October 2009. Informed trading and portfolio returns, working paper.

Brav, A., Jiang, W., Partnoy, F., Thomas, R., August 2008. Hedge fund activism, corporate governance, and firm performance. The Journal of Finance 63 (4), 1729–1775.

Brockman, P., Chung, D., 2001. Managerial timing and corporate liquidity:: evidence from actual share repurchases. Journal of Financial Economics 61 (3), 417 – 448.

Cao, C., Field, L., Hanka, G., 2004. Does insider trading impair market liquidity? Evidence from IPO lockup expirations. The Journal of Financial and Quantitative Analysis 39 (1), 25–46.

Charoenwong, C., Chung, K., 2000. An empirical analysis of quoted depths of nyse and amex stocks. Review of Quantitative Finance and Accounting 14, 85–102.

Cheng, L., Firth, M., Leung, T., Rui, O., 2006. The effects of insider trading on liquidity. Pacific-Basin Finance Journal 14 (5), 467 – 483.

Chung, K., Charoenwong, C., 1998. Insider trading and the bid-ask spread. Financial Review 33 (3), 1–20.

Cohen, L., Malloy, C., Pomorski, L., 2012. Decoding inside information. The Journal of Finance Forthcomming.

Collin-Dufresne, P., Fos, V., March 2012. Insider trading, stochastic liquidity, and equilibrium prices, working paper.

Collin-Dufresne, P., Fos, V., April 2013. Moral hazard and informed trading by activist shareholders, working paper.

Copeland, T., Galai, D., 1983. A simple implicit measure of the effective bid-ask spread in an efficient market. The Journal of Finance 38 (5), 1457–1469.

Cornell, B., Sirri, E., 1992. The reaction of investors and stock prices to insider trading. The Journal of Finance 47 (3), 1031–1059.

Duarte, J., Han, X., Harford, J., Young, L., 2008. Information asymmetry, information dissemination and the effect of regulation fd on the cost of capital. Journal of Financial Economics 87 (1), 24–44.

Easley, D., Kiefer, N. M., O'Hara, M., Paperman, J. B., 1996. Liquidity, information, and infrequently traded stocks. The Journal of Finance 51 (4), 1405–1436.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19 (1), 69 – 90.

Fama, E. F., French, K. R., 1997. Industry costs of equity. Journal of Financial Economics 43 (2), 153 – 193.

Fos, V., February 2012. The disciplinary effects of proxy contests, working paper.

Franz, D., Rao, R., Tripathy, N., 1995. Informed trading risk and bid-ask spread changes around open market stock repurchases in the NASDAQ market. Journal of Financial Research 18, 311327.

Gantchev, N., Jotikasthira, C., February 2013. Hedge fund activists: Do they take cues from institutional exit?, working paper.

Garfinkel, J., Nimalendran, M., 2003. Market structure and trader anonymity: An analysis of insider trading. The Journal of Financial and Quantitative Analysis 38 (3), 591–610.

Ginglinger, E., Hamon, J., 2007. Actual share repurchases, timing and liquidity. Journal of Banking & Finance 31 (3), 915 – 938.

Glosten, L. R., 1987. Components of the bid-ask spread and the statistical properties of transaction prices. The Journal of Finance 42 (5), 1293–1307.

Glosten, L. R., Harris, L. E., 1988. Estimating the components of the bid/ask spread. Journal of Financial Economics 21 (1), 123–142.

Glosten, L. R., Milgrom, P. R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14 (1), 71–100.

Goyenko, R., Holden, C., Trzcinka, C., May 2009. Do liquidity measures measure liquidity? Journal of Financial Economics 92 (2), 153–181.

Hasbrouck, J., 1991a. Measuring the information content of stock trades. The Journal of Finance 46 (1), 179–207.

Hasbrouck, J., 1991b. The summary informativeness of stock trades: An econometric analysis. The Review of Financial Studies 4 (3), 571–595.

Hasbrouck, J., 2009. Trading costs and returns for U.S. equities: Estimating effective costs from daily data. The Journal of Finance 64 (3), 1445–1477.

Hasbrouck, J., October 2010. The best bid and offer: A short note on programs and practices, working paper.

Hendershott, T., Jones, C. M., Menkveld, A. J., 2011. Does algorithmic trading improve liquidity? The Journal of Finance 66 (1), 1–33.

Holden, C. W., Jacobsen, S., August 2011. The breakdown of standard microstructure techniques: And what to do about it, working paper.

Jain, P. C., Joh, G.-H., 1988. The dependence between hourly prices and trading volume. The Journal of Financial and Quantitative Analysis 23 (3), 269–283.

Kaniel, R., Liu, H., 2006. So what orders do informed traders use? Journal of Business 79 (4), 1867–1913.

Kelly, B., Ljungqvist, A., July 2011. Testing asymmetric-information asset pricing models, working paper.

Klein, A., Zur, E., January 2009. Entrepreneurial shareholder activism: Hedge funds and other private investors. The Journal of Finance 64 (1), 187–229.

Kyle, A., November 1985. Continuous auctions and insider trading. Econometrica 53 (6), 1315–1335.

Kyle, A., Vila, J.-L., 1991. Noise trading and takeovers. RAND Journal of Economics 22 (1), 54–71.

Lakonishok, J., Lee, I., 2001. Are insider trades informative? Review of Financial Studies 14 (1), 79–11.

Lee, C. M. C., Ready, M. J., 1991. Inferring trade direction from intraday data. The Journal of Finance 46 (2), 733–746.

Lin, J.-C., Sanger, G. C., Booth, G. G., 1995. Trade size and components of the bid-ask spread. The Review of Financial Studies 8 (4), 1153–1183.

Lyons, R. K., 1997. A simultaneous trade model of the foreign exchange hot potato. Journal of International Economics 42 (3-4), 275 – 298.

Maug, E., February 1998. Large shareholders as monitors: Is there a trade-off between liquidity and control? The Journal of Finance 53 (1), 65–98.

Miller, J. M., McConnell, J. J., 1995. Open-market share repurchase programs and bid-ask spreads on the nyse: Implications for corporate payout policy. The Journal of Financial and Quantitative Analysis 30 (3), 365–382.

Obizhaeva, A., March 2011. Selection bias in liquidity estimates, working paper.

Singh, A., Zaman, M., Krishnamurti, C., 1994. Liquidity changes associated with open market repurchases. Financial Management 23 (1), 47–55.

Stoll, H. R., 1989. Inferring the components of the bid-ask spread: Theory and empirical tests. The Journal of Finance 44 (1), 115–134.

Vega, C., 2006. Stock price reaction to public and private information. Journal of Financial Economics 82 (1), 103 – 133.

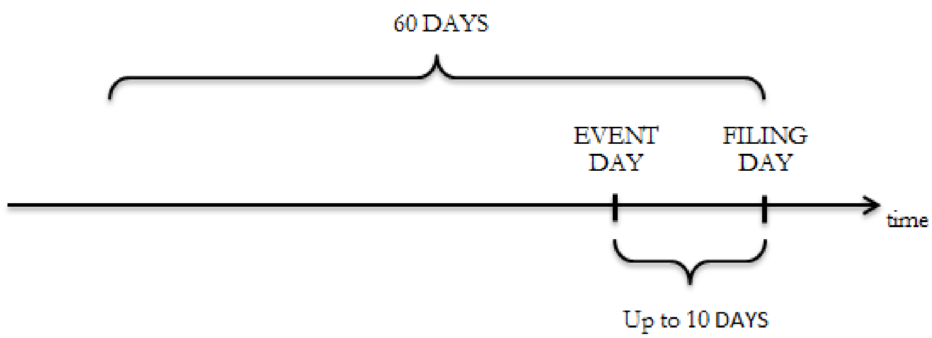


Figure 1: **The Schedule 13D Time Line** This figure summarizes the time line of a Schedule filing. The event date is the day on which Schedule 13D filer's ownership crosses the 5% threshold. Within ten days after the event date the filer files with the SEC and the filing date is determined. The filing includes information on trades during the sixty-day period that precedes the filing date ("sixty-day disclosure period").

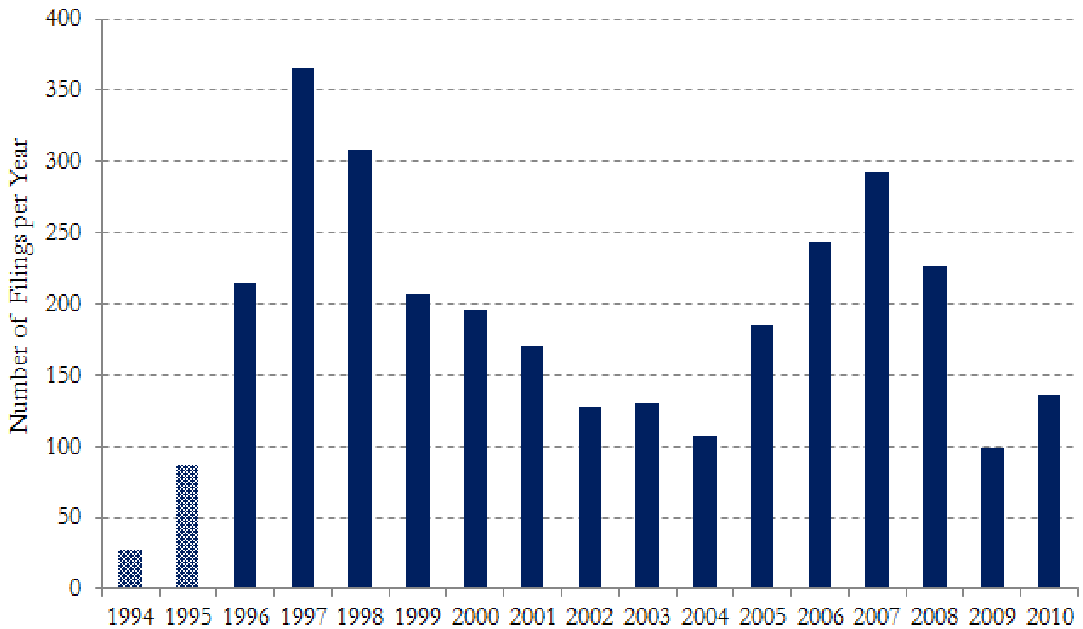


Figure 2: **Time Distribution of Schedule 13D Filings with Information on Trades.** The dark bars represent the number of Schedule 13D filings that satisfy the criteria listed in Section 2.1. The total number of Schedule 13D filings that satisfy these criteria is 3,126 during 1994-2010. 1994 and 1995 bars are dashed because during 1994-1995 the submission of filings to EDGAR was voluntarily. After 1996 the submission of filings EDGAR is obligatory.

