

Market Quality of Informed Trades^{*}

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Abstract

We investigate prices around timestamped informed trades using approximately 500,000 13D transactions from activist investors matched to TAQ trades. Activists are more price sensitive than non-activists and are more likely to attempt to hide their trading by strategically choosing when and how to trade. Activists have higher execution quality, but also higher price impact and lower realized spreads, suggesting that activists, on average, fail to hide among the uninformed. Activists with less information (as measured by lower returns) are better at hiding (that is, they have better execution quality). These results are reversed for hedge funds: hedge funds with better execution quality generate higher returns.

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JEL: G14, G23

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1. Introduction

Microstructure theory makes a sharp prediction: informed trades move prices. Liquidity providers lose money when they trade against better-informed counterparties, prices adjust toward fundamental value, and standard adverse selection measures, such as price impact and realized spreads, should detect the informed trader’s presence (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O’Hara, 1987). However, the empirical evidence contradicts this thesis. On days when Schedule 13D activists accumulate shares - trades that earn abnormal returns of roughly 9% over the following 40 days - spreads and adverse selection measures are lower, not higher (Collin-Dufresne and Fos, 2015). The same is true on days when insiders subsequently prosecuted by the SEC were trading (Kacperczyk and Pagnotta, 2019). Measures designed to detect informed trading appear to fail precisely when informed traders are known to be present.

This paper asks two questions. First, do informed trades leave a detectable mark on prices, as theory predicts? Second, can informed traders avoid leaving that mark - that is, can they hide? Our answer to the first question is yes: the footprint of informed trading is clearly visible, but only at the frequency at which liquidity provision actually operates. Our answer to the second is that only the most sophisticated informed traders manage to hide.

The missing footprint in daily data has a natural explanation. As Kyle (1985, abstract) put it, “noise trading provides camouflage which conceals [informed] trading,” and informed traders choose when and how to seek that camouflage.¹ We use activists as informed traders - since activists can change a firm in ways intimately known to only themselves, they are by definition informed. They also generate abnormal returns (Collin-Dufresne and Fos, 2015), consistent with the idea of being informed. If activists concentrate their trading at times when liquidity is high, comparing days with and without activist trading confounds the market’s reaction to their trades with their selection of favorable trading conditions. The appropriate comparison is between informed and uninformed trades executed at the same moment, under the same market conditions.

¹For theory and evidence on how informed traders conceal their trading, see, e.g., Brogaard, Hendershott, and Riordan (2019), Roşu (2020), Kwan, Philip, and Shkilko (2024), and Goyal, Reed, Smajlbegovic, and Soebhag (2025).

We construct that comparison. From all initial Schedule 13D filings between 1994 and 2021 we extract roughly 500,000 reported trades, which filers must disclose under Item 5(c), and match them to timestamped trades in the Trade and Quote (TAQ) database by date, price, and size. Because this match is not always unique, we verify our results under progressively stricter matching schemes, from allowing multiple candidate matches to requiring one-to-one pairs. We then compute standard microstructure measures at the trade level and compare matched 13D trades to all other trades in the same stock - both across the trading day and, more stringently, within the same one-minute interval - in panel regressions with stock, date, time-of-day, and stock-by-date fixed effects.

Activists work at hiding along every dimension we can measure. They trade when quoted and effective spreads are narrow, and a vector autoregression confirms that they pull back when spreads widen. They execute about half of their trades with limit orders and turn to limit orders precisely when spreads are relatively high, supplying liquidity when demanding it is expensive (Kaniel and Liu, 2006). A substantial fraction of reported trades are sells - more than one-quarter in the filings and roughly 40% to 50% among TAQ-matched trades - even though every filer in our sample is accumulating shares toward the 5% ownership threshold. And whereas uninformed buys and sells receive systematically different execution, this buy-sell asymmetry largely disappears for activist trades, so trade direction gives little away. Neither does trade size: activist trades are no larger than other trades in the same minute, and their dollar volume is, if anything, smaller. In modern markets, it appears, large trades are a poor proxy for informed trading (Barclay and Warner, 1993; Goldstein, Spatt, and Ye, 2024).

None of this is enough to fully hide their presence. Conditional on the moment of execution, the footprint microstructure theory predicts is plainly there. Price impact is about 0.5 basis points higher and realized spreads about 0.9 basis points lower for 13D trades than for other trades in the same minute - liquidity providers systematically earn less money when trading against activists. The pattern holds for market and limit orders alike and strengthens as the matching becomes stricter. Impulse response functions from the vector autoregression confirm the interpretation: prices rise permanently after 13D trades, while the price effect of other trades is transitory. The daily-level evidence and ours are thus two views of the same

behavior. At the daily horizon, the activists' timing dominates and liquidity looks good; at the one-minute horizon, timing is held fixed and their information shows through.

Not all informed traders are equally visible, however, which brings us to our second question. When we split activists by sophistication, the baseline footprint turns out to be driven largely by filers that are not hedge funds. Hedge fund trades are statistically indistinguishable from uninformed trades executed in the same minute on every adverse selection measure. One interpretation is that hedge fund activists simply know less. The data reject it: aggregating trades to the filing level, hedge funds earn announcement-day abnormal returns of 1.5%, compared with essentially zero for other activists, and their returns remain higher over the following month. Hedge funds are the best informed traders in our sample and the only ones the market cannot see.

How do they do it? Hiding is costly. Trading patiently and supplying liquidity improve execution but risk non-execution and information decay, so a trader with valuable, short-lived information should sacrifice execution quality for speed. The activists who are not hedge funds behave exactly this way: their post-filing returns decline in their execution quality - filings in the best execution group underperform those in the worst by about four percentage points over ten days - and the trade-off is steepest for impatient trades executed in the twenty days before the filing, when the disclosure deadline leaves little room to wait. For hedge funds the trade-off disappears: in cross-sectional regressions that control for firm characteristics and campaign objectives, their post-filing returns, if anything, increase with execution quality. For the most sophisticated traders, execution skill and information appear to be complements rather than substitutes.

Our contribution to the literature on informed trading and liquidity is to observe informed traders trade, trade by trade. Collin-Dufresne and Fos (2015) use the same filings but measure liquidity at the stock-day level, and in doing so conclude that informed trading is associated with lower adverse selection; we show that this reflects the activists' timing rather than their invisibility. Kacperczyk and Pagnotta (2019), Kacperczyk and Pagnotta (2024), and Akey, Grégoire, and Martineau (2022) reach similarly negative conclusions about detecting informed trading, again from daily data. Studies with intraday data on identified informed traders, such as Inci, Lu, and Seyhun (2010) and Shkilko (2020), predate Regulation

NMS and algorithmic trading, an era when insiders still executed large, conspicuous trades; Jame (2018) observes intraday hedge fund trades but cannot match them to TAQ and so cannot measure their price impact. Relative to Henry and Koski (2017), who show that only traders with superior execution quality are profitable at dividend arbitrage - a trade on public information with thin margins - we show that execution quality, in general, is negatively correlated with profitability but differs systematically across traders, even when private information rents are large.

Our evidence also bears on the debate over 13D disclosure rules (Chabakauri, Fos, and Jiang, 2026). Publicly available microstructure data allow the market to detect an average activist’s accumulation as it happens, well before the filing, but not a hedge fund’s. Whatever protection adverse selection measures offer uninformed investors, it fails against precisely the traders with the most valuable information.

The remainder of the paper proceeds as follows. Section 2 describes the 13D trade data and the match to TAQ. Section 3 presents the trade-level evidence on liquidity and adverse selection, Section 4 links execution quality to returns, and Section 5 concludes.

2. Sample Construction and Summary Statistics

Data on trades by Schedule 13D filers come from Schedule 13D filings, publicly available on EDGAR. We collected Schedule 13D filings from 1994 to 2021, excluding amendments. Those trades are then combined with data from the Center for Research in Security Prices (CRSP) and with the NYSE Trade and Quote (TAQ) database. Further details on the data collection are described in Section 2.2.1.

We categorize 13D filers into two groups: hedge funds and other activist investors. We identify hedge funds by using the methodology of Brav, Jiang, Partnoy, and Thomas (2008a) and then expanding their list by hedge funds from major commercial databases merged by Joenväärä, Kauppila, Kosowski, and Tolonen (2021). Since some activist hedge funds do not report to these commercial databases (Brav, Jiang, Partnoy, and Thomas (2008b)), we address potential selection bias by collecting the non-reporting funds from Form ADV filings, following the approach of Barth, Joenväärä, Kauppila, and Wermers (2023). We further supplement this classification using WhaleWisdom, manually reviewing filers and

classifying them as hedge funds when they are identified as such on the platform, report performance fees, or are clearly affiliated with a hedge fund family.

2.1. Schedule 13D filings

Rule 13d-1(a) of the 1934 Securities Exchange Act requires investors who acquire over 5% of any class of security of a publicly traded company to file a report with the SEC within 10 days.² This requirement applies specifically when the investor expresses an interest in actively influencing the management of the company. If the investor is not interested in the activism, they must file Schedule 13G instead, which is a shorter version of Schedule 13D with fewer reporting requirements. Item 5 (c) of Schedule 13D requires the filer to describe the identity of the person, date, price, and quantity of any transactions in the target company’s securities during the past 60 days or since the most recent filing of Schedule 13D. In many cases, detailed information about the trades is attached to the appendix, in Item 7 (Schedule A). However, there appears to be no specific guideline regarding the reporting of transactions. Some filings provide detailed tables, while others offer sparse information in sentences. The reporting frequency also varies, with some aggregating daily and others detailing each trade. This variation in reporting formats presents a key challenge for our data collection.

2.2. Data Construction

2.2.1. Collection and Refinement of the Schedule 13D Trades

We download all 13D filings from EDGAR by extracting those with form types labeled “SC13D” from the SEC index file. Within each filing, we identify lines that contain a date, a decimal, and an integer, which represent the trade date, price, and size, respectively. For Schedule 13D filings that contain transaction data, we collect the filing date and event date, as well as the company name, CIK, and CUSIP for both the subject and the filing companies. To verify the identity of the target company, we use the WRDS CIK-CUSIP link table. Often, a single 13D filing involves multiple entities participating in the transaction,

²This rule has been amended. The SEC has revised Schedule 13D rules, shortening the initial filing deadline from 10 calendar days to 5 business days after acquiring more than 5% beneficial ownership. This amendment took effect on February 5, 2024. Details on this change can be found at <https://www.sec.gov/files/33-11030-fact-sheet.pdf> and <https://www.sec.gov/newsroom/press-releases/2023-219>. Our sample period predates this amendment, and therefore, we use the 10-day deadline in our analysis.

referred to as “Persons” in the filings. When available, we collect detailed information about the Persons involved in these 13D trades.³

We first extract all reported transactions from the filings and then apply a series of filters. The changes in the number of filings, filers, and trades at each stage are documented in Table 1, with Panel A reporting all 13D filers and Panel B reporting hedge fund filers separately. Of the 114,241 13D filings from the SEC, only a small fraction contain detailed transaction records. Additionally, upon closer inspection, we found that some index files contained duplicate 13D filings listed under different names. After excluding filings without transaction information and removing duplicated filings, we are left with 8,904 filings from 3,217 unique filers, comprising a total of 864,714 13D trades (614,586 buys and 250,128 sells) as reported in the *Raw* column of Table 1. Of these, 2,561 filings from 263 hedge fund filers account for 329,010 trades. To ensure data accuracy, we cross-referenced the filings with a CIK-CUSIP link table. Filings lacking CIK for both the filing entity and the target company were excluded from our sample. Additionally, filings without a corresponding CUSIP for the target company were also removed. This refinement process resulted in 7,753 filings from 2,774 filers, encompassing 799,018 13D trades as reported in the *CUSIP matched* column. We further restrict the sample to retain only assets with CRSP share codes 10 or 11, indicating common stocks. We also exclude stocks priced below \$1 or above \$1,000, following the methodology of Collin-Dufresne and Fos (2015). This resulted in a dataset of 4,103 filings from 1,518 filers,⁴ comprising 505,112 13D trades (369,328 buys and 135,784 sells) as presented in column *Common Stock (\$1 - \$1000)*. In Panel B, the corresponding hedge fund sample comprises 1,513 filings from all 263 hedge fund filers, with 245,325 trades (166,397 buys and 78,928 sells).

2.2.2. Identification of Schedule 13D Trades

Matching 13D trades to the TAQ database presents several challenges due to varying reporting practices among filers. According to 17 CFR § 240.13d-101, a regulation detailing

³The filing format changes over time. From 1994 to the late 1990s, most filings were in plain text (.txt) format. However, beginning in 2005, the predominant format shifted to HTML. During the transitional period, both formats were in use, resulting in a mix of file types.

⁴After applying a similar filtering process, Collin-Dufresne and Fos (2015) identify 3,126 filings from their sample period spanning 1994 to 2010.

the filing requirements for Schedule 13D, filers must 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 ...”.⁵ However, interpretations of this requirement differ, resulting in diverse reporting formats. Some filers report transactions in a daily aggregated format, others provide details at the individual trade level, and some use a combination of both approaches.

Given the variation in reporting formats, aggregated 13D transactions are unlikely to match one-to-one with individual TAQ trades. Because these reports combine multiple underlying trades, they typically report large aggregate volumes and volume-weighted average prices, often to four decimal places. For example, on May 3, 2018, GAMCO Asset Management Inc. reported purchasing 45,298 shares of EnPro Industries at an average price of \$68.4091, for a total value exceeding \$3 million. A transaction reported in this form is unlikely to correspond directly to a single TAQ record.⁶ By contrast, filings that report individual trades typically contain round-lot quantities and prices to two decimal places, making direct matches with TAQ records more likely.⁷

Even transactions reported at the individual-trade level may not match uniquely. We match 13D transactions to TAQ records within each stock-day using price and size. Because round-lot quantities and common prices recur frequently, a single 13D transaction may correspond to multiple TAQ records. We therefore construct four samples with progressively stricter matching requirements: *TAQ Multiple Match*, *TAQ Simple Match*, *TAQ Unique Match*, and *TAQ Unique Match 5 Trade*.

Before describing these procedures, we account for differences in how exchanges report executions to the consolidated tape. As discussed in Bartlett and O’Hara (2024), over our sample period, NYSE aggregated multiple executions from the same marketable order into a single trade report on the SIP, whereas other exchanges reported each execution against

⁵For legal details on Schedule 13D filings, see <https://www.law.cornell.edu/cfr/text/17/240.13d-101>. Item 5(c) requires the reporting of trades conducted within 60 days prior to filing.

⁶The full example of the Schedule 13D filing by GAMCO Investors is available at <https://www.sec.gov/Archives/edgar/data/1164863/0000807249-18-000114.txt>.

⁷An example of a filing that reports transactions at the individual-trade level is available at <https://www.sec.gov/Archives/edgar/data/105744/0001742576-18-000014.txt>.

individual limit orders separately.⁸ Consequently, a 13D trade executed on NYSE is more likely to match directly to a single TAQ record, while a 13D trade executed on a non-NYSE venue may appear as multiple smaller records sharing the same timestamp. To account for this difference, we aggregate TAQ trades at the stock-day-timestamp-exchange level to construct *Collapsed Trades*, using millisecond timestamps for DTAQ and second timestamps for MTAQ. We apply each matching procedure to both the original and collapsed TAQ records. Sample counts based on the collapsed records are reported in the *Collapsed Trd* row of Table 1, while analyses based on collapsed matches are presented in the Appendix.

The first approach, which we call *TAQ Multiple Match*, permits many-to-many matching: each reported 13D transaction may match multiple TAQ trades, and each TAQ trade may match multiple reported 13D transactions. This produces the broadest matched sample, with approximately 1.5 million TAQ trades, or 699,000 using collapsed trades. The sample contains 1,764 filings from 711 unique filers. As reported in Panel B, 652 filings from 253 hedge fund filers account for approximately 813,000 matched trades, or 345,000 using collapsed trades.

