Stealth-trading: Which traders' trades move stock prices?[☆]

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Abstract

Using audit trail data for a sample of NYSE firms we show that medium-size trades are associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume. This result is consistent with the predictions of Barclay and Warner's (1993) stealth-trading hypothesis. We find that the source of this disproportionately large cumulative price impact of medium-size trades is trades initiated by institutions. This result is robust to various sensitivity checks. Our findings appear to confirm street lore that institutions are informed traders. © 2001 Elsevier Science S.A. All rights reserved.

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1. Introduction

Extant theoretical research posits that an investor with private information will tend to trade gradually in order to profit before his trades fully reveal the information (see, for example, Kyle (1985) and Admati and Pfleiderer (1988)).[1] Barclay et al. (1993) argue that if informed investors' trades are the main cause of stock price changes and informed traders concentrate their trades in trades of certain sizes – not too large (which could give them away) and not too small (too expensive in terms of trading costs) – then most of a stock's cumulative price change should take place on trades of medium-sizes. We would then expect to see medium-size trades display a disproportionately large cumulative price change relative to their overall proportion of trades and/or volume. This is the "stealth-trading" hypothesis, whose validity is an empirical issue. Barclay and Warner examine a sample of 108 tender offers between 1981 and 1984 and find that medium-size trades (defined as trades of 500–9,999 shares) account for an estimated 92.8% of the cumulative price-change during the pre-tender offer announcement period. These, and related findings they report, support the stealth-trading hypothesis.

In an effort to enrich our understanding of the stealth-trading hypothesis, we attempt to link the price impact of a trade of a specific size with whether the trade was initiated by individual investors and institutions – the two main investment groups. Our bifurcation of the sample is, in part, motivated by prior research that indicates that these two investor groups may differ in their level of sophistication in response to information, with the implication being that institutions are "smart," or informed, traders.[2]

To maximize the probability of detecting stealth-trading, we restrict attention only to stocks in the data that displayed a significant price increase over the sample period. The intuition behind selecting stocks with significant price increases is that any (possible) stealth-trading activity is likely to be focused on one side of the market and can be detected by our tests. We do not condition the sample on any particular information event.

Defining a price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade, we initially show that medium-size trades are associated with the highest cumulative stock price

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[1] Numerous other studies have also investigated the impact of trades on stock prices. See, for example, Easley and O'Hara (1987, 1992a,b), Burdette and O'Hara (1987), Holthausen et al. (1987), Ball and Finn (1989), Seppi (1990), Hasbrouck (1991a,b), Grossman (1992), Madhavan and Smidt (1991, 1993), Chan and Lakonishok (1993, 1995), Huang and Stoll (1994), Bertsimas and Lo (1996) and Keim and Madhavan (1996).

[2] See Arbel and Strebel (1983), Bhusan (1989), Lo and MacKinlay (1990), Hand (1990), Lee (1992), Meulbroek (1992), Cornell and Sirri (1992), Badrinath et al. (1995), Sias and Starks (1997), Chakravarty and McConnell (1997, 1999), Walther (1997) and Koski and Scruggs (1998).

change (about 79%) across all trade sizes. This result is consistent with the prediction of the stealth-trading hypothesis.

Upon further decomposition of trades into those initiated by institutions and by individuals, we find that almost all of the 79% cumulative stock price change is associated with medium-size trades initiated by institutions. Put differently, medium-size institutional trades cause a disproportionately larger proportion of cumulative price change than would be warranted based either on their proportion of all trades or on their proportion of the total volume. Our results appear to confirm that the root of stealth-trading lies in trades by institutions, one implication of which is that institutions are informed traders. We also perform several sensitivity checks to ensure the robustness of our results. Notable among them is the recognition, and control, for larger medium-size institutional trades relative to medium-size individual trades. The significantly large contribution of medium-size institutional trades to the overall disproportionately large cumulative price impact of medium-size trades, is also evident throughout the universe of stocks in our data set. The evidence, however, is relatively stronger in large firms.

The remainder of the paper is arranged as follows. Section 2 provides details of the data, including sample selection and classification of trades. Section 3 provides the analyses. Section 4 provides sensitivity checks. Section 5 concludes.

2. Data and classification procedures

Almost all publicly available data restrict the nature and quality of inferences that can be made about the origin of the orders behind the reported trades. But, the TORQ data that we use in our analysis contain information on trades, quotes, order processing, and audit trails for a size-stratified random sample of NYSE stocks, for the three-month period of November 1990 through January 1991 (63 trading days). The selection process ensures that the stocks in the sample are representative of the population of all NYSE stocks. Hasbrouck (1992) provides other relevant details on this process. The usefulness/representativeness of the TORQ data is evident in its widespread use in previous research such as Hasbrouck (1996), Sias and Starks (1997), Koski and Scruggs (1998), Angel (1998), Chung et al. (1999) and Ready (1999).

