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Do Prices Reveal the Presence of Informed Trading?

PIERRE COLLIN-DUFRESNE and VYACHESLAV FOS*

ABSTRACT

Using a comprehensive sample of trades from Schedule 13D filings by activist investors, we study how measures of adverse selection respond to informed trading. We find that on days when activists accumulate shares, measures of adverse selection and of stock illiquidity are lower, even though prices are positively impacted. Two channels help explain this phenomenon: (1) activists select times of higher liquidity when they trade, and (2) activists use limit orders. We conclude that, when informed traders can select when and how to trade, standard measures of adverse selection may fail to capture the presence of informed trading.

An extensive body of theory suggests that stock illiquidity, as measured by the bid-ask spread and by the price impact of trades, should be increasing in the information asymmetry between market participants (Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hare (1987)). Based on this literature, there have been many attempts to measure trading costs empirically, and to decompose such costs into different components such as adverse selection, order processing, and inventory costs (Glosten (1987), Glosten and Harris (1988), Stoll (1989), Hasbrouck (1991a)). Empirical measures of adverse selection typically rely on an estimate of the persistent price impact of trades to capture the amount of private information in trades.[1] An extensive empirical

*Collin-Dufresne is with École Polytechnique de Lausanne and SFI. Fos is with Boston College's Carroll School of Management. A significant part of this project was completed when Fos was with University of Illinois at Urbana–Champaign. We thank Azi Ben-Rephael, Bruno Biais (the Editor), Terry Hendershott, Gur Huberman, Wei Jiang, Ohad Kadan (TAU 2013 discussant), Robert Korajczyk (AFA discussant), Norman Schuerhoff, two anonymous referees, 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, Kellogg, UT Sydney, UNSW, University of Sydney, UC Berkeley, Stanford, Federal Reserve Bank of San Francisco, the Board of Governors of the Federal Reserve System, ETH Zurich, Imperial College, University of Lugano, Bocconi University, University of Toulouse, Aalto University, Stockholm School of Economics, Cambridge University, and London School of Economics, as well as participants at the Liquidity and Arbitrage Trading (GFRI) 2012 conference, the AFA 2013 Annual Meeting, the AFFI 2013 annual meeting, IDC Summer Conference, the University of Oregon 2013 Finance Conference, and the Tel Aviv 2013 Finance 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.

[1] Based on the theory discussed, it is natural to think that price impact should be positively related to adverse selection. For example, the seminal model of insider trading of Kyle (1985)

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literature employing these adverse selection measures thus assumes that they capture information asymmetry (Barclay and Hendershott (2004), Vega (2006), Duarte et al. (2008), Bharath, Pasquariello, and Wu (2009), Kelly and Ljungqvist (2012)).

But, do these empirical measures of adverse selection actually capture information asymmetry? To test this question, one would ideally separate informed from uninformed trades ex ante and measure their relative impact on price changes. However, since we generally do not know the traders' information sets, this is hard to do in practice.[2]

In this paper, we use a novel data set of trades by investors that we can identify as having substantial private information to study how illiquidity measures are actually related to informed trading. More specifically, we exploit a disclosure requirement Rule 13d-1(a) of the 1934 Securities Exchange Act to identify trades that rely on valuable private information. Rule 13d-1(a) 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 addition to having to report their actual position at the time of filing, Item 5(c) of Schedule 13D requires the filer to report the date, price, and quantity of all trades in the target company executed during the 60 days that precede the filing date.[3]

We collect a comprehensive sample of trades from the Schedule 13D filings. We view this sample as an interesting laboratory to study the liquidity and price impact of informed trades. An average Schedule 13D filing in our sample is characterized by a positive and significant market reaction upon announcement. For example, the 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. To summarize, the evidence implies that Schedule 13D filers' information is valuable. We can therefore classify the pre-announcement trades by Schedule 13D filers as informed trades. Note that, by its very nature, the information held by Schedule 13D filers is likely to qualify as "private information" and to be long-lived.[4]

predicts that "Kyle's lambda," which can be estimated from a regression of price change on signed order flow, should be higher for stocks with more informed trading (relative to noise trading). Indeed, in their well-known survey of the microstructure literature, Biais, Glosten, and Spatt (2005) describe the empirical relation between adverse selection and effective spread (measured by the price impact λ) as follows: "As the informational motivation of trades becomes relatively more important, λ goes up" (p. 232).

[2] As a result, it is often assumed that some types of investors are informed. For example, Boulatov, Hendershott, and Livdan (2013) use the institutional order flow as a proxy for informed trading.

[3] To quote from Item 5(c), filers have 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, ..."

[4] Collin-Dufresne and Fos (2015) 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

Our main empirical result is that standard measures of adverse selection and stock illiquidity do not reveal the presence of informed trading. Specifically, we find that several measures of adverse selection are *lower* on days when Schedule 13D filers trade, which suggests that adverse selection is lower and the stock is more liquid when there is significant informed trading in the stock. For example, on an average day when Schedule 13D filers trade, the measured price impact (λ) is almost 30% lower relative to the sample average. 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. Adverse selection measures, however, fail to detect that price impact.

This result is closely related to Cornell and Sirri (1992), who 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. The authors find that, surprisingly, liquidity increases when there is active informed trading. Our evidence is consistent with their case study, but is based on a comprehensive data set of trades by legal "insiders."

The above result rejects the hypothesis that standard measures of stock price illiquidity, and in particular of adverse selection, capture the severity of the adverse selection problem (at least not when informed traders have long-lived private information similar to that of Schedule 13D filers). We consider two possible mechanisms that could explain this result.

First, and consistent with the theoretical model presented in Collin-Dufresne and Fos (2014), Schedule 13D filers might *select* the timing of trades, stepping in when the market and/or the target stock happen to be liquid. In their model, noise trading volatility is stochastic. Informed agents strategically choose to trade more when noise trading is high, which leads to a negative relation between informed trading and measured price impact.[5]

Second, while standard liquidity measures are based on models that assume informed traders mostly demand immediacy, that is, use market orders, Schedule 13D filers 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 measured stock liquidity (and receive the spread rather than pay it).

We note that standard asymmetric information models also typically assume that the presence of the insider is common knowledge. In practice, market makers may have to learn that an insider is present from the order flow. This

part of the valuable private information pertains to the activist's own holdings, which by definition is information known only to him.