Building on this approach, *TAQ Simple Match* permits one-to-many matching: each reported 13D transaction may match multiple TAQ trades, but each TAQ trade may match only one reported transaction. This sample is particularly useful for analyses that require trade-direction and order-type classifications. Schedule 13D filings report whether each transaction is a buy or sell, so we use the filing rather than the Lee and Ready (1991) algorithm to determine transaction direction. Restricting each TAQ trade to a single 13D match assigns it a unique reported direction and prevents the same TAQ trade from being classified as both a buy and a sell. Following Collin-Dufresne and Fos (2015), we infer whether a transaction was executed through a market or limit order by comparing its reported direction with the trade-initiation direction assigned by the Lee and Ready (1991) algorithm. Agreement between the two directions indicates a likely market order, whereas disagreement indicates a likely limit order. Following Bogousslavsky, Fos, and Muravyev (2024), we also classify trades executed within 20 days of the filing date as impatient and those executed 20 or more

⁸Since July 28, 2025, NYSE has also reported individual trades. See nyse.com/trader-update/history.

days before the filing date as patient. The resulting sample contains 505,602 matched TAQ trades, or 267,964 using collapsed trades, from 1,696 filings and 692 filers. It includes 272,397 sells, slightly more than the 233,205 buys. We classify 262,780 trades as limit orders and 242,822 as market orders, while approximately 60% are patient. In Panel B, 622 hedge fund filings from 246 filers account for 297,675 matched trades, or 143,470 using collapsed trades.

The more stringent *TAQ Unique Match* requires one-to-one matching between reported 13D transactions and TAQ trades. This restriction reduces the sample to 47,901 matched trades, or 40,954 using collapsed trades, while the number of filings and filers remains at 1,696 and 692, respectively. This occurs because nearly every retained filing contains at least one uniquely matched transaction. Approximately 62% of the matched trades are buys, and the sample is roughly evenly split between limit and market orders. The patient-to-impatient composition remains approximately 60/40. In Panel B, 622 hedge fund filings from 246 filers account for 22,382 uniquely matched trades, or 19,342 using collapsed trades.

Finally, because an aggregated transaction can occasionally produce a unique match by chance, we impose an additional restriction to construct our most stringent sample, *TAQ Unique Match 5 Trade*. Following Collin-Dufresne and Fos (2015), we retain only filings that report at least five transactions on the same day, as these filings are more likely to provide trade-level information. This restriction reduces the sample to 45,961 matched TAQ trades, or 39,012 using collapsed trades, from 658 filings and 275 unique filers. The number of matched trades remains close to that in the *TAQ Unique Match* sample because the restriction primarily removes filings with fewer than five same-day transactions. Approximately 60% of the matched trades are buys, and about half are classified as limit orders. In Panel B, 170 hedge fund filings from 81 filers account for 21,611 matched trades, or 18,568 using collapsed trades.

Table 1 around here.

2.3. Illiquidity Measures

In this study, we employ several key measures to assess market illiquidity, each capturing a distinct aspect of market microstructure. These include the quoted spread, effective spread, price improvement, realized spread, and price impact. All measures are calculated relative to

the National Best Bid and Offer (NBBO), which we construct following the filtering method of Holden and Jacobsen (2014). Specifically, we exclude quotes with non-normal quote conditions⁹, require positive bid and ask prices and sizes, and ensure that the ask price is at least as high as the bid. We drop observations with quoted spreads above \$5. For trades, we require strictly positive prices. Trades and quotes are merged without imposing a time lag, as reporting accuracy improves over the course of the late 1990s (Rösch, Subrahmanyam, and van Dijk, 2017).

The quoted spread is measured as the difference between the best ask and bid prices available in the market. For each trade at time t , the quoted spread is calculated as:

$$\text{Quoted Spread}_t = \frac{(Ask_t - Bid_t)}{\text{Midpoint}_t} \quad (1)$$

where Ask_t and Bid_t are the best ask and bid prices at time t , and MidPoint_t is the bid-ask midpoint of the quote.

The effective spread captures trading costs by comparing the execution price with the bid-ask midpoint, a proxy for fair value at the time of the trade. We measure effective spread for trade m at time t as:

$$\text{Effective Spread}_{m,t} = \frac{2 \times \text{BuySell}_m(\text{Price}_m - \text{Midpoint}_t)}{\text{Midpoint}_t} \quad (2)$$

where Price_m is the execution price of the trade and BuySell_m is the buy-sell indicator following Lee and Ready (1991).

Price improvement occurs when an order executes at a price more favorable than the quoted price at order submission. It is quantified as the difference between the quoted spread and the effective spread. A positive price improvement indicates that the execution price is closer to the bid-ask midpoint—the proxy for fair value—than either the bid or ask quotes. We measure the price improvement of trade m at time t as:

$$\text{Price Improvement}_t = \text{Quoted Spread}_t - \text{Effective Spread}_t. \quad (3)$$

⁹We keep only quotes with normal quote conditions in DTAQ (A, B, H, O, R, W) and exclude those with non-normal conditions in MTAQ (4, 7, 9, 11, 13, 14, 15, 19, 20, 27, 28).

Realized spread measures the profitability of liquidity providers by comparing the trade price to the bid-ask midpoint at a fixed interval after the trade, typically one minute. Following Conrad and Wahal (2020), we use the midpoint price one minute post-trade to capture most of the price impact. If an exact one-minute midpoint is unavailable, we allow some flexibility by considering midpoints within a surrounding window. To balance precision and practicality, we exclude observations where the lagged available midpoint is recorded less than 10 seconds or more than 5 minutes after the trade. For trade m at time t , the realized spread is measured as:

$$\text{Realized Spread}_{m,t} = \frac{2 \times \text{BuySell}_m(\text{Price}_m - \text{Midpoint}_{t+1\text{min}})}{\text{Midpoint}_t} \quad (4)$$

where $\text{Midpoint}_{t+1\text{min}}$ is the bid-ask midpoint one minute after the trade.

Price impact measures the signed change in the bid-ask midpoint following a trade. A larger price impact indicates that prices move more strongly in the direction of the trade and may signal informed trading. The price impact for trade m at time t is measured as:

$$\text{Price Impact}_{m,t} = \frac{2 \times \text{BuySell}_m(\text{Midpoint}_{t+1\text{min}} - \text{Midpoint}_t)}{\text{Midpoint}_t} \quad (5)$$

In addition to these illiquidity measures, following common practice in the literature, we also include trade size (number of shares) and dollar volume in our analysis as proxies for informed trading.

2.4. Summary Statistics: Illiquidity Measures

We aggregate trade-level illiquidity measures to the one-minute level separately for 13D and non-13D trades. An interval containing at least one 13D trade produces separate aggregates for 13D and non-13D trades, whereas an interval without 13D activity produces only a non-13D aggregate. We also separately report trades executed by hedge fund activists. Table 2 presents the mean, median, standard deviation, and number of one-minute intervals for each measure. For interpretability, we multiply all illiquidity measures except trade size (*SIZE*) and dollar volume (*DVOL*) by 10,000 and report them in basis points.

Panel A reports descriptive statistics for non-13D trades aggregated across stock-day-minute intervals. These observations serve as a benchmark for the 13D trades reported in

the subsequent panels. The average quoted spread is 28.08 basis points. Their average price improvement is 1.86 basis points, and their average effective spread is 26.22 basis points. The average price impact is 7.01 basis points, while the average realized spread is 19.22 basis points. The latter represents the portion of the effective spread retained by liquidity providers after subsequent price movements. Non-13D trades have an average size of approximately 690 shares and an average dollar volume of about \$18,500. Means generally exceed medians, and standard deviations are relatively large, indicating right-skewed distributions. The panel contains approximately 1.5 million one-minute intervals.

Panel B reports results based on the *TAQ Multiple Match* sample, which allows many-to-many matching between 13D and TAQ trades. Summary statistics are reported for 13D trades, non-13D trades occurring within the same one-minute intervals, and the subset of 13D trades executed by hedge fund filers. The average quoted spread is 19.46 basis points for 13D trades and 19.89 basis points for non-13D trades in the same intervals. Average price improvement is similar across the two groups, at 1.32 and 1.34 basis points, respectively. The average effective spread is 18.14 basis points for 13D trades and 18.55 basis points for non-13D trades, while the corresponding realized spreads are 11.69 and 12.56 basis points. In contrast, the average price impact is higher for 13D trades, at 6.45 versus 5.99 basis points, which may reflect greater adverse selection. 13D trades are also smaller on average. Among 13D trades executed by hedge fund filers, the average quoted and effective spreads are lower, at 14.43 and 13.38 basis points, respectively. Their average price impact is 4.21 basis points, lower than that of both the full 13D sample and contemporaneous non-13D trades. We examine this pattern more formally in later sections.

Panel C reports results based on the *TAQ Simple Match* sample, which restricts each TAQ trade to a single 13D match. The patterns are broadly similar to those in Panel B. The average quoted spread is 20.15 basis points for 13D trades and 20.51 basis points for contemporaneous non-13D trades. The corresponding effective spreads are 19.14 and 19.40 basis points. Price impact is again slightly higher for 13D trades, at 6.68 basis points, than for non-13D trades, at 6.48 basis points. Trades executed by hedge fund activists continue to exhibit lower spreads and lower price impact, with averages of 14.74 and 4.33 basis points, respectively. The next section formally evaluates these differences across trader groups using

fixed-effects panel regressions.

Table 2 around here.

3. Execution Quality

3.1. Intraday Illiquidity and Adverse Selection of 13D Trades

Standard market microstructure models predict that informed trading increases adverse-selection risk, reduces liquidity, and raises the cost of capital.¹⁰ Direct empirical evidence is limited, however, and several studies document the opposite relation.¹¹ In the sample studied by Henry and Koski (2017), informed trading is profitable only when informed traders blend effectively with uninformed order flow and obtain superior execution quality. Informed traders may therefore benefit from mimicking uninformed trading. Consistent with this view, Collin-Dufresne and Fos (2015) find lower illiquidity and adverse-selection measures on days when 13D trades occur.

To examine whether these patterns hold at the transaction level, we use time-stamped 13D transactions from 1994 to 2021 matched to TAQ trades. We first estimate a fixed-effects panel regression that relates each illiquidity measure to an indicator for 13D trades:

$$IlliquidityMeasure_{i,s,d,t} = \beta_{13D} 13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t} \quad (6)$$

where the variable $IlliquidityMeasure_{i,s,d,t}$ represents an illiquidity measure aggregated separately for 13D and non-13D trades within each one-minute interval. The measures include quoted spread (QSP), effective spread (ESP), price improvement ($PIMPRV$), realized spread (RSP), price impact ($PIMPCT$), size ($SIZE$), and dollar volume ($DVOL$). The indicator $13D_{i,s,d,t}$ equals one for 13D trades and zero for non-13D trades. The specification includes fixed effects for 30-minute intraday intervals, dates, stocks, and stock-by-date combinations. Standard errors are clustered by stock and date to account for serial correlation and heteroskedasticity. The analysis uses the *TAQ Multiple Match* sample.

¹⁰e.g., Glosten and Milgrom (1985), Kyle (1985), and Amihud and Mendelson (1986).

¹¹e.g., Collin-Dufresne and Fos (2015), Collin-Dufresne and Fos (2016), Goyal et al. (2025), Röscher (2021), and Roşu (2020).

Table 3 compares one-minute aggregates of illiquidity measures for 13D and non-13D trades. Panel A compares 13D and non-13D aggregates within the same stock-day, allowing the two groups to trade at different times of the day. Panel B restricts the sample to one-minute intervals containing both 13D and non-13D trades. Trades within the same narrow window face similar observable market conditions, making Panel B a more tightly controlled comparison of execution outcomes for 13D and non-13D trades.

Quoted spreads are set before a trade arrives, and traders observe them when deciding whether and when to trade. In both panels, 13D trades are associated with lower quoted spreads than non-13D trades, by 0.93 basis points (t-statistic: -3.64) in Panel A and 0.43 basis points (t-statistic: -5.18) in Panel B. Effective spreads show a similar pattern. 13D trades have lower effective spreads by 0.74 basis points (t-statistic: -2.55) in Panel A and 0.41 basis points (t-statistic: -3.09) in Panel B. These results are consistent with informed traders choosing to trade when liquidity conditions are favorable, confirming the daily-level findings of Collin-Dufresne and Fos (2015) and extending them to the trade level. More broadly, the results contrast with the standard market microstructure prediction that informed trading is associated with greater illiquidity.

Although informed traders can influence the spreads they face by timing their trades, they have less control over price movements after execution. The post-trade measures show a different pattern. Price impact is higher for 13D trades by 0.48 basis points (t-statistic: 2.73) in Panel A and 0.45 basis points (t-statistic: 2.56) in Panel B. Thus, despite being associated with lower spreads at execution, 13D trades are followed by larger price movements in the direction of the trade. This evidence indicates greater adverse selection at the intraday level and contrasts with the daily-level findings of Collin-Dufresne and Fos (2015). Realized spreads are correspondingly lower for 13D trades by 1.22 basis points (t-statistic: -3.79) in Panel A and 0.86 basis points (t-statistic: -3.50) in Panel B, indicating that liquidity providers earn less when trading against 13D filers.

Following common practice in the literature, we also examine trade size and dollar volume as proxies for informed trading. In Panel A, 13D trades are larger by approximately 279 shares (t-statistic: 3.22), while the difference in dollar volume is not statistically significant. In Panel B, the difference in trade size is not statistically significant, while the dollar volume

of 13D trades is lower by approximately \$2,936 (t-statistic: -2.51). These findings suggest that trade size and dollar volume are imperfect proxies for informed trading, particularly in recent market environments where institutional investors split large orders into smaller transactions.

We present fixed-effects panel regressions using alternative matching criteria in Appendix Table A.1 for the *TAQ Simple Match*, Appendix Table A.2 for the *TAQ Unique Match*, and Appendix Table A.3 for the *TAQ Collapsed Multiple Match*. The collapsed match aggregates TAQ trades at the stock-day-timestamp-exchange level to account for differences in how exchanges report executions to the consolidated tape, as described in Section 2.2.2. Across all matching methods, 13D trades are associated with lower quoted spreads, lower realized spreads, and higher price impact than non-13D trades. As the matching criteria become more restrictive, from the multiple match to the simple match and then to the unique match, the estimated adverse-selection effects generally become stronger. For example, the Panel A price-impact coefficient increases from 0.48 basis points in the baseline specification to 0.76 basis points under the simple match and 3.37 basis points under the unique match. The corresponding coefficient under the collapsed multiple match is 1.42 basis points.

The effective-spread coefficient, however, changes sign across matching methods. It is negative in the baseline and collapsed-match specifications, marginally negative under the simple match, and positive under the unique match. Under the unique match, the positive effective-spread coefficient is accompanied by a large negative price-improvement coefficient. This variation is not surprising because quoted spreads, effective spreads, and price improvement are mechanically related, and 13D traders endogenously choose when to trade.

The key takeaway is that isolating the true 13D trades amplifies the estimated adverse selection. At the same time, the consistency of results under the less restrictive multiple match suggests that allowing multiple potential matches is reliable. While each 13D trade has only one true match in the TAQ data, our process includes multiple potential matches, which effectively act as noise that averages out over the dataset. As a result, the estimates remain stable across alternative matching criteria.

Table 3 around here.

3.2. Addressing Endogeneity: Strategic Timing of 13D Trades

While our adverse selection measures detect the presence of informed traders at the trade level, illiquidity measures are lower when 13D traders are active. Collin-Dufresne and Fos (2015) propose two mechanisms through which illiquidity may decrease in the presence of informed traders. The first mechanism suggests that 13D traders strategically time their trades, entering when liquidity is high. The second mechanism involves the use of limit orders by informed traders. We investigate whether these channels hold in our setting.