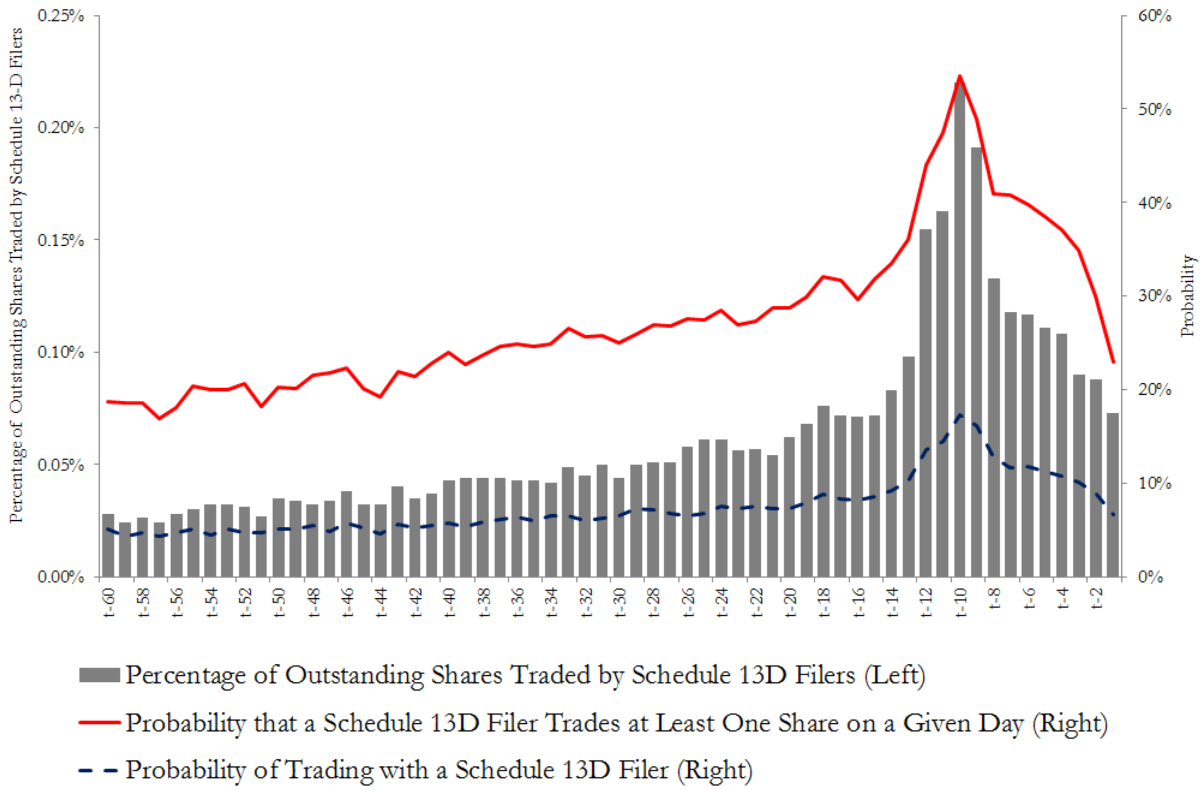


Figure 3: **Trading Strategy of Schedule 13D Filers before the Filing Day.** The solid line (right axis) plots the probability that a Schedule 13D filer trades at least one share on a given day. For every distance to the filing date, $t - \tau$, the probability that a Schedule 13D filer trades at least one share is the number of filings with a non-zero trade by the filer divided by the total number of Schedule 13D filings in the sample. We define the distance to the filing date as the number of days between a trading day, τ, and the filing date, t. The filing date corresponds to the day of filing with the SEC. The dark bars (left axis) represent the percentage of outstanding shares traded by Schedule 13D filers, from 60 days prior to the filing date. For every Schedule 13D filing and distance to the filing date, $t - \tau$, we calculate the percentage of outstanding shares traded by the filer as the ratio between the number of shares traded by the filer and the number of shares outstanding. If no trade is reported on a given day by the filer, the percentage of outstanding shares traded by the filer is set to zero. Then, for every distance to the filing date, $t - \tau$, the percentage of outstanding shares traded by Schedule 13D filers is the average of the percentage of outstanding shares traded among all filings. The dashed line (right axis) plots the probability of trading with a Schedule 13D filer. For every distance to the filing date, $t - \tau$, the probability of trading with a Schedule 13D filer is the average of the number of shares traded by the filer divided by security's volume from CRSP.

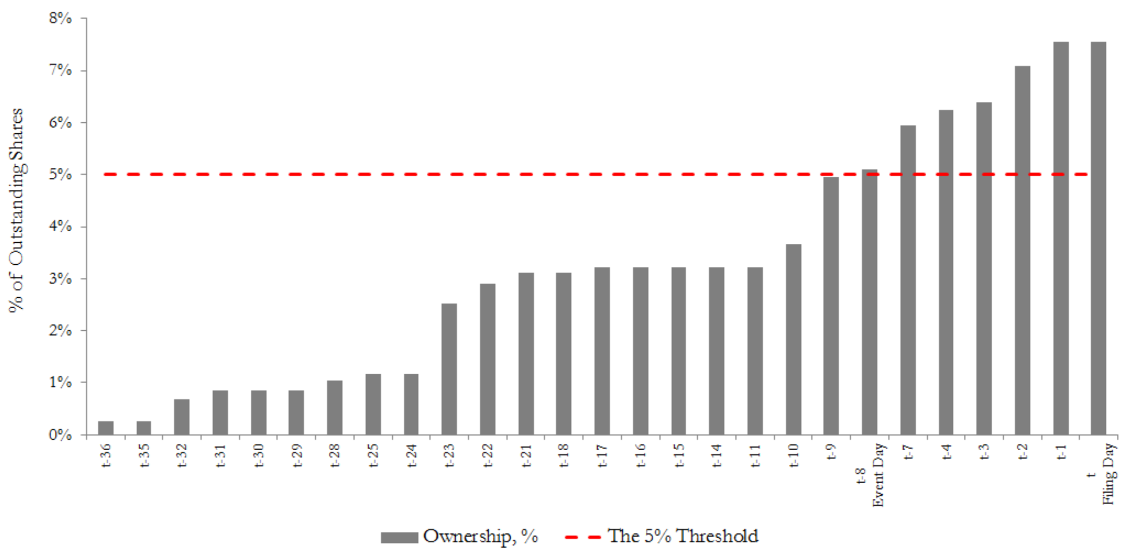
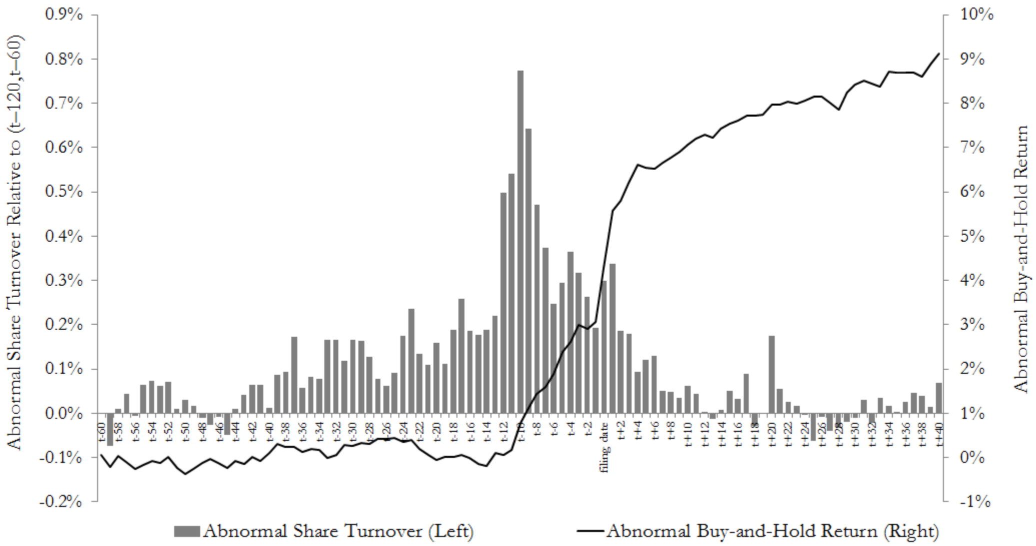
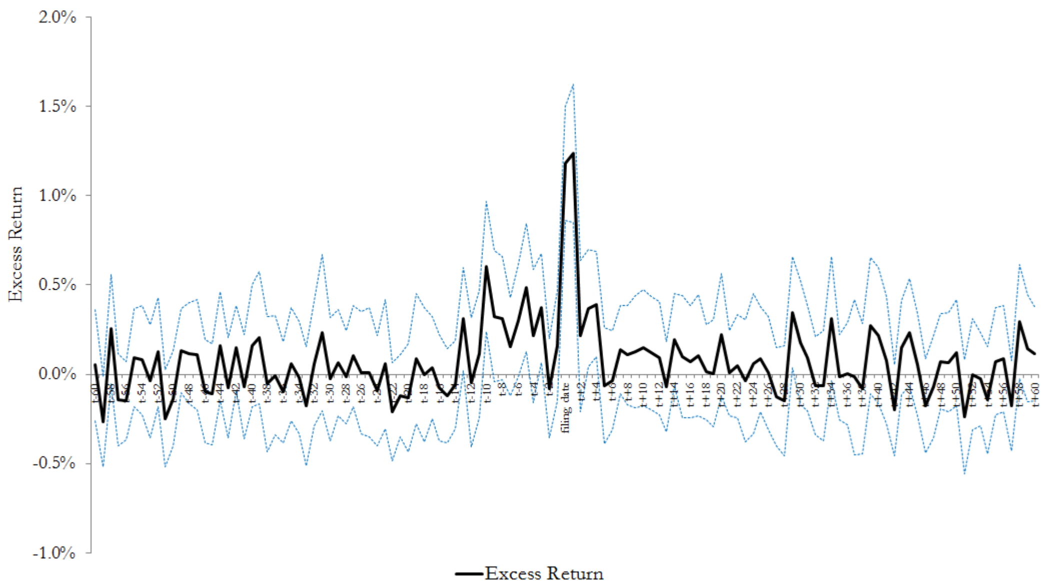