[5] Admati and Pfleiderer (1988) also generate a negative relation between price impact and informed trading, but via a different mechanism. In their model, information is short-lived, but information acquisition is endogenous. Since information is more valuable when noise trading is high, insiders optimally acquire more information (and trade more) in times of high noise trading volatility.

may also affect the relation between adverse selection measures and informed trading.[6]

We perform several tests that indicate that these two mechanisms contribute to our findings. For a subsample of trades for which we can identify the individual "time-stamped" trades, we find clear evidence that Schedule 13D filers use limit orders. Further, we find that, before their ownership crosses the 5% threshold, Schedule 13D filers are more likely to use limit orders than after, when they have only 10 days left to trade. We also construct a proxy for the usage of market orders based on the average Schedule 13D trader's buy price relative to the value-weighted average price (VWAP) and show that, when Schedule 13D filers are more likely to use market orders, adverse selection measures are less negatively related to their trades. However, using two 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 in which limit orders were not (or less) available to informed traders, there is no significant positive relation between informed trades and liquidity measures.

Instead, there is strong statistical evidence that the pattern in abnormal volume observed on (and around) days when insiders trade is not random (both comparing the target firm's abnormal volume to its own past history or to a matched sample of firms). This clearly shows that 13D filers trade when available liquidity is high. 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, a high aggregate volume and a 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 (1) to trade when stock liquidity is high for exogenous as well as endogenous reasons, and (2) to use limit orders, which leads to an inverse relation between standard empirical measures of adverse selection and the informational motivation of trades.

The paper is organized as follows. Section I describes the data. The magnitude of information asymmetry is analyzed in Section II. Section III describes liquidity measures used in the analysis. Section IV presents the main evidence on the effect of informed trading on liquidity measures. Section V studies mechanisms that are consistent with the inverse relation between adverse selection measures and informed trading. Section VI introduces directional liquidity measures. Finally, Section VII concludes.

I. Sample Description

A. Data Sources

We compile data from several sources. Stock returns, volume, and prices come from the Center for Research in Security Prices (CRSP). Intraday transactions

[6] Li (2011) and Back, Crotty, and Li (2013) study models where the insider is potentially not informed (they do not relax the common-knowledge assumption entirely, however).

data (trades and quotes) come from the Trade and Quote (TAQ) database. Data on trades by Schedule 13D filers come from Schedule 13D filings (available on EDGAR) and are described next.

B. 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 script 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, that is, we discard certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the United States, Americus Trust components, closed-end funds, preferred stocks, and Real Estate Investment Trusts (REITs). We further 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.[7] The final sample comprises the universe of all Schedule 13D filings that satisfy the above criteria from 1994 to 2010, which totals 3,126 events. Importantly, our top-down approach guarantees that the sample contains *all* Schedule 13D filings with information on trades. Also, the sample covers a 17-year period, during which several changes in microstructure took place. These changes allow us to test several hypotheses related to informed trading (see Section V for further details). In the Internet Appendix we present the time-series distribution of the events and report characteristics of firms that are likely to appear in Schedule 13D filings.[8]

For each event we extract the following information from the Schedule 13D filings: the CUSIP of the underlying security, transaction date, transaction type (purchase or sell), transaction size, and transaction price. In addition, we extract the filing date, event date (date on which the 5% threshold is crossed), and beneficial ownership of the Schedule 13D filer at the filing date. In the vast majority of cases, transaction data are reported at a daily frequency. If the transaction data are at a higher-than-daily frequency, we aggregate them to the daily level. Specifically, for each 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.

[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 shares outstanding, either positive or negative. We restrict our sample to original Schedule 13D filings only, that is, amendments to previously submitted filings are excluded from the sample (this maximizes the "asymmetric information" content of the trades by the informed trader).

[8] The Internet Appendix may be found in the online version of this article.

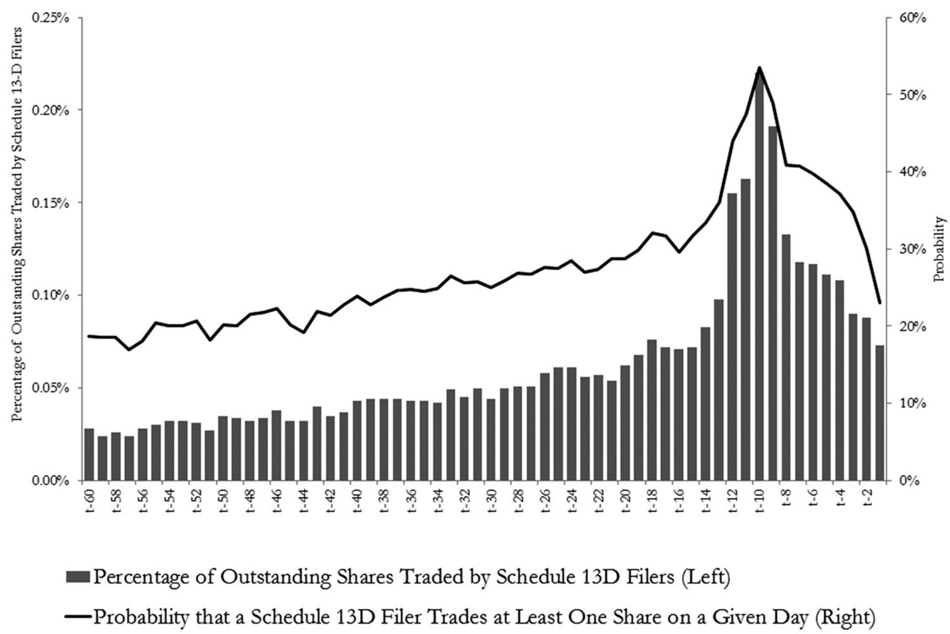

Figure 1. Trading strategy of Schedule 13D filers before the filing day. The solid line (right axis) plots the probability that a Schedule 13D filer trades at least one share on a given day. For every distance to the filing date, $t - \tau$, the probability that a Schedule 13D filer trades at least one share is the number of filings with a nonzero 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 (across all filings) of the percentage of outstanding shares traded.

We analyze the trading strategy of Schedule 13D filers using the following two measures: (1) the probability that a Schedule 13D filer trades at least one share on a given day,[9] and (2) the percentage of outstanding shares traded by Schedule 13D filers.[10] Each measure of trading activity is calculated at a daily frequency. Figure 1 presents each measure for the 60 days prior to the filing date, plotted as a function of the distance to the filing date.