The first mechanism suggests that 13D traders avoid trading when market liquidity is low and spreads are wide. The negative coefficients on the 13D indicator in the quoted- and effective-spread regressions reported in Table 3 are consistent with this explanation. However, these contemporaneous relations do not establish whether 13D traders respond to prevailing spreads or whether their trading activity affects subsequent spreads. To examine the dynamic relations among spreads, trading activity, and returns, and to assess whether strategic timing contributes to the lower spreads associated with 13D trades, we estimate the following vector autoregression (VAR):

$$\begin{aligned} \text{LHS}_{s,d,t} = & \sum_{l=1}^5 \beta_{1,l} \text{QSP}_{s,d,t-l} + \sum_{l=1}^5 \beta_{2,l} \text{13D}_{s,d,t-l} + \sum_{l=1}^5 \beta_{3,l} \text{non13D}_{s,d,t-l} \\ & + \sum_{l=1}^5 \beta_{4,l} \text{RET}_{s,d,t-l} + \text{FE} + \epsilon_{s,d,t}. \end{aligned} \quad (7)$$

where the quoted spread (*QSP*), 13D indicator (*13D*), non-13D indicator (*non13D*), and log return (*RET*) are endogenous variables, with *RET* derived from midpoint prices at one-minute intervals. The model includes five lags of all endogenous variables and is estimated as a panel with fixed effects for both stock-day and intra-day 30 minute interval. Each stock-day is treated as a separate time series, so lagged values do not carry over across trading days. Observations at the beginning of each trading day are assigned missing values for lagged terms, ensuring that intra-day dynamics are not influenced by prior-day information. The subscripts *s*, *d*, and *t* denote stock, day, and time, respectively. The trade indicators separately measure the presence of *13D* and *non13D* trades within each one-minute interval. Both are set to zero in intervals without any trades, where only quotes are observed. The

reported coefficients represent the cumulative sum of lagged effects. When the cumulative effect of *13D* or *non13D* explains the quoted spread or log return, we scale them by 10,000 to express the impact in basis points for better readability. The sample covers January 1994 to December 2021, using data from *TAQ Multiple Match*.

In dynamic panel regressions, lagged dependent variables appear as regressors. As such, fixed-effects estimates can be biased, as noted by Arellano and Bond (1991). In principle, estimation requires using the Generalized Method of Moments (GMM). However, Judson and Owen (1999) show that this concern is primarily relevant when the time dimension (T) is small (less than 30). Since our panel is estimated at one-minute intervals, each stock-day contains a time dimension well above this threshold. We therefore expect the bias to be limited and use fixed-effects estimation rather than GMM in this setting.

Table 4 reports Granger-causality tests of the dynamic relations among quoted spreads, trading activity, and returns. We first examine whether 13D and non-13D traders strategically time their trades in response to liquidity conditions. When QSP is the dependent variable, the cumulative coefficients on the five lags of both trade indicators are positive, indicating that quoted spreads tend to widen following trade execution. The cumulative effect is 2.98 basis points for 13D trades and 3.21 basis points for non-13D trades. Wald tests reject the null hypothesis that the sum of the five lagged coefficients equals zero, with chi-squared statistics of 160.86 and 203.94, respectively. Conversely, higher quoted spreads over the previous five minutes predict lower subsequent trading activity. When the 13D and non-13D trade indicators are the dependent variables, the cumulative coefficients on QSP are -0.57 (chi-squared statistic: 42.51) and -2.85 (chi-squared statistic: 177.57), respectively. Together, these results support the idea that both 13D and non-13D traders time their activity based on liquidity conditions, trading when spreads are low and holding back when spreads widen.

We next examine whether 13D trades generate stronger subsequent price responses than non-13D trades. The cumulative effect of the five lags of 13D trading activity on log returns (RET) is approximately 0.61 basis points (chi-squared statistic: 12.26). In contrast, the corresponding effect of non-13D trading activity is 0.14 basis points and is not statistically significant (chi-squared statistic: 1.38). These results indicate that prices respond more

strongly following 13D trades, consistent with 13D trades containing more information than non-13D trades. We next use impulse response functions to examine the magnitude and persistence of these price responses.

Since Granger causality tests examine one equation at a time, they do not fully capture the joint dynamics of the system. Impulse Response Functions (IRFs) provide a clearer picture by tracing how shocks to one variable propagate through all variables over time. We therefore use Generalized Impulse Response Functions (GIRFs) to analyze the dynamic effects of informed trading on market conditions. To construct confidence bands for the GIRFs, we employ a blockwise residual bootstrap. Specifically, we resample contiguous blocks of the estimated VAR residual vectors, stacked across equations, to preserve both cross-equation correlation and short-run serial dependence. The estimated VAR coefficients are held fixed, and GIRFs are recomputed in each bootstrap replication using the resampled residuals. We repeat this procedure across 2,000 bootstrap replications and construct pointwise confidence bands at each horizon, reporting both 90% and 68% intervals.

Figure 1 illustrates the GIRF estimates from the panel VAR model, along with confidence bands. Each cell displays the response of an endogenous variable to a one-standard-deviation shock to another endogenous variable over a 20-minute horizon. Responses of log returns are cumulative and can therefore be interpreted as changes in the log price level; responses of all other variables are reported in levels. Consistent with the VAR estimates, quoted spreads widen following shocks to both the 13D and non-13D trade indicators. The responses peak within the first few minutes after the shock and then gradually decline, approaching zero by the end of the 20-minute horizon. The liquidity effects of trading are thus short-lived rather than permanent.

Turning to returns, the cumulative return response to a 13D trade shock rises steadily over the first several minutes and then remains positive over the entire horizon. After the first few minutes, the confidence bands lie entirely above zero, and there is no evidence of subsequent reversion: the price response following 13D trade shocks is persistent. Prices therefore incorporate the information revealed by 13D trades in a lasting manner, consistent with 13D trades reflecting long-lived private information rather than temporary liquidity shocks. In contrast, the cumulative return response to a non-13D trade shock is positive

initially but declines gradually toward zero over the horizon. The confidence bands are wide throughout and overlap zero from early on, so the initial price move is neither sustained nor statistically distinguishable from zero at most horizons. This pattern is consistent with transitory price pressure rather than information-based trading. Taken together, the GIRF evidence indicates that 13D trades generate a persistent price response with no sign of reversion over the horizon we examine, whereas non-13D trades generate only transitory price movements with no lasting effect.

Table 4 around here.

Figure 1 around here.

3.3. Addressing Endogeneity: Strategic Order Choice of 13D Trades

The interpretation of Tables 3 and 4 may depend on whether the 13D filer demands or supplies liquidity. Table 1 shows that a substantial fraction of 13D trades are classified as limit orders. For market orders, wider quoted and effective spreads represent higher execution costs. For a limit order, however, high spreads may reflect a strategic decision to earn the spread rather than a cost incurred. This distinction relates directly to the second mechanism proposed by Collin-Dufresne and Fos (2015), in which informed traders strategically use limit orders to capture the spread and reduce their execution costs. Under certain conditions, this behavior may also reduce measured illiquidity. To assess whether this mechanism operates in our setting, we first examine how frequently 13D filers use limit orders.

We identify limit orders following Collin-Dufresne and Fos (2015) by comparing the trade direction reported in the 13D filing with the direction inferred from the Lee and Ready (1991) algorithm. If the two directions align — for example, the filing reports a buy and the algorithm classifies the trade as buy-initiated — the trade is classified as a market order. If the directions differ — the filing reports a buy but the algorithm classifies the trade as sell-initiated — the trade is classified as a limit order, because the 13D filer likely posted a buy limit order that was executed against an incoming sell order. Nearly 40% of 13D trades in our matched sample are reported as sells, which is notable given that we include only initial filings, not amendments. Consistent with Collin-Dufresne and Fos (2015), approximately 50% of 13D trades are classified as limit orders.

A potential limitation is that hidden limit orders may be misclassified. For example, a 13D filer may submit a hidden buy limit order inside the quoted spread but above the midpoint. Because the order is not displayed, other traders cannot observe or respond to it. When an incoming sell order executes against the hidden buy order, the transaction occurs above the midpoint. The Lee and Ready (1991) algorithm therefore classifies the trade as buy-initiated. Because the 13D filing also reports the transaction as a buy, our method classifies it as a market order even though the 13D filer supplied liquidity through a limit order. Such misclassification would attenuate the estimated differences between market and limit orders by mixing the two categories.

Order-type classification requires each TAQ trade to have a unique reported direction. Under the *TAQ Multiple Match* procedure, however, a single TAQ trade may match several reported 13D trades with conflicting directions, making the classification ambiguous. We therefore use the *TAQ Simple Match* sample for analyses that distinguish between buy and sell trades, including Table 5 and Table 6. By allowing each TAQ trade to match only one reported 13D transaction, this procedure assigns each matched trade a unique direction and permits a consistent classification of market and limit orders.

To test whether the use of limit orders accounts for the lower illiquidity measures documented in Table 3, we extend the baseline specification by separating 13D market and limit orders. The model includes an indicator MKT_13D , which equals one for 13D market orders and zero otherwise, and an indicator $LIMIT_13D$, which equals one for 13D limit orders and zero otherwise. The specification is given by:

$$\begin{aligned} IlliquidityMeasure_{i,s,d,t} = & \beta_{MKT_13D}MKT_13D_{i,s,d,t} \\ & + \beta_{LIMIT_13D}LIMIT_13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t} \end{aligned} \quad (8)$$

where $IlliquidityMeasure_{i,s,d,t}$ denotes an illiquidity measure, calculated as the average across trades for stock s on day d within the 1-minute interval t , and estimated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$). We include separate indicators MKT_13D and $LIMIT_13D$ rather than interacting the 13D indicator with order type because order type is not observed for non-13D trades.

Table 5 shows that 13D market and limit orders are associated with different execution outcomes relative to non-13D trades. In Panel A, both 13D market and limit orders are associated with lower quoted spreads, by 0.54 basis points (t-statistic: -2.46) and 0.61 basis points (t-statistic: -2.50), respectively. This result is consistent with 13D traders choosing favorable liquidity conditions regardless of order type. The two order types differ more clearly in price improvement and effective spreads. Relative to non-13D trades, 13D market orders receive 0.66 basis points more price improvement (t-statistic: 2.23) and have effective spreads that are 1.19 basis points lower (t-statistic: -3.44). By contrast, 13D limit orders receive 1.09 basis points less price improvement (t-statistic: -3.53), while their effective spreads do not differ significantly from those of non-13D trades. The signs of the price-improvement coefficients are consistent with the proposed order-type classification. Market orders execute inside the spread, receiving prices better than the quoted spread. The negative price improvement for limit orders is consistent with this classification, as these trades do not benefit from execution inside the spread. Panel B, which restricts the comparison to trades within the same one-minute intervals, shows a similar pattern.

Turning to price impact, both order types have positive and statistically significant coefficients in Panel A. The coefficient is 1.16 basis points for market orders (t-statistic: 3.83) and 0.68 basis points for limit orders (t-statistic: 2.14), although neither coefficient is statistically significant in Panel B. The larger coefficient for market orders is consistent with classical microstructure models in which informed traders demand immediacy and convey private information through marketable orders (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987; Hasbrouck, 1991). The positive coefficient for limit orders indicates that they also contain information, consistent with the view that informed traders with long-lived information may use limit orders to reduce execution costs and make their trading intentions less visible (Kaniel and Liu, 2006; Collin-Dufresne and Fos, 2015).

Overall, 13D market and limit orders exhibit distinct execution outcomes. Market orders receive better execution and impose greater costs on liquidity providers through higher price impact and lower realized spreads. Limit orders, by contrast, do not benefit from execution inside the spread, resulting in negative price improvement. This is a natural consequence of their execution mechanics rather than a sign of poor execution. Both order types are

nevertheless associated with higher price impact in Panel A, indicating that 13D filers convey information through both market and limit orders.

Using collapsed trades, Appendix Table A.4 yields broadly consistent results, with generally larger coefficient magnitudes. The key patterns - market orders being associated with lower effective spreads and limit orders receiving less price improvement relative to non-13D trades - hold across both panels. Price impact is also larger and statistically significant for both order types. In Panel B, the price-impact coefficient is 1.47 basis points for market orders (t-statistic: 3.76) and 1.19 basis points for limit orders (t-statistic: 2.95), compared with statistically insignificant estimates in Panel B of Table 5. The realized-spread coefficients for limit orders also become statistically significant in the collapsed specification: -1.37 basis points in Panel A (t-statistic: -2.90) and -1.30 basis points in Panel B (t-statistic: -3.19). These results reinforce the conclusion that 13D filers convey information through both market and limit orders.

Table 5 around here.

3.4. Buy versus Sell Trades of 13D Filers

A substantial fraction of trades reported in initial 13D filings are sells, even though the filers are accumulating shares to build positions exceeding the 5% ownership threshold. Across matching procedures, approximately 38% to 54% of matched 13D trades are classified as sells. We therefore examine whether execution outcomes differ between activist buys and sells.

To assess whether trade direction affects the relationship between 13D trades and illiquidity measures, we extend the analysis in Table 3 by distinguishing between buy and sell trades. The model includes a $13D$ indicator, a Buy indicator (equal to one for buy trades and zero for sell trades), and their interaction $13D \times Buy$. The regression is specified as follows:

$$\begin{aligned} IlliquidityMeasure_{i,s,d,t,b} = & \beta_{13D}13D_{i,s,d,t,b} + \beta_{Buy}Buy_{i,s,d,t,b} \\ & + \beta_{13D \times Buy}(13D \times Buy)_{i,s,d,t,b} + FE + \epsilon_{i,s,d,t,b} \end{aligned} \quad (9)$$

where $IlliquidityMeasure_{i,s,d,t,b}$ represents one of the illiquidity measures, calculated as the

average of all trades for stock s on day d within the 1-minute interval t . These measures are computed separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$), as well as for trade direction b . For 13D trades, direction is obtained from the filing. For non-13D trades, direction is inferred using the Lee and Ready (1991) algorithm. The coefficient β_{Buy} captures the buy–sell difference for non-13D trades, while $\beta_{13D \times Buy}$ captures how that buy–sell difference changes for 13D trades relative to non-13D trades. The total difference between 13D buys and sells is therefore given by $\beta_{Buy} + \beta_{13D \times Buy}$. As discussed in Section 3.3, the analysis uses the *TAQ Simple Match* sample to ensure that each matched trade has an unambiguous direction.

Table 6 presents the results. Non-13D trades exhibit clear buy–sell asymmetry across most illiquidity measures, whereas this asymmetry is substantially weaker for 13D trades, particularly in Panel B, which compares trades within the same one-minute interval. Non-13D buy trades have effective spreads that are 2.55 basis points lower than those of non-13D sell trades (t-statistic: -7.90). However, the interaction term $13D \times Buy$ is positive and significant at 2.73 basis points (t-statistic: 6.55), largely offsetting the buy–sell difference for 13D trades. An untabulated Wald test fails to reject the null hypothesis that $\beta_{Buy} + \beta_{13D \times Buy} = 0$, indicating no statistically significant difference in effective spreads between 13D buy and sell trades.

This attenuation is primarily driven by price improvement. Non-13D buy trades receive substantially greater price improvement than non-13D sell trades ($\beta_{Buy} = 2.53$ basis points, t-statistic: 8.33), while the $13D \times Buy$ interaction of -2.93 basis points (t-statistic: -7.24) offsets this difference for 13D trades. A similar pattern appears for realized spreads. Non-13D buy trades have lower realized spreads ($\beta_{Buy} = -2.73$ basis points, t-statistic: -4.57), while the interaction coefficient of 2.36 basis points (t-statistic: 4.38) largely offsets this difference. 13D buy and sell trades remain statistically indistinguishable in both price improvement and realized spreads. We also find no meaningful buy–sell difference in price impact among 13D trades.

In contrast, the buy–sell differences in trade size and dollar volume are more positive for 13D trades than for non-13D trades. The interaction coefficients are positive and significant for both trade size (547.01 shares, t-statistic: 3.95) and dollar volume (\$11,572.72, t-statistic:

4.42). Together with the corresponding *Buy* coefficients, the estimates imply that 13D buy trades are larger than 13D sell trades. Panel A shows similar patterns, although the statistical significance is weaker. The results are also robust when we use the *TAQ Collapsed Simple Match* sample in Table A.5.