The data consist of four files: (1) the consolidated trade file, (2) the consolidated quote file, (3) the system order database (SOD) file, and (4) the consolidated audit file. The first two, the trade and quote files, are essentially similar to what is available through ISSM or TAQ data sets. It is the last two files, particularly the audit file that makes the TORQ data set unique, and is the one we use for the current analysis. The NYSE maintains the audit trail records for surveillance and general management information purposes, and

Hasbrouck et al. (1993) report that the overall accuracy of the audit trail is approximately 98%.

The audit file seeks to provide a detailed description of each trade, including price, time, volume, and identities of the participants. The focus of this study is the initiating trader of a transaction and the impact of that trade on price. Initiating trades are, almost always, market orders. Yet, there are three ways in which an initiating order can be a limit order. The first, and most likely, case occurs when the order happens to be a marketable limit order (which is like a market order) or when limit orders cross inside the spread. Second, and less likely, the limit order could be matched with a market order that has been stopped, or the limit order appears the second after the market order and the price of the limit order improves upon the existing quote. But it is debatable if these transactions can be classified as being initiated by a limit order. Third, and least likely, is if the specialist took the other side of a limit order, then the limit order would be viewed as the trade initiator. We discuss identification of the trade initiator in Section 2.3.

The comprehensiveness of the audit file is achieved through a synthesis of a variety of computerized and paper sources. For example, the Consolidated Trade System contains price, time, and volume, but not trader identities (or account-type information), and corresponds to orders from the following sources: (1) SuperDOT (Digital Order Turnaround), the electronic order submission system; (2) the Opening Automated Report System used at market openings; and (3) the Intermarket Trading System (ITS) used to transfer orders between market centers. The clearing records for the individual brokerage firms contain price, time, and account type information – but not necessarily an accurate time stamp. Specifically, the account-type information is obtained as follows. At the end of each trading day, any exchange member (brokerage firm) submitting a trade is asked to furnish details about the trade. If the trade is from the member itself for its personal account, it is classified as Account Type *P*. It does not include trades by specialists. Inferring specialist trades from TORQ data is not easy. As conversations with exchange officials reveal, trades by specialists have the corresponding account type and order type identifiers stripped out of the TORQ data for confidentiality purposes. Recently, Chung et al. (1999) have attempted to measure how much of a quote reflects the trading interest of the specialist, the limit order book or both. If a trade is from an individual investor, the order is classified as Account Type *I*. Brokers are encouraged to provide this information, so that their clients can receive preferential routing through the Individual Investor Express Delivery Service (IIEDS). Finally, if a trade is from an institution, it is classified as Account Type *A*. This could also include trades from the exchange member itself representing another exchange member. However, discussions with exchange officials indicate that a vast majority of trades under the *A* classification are non-exchange member institutional trades.

For the current analysis, we combine the Account Types *P* and *A* into trades from institutions, under the assumption that almost all exchange members are, arguably, institutions. But, to ensure that our results are not an artifact of this assumption, we replicate our analysis with only Account Type *A* trades as institutional trades, and obtain virtually identical results.

While the reporting by the brokerages on the Account Type variable is not independently monitored, there is little reason to suspect broker misrepresentation. As Radhakrishna (1994) reports, the total volume of individual trades in the TORQ data is similar to the total volume of individual trades estimated by Securities Industry Association (SIA) over the same time period. The SIA estimation procedure is based on an independent data source, namely the regulatory filings by institutional investors.

Although the audit file is the only publicly available data that can shed light on the parties behind transactions, in determining their relative impact on prices, the data includes only orders submitted through the electronic routing systems. Specifically, these SuperDOT orders can originate from terminals in member firm's branch offices or from a customer's office. Upon arrival, SuperDOT orders appear on the screen of the specialist's display book. If one or both sides of a transaction are orders that have been hand-carried to the specialist's post by floor brokers, the audit trail information of such orders is missing. The transaction-related information, however, is complete and represents the entire scope of trading activities on the corresponding stocks.