[9] 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 nonzero trade by the filer divided by the total number of Schedule 13D filings in the sample.

[10] 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.

We see that the probability that a Schedule 13D filer trades at least one share on a given day is approximately 25% and reaches 50% 10 days prior to the filing date. Figure 1 also shows that Schedule 13D filers gradually increase the percentage of outstanding shares purchased on every trading day until 10 days prior to the filing date. For example, the average percentage of outstanding shares purchased on every trading day by the Schedule 13D filers increases from (0.03% to 0.05%) to (0.15% to 0.20%) closer to the 10 days prior to the filing date, and then gradually decreases from (0.15% to 0.20%) to (0.06% to 0.10%). In the Internet Appendix, we show that the increase in the trading activity during the $(t-12, t-9)$ period prior to the filing date is driven by the trading activity on the event date. Schedule 13D filers purchase close to 1% of outstanding shares on the event date, compared to 0.10% to 0.15% on the days before and after the event date. The increase in trading activity during the $(t-12, t-9)$ period prior to the filing date is therefore consistent with event dates being clustered during that period.[11]

Summary statistics for the trading strategies of Schedule 13D filers are reported in Table I. Columns (1) and (5) 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 the 60-day period prior to the filing date. This corresponds to an average (median) purchase of 899,692 (298,807) shares at an average (median) cost of \$16.4 (\$2.5) million. On days with nonzero informed volume, the filer purchases 0.5% (0.2%) of all outstanding shares.

Summary statistics for trades executed by Schedule 13D filers during the preevent date period are reported in columns (2) and (6), summary statistics for trades on the event date are reported in columns (3) and (7), and summary statistics for trades during the postevent date period are reported in columns (4) and (8). Schedule 13D filers trade more aggressively on the event date. For example, the average (median) increase in the ownership per trading day with nonzero informed volume is 0.9% (0.4%) on the event date compared with 0.3% (0.2%) during the preevent 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, Schedule 13D filers trade a relatively large fraction of the daily volume (around one quarter of the daily volume), and (3) Schedule 13D filers trade more aggressively on the event date. To further illustrate our data, in the Internet Appendix we present a case study of one Schedule 13D filer.

II. 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

[11] Rule 13d-1(a) requires Schedule 13D filers to file with the SEC within 10 days after the event date. When we consider the distance between the event date and the filing date, we find that Schedule 13D filers often interpret the 10-day period in terms of business days and not calendar days. This is why event dates are clustered during the $(t-12, t-9)$ period prior to the filing date.

Table I

Trading Strategy of Schedule 13D Filers

This table presents descriptive statistics on Schedule 13D filers' trading strategies. Columns (1) to (4) report cross-event means of characteristics and columns (5) to (8) report cross-event medians of characteristics. Columns (1) and (5) report descriptive statistics for the full sample, which covers all days with informed trades during the 60-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 (6) report descriptive statistics for days with informed trades during the preevent date period ("Before"). The event date is the day on which the filer's ownership exceeds the 5% threshold. Columns (3) and (7) report descriptive statistics for the event date. Columns (4) and (8) report descriptive statistics for days with informed trades during the postevent date period ("After"). An 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 stock ownership (per trading day) is the increase in stock ownership (per trading day), as a percentage of the number of shares outstanding, on days with informed trades. Market-adjusted return is the stock return in excess of the CRSP value-weighted return. Daily turnover is daily volume on days with informed trades divided by the number of shares outstanding. % 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)	Event Date (3)	After (4)	Full Sample (5)	Before (6)	Event Date (7)	After (8)
Stock ownership on the filing date	7.51%				6.11%			
Number of trading days	13.8	11.8	1.0	3.8	11	9	1	3
% of trading days with informed trades	31.1%	29.7%	100.0%	30.2%	25.6%	24.2%	100.0%	23.5%
Informed volume	899,692	661,578	185,352	259,103	298,807	182,565	50,000	69,793
Informed volume per trading day	82,642	69,701	185,352	68,599	24,984	18,475	50,000	20,572
Informed volume (m$)	16.4	12.1	3.3	4.7	2.5	1.6	0.5	0.7
Informed volume per trading day (m$)	1.3	1.2	3.3	1.2	0.2	0.2	0.5	0.2
Change in stock ownership	3.8%	2.5%	0.9%	1.1%	2.8%	1.7%	0.4%	0.6%
Change in stock ownership per trading day	0.5%	0.3%	0.9%	0.3%	0.2%	0.2%	0.4%	0.2%
Market-adjusted return	0.63%	0.61%	0.94%	0.60%	0.28%	0.18%	0.31%	0.22%
Daily turnover	1.8%	1.9%	2.8%	1.4%	0.9%	0.8%	1.2%	0.8%
% of informed turnover (real PIN)	31.5%	28.1%	41.0%	30.2%	25.4%	22.4%	35.9%	23.5%

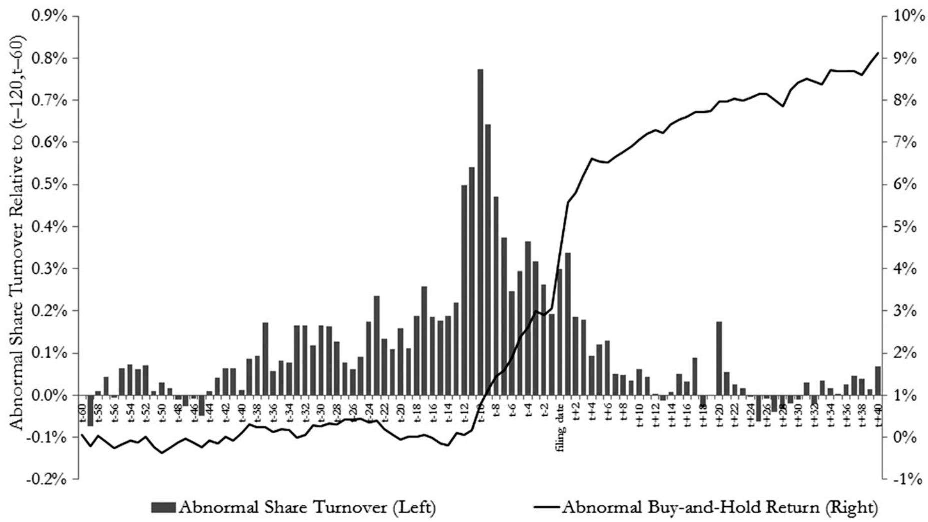

Figure 2. Buy-and-hold abnormal return around the filing date. The solid line (right axis) plots the average buy-and-hold return around the filing date in excess of the buy-and-hold return of the value-weighted market from 60 days prior to the filing date to 40 days afterwards. The filing date is the 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.

the preannouncement period. We use announcement event-day returns upon Schedule 13D filings and total trading profits of Schedule 13D filers to assess the value of their private information.