The weaker buy–sell asymmetry for 13D trades largely reflects opposing patterns across market and limit orders. Appendix Table A.6 separates trades by both direction and order type. Among market orders, 13D trades exhibit the same buy–sell asymmetry as non-13D trades: in Panel B, the $13D \times Buy$ interaction on effective spreads falls to 0.14 basis points (t-statistic: 0.48), producing a buy–sell gap of -2.45 basis points. Among limit orders, however, the asymmetry reverses: the $Buy \times Limit_13D$ interaction is 5.09 basis points (t-statistic: 7.58), producing a buy–sell gap of $+2.64$ basis points. This reversal follows from our classification: a reported limit buy is, by construction, a seller-initiated execution (Section 3.3), and seller-initiated trades tend to execute at wider effective spreads. Because 13D trades are split roughly evenly between market and limit orders, these opposing gaps offset each other and produce the near-zero difference in Table 6.

Table 6 around here.

4. Returns and Execution Quality

4.1. Can Markets Detect Sophisticated Informed Traders?

We next examine cross-sectional differences among 13D traders by distinguishing hedge funds from other activist investors. Hedge funds face strong performance incentives and often employ specialized trading infrastructure, concentrated positions, and flexible trading strategies. Prior research documents that hedge funds possess informational and execution advantages, including profitable trading around corporate events and skill in processing news.¹² These characteristics make hedge-fund activists a natural group in which to examine whether sophisticated informed traders are less detectable.

Similar to Table 3, we estimate a fixed-effects panel regression that partitions 13D trades

¹²See, for example, Kosowski, Naik, and Teo (2007), Jagannathan, Malakhov, and Novikov (2010), Agarwal, Jiang, Tang, and Yang (2013), Ha, Hu, and Tang (2024), Huang, Tan, and Wermers (2020), Bolandnazar, Jackson, Jiang, and Mitts (2020), and Ljungqvist and Qian (2016).

into hedge-fund (*HF13D*) and non-hedge-fund (*Non-HF13D*) trades. The specification is given by:

$$IlliquidityMeasure_{g,s,d,t} = \beta_{Non-HF13D} Non-HF13D_{g,s,d,t} + \beta_{HF13D} HF13D_{g,s,d,t} + FE + \epsilon_{g,s,d,t}. \quad (10)$$

where $IlliquidityMeasure_{g,s,d,t}$ represents an illiquidity measure averaged across trades for group g , stock s , day d , and one-minute interval t . The three groups are non-HF 13D trades, HF 13D trades, and non-13D trades, which serve as the omitted category.

Table 7 presents the regression results. Panel A compares non-HF 13D and HF 13D trades with non-13D trades throughout the trading day. Non-HF 13D trades show patterns consistent with the baseline results in Table 3. They are associated with lower quoted spreads (-1.30 basis points, t-statistic: -3.21), lower effective spreads (-1.11 basis points, t-statistic: -2.46), lower realized spreads (-1.71 basis points, t-statistic: -3.48), and higher price impact (0.59 basis points, t-statistic: 2.20). HF 13D trades show the same directional patterns, but the magnitudes are smaller and the statistical significance is weaker. Realized spread is lower by 0.58 basis points (t-statistic: -1.87) and price impact is higher by 0.34 basis points (t-statistic: 1.71). While these differences are marginally significant in the broader stock-day comparison in Panel A, they disappear when trades are compared within the same one-minute interval in Panel B.

The within-minute comparison reveals a clear distinction between HF and non-HF 13D traders. Non-HF 13D trades remain distinguishable from non-13D trades. They are associated with lower quoted spreads (-0.62 basis points, t-statistic: -4.45), lower effective spreads (-0.75 basis points, t-statistic: -3.44), lower realized spreads (-1.34 basis points, t-statistic: -3.34), and higher price impact (0.59 basis points, t-statistic: 2.10). Thus, non-HF 13D traders concentrate their activity in more favorable liquidity conditions, but post-trade adverse selection measures still detect their presence. The adverse selection results in Table 3 therefore appear to be driven primarily by non-HF 13D traders.

HF 13D trades, by contrast, are largely indistinguishable from non-13D trades. The statistically significant differences are a 0.22 -basis-point lower quoted spread (t-statistic:

-3.28), a 0.18-basis-point lower price improvement (t-statistic: -2.01), and, depending on the comparison, lower trade size or dollar volume. Effective spreads, realized spreads, and price impact do not differ significantly. Thus, standard adverse-selection measures do not distinguish HF 13D trades from non-13D trades, suggesting that hedge-fund trades are less detectable.

This raises a natural question: do hedge funds appear less detectable because they better manage the execution of informed trades, or because their trades contain less information? We address this in the next section by examining returns associated with 13D filings. Section 4.5 then examines the specific channels through which hedge funds may make their trading less detectable, including venue choice, hidden orders, and the management of order-flow information.

Table 7 around here.

4.2. *Post-Filing Abnormal Returns of 13D Filers*

The absence of a detectable trading footprint does not by itself establish superior concealment: hedge fund trades may simply contain less information. We therefore examine whether hedge funds generate larger post-filing abnormal returns. While our previous analysis focused on individual trades, we now shift our perspective by aggregating trades at the filing level.

For each filing, we construct the value-weighted average abnormal return ($VW AAR$) from the filing date ($t = 0$) through 20 trading days afterward ($t = 20$). Equation (11) defines $VW AAR_{f,t}$ as the value-weighted average abnormal return across the individual 13D trades reported in filing f . For each trade i , the abnormal return is the difference between its holding-period return and the corresponding market holding-period return. We then aggregate these trade-level abnormal returns within each filing using dollar-volume weights:

$$VW AAR_{f,t} = \frac{\sum_{i \in f} V_i (HPR_{i,t} - MR_t)}{\sum_{i \in f} V_i}, \quad (11)$$

where V_i is the dollar volume of trade i , $HPR_{i,t}$ is the holding-period return from the reported transaction price of trade i to the closing price of the target stock on day t , and MR_t is the corresponding market holding-period return.

To ensure that *VWAAR* accurately reflects the returns to the positions accumulated by each filer, we exclude sell trades, option-like trades (i.e., those executed outside the bid-ask spread), and stocks delisted within 20 days of the filing date. This approach treats all trades within a filing as part of a single “order” or, as Chan and Lakonishok (1995) described, a “package” of trades executed by the filer.

Table 8 reports the average *VWAAR* across filings for each day following the filing date. The results are presented for the full sample, hedge-fund filers, and non-hedge-fund filers. On the filing date (Day 0), the mean abnormal return is 0.60% for the full sample. Hedge-fund filings earn a substantially higher abnormal return of 1.50%, compared with -0.07% for non-hedge-fund filings. The near-zero Day 0 return for non-hedge-fund filings indicates a weaker immediate price response, whereas hedge-fund filings exhibit positive abnormal returns from the outset. Abnormal returns continue to rise after the filing date. By Day 20, *VWAAR* reaches 4.19% for the full sample and 5.32% for hedge-fund filings. Hedge funds consistently generate higher abnormal returns than non-hedge fund activists, consistent with their trades containing more information.

These return differences make it unlikely that hedge-fund trades are less detectable merely because they contain less information. Instead, the findings suggest that hedge funds manage their trade execution in a way that leaves a smaller footprint in adverse selection measures, while still earning higher returns than other 13D filers.

The results are also consistent with the broader evidence on returns surrounding 13D filings. Figure 2 of Collin-Dufresne and Fos (2015) and Figure 1 of Brav et al. (2008a) show that stock prices remain relatively stable before 13D filings but rise substantially afterward. This persistence supports the interpretation that 13D filers act on information about future firm performance rather than short-term mispricing.

The nature of this information becomes clearer when 13D filers are compared with corporate insiders who disclose their trades through Form 4 filings. Inci et al. (2010) show that insider purchases typically follow price declines and are followed by subsequent price reversals. This pattern is more consistent with insiders exploiting temporary undervaluation, whereas the persistent returns following 13D filings suggest information about longer-term improvements in firm value. Thus, the distinction is not simply that both groups are in-

formed, but that they appear to trade on different types of information. Although both discount rates and expected cash flows affect stock prices (e.g., Bordalo, Gennaioli, Porta, and Shleifer (2024)), the timing and persistence of returns suggest that 13D filers anticipate longer-term improvements in firm value, whereas Form 4 traders exploit temporary pricing distortions.

Table 8 around here.

4.3. Do Hedge Funds Overcome the Execution–Profitability Trade-off?

Informed traders may face a trade-off between execution quality and profitability. Using limit orders or waiting for favorable liquidity conditions may reduce execution costs and make informed trading less conspicuous. These strategies, however, come at a cost. Limit orders face the risk of non-execution, while waiting for favorable conditions may allow information to decay. Traders with stronger or more short-lived private information may therefore accept worse execution to trade quickly, whereas traders with weaker information can devote greater attention to execution quality. This trade-off predicts a negative relationship between execution quality and subsequent profitability.

The trade-off may be weaker for hedge funds. Our earlier results show that hedge-fund 13D trades are largely indistinguishable from non-13D trades on adverse-selection measures, even though hedge-fund filers earn higher abnormal returns than non-hedge-fund filers. Hedge funds may therefore be able to preserve execution quality without sacrificing profitability. We expect the negative relationship between execution quality and profitability to be more pronounced among non-hedge-fund filers than among hedge-fund filers.

To test this, we first classify 13D filings into high- and low-execution-quality groups and compare their *VWAAR*, constructed as described previously, on the filing date and 5 and 10 trading days afterward. We conduct the analysis separately for the full sample, non-hedge-fund filers, and hedge-fund filers.

We use two complementary measures of execution quality. The first is the effective spread (*ESP*), which measures a trade’s execution cost relative to the prevailing midpoint. Lower effective spreads indicate better execution quality, but *ESP* does not adjust for differences in trading conditions. The second is the percentile trader-skill ranking proposed by Anand,

Irvine, Puckett, and Venkataraman (2012), which we refer to as *AIPV*. *AIPV* is constructed from a regression of execution shortfall on determinants of trading costs, including stock and market volatility, order imbalance, price trends, stock price, and their interactions, together with filer fixed effects. The estimated filer-specific alpha captures the component of execution costs not explained by market conditions or trade characteristics, providing a cleaner measure of execution skill.

Table 9 presents the results. Panel A reports the findings for the full sample of 1,410 filings. On the filing date, filings in the low execution quality group generate higher abnormal returns than those in the high execution quality group. The high-minus-low difference is -1.51% (t-statistic: -2.12) under *ESP* and -1.08% (t-statistic: -1.51) under *AIPV*. The difference widens over longer horizons. By Day +5, it reaches -2.11% (t-statistic: -2.65) under *ESP* and -1.48% (t-statistic: -1.85) under *AIPV*. By Day +10, the corresponding differences are -3.04% (t-statistic: -3.45) and -2.45% (t-statistic: -2.77). Thus, lower execution quality is associated with higher subsequent profitability in the full sample, consistent with an execution–profitability trade-off.

Panel B shows that this relationship is concentrated among non-hedge fund filers. At Day +5, the high-minus-low difference is -3.05% (t-statistic: -2.73) under *ESP* and -3.22% (t-statistic: -2.89) under *AIPV*. By Day +10, the differences widen to -4.01% (t-statistic: -3.30) and -4.41% (t-statistic: -3.63), respectively. Non-hedge fund filings in the high execution quality group therefore generate substantially lower subsequent returns than those in the low execution quality group.

Panel C shows that hedge funds do not exhibit this trade-off. The difference between high and low execution quality groups is statistically indistinguishable from zero across all horizons and both measures. Under *AIPV*, the difference at Day +10 is essentially zero (-0.09% , t-statistic: -0.07). Under *ESP*, the corresponding difference is -1.33% (t-statistic: -1.05). Both groups earn positive and economically large abnormal returns at all horizons. Hedge funds therefore earn high returns regardless of execution quality.

Table 9 around here.

The results in Table 9 show that the execution–profitability trade-off is not statistically evident among hedge funds. They do not, however, establish that better execution is as-

sociated with higher returns or account for differences in firm characteristics and campaign objectives. We therefore estimate cross-sectional regressions of post-filing abnormal returns on execution quality, investor type, and their interaction:

$$VWAAR_{f,t} = \beta_1 EQ_f + \beta_2(EQ_f \times HF_f) + \beta_3 HF_f + \gamma' X_f + \epsilon_f \quad (12)$$

where $VWAAR_{f,t}$ is the value-weighted average abnormal return for filing f measured t days after the filing date, EQ_f is a standardized execution quality measure for filing f , HF_f is an indicator equal to one for hedge fund filers, and X_f is a vector of controls including log market capitalization, Tobin's Q , leverage, ROA, and Item 4 campaign objective indicators. We estimate the regression separately for $t = 0, +5$, and $+10$. Following Brav et al. (2008a), we classify campaign objectives using Item 4 of each Schedule 13D filing. Item 4 requires filers to disclose the purpose of acquiring the shares, including potential mergers, asset sales, changes in capital structure or dividend policy, and other corporate actions. The resulting indicators control for differences in returns associated with the nature of the activist campaign.¹³

We use the same two execution-quality measures as in Table 9: *AIPV* and *ESP*. Both measures are multiplied by -1 so that higher values indicate better execution quality. We winsorize the variables at the 1st and 99th percentiles and standardize them to have a mean of zero and a standard deviation of one. The reported coefficients are multiplied by 100 and represent the percentage-point change in *VWAAR* associated with a one-standard-deviation improvement in execution quality.

Table 10 reports the results. The coefficient on *Exec.Quality* captures the relationship between execution quality and returns for non-hedge fund filers. This coefficient is negative and statistically significant at longer horizons. A one-standard-deviation improvement in execution quality is associated with returns that are 1.00 percentage points lower (t-statistic: -2.12) under *AIPV* and 1.29 percentage points lower (t-statistic: -2.74) under *ESP* at Day $+5$. At Day $+10$, the corresponding estimates are 1.35 percentage points lower (t-statistic:

¹³Among the campaign controls, *Sale of Target* is the strongest predictor of post-filing returns across all horizons, consistent with Brav et al. (2008a), while the remaining campaign indicators are largely insignificant. The estimates on execution quality and its interaction with the hedge-fund indicator remain similar after including these controls.

−2.49) and 1.31 percentage points lower (t-statistic: −2.40). These results confirm the negative relation between execution quality and subsequent profitability among non-hedge fund filers.

The interaction coefficient captures how this relationship differs for hedge fund filers. Under *AIPV*, the interaction is positive and statistically significant at Day +5 and Day +10, with coefficients of 1.98 (t-statistic: 2.16) and 2.87 (t-statistic: 2.71), respectively. Under *ESP*, the interaction is marginally significant at Day +10, with a coefficient of 1.84 (t-statistic: 1.87). The point estimates of $\beta_1 + \beta_2$ are positive at longer horizons under both measures. Thus, the negative execution quality–return relationship observed among non-hedge fund filers does not extend to hedge funds. Under *AIPV*, the estimates instead point to a positive relationship between execution quality and subsequent returns. The hedge fund indicator is negative and at most marginally significant at the ten-day horizon, indicating little remaining return difference between the two groups after controlling for execution quality, firm characteristics, and campaign objectives. Notably, these relationships are not statistically evident on the filing date and emerge only at longer horizons. This pattern suggests that the market does not immediately differentiate activists based on execution quality at the time of the announcement. Rather, the return differences become apparent as information is incorporated into prices over time.

Table 10 around here.

4.4. Patient versus Impatient Trades

We next examine whether the execution–profitability trade-off varies with the urgency of trading. Schedule 13D requires investors to file with the SEC within ten days after crossing the 5% ownership threshold (the event date), as mandated by Rule 13d-1(a) of the Securities Exchange Act of 1934.¹⁴ The filing date marks the public disclosure of the position. The timing of trades relative to this date provides a natural way to distinguish between patient and impatient trading.

Following Bogousslavsky et al. (2024), we define patient trades as those executed at least

¹⁴As previously noted, this rule has been updated. The SEC reduced the initial filing deadline from 10 calendar days to 5 business days, effective February 5, 2024. Our sample period precedes this amendment, so we apply the 10-day deadline.