Figure 4: **Icahn Capital LP and Chesapeake Energy Corporation.** The event date is the day on which filer's ownership exceeds the 5% threshold. The filing date corresponds to the day of filing with the SEC. The dark bars plot the percentage of outstanding shares owned by the filer. The dashed line plots the 5% threshold. Since during the (t-60,t-37) period the filer did not trade stocks of Chesapeake Energy Corporation, this period is not plotted in this figure.

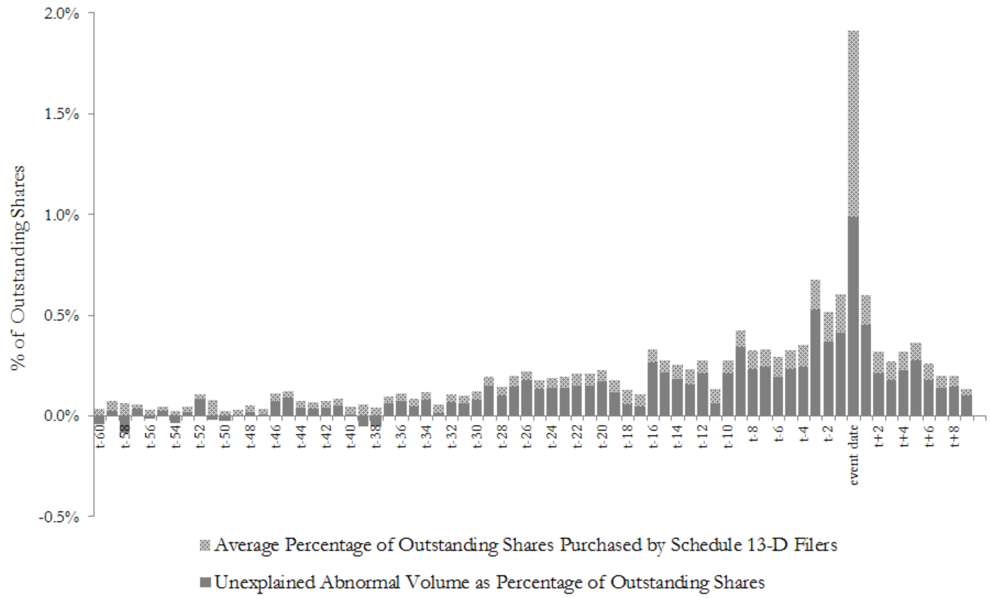


(a) Panel A: Buy-and-Hold Abnormal Return and Abnormal Share Turnover

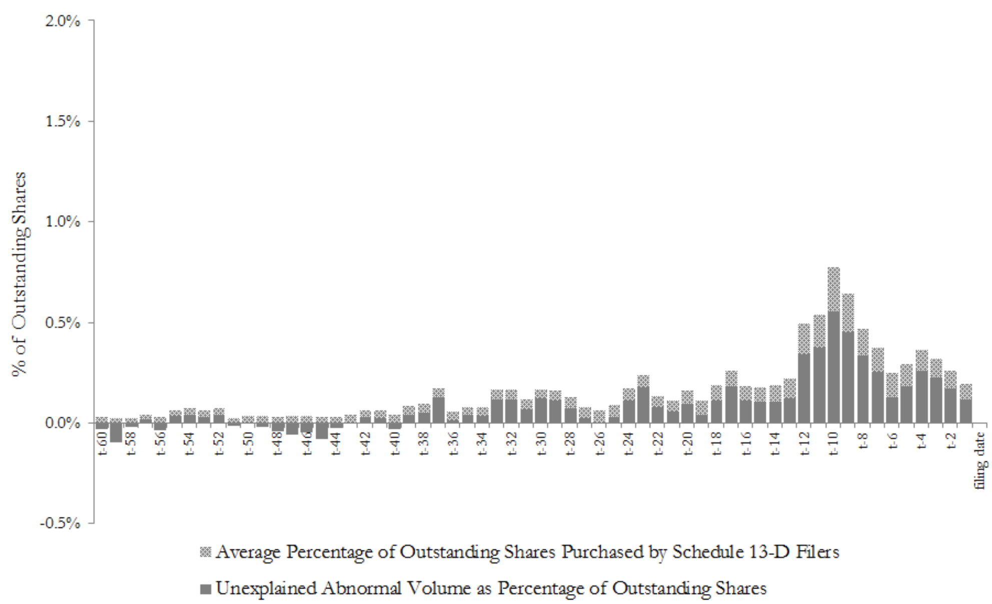


(b) Panel B: Abnormal Return

Figure 5: **Buy-and-Hold Abnormal Return around the Filing Date.** In Panel A the solid line (right axis) plots the average buy-and-hold return around the filing date in excess of the buy-and-hold return of the value-weighted market from 60 days prior the filing date to 40 days afterwards. The filing date is the day on which the Schedule 13D filing is submitted to the SEC. The dark bars (left axis) plot the increase (in percentage points) in the share turnover during the same time window compared to the average turnover rate during the preceding (t-120, t-60) event window. In Panel B the solid line plots daily abnormal return. The abnormal return is average daily return in excess of the value-weight market return. The dashed lines plot lower and upper 1% confidence bounds.



(a) Panel A



(b) Panel B

Figure 6: **Decomposition of Abnormal Share Turnover.** The bars plot the abnormal volume as percentage of outstanding shares, measured as the increase (in percentage points) in the share turnover during the same time window compared to the average turnover rate during the preceding (t-120, t-60) event window. The dashed part of each bar plots the average percentage of outstanding shares purchased by Schedule 13D filers. The dark part of each bar plots the abnormal volume that does not come from Schedule 13D filers. Panel A plots the abnormal volume from 60 days prior to the event date to 10 days after the event date. Panel B plots the abnormal volume from 60 days prior to the filing date to the filing date.

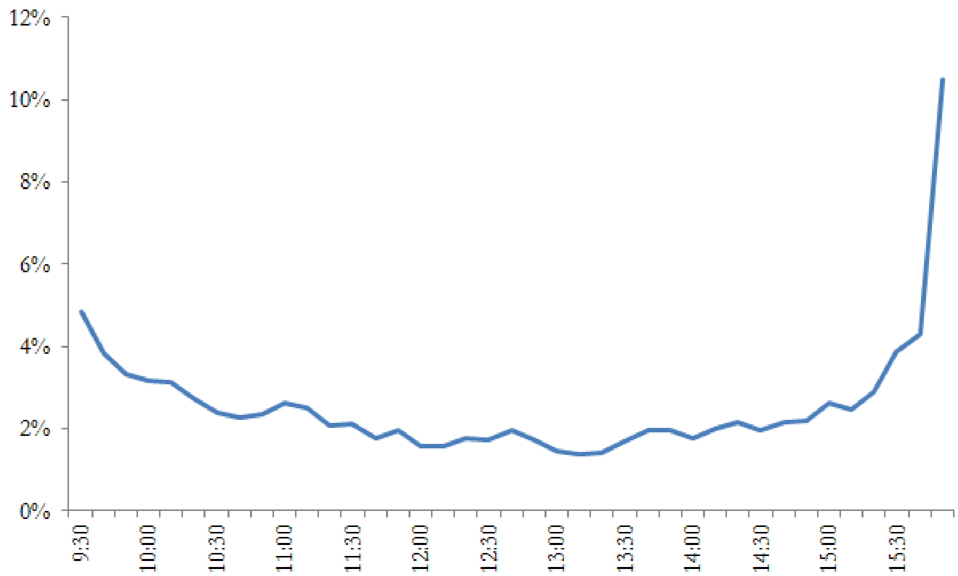


Figure 7: **Informed Trading during a Trading Day.** The solid line plots the percentage of trades by Schedule 13D filers during a trading day. The sample covers 12,576 trades that have a unique match to the TAQ data (see Section 8.1).