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 shareholders 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 shareholdership that constitute the "private" information in many cases. Only when they file with the SEC, 10 days after their holdings reach the 5% threshold, does the information become public. We can measure the extent to which the market believes their future actions have value over and above what is already impended in prices by looking at announcement returns. These results, in addition to Schedule 13D filers' preannouncement profits, allow us to measure the private information content of their trades.

Figure 2 plots the average buy-and-hold return, in excess of the buy-and-hold return on the value-weighted NYSE/Amex/NASDAQ index from CRSP, from 60 days prior to the filing date to 40 days afterward. The sample includes data from 1994 to 2010. As can be seen, there is a run-up of about 3% from 60 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 postfiling "drift" cumulates to a total of 9%.[12] In the Internet Appendix, we graphically show confidence bounds on the daily abnormal return and find that the filing-date abnormal return is positive and statistically significant. To further test the magnitude of the filing-date announcement return, we also regress the average daily return in excess of the value-weighted market return on indicators for $(t-2, t+2)$, $(t-1, t)$, and t, where t is the filing date. We find significant positive abnormal returns around the filing date. Overall, the evidence strongly supports the assumption that Schedule 13D filers possess valuable information on the underlying securities when they trade in the preannouncement period.[13]

In addition to the average buy-and-hold return, we also analyze profits made by Schedule 13D filers on purchasing stocks at the preannouncement prices. The results are reported in the Internet Appendix and suggest that Schedule 13D filers 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 60-day period and a \$0.4 million profit on the initial ownership, purchased prior to the 60-day window. The evidence also suggests that the main beneficiaries are shareholders who own shares on the announcement date. For example, shareholders of a \$293 million market cap company gain \$15 million during an average event whereas Schedule 13D filers gain \$0.8 million. Therefore, while Schedule 13D filers benefit from uninformed traders who sell their shares during the preannouncement period, they create significant value for all other shareholders by deciding to file a Schedule 13D and intervene in a company's governance.

Finally, we investigate the relation between Schedule 13D filers' trades and price changes. We compare the market-adjusted returns on days when Schedule 13D filers trade and on days when Schedule 13D filers do not trade during the 60-day disclosure period. Results are reported in Table II.

The evidence is consistent with trades by Schedule 13D filers affecting stock prices. Market-adjusted returns (*eret*) 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 filers do not trade. Importantly, the change is not only statistically but also economically significant. Overall, the evidence indicates that, on days when

[12] The evidence is consistent with Brav et al. (2008) and Klein and Zur (2009), who report a significant positive stock reaction to the 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 accumulates shares and crosses the 5% threshold.

[13] As we show in the Internet Appendix, there is no evidence of reversal in the buy-and-hold return during the 120-day period after the filing date.

Table II

Market-Adjusted Returns and Informed Trading

This table compares the level of market-adjusted returns on days when Schedule 13D filers trade and on days when Schedule 13D filers do not trade. The sample covers the 60-day disclosure period only. Market-adjusted return (*eret*) is the stock return in excess of the CRSP value-weighted return. For every Schedule 13D filing, we calculate the average level of market-adjusted returns during the 60-day disclosure period on days with and without trades by the Schedule 13D filer. Column (1) reports the average level of market-adjusted returns on days with trades by Schedule 13D filers among all events. Column (2) reports the average level of market-adjusted returns on days with no trades by Schedule 13D filers among all events. Column (3) reports the difference between columns (1) and (2). Column (4) reports the *t*-statistic of the difference. *** indicates statistical significance at the 1% level.

	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

Schedule 13D filers trade, prices move up. In that sense the adverse selection risk seems worse on days when they trade.

III. 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.[14] In addition, we use three low-frequency measures of stock liquidity: Amihud (2002) illiquidity, the daily bid-ask spread, and the probability of informed trade (*pin*) introduced by Easley et al. (1996). Results obtained using these three lower-frequency measures are reported in the Internet Appendix.

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 the variance of changes in the efficient price, Amihud illiquidity, and *pin*) and (2) other measures (realized spread, effective spread, and daily bid-ask spread).

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

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

The evidence reported in Section II suggests that Schedule 13D filers do indeed possess valuable private information and benefit from trading with uninformed traders. Thus, we can confidently argue that there is a substantial

[14] The cumulative impulse response and the trade-related component of the variance of changes in the efficient price are from Hasbrouck (1991a, 1991b).

Table III

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 60-day disclosure period. λ is the slope coefficient of $ret_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \varepsilon_{itn}$, *pimpact* is dollar-weighted price impact, *cumir* is cumulative impulse response, *trade − related* is trade-related component of the variance of changes in the efficient price, *rspread* is dollar-weighted realized spread, and *espread* is dollar-weighted effective spread (see the Internet Appendix for further details about the construction of these variables). Liquidity measures are 99.9% winsorized. For every Schedule 13D filing, we calculate the average level of a liquidity measure during the 60-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 60-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 the sample of matched stocks. Matched stocks are assigned based on the same industry, exchange, size, and low-frequency volatility (see Section IV for further details). Column (5) reports the diff-in-diff estimate and the t-statistic (in brackets) 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, respectively.

	Days with Informed Trading (1)	Days with No Informed Trading (2)	Diff (3)	Matched Diff (4)	Diff-in-Diff (5)
Adverse Selection Measures					
$\lambda \times 10^6$	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]
Other Liquidity Measures					
rspread	0.0081	0.0089	−0.0008***	0.0003	−0.0012***
			[−3.43]	[1.19]	[−3.35]
espread	0.0145	0.0155	−0.001***	0.0003	−0.0014***
			[−3.25]	[0.8]	[−2.58]

amount of asymmetric information in Schedule 13D trades. Moreover, the evidence indicates that, on days when Schedule 13D filers trade, prices move up. Therefore, Schedule 13D filings are 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 III, reveal the presence of informed trading.