20 days before the filing date and impatient trades as those executed within the 20 days preceding the filing date. Patient trades allow greater flexibility in execution, whereas trades closer to the filing date may face tighter timing constraints. These constraints may strengthen the execution–profitability trade-off by limiting traders’ ability to wait for favorable liquidity conditions.

Table 11 reports profitability, measured by *VWAAR*, by execution-quality group separately for the patient- and impatient-trade subsamples. The table follows the structure of Table 9. Execution quality is measured using *ESP* and *AIPV*, and returns are reported for the filing date, Day +5, and Day +10. Panel A shows a clear execution–profitability trade-off among impatient trades. Filings in the low execution quality group generate higher abnormal returns than those in the high execution quality group at all horizons. On the filing date, the low-execution-quality group earns 1.19% under *ESP* and 1.27% under *AIPV*, whereas the high-execution-quality group earns -0.09% and -0.19% , respectively. The high-minus-low difference widens over time. By Day +5, it reaches -1.87% (t-statistic: -2.19) under *ESP* and -2.51% (t-statistic: -2.95) under *AIPV*. By Day +10, the corresponding differences are -2.95% (t-statistic: -3.12) and -3.96% (t-statistic: -4.21). These economically large and statistically significant differences indicate a pronounced execution–profitability trade-off among impatient trades.

Panel B shows a weaker relationship among patient trades. Filings in the low-execution-quality group also generate somewhat higher returns than those in the high-execution-quality group, but the differences are not statistically significant under either measure. At Day +10, the high-minus-low difference is -1.58% (t-statistic: -1.14) under *ESP* and -1.90% (t-statistic: -1.37) under *AIPV*. Thus, the execution–profitability trade-off is not statistically evident when traders have greater flexibility over the timing of their trades.

Taken together, the results indicate that both trader type and timing constraints shape the execution–profitability trade-off. The trade-off is strongest among non-hedge-fund filers in Table 9 and among impatient trades in Table 11, but is largely absent among hedge funds and patient trades.

Table 11 around here.

4.5. *How Can Informed Traders Hide?*

Our results show that hedge fund activists leave less of a detectable trace in measures of adverse selection than other activists. This raises the question of what, concretely, a sophisticated trader can do to hide. The strategies we measure directly - trading when spreads are low, alternating between market and limit orders, mixing sells with buys, and splitting orders so that individual trades are unremarkable in size (Barclay and Warner, 1993; Chakravarty, 2001) - are available to every filer in our sample, and most filers use them. Modern market structure offers at least three additional channels of concealment, and the literature associates each of them with sophisticated traders.

The first channel is venue choice. Equity markets comprise a spectrum of venues with different degrees of pre-trade transparency, from lit exchanges to dark pools that display no quotes at all. In the model of Zhu (2014), dark pools are a poor hiding place: informed traders cluster on the same side of the market, face low execution probability in the dark, and self-select onto lit exchanges.

The second channel is best execution within lit markets. Exchanges permit odd-lot, iceberg, and fully hidden orders, which are collectively referred to as hidden liquidity. Hidden liquidity inside the NBBO is pervasive and can be difficult for less sophisticated market participants to detect (Bartlett, McCrary, and O’Hara, 2023; Bartlett and O’Hara, 2024). Sophisticated traders may therefore improve execution by identifying and interacting with liquidity that is not reflected in displayed quotations.

The third channel is managing the information trail of the order flow itself. A large parent order leaves a correlated sequence of child orders that others can detect: high-frequency traders identify institutional orders in progress and trade along with the most informed ones (van Kervel and Menkveld, 2019), and brokers may leak information about client order flow to favored customers (Barbon, Di Maggio, Franzoni, and Landier, 2019). Traders may reduce this exposure by executing more quickly. Intermarket Sweep Orders (*ISOs*), for example, facilitate rapid execution across venues and are frequently associated with informed trading (Chakravarty, Jain, Upson, and Wood, 2012).

We investigate the pervasiveness of each of these techniques in the following way. For each filing, we count the number of off-exchange trades, trades executed at the midpoint,

trades executed within the NBBO, odd-lot trades, trades using ISOs, and trades executed in the last thirty minutes of the session. Each proxy is then computed as the percentage of the filing's trades with the given characteristic.

Table 12 reports the mean and median filing-level percentages separately for hedge-fund and non-hedge-fund filers. Both groups use each of these techniques. Hedge-fund filers execute a significantly larger share of their trades within the NBBO, consistent with interacting with hidden liquidity inside the spread. They also appear to concentrate marginally more of their trading in the last thirty minutes of the session, when volume is heaviest and individual trades are likely easier to camouflage. Their off-exchange share tends to be lower than that of other filers - directionally in line with Zhu (2014), in which informed traders self-select onto lit exchanges - though the difference is estimated with limited statistical power. Hedge funds also seem to use ISOs somewhat more frequently, while differences in midpoint and odd-lot usage are modest. The clearest distinction between the two groups is thus where they source liquidity: hedge funds trade disproportionately inside the quoted spread, where hidden liquidity resides.

5. Conclusion

This paper asks two questions. Do informed trades leave a visible mark on prices, as microstructure theory predicts? And can informed traders avoid leaving one? By matching roughly 500,000 trades disclosed in Schedule 13D filings to timestamped TAQ trades, we observe informed traders trade by trade, and can answer both.

The answer to the first question is yes - at the right frequency. Activists choose their trading conditions carefully: they trade when spreads are narrow, turn to limit orders when spreads widen, sell even as they accumulate, and split their orders so that neither trade size nor trade direction gives them away. At the daily horizon this selection dominates, and liquidity looks better, not worse, when informed traders are active - the puzzle documented in earlier work. Within the one-minute interval, where trading conditions are held fixed, the prediction of theory reappears: activist trades have higher price impact and lower realized spreads than other trades executed at the same moment, and prices rise permanently after them while the effect of other trades is transitory. Liquidity providers do lose money to

informed traders; one simply has to look at the horizon on which liquidity provision operates.

The answer to the second question: only the most sophisticated can avoid it. The visible footprint is driven by activists that are not hedge funds. Hedge fund trades are indistinguishable from uninformed trades on every adverse selection measure, even though hedge fund filings earn the highest post-filing returns. Their advantage shows up again in the trade-off between execution quality and profits. Other activists pay for their information with worse execution, and the price is steepest when the filing deadline leaves no time to be patient. Hedge funds escape this trade-off entirely - their returns, if anything, increase with execution quality. Among the best informed traders, execution skill and information are complements, not substitutes.

These results carry two messages. For the debate over 13D disclosure rules, they imply that publicly available microstructure data already let the market detect an average activist's accumulation in real time, well before the filing itself. But detection fails exactly where it would matter most: against the traders with the most valuable information. Standard adverse selection measures capture the presence of informed trading; they do not capture sophistication. Developing measures that do - and understanding what hedge funds do differently at the moment of execution - strikes us as a promising direction for future research.

Table 1
Summary Statistics

This table reports descriptive statistics on trading and filing activity of Schedule 13D filers from 1994 to 2021, tracing the data from raw filing counts through successive filters: CUSIP matching, restriction to common stocks priced between \$1 and \$1,000, and unique trade identification. Trades are matched between 13D filings and TAQ data using four methods. *TAQ multiple match* allows many-to-many matching. *TAQ simple match* allows 13D trades to match multiple TAQ trades but not the reverse. *TAQ unique match* requires one-to-one matching. *TAQ unique match 5 trade* further restricts to filings with at least five daily transactions, following Collin-Dufresne and Fos (2015), as such filers are more likely to report trade-level rather than aggregated data. Collapsed trades refer to 13D trades that match TAQ records only after aggregating them at the stock-day-time-exchange level using size-weighted average prices and summed shares. These are excluded from main results and used only for robustness. Patient trades are executed 20 or more days before the filing date; impatient trades are executed closer to it, following Bogousslavsky et al. (2024). Order type is classified by comparing 13D trading direction with the direction inferred via Lee and Ready (1991): aligned directions indicate market orders, misaligned indicate limit orders. Hedge fund filers are reported separately.

	Raw	CUSIP Matched	Common Stock (\$1 - \$1K)	TAQ Multiple Match	TAQ Simple Match	TAQ Unique Match	TAQ Unique Match 5 Trade
Panel A: Full 13D Trading							
13D Trade	864,714	799,018	505,112	1,455,409	505,602	47,901	45,961
Collapsed Trd	-	-	-	698,875	267,964	40,954	39,012
13D Filings	8,904	7,753	4,103	1,764	1,696	1,696	658
13D Filers	3,217	2,774	1,518	711	692	692	275
13D Buy	614,586	565,324	369,328	-	233,205	29,587	27,805
13D Sell	250,128	233,694	135,784	-	272,397	18,314	18,156
Limit Order	-	-	-	-	262,780	23,666	22,691
Market Order	-	-	-	-	242,822	24,235	23,270
Impatient (%)	37.38%	37.23%	36.20%	40.62%	40.14%	39.76%	39.33%
Patient (%)	62.62%	62.77%	63.80%	59.38%	59.86%	60.24%	60.67%
Panel B: Hedge Fund 13D							
13D Trade	329,010	317,924	245,325	813,029	297,675	22,382	21,611
Collapsed Trd	-	-	-	345,374	143,470	19,342	18,568
13D Filings	2,561	2,331	1,513	652	622	622	170
13D Filers	263	263	263	253	246	246	81
13D Buy	226,608	217,526	166,397	-	101,362	10,467	9,760
13D Sell	102,402	100,398	78,928	-	196,313	11,915	11,851
Limit Order	-	-	-	-	158,892	11,795	11,386
Market Order	-	-	-	-	138,783	10,587	10,225
Impatient (%)	35.87%	35.59%	34.84%	41.50%	43.19%	40.61%	40.41%
Patient (%)	64.13%	64.41%	65.16%	58.50%	56.81%	59.39%	59.59%

Table 2
Summary Statistics: Illiquidity Measures

This table reports descriptive statistics for illiquidity measures of non-13D and Schedule 13D trades, including quoted spread (*QSP*), effective spread (*ESP*), price improvement (*PIMPRV*), realized spread (*RSP*), price impact (*PIMPCT*), trade size (*SIZE*), and dollar volume (*DVOL*). Illiquidity measures are scaled by 10,000 for interpretability, except *SIZE* and *DVOL*. Each panel reports the mean, median, standard deviation, and number of one-minute intervals (*N.1min*) for non-13D trades, 13D trades, and hedge fund filers. Panel A uses pre-aggregated one-minute measures for non-13D trades, while Panels B and C apply the Multiple Match and Simple Match methods, respectively.

	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: Non-13D Trades Throughout a Day							
<i>Mean</i>	28.08	26.22	1.86	19.22	7.01	690.22	18,487.50
<i>Median</i>	9.23	7.60	0.00	4.79	0.00	181.58	4,569.50
<i>Std.Dev</i>	76.82	758.15	756.22	757.54	48.84	5,880.84	177,895.43
<i>N.1min</i>	1,507,148	1,507,148	1,507,148	1,507,148	1,507,148	1,507,148	1,507,148
Panel B: Illiquidity Measures: Multiple Match							
<u>Non-13D Trades: 13D-Interval</u>							
<i>Mean</i>	19.89	18.55	1.34	12.56	5.99	629.74	14,698.41
<i>Median</i>	9.10	8.20	0.00	5.47	0.00	228.57	4,977.06
<i>Std.Dev</i>	46.37	51.42	33.40	52.09	37.71	5,452.69	120,056.52
<i>N.1min</i>	179,420	179,420	179,420	179,420	179,420	179,420	179,420
<u>13D Trades</u>							
<i>Mean</i>	19.46	18.14	1.32	11.69	6.45	610.77	11,763.10
<i>Median</i>	8.99	8.17	0.00	5.28	0.00	100.00	2,711.33
<i>Std.Dev</i>	44.50	48.77	31.40	55.22	44.91	11,042.98	134,702.21
<i>N.1min</i>	179,445	179,445	179,445	179,445	179,445	179,445	179,445
<u>Hedge Fund 13D Trades</u>							
<i>Mean</i>	14.43	13.38	1.05	9.18	4.21	612.37	10,605.32
<i>Median</i>	8.16	7.48	0.00	5.27	0.00	100.00	3,854.00
<i>Std.Dev</i>	32.01	30.87	20.46	37.40	30.02	11,740.85	132,677.45
<i>N.1min</i>	85,734	85,734	85,734	85,734	85,734	85,734	85,734
Panel C: Illiquidity Measures: Simple Match							
<u>Non-13D Trades: 13D-Interval</u>							
<i>Mean</i>	20.51	19.40	1.10	12.92	6.48	642.32	16,230.82
<i>Median</i>	8.59	7.71	0.00	4.94	0.00	229.00	5,572.85
<i>Std.Dev</i>	50.56	57.07	37.56	57.04	41.34	5,663.72	126,154.67
<i>N.1min</i>	120,863	120,863	120,863	120,863	120,863	120,863	120,863
<u>13D Trades</u>							
<i>Mean</i>	20.15	19.14	1.01	12.46	6.68	811.57	16,118.87
<i>Median</i>	8.53	7.68	0.00	4.97	0.00	100.00	4,089.82
<i>Std.Dev</i>	48.99	54.78	36.31	63.02	51.46	11,479.87	160,477.09
<i>N.1min</i>	120,882	120,882	120,882	120,882	120,882	120,882	120,882
<u>Hedge Fund 13D Trades</u>							
<i>Mean</i>	14.74	13.70	1.04	9.37	4.33	776.33	13,386.87
<i>Median</i>	7.48	6.56	0.00	4.81	0.00	101.26	4,452.94
<i>Std.Dev</i>	35.88	34.57	23.26	41.65	33.95	12,724.86	148,724.90
<i>N.1min</i>	61,384	61,384	61,384	61,384	61,384	61,384	61,384

Table 3

Panel Regression of Illiquidity Measures on 13D Indicator with Stock-Day-Time Fixed Effects

This table reports the results from stock-day-time fixed-effect panel regressions to estimate the impact of 13D-reported trades on various illiquidity measures. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t} = \beta_{13D} 13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t}$ where $IlliquidityMeasure_{i,s,d,t}$ denotes one of the illiquidity measures, estimated as the average of all trades for stock s on day d within the 1-minute interval t , calculated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$). The illiquidity measures include quoted spread (QSP), effective spread (ESP), price improvement ($PIMPRV$), realized spread (RSP), price impact ($PIMPCT$), size ($SIZE$), and dollar volume ($DVOL$). The indicator variable $13D$ equals 1 for trades reported under 13D filings and 0 otherwise. The model includes fixed effects for intraday 30-minute intervals, dates, stocks, and stock-by-date interactions to control for unobserved heterogeneity at various levels. Standard errors are clustered by stock and date to account for serial correlation and heteroskedasticity. The sample spans January 1994, to December 2021, with data aggregated at 1-minute intervals. The data used in this analysis is sourced from TAQ multiple match. Coefficients for $13D$ measure its marginal impact on illiquidity measures relative to the baseline and are scaled by 10,000 to improve interpretability, except for $SIZE$ and $DVOL$, which retain their original units. Panel A compares 13D trades to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