Table 1: **Trading Strategy of Schedule 13D Filers.** This table presents descriptive statistics of Schedule 13D filers' trading strategies. Columns (1)-(3) report cross-event means of characteristics and columns (4)-(6) report cross-event medians of characteristics. Columns (1) and (4) report descriptive statistics from the full sample, which covers all days with informed trades during the sixty-day period before the filing date. The filing date is the day on which the Schedule 13D filing is submitted to the SEC. Columns (2) and (5) report descriptive statistics from days with informed trades during the pre-event date period ('Before'). The event date is the day on which filer's ownership exceeds the 5% threshold. Columns (3) and (6) report descriptive statistics from days with informed trades during the post-event date period ('After'). 'Informed trade' is a trade executed by a Schedule 13D filer. Stock ownership on the filing date is the total beneficial ownership of the Schedule 13D filer on the filing date. Number of trading days is the number of days with informed trades during the corresponding period. % of trading days with informed trades is the ratio of days with informed trades to the number of trading days. Informed volume (per trading day) is the total number of shares traded by a Schedule 13D filer (per trading day) on days with informed trades. Dollar informed volume (per trading day) is the total dollar amount traded by a Schedule 13D filer (per trading day) on days with informed trades. Change in ownership (per trading day) is the increase in stock ownership (per trading day), as percentage of number of shares outstanding, on days with informed trades. Informed turnover is the percentage of daily turnover that corresponds to the trades executed by Schedule 13D filers.

	Mean			Median		
	Full Sample (1)	Before (2)	After (3)	Full Sample (4)	Before (5)	After (6)
Stock ownership on the filing date	7.51%			6.11%		
Number of trading days	13.8	11.8	3.5	11	9	3
% of trading days with informed trades	31.1%	29.7%	45.5%	25.6%	24.2%	40.0%
Informed volume	899,692	661,578	350,452	298,807	182,565	99,000
Informed volume per trading day	82,642	69,701	124,000	24,984	18,475	35,500
Informed volume (m$)	16.4	12.1	6.3	2.5	1.6	1.0
Informed volume per trading day (m$)	1.3	1.2	2.1	0.2	0.2	0.4
Change in stock ownership	3.8%	2.5%	1.8%	2.8%	1.7%	0.9%
Change in ownership per trading day	0.5%	0.3%	0.8%	0.2%	0.2%	0.3%
Market-adjusted return	0.63%	0.61%	0.70%	0.28%	0.18%	0.27%
Daily turnover	1.8%	1.9%	2.1%	0.9%	0.8%	1.1%
% of informed turnover (real PIN)	31.5%	28.1%	37.3%	25.4%	22.4%	30.8%

Table 2: **Schedule 13D Filing Abnormal Return.** This table presents the impact of Schedule 13D filing on abnormal return. We regress average daily return in excess of the value-weighted market return on indicator of a two-day window around the filing date (column (1)), indicator of a one-day window around the filing date (column (2)), or indicator of the filing date (column (3)). The analysis is based on 121 daily observations of cross-event average abnormal return from 60 days before the filing date to 60 days after the filing date, where the filing date is the day on which the Schedule 13D filing is submitted to the SEC. In each column, we report estimated coefficients and their t-statistics. *** indicates statistical significance at the 1% level.

Window around filing date (days)	$(t-2, t+2)$ (1)	$(t-1, t+1)$ (2)	t (3)
Indicator of window around filing date	0.0049***	0.0080***	0.0112***
	[5.50]	[7.77]	[5.79]
Constant	0.0006***	0.0006***	0.0007***
	[3.11]	[3.45]	[3.82]
Observations	121	121	121
R-squared	0.203	0.337	0.220

Table 3: **Profits from Informed Trades.** This table presents summary statistics of three measures of profits. *Trading Profit* is defined as $\mathbf{q}'(p_{post} - \mathbf{p})$, where $\mathbf{q}$ is the vector of trades (purchases are positive and sales are negative), p_{post} is the post-announcement price, and $\mathbf{p}$ is the vector of transaction prices. The post-announcement price is the average price during the week that follows the filing date. *Total Profit* is defined as $Trading\ Profit + (p_{post} - p_0)w_0$, where p_0 is the price of the first transaction disclosed in the Schedule 13D filing and w_0 is the initial ownership, established prior to the first transaction disclosed in the Schedule 13D filing. $Value\ Created$ is defined as $(p_{post} - p_0)SHOUT$, where $SHOUT$ is the number of shares outstanding. Average measures of profits as well as t-statistics are reported for five Market CAP quantiles, where Market CAP is market capitalization of the targeted company. ** and *** indicate statistical significance at the 5% and 1% levels.

Market CAP Quantile	Market CAP (1)	Trading Profit (2)	Total Profit (3)	Value Created (4)
Q1 - low	19,773,876	43,998***	56,590***	908,857**
		[4.52]	[3.97]	[2.17]
Q2	52,884,243	104,907***	192,926***	2,607,513***
		[5.71]	[4.22]	[2.99]
Q3	119,969,759	216,250***	298,363***	4,226,135***
		[7.31]	[6.01]	[3.37]
Q4	293,003,259	403,214***	801,141***	15,000,273***
		[9.24]	[7.59]	[5.56]
Q5 - high	1,346,301,018	907,584***	1,818,721***	33,239,501***
		[13.73]	[11.08]	[8.09]

Table 4: **Market-Adjusted Returns and Daily Turnover.** This table reports market-adjusted returns and daily turnover during periods with trades by Schedule 13D filers. Market-adjusted return (*eret*) is the stock return in excess of the CRSP value-weighted return. Daily turnover (*to*) is daily volume divided by the number of shares outstanding. Panel A compares level of market-adjusted returns and daily turnover during the sixty-day disclosure period, (t-60,t-1), and the corresponding sixty-day period of the year before the Schedule 13D filing, (t-420,t-361). First, for every Schedule 13D filing we calculate the average level of market-adjusted returns and daily turnover during the sixty-day disclosure period, (t-60,t-1). Then, we calculate the average level of market-adjusted returns and daily turnover among all events. Column (1) reports the average level of market-adjusted returns and daily turnover during the sixty-day disclosure period among all events. Similarly, Column (2) reports the average level of market-adjusted returns and daily turnover during the corresponding sixty-day period of the year before the Schedule 13D filing, (t-420,t-361). Panel B compares level of market-adjusted returns and daily turnover during on days when Schedule 13D filers trade and on days when Schedule 13D filers do not trade. The sample covers the sixty-day disclosure period only. First, for every Schedule 13D filing we calculate the average level of market-adjusted returns and daily turnover during the sixty-day disclosure period on days with trades by the Schedule 13D filer. Column (1) reports the average level of market-adjusted returns and daily turnover on days with trades by Schedule 13D filers among all events. Column (2) reports the average level of market-adjusted returns and daily turnover on days with no trades by Schedule 13D filers during the sixty-day disclosure period. Column (3) reports the differences between columns (1) and (2). Column (4) reports the t-statistic of the difference. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A

	(t-60,t-1) (1)	(t-420,t-361) (2)	difference (3)	t-stat (4)
eret	0.0009	0.0000	0.0009***	5.04
to	0.0093	0.0066	0.0026***	12.44

Panel B

	days with informed trading (1)	days with no informed trading (2)	difference (3)	t-stat (4)
eret	0.0064	-0.0004	0.0068***	9.94
to	0.0191	0.0077	0.0115***	21.67

Table 5: **Liquidity Measures during the Sixty-Day Disclosure Period.** This table reports the average level of liquidity measures during the sixty-day disclosure period, (t-60,t-1), and the corresponding sixty-day period during the year before the Schedule 13D filing, (t-420,t-361). All liquidity measures are defined in Section 6 and are 99.9% winsorized. Column (1) reports the average level of liquidity measures during (t-60,t-1). Column (2) reports the average level of liquidity measures during (t-420,t-361). Column (3) reports the differences between columns (1) and (2) and the t-statistic of the difference among all events. Column (4) reports the average level of liquidity measures for matched stocks during (t-60,t-1). Column (5) reports the average level of liquidity measures for matched stocks during (t-420,t-361). Column (6) reports the differences between columns (4) and (5) and and the t-statistic of the difference. Column (7) reports the diff-in-diff estimate and the t-statistic of the diff-in-diff estimate, where the diff-in-diff estimate is the difference between columns (3) and (6). The matched stock is assigned from the same industry, same exchange, same size, and same low frequency volatility (See Section 7 for further details). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	Schedule 13D Sample			Matched Sample			
	(t-60,t-1)	(t-420,t-361)	diff	(t-60,t-1)	(t-420,t-361)	diff	diff-in-diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Adverse Selection Measures							
$\lambda * 10^6$	19.0011	22.3285***	-3.3274***	24.6448	23.3934	1.2514	-4.5788**
			[-3.36]			[0.92]	[-2.31]
pimpact	0.0066	0.0066	0.0000	0.0073	0.0075	-0.0002	0.0002
			[-0.21]			[-0.76]	[0.72]
cumir	0.0015	0.0017	-0.0002**	0.0016	0.0017	-0.0001	-0.0001
			[-2.16]			[-1.06]	[-0.99]
$trade-related$	0.0691	0.0686	0.0005	0.0729	0.0747	-0.0018	0.0022
			[0.24]			[-0.99]	[0.06]
illiquidity	0.4611	0.5025	-0.0413***	0.6610	0.6297	0.0312**	-0.0726***
			[-4.12]			[1.96]	[-4.24]
pin	0.4385	0.4943	-0.0559***	0.4819	0.5120	-0.0301***	-0.0257***
			[-13.1]			[-6.97]	[-3.52]
Market Power Measure							
rspread	0.0095	0.0109	-0.0014***	0.0127	0.0129	-0.0002	-0.0012***
			[-4.69]			[-0.59]	[-2.74]
Liquidity Measures							
espread	0.0162	0.0175	-0.0012***	0.0194	0.0199	-0.0004	-0.0008
			[-2.99]			[-0.92]	[-1.23]
baspread	0.0219	0.0239	-0.0020***	0.0284	0.0288	-0.0004	-0.0016**
			[-4.85]			[-0.54]	[-2.32]

Table 6: **Liquidity Measures on Days when Schedule 13D Filers Trade.** This table reports the average level of liquidity measures on days when Schedule 13D filers trade. The sample covers the sixty-day disclosure period. All liquidity measures are defined in Section 6 and are 99.9% winsorized. For every Schedule 13D filing we calculate the average level of a liquidity measure during the sixty-day disclosure period on days with trades by the Schedule 13D filer. Column (1) reports the average level of liquidity measures on days with trades by Schedule 13D filers among all events. Similarly, Column (2) reports the average level of liquidity measures on days with no trades by Schedule 13D filers during the sixty-day disclosure period. Column (3) reports the differences between columns (1) and (2) and the t-statistic of the difference. Column (4) replicates column (3) for sample of matched stocks. The matched stock is assigned from the same industry, same exchange, same size, and same low frequency volatility (See Section 7 for further details). Column (5) reports the diff-in-diff estimate and the t-statistic of the diff-in-diff estimate, where the diff-in-diff estimate is the difference between columns (3) and (4). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	days with informed trading (1)	days with no informed trading (2)	diff (3)	matched diff (4)	diff-in-diff (5)
Adverse Selection Measures					
$\lambda * 10^6$	14.3311	20.1644	-5.8334***	-0.8126	-5.0208***
			[-8.38]	[-0.63]	[-4.05]
pimpact	0.0060	0.0064	-0.0004**	-0.0003*	-0.0001
			[-2.18]	[-1.65]	[0.1]
cumir	0.0013	0.0015	-0.0002**	0.0000	-0.0002
			[-2.06]	[0.41]	[-1.25]
$trade - related$	0.0654	0.0673	-0.0019	-0.0021	0.0002
			[-0.99]	[-1.28]	[1.45]
Market Power Measure					
rspread	0.0081	0.0089	-0.0008***	0.0003	-0.0012***
			[-3.43]	[1.19]	[-3.35]
Liquidity Measure					
espread	0.0145	0.0155	-0.001***	0.0003	-0.0014***
			[-3.25]	[0.8]	[-2.58]

Table 7: **Informed Trading and Liquidity Measures.** This table shows the relation between informed trading and liquidity measures. We regress each of the liquidity measures described in Section 6 on indicator of informed trading, using the following specification: $liq_{it} = \alpha + \gamma itrade_{it} + \eta_i + \epsilon_{it}$, where liq_{it} is a measure of liquidity for company i on day t, *itrade* indicates days on which Schedule 13D filers trade, and η_i are event fixed effects. For each measure of stock liquidity, we use the raw liquidity measures as well as the difference between liquidity measures for targeted and matched stocks. The matched stock is assigned from the same industry, same exchange, same size, and same low frequency volatility (See Section 7 for further details). The analysis is based on daily observations from 60 days before the filing date to the filing date. Panel A covers the sample of all Schedule 13D filings. Panel B covers the pre-crisis period (prior to 2007). Panel C covers stocks listed on NASDAQ. Panel D covers stocks listed on NYSE. Panel E covers $(t-30, t)$ period before the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	$\lambda * 10^6$		*pimpact*		*cumir*		$trade-related$		*rspread*		*espread*	
Matched	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Full Sample												
itrade	-3.4855***	-3.1775***	-0.0004***	-0.0003	-0.0001***	-0.0001***	-0.0013	-0.0007	-0.0008***	-0.0009***	-0.0009***	-0.0010***
	[-11.51]	[-6.20]	[-2.83]	[-1.54]	[-5.46]	[-3.11]	[-1.40]	[-0.60]	[-6.22]	[-4.31]	[-4.50]	[-2.80]
Panel B: Pre-Crisis Sample												
itrade	-4.2098***	-3.5294***	-0.0004**	-0.0004	-0.0002***	-0.0001***	-0.0020	-0.0017	-0.0010***	-0.0010***	-0.0011***	-0.0012***
	[-10.37]	[-4.91]	[-2.09]	[-1.54]	[-5.04]	[-2.95]	[-1.54]	[-1.10]	[-6.18]	[-4.05]	[-4.17]	[-2.85]
Panel C: NASDAQ Sample												
itrade	-4.3652***	-3.8136***	-0.0006***	-0.0009***	-0.0002***	-0.0001**	-0.0017	0.0004	-0.0010***	-0.0010***	-0.0012***	-0.0016***
	[-10.08]	[-4.56]	[-3.62]	[-3.42]	[-4.57]	[-2.58]	[-1.31]	[0.25]	[-5.13]	[-2.99]	[-4.73]	[-3.50]
Panel D: NYSE Sample												
itrade	-2.0876***	-2.1727***	-0.0001	-0.0001	-0.0001***	-0.0001***	0.0001	-0.0022	-0.0002	-0.0002	-0.0001	0.0000
	[-5.32]	[-4.38]	[-0.56]	[-0.14]	[-3.78]	[-2.59]	[0.06]	[-1.60]	[-1.62]	[-1.45]	[-0.33]	[0.02]
Panel E: (t-30,t) Sample												
itrade	-3.5582***	-2.4045***	-0.0003	-0.0001	-0.0001***	-0.0000	-0.0006	0.0006	-0.0007***	-0.0011***	-0.0007***	-0.0012**
	[-9.49]	[-4.55]	[-1.46]	[-0.29]	[-3.48]	[-0.74]	[-0.46]	[0.38]	[-4.21]	[-3.92]	[-2.75]	[-2.54]

Table 8: **Informed Trading in the Post Event Day Period.** This table shows the relation between informed trading and liquidity measures during the post event date period. We regress each of the liquidity measures described in Section 6 and order imbalance (*orderim*) on indicator of informed trading, using the following specification: $liq_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 postevent_{it} + \gamma_3 itrade_{it} * postevent_{it} + \eta_i + \epsilon_{it}$, where liq_{it} is a measure of liquidity for company i on day t, *itrade* indicates days on which Schedule 13D filers trade, η_i are event fixed effects. $postevent_{it}$ indicates trading days between day after the event date and the day before the filing date. Order imbalance is the difference in proportion of buy- and sell-initiated returns. The F-test tests whether during the post event date period stock liquidity on days with informed trading is different from stock liquidity on days without informed trading. The analysis is based on daily observations from 60 days before the filing date to the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	$\lambda * 10^6$ (1)	*pimpact* (2)	*cumir* (3)	$trade - related$ (4)	*rspread* (5)	*espread* (6)	*orderim* (7)
itrade	-3.4602***	-0.0004***	-0.0001***	-0.0017*	-0.0008***	-0.0009***	-0.0411***
	[-11.20]	[-2.69]	[-5.01]	[-1.71]	[-5.95]	[-4.40]	[-7.03]
postevent	-1.2623**	-0.0001	-0.0001	-0.0044***	-0.0009***	-0.0010**	-0.0066
	[-2.06]	[-0.42]	[-1.40]	[-2.63]	[-3.31]	[-2.48]	[-0.71]
$itrade * postevent$	0.4685	0.0002	0.0000	0.0047**	0.0005	0.0006	0.0254**
	[0.65]	[0.39]	[0.13]	[2.04]	[1.47]	[1.15]	[1.98]
F-test: $\gamma_1 + \gamma_3 = 0$							
Point estimate	-2.9917	-0.0002	-0.0001	0.0030	-0.0003	-0.0003	-0.0157
F-statistics	17.2316	0.4148	3.5768	1.9484	1.2561	0.4556	1.5906
p-value	0.0000	0.5196	0.0588	0.1630	0.2625	0.4998	0.2074

Table 9: **Informed Trading, Order Imbalance, and Stock Prices.** This table presence the relation between informed trading, order imbalance, and stock prices. We estimate the following regression: $y_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 itrade_{it} * above\_vwap\_buy_{it} + \eta_i + \epsilon_{it}$, where y_{it} is either order imbalance or market-adjusted return for company i on day t, *itrade* indicates days on which Schedule 13D filers trade, $above\_vwap\_buy_{it}$ indicates days when the average price paid by informed investor is higher than the volume-weighted average price of buy-initiated transactions, and η_i are event fixed effects. Order imbalance (*orderim*) is the difference in proportion of buy- and sell-initiated trades. Market-adjusted return (*eret*) is the stock return in excess of the CRSP value-weighted return. The analysis is based on daily observations from 60 days before the filing date to the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	(1) *orderim*	(2) *orderim*	(3) *eret*	(4) *eret*
itrade	-0.0378***	-0.0868***	0.0060***	0.0052***
	[-6.67]	[-13.42]	[11.86]	[9.22]
$itrade * above\_vwap\_buy$		0.1221***		0.0021**
		[16.78]		[2.57]
Constant	-0.0344***	-0.0344***	-0.0002	-0.0002
	[-18.96]	[-19.22]	[-0.96]	[-0.96]
F-test: $\gamma_1 + \gamma_2 = 0$				
Point estimate		0.0353		0.0073
F-statistics		26.6100		94.0800
p-value		0.0000		0.0000

Table 10: **Informed Trading and Order Type.** This table presence the relation between informed trading and order type. In Panel A we report estimates of the basic regression: $y_{it} = \alpha + \gamma_1 itrade_{it} + \eta_i + \epsilon_{it}$, where y_{it} is a measure of liquidity for company i on day t, *itrade* indicates days on which Schedule 13D filers trade, and η_i are event fixed effects. To capture usage of market orders by Schedule 13D filers, we augment the basic specification with the interaction of $itrade_{it}$ and $above\_vwap\_buy_{it}$, which indicates days when the average price paid by informed investor is higher than the volume-weighted average price of buy-initiated transactions. Panel B reports estimates of the augmented regression: $y_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 itrade_{it} * above\_vwap\_buy_{it} + \eta_i + \epsilon_{it}$. The analysis is based on daily observations from 60 days before the filing date to the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	$\lambda * 10^6$ (1)	*pimpact* (2)	*cumir* (3)	$trade - related$ (4)	*rspread* (5)	*espread* (6)
Panel A						
itrade	-3.4855***	-0.0004***	-0.0001***	-0.0013	-0.0008***	-0.0009***
	[-11.51]	[-2.83]	[-5.46]	[-1.40]	[-6.22]	[-4.50]
Panel B						
itrade	-2.9366***	-0.0007***	-0.0002***	-0.0040***	-0.0003*	-0.0007**
	[-8.39]	[-3.55]	[-4.85]	[-3.45]	[-1.84]	[-2.54]
$itrade * above\_vwap\_buy$	-0.7673**	0.0008***	0.0000	0.0030**	-0.0014***	-0.0007**
	[-2.29]	[3.63]	[1.29]	[1.96]	[-7.59]	[-2.38]
F-test: $\gamma_1 + \gamma_2 = 0$						
Point estimate	-3.7039	0.0001	-0.0002	-0.0010	-0.0017	-0.0014
F-statistics	70.39	12.61	23.55	11.90	3.39	6.47
p-value	0.0000	0.0004	0.0000	0.0006	0.0659	0.0111

Table 11: **Trading Volume** This table analysis the probability of observing the realized level of volume over (t, t), $(t-1, t)$, $(t-4, t)$, $(t-9, t)$, and $(t-29, t)$ periods around the Schedule 13D event date. For every period we calculate the average volume and calculate the probability of drawing that average volume from the empirical distribution of volume of the stock. If the average volume is drawn randomly, the empirical probability of having at least the average volume should be uniformly distributed on [0,1] interval. Columns (1) and (2) report mean and standard deviation of a random variable with [0,1] uniform distribution. Columns (3) and (4) report mean and standard deviation from empirical distribution of daily volume of target stocks. Columns (5) and (6) report mean and standard deviation from empirical distribution of net daily volume of targeted stocks, where the net daily volume is the difference between total volume and volume that comes from Schedule 13D filers. Columns (3) and (4) report mean and standard deviation from empirical distribution of daily volume of matched stocks. The matched stock is assigned from the same industry, same exchange, same size, and same low frequency volatility (See Section 7 for further details). p-values of mean being higher than mean of the [0,1] uniform random variable (i.e., 50%) are reported in parenthesizes. *** indicates statistical significance at the 1% level.

	Uniform Distribution		Volume		Net Volume		Matched Stocks (Volume)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event Day	50%	29%	79%***	26%	67%***	32%	57%***	31%
			(0.0000)		(0.0000)		(0.0000)	
$(t-1, t)$	50%	29%	78%***	26%	66%***	32%	58%***	31%
			(0.0000)		(0.0000)		(0.0000)	
$(t-4, t)$	50%	29%	75%***	28%	64%***	32%	57%***	31%
			(0.0000)		(0.0000)		(0.0000)	
$(t-9, t)$	50%	29%	72%***	29%	62%***	32%	58%***	31%
			(0.0000)		(0.0000)		(0.0000)	
$(t-29, t)$	50%	29%	67%***	30%	60% ***	33%	58%***	31%
			(0.0000)		(0.0000)		(0.0000)	

Table 12: **Informed Trading and Liquidity Measures: Placebo Tests.** This table shows the relation between informed trading and liquidity measures on stocks listed on NASDAQ and NYSE. We regress each of the liquidity measures described in Section 6 on indicator of informed trading, using the following specification: $liq_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 before_{it} + \gamma_3 itrade_{it} * before_{it} + \eta_i + \epsilon_{it}$, where liq_{it} is a measure of liquidity for company i on day t, $itrade$ indicates days on which Schedule 13D filers trade, $before_{it}$ indicates 1994-1997 period in Panel A (before NASDAQ limit-orders reform) and 1994-2002 period in Panel B (before introduction of algorithmic trading on NYSE), η_i are event fixed effects. The $F-test$ tests whether during the placebo period stock liquidity on days with informed trading is different from stock liquidity on days without informed trading. The analysis is based on daily observations from 60 days before the filing date to the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	$\lambda * 10^6$ (1)	$pimpact$ (2)	$cumir$ (3)	$trade-related$ (4)	$rspread$ (5)	$espread$ (6)
Panel A: NASDAQ						
$itrade$	-3.8967***	-0.0006***	-0.0002***	-0.0017	-0.0010***	-0.0013***
	[-8.58]	[-3.17]	[-4.64]	[-1.21]	[-4.73]	[-4.77]
$before$	6.4555**	-0.0003	-0.0003	-0.0302	0.0014	0.0019
	[2.14]	[-0.42]	[-0.79]	[-1.41]	[1.16]	[1.09]
$itrade * before$	-3.4217***	0.0002	0.0002	-0.0002	-0.0002	0.0006
	[-2.63]	[0.49]	[1.54]	[-0.06]	[-0.32]	[0.68]
F-test: $\gamma_1 + \gamma_3 = 0$						
Point estimate	-7.3184	-0.0004	0.0000	-0.0019	-0.0012	-0.0007
F-statistics	35.8892	3.8463	0.0030	0.3554	4.6667	0.8875
p-value	0.0000	0.0501	0.9565	0.5512	0.0310	0.3464
Panel B: NYSE						
$itrade$	-0.7534**	-0.0003	-0.0000	-0.0004	0.0000	-0.0002
	[-2.27]	[-0.92]	[-1.54]	[-0.33]	[0.33]	[-0.54]
$before$	1.4968	-0.0007	0.0001***	0.0068***	0.0022	0.0027
	[0.89]	[-0.48]	[3.50]	[3.22]	[1.04]	[1.65]
$itrade * before$	-3.9324***	0.0005	-0.0002***	0.0015	-0.0005**	0.0003
	[-3.91]	[0.97]	[-2.71]	[0.46]	[-2.04]	[0.43]
F-test: $\gamma_1 + \gamma_3 = 0$						
Point estimate	-4.6858	0.0002	-0.0002	0.0011	-0.0005	0.0001
F-statistics	24.2906	0.2123	11.0662	0.1329	4.2478	0.0125
p-value	0.0000	0.6452	0.0010	0.7156	0.0398	0.9111

Table 13: **Determinants of Trading by Schedule 13D Filers.** This table presents the relation between several observable variables and trading strategy of Schedule 13D filers. We estimate the following specification: $itrade_{it} = \alpha + X_{it}\gamma + \eta_i + \epsilon_{it}$, where $itrade$ indicates days on which Schedule 13D filers trade, X_{it} is a vector of observable market-wide and stock-specific characteristics, and η_i are event fixed effects. X_{it} includes the percentage deviation of CRSP volume from its annual average level ($crspvol$), market return in excess of the risk-free rate (mkt), the average level of the liquidity measure on day t (liq_t), liquidity measure for the matched stock ($liqm$), daily turnover (to) as well as lagged values of these variables. In addition, X_{it} includes the lead level of the daily turnover (to_{it+1}) and of liquidity measure for the matched stock ($liqm_{it+1}$). The matched stock is assigned from the same industry, same exchange, same size, and same low frequency volatility (See Section 7 for further details). The analysis is based on daily observations from 60 days before the filing date to the filing date, where the filing date is the day on which the Schedule 13D filing is submitted to the SEC. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent variable: $itrade$						
Liquidity Measure	$\lambda * 10^6$	$pimpact$	$cumir$	$trade-related$	$rspread$	$espread$
	(1)	(2)	(3)	(4)	(5)	(6)
Market-wide variables						
$crspvol_{t-1}$	-0.0179	-0.0021	0.0038	0.0037	-0.0014	-0.0017
	(-0.78)	(-0.11)	-0.1600	-0.1600	(-0.07)	(-0.09)
$crspvol_t$	0.0666***	0.0608***	0.0695***	0.0707***	0.0596***	0.0596***
	-2.7300	-2.9900	-2.8600	-2.9000	-2.9300	-2.9300
mkt_{t-1}	-0.3872*	-0.4026**	-0.4592**	-0.4470**	-0.3905**	-0.3972**
	(-1.77)	(-2.23)	(-2.16)	(-2.11)	(-2.16)	(-2.19)
mkt_t	-0.3914	-0.2700	-0.3088	-0.3091	-0.2573	-0.2746
	(-1.62)	(-1.37)	(-1.31)	(-1.31)	(-1.31)	(-1.39)
liq_{t-1}	0.0003	-0.1424	0.0000	0.0934	-0.5499	-0.3517
	-1.1900	(-0.65)	(-1.64)	-0.8600	(-1.00)	(-1.53)
liq_t	0.0000	0.1673	-0.0000*	0.0996	-0.7352	-0.1717
	-0.1000	-0.7800	(-1.81)	-0.9300	(-1.27)	(-0.75)
Stock-specific variables						
$liqm_{it-1}$	-0.0001	0.0819	-1.4634	0.0082	-0.0989	0.1118
	(-1.07)	-0.4500	(-0.69)	-0.1400	(-0.60)	-1.0800
$liqm_{it}$	0.0001	-0.0342	-0.6336	-0.0062	0.0840	0.1394
	-1.2300	(-0.19)	(-0.31)	(-0.12)	-0.5200	-1.3200
$liqm_{it+1}$	-0.0001	-0.1893	-0.5011	-0.0467	-0.0013	-0.0442
	(-0.91)	(-1.05)	(-0.23)	(-0.92)	(-0.01)	(-0.44)
to_{it-1}	1.1699***	1.1799***	1.2250***	1.2232***	1.1794***	1.1802***
	-6.5600	-7.3700	-7.2700	-7.2500	-7.3600	-7.3700
to_{it}	3.2082***	3.4487***	3.1164***	3.1172***	3.4445***	3.4464***
	-14.7900	-16.9000	-15.6800	-15.7000	-16.8700	-16.8700
to_{it+1}	0.2106	0.2378*	0.1009	0.1030	0.2398*	0.2383*
	-1.3600	-1.7000	-0.7200	-0.7400	-1.7100	-1.7000