We begin by testing how liquidity measures behave on days when Schedule 13D filers trade compared to days when they do not trade during the 60-day disclosure period. That is, we perform a within-60-day-period analysis of liquidity measures. The evidence reported in column (3) of Table III suggests that all liquidity measures indicate lower adverse selection on days when there is informed trading. 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.

All other liquidity measures indicate higher stock liquidity during the disclosure period. This evidence is consistent with liquidity being high when informed trading takes place. We return to the discussion of this result in the next section.[15]

Next, we use 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. For each stock, we identify a match based on industry (Fama and French (1997)), exchange, size (market cap), and low-frequency volatility (annual return volatility). We then test whether the change in liquidity measures for event stocks is 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 not confound the results.[16] Column (5) in Table III indicates that none of the measures is statistically significantly higher for target stocks than for matched stocks. Instead, for several measures (λ, *rspread*, *espread*, and *espread*), they are significantly lower for target stocks. Thus, measured adverse selection and stock illiquidity are lower not only *when* informed trading takes place, but also *relative* to stocks with similar characteristics.[17]

We also test whether average liquidity measures during the 60-day disclosure period differ from average liquidity measures during the same calendar window in the year prior to the filing date. The evidence, reported in the Internet Appendix, suggests that none of the adverse selection measures indicate the presence of informed traders during the 60-day disclosure period. Instead, four out of six measures indicate that adverse selection is significantly lower on average during the 60-day period. Similar results obtain when we adopt the diff-in-diff approach. One advantage of looking at a longer period is that doing so allows us to study the *pin* measure. This is because the estimation of this measure requires a time series of a certain length, and cannot be performed on adjacent days. It is typically suggested that *pin* be measured over a horizon of at least one month. We find that the *pin* measure performs similarly to other measures of adverse selection: it is lower when informed trading takes place.

We perform several robustness tests. The results are reported in the Internet Appendix. The main findings are as follows.

[15] In the Internet Appendix we show that results obtained using two low-frequency measures (*baspread* and Amihud *illiquidity*) are similar to results obtained using high-frequency measures.

[16] Note that, to confound the results, time-series changes in liquidity measures would have to be quite unusual: these changes would need to be unrelated to the trading by Schedule 13D filers but take place exactly when Schedule 13D filers trade. That is, liquidity measures would need to change back and forth at a daily frequency during a 60-day period in unison with Schedule 13D's trades but independently of them.

[17] In the Internet Appendix, we show that the results are similar when an alternative matching procedure is used. Specifically, in addition to matching stocks on exchange, we follow Davies and Kim (2009) and match stocks on market capitalization and share price. The evidence indicates no material difference in the results.

First, we adopt the regression methodology used in Hendershott, Jones, and Menkveld (2011). We regress measures of liquidity on an indicator equal to one on a day with trades by Schedule 13D filers, and zero otherwise, and 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. The results are consistent with the evidence reported in Table III, suggesting *lower* adverse selection and *higher* stock liquidity on days with trades by Schedule 13D filers.

Second, almost 25% of the events in the sample take place during the financial crisis. Since the financial crisis period was characterized by higher trading volume and volatility, we test whether adverse selection and liquidity measures reveal the presence of informed trading in the precrisis period (i.e., pre-2007 period). We find that our results are not affected by removing the financial crisis period and restricting the sample to the precrisis period.

Third, in our sample, 62% of companies are listed on NASDAQ and 29% are listed on NYSE (the remaining 9% are listed on Amex). To test whether the adverse selection and liquidity measures perform differently across NASDAQ and NYSE market structures, we split the sample into NASDAQ- and NYSE-listed stocks.[18] We find that the results are stronger for the sample of NASDAQ-listed stocks. While for several liquidity measures the results are less significant for stocks listed on the NYSE, those measures still do not reveal the presence of informed trading.

To summarize, the evidence rejects the hypothesis that empirical measures of adverse selection increase when there is more informed trading. Instead, we find that measured adverse selection is smaller when informed investors trade. Moreover, stock price liquidity measures indicate higher stock liquidity when informed investors trade.

V. Why Do Adverse Selection Measures Fail?

In the previous section, we show that traditional measures of adverse selection often indicate a lower adverse selection cost and higher liquidity when informed Schedule 13D filers trade. We consider two possible mechanisms that could explain this result.

First, schedule 13D traders might *select* the timing of trades and step in when the market and/or the target stock happen to be liquid. This is consistent with the theoretical model of Collin-Dufresne and Fos (2014), who extend Kyle's (1985) model to stochastic noise trader volatility. In their model, informed traders trade more aggressively when uninformed order-flow volatility is high,

[18] 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 consistent with less anonymity on the NYSE specialist system compared to the NASDAQ dealer system. After Regulation National Market System ("Reg NMS") was implemented, however, Post-Reg NMS U.S. exchanges have become more similar in structures and trading mechanisms.

which can lead to a negative correlation between measures of price impact, insider trading, and aggregate execution costs paid by noise traders. A negative relation between informed trading and measured price impact is also predicted by Admati and Pfleiderer (1988). In their model, informed agents are myopic but can choose to acquire information at different points in the day. They optimally acquire more information (and thus trade more) in periods of high noise trading volatility, when price impact is lower.

Second, standard liquidity measures are based on models that assume informed traders mostly demand immediacy, that is, 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)).[19] Thus, informed investors with long-lived information might improve stock liquidity.[20]

We first present some evidence consistent with both mechanisms. Recall that Schedule 13D filers have at most 10 days to file with the SEC after the event date (the day when their ownership reaches 5%). Because of this time constraint, they have less flexibility with respect to their trading strategy after the event date. We therefore test whether the relation between informed trading and liquidity measures changes after the event date. Table IV presents the results.

Coefficients on *itrade* suggest that, on days when Schedule 13D filers trade during the preevent 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 preevent date period). Coefficients on *postevent* show that the adverse selection measures are lower and stock liquidity is higher on days when Schedule 13D filers do not trade during the postevent date period (relative to days when Schedule 13D filers do not trade during the preevent date period). This suggests that Schedule 13D filers choose to cross the 5% ownership threshold at times when stock liquidity is higher. The interaction term indicates that the trade-related component of the variance of changes in the efficient price increases significantly on days with informed trading during the postevent date period, relative to days with informed trading during the preevent date period. The variables λ, *pimpact*, *respread*, and *espread* increase as well, though the change is not statistically significant.