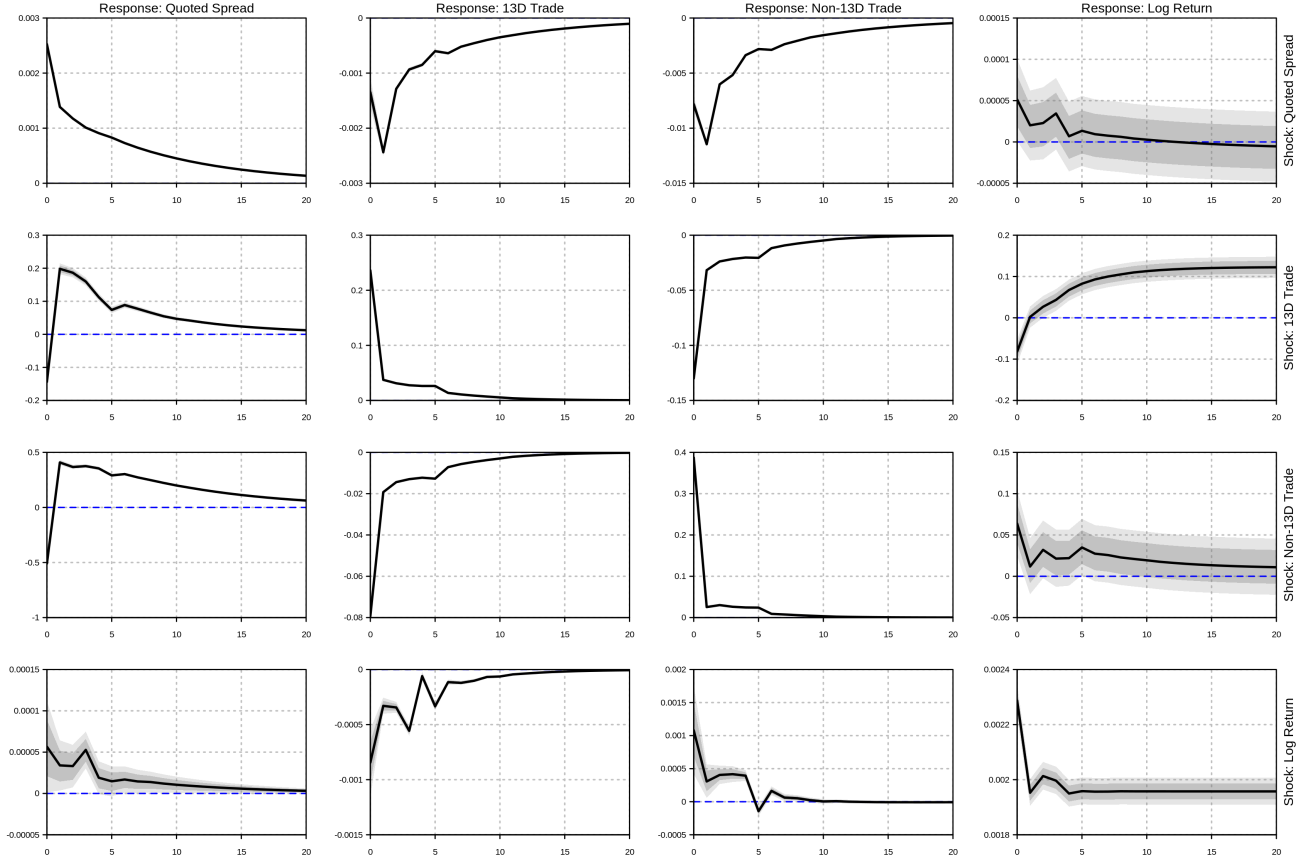
Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
<i>13D</i>	-0.93*** (-3.64)	-0.74** (-2.55)	-0.19 (-0.93)	-1.22*** (-3.79)	0.48*** (2.73)	279.23*** (3.22)	1553.90 (1.18)
<i>Adjusted-R2</i>	0.63	0.00	-0.00	-0.00	0.14	0.03	0.05
<i>N</i>	1,771,373	1,771,373	1,771,373	1,771,373	1,771,373	1,771,373	1,771,373
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
<i>13D</i>	-0.43*** (-5.18)	-0.41*** (-3.09)	-0.02 (-0.15)	-0.86*** (-3.50)	0.45** (2.56)	-18.89 (-0.30)	-2935.87** (-2.51)
<i>Adjusted-R2</i>	0.82	0.69	0.35	0.43	0.25	0.39	0.21
<i>N</i>	358,866	358,866	358,866	358,866	358,866	358,866	358,866
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4
Intraday Vector Autoregressions and Granger Causality

This table presents results from panel vector autoregression *VAR* models that estimate the dynamic relationships among quoted spread *QSP*, 13D indicator *13D*, non-13D indicator *non13D*, and log return *RET* as endogenous variables. *RET* is calculated using midpoint prices at one-minute intervals. Each model includes five lags of all endogenous variables, structured as a panel with stock-day and time fixed effects. The regression model is specified as: $LHS_{s,d,t} = \sum_{l=1}^5 \beta_{1,l} QSP_{s,d,t-l} + \sum_{l=1}^5 \beta_{2,l} 13D_{s,d,t-l} + \sum_{l=1}^5 \beta_{3,l} non13D_{s,d,t-l} + \sum_{l=1}^5 \beta_{4,l} RET_{s,d,t-l} + FE$. Here, the subscripts *s*, *d*, and *t* denote stock, day, and time, respectively. The endogenous variables are calculated over 1-minute intervals. To account for intervals without trades, where only quotes are available, the 13D trade indicators are divided into *13D* and *non13D* categories. The reported coefficients represent the cumulative sum of all lagged coefficients for each endogenous variable. Chi-squared statistics based on a Wald test are provided in parentheses to test the null hypothesis that the cumulative sum of all lagged coefficients is zero, indicating no cumulative effect. Coefficients are scaled by 10,000 in cases where the sum of coefficients from the five lags of either the *13D* or *non-13D* indicator explains the quoted spread or log return. The sample spans January 1994, to December 2021, and the data for this analysis is sourced from TAQ Multiple Match. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% significance levels, respectively.

Variable	QSP	13D	non13D	RET
$\sum_{l=1}^5 QSP_{i,t-l,d}$	0.82*** (9,706.52)	-0.57*** (42.51)	-2.85*** (177.57)	0.00 (2.69)
$\sum_{l=1}^5 13D_{i,t-l,d}$	2.98*** (160.86)	0.44*** (1,404.70)	-0.23*** (326.89)	0.61*** (12.26)
$\sum_{l=1}^5 non13D_{i,t-l,d}$	3.21*** (203.94)	-0.04*** (79.38)	0.23*** (1,240.36)	0.14 (1.38)
$\sum_{l=1}^5 RET_{i,t-l,d}$	0.00 (0.06)	-0.31 (1.18)	0.64* (3.43)	-0.17*** (77.42)
<i>Adjusted-R²</i>	0.92	0.44	0.39	0.02
<i>N</i>	2,297,756	2,297,756	2,297,756	2,297,756
<i>Fixed Effects</i>	<i>Stock*Day+Time</i>	<i>Stock*Day+Time</i>	<i>Stock*Day+Time</i>	<i>Stock*Day+Time</i>

Figure 1. Generalized Impulse Response Functions (GIRFs) from a Panel VAR Model



This figure presents Generalized Impulse Response Functions (GIRFs) from the panel VAR model reported in Table 4. Each row shows the effect of a one-standard-deviation shock to *Quoted Spread*, *13D Trades*, *non13D Trades*, or *Log Return*. Each column shows the response of the corresponding variable over a 20-minute horizon. Responses of *Log Return* are cumulative and can therefore be interpreted as changes in the log price level. Responses of all other variables are reported in levels at each horizon. Coefficients are multiplied by 10,000 when the shock originates from either the *13D Trades* or *non13D Trades* indicator and the response variable is the quoted spread or log return. The darker shaded area shows the 68% bootstrap confidence interval, and the lighter shaded area shows the 90% interval. Bootstrap samples are constructed by resampling contiguous blocks of VAR residual vectors and recomputing the GIRFs while holding the estimated VAR coefficients fixed.

Table 5

Panel Regression of Illiquidity Measures on 13D Indicator and Limit Order Indicator with Stock-Day-Time Fixed Effects

This table extends the analysis in Table 3 by distinguishing between market and limit orders for 13D-reported trades. The regression model includes a *MKT_13D* indicator, set to 1 for 13D trades executed as market orders and 0 for non-13D trades, and a *LIMIT_13D* indicator, set to 1 for 13D trades executed as limit orders and 0 for non-13D trades. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t} = \beta_{MKT_13D}MKT_13D_{i,s,d,t} + \beta_{LIMIT_13D}LIMIT_13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t}$ where $IlliquidityMeasure_{i,s,d,t}$ denotes one of the illiquidity measures, estimated as the average of all trades for stock s on day d within the 1-minute interval t , calculated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$). The classification of *LimitOrder* is determined by comparing the order direction reported in the filing with the direction identified using the Lee and Ready (1991) algorithm. A 13D trade is classified as a market order if the two directions align, and as a limit order if the two directions are opposite. For non-13D trades, we assume all transactions are executed as market orders. Since all trades classified as limit orders are 13D trades, the 13D trades are further classified into market 13D trades (MKT_13D) and limit 13D trades (LIMIT_13D). Methodology and scaling are consistent with Table 2. Specifically, all coefficients are scaled by 10,000, except those associated with SIZE and DVOL. Standard errors are clustered by stock and date to address serial correlation and heteroskedasticity. The sample spans January 1994 to December 2021, with data aggregated at 1-minute intervals, sourced from TAQ simple match. Panel A compares 13D trades (market and limit orders) to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
<i>MKT_13D</i>	-0.54** (-2.46)	-1.19*** (-3.44)	0.66** (2.23)	-2.35*** (-5.19)	1.16*** (3.83)	414.13*** (4.32)	4661.08*** (2.73)
<i>LIMIT_13D</i>	-0.61** (-2.50)	0.48 (1.41)	-1.09*** (-3.53)	-0.21 (-0.44)	0.68** (2.14)	441.26*** (4.17)	2820.90* (1.86)
<i>Adjusted-R2</i>	0.62	-0.00	-0.01	-0.00	0.13	0.03	0.05
<i>N</i>	1,692,227	1,692,227	1,692,227	1,692,227	1,692,227	1,692,227	1,692,227
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
<i>MKT_13D</i>	-0.26*** (-2.94)	-0.76*** (-3.56)	0.50** (2.49)	-1.13*** (-2.82)	0.36 (1.14)	108.39 (1.57)	-481.81 (-0.33)
<i>LIMIT_13D</i>	-0.48*** (-4.05)	-0.07 (-0.37)	-0.41** (-1.98)	-0.39 (-1.03)	0.32 (0.94)	160.07** (2.04)	-899.68 (-0.62)
<i>Adjusted-R2</i>	0.84	0.69	0.37	0.36	0.18	0.39	0.22
<i>N</i>	269,602	269,602	269,602	269,602	269,602	269,602	269,602
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6

Panel Regression of Illiquidity Measures on 13D Indicator and Buy Indicator with Stock-Day-Time Fixed Effects

This table extends the analysis from Table 3 by differentiating between buy and sell orders for 13D-reported trades. In addition to the 13D indicator, the model incorporates a *Buy* indicator set to 1 for buy trades and 0 for sell trades, along with the interaction term $13D \times Buy$. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t,b} = \beta_{13D}13D_{i,s,d,t,b} + \beta_{Buy}Buy_{i,s,d,t,b} + \beta_{13D \times Buy}(13D \times Buy)_{i,s,d,t,b} + FE + \epsilon_{i,s,d,t,b}$ where $IlliquidityMeasure_{i,s,d,t}$ denotes one of the illiquidity measures, estimated as the average of all trades for stock s on day d within the 1-minute interval t , calculated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$), as well as for trade directions b . For 13D trades, order direction is classified based on the details provided in the filing. For non-13D trades, it is determined using the Lee and Ready (1991) algorithm. Unlike Tables 2 and 3, this table further segments each 1-minute time unit (t) by both 13D versus non-13D trades and buy versus sell trades. This additional categorization increases the number of observations compared to the earlier tables. All coefficients are scaled by 10,000, except those associated with SIZE and DVOL. The sample spans January 1994 to December 2021, with data aggregated at 1-minute intervals and sourced from TAQ simple match. Panel A compares 13D trades (buy and sell orders) to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
13D	-0.41*	-1.26	0.85	-2.12**	0.86***	-123.29***	-4807.75***
	(-1.79)	(-1.44)	(0.98)	(-2.27)	(3.15)	(-4.05)	(-4.25)
Buy	0.40***	-2.50	2.90*	-2.00	-0.50***	-40.41***	-643.08
	(3.75)	(-1.51)	(1.74)	(-1.20)	(-2.91)	(-2.72)	(-1.11)
$13D \times Buy$	-0.31	2.95*	-3.26*	1.86	1.09**	950.62***	14926.43***
	(-1.26)	(1.69)	(-1.87)	(1.05)	(2.50)	(6.08)	(5.63)
Adjusted-R2	0.59	-0.00	-0.00	-0.00	0.09	0.03	0.03
N	2,410,523	2,410,523	2,410,523	2,410,523	2,410,523	2,410,523	2,410,523
StockDayTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
13D	-0.31***	-1.17***	0.86***	-2.23***	1.06***	-164.27***	-6961.18***
	(-2.84)	(-5.84)	(5.42)	(-4.71)	(2.92)	(-5.41)	(-4.69)
Buy	-0.03	-2.55***	2.53***	-2.73***	0.17	-28.25	-1893.11*
	(-0.17)	(-7.90)	(8.33)	(-4.57)	(0.33)	(-0.81)	(-1.88)
$13D \times Buy$	-0.20	2.73***	-2.93***	2.36***	0.36	547.01***	11572.72***
	(-1.04)	(6.55)	(-7.24)	(4.38)	(0.91)	(3.95)	(4.42)
Adjusted-R2	0.80	0.67	0.33	0.30	0.13	0.25	0.10
N	321,236	321,236	321,236	321,236	321,236	321,236	321,236
StockDayTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7

Panel Regression of Illiquidity Measures on 13D Indicator and 13D Hedge Fund Indicator with Stock-Day-Time Fixed Effects

This table extends the analysis in Table 3 by partitioning 13D trades into hedge-fund and non-hedge-fund trades. The regression model is specified as: $IlliquidityMeasure_{g,s,d,t} = \beta_{Non_HF13D} Non_HF13D_{g,s,d,t} + \beta_{HF13D} HF13D_{g,s,d,t} + FE + \epsilon_{g,s,d,t}$, where $IlliquidityMeasure_{g,s,d,t}$ denotes an illiquidity measure averaged across trades for group g , stock s , day d , and one-minute interval t . The three groups are non-HF 13D trades, HF 13D trades, and non-13D trades, which serve as the omitted category. The indicator Non_HF13D equals one for 13D trades reported by non-hedge-fund filers, while $HF13D$ equals one for 13D trades reported by hedge-fund filers. All coefficients are scaled by 10,000, except those associated with SIZE and DVOL. The sample spans January 1994 to December 2021, with data aggregated at 1-minute intervals and sourced from TAQ multiple match. Panel A compares 13D trades (buy and sell orders) to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
<i>NON_HF13D</i>	-1.30*** (-3.21)	-1.11** (-2.46)	-0.19 (-0.58)	-1.71*** (-3.48)	0.59** (2.20)	238.98** (2.08)	2530.17 (1.30)
<i>HF13D</i>	-0.43* (-1.94)	-0.24 (-0.97)	-0.19 (-1.07)	-0.58* (-1.87)	0.34* (1.71)	332.71** (2.56)	254.42 (0.16)
<i>Adjusted-R2</i>	0.63	0.00	-0.00	-0.00	0.14	0.03	0.05
<i>N</i>	1,771,386	1,771,386	1,771,386	1,771,386	1,771,386	1,771,386	1,771,386
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
<i>NON_HF13D</i>	-0.62*** (-4.45)	-0.75*** (-3.44)	0.13 (0.62)	-1.34*** (-3.34)	0.59** (2.10)	-87.43 (-1.06)	-2504.18 (-1.46)
<i>HF13D</i>	-0.22*** (-3.28)	-0.04 (-0.48)	-0.18** (-2.01)	-0.35 (-1.54)	0.30 (1.51)	55.86 (0.57)	-3407.25** (-2.16)
<i>Adjusted-R2</i>	0.82	0.69	0.35	0.43	0.25	0.39	0.21
<i>N</i>	358,865	358,865	358,865	358,865	358,865	358,865	358,865
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8

Value-Weighted Average Abnormal Returns (VWAAR) of 13D Filers: Post-Filing Comparison Across Full Sample, Hedge Funds, and Non-Hedge Funds

The table summarizes the mean value-weighted average abnormal return (VWAAR) for 13D filers, calculated for each day after the filing date. The VWAAR for each filing is the value-weighted average of abnormal returns from individual 13D trades, where abnormal returns are defined as the difference between a 13D trade's holding period return and the corresponding market return (see equation (11)). Daily average VWAARs are computed by averaging across all 13D filings, with returns expressed as arithmetic values. The analysis uses a sample of 13D trades classified as common stock, priced between \$1 and \$1,000. It is restricted to trades executed on stock-days with multiple TAQ matches, excluding sell trades, option-like trades (executed outside the bid-ask spread), and stocks delisted within 20 days of the filing date. Results are further grouped into three categories: all 13D filers, hedge fund filers, and non-hedge fund filers.