2.1. Sample selection

To maximize the probability of detecting stealth-trading, we restrict attention only to stocks in the data that displayed a significant price increase over the sample period. Barclay and Warner also *initially* restrict attention to a sample of tender-offer targets, which display abnormal price increases before the initial tender-offer announcement. The authors argue that some traders may have valuable private information during the preannouncement period. Our partitioning is in the same spirit. Accordingly, we select 97 stocks that had at least a 5% price increase over the three-month period covered by the data. The average price increase of the 97 stocks in our sample is 28% with a maximum price increase of 124%. Since the market increase over the same period was about 12%, the stocks in our sample represent a spectrum of activity over and above the market increase. Any stealth-trading activity, if present, is therefore likely to be detected by our tests.

It is, of course, theoretically possible that stocks displaying a significant price decrease are also likely to have significant insider activity (on the sell side) and should display evidence of stealth-trading. In reality, however, insider sales are more restrictive than insider purchases. For example, the Securities Exchange Act of 1934 prohibits corporate insiders from short selling.

Thus, it is not clear if insiders would be active in declining stocks, and even if they were, if the direction of their trades would necessarily be informative. Additionally, the TORQ data are limited in the number of stocks with a significant price decrease over the sample period. Specifically, only 14 stocks display a price decrease of 5% or more, over the sample period, and most of these appear to be relatively thinly traded. Thus, the reliability of any conclusions made from analyzing such stocks is questionable. Investigating stocks showing little or no price changes over the sample period is also problematic. Such stocks probably have informed trading activities on both sides of the market, and it is difficult to reliably estimate stealth-trading in those cases.

2.2. Identifying individual and institutional trades

To attribute the price response to an order with certain characteristics, we need to establish that such orders are, at least partially, identified by some market participants, including the market maker. In our case, these characteristics involve the identification of whether an order originated from an individual investor or an institutional client.

Aside from the basic features of an order necessary for its proper execution, such as ticker symbol, buy/sell, market/limit, size, and price (if limit), the market maker knows, or can deduce, further information about incoming orders, especially if an order is from an institutional or a retail (individual) investor, as they flash on his computer screen. For example, the size of an order itself can sometimes provide important clues. Larger orders are more likely to be from institutions than individuals. If a market maker is curious about the origin of an order, he can go to a special screen on his monitor that provides him with certain mnemonics through which he may identify the submitting broker's identity. Over time, specialists believe they can recognize patterns in trades associated with certain mnemonics and, in turn, deduce the trader type behind an order.[3] In sum, all evidence points to the probability that market makers are able to deduce the trader type submitting the order, should they be interested.

A practical reason for market makers wanting to keep track of who is behind an order is that the trades of certain investors (or investor-groups) are followed and mimicked by other investors. This is known as "follow-on trading" and has been discussed by many researchers (see, for example, Barclay and Dunbar (1996), Chakravarty and McConnell (1997, 1999) and Chakravarty and Sarkar (1998)). Given that such practices can seriously jeopardize the profits of market makers, their self-preservation instinct itself will dictate their attempting to discover the identity behind certain trades. That way, they can proactively

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[3] I thank Joel Hasbrouck for providing these insights in private conversations.

manage their spreads and the corresponding spread sizes to protect themselves from adverse market conditions.

Finally, Hasbrouck (1996) assumes that market participants are able to distinguish between program and non-program trades within the context of the TORQ data. And, more relevant to us, Sias and Starks (1997, p. 109) use the TORQ data to test if institutional holdings can effectively proxy for institutional trading – a procedure that requires the assumption that the specialist is able to distinguish between individual and institutional trades.

2.3. Relationship between orders and trades

All publicly available transaction data sets suffer from two important drawbacks that adversely affect the current analysis. First, the reported transactions do not have a one-to-one correspondence with the orders that make up the transaction. This is an important distinction because, as Bronfman (1992) reports, transactions data, such as those employed by Barclay and Warner, do not always have a one-to-one correspondence with individual orders. Thus, an 800-share transaction reported in the data could represent a paring of a market buy order for 800 shares with two market sell orders for 400 shares each. But the specialist could report this trade either as a single transaction of 800 shares (a medium-size trade) or as two transactions of 400 shares each (small-size trades). This introduces noise in the system in trying to determine the effect of trade-size on price change. Second, the audit file in TORQ does not identify whether the buyer or the seller in a transaction was the trade initiator.

Since the market maker has the freedom to report a transaction in multiple ways, absent a direct mapping between a trade and its underlying orders, it is unreliable to use transactions data directly to measure the effect of trade size on stock prices. The audit file of the TORQ data set, however, identifies the traders (and their order sizes) on either side of a transaction.