[19] Some other models can be viewed as being about informed traders using limit orders. For example, in Rochet and Vila (1994), informed traders can condition their order on the noise trading order. We thank an anonymous referee for pointing this out.

[20] Another channel through which informed investors might improve stock liquidity is by attracting 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, uninformed investors facing large liquidity shocks may choose to trade more in the stock where they experience least price impact. One example is mutual funds facing redemptions and seeking to place large trades, as suggested in Gantchev and Jotikasthira (2013). Another example could be "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. In addition, there may be some high-frequency traders who initially provide liquidity for the trades of the 13D filers, but ultimately lead to a "hot-potato" style increase in trading volume (Lyons (1997)).

Table IV

Informed Trading in the Postevent Day Period

This table shows the relation between informed trading and liquidity measures during the postevent date period. We regress each of the liquidity measures and order imbalance (*orderim*) on an indicator for informed trading, using the following specification: $liq_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 postevent_{it} + \gamma_3 itrade_{it} \times postevent_{it} + \eta_i + \epsilon_{it}$, 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, and $postevent_{it}$ indicates trading days between the event date and the filing date. λ is the slope coefficient of $ret_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \varepsilon_{itn}$, *pimpact* is dollar-weighted price impact, *cumir* is cumulative impulse response, *trade-related* is the trade-related component of the variance of changes in the efficient price, *rspread* is dollar-weighted realized spread, *espread* is dollar-weighted effective spread, and *orderim* is the difference in the proportion of buy- and sell-initiated returns (see the Internet Appendix for further details about the construction of these variables). The F-test tests whether during the postevent-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 (in brackets), calculated using heteroskedasticity-robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

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

In addition to the liquidity measures, we study the relation between informed trading and order imbalance. Order imbalance is the difference in the proportion of buy- and sell-initiated trades. Results are reported in column (7) of Table IV. The coefficient on *itrade* indicates that the order imbalance is lower on days with informed trading, indicating either abnormal selling pressure or usage of buy limit orders by Schedule 13D filers. For example, during the preevent 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 postevent date period relative to days with informed trading in the preevent date period. This result is consistent with Schedule 13D filers having less flexibility to select trading days and to use limit orders once their information becomes short-lived.

In the Internet Appendix, we also study abnormal trading activity during the 60-day disclosure period. We find that, closer to the event date, both Schedule 13D trading and uninformed trading activity increase, reaching a maximum at the event date. The correlation between the two series is 80% during the (t − 60, t − 1) period and 96% during the (t, t + 9) period.[21] The evidence is consistent with both the selection and the limit order 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. The limit order mechanism implies that limit orders placed by Schedule 13D filers are executed when trading activity is high.

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

A. Limit Orders

In this section, we provide evidence consistent with informed traders using both limit orders and market orders. Rule 13d-1(a) of the 1934 Securities

[21] In the Internet Appendix, we also analyze the distribution of Schedule 13D trades over the trading day. The evidence indicates that Schedule 13D filers are more likely to trade at the beginning and at the end of the trading day. This trading pattern is consistent with Schedule 13D filers trading when intraday trading activity is high, that is, at the beginning and at the end of the trading day (e.g., Jain and Joh (1988)).

Exchange Act does not require investors to disclose what type of orders they use. We use two approaches to overcome this.

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. A matching procedure, described in the Internet Appendix, leaves us with 12,576 trades that have a unique match to the TAQ data.

Using the sample of 12,576 transactions, we study whether these trades are categorized as buy or sell orders by the Lee and Ready (1991) algorithm. We find that only 52.8% of purchase transactions are classified as buy-initiated transactions by the algorithm, implying that Schedule 13D filers often use limit orders. In addition, the evidence suggests that Schedule 13D filers often receive and do not pay the trading costs. We also find that more trades are classified as buy-initiated transactions *after* the event date: the percentage of trades classified as buy-initiated transactions increases from 51.5% before the event date to 56.3% after the event date. This indicates that Schedule 13D filers are less likely to use limit orders after the event date.[22]

Second, we develop a proxy for usage of market orders. We start by calculating a version of the volume-weighted average transaction price for every trading day using only buy-initiated transactions (*vwap_buy*). Next, we augment the data with the average price Schedule 13D filers pay (obtained from Schedule 13D filings). Finally, we hypothesize that, if the average price paid by a Schedule 13D filer is above *vwap_buy*, then the filer is likely to use market orders.[23]

In the Internet Appendix, we provide evidence to support the validity of our proxy for the usage of market orders. First, we show that, on days when the average price paid by Schedule 13D filers is higher than *vwap_buy*, order imbalance increases. Second, we show that, on days when the average price paid by Schedule 13D filers is higher than *vwap_buy*, price appreciation is higher. These results are consistent with the usage of market orders by the filers on these days.

An additional piece of evidence to support the validity of the proxy comes from matched trades. We separate 12,576 trades that have a unique match to the

[22] What do these numbers tell us about how often 13D filers use limit orders? This depends on the accuracy of the Lee and Ready (1991) ("LR") algorithm. Suppose, for example, that 70% of the trades are correctly classified by the LR algorithm (Cornell and Sirri (1992) report such numbers). Then, if we measure 56.3% buy orders, Bayes's rule would imply that 13D filers are using limit orders in 34.25% of cases. Instead, 51.5% of measured buy orders would imply that they use limit orders in 46.25% of cases.

[23] 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 toward the end of the day at prices exceeding *vwap*, which would be an extraordinarily poorly designed limit order strategy.

TAQ data into two groups: (1) trades executed on days when Schedule 13D filers' average transaction price is above *vwap_buy*, and (2) trades executed on days when Schedule 13D filers' average transaction price is below *vwap_buy*. The evidence suggests that 61% (48%) of purchase transactions in the first (second) group are classified as buy-initiated transactions by the Lee and Ready (1991) algorithm. The difference in the proportion of trades classified as buy initiated between the two groups is highly significant (*t*-statistic of the difference is 11.43). Therefore, more transactions are (correctly) classified as buy-initiated by the algorithm when our proxy indicates that 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. Table V presents the results. Panel A reports estimates of the basic specification. In Panel B we augment the basic specification with the interaction between *itrade* and *above_vwap_buy*.