Days After Filing	Full Sample			Hedge Fund			Non HF		
	Ret	Median	n_obs	Ret	Median	n_obs	Ret	Median	n_obs
0	0.60	-0.23	1,411	1.50	0.03	604	-0.07	-0.54	807
1	0.89	0.11	1,411	1.72	0.60	604	0.28	-0.34	807
2	1.27	0.37	1,411	2.10	0.76	604	0.65	0.09	807
3	1.64	0.51	1,411	2.30	0.95	604	1.14	0.15	807
4	1.85	0.72	1,411	2.56	1.24	604	1.31	0.53	807
5	2.16	0.94	1,411	3.01	1.76	604	1.53	0.39	807
6	2.26	0.97	1,411	3.17	1.43	604	1.58	0.41	807
7	2.71	1.34	1,411	3.55	2.14	604	2.08	0.60	807
8	3.32	1.70	1,411	4.14	2.55	604	2.70	1.08	807
9	3.62	2.14	1,411	4.53	3.13	604	2.94	1.10	807
10	3.76	2.19	1,411	4.70	3.22	604	3.05	1.09	807
11	3.83	2.17	1,411	4.73	3.33	604	3.15	1.38	807
12	4.12	2.37	1,411	5.10	3.36	604	3.39	1.23	807
13	4.04	2.02	1,411	4.99	3.38	604	3.33	1.14	807
14	4.04	1.93	1,411	5.01	2.77	604	3.30	1.37	807
15	3.94	2.08	1,411	4.98	2.90	604	3.15	1.46	807
16	4.08	2.25	1,411	5.20	3.18	604	3.24	1.41	807
17	4.07	1.85	1,411	5.19	2.86	604	3.22	1.21	807
18	4.02	1.62	1,411	5.20	2.92	604	3.13	0.99	807
19	4.16	1.97	1,411	5.42	3.00	604	3.22	1.32	807
20	4.19	2.08	1,411	5.32	3.33	604	3.34	1.29	807

Table 9**Profitability and Execution Quality of 13D Trades: A Comparison Across Fund Types and Skill Levels**

This table summarizes the profitability of 13D trades by execution quality groups (high vs. low) and fund types (full sample, non-hedge funds, and hedge funds) across three time intervals: Day 0 (filing day), Day +5, and Day +10. Execution quality is evaluated using two measures. The first measure, *ESP*, directly reflects the effective spread of execution. The second measure, *AIPV(ESP)*, is based on the percentile trader skill ranking proposed by Anand et al. (2012). It captures execution quality adjustments after controlling for key economic determinants of trading costs, allowing for a refined assessment of execution cost reductions. Schedule 13D filers are divided into top and bottom halves based on these execution quality measures. Their value-weighted average abnormal return (VWAAR), as previously described (see Equation (11)), is then computed and compared across groups. Panel A reports results for the full sample, highlighting differences in profitability between high-execution-quality and low-execution-quality groups (High - Low). Panel B focuses on non-hedge funds, while Panel C isolates hedge funds, maintaining the same structure for comparison. Profitability is winsorized at the 1% and 99% levels. Returns are expressed in percentage terms.

Execution Quality	N	Filing Date + 0 Days		+ 5 Days		+ 10 Days	
		Profit	<i>t</i> -Statistics	Profit	<i>t</i> -Statistics	Profit	<i>t</i> -Statistics
Panel A: Full Sample							
ESP							
Execution Quality = Low	705	1.35%	(2.39)	3.21%	(5.06)	5.28%	(7.43)
Execution Quality = High	705	-0.16%	(-0.37)	1.10%	(2.29)	2.24%	(4.27)
High – Low		-1.51%	(-2.12)	-2.11%	(-2.65)	-3.04%	(-3.45)
AIPV (ESP)							
Execution Quality = Low	705	1.14%	(2.07)	2.90%	(4.64)	4.98%	(7.11)
Execution Quality = High	705	0.06%	(0.13)	1.42%	(2.88)	2.53%	(4.70)
High – Low		-1.08%	(-1.51)	-1.48%	(-1.85)	-2.45%	(-2.77)
Panel B: Non-Hedge Funds							
ESP							
Execution Quality = Low	403	0.77%	(0.88)	3.05%	(3.09)	5.05%	(4.75)
Execution Quality = High	403	-0.91%	(-1.99)	0.00%	(0.01)	1.03%	(1.74)
High – Low		-1.68%	(-1.70)	-3.05%	(-2.73)	-4.01%	(-3.30)
AIPV (ESP)							
Execution Quality = Low	403	0.87%	(1.02)	3.10%	(3.20)	5.22%	(5.02)
Execution Quality = High	403	-1.02%	(-2.08)	-0.12%	(-0.22)	0.81%	(1.30)
High – Low		-1.89%	(-1.92)	-3.22%	(-2.89)	-4.41%	(-3.63)
Panel C: Hedge Funds							
ESP							
Execution Quality = Low	302	1.81%	(2.89)	3.18%	(4.54)	5.36%	(6.14)
Execution Quality = High	302	1.17%	(1.46)	2.83%	(3.32)	4.03%	(4.41)
High – Low		-0.64%	(-0.63)	-0.35%	(-0.32)	-1.33%	(-1.05)
AIPV (ESP)							
Execution Quality = Low	302	1.67%	(2.73)	2.90%	(4.10)	4.74%	(5.43)
Execution Quality = High	302	1.31%	(1.61)	3.12%	(3.67)	4.64%	(5.08)
High – Low		-0.36%	(-0.35)	0.22%	(0.20)	-0.09%	(-0.07)

Table 10
Execution Quality and Post-Filing Returns: Regression Across Investor Types

This table presents cross-sectional regressions of value-weighted abnormal announcement returns (VWAAR) on execution quality and investor type. Two alternative execution quality measures are used: (i) $-1 \times$ AIPV skill ranking of Anand et al. (2012) and (ii) $-1 \times$ Execution Shortfall (ES). Both measures are winsorized at the 1st and 99th percentiles and standardized to mean zero, unit standard deviation so that higher values indicate better execution quality. Coefficients are multiplied by 100 and represent percentage point changes in VWAAR per one-standard-deviation improvement in execution quality. The interaction *Exec. Quality* $\times$ *HF* captures whether the execution quality–return relationship differs for hedge fund activists. Controls include log market cap, Tobin’s Q, leverage, ROA, and Item 4 campaign dummies. Standard errors are OLS. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. *t*-statistics are in parentheses below the coefficients.

Exec. Quality: Dependent is VWAAR:	–AIPV Skill			–Exec. Shortfall (ES)		
	Day 0 (1)	Day +5 (2)	Day +10 (3)	Day 0 (4)	Day +5 (5)	Day +10 (6)
Exec. Quality	–0.26 (–0.65)	–1.00** (–2.12)	–1.35** (–2.49)	–0.34 (–0.85)	–1.29*** (–2.74)	–1.31** (–2.40)
Exec. Quality $\times$ HF	0.33 (0.43)	1.98** (2.16)	2.87*** (2.71)	–0.04 (–0.05)	1.38 (1.62)	1.84* (1.87)
Hedge Fund	–0.13 (–0.18)	–1.24 (–1.45)	–1.89* (–1.92)	–0.06 (–0.09)	–1.07 (–1.27)	–1.71* (–1.75)
Log(Market Cap)	–0.45* (–1.87)	–0.26 (–0.92)	–0.17 (–0.52)	–0.41* (–1.73)	–0.17 (–0.62)	–0.15 (–0.45)
Tobin’s Q	–0.14 (–0.48)	–0.55 (–1.53)	–0.55 (–1.32)	–0.14 (–0.47)	–0.55 (–1.54)	–0.55 (–1.32)
Leverage	–1.35 (–0.95)	–0.06 (–0.04)	0.95 (0.49)	–1.38 (–0.98)	–0.16 (–0.09)	0.88 (0.45)
ROA	1.36 (0.64)	2.63 (1.04)	–1.59 (–0.55)	1.43 (0.67)	2.80 (1.11)	–1.34 (–0.46)
General Undervaluation	–0.56 (–0.68)	1.10 (1.12)	1.24 (1.09)	–0.55 (–0.67)	1.09 (1.11)	1.17 (1.03)
Capital Structure	–1.26 (–1.36)	–1.85* (–1.68)	–3.75*** (–2.95)	–1.22 (–1.31)	–1.73 (–1.58)	–3.60*** (–2.84)
Business Strategy	0.33 (0.36)	–1.71 (–1.60)	–0.94 (–0.76)	0.34 (0.38)	–1.70 (–1.58)	–0.98 (–0.79)
Sale of Target	2.06*** (2.77)	2.62*** (2.96)	3.45*** (3.39)	2.06*** (2.78)	2.61*** (2.97)	3.41*** (3.35)
Governance	–0.50 (–0.60)	0.42 (0.43)	1.17 (1.02)	–0.45 (–0.54)	0.56 (0.56)	1.37 (1.20)
Adj. R^2	0.007	0.016	0.022	0.008	0.017	0.019
<i>N</i>	1,144	1,144	1,144	1,144	1,144	1,144

Table 11**Profitability of 13D Trades by Execution Quality and Trade Type Across Time Intervals**

This table summarizes the profitability of 13D trades categorized by execution quality groups (high vs. low) and trade types (patient vs. impatient) across three time intervals: Day 0 (filing day), Day +5, and Day +10. Patient trades are defined as those executed 20 days or more before the filing date, while impatient trades refer to those executed closer to the filing date, following the methodology outlined by Bogousslavsky et al. (2024). Execution quality is evaluated using two measures: *ESP*, which directly reflects the effective spread of execution, and *AIPV(ESP)*, which adjusts for economic determinants of trading costs to capture execution-related cost reductions. Both measures follow the same methodology and calculation as in Table 9. Schedule 13D filers are divided into top and bottom halves based on these execution quality measures, and their VWAAAR is calculated and compared across groups. Panel A reports results for impatient trades, showing the differences in profitability between high- and low-execution-quality groups (High - Low). Panel B presents results for patient trades, using the same structure. Profitability is winsorized at the 1% and 99% levels. Returns are expressed in percentage terms.

		Filing Date + 0 Days		+ 5 Days		+ 10 Days	
Execution Quality	N	Profit	<i>t</i> -Statistics	Profit	<i>t</i> -Statistics	Profit	<i>t</i> -Statistics
Panel A: Impatient Trades							
ESP							
Execution Quality = Low	412	1.19%	(1.85)	3.01%	(3.97)	4.93%	(6.00)
Execution Quality = High	412	-0.09%	(-0.27)	1.14%	(2.91)	1.98%	(4.22)
High – Low		-1.28%	(-1.77)	-1.87%	(-2.19)	-2.95%	(-3.12)
AIPV (ESP)							
Execution Quality = Low	412	1.27%	(1.94)	3.33%	(4.32)	5.43%	(6.50)
Execution Quality = High	412	-0.19%	(-0.63)	0.81%	(2.23)	1.47%	(3.37)
High – Low		-1.46%	(-2.02)	-2.51%	(-2.95)	-3.96%	(-4.21)
Panel B: Patient Trades							
ESP							
Execution Quality = Low	395	1.54%	(1.89)	2.95%	(3.26)	4.96%	(5.20)
Execution Quality = High	395	1.24%	(1.30)	2.40%	(2.41)	3.37%	(3.33)
High – Low		-0.29%	(-0.24)	-0.56%	(-0.41)	-1.58%	(-1.14)
AIPV (ESP)							
Execution Quality = Low	395	1.71%	(2.08)	3.03%	(3.30)	5.09%	(5.25)
Execution Quality = High	395	1.07%	(1.12)	2.28%	(2.32)	3.19%	(3.20)
High – Low		-0.64%	(-0.51)	-0.74%	(-0.55)	-1.90%	(-1.37)

Table 12

Concealment Proxies at the Filing Level: Hedge Fund versus Non-Hedge Fund 13D Filers

This table reports filing-level means and medians of hiding and sophistication proxies for 13D filings with at least 10 matched trades in the TAQ Multiple Match sample. For each filing, each proxy is computed as the percentage of the filing's trades with the given characteristic; the table then reports the mean and median of these filing-level percentages across non-hedge fund and hedge fund filers. *Off-exchange share* is the fraction of trades reported through FINRA trade reporting facilities (TAQ exchange code D), and *ISO share* is the fraction flagged as intermarket sweep orders (sale condition F). *Midpoint share* and *inside-NBBO share* are the fractions of on-exchange trades executed at the midpoint and strictly inside the prevailing NBBO, respectively. *Odd-lot share* is based on trades below 100 shares and is measured from 2014 onward, when odd lots began to be reported to the SIP. *Last 30 min share* is the fraction of trades executed during the final half hour of trading. Off-exchange and ISO shares are measured over 2008–2021, after Regulation NMS. Under HF – Non-HF, the Mean column reports the difference in means, estimated from the filing-level regression $Proxy_f = \alpha + \beta_{HF} HF_f + \epsilon_f$, where HF_f equals one for hedge fund filers, with heteroskedasticity-robust t -statistics in parentheses; the Median column reports the difference in medians, with stars and p -values in brackets from a Wilcoxon rank-sum test of the null that the two distributions are identical. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Measure	Non-HF 13D		HF 13D		HF – Non-HF		
	Mean	Median	Mean	Median	Mean	Median	N filings
Off-exchange share (%)	27.47	21.98	25.39	19.13	-2.08 (-0.88)	-2.85 [0.33]	306
ISO share (%)	30.25	32.32	33.29	38.34	3.04 (1.04)	6.02 [0.25]	306
Midpoint execution share (%)	6.68	3.19	5.49	3.37	-1.19 (-1.47)	0.19 [0.85]	756
Inside-NBBO share (%)	35.06	33.56	38.84	39.62	3.78** (2.17)	6.05** [0.02]	756
Odd-lot share (%)	2.20	0.00	7.50	0.00	5.30 (1.26)	0.00 [0.21]	96
Last 30 min share (%)	20.75	18.23	23.31	20.00	2.56* (1.78)	1.77 [0.19]	759

Appendix A.1. Robustness Tests

Table A.1

Panel Regression of Illiquidity on 13D Trades: Stock-Day-Time Fixed Effects using TAQ Simple Match

This table reports the results from stock-day-time fixed-effect panel regressions to estimate the impact of 13D-reported trades on various Illiquidity measures. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t} = \beta_{13D} 13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t}$ where $IlliquidityMeasure_{i,s,d,t}$ represents one of the illiquidity measures for stock s on day d , calculated over 1-minute intraday intervals t with i indicating whether the 1-minute interval includes 13D trades (1) or not (0). The illiquidity measures include quoted spread (QSP), effective spread (ESP), price improvement ($PIMPRV$), realized spread (RSP), price impact ($PIMPCT$), size ($SIZE$), and dollar volume ($DVOL$). The indicator variable $13D$ equals 1 for trades reported under 13D filings and 0 otherwise. The model includes fixed effects for intraday 30-minute intervals, dates, stocks, and stock-by-date interactions to control for unobserved heterogeneity at various levels. Standard errors are clustered by stock and date to account for serial correlation and heteroskedasticity. The sample spans January 1994, to December 2021, with data aggregated at 1-minute intervals. The data used in this analysis is sourced from TAQ simple match. Coefficients for $13D$ measure its marginal impact on illiquidity measures relative to the baseline and are scaled by 10,000 to improve interpretability, except for $SIZE$ and $DVOL$, which retain their original units. Panel A compares 13D trades to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
<i>13D</i>	-0.58*** (-2.64)	-0.18 (-0.63)	-0.40* (-1.76)	-0.94*** (-2.73)	0.76*** (3.56)	494.92*** (4.69)	4737.31*** (2.88)
<i>Adjusted-R²</i>	0.62	-0.00	-0.01	-0.00	0.14	0.03	0.05
<i>N</i>	1,661,469	1,661,469	1,661,469	1,661,469	1,661,469	1,661,469	1,661,469
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
<i>13D</i>	-0.35*** (-4.29)	-0.26* (-1.67)	-0.10 (-0.64)	-0.46* (-1.80)	0.20 (1.11)	169.21** (2.16)	-112.97 (-0.08)
<i>Adjusted-R²</i>	0.84	0.70	0.38	0.44	0.25	0.38	0.22
<i>N</i>	241,726	241,726	241,726	241,726	241,726	241,726	241,726
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.2

Panel Regression of Illiquidity on 13D Trades: Stock-Day-Time Fixed Effects using TAQ Unique Match

This table reports the results from stock-day-time fixed-effect panel regressions to estimate the impact of 13D-reported trades on various illiquidity measures. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t} = \beta_{13D} 13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t}$ where $IlliquidityMeasure_{i,s,d,t}$ denotes one of the illiquidity measures, estimated as the average of all trades for stock s on day d within the 1-minute interval t , calculated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$). The illiquidity measures include quoted spread (QSP), effective spread (ESP), price improvement ($PIMPRV$), realized spread (RSP), price impact ($PIMPCT$), size ($SIZE$), and dollar volume ($DVOL$). The indicator variable $13D$ equals 1 for trades reported under 13D filings and 0 otherwise. The model includes fixed effects for intraday 30-minute intervals, dates, stocks, and stock-by-date interactions to control for unobserved heterogeneity at various levels. Standard errors are clustered by stock and date to account for serial correlation and heteroskedasticity. The sample spans January 1994, to December 2021, with data aggregated at 1-minute intervals. The data used in this analysis is sourced from TAQ unique match. Coefficients for $13D$ measure its marginal impact on illiquidity measures relative to the baseline and are scaled by 10,000 to improve interpretability, except for $SIZE$ and $DVOL$, which retain their original units. Panel A compares 13D trades to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
<i>13D</i>	-0.54 (-1.19)	2.05** (2.49)	-2.59*** (-3.37)	-1.31 (-1.50)	3.37*** (5.68)	2316.14*** (6.93)	31759.39*** (6.77)
<i>Adjusted-R2</i>	0.62	-0.00	-0.01	-0.00	0.14	0.04	0.05
<i>N</i>	1,543,182	1,543,182	1,543,182	1,543,182	1,543,182	1,543,182	1,543,182
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
<i>13D</i>	-0.81*** (-2.82)	0.35 (0.64)	-1.16** (-2.10)	-1.06 (-1.39)	1.41** (2.48)	1683.44*** (5.53)	25386.47*** (5.46)
<i>Adjusted-R2</i>	0.84	0.72	0.43	0.41	0.23	0.35	0.22
<i>N</i>	55,528	55,528	55,528	55,528	55,528	55,528	55,528
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.3**Panel Regression of Illiquidity on 13D Trades: Stock-Day-Time Fixed Effects using TAQ Collapsed Multiple Match**

This table reports the results from stock-day-time fixed-effect panel regressions to estimate the impact of 13D-reported trades on various Illiquidity measures. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t} = \beta_{13D} 13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t}$ where $IlliquidityMeasure_{i,s,d,t}$ represents one of the illiquidity measures for stock s on day d , calculated over 1-minute intraday intervals t with i indicating whether the 1-minute interval includes 13D trades (1) or not (0). The illiquidity measures include quoted spread (QSP), effective spread (ESP), price improvement ($PIMPRV$), realized spread (RSP), price impact ($PIMPCT$), size ($SIZE$), and dollar volume ($DVOL$). The indicator variable $13D$ equals 1 for trades reported under 13D filings and 0 otherwise. The model includes fixed effects for intraday 30-minute intervals, dates, stocks, and stock-by-date interactions to control for unobserved heterogeneity at various levels. Standard errors are clustered by stock and date to account for serial correlation and heteroskedasticity. The sample spans January 1994, to December 2021, with data aggregated at 1-minute intervals. The data used in this analysis is sourced from TAQ Collapsed Multiple match. Coefficients for $13D$ measure its marginal impact on illiquidity measures relative to the baseline and are scaled by 10,000 to improve interpretability, except for $SIZE$ and $DVOL$, which retain their original units. Panel A compares 13D trades to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
<i>13D</i>	-1.55*** (-4.94)	-0.94*** (-3.14)	-0.61*** (-2.91)	-2.36*** (-6.53)	1.42*** (6.43)	319.85*** (3.46)	2049.60 (1.51)
<i>Adjusted-R2</i>	0.62	0.00	-0.01	-0.00	0.14	0.03	0.05
<i>N</i>	1,756,492	1,756,492	1,756,492	1,756,492	1,756,492	1,756,492	1,756,492
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
<i>13D</i>	-0.87*** (-6.17)	-0.34*** (-2.59)	-0.53*** (-3.60)	-2.01*** (-6.31)	1.68*** (5.98)	30.91 (0.43)	-2231.06* (-1.77)
<i>Adjusted-R2</i>	0.82	0.69	0.35	0.41	0.26	0.40	0.20
<i>N</i>	321,536	321,536	321,536	321,536	321,536	321,536	321,536
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4

Panel Regression of Illiquidity Measures on 13D Indicator and Limit Order Indicator with Stock-Day-Time Fixed Effects with Collapsed Simple Match

This table extends the analysis in Table 3 by distinguishing between market and limit orders for 13D-reported trades. The regression model includes a MKT_13D indicator, set to 1 for 13D trades executed as market orders and 0 for non-13D trades, and a $LIMIT_13D$ indicator, set to 1 for 13D trades executed as limit orders and 0 for non-13D trades. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t} = \beta_{MKT_13D}MKT_13D_{i,s,d,t} + \beta_{LIMIT_13D}LIMIT_13D_{i,s,d,t} + FE + \epsilon_{i,s,d,t}$ where $IlliquidityMeasure_{i,s,d,t}$ denotes one of the illiquidity measures, estimated as the average of all trades for stock s on day d within the 1-minute interval t , calculated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$). The classification of $LimitOrder$ is determined by comparing the order direction reported in the filing with the direction identified using the Lee and Ready (1991) algorithm. A 13D trade is classified as a market order if the two directions align, and as a limit order if the two directions are opposite. For non-13D trades, we assume all transactions are executed as market orders. Since all trades classified as limit orders are 13D trades, the 13D trades are further classified into market 13D trades (MKT_13D) and limit 13D trades (LIMIT_13D). Methodology and scaling are consistent with Table 2. Specifically, all coefficients are scaled by 10,000, except those associated with SIZE and DVOL. Standard errors are clustered by stock and date to address serial correlation and heteroskedasticity. The sample spans January 1994 to December 2021, with data aggregated at 1-minute intervals, sourced from TAQ collapsed simple match. Panel A compares 13D trades (market and limit orders) to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
MKT_13D	-1.23*** (-4.36)	-1.40*** (-3.72)	0.17 (0.56)	-3.45*** (-6.73)	2.05*** (5.96)	478.95*** (4.59)	5887.30*** (3.20)
$LIMIT_13D$	-1.43*** (-4.61)	0.01 (0.03)	-1.44*** (-4.34)	-1.37*** (-2.90)	1.38*** (3.97)	526.25*** (4.37)	3486.53** (2.22)
<i>Adjusted-R2</i>	0.62	-0.00	-0.01	-0.00	0.13	0.03	0.05
N	1,672,722	1,672,722	1,672,722	1,672,722	1,672,722	1,672,722	1,672,722
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
MKT_13D	-0.67*** (-4.92)	-0.65*** (-3.12)	-0.02 (-0.08)	-2.12*** (-4.60)	1.47*** (3.76)	175.60** (2.16)	798.39 (0.50)
$LIMIT_13D$	-0.97*** (-5.85)	-0.11 (-0.54)	-0.86*** (-3.49)	-1.30*** (-3.19)	1.19*** (2.95)	240.12** (2.58)	45.38 (0.03)
<i>Adjusted-R2</i>	0.85	0.70	0.38	0.36	0.19	0.39	0.21
N	229,576	229,576	229,576	229,576	229,576	229,576	229,576
<i>StockDayTimeFE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5

Panel Regression of Illiquidity Measures on 13D Indicator and Buy Indicator with Stock-Day-Time Fixed Effects with Collapsed Simple Match

This table extends the analysis from Table 3 by differentiating between buy and sell orders for 13D-reported trades. In addition to the 13D indicator, the model incorporates a *Buy* indicator set to 1 for buy trades and 0 for sell trades, along with the interaction term $13D \times Buy$. The regression model is specified as: $IlliquidityMeasure_{i,s,d,t,b} = \beta_{13D}13D_{i,s,d,t,b} + \beta_{Buy}Buy_{i,s,d,t,b} + \beta_{13D \times Buy}(13D \times Buy)_{i,s,d,t,b} + FE + \epsilon_{i,s,d,t,b}$ where $IlliquidityMeasure_{i,s,d,t,b}$ denotes one of the illiquidity measures, estimated as the average of all trades for stock s on day d within the 1-minute interval t , calculated separately for 13D trades ($i = 1$) and non-13D trades ($i = 0$), as well as for trade directions b . For 13D trades, order direction is classified based on the details provided in the filing. For non-13D trades, it is determined using the Lee and Ready (1991) algorithm. Unlike Tables 2 and 3, this table further segments each 1-minute time unit (t) by both 13D versus non-13D trades and buy versus sell trades. This additional categorization increases the number of observations compared to the earlier tables. All coefficients are scaled by 10,000, except those associated with SIZE and DVOL. The sample spans January 1994 to December 2021, with data aggregated at 1-minute intervals and sourced from TAQ Collapsed Simple match. Panel A compares 13D trades (buy and sell orders) to all trades within the same stock-day, while Panel B focuses on trades occurring in the same 1-minute intervals. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and * respectively. t -statistics are in parentheses below the coefficients.

Variable	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
13D	-0.93*** (-3.13)	-1.44 (-1.63)	0.51 (0.58)	-3.41*** (-3.55)	1.97*** (5.86)	-107.42*** (-3.42)	-4267.83*** (-3.87)
Buy	0.39*** (3.69)	-2.49 (-1.51)	2.88* (1.74)	-1.95 (-1.18)	-0.54*** (-3.12)	-37.99** (-2.52)	-445.58 (-0.76)
$13D \times Buy$	-0.73** (-2.47)	2.57 (1.42)	-3.29* (-1.82)	1.38 (0.75)	1.18** (2.30)	1039.00*** (6.11)	15357.53*** (5.55)
Adjusted-R ²	0.58	-0.00	-0.00	-0.00	0.08	0.03	0.04
N	2,405,157	2,405,157	2,405,157	2,405,157	2,405,157	2,405,157	2,405,157
StockDayTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
13D	-0.64*** (-3.82)	-1.20*** (-5.48)	0.56*** (3.13)	-3.70*** (-6.48)	2.50*** (5.17)	-139.02*** (-4.13)	-6329.11*** (-4.24)
Buy	-0.02 (-0.15)	-2.59*** (-7.60)	2.57*** (8.02)	-2.92*** (-4.23)	0.32 (0.55)	-21.46 (-0.51)	-1642.90 (-1.39)
$13D \times Buy$	-0.37** (-2.07)	2.66*** (6.18)	-3.03*** (-7.11)	2.26*** (3.67)	0.40 (0.80)	629.29*** (3.97)	12128.82*** (4.20)
Adjusted-R ²	0.83	0.68	0.35	0.30	0.14	0.26	0.10
N	279,342	279,342	279,342	279,342	279,342	279,342	279,342
StockDayTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.6

Panel Regression of Liquidity Measures on 13D, Buy, and 13D Limit Order Indicators with Stock-Day-Time Fixed Effects

This table extends Tables 5 and 6 by jointly distinguishing trade direction and order type for 13D-reported trades. The regression is: $LiquidityMeasure_{i,s,d,t,b} = \beta_{13D}13D_{i,s,d,t,b} + \beta_{Buy}Buy_{i,s,d,t,b} + \beta_{Limit_13D}Limit_13D_{i,s,d,t,b} + \beta_{13D \times Buy}(13D \times Buy)_{i,s,d,t,b} + \beta_{Buy \times Limit_13D}(Buy \times Limit_13D)_{i,s,d,t,b} + FE + \epsilon_{i,s,d,t,b}$, where $LiquidityMeasure_{i,s,d,t,b}$ is the average across trades for stock s on day d within 1-minute interval t , computed separately by 13D status i and trade direction b . Direction is taken from the filing for 13D trades and inferred via Lee and Ready (1991) for non-13D trades; $Limit_13D$ identifies 13D limit orders following Table 5. Because limit orders are identified only for 13D trades, interactions of $13D$ with $Limit_13D$ are collinear and omitted; $Buy \times Limit_13D$ thus captures how the buy–sell gap of 13D limit orders differs from that of 13D market orders. Coefficients are scaled by 10,000 except SIZE and DVOL. Standard errors are clustered by stock and date. The sample spans January 1994–December 2021 (TAQ simple match). Panel A compares 13D trades to all trades within the same stock-day; Panel B restricts to the same 1-minute intervals. t -statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	QSP	ESP	PIMPRV	RSP	PIMPCT	SIZE	DVOL
Panel A: 13D vs trades throughout the day							
13D	-0.48** (-2.27)	-0.39 (-0.47)	-0.09 (-0.11)	-1.32 (-1.53)	0.93*** (3.28)	-116.30*** (-3.74)	-4910.61*** (-4.36)
Buy	0.40*** (3.74)	-2.51 (-1.51)	2.91* (1.74)	-2.01 (-1.21)	-0.50*** (-2.91)	-40.47*** (-2.72)	-641.01 (-1.11)
Limit_13D	0.09 (0.52)	-2.01*** (-5.64)	2.10*** (6.52)	-2.18*** (-3.52)	0.18 (0.42)	-11.98 (-0.64)	-138.96 (-0.36)
13D × Buy	-0.13 (-0.46)	-0.55 (-0.32)	0.42 (0.25)	-2.12 (-1.18)	1.57** (2.40)	789.00*** (5.76)	14706.36*** (5.64)
Buy × Limit_13D	-0.32 (-0.92)	6.92*** (8.45)	-7.24*** (-8.55)	8.11*** (5.86)	-1.19 (-1.10)	137.81 (1.23)	-1920.99 (-1.29)
Adjusted-R ²	0.59	-0.00	-0.00	-0.00	0.08	0.03	0.03
N	2,439,601	2,439,601	2,439,601	2,439,601	2,439,601	2,439,601	2,439,601
StockDayTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 13D vs trades within the same interval							
13D	-0.29*** (-2.67)	-0.43* (-1.95)	0.14 (0.74)	-1.50*** (-4.32)	1.07*** (3.79)	-165.93*** (-5.62)	-7171.08*** (-4.83)
Buy	-0.03 (-0.21)	-2.59*** (-7.87)	2.56*** (8.29)	-2.76*** (-4.56)	0.17 (0.32)	-28.91 (-0.83)	-1884.30* (-1.87)
Limit_13D	-0.14 (-0.83)	-1.82*** (-5.53)	1.68*** (6.03)	-2.14*** (-3.22)	0.31 (0.64)	7.23 (0.59)	250.21 (0.95)
13D × Buy	-0.07 (-0.34)	0.14 (0.48)	-0.21 (-0.73)	-0.37 (-0.77)	0.51 (1.10)	414.19*** (3.55)	10950.92*** (4.31)
Buy × Limit_13D	-0.23 (-0.87)	5.09*** (7.58)	-5.32*** (-7.68)	5.78*** (3.85)	-0.70 (-0.52)	139.03* (1.84)	-544.58 (-0.42)
Adjusted-R ²	0.79	0.66	0.32	0.25	0.09	0.25	0.11
N	347,622	347,622	347,622	347,622	347,622	347,622	347,622
StockDayTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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