But, even with this correspondence between orders and transactions, the initiating order side may have multiple parties involved in the trade. For example, a 5,000-share buyer-initiated transaction may comprise of an individual buyer for 2,000 shares and an institutional buyer for 3,000 shares, matched with an institutional seller for 5,000 shares. This would make a difficult, if not impossible, task of identifying whose trades impacted the price change. We overcome this hurdle by eliminating all transactions where the active (or, initiating) side has less than 100% participation in any single trader type. Thus, if the initiating buy side of a 20,000-share trade has four traders each with a 5,000-share order, and if all four are institutional buyers, the observation is included in our data. Using this filter, we are left with 151,367 (a little over 60% of the initial) observations in the audit file in the 97 chosen stocks. This is the sample used in the current study.

For robustness purposes, however, we replicated the analysis using the less stringent 90% and 75% and 50% cutoff rules, successively. That is, we eliminated all transactions where the initiating side of a transaction has less than 90%, 75% and 50% participation, respectively, in any specific trader-group. Hence, if 15,000 shares (out of a 20,000-share, buyer-initiated, trade) are from three institutional buyers and a 5,000-share order is from a single individual buyer, then under the 75% cutoff rule, we would still classify this transaction as an institution-initiated trade. Using the 50% cutoff rule (the least stringent inclusion criterion), we retain over 80% of the initial observations. The tradeoff in using progressively less (more) stringent cutoff rules is between including more (less) observations and introducing more (less) noise and, thereby, lowering (increasing) the power of our tests to detect stealth-trading. The results, through these successive iterations, however, remain materially similar.

It is important to infer the initiator of a trade (buyer or seller) because all extant theories of market microstructure, modeling the impact of trades on prices and other observables, are based on the trade initiator. O'Hara (1995) provides a survey on this impact. Hence, the validity of all economic studies, based on such theories, also hinges critically on the *accurate* classification of trades as buyer- or seller-initiated.

We use the Lee and Ready (1991) algorithm to classify trades as buyer- or seller-initiated. Thus, if a trade occurs at the prevailing bid (ask) or anywhere between the bid (ask) and the midpoint of the prevailing bid-ask spread, it is considered a seller-initiated (buyer-initiated) trade. For trades occurring at the prevailing spread midpoint, the tick test rule is applied to determine the trade initiator, whereby a trade is buyer-initiated (seller-initiated) if the price move from the previous transaction price is upwards (downwards). Also, the prevailing spread is assumed to be at least five seconds old. Otherwise, the previous quote is used to compute the prevailing spread.

Recently, Odders-White (1999) has proposed an alternative classification scheme whereby the initiator of a transaction is the investor (buyer or seller) who placed his order last, chronologically. As a robustness check, we repeat our analyses with this alternative classification scheme to verify that our results are not sensitive to the particular classification scheme. The results are virtually identical.

3. Analyses

In this section, our primary objective is to document how much of a security's cumulative price change over the sample period is attributable to trades in each size category. Consistent with Barclay et al. (1993), we define small-size trades as trades of 100–499 shares; medium-size trades as trades

between 500 and 9,999 shares; and large-size trades as trades of 10,000 shares or greater.

3.1. Cumulative stock price changes and trade size

We test if the proportion of the cumulative price change associated with trades in each size category is the same as the proportion of trades (and/or the proportion of volume) in each category. If stealth-trading exists, we would expect to see medium-size trades display a disproportionately larger proportion of cumulative price change relative to their proportion of all trades (and volume) in the sample. Alternatively, if the cumulative price change occurring in trades in a given size category is directly proportional to the fraction of transactions in that category, it would indicate that most stock price changes are caused by the release of public information (the public information hypothesis). Yet another alternative, following from the idea that large trades should move prices more than do small trades, is where the cumulative price change in each trade-size category is proportional to the fraction of the total trading volume in that category (the trading volume hypothesis).

We define a price change that occurs on a given trade as the difference between the trade's price and the price of the previous transaction. Corresponding to each trade in the audit file, the previous trade is identified from the transactions file (by time and a unique identification number that links the two files) that lists all transactions in that stock.

Our method of computing the cumulative stock price return follows Barclay et al. (1993). For each of the 97 stocks, we sum all price changes that occur on trades in a given trade size category over the sample of observations. We then divide this sum by the cumulative price change for the stock over the sample. Finally, we estimate the weighted cross-sectional mean of the cumulative stock price change (over the 97 stocks) where the weights are the absolute value of the cumulative price change in each stock over the sample.

For the cross-section of 97 stocks, Table 1 reports the mean percentage of the cumulative stock price changes, the corresponding numbers and percentages of trades, and the volume and volume percentages in each of the three trade size categories.