The analysis reveals interesting differences between measures of stock liquidity. 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 limit orders as indicated by the positive sign of the coefficient on the interaction term γ_2. Instead, other measures of illiquidity 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. This result also suggests that different measures do indeed pick up different components 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. In fact, we find that λ behaves more like a liquidity measure than an adverse selection measure.

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

B. Selection

In this section, we provide evidence to support the selection mechanism. We start by analyzing the likelihood of observing the abnormal volume around the event date. To differentiate between the limit order and selection mechanisms, we ask how likely it is 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 identically distributed, the distribution of these probabilities across firms should be uniform on the [0,1] interval. If, however, Schedule 13D filers choose to trade when volume is high, *p*-values should be higher than under the null.

Table VI reports the results. The evidence suggests that the observed (cumulative) volume is typically higher than under the null. For example, during the

Table V

Informed Trading and Order Type

This table presents 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 the 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 investors is higher than the volume-weighted average price of buy-initiated transactions. Panel B reports estimates of the augmented regression: $y_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 itrade_{it} \times above\_vwap\_buy_{it} + \eta_i + \epsilon_{it}$. λ is the slope coefficient of $ret_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \varepsilon_{itn}$, *pimpact* is dollar-weighted price impact, *cumir* is cumulative impulse response, $trade - related$ is trade-related component of the variance of changes in the efficient price, *rspread* is dollar-weighted realized spread, and *espread* is dollar-weighted effective spread (see the Internet Appendix for further details about the construction of these variables). 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 (in brackets), calculated using heteroskedasticity-robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$\lambda \times 10^6$ (1)	*pimpact* (2)	*cumir* (3)	*trade-related* (4)	*rspread* (5)	*espread* (6)
Panel A: Basic Regression						
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: Informed Trading and Order Type						
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]

Table VI

Trading Volume

This table analyzes the probability of observing the realized level of volume over the (t, t), $(t-1, t)$, $(t-4, t)$, $(t-9, t)$, and $(t-29, t)$ periods around the Schedule 13D event date. For a given event period, we calculate the cumulative volume and the probability, p_i, of drawing a volume less than or equal to the observed event volume from the empirical distribution of the same stock's volume. If the volume were drawn randomly from i.i.d. distributions across stocks, then the distribution of the estimated p_i would be uniform on [0,1]. Columns (1) and (2) report the mean and standard deviation of a random variable with [0,1] uniform distribution. Columns (3) and (4) report the mean and standard deviation of the empirical distribution of the event volume of target stocks. Columns (5) and (6) report the mean and standard deviation of the empirical distribution of the net daily event volume of targeted stocks, where the net volume is the the total volume net of trades by Schedule 13D filers. Columns (7) and (8) report the mean and standard deviation of the empirical distribution of event volume for matched stocks. Matched stocks are assigned based on the same industry, exchange, size, and low-frequency volatility (see Section IV for further details). p-values for the mean being higher than the mean of the [0,1] uniform random variable (i.e., 50%) are reported in parentheses. *** indicates statistical significance at the 1% level.

	Uniform Distribution		Volume		Net Volume		Matched Stocks (Volume)	
	Mean (1)	Std Dev (2)	Mean (3)	Std Dev (4)	Mean (5)	Std Dev (6)	Mean (7)	Std Dev (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)	

$(t-4, t)$ period around the event date, the average p-value is 75%, indicating that in 75% of cases the volume over a five-day period will be lower than the $(t-4, t)$ volume observed prior to the event date. Importantly, the hypothesis of the average p-value being equal to 50% (null hypothesis) is rejected at any reasonable confidence level, indicating that the observed volume is not drawn randomly. Consistent with the trading strategy of Schedule 13D filers, column (3) suggests that the volume is "more abnormal" closer to the event date. When we consider the net volume (i.e., total volume net of Schedule 13D purchases) in columns (5) and (6), we find that the volume is still more abnormal closer to the event date, though the evidence is weaker than for total volume.

The fact that the volume of target stocks is abnormally high is consistent with both the selection and the endogenous volume mechanisms. Therefore, we next study the volume of *matched* stocks around the event date. Columns (7) and (8) report the results. The evidence indicates that Schedule 13D filers trade when the liquidity of matched stocks is high as well. Since trading target

Table VII

Informed Trading and Restrictions on Usage of Limit Orders

This table shows the relation between informed trading and liquidity measures on stocks listed on NASDAQ. We regress each of the liquidity measures on an indicator for informed trading using the following specification: $liq_{it} = \alpha + \gamma_1 itrade_{it} + \gamma_2 before_{it} + \gamma_3 itrade_{it} \times before_{it} + \eta_i + \epsilon_{it}$, 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 the 1994 to 1997 period (before the NASDAQ limit orders reform), and η_i are event fixed effects. λ is the slope coefficient of $ret_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \varepsilon_{itn}$, *pimpact* is dollar-weighted price impact, *cumir* is cumulative impulse response, *trade-related* is the trade-related component of the variance of changes in the efficient price, *rspread* is dollar-weighted realized spread, and *espread* is dollar-weighted effective spread (see the Internet Appendix for further details about the construction of these variables). The F-test tests whether, during the period when usage of limit orders by informed investors was severely limited, 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 (in brackets), calculated using heteroskedasticity-robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$\lambda \times 10^6$ (1)	*pimpact* (2)	*cumir* (3)	*trade − related* (4)	*rspread* (5)	*espread* (6)
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

stocks (even using limit orders) is not likely to cause an increase in the volume of matched stocks, the results for matched stocks clearly support the selection mechanism.

Next, we perform a test on the role of limit orders on NASDAQ. The test exploits the fact that in 1997 NASDAQ was required to reform its Order Handling Rules, which require that public investors be allowed to supply liquidity by placing limit orders, thereby competing with NASDAQ dealers (Biais, Glosten, and Spatt (2005)). Prior to this, it was more difficult for nondealers to use limit orders. If the selection mechanism operates, the main results of the paper should hold during the prereform period. If, in contrast, only the limit order mechanism operates, the main result of the paper should not hold during the prereform period.