Table 14: **Informed Trading and Selection on Observables.** This table shows the impact of informed trading on liquidity measures, while controlling for several market-wide and stock-specific variables. In Panel A we regress each of liquidity measures described in Section 6 on indicator of informed trading, using the following specification: $liq_{it} = \alpha + \gamma itrade_{it} + \eta_i + \epsilon_{it}$, where liq_{it} is a measure of liquidity for company i on day t, $itrade$ indicates days on which Schedule 13D filers trade, and η_i are event fixed effects. In Panel B we augment the regression with date fixed effects. In Panel C we augment the regression with market-wide and stock-specific controls, analyzed in Table 13. The analysis is based on daily observations from 60 days before the filing date to the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Liquidity Measure	$\lambda * 10^6$ (1)	$pimpact$ (2)	$cumir$ (3)	$trade - related$ (4)	$rspread$ (5)	$espread$ (6)
Panel A: Basic Model						
itrade	-3.4855***	-0.0004***	-0.0001***	-0.0013	-0.0008***	-0.0009***
	[-11.51]	[-2.83]	[-5.46]	[-1.40]	[-6.22]	[-4.50]
Panel B: Basic Model with Date Fixed Effects						
itrade	-2.3634***	-0.0006**	-0.0001***	-0.0012	-0.0006***	-0.0009***
	[-6.64]	[-2.38]	(-3.66)	(-1.24)	[-3.44]	[-3.29]
Panel C: Basic Model with Current and Lagged Controls						
itrade	-2.2297***	-0.0005***	-0.0001***	-0.0011	-0.0005***	-0.0008***
	[-8.08]	[-2.93]	[-4.41]	[-1.18]	[-3.87]	[-3.29]

Table 15: **Informed Trading and Directional Liquidity Measures.** This table presence the relation between informed trading and directional liquidity measures. We estimate the following regression: $y_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 mkt_t + \eta_i + \epsilon_{it}$, where y_{it} is a directional measure of liquidity for company i on day t, *itrade* indicates days on which Schedule 13D filers trade, mkt_t is market return in excess of the risk-free rate, η_i are event fixed effects. Directional liquidity measures are calculated using either buy-initiated transactions or sell-initiated transactions only. In Panel A we impose $\gamma_2 = 0$. In Panel B we estimate the unrestricted version. In Panels C and D y_{it} is a directional measure of liquidity for matched stock. In Panel C we impose $\gamma_2 = 0$. In Panel D we estimate the unrestricted version. The analysis is based on daily observations from 60 days before the filing date to the filing date. In each column, we report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	$\lambda * 10^6$		*pimpact*		*rspread*	
Order type	*buy*	*sell*	*buy*	*sell*	*buy*	*sell*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
itrade	-1.1114***	-1.5501***	0.0003*	-0.0012***	-0.0015***	-0.0003*
	[-5.97]	[-7.36]	[1.83]	[-4.64]	[-8.57]	[-1.79]
Panel B						
itrade	-1.1122***	-1.5585***	0.0003*	-0.0012***	-0.0015***	-0.0003*
	[-5.96]	[-7.38]	[1.89]	[-4.68]	[-8.62]	[-1.74]
mkt	-1.5182	-14.8346	0.0247***	-0.0366***	-0.0292***	0.0214***
	[-0.17]	[-1.32]	[4.44]	[-3.93]	[-5.04]	[3.93]
Panel C: Matched Stocks						
itrade	-0.6272	-0.2158	0.0000	-0.0000	-0.0001	0.0000
	[-1.49]	[-0.49]	[0.03]	[-0.19]	[-0.51]	[0.16]
Panel D: Matched Stocks						
itrade	-0.6115	-0.2032	0.0000	-0.0001	-0.0001	0.0001
	[-1.45]	[-0.46]	[0.17]	[-0.28]	[-0.63]	[0.22]
mkt	36.0259**	24.6344	0.0417***	-0.0359***	-0.0456***	0.0284***
	[2.16]	[1.04]	[6.59]	[-5.67]	[-5.16]	[3.35]

Appendix A. Case Study: Icahn Capital LP vs. Chesapeake Energy Corporation

To illustrate the informed trades that are the focus of this paper, we give a detailed description of one specific case.

On May 25, 2012, Icahn Capital LP filed a Schedule 13D indicating that it owned 7.56% of Chesapeake Energy Corporation (50,085,202 shares of common stock), which operates in the Oil & Gas Operations industry. The filer in a letter to the Chesapeake board included in the Schedule 13D filing, said that Icahn Capital LP planned to force the break up of Chesapeake's board and the installation of new directors nominated by Icahn Capital LP and other leading shareholders. Therefore, the filer explicitly highlighted the possibility of active engagement in company's corporate governance.

Figure 4 presents the percentage of outstanding shares owned by Icahn Capital LP during the (t-36,t) period around the filing date.[24] The filer's ownership prior to the sixty-day disclosure period was 0.11% of Chesapeake Energy (702,367 shares of common stock). During the sixty-day period before the filing date the filer purchased 7.46% of Chesapeake Energy (49,382,835 shares of common stock). All these shares where purchased during the (t-36,t-1) period. The filer's ownership crossed the five-percent threshold on May 17, 2012 (the "event date").

[Insert Figure 4 here]

The filer disclosed that the 50,085,202 shares of common stock were purchased for $785,300,000, i.e., $15.68 per share. The filing reveals that the 702,367 shares purchased prior to the sixty-day period were acquired at an average price of $14.54 per share while the 49,382,835 shares that were purchased during the sixty-day period were acquired at an average price of $15.70 per share. The average price of Chesapeake Energy shares reached $17 per share level in the ten days after the filing and remained at $17.52 per

[24]Since during the (t-60,t-37) period the filer did not trade stocks of Chesapeake Energy, this period is not plotted in this figure.

share during the post-filing month, suggesting that the filer gained \$1.82 on average per share purchased. This gain aggregates to \$91,981,854. In the forty days after the filing the stock price reached \$19.36 per share, raising Icahn Capital LP's gain to \$183,311,839.

The price of Chesapeake Energy shares increased by 4.95% during the filing date (May 25, 2012) and the following trading day (May 29, 2012). Therefore, the market's perception of the value created by Icahn Capital LP was clearly positive.

Consistent with the evidence in Table 1, Figure 4 suggests that Icahn Capital LP did not trade on every trading day during the sixty-day pre-filing period. Specifically, the filer traded on eighteen trading days during the sixty-day period. Interestingly, the filer traded when stock liquidity was high. For example, during the sixty-day period, the average level of the Amihud (2002) illiquidity measure during days with trades by Icahn Capital LP was 38% *lower* than during days with no trades by Icahn Capital LP.[25]

On January 30, 2013 the company announced that the CEO Aubrey McClendon is to leave the company on April 1. The CEO departure was follows a series of disagreements between the CEO and newly appointed board members, who were nominated by Icahn Capital LP. Consistently with the hedge fund activism literature, this example therefore emphasizes that activist shareholders often achieve their long term goals and not simply trade on a short-lived information (e.g., Brav et al., 2008).

Appendix B. Liquidity Measures

Appendix B.1. Adverse Selection Measures

Kyle's lambda is a measure of price impact, which can be interpreted as the cost of demanding a certain amount of liquidity over some given time period. In constructing this measure, we follow Hasbrouck (2009) and Goyenko et al. (2009) and calculate the

[25] Amihud (2002) illiquidity measure is the ratio of absolute value of daily stock return to the dollar trading volume, multiplied by 1000.

price impact as the slope coefficient λ_{it} in the regression:

$$ret_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \varepsilon_{itn}, \tag{B.1}$$

where for the nth five-minute period on date t and stock i, ret_{itn} is the stock return and S_{itn} is the sum of signed square-root dollar volume, that is, $\sum_k sign(dvol_{itnk})\sqrt{|dvol_{itnk}|}$. The trades are signed according to the Lee and Ready (1991) algorithm.

The five-minute price impact is the permanent component of the effective spread. It measures gross losses to liquidity demanders due to adverse selection (Glosten and Harris, 1988). For a given stock i and day t, the five-minute price impact of the kth trade is defined as:

$$pimpact_{itk} = 2q_{itk}(ln(M_{itk+5}) - ln(M_{itk})), \tag{B.2}$$

where q_{itk} is the buy–sell indicator (+1 for buys, –1 for sells), M_{itk+5} is the midpoint of the consolidated BBO prevailing five-minutes after the kth trade, and M_{itk} is the midpoint of the consolidated BBO prevailing at the time of the kth trade.[26] Aggregating over day t, a stock's price impact $pimpact_{it}$ is the dollar-volume-weighted average of price impact $pimpact_{itk}$ computed over all trades on day t.

Hasbrouck (1991a,b) introduce a model based on a vector autoregression (VAR) that infers the nature of information and trading from the observed sequence of quotes and trades. In this framework, all stock price moves end up being assigned to one of two categories: they are either associated or unassociated with a recent trade. Price moves that are associated with a recent trade are usually referred to as private information-based. We construct a VAR with two equations: the first describes the trade-by-trade evolution of the quote midpoint, while the second describes the persistence of order flow. Define $q_{it\tau}$ to be the buy-sell indicator for stock i on date t and trade τ (+1 for buys,

[26] We exclude NBBO crossed and locked observations from the analysis (Holden and Jacobsen, 2011).

–1 for sells), and define $r_{it\tau}$ to be the log return based on the quote midpoint of stock i on date t from trade $\tau - 1$ to trade τ. The VAR picks up order flow dependence out to 10 lags:

$$r_\tau = \sum_{k=1}^{10} \alpha_k r_{\tau-k} + \sum_{k=0}^{10} \beta_k q_{\tau-k} + \varepsilon_{r\tau}, \tag{B.3}$$

$$q_\tau = \sum_{k=1}^{10} \gamma_k r_{\tau-k} + \sum_{k=1}^{10} \phi_k q_{\tau-k} + \varepsilon_{q\tau}, \tag{B.4}$$

where the stock subscript i and the date subscript t are suppressed.[27] The VAR is inverted to get the vector moving average (VMA) representation:

$$y_\tau = \begin{bmatrix} r_\tau \\ q_\tau \end{bmatrix} = \theta(L)\varepsilon_\tau = \begin{bmatrix} a(L) & b(L) \\ c(L) & d(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{r\tau} \\ \varepsilon_{q\tau} \end{bmatrix}, \tag{B.5}$$

where $a(L)$, $b(L)$, $c(L)$, and $d(L)$ are lag polynomial operators. The variance of the random work component can be written as

$$\sigma_\omega^2 = \left(\sum_{j=0}^{\infty} b_j\right)^2 \sigma_q^2 + \left(\sum_{j=0}^{\infty} a_j\right)^2 \sigma_r^2. \tag{B.6}$$

The first term captures the component of price discovery that is related to recent trades, and the second term captures price changes that are orthogonal to trading. Following Hasbrouck (1991b), we define the trade-related component of variance of changes in the efficient price as $R_\omega = \left(\sum_{j=0}^{\infty} b_j\right)^2 \sigma_q^2/\sigma_\omega^2$. R_ω is a comprehensive relative measure of trade informativeness. Following Hasbrouck (1991a), we define the cumulative impulse response as $\left(\sum_{j=0}^{\infty} b_j\right)$.

Amihud's illiquidity measure $illiquidity_{it}$ is defined as:

$$illiquidity_{it} = 1000\frac{|r_{it}|}{volume_{it}}, \tag{B.7}$$

[27] We borrow notation from Hendershott et al. (2011).

where r_{it} is the stock i return on day t and $volume_{it}$ is stock i dollar volume on day t. A smaller value of *illiquidity* implies a lower price impact, and therefore a higher stock liquidity.

The Easley et al. (1996) *pin* measure is:

$$pin = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}, \tag{B.8}$$

where α is the probability of an information event, μ is the arrival rate of of traders who know the new information if it exists, and ε is the arrival rate of uninformed traders. Maximum likelihood estimators of these parameters are described in Easley et al. (1996), pages 1412-1414. A higher value of *pin* implies a higher probability of informed trade.

Appendix B.2. Market Power Measure

The realized spread is the temporary component of the effective spread. It measures the revenue to liquidity providers assuming that the liquidity provider is able to close her position at the midpoint prevailing five minutes after the trade. For a given stock i and day t, the realized spread on the kth trade is defined as:

$$rspread_{itk} = 2q_{itk}(ln(P_{itk}) - ln(M_{itk+5})), \tag{B.9}$$

where P_{itk} is the price of the kth trade, M_{itk+5} is the midpoint of the consolidated BBO prevailing five-minutes after the kth trade, and q_{itk} is the buy–sell indicator (+1 for buys, –1 for sells). Aggregating over day t, a stock's realized spread $rspread_{it}$ is the dollar-volume-weighted average of the realized spread $rspread_{itk}$ computed over all trades on day t.

The effective spread is the difference between the natural logarithm of the actual transaction price and the natural logarithm of the midpoint prevailing at the time of the trade:

$$espread_{itk} = 2|ln(P_{itk}) - ln(M_{itk})|, \tag{B.10}$$

where P_{itk} is the price of the kth trade and M_{itk} is the midpoint of the consolidated BBO prevailing at the time of the kth trade (Hasbrouck, 2010). Aggregating over day t, a stock's effective spread $espread_{it}$ is the dollar-volume-weighted average of the effective spread $espread_{itk}$ computed over all trades on day t. The wider the effective spread, the less liquid is the stock.

The bid-ask spread $basperad_{it}$ of stock i on day t is defined as:

$$baspread_{it} = \frac{ask_{it} - bid_{it}}{0.5(ask_{it} + bid_{it})}, \tag{B.11}$$

where ask_{it} and bid_{it} are daily closing ask and bid from CRSP. A smaller value of $baspread$ implies a higher stock liquidity.

Appendix B.3. Descriptive Statistics

Table 16 provides summary descriptive statistics of the stock liquidity measures. Panel A describes high-frequency stock liquidity measures and Panel B describes low-frequency stock liquidity measures.

[Insert Table 16 here]

Appendix C. Abnormal Buy-and-Hold Return

Figure 8 plots the average buy-and-hold return, in excess of the buy-and-hold return on the value-weighed NYSE/AMEX/NASDAQ index from CRSP, from sixty days prior to the filing date to 120 days afterward. The sample includes data from the 1994 to 2010 sample period. There is a run-up of about 3% between sixty days to one day prior to the filing date. The two-day jump in excess return observed at the filing date is around 2.5%. After that the excess return remains positive and the post-filing 'drift' cumulates to a total of 10%. When we compare Figure 8 and 5, we learn that there is no reversal. The abnormal buy-and-hold return over (t-40,t-120) period is slightly above 1%.

[Insert Figure 8 here]

Table 16: **Summary Statistics of Liquidity Measures.** This table reports the summary statistics of liquidity measures on daily data. All liquidity measures are defined in Section 6. The sample covers (t-421,t-361) period, where t is the Schedule 13D filing date. First, for every Schedule 13D filing we calculate the average level of a liquidity measure during the (t-421,t-361) period. Then, we calculate summary statistic of liquidity measure among all events. The data set combines TAQ, CRSP, and the hand-collected sample of Schedule 13D filings (see Section 3).

Liquidity Measure	Description	Min	Percentile					Max	Mean	Std Dev
			5th	25th	Median	75th	95th			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Adverse Selection Measures										
$\lambda * 10^6$	the slope coefficient of $ret_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \varepsilon_{itn}$	-46.12	0.54	2.86	9.68	29.25	107.28	414.59	25.48	42.54
pimpact	dollar-weighted price impact	-0.0609	0.0006	0.0019	0.0039	0.0078	0.0229	0.4827	0.0075	0.0186
cumir	cumulative impulse response (VAR)	-0.0402	0.0001	0.0004	0.0010	0.0022	0.0073	0.0330	0.0019	0.0036
$trade - related$	trade-related component of variance of changes in the efficient price	0.0000	0.0146	0.0329	0.0511	0.0830	0.1896	0.6476	0.0711	0.0725
illiquidity	Amihud's illiquidity	0.0033	0.0225	0.0819	0.2185	0.5881	2.1300	19.0555	0.5422	0.9392
pin	the probability of informed trade	0.0000	0.1500	0.3278	0.4637	0.6462	0.8999	0.9988	0.4899	0.2233
Panel B: Other Liquidity Measures										
rspread	dollar-weighted realized spread	-0.0765	0.0000	0.0008	0.0046	0.0155	0.0432	0.1792	0.0111	0.0169
espread	dollar-weighted effective spread	0.0003	0.0014	0.0053	0.0133	0.0244	0.0523	0.4431	0.0185	0.0228
baspread	Closing bid-ask spread	-0.0002	0.0009	0.0043	0.0160	0.0349	0.0877	0.5000	0.0262	0.0340

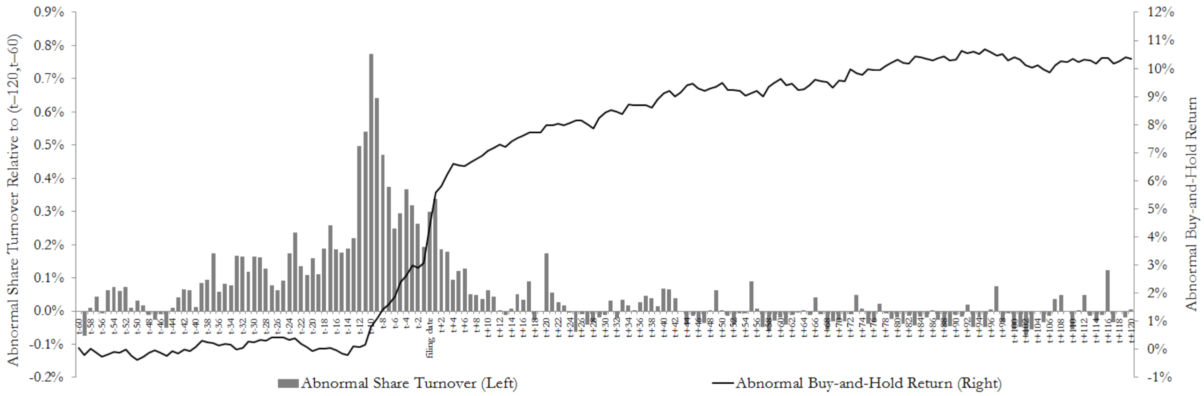


Figure 8: **Buy-and-Hold Abnormal Return around the Filing Date.** The solid line (right axis) plots the average buy-and-hold return around the filing date in excess of the buy-and-hold return of the value-weighted market from 60 days prior the filing date to 120 days afterwards. The filing date is the day on which the Schedule 13D filing is submitted to the SEC. The dark bars (left axis) plot the increase (in percentage points) in the share turnover during the same time window compared to the average turnover rate during the preceding (t-120, t-60) event window. In Panel B the solid line plots daily abnormal return. The abnormal return is average daily return in excess of the value-weight market return.