From Table 1, most of the cumulative price change occurs in medium-size trades. Trades in this category cause about 79% of the cumulative price change in our sample and comprise 57% of the transactions and 47% of the volume. The large-size trades cause about 25% of the cumulative price change and comprise 6% of the transactions and 51% of the volume. The small-size trades cause about −4% of the cumulative price change and comprise 36% of transactions and 3% of the volume. Thus, medium-size trades appear to have a disproportionately large role in the cumulative price change, relative to their

Table 1

Cumulative price change, trades, and volume by trade sizes

The table provides the mean percentage of the cumulative stock price change, percentage of trades, and percentage of share volume by trade size. Trade sizes are classified as small (100 to 499 shares), medium (500 to 9,999 shares), and large (10,000 + shares). A stock price change corresponding to a specific trade is defined as the difference between that trade's price and the price of the previous trade. For each stock, the percentage of cumulative price change for a trade of a given size is the sum of all stock price changes occurring on trades in that size category divided by the total cumulative price change in that stock over the sample. The weighted cross-sectional mean of the cumulative stock price change are then estimated and reported below where the weights are the absolute value of the cumulative price change of each stock in the sample. The proportion of trade (volume) is the sum of all transactions (volume), in a given size category, divided by the total cumulative trade (volume) in the sample. The sample consists of 97 NYSE firms in the TORQ database with significant price increases between November 1, 1990 and January 31, 1991.

Trade size	% of cumulative price change	Number of trades	% of trades	Volume	% of volume
Small (100–499 shares)	−3.86	55,129	36.42	10,973,600	2.81
Medium (500–9999 shares)	78.63	86,807	57.35	182,056,300	46.69
Large (10,000 + shares)	25.23	9,431	6.23	196,913,600	50.50

proportion of trades and volume in the sample – a result consistent with that of Barclay and Warner and the predictions of the stealth-trading hypothesis.

There also appears to be little support for the public information hypothesis. Small trades cause about −4% of the cumulative price change but account for 36% of all trades, while large trades cause about 25% of the cumulative price change but comprise only 6% of all trades in the sample. The hypothesis that the percentage cumulative price change equals the percentage of trades is rejected at the 1% level. The trading volume hypothesis also appears without support. While the medium-size trades cause about 79% of the cumulative price change and comprises 47% of the volume, the large-size trades cause about 25% of the cumulative price change and comprises 51% by volume. The hypothesis that the percentage cumulative price change equals the volume percentage is rejected at the 1% level. We also use the non-parametric Spearman rank correlation test between the cumulative price change in each trade size category and the corresponding proportion of trades on a stock-by-stock basis and find that the correlation between the two is insignificantly different from zero at the 5% level. The implication is that the cumulative price changes in each trade size category and the corresponding proportion of trades are randomly paired and not proportional to one another. Further, a Spearman rank correlation test between the cumulative price change in each trade size category and the corresponding proportion of volume finds that the correlation between the two is insignificantly different from zero at the 5% level.

3.2. Cumulative stock price changes, trade size, and trader identity

Table 2 presents descriptive data on the average percent of cumulative stock price change for trades initiated by each trader group in each of the three trade size categories, the corresponding number and percentage of trades, and the volume and volume percentages. In estimating the percentages of cumulative price run-up, the denominator is the cumulative price change on all trades of all sizes in our sample. Well over 90% of the cumulative price run up takes place in the trades we study. The computation of these variables is discussed in Section 3.1. The discrepancy in the number of observations in each trade size category, between Tables 1 and 2, is due to the fact that, in some observations, whether the trade initiator is the buyer or the seller cannot be uniquely determined. Hence, these observations cannot be classified as originating from either individuals or institutions.

Large-size trades by institutions are associated with a cumulative price change of about 23% of the total cumulative price change across all trade sizes and trader types in our sample. In contrast, large-size individual trades are only associated with about 1% cumulative price change, even though the average individual and institutional trade sizes are roughly comparable at 19,000 ($\approx 10,383,800/547$) and 20,400 ($\approx 158,856,300/7,797$) shares, respectively. The implication is that, relative to large-size individual trades, large institutional trades are considered informed trades by the market, resulting in their significantly greater cumulative price impact.

More interestingly, however, medium-size trades initiated by institutions cause the highest average cumulative price change, of about 79%, across all trade sizes and trader types in our sample and comprise 40% of the trades and 38% of the volume. In contrast, medium-size trades initiated by individuals cause an average cumulative price change of about -2%, and comprise 14% of the trades and 7% of the volume.

Based on the evidence, stealth-trading appears to be primarily driven by medium-size trades initiated by institutions. Specifically, about 103% (-3%) of the cumulative price change associated with medium-size trades is attributable to institutional (individual) trades.[4]

A closer examination of the numbers in Table 2 also reveals that the average medium-size individual trade is significantly smaller than the average medium-size institutional trade. The average medium-size institutional trade is about 2,424 shares ($\approx 125,378,400/51,721$) while the average medium-size individual trade is about 1,358 shares ($\approx 24,512,700/18,056$) – and this difference (in

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[4] We compute these numbers as follows. From Table 2, the sum of the magnitudes of the mean percentage cumulative price change for medium-size trades from individuals and institutions is 77.17% ($= 79.16 + (-1.99)$). The reported percentages are simply $102.57 (= 79.16 \times (100/77.17))$ and $-2.57 (= -1.99 \times (100/77.17))$ for institutions and individuals, respectively.

Table 2
Cumulative price change, trades and volume by trade sizes and trader types

Trade sizes are classified as small (100–499 shares), medium (500–9,999 shares), and large (10,000 + shares). Trades are further identified as initiating from individuals or institutions. The medium trade size category is subdivided into four sub-categories of trade sizes. The table reports the (cross-sectional) mean cumulative stock price change, the proportion of trades, and the proportion of share volume, by trade size and, further, by trade initiator. Sample consists of 97 NYSE firms in the TORQ database with significant price increases between November 1, 1990 and January 31, 1991.

Trade size	% of Cumulative price change	Number of trades	% of trades	Volume	% of volume
Trades initiated by individuals					
Small (100–499 shares)	7.39	30,425	23.44	5,687,600	1.73
Medium (500–9,999 shares)	−1.99	18,056	13.91	24,512,700	7.45
500–999 shares	0.965	12,235	9.425	8,877,000	2.697
1000–2,999 shares	−4.824	4,362	3.360	8,286,100	2.518
3,000–5,999 shares	1.529	1,233	0.950	5,625,800	1.709
6,000–9,999 shares	0.338	226	0.174	1,723,800	0.524
Large (10,000 + shares)	1.12	547	0.42	10,383,800	3.16
Trades initiated by institutions					
Small (100–499 shares)	−8.54	21,268	16.38	4,287,300	1.30
Medium (500–9,999 shares)	79.16	51,721	39.84	125,378,400	38.10
500–999 shares	29.943	20,609	15.876	16,023,800	4.869
1000–2,999 shares	21.207	17,199	13.249	35,518,800	10.793
3,000–5,999 shares	22.108	10,866	8.370	50,324,500	15.291
6,000–9,999 shares	5.900	3,047	2.347	23,511,300	7.144
Large (10,000 + shares)	22.86	7,797	6.01	158,856,300	48.27

trade sizes) is statistically significant. Thus, any investigation on the price impact of medium-size trades by these two groups of traders needs to control for the difference in trade sizes. We do so in three ways.

First, we decompose the medium trade size category into four sub-partitions of trades sizes of 500–999 shares, 1,000–2,999 shares, 3,000–5,999 shares, and 6,000–9,999 shares. Statistical tests reveal that the average individual and institutional trade sizes in each of these sub-categories is similar. Specifically, in the 500–999 share category, the average individual and institutional trade sizes are 726 shares and 778 shares, respectively. In the three remaining sub-categories, the corresponding average individual and institutional trade sizes are 1,900 shares and 2,065 shares; 4,563 shares and 4,631 shares; and 7,627 shares and 7,716 shares, respectively. Table 2 also provides the percentage of

cumulative price change, the number and percentage of trades, and trading volume and volume percentages, of each initiating trader type, for each of the four medium trade size sub-categories discussed above.

Within each medium trade size sub-category, the average cumulative price change associated with institutional trades is significantly greater than that associated with individual trades. For example, in the 500–999 share trade size sub-category, the cumulative price change for institutional trades is about 30% compared to about 1% for individual trades. The results in the remaining sub-categories follow similarly.

Second, we investigate the distribution of transaction-by-transaction stock price changes (in units of cents per 100 shares) for trades in various size categories initiated by individuals and institutions. Table 3 presents the means and standard deviations and the *p*-values of tests of equality of means across individual and institutional trades in each size category. Both small and large-size trades initiated by individuals display significantly greater (and positive) mean stock price impact per unit volume than institutional trades in the same trade size category. But, more relevant for us, for all sub-categories of medium-size trades, the average price impact of institutional trades is between two-and-half times to over eight times greater than the average price impact of individual trades. The difference between the averages in all sub-categories is also statistically significant at reasonable levels of confidence. Thus, in the 500–999 share category, for example, the average price impact of individual trades is 0.009 cents versus 0.073 cents for institutional trades, each on a 100-share basis. The remaining sub-categories follow similarly.

Third, we perform regressions on each of the 97 stocks in our sample, where the dependent variable is the transaction-by-transaction price change per unit volume and the independent variables are the lagged dependent variable, and six dummy variables to capture the small, medium, and large-size trades of institutions and individuals. The dependent variable, defined on an unit volume basis, controls for systematic differences in trade size between individual and institutional trades while the lagged dependent variable is added as an independent variable to focus on the price impact of the current transaction.

From the regression results (not reported), based on the significantly higher proportion of positive and significant coefficients, and the relatively low average standard error (compared to the average coefficient estimate), the positive and significant impact of medium-size institutional trades is evident. The impact of medium-size institutional trades on transaction-by-transaction price changes is the most significant of trades in all size categories.

In summary, stealth-trading appears to be driven primarily by medium-size trades initiated by institutions. This result holds even after controlling for the relatively larger medium-size institutional trades compared to medium-size individual trades.

Table 3

Distribution of transaction-by-transaction price change per unit volume

The table provides the mean and standard deviation of transaction-by-transaction stock price change (in units of cents per 100 shares) for small (100–499 shares), medium (500–9,999 shares), and large-size (10,000 + share) trades originating from individuals and institutions. The medium-trade size category is subdivided into four sub-categories of trade sizes. Additionally, the *p*-values of a two-tailed test of equality of the mean price change for individual and institutional trades in each trade size category are presented. The sample consists of 97 NYSE firms in the TORQ database with significant price increases between November 1, 1990 and January 31, 1991.

Trade size	Trades initiated by individuals	Trades initiated by institutions	
	Mean price change (Std. Deviation) cents per 100 shares	Mean price change (Std. Deviation) cents per 100 shares	*p*-value of two-tailed test of equality of means
Small (100–499 shares)	0.091 (0.044)	−0.082 (0.053)	0.012
Medium (500–9,999 shares)			
500–999 shares	0.009 (0.022)	0.073 (0.018)	0.025
1000–2,999 shares	−0.007 (0.021)	0.042 (0.008)	0.007
3,000–5,999 shares	0.006 (0.007)	0.018 (0.002)	0.069
6,000–9,999 shares	0.004 (0.009)	0.01 (0.002)	0.071
Large (10,000 + shares)	0.019 (0.017)	0.006 (0.000)	0.019

4. Sensitivity checks

In this section, we provide the results of two sensitivity analyses to ensure the robustness of our main result.

4.1. Stealth-trading and firm size

Here, we investigate if stealth-trading is related to firm size. This sensitivity analysis is motivated by the extant literature that documents the importance of firm size in equity price dynamics. Bhusan (1989), Lo and MacKinlay (1990), and Badrinath et al. (1995) provide a discussion of these dynamics.

We partition the 30 largest firms in our sample into a LARGE firm subsample and the 30 smallest firms into a SMALL firm subsample. The market value of each firm, as of October 31, 1990 is computed from the closing stock price times the number of shares outstanding. Once again, the four sub-partitions of medium-size trades are maintained to ensure that the average individual and institutional trade trades are similar within each medium trade size sub-partition.

We find (not reported) the following characteristics associated with LARGE firms. Medium-size trades have a disproportionately large cumulative price change associated with them (92%) relative to their proportion of all trades or overall volume. Further, the bulk of the cumulative price change in medium-size trades appears to originate from institutional trades (108% versus −19% for medium-size individual trades). Also, within each medium trade size sub-partition, institutional trades display significantly higher cumulative price change than the corresponding size individual trades.

For SMALL firms, even though medium-size trades display the highest cumulative price change (103%), there also appears to be a proportional relationship between cumulative price change and the corresponding volume. Our statistical tests are unable to reject the trading volume hypothesis. Also, the cumulative price impact of medium-size individual trades turns out to be somewhat larger than medium-size institutional trades (58% and 45%, respectively). And within each of the four sub-partitions of medium-size trades, the cumulative price change associated with individual trades is greater in all but one sub-partition. Thus, medium-size institutional trades in SMALL firms appear, overall, to have a less dominant price impact role than those in LARGE firms.

4.2. Stealth-trading in the TORQ universe

In another sensitivity check, we look for stealth-trading in the universe of TORQ stocks. Our approach is comparable to and Barclay et al. (1993) who investigate and find (relatively weaker) support for the stealth-trading hypothesis in the universe of NYSE stocks in the 1981–1984 period. Specifically, we use all valid observations in the audit file for the entire sample of 144 stocks.

The upper panel of Table 4 reports the mean percentage of the cumulative stock price change occurring on trades in each trade size category, the corresponding number and percentage of transactions, and transaction volume and volume percentages for all TORQ stocks. We also provide, in the lower panel of Table 4, numbers similar to Table 2 for small, medium, and large-size trades initiated by individuals and institutions. Finally, as in Table 2, we partition the medium-size trades into four sub-partitions to control for the relatively larger institutional trades in the original medium trade size partition.

Table 4
Cumulative price change, trades, and volume by trade size and trader types for the universe of TORQ stocks

Trade sizes are classified as small (100–499 shares), medium (500–9,999 shares), and large (10,000 + shares). Trades are further identified as initiating from individuals or institutions. The medium trade size category is subdivided into four sub-categories of trade sizes. The table reports the (cross-sectional) mean cumulative stock price change, the proportion of trades, and the proportion of share volume, by trade size and, further, by trade initiator. The sample consists of all valid transactions in 144 NYSE firms in the TORQ database.

Trade size	% of Cumulative price change	Number of trades	% of trades	Volume	% of volume
Small (100–499 shares)	13.31	90,321	41.02	17,852,700	3.41
Medium (500–9,999 shares)	65.46	117,617	53.42	240,022,400	45.84
Large (10,000 + shares)	21.23	12,228	5.55	265,695,000	50.75
Trades initiated by individuals					
Small (100–499 shares)	36.02	53,301	28.16	9,904,200	2.24
Medium (500–9,999 shares)	−3.50	26,698	14.10	34,812,200	7.86
500–999 shares	2.175	18,547	9.798	13,218,900	2.986
1000–2,999 shares	−6.141	6,158	3.253	11,565,800	2.612
3,000–5,999 shares	−0.303	1,679	0.887	7,621,800	1.722
6,000–9,999 shares	0.772	314	0.166	2,405,700	0.543
Large (10,000 + shares)	1.61	714	0.38	13,965,400	3.15
Trades initiated by institutions					
Small (100–499 shares)	−17.61	31,437	16.61	6,329,100	1.43
Medium (500–9,999 shares)	66.73	66,995	35.39	160,980,700	36.36
500–999 shares	31.322	27,079	14.305	20,857,400	4.711
1000–2,999 shares	8.183	22,048	11.648	45,247,300	10.220
3,000–5,999 shares	22.615	13,912	7.350	64,366,000	14.538
6,000–9,999 shares	4.606	3,956	2.090	30,510,000	6.891
Large (10,000 + shares)	16.76	10,146	5.36	216,742,700	48.96

For transactions classified by trade size alone, medium-size trades cause the highest cumulative price change at 65% and comprises 53% of the transactions and 46% of the volume. Our statistical tests reject the alternatives of public information and trading volume hypotheses. Also, the bulk of the cumulative price change in medium-size trades appears to be driven by institutions. Finally, within each of the four medium trade size sub-partitions, institutional trades cause significantly higher cumulative price change relative to individual trades.

In summary, stealth-trading appears to be present in transactions encompassing all stocks in the TORQ data – albeit not as dominantly as in our sample of 97 stocks. Stealth-trading also appears to be driven by institutional trades, even after controlling for their relatively larger trade sizes.

5. Conclusion

Using audit trail data for a sample of NYSE firms, we first show that medium-size trades are associated with the largest cumulative stock price change – a result consistent with the stealth-trading hypothesis. Next, we find that the source of the disproportionately large cumulative price impact (relative to the proportion of trades and volume) of medium-size trades is almost entirely due to those initiated by institutions. This result holds even after controlling for the relatively larger (medium-size) institutional trades compared to individual trades in the same trade size category. Finally, the significantly large contribution of medium-size institutional trades to the overall cumulative price impact of medium-size trades is also evident in the universe of TORQ stocks. The evidence, however, is relatively stronger in large firms.

In conclusion, through a careful empirical design and a detailed data set we provide a glimpse into the complex world of strategic traders and the price impact of their trades. But informed (or strategic) traders can use a variety of other ways to disguise their trades. Some possible avenues include hiding behind liquidity trades and fragmenting orders across exchanges, across time, and across stock and options markets. We leave it for future research to consider some or all of these avenues of informed trading in order to enhance our understanding of stealth-trading and its impact on stock prices.

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