Table VII reports the results. The evidence indicates that the relation between adverse selection and liquidity measures was overall negative or insignificant when the usage of limit orders by informed investors was severely limited. 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 investors trade than when they do not.[24]

To further study the selection mechanism, we next examine how variations in market-wide and stock-specific conditions affect the trading strategies of Schedule 13D filers. The evidence in Table VIII 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}) positively affect the likelihood of informed trading. In contrast, future turnover is weakly correlated with the likelihood of informed trading: the coefficient is only marginally significant in some specifications. In addition, we find no evidence that current, lagged, or lead liquidity of matched stocks has a significant impact on the likelihood of informed trading.[25]

[24] Whereas only 29% of firms from our sample are listed on NYSE, in the Internet Appendix we report results of an additional test, which exploits the start of autoquoting on NYSE (Hendershott, Jones, and Menkveld (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 prereform period. The evidence suggests that the main result of the paper holds prior to the start of autoquoting on NYSE as well, again suggesting that the limit order mechanism is not the only mechanism that explains the main result.

[25] The result is not in conflict with Schedule 13D filers trading when liquidity of the matched stock is high. As Table VI 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).

Table VIII

Determinants of Trading by Schedule 13D Filers

This table presents the relation between several observable variables and the 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*), the market return in excess of the risk-free rate (*mkt*), the average level of the liquidity measure on day t (liq_t), the liquidity measure for the matched stock (*liqm*), the daily turnover (*to*) as well as lagged values of these variables. In addition, X_{it} includes the lead level of daily turnover (to_{it+1}) and of the liquidity measure for the matched stock ($liqm_{it+1}$). Matched stocks are assigned based on the same industry, exchange, size, and low-frequency volatility (see Section IV 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 (in brackets), calculated using heteroskedasticity-robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: *itrade*						
Liquidity Measure	$\lambda \times 10^6$ (1)	*pimpact* (2)	*cumir* (3)	*trade − related* (4)	*rspread* (5)	*espread* (6)
Market-Wide Variables						
$crspvol_{t-1}$	−0.0179	−0.0021	0.0038	0.0037	−0.0014	−0.0017
	[−0.78]	[−0.11]	[0.16]	[0.16]	[−0.07]	[−0.09]
$crspvol_t$	0.0666***	0.0608***	0.0695***	0.0707***	0.0596***	0.0596***
	[2.73]	[2.99]	[2.86]	[2.90]	[2.93]	[2.93]
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
	[1.19]	[−0.65]	[−1.64]	[0.86]	[−1.00]	[−1.53]
liq_t	0.0000	0.1673	−0.0000*	0.0996	−0.7352	−0.1717
	[0.10]	[0.78]	[−1.81]	[0.93]	[−1.27]	[−0.75]
Stock-Specific Variables						
$liqm_{it-1}$	−0.0001	0.0819	−1.4634	0.0082	−0.0989	0.1118
	[−1.07]	[0.45]	[−0.69]	[0.14]	[−0.60]	[1.08]
$liqm_{it}$	0.0001	−0.0342	−0.6336	−0.0062	0.0840	0.1394
	[1.23]	[−0.19]	[−0.31]	[−0.12]	[0.52]	[1.32]
$liqm_{it+1}$	−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***
	[6.56]	[7.37]	[7.27]	[7.25]	[7.36]	[7.37]
to_{it}	3.2082***	3.4487***	3.1164***	3.1172***	3.4445***	3.4464***
	[14.79]	[16.90]	[15.68]	[15.70]	[16.87]	[16.87]
to_{it+1}	0.2106	0.2378*	0.1009	0.1030	0.2398*	0.2383*
	[1.36]	[1.70]	[0.72]	[0.74]	[1.71]	[1.70]

VI. Directional Liquidity Measures

How might one improve measures of adverse selection when a strategic trader with long-lived information may be active in the market? One feature of the trading strategies of Schedule 13D filers is that for extended periods

Table IX

Informed Trading and Directional Liquidity Measures

This table presents 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 the market return in excess of the risk-free rate, and 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 stocks. 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 (in brackets), calculated using heteroskedasticity-robust standard errors clustered by event. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$\lambda \times 10^6$		*pimpact*		*rspread*	
Order Type	Buy (1)	Sell (2)	Buy (3)	Sell (4)	Buy (5)	Sell (6)
	Panel A: Basic Regression ($\gamma_2 = 0$)					
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: Basic Regression ($\gamma_2 \neq 0$)					
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, Basic Regression ($\gamma_2 = 0$)					
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, Basic Regression ($\gamma_2 \neq 0$)					
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]

of time they actively or passively buy shares via strategically timed market and limit orders. This observation suggests that we consider "directional liquidity measures," that is, measures that are calculated separately for buy- and sell-initiated trades. For example, *pimpact* of buy orders is calculated based on buy-initiated orders only.[26]

In Table IX, we present the relation between informed trading and the directional versions of the liquidity measures λ, *pimpact*, and *rspread*. The evidence

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

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 on buy- and sell-initiated trades seems to suggest that an intensive purchasing of shares is taking place (using either market or limit orders). We also find that the realized spread is significantly lower both for buy- and sell-initiated orders when insiders trade, but much more so for buy-initiated than for sell-initiated trades. Since the realized spread measures the revenue to liquidity providers (Hendershott, Jones, and Menkveld (2011)), this is consistent with liquidity providers making lower profits on days when informed investors trade. Most notably, their profits are significantly lower when they provide liquidity to buy-initiated trades. Panel B shows that the results are not affected by controlling for market excess returns.

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 for matched stocks. We conjecture that this asymmetry in the behavior of directional (i.e., buy- versus sell-initiated) measures of adverse selection and liquidity may be an informative signal of the presence of a strategic trader with long-lived information who uses both market orders and limit orders to acquire shares.

VII. Conclusion

In this paper, we exploit a novel data set on stock transactions by Schedule 13D filers. We find robust, consistent strong 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, on days when Schedule 13D filers trade, prices tend to move up. We therefore classify prefiling trades by Schedule 13D filers as informed.

The data set allows us to test how measures of adverse selection proposed in the literature behave in the presence of informed traders. The evidence suggests that neither high-frequency nor low-frequency measures of stock liquidity increase when insiders trade. Instead, measured adverse selection decreases and measured liquidity increases 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 evidence that insiders choose to trade on days when liquidity is abnormally high (e.g., when the aggregate S&P500 volume is high) and measured adverse selection is low.

The paper's main implication is that standard adverse selection measures are not robust to informed trading by strategic traders with long-lived information who can choose when and how to trade.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix