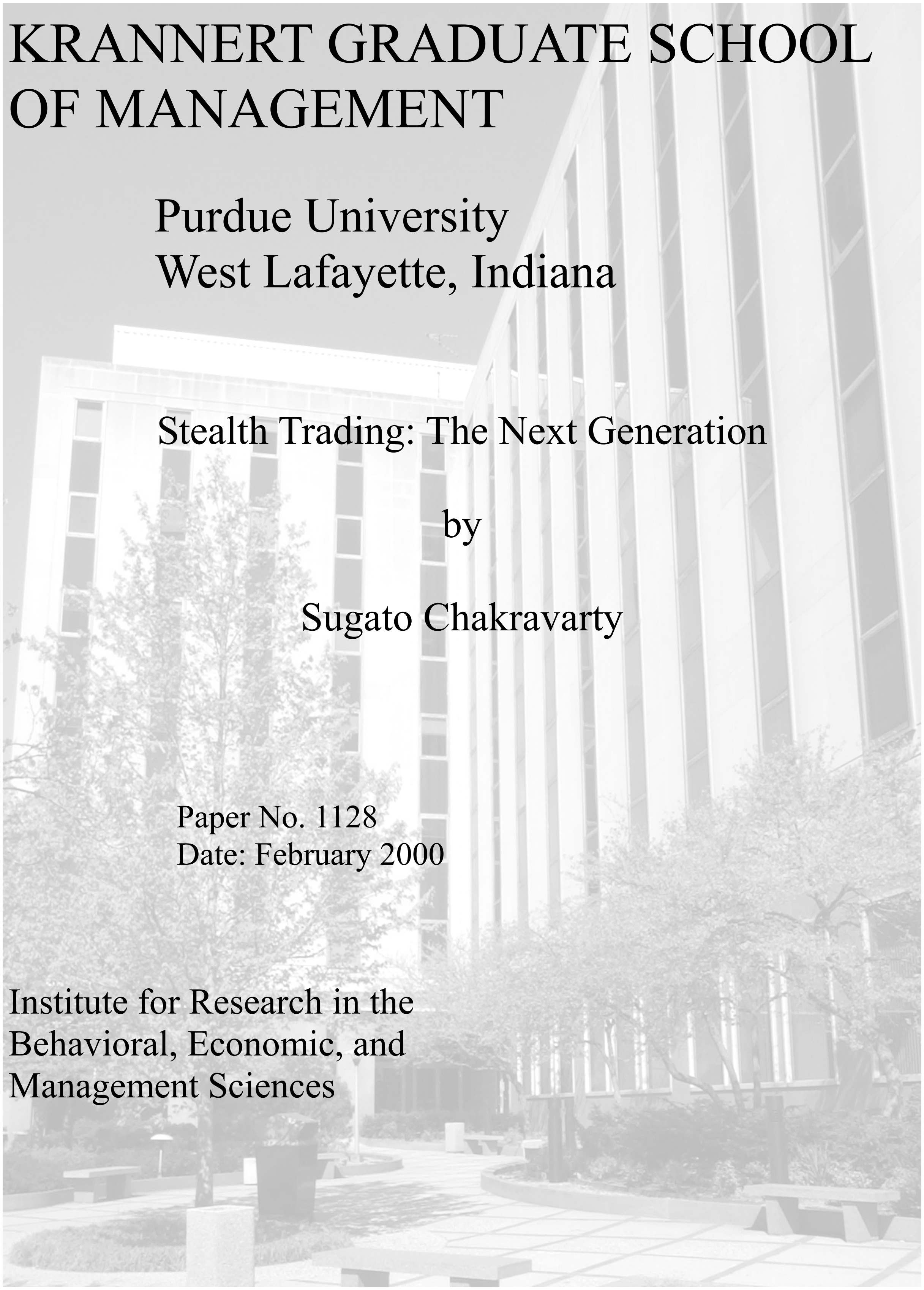

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Stealth Trading: The Next Generation

by

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Stealth Trading: The Next Generation

Which Trader's Trades Move Prices?

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Stealth Trading: The Next Generation

Which Trader's Trades Move Prices?

Abstract

Using intra-day transaction data for a sample of NYSE firms, I show that medium size trades have the highest percent cumulative price change and greatest impact on transaction-by-transaction stock price changes. Even though large size trades have the highest price impact per transaction, it is the medium size trades that have the greatest price impact per unit volume. These results are consistent with the predictions of the stealth trading hypothesis (Barclay and Warner (1993)). Upon further decomposition of trades, using audit trail information, into those initiated by institutions and those initiated by individuals, I find that stealth trading is present mainly in medium size trades initiated by institutions. I also find stronger evidence of stealth trading (driven by the medium size institutional trades) in large firms, than in small firms.

Stealth Trading: The Next Generation

Which Trader's Trades Move Prices?

1. Introduction

Kyle (1985) shows that an investor with private information will tend to trade gradually in a manner that reveals a constant fraction of his information with each successive trade. While the Kyle model depends on noise traders to provide cover for the informed trader's trades in each period, in reality, other factors such as wealth constraints may also influence an informed trader's decision to split his trade over time. Easley and O'Hara (1987) demonstrate that, under the assumption that informed traders will prefer to trade larger amounts at any given price, market prices will differ with trade sizes, with large trades occurring at "worst" prices. If informed investors' trades are the main cause of stock price moves (see French and Roll (1986) and Barclay, Litzenberger and Warner (1990)), and informed traders concentrate their trades in trades of certain sizes -- not too large (which can give them away) and not too small (too expensive in terms of trading and opportunity costs) -- then most of a stock's cumulative price change should take place on trades of intermediate sizes. Whether or not this is true is an empirical question and forms the basis of the "stealth-trading" hypothesis.

Barclay and Warner (1993) (hereafter, BW), focus on a sample of tender offer targets and find that medium-size trades (defined as 500 - 9,999 share trades) account for an estimated 92.8% of the cumulative price-change during the pre-tender offer announcement period. These findings support the idea that informed traders may indeed be using trades of intermediate sizes to maximize their profits and the stealth trading hypothesis.

In an effort to enrich our understanding of the stealth-trading hypothesis, I attempt to link the price impact of a trade of a specific size with a specific investor-type behind that trade. I do so with a unique data set, known as TORQ, that identifies the trader-type (such as individual investor or institutional trader) on either side of a transaction, in addition to providing transaction and quote information similar to intra-day transactional data sets like those from the Institute for the study of Security Markets (ISSM) and Trade and Quote (TAQ) data from the New York Stock Exchange (NYSE).[2] Also, the transactions in my data set have a one-to-one mapping with individual orders. I am, therefore, better able to examine the sources of price changes around trades. The latter is an important distinction because, as Bronfman (1992) reports, transactions data, such as those employed by BW, do not always have a one-to-one correspondence with individual orders. Thus, a 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.

In order to maximize the probability of detecting stealth trading, I restrict attention only to stocks in the data that displayed a "significant" price increase over the sample period. I define a significant price increase, somewhat arbitrarily, as at least a 5% price increase in stock price over the sample period. The average price increase in our sample of stocks is 27.5%. 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 (the buy side) and can be detected by my tests. I do not condition the sample on any particular information event.

Defining a stock-price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade, I initially show that medium size trades[3] are associated with

[2] The usefulness of TORQ is evident in the number of studies that, in recent years, have used the data to investigate a cornucopia of issues related to market liquidity, including spreads and volumes, stopped orders, limit orders, specialist behavior, etc. (see, for example, Sias and Starks (1997), Koski and Scruggs (1998), Angel (1998), Chung et al. (1999), and Ready (1999)).

[3] My definitions of small, medium and large size trades mirror those of BW.

the highest percent cumulative price change (about 79%) and with the greatest impact on transaction by transaction stock price changes. Even though large size trades (defined as 10,000 share trades or greater) have the highest price impact per transaction, it is the medium size trades that have the greatest price impact per unit volume. My results are consistent with the predictions of the stealth trading hypothesis. Upon further decomposition of trades into those initiated by institutions and by individuals, I find that stealth trading is associated mainly with 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. Consistent with theory, which postulates that informed trading is likely to be concentrated in stocks that provide these strategic traders with cover for their activities, I find stronger evidence of stealth trading in large firms with significantly greater transactions and transaction volume than small firms with fewer transactions and smaller trading volume.

Finally, under the assumption that stealth trading is a pervasive phenomenon, I investigate for its presence among *all* stocks in the TORQ data set. Here too, I find support for the stealth trading hypothesis and its dominance by medium size trades from institutions, although the evidence is somewhat weaker than in the sample with (transactions in) stocks having significant price increases.

My results confirm the widely held belief, among academics and practitioners alike, that institutions are "smart", or informed, traders. My research appeals to the body of work, both theoretical and empirical, that investigates the relationship between informed trading and the size of their trades[4], and those studies investigating the identity of informed traders[5].

The remainder of the paper is organized as follows. Section 2 sets the stage for my analysis

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[4] See, for example, Kyle (1985), Easley and O'Hara (1987, 1992a, 1992b), Burdette and O'Hara (1987), Holthausen et al. (1987, 1990), Ball and Finn (1989), Seppi (1990), Hasrbrouck (1991), Choe, McInish and Wood (1991), Grossman (1992), and Keim and Madhavan (1996).

[5] See, Arbel and Strebel (1983), Bhusan (1989), Lo and MacKinlay (1990), Meulbroek (1992), Cornell and Sirri (1992), Badrinath, Kale and Noe (1995), Sias and Starks (1997), Chakravarty and McConnell (1997, 1999) and Koski and Scruggs (1998).

by summarizing the extant literature on informed trading, market impact (both price and bid-ask spreads) and trade size. Section 3 provides details of the TORQ data, including the classification of trades, sample selection, determination of trade initiators (buyers/sellers) and other data related issues. Section 4 provides the benchmark tests of the stealth trading hypothesis with my data. Section 5 examines the source of stealth-trading. Section 6 investigates the relationship between stealth trading and firm size. Section 7 provides a simple robustness check of my main conclusions. Section 8 concludes with a discussion of the broader implications of my results. The appendix contains some details of the stocks in my sample.

2. Informed Trading, Market Impact and Trade Size

The theoretical literature related to information-based trading[6] and/or the inventory-based models[7] suggest that a large trade should move prices more than a small trade. In the information based models, a large trade has a higher probability of being information based and, so, should impact the market more than a small trade. In the inventory models, a large trade implies a greater inventory risk for a risk-averse dealer and impacts the market greater than a small trade.

The corresponding empirical research has sought to measure the relationship between price (and other measures of market impact) and trade size.[8] Overall, the empirical research (with the exception of BW) finds a direct relationship between price impacts (or bid-ask spreads) and trade size, and, by extension, with informed trading, a result consistent with the intuition from the theoretical adverse selection models cited above. But informed (or, strategic) trading, by its very nature, is unobservable.

[6] Kyle (1985), Glosten and Milgrom (1985) and Easley and O'Hara (1987, 1992a, 1992b), Burdette and O'Hara (1987), Seppi (1990) and Grossman (1992).

[7] Stoll (1978) and Ho and Stoll (1981, 1983).

[8] Holthausen et al. (1987, 1990), Ball and Finn (1989), Choe, McInish and Wood (1991), Hasbrouck (1991), Barclay and Warner (1993) and Keim and Madhavan (1996).

As a result, most empirical research attempts to *infer* informed trading activity around some significant corporate event such as earnings announcements or mergers/tender-offer announcements.[9]

However, recent studies by Meulbroek (1992), Cornell and Sirri (1992) and Chakravarty and McConnell (1997, 1999) examine informed trading activity by analyzing *actual* insider trading episodes, although the first two studies do not report any results related to insider trading and trade size. BW, however, report some informal evidence on insider trade size gleaned from private conversations with Meulbroek and from computations from the raw data provided in the appendix of Cornell and Sirri (1992). Specifically, BW infer that in Cornell and Sirri's (1992) case study of an insider trading prosecution involving 38 traders, 78.2% of the insider trades are of medium size, 18.5% are in the small size category and 3.2% are large size trades. They also report that, where such detail is available in Meulbroek's data, most insider trades fall in the medium size category.

In contrast, Chakravarty and McConnell (1997) explicitly investigate the impact of insider trade size on stock price. After examining Ivan Boesky's illegal trading in Carnation stock immediately before its merger with Nestle in 1984, the authors report that about 1% of Boesky's transactions were small size trades, 40% of the transactions were medium size trades and 59% of his transactions were large size trades. Additionally, in a regression analysis, they find that it is Boesky's large size trades that significantly impact Carnation's hourly returns (to the exclusion of small and medium size trades).

In summary, the evidence from the above studies, on the frequency and price impact of medium size trades used by insiders, appears mixed.

In the current paper, I test if the cumulative price change(discussed earlier and detailed in section 4.1) associated with medium size trades (defined earlier) is the greatest. I then test for stealth trading at the individual transaction level by investigating if the transaction-by-transaction stock price changes associated with medium size trades are the greatest (compared to other size trades). Next, I

[9] see, for example, Barclay and Warner (1993) and Lee, Mucklow and Ready (1993), among others.

move to the specific innovation of my paper by investigating the cumulative price change, as well as transaction-by-transaction stock price changes, associated with trades of various sizes initiated by individuals and institutions. This provides us with a better understanding of the source of stealth trading. I then test for stealth trading in further refinements of the data, including a test of robustness of the stealth trading hypothesis itself.

3. Data and Classification Procedures

3.1 TORQ details and trader-group classification

The TORQ data set contains trades, quotes, order processing and audit trail data for a sample of NYSE stocks for the a three-month period between November, 1990 and January, 1991 (63 trading days). The following process was used to select the original set of firms in the data set. The entire universe of companies listed on the NYSE in the summer of 1990 was divided into ten size deciles based on market value of equity. Within each size decile, fifteen firms were selected by random drawing. By the time actual data collection for the 150 chosen firms began in November of 1990, six of the originally chosen securities were no longer listed -- thereby reducing the total number of stocks in the data to 144. Other relevant details are provided in Hasbrouck (1992).

The TORQ data set consists 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 I 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 all participants. It is this last property that makes the TORQ data unique relative to other transactional databases. I elaborate on this below. I should also note here that the audit file also allows me, in some cases, to infer whether the order is a market or a limit order. But, the focus of my study is the initiating trader of a transaction and the impact of his trade on price. Initiating trades are, almost always, market orders.[10] I discuss the issue of identifying the trade initiator later in section 3.4.

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, the electronic order submission system;[11] (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

[10] There are three ways in which an initiating order can be a limit order. One, and most likely, is if it happens to be a marketable limit order (which is like a market order) or when limit orders cross inside the spread. Two, 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. Three, 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. I thank Elizabeth Odders-White for private communications that resulted in the above insights.

[11] The SuperDot (Digital Order Turnaround) system is part of an electronic communications network that transmits orders from member firms to the NYSE trading floor. Other details are available in Hasbrouck et al. (1993).

include trades by specialists.[12] If a trade is from an individual investor, then 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 reveal that a vast majority of trades under the ***A*** classification include non exchange member institutional trades.

An example might further clarify this account type classification. If Merrill Lynch (an exchange member), trades on its own account, then, at the end of the day, this trade is classified by Merrill as *P*. If Merrill trades on behalf of American Capital Investments (a non-member institution), then the trade is classified as *A*. Finally, if Merrill trades on behalf of Joe Smith (an individual), then Merrill will classify this trade as *I*.

For the current analysis, I combine the Account Types ***P*** and ***A*** into trades from institutions, under the assumption that almost all exchange members are, arguably, institutions. But, to satisfy myself that my results are not an artifact of this assumption, I replicate all my results with only Account Type *A* trades as institutional trades, and obtain virtually identical results. [13]

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

[12] 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.

[13] The audit trail data also allows me to identify, in principle, program trades, which is any trading strategy involving the simultaneous or near simultaneous purchase or sale of fifteen or more stocks with a total aggregate value of one million dollars or more. I exclude program trades from the analysis because there are less than 200 program trades in my final sample of stocks. Also, program trades can be from both individuals and institutions and it is difficult to reliably separate the two.

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 best and 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. If one or both sides of a transaction are orders that have been hand-carried to the specialist's post by floor brokers, then the audit-trail information of such orders is missing. The transactions-related information, however, is complete and represents the whole scope of trading activity on the corresponding stocks.

3.2 Sample selection

In order to maximize the probability of detecting stealth trading, I restrict attention only to stocks in the data that displayed a "significant" price increase over the sample period. The intuition behind selecting stocks with a significant price increase over the sample period is that any (possible) stealth trading activity is likely to be focused on one side of the market (the buy side) and can be detected by my tests. BW 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. My partitioning is in the same spirit.

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 that 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 (or even the direction of their trades). Additionally, the TORQ data is 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 infrequently traded stocks. 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 activity on both sides of the market and it is difficult to reliably estimate stealth trading in such cases.

I define a "significant" price increase over the sample period somewhat arbitrarily as at least a 5% increase between the opening price on November 1, 1990, and the closing price on January 31, 1991. Note that the opening and closing prices used to compute price increases in stocks over the sample period, are taken from the transactions data, representing the whole range of trading activity, in these stocks. This precludes introducing any bias in stock selection.

A total of 97 stocks (out of 144) meet the above criteria and I restrict attention to these stocks only. The average price increase in these 97 stocks is 27.5% (minimum of 5% and maximum of 124%). The appendix provides some details of the 97 stocks, including their ticker symbols, the total number of transactions and their three-month price increases.

3.3 Identifying traders

Given that the focus of the paper is to go beyond the BW study in establishing which traders' trades are actually moving prices, it is important to understand how this trader identity may actually be established -- especially to the specialist, who is primarily responsible for setting prices.

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 specialist 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 gives him a pretty good idea. If a market maker is further 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 can identify the submitting brokers' identity, and other details of the order. Over time, the specialists believe that they can recognize patterns in trades associated with certain mnemonics and, in turn, to deduce the trader type behind an order.[14] In short, all evidence indicates to the fact that market makers are able to deduce the trader-type submitting the order, should they be interested.[15]

Finally, Sias and Starks (p.109, 1997) also assume that the specialist is able to distinguish across individual and institutional trades when they use the TORQ data to test if institutional holdings can effectively proxy for institutional trading by measuring the price-setting volume of both groups of investors.

3.4 Determining the trade initiator

Unfortunately, the Audit file in TORQ does not identify whether the buyer or the seller in a transaction was the trade initiator. It is important to infer the initiator because in all extant theories of market microstructure, modeling the impact of trades on prices and other observables, are based on the classification of the trade initiator (see O'Hara (1995) for a survey). 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.

The most common algorithm for identifying the trade initiator is that proposed by Lee and Ready (1991). Under this algorithm, if a trade occurs at the prevailing bid price or anywhere between the bid and the midpoint of the prevailing bid ask spread, it is considered a seller-initiated trade. Likewise, if a trade occurs at the prevailing ask price or anywhere between the ask and the midpoint of the prevailing bid ask spread, it is considered a buyer-initiated trade. For trades occurring at the

[14] Other relevant details are provided in Hasbrouck et al. (1993). I thank Joel Hasbrouck for providing me with these insights in private conversations.

[15] 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), 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 manage their spreads and the corresponding spread sizes to protect themselves from adverse market conditions.

prevailing spread midpoint, the tick-test rule is applied to determine the trade initiator. By the tick test rule, a trade is buyer-initiated if the price move from the previous transaction price is upwards, and vice versa. 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, however, Odders-White (1999) has proposed an alternative classification scheme that appears to classify trades occurring within the prevailing spread more accurately. Specifically, the initiator of a transaction is the investor (buyer or seller) who placed his order last, chronologically. Since the audit files in TORQ identify the buyer's and the seller's order submission times, wherever the buyer and seller order submission times are distinct, I use the Odders-White definition of classifying trades. For those cases where the order submission times are identical, I use the traditional Lee-Ready algorithm for trade classification.

3.5 Other data-related issues

In all of the publicly available transaction data sets, the reported transactions do not have a one-to-one correspondence with the orders that make up the transaction. As my discussion in the introduction reveals, the market maker has the freedom to report a transaction in multiple ways, and 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. Fortunately, since the audit trail file of the TORQ data set enables me to identify the traders (and their order sizes) on either side of a transaction, I am able to surmount the problem easily.

But, even with the 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 the task of identifying whose trades impacted the price change, difficult, if not impossible. I overcome this hurdle by eliminating all transactions where the active side has less than 100% participation in any one trader-group. Thus, if the initiating BUY side of a 20,000 share trade has 4 traders each with a 5,000 share order, and if all 4 are institutional buyers, then this particular observation is included in our data. Using this filter, I am left with 151,367 (a little over 60% of the initial) observations in the audit file in the 97 chosen stocks.

But I also replicated all my results using the less stringent 90% and 75% and 50% cutoff rules. That is, I eliminated all transactions where the initiating side of a transaction has less than 90%, 75% and less than or equal to 50% participation, respectively, in any specific trader-group. Hence, if 15,000 shares (out of a 20,000 share, buyer-initiated, trade) are from 3 institutional buyers and a 5,000 share order is from a single individual buyer, then under the 75% cutoff rule, I still classify this transaction as an institution-initiated trade. Using the 50% cutoff rule (the least stringent inclusion criterion), I 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 my tests to detect stealth trading. The results, through these successive iterations, however, remain materially similar.

4. Benchmark Analyses

4.1 Cumulative stock price changes and trade size: univariate tests

In this section, my 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 (i.e., small, medium and large).

I define a stock-price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade. Corresponding to each trade in the audit file, the previous trade is identified (by time and a unique identification number that links the audit file with the transactions file) from the transactions file which lists all transactions in that stock. For each firm in the sample, I sum all stock-price changes that occur on trades in a given trade size category over the sample period. I then divide this sum by the cumulative price change for the firm over the sample period. Finally, I estimate the weighted cross sectional mean of the cumulative stock price change, reported in table 1, where the weights are the absolute value of the cumulative price change, in a stock, over the sample period. In the current situation, the weights allow me to aggregate across the cross section of stocks. They also have another purpose that I discuss in section 4.2.

Specifically, 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. Consistent with BW, I define small-size trades as trades of 100-499 shares; medium-size trades as trades between 500-9999 shares; and large-size trades as trades of 10,000 shares or greater.

From table 1, most of the cumulative price change occurs in the medium size trades. Trades in this category are responsible for an average of about 79% of the cumulative price change, and comprise 57% of the transactions and 47% of the volume. The large size trades average about 25% of the cumulative price change, and comprise 6% of the transactions and 51% of the volume. The small size trades average about -4% of the cumulative price change, and comprise 36% of transactions and 3% of the volume. By comparison, BW report that, in their sample, the medium size trades average about 93% of the cumulative price change, and consist of 46% of the trades and 64% of the volume. The large size trades average about 10% of the cumulative stock price change, and consist of 2% of the trades and 24% of the volume. Small size trades average about –2% the cumulative stock price change and consist of 53% of the trades and 12% of the volume. These findings are consistent with the predictions of the stealth trading hypothesis.

Note that in both my results and those of BW, while the large size trades have the greatest price impact per transaction, the medium size trades have the greatest price impact per unit volume. While the former is consistent with the adverse selection literature exemplified by Kyle (1985), Easley and O'Hara (1987), among others, and also follows from pure liquidity effects associated with a large trade, the latter result is not. The highest price impact per unit volume of medium size trades may be indicative of the fact that the market is, in fact, aware that informed traders may strategically be using medium size trades to maximize profits.

To ensure that my conclusions of stealth trading associated with medium size trades are not driven by the specific filters used on the audit trail data (discussed in section 3.5), I replicate table 1 with the transactions data file in TORQ for the 97 stocks (involving over 250,000 observations). Recall that the transactions file only provides information on the ticker, date, time, price and size of trades (without any audit trail information such as trader identity and order components). The transactions data in TORQ are identical to the ISSM and TAQ data sets that are used by most researchers, including BW, to investigate various intra-day phenomena. Replicating table 1 with the transactions data, I obtain results very similar to those reported in table 1. I omit these results for brevity, since they provide no new information. My finding of stealth trading in medium size trades appears independent of the (nature of the) data set used for the analysis.

One alternative to the stealth-trading hypothesis is the hypothesis that most stock-price changes are caused by the release of public information. Assuming that public announcements do not affect the distribution of trade sizes, the likelihood that the stock-price change associated with a public information release will occur on a trade of a given size is directly proportional to the relative frequency of that trade size. Thus, under the public information hypothesis, the percentage of the cumulative price change occurring in a given trade size category is directly proportional to the percentage of transactions in that category. From table 1, the public information hypothesis is rejected. Specifically, small trades average about -4% of the cumulative price change but account for 36% of all trades, while large trades average about 25% of the cumulative price change but comprise only 6% of all trades in the sample.

Yet another alternative is the trading volume hypothesis. Recall from earlier discussion that large trades should move prices more than small trades. The trading volume hypothesis therefore requires that the percentage of the cumulative price change in each trade-size category should be proportional to the fraction of the total trading volume in that category. I examine the simplest case of the price change associated with a trade being directly proportional to trade size. Based on table 1, the trading volume hypothesis appears to be rejected also. While the medium size trades average about 79% of the cumulative price change and comprise 47% of the volume, the large size trades average about 25% of the cumulative price change and comprise 51% by volume.

4.2 Impact of trade size dummies on transaction-by-transaction stock price change

In section 4.1, I provided evidence of the existence of stealth trading, based on cumulative price changes in response to trades of different sizes, and also provided evidence to reject some reasonable alternative hypotheses. I now turn to a micro-level investigation of the specific impact of trades of various sizes on transaction-by-transaction stock price changes. That is, I look for evidence of stealth trading at the individual transaction level, in contrast to BW, who run pooled regressions across the 106 firms in their initial sample.

Specifically, I estimate the impact of transaction-by-transaction stock price changes on dummy variables for large, medium and small size trades. If the stealth trading hypothesis holds at the individual transaction level, I should see a statistically significant positive impact of medium size trades on stock price change that is greater than the impact of small or large size trades. I expect a positive impact because I examine stocks with significant price increases over the sample period. Any informed trading, therefore, is also likely to be on the buy side of the market.

It is important to recognize that, given the tick-by-tick (high frequency) nature of the data, the dependent variable, and, by extension, the error term, is likely to be serially correlated. Thus, if the current price change is a function of the past price change, it has to be explicitly controlled for, when determining the impact of (current) trades on the current stock price change. I handle this issue two ways. One, I include a lagged dependent variable, $\Delta \boldsymbol{P}_{t-1}$,[16] as an added independent variable; and, two, I employ the Generalized Method of Moments (GMM) technique, proposed by Hansen (1982), as the estimating vehicle. GMM is an appropriate estimation technique that demands very weak assumptions on the error term -- only that it have well-defined unconditional moments, including when the moments are conditionally varying and/or when the errors are serially correlated.

Specifically, I estimate the model, on a stock-by-stock basis, using *weighted* GMM regressions, with the weights being the absolute cumulative price change in that stock over the sample period. The weights allow me an added degree of control for heteroskedasticity in the error term. To better focus on the explanatory power of trade size, I include the trade size dummies only, along with the lagged dependent variable, as explanatory variables, in my regression model.

By estimating the regressions individually on each of the 97 stocks in my sample, I obtain 97 different regression estimates. Therefore, in table 2, I provide the summary results of the regressions, including the average coefficient estimate, the average standard error, and the number of positive and negative coefficients corresponding to each independent variable in the model. The numbers in parenthesis under the number of positive and negative coefficients, for each independent variable in the regression, denote the corresponding numbers of statistically significant coefficients at the 0.10 level or lower.[17]

From table 2, I see that the average coefficient estimate for $\Delta \boldsymbol{P}_{t-1}$ is -0.1636 and the corresponding average standard error is 0.0526. Eighty five coefficients are negative (seventy are statistically significant) while twelve are positive (one is statistically significant). There appears to be a

[16] To decide on the optimal lag length to use in all regressions, I regressed, on a stock-by-stock basis, the price change variable on five of its lags. For 9 stocks, no lagged values were significant at the 0.05 level. For 73 stocks, only the first lag was statistically significant at the 0.05 level. The remaining 15 stocks displayed significant higher order lags in the price change variable. I report results corresponding to a single lag for all stocks, although I replicated all results with up to three lags of the dependent variable as independent variables. The results remain materially the same.

[17] The individual regression estimates are available from the author on request.

strong negative correlation between successive price changes and is consistent with results reported by earlier researchers in stock price movements.

The average coefficient estimate of the Large Trade Dummy is -0.0101, and the average standard error is 0.0336. Forty seven (twenty are statistically significant) of the Large Trade Dummy coefficient estimates are positive, while fifty (thirty are statistically significant) are negative. Thus, large trades appear to have a negative overall impact on transaction-by-transaction stock price changes, although the effect, due to the high average standard error, does not appear statistically significant at reasonable levels.

The average coefficient estimate of the Small Trade Dummy is -0.0029 and the average standard error is 0.0087. Forty two (twenty five are statistically significant) of the Small Trade Dummy coefficients are positive; fifty five (forty are statistically significant) are negative. These results show that, overall, small trades are negatively correlated with transaction-by-transaction stock price changes, although, once again, the result does not appear statistically significant.

The average coefficient estimate of the Medium Trade Dummy is 0.0093, the average standard error is 0.0044. Fifty nine (forty four are statistically significant) Medium Trade Dummy coefficients are positive, and thirty eight (eight are statistically significant) are negative. Also notice the relatively smaller magnitude of the average standard error in comparison to the average coefficient estimate. Note that even though the magnitude of the average Large Trade Dummy coefficient is larger than that of the Medium Trade Dummy coefficient, the average standard error for the former is also significantly higher that that of the latter. Thus, the significantly positive impact of medium size trades (among all trade sizes) on transaction-by-transaction stock price changes, is clear. These results are, by far, the most significant among all three trade size dummies and imply, on average, about a, statistically significant, 1 cent price increase in response to a medium size trade.

I also perform Chi-squared tests of equality of the three size coefficient estimates, both pairwise and jointly, and reject the null hypothesis of equality in most cases, at reasonable levels of confidence.

Table 3 reports regression estimates for five randomly chosen stocks from our sample. These results appear consistent with the overall regression results in table 2. The lagged dependent variable is negative and highly significant and the impact of medium size trades on transaction-by-transaction stock price changes appears to be positive and significant at reasonable levels. The small and large trade size dummies are, for the most part, either negative and significant, or positive and statistically insignificant, at reasonable levels of significance.

In summary, the individual stock regression results supplement the univariate results of section 4.1 in demonstrating the positive and statistically significant impact of medium size trades (over other size trades) on stock price changes.

5. Trader Identity and Stealth Trading

In the last section, I obtained results consistent with the stealth-trading hypothesis -- both in cumulative and transaction-by-transaction stock price changes. The richness of the TORQ data, however, enables me to investigate the source of stealth trading in greater detail. In this section, I examine the relative impact of trades from individuals and institutions, in addition to their trade sizes, first on cumulative stock price changes, and then on transaction-by-transaction stock price changes.

5.1 Sources of cumulative stock price changes from distinct trader groups: univariate tests

I investigate how much of a security's cumulative price change over the sample period is attributable to trades initiated by individuals and institutions, within each trade size category.

Table 4 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 numbers and percentages of trades, and the volume and volume percentages. The computation of these variables is discussed in section 4. To take a closer look at the relative impact of the different size trades initiated by individuals and institutions, I also present the percentage of cumulative price change, and the percentage of trade frequency and volume, of each initiating trader group. These are in columns 3, 6 and 9 of table 4. The numbers in table 4 do not add up to the corresponding numbers in table 1. The reason for this discrepancy is that some of the trades, in each trade size category, cannot be uniquely assigned as originating from either individuals or institutions.

From table 4, medium size trades initiated by institutions have the highest average cumulative price change at about 79% and comprise 40% of the trades and 38% of the volume. In stark contrast, medium size trades initiated by individuals have an average cumulative price change of about -2%, and comprise 14% of the trades and 7% of the volume. Although, large size institutional trades have the largest price impact per transaction, the medium size institutional trades display the largest price impact per unit volume.

Based on the evidence in table 4, 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.[18] The hypothesis of proportionality between percent cumulative price change and the corresponding percent trades (the public information hypothesis) is clearly rejected, as is the hypothesis of proportionality between percent cumulative price change and the corresponding percent volume (the trading volume hypothesis).

In summary, medium size trades initiated by institutions display the largest cumulative price change and the greatest price impact per unit volume. Stealth trading appears to be dominant primarily among trades initiated by institutions. There is little or no support for either alternative hypothesis.

5.2 Impact of trader groups and trade sizes on transaction-by-transaction stock price change

In this section, I examine the impact of small, medium and large size trades initiated by both individuals and institutions (6 dummy variables) on transaction-by-transaction stock price changes.

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[18] I compute these numbers as follows. From table 4, 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 x(100/77.17)) and -2.57 (= -1.99 x (100/77.17)), for institutions and individuals, respectively.

Based on the results of the previous section, I expect to see the greatest positive and statistically significant impact of medium size trades from institutions on stock price changes.

As before, I estimate the weighted GMM regressions on each of the 97 stocks in our sample, where the weights are the absolute cumulative price change in that stock over the sample period, and the lagged dependent variable, $\Delta \boldsymbol{P}_{t-1}$, is included as an added independent variable to enable me to focus on the price impact of the current transaction. Table 5 presents summary regression results.

For medium size institutional trades, the average coefficient estimate (average standard error) is 0.0063 (0.0028). Seventy one (forty five are significant) coefficients are positive, and twenty six (eleven are significant) are negative. Based on the relatively low average standard error compared to the average coefficient estimate, and the significantly higher proportion of positive and significant coefficients, the positive and significant impact of medium size institutional trades, at the individual stock level, is clearly evident. The impact of the medium size institutional trades on stock price change is the most significant of all size trades. Recall from table 2 that the average medium trade size dummy coefficient is 0.0093. Thus, on average, about 70% of the overall contribution of medium size trades to transaction-by-transaction stock price change, appears to originate from medium size institutional trades.

In contrast, large institutional trades can have both a positive and a negative impact on stock price changes, while small institutional trades appear more likely to negatively impact stock price changes. But, given the relatively large average standard errors for both (compared to the respective average coefficient estimates), they appear statistically insignificant at all reasonable levels.

Based on the average and the direction of the coefficient estimates, and the relatively low average standard error, it appears as though large size individual trades are more likely to negatively (and significantly) impact stock price changes. By the same token, the effects of medium and small size individual trades appear ambiguous and of questionable statistical significance. If anything, the significant negative impact of large individual trades on prices, in rising stocks, may indicate the liquidity providing role of these orders. This is further confirmed, from table 4, by the relatively small average cumulative price increase (about 1%) associated with such trades.

Overall, the regression results indicate that the greatest positive and statistically significant impact on transaction-by-transaction stock price changes comes from medium size trades of institutions. These results provide additional evidence to support the notion that stealth trading is driven primarily by medium size institutional trades.

I provide, in table 6, the individual coefficient estimates of the five randomly chosen stocks. These results support the conclusions from tables 4 and 5, in highlighting the statistically significant and positive impact of medium size institutional trades on stock price changes.

6. Stealth Trading and Firm Size

Bhusan (1989) argues that large firms are followed by more analysts, which results in greater private information acquisition. This would argue for greater institutional trading activity in such stocks, and, by extension, greater stealth trading (see also, Brennan and Subrahmanyam (1995)). In contrast, smaller firms have less analyst following and less spotlight is focused on their corporate activities. Hence, less private information is generated on such firms, which, in turn, argues for less institutional involvement in such stocks and, by extension, little (or no) stealth trading. In this section, I further refine the data to investigate if stealth trading is related to firm size.

I collect the thirty largest firms in our sample into a LARGE firm subsample and the thirty smallest firms into a SMALL firm subsample. The market value of each firm, as of October 31, 1990, is obtained from the closing stock price times the number of shares outstanding. The mean size of the LARGE (SMALL) firms is $8,107,955,000 ($40,016,500).

Panel A in table 7 presents the results for the LARGE firms. The salient features are that the medium size trades have the highest cumulative price change associated with them (92%) and there does not appear to be any proportional relationship between percent cumulative price change and either the corresponding percent transactions or the corresponding percent volume. Stealth trading is supported over competing hypotheses. On decomposing the transactions into those initiated by individuals and institutions, the bulk of the cumulative price change appears to come from institutional trades (108% versus -19% for medium size individual trades).

Panel B of table 7 presents corresponding results for the SMALL firms. Once again, medium size trades have the highest cumulative price change associated with them (103%), but there also appears to be a proportional relationship between percent cumulative price change and the corresponding volume percentages. Thus, the trading volume hypothesis cannot be rejected either. I interpret these results as weak evidence of stealth trading. On decomposing the medium size trades into those initiated by individuals and institutions, I see that the cumulative price impact of medium size individual trades is actually somewhat larger than medium size institutional trades (58% to 45%, respectively). This greater price impact of individual trades over institutional trades can be understood by noticing that the former outnumber the latter (2,260 trades to 1,460 trades, respectively) and have comparable volume (2,935,400 shares to 3,150,400 shares, respectively). Thus, consistent with Bhusan's (1989) intuition, institutions appear to be less active relative to individuals, in small firm stocks.

Also notice from table 7 that trades (volume) in SMALL firms are about 7% (4%) of the trades (volume) in LARGE firms. Thus, LARGE firms are associated with significantly higher trading activity than SMALL firms. Institutional traders needing stealth in their trading would prefer to trade in LARGE firms because of the greater cover for their activities, an intuition consistent with Kyle (1985). SMALL firms, with relatively little trading, do not provide them with the needed cover. Correspondingly, I see relatively stronger effects of stealth trading in LARGE firms, and relatively less so, in SMALL firms.

In conclusion, stealth trading appears to be related to firm size and manifests primarily through medium size institutional trades in large firms.

7. A Robustness Check

In an effort to investigate the (possible) generality of the stealth trading hypothesis, I repeat my univariate tests on the whole universe of TORQ stocks. My approach is comparable to BW who investigate, and find (relatively weaker) support for the stealth-trading hypothesis in the entire universe of NYSE stocks in the 1981-1984 period. Specifically, I run my tests on all valid observations in the audit file for the entire sample of 144 stocks over the 63-day sample period between November 1, 1990, and January 31, 1991.

The upper panel of table 8 reports the mean percentage of the cumulative stock price change occurring on trades in each trade-size category, the corresponding percentage of transactions and trading volume for the whole sample of TORQ stocks. I also provide, in the lower panel of table 8, similar numbers for small, medium and large size trades initiated by individuals and institutions.

For transactions classified by trade size alone, medium size trades average 65% of the cumulative price change and comprise 53% of the transactions and 46% of the volume. Large size trades average 21% of the cumulative price change and comprise about 6% of the transactions and 51% of the volume. Small size trades average about 13% of the cumulative price change and comprise 41% of the trades and about 3% of the volume. Medium size trades have the highest cumulative price change. On further partitioning of the trades into those initiated by individuals and institutions, stealth trading appears to be driven by medium size institutional trades. Specifically, medium size trades from institutions (individuals) account for approximately 67% (-3.5%) of the cumulative price change.

In summary, stealth trading appears to be present in transactions encompassing all stocks in the TORQ data -- although not as dominantly as in our sample of 97 stocks. Contrary to the public information and the trading volume hypotheses, the mean percentage of cumulative price change associated with the three trade sizes is not proportional to either the percent of trades or the corresponding volume percent. Also, stealth trading appears to be driven by medium size trades originating from institutions.

8. Conclusion

Using intra-day transaction data for a sample of NYSE firms, I show that medium size trades have the highest percent cumulative price change associated with them. Even though large size trades have the highest price impact per transaction, it is the medium size trades that have the greatest price impact per unit volume. My results are consistent with the stealth trading hypothesis and inconsistent with the public information and trading volume hypotheses.

Upon further decomposition of trades into those initiated by institutions and individuals, I find that stealth trading is present primarily in medium size trades initiated by institutions. I also find stronger evidence of stealth trading in large firms, with significantly more transactions and transaction volume, than in small firms. This evidence is consistent with theory. Finally, my main conclusions appear robust to the sample selection procedure.

My findings extend those of Barclay and Warner (1993), and provide direct evidence regarding institutional investors being "smart" or informed traders.

In conclusion, through a careful empirical design and a detailed data set, I provide some insights into the complex world of strategic traders and the price impact of their trades. The weakness of the current research is a limited time series of data over a limited number of stocks. The strengths are a detailed data set providing a peek behind the curtain at the specific traders initiating a transaction in selected stocks, carefully constructed empirical design to mitigate confounding effects (such as sample selection, classification of trade initiators, and the exclusion of multiple trader groups on the active side of a trade), appropriate econometric analysis (such as the use of GMM a stock-by-stock basis) and robust tests (such as investigating stealth trading at a transactional level). But informed (or strategic) traders use a variety of ways to disguise their trades including, but not limited to, piggybacking their trades with uniformed traders, strategically submitting orders to test the market and then canceling all or a part of it, using limit orders, fragmenting orders across exchanges, across time, across multiple shell companies acting as fronts for their activities and across stock and options markets. I 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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Table 1. Cumulative Price Change, Trades and Volume by Trade Sizes

Sample consists of 97 NYSE firms in the TORQ database each with at least a 5% price increase between November 1, 1990 and January 31, 1991. I provide 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 and over). I define a stock-price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade. The percentage of cumulative price change, for a given firm, is the sum of all stock price changes occurring on trades in a given size category divided by the total cumulative price change over the sample period. I, then, estimate the weighted cross sectional mean of the cumulative stock price change, reported below, where the weights are the absolute value of the cumulative price change, in a stock, over the sample period. The percentage of trade (volume) is the sum of all transactions (volume), in a given size category, divided by the total cumulative trade (volume) over the sample period.

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 (10000+ shares)	25.23	9,431	6.23	196,913,600	50.50

Table 2. Summary Result of GMM Regressions on Individual Stocks

The dependent variable is the transaction-by-transaction stock price change and the independent variables are the lagged dependent variable, a large size trade dummy, a medium size trade dummy and a small size trade dummy. The estimation procedure is a weighted Generalized Method of Moments (GMM), run individually on each of the 97 stocks in the sample. The weights are the absolute cumulative price change in that stock over the sample period. The summary regression results presented below are the average coefficient estimates and the average standard errors for each of the independent variables in the regression model. I also provide the number of positive and negative coefficients for each of the independent variables in the model. The numbers in parenthesis denote the corresponding number of coefficients that are statistically significant at the 0.10 level or lower.

	ΔP_{t-1}	**Large Trade Dummy**	**Medium Trade Dummy**	**Small Trade Dummy**
Average Coefficient Estimate	-0.1636	-0.0101	0.0093	-0.0029
Average Standard Error	0.0526	0.0336	0.0044	0.0087
Number of Positive Coefficients	12 (1)	47 (20)	59 (44)	42 (25)
Number of Negative Coefficients	85 (70)	50 (30)	38 (8)	55 (40)
Total number of Stocks	97			

Table 3. GMM Regression Results of Randomly Selected Stocks

The dependent variable is the transaction-by-transaction stock price change and the independent variables are the lagged dependent variable, a large size trade dummy, a medium size trade dummy and a small size trade dummy. The estimation procedure is a weighted Generalized Method of Moments (GMM), run individually on each stock. The weights are the absolute cumulative price change in that stock over the sample period. The results presented below are for a randomly selected sample of stocks in the sample. The parameter estimates are provided along with their p-values in parenthesis under the respective estimates.

Stocks	Market Value (Dollars)	% price increase over sample period	ΔP_{t-1}	Large Trade Dummy	Medium Trade Dummy	Small Trade Dummy	Adjusted R-square	Number of Observations
MO	44,140,482,000	18.0	-0.2567 (0.000)	0.00955 (0.000)	0.0012 (0.049)	-0.00095 (0.229)	0.07	21,940
RDA	2,454,433,000	18.7	-0.19302 (0.000)	0.0129 (0.441)	0.01271 (0.020)	0.00834 (0.109)	0.04	904
FBO	551,458,000	36.9	-0.09249 (0.009)	0.00208 (0.837)	0.00769 (0.020)	0.00251 (0.650)	0.02	1,041
DP	411,514,000	45.5	-0.05637 (0.364)	-0.05399 (0.177)	0.03622 (0.005)	-0.02579 (0.044)	0.04	441
KWD	111,796,000	124	-0.03675 (0.454)	0.0130 (0.455)	0.0115 (0.029)	-0.0060 (0.383)	0.08	509

Table 4. Cumulative Price Change, Trades and Volume by Trade Sizes and Trader Types

Sample consists of 97 NYSE firms in the TORQ database each with at least a 5% price increase over November 1, 1990 and January 31, 1991. 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 and over). Additionally, within each trade size, trades are identified as initiating from individuals and institutions. I define a stock-price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade. The percentage of cumulative price change, for a given stock, is the sum of all stock price changes occurring on trades in a given size-trader category divided by the total cumulative price change over the sample period. I, then, estimate the weighted cross sectional mean of the cumulative stock price change, reported below, where the weights are the absolute value of the cumulative price change, in a stock, over the sample period. The percentage of trades (volume) is the sum of all transactions (volume) in a given size category divided by the total cumulative trades (volume) over the sample period. The percentage of trades (volume) by a specific trader group recalculates the corresponding percentages within each trader group. These are presented in columns 3, 6 and 9. Also note that the reason for the discrepancy between the sums in each size category in this table and the corresponding numbers in table 1, is because some of the trades, in each size category, cannot be uniquely assigned as originating from either individuals or institutions.

Trade Size (1)	% of Cumulative Price Change (2)	% of Cumulative Price Change by Specific Trader Group (3)	Number of Trades (4)	% of Trades (5)	% of Trades by Specific Trader Group (6)	Volume (7)	% of Volume (8)	% of Volume by Specific Trader Group (9)
Trades Initiated by Individuals								
Small(100-499 shares)	7.39	113.38	30,425	23.44	62.06	5,687,600	1.73	14.01
Medium(500-9999 shares)	-1.99	-30.54	18,056	13.91	36.83	24,512,700	7.45	60.40
Large(10000+ shares)	1.12	17.16	547	0.42	1.12	10,383,800	3.16	25.59
Trades Initiated by Institutions								
Small(100-499 shares)	-8.54	-9.13	21,268	16.38	26.33	4,287,300	1.30	1.49
Medium(500-9999 shares)	79.16	84.68	51,721	39.84	64.02	125,378,400	38.10	43.46
Large(10000+ shares)	22.86	24.45	7,797	6.01	9.65	158,856,300	48.27	55.06

Table 5. Summary Results of GMM Regressions on Individual Stocks

The dependent variable is the transaction-by-transaction stock price change and the independent variables are the lagged dependent variable, a large size individual trade dummy, a medium size individual trade dummy, a small size individual trade dummy, a large size institutional trade dummy, a medium size institutional trade dummy, a small size institutional trade dummy. The estimation procedure is a weighted Generalized Method of Moments (GMM), run individually on each of the 97 stocks in the sample. The weights are the absolute cumulative price change in that stock over the sample period. The results presented below are the average coefficient estimates and the average standard errors for each of the independent variables in the regression model. I also provide the number of positive and negative coefficients for each of the independent variables in the model. The numbers in parentheses denote the corresponding number of coefficients that are statistically significant at the 0.10 level or lower.

	ΔP_{t-1}	**Large Individual Trade Dummy**	**Medium Individual Trade Dummy**	**Small Individual Trade Dummy**	**Large Institutional Trade Dummy**	**Medium Institutional Trade Dummy**	**Small Institutional Trade Dummy**
Average Coefficient Estimate	-0.1696	-0.0254	-0.0114	-0.0032	-0.0096	0.0063	-0.0040
Average Standard Error	0.0248	0.0116	0.0097	0.0056	0.0102	0.0028	0.0165
Number of Positive Coefficients	11 (2)	43 (23)	46 (26)	43 (27)	48 (26)	71 (45)	39 (16)
Number of Negative Coefficients	86 (71)	54 (40)	51 (27)	54 (27)	49 (32)	26 (11)	58 (31)
Total number of Stocks	97						

Table 6. GMM Regression Results of Randomly Selected Stocks

The dependent variable is the transaction-by-transaction stock price change and the independent variables are the lagged dependent variable, a large size individual trade dummy, a medium size individual trade dummy, a small size individual trade dummy, a large size institutional trade dummy, a medium size institutional trade dummy, a small size institutional trade dummy. The estimation procedure is a weighted Generalized Method of Moments (GMM), run individually on each stock. The weights are the absolute cumulative price change in that stock over the sample period. The results presented below are for a randomly selected sample of stocks in the sample. The parameter estimates are provided along with their p-values in parenthesis under the respective estimates.

Stocks	Market Value (Dollars)	% price increase over sample period	ΔP_{t-1}	Trades Initiated by Individual Investors			Trades Initiated by Institutional Investors			Adjusted R-square	Sample size
				Large Trade Dummy	Medium Trade Dummy	Small Trade Dummy	Large Trade Dummy	Medium Trade Dummy	Small Trade Dummy		
MO	44,140,482,000	18.0	-0.25186 (0.000)	0.01786 (0.035)	-0.00163 (0.438)	-0.00098 (0.408)	0.00943 (0.000)	0.00264 (0.001)	-0.00078 (0.509)	0.07	21,940
RDA	2,454,433,000	18.7	-0.17809 (0.000)	-0.05000 (0.462)	0.00214 (0.862)	0.00672 (0.382)	0.01832 (0.276)	0.01238 (0.044)	0.01249 (0.147)	0.04	904
FBO	551,458,000	36.9	-0.10130 (0.009)	0.06250 (0.078)	-0.00432 (0.652)	0.01499 (0.084)	0.00218 (0.839)	0.01600 (0.000)	-0.00935 (0.309)	0.03	1,041
DP	411,514,000	45.5	-0.08258 (0.195)	-0.00541 (0.441)	0.03421 (0.195)	-0.01658 (0.361)	-0.05326 (0.182)	0.04793 (0.003)	-0.04528 (0.038)	0.04	441
KWD	111,796,000	124	0.00473 (0.000)	-0.00118 (0.672)	0.00462 (0.697)	-0.01246 (0.399)	0.01174 (0.510)	0.02106 (0.008)	-0.00595 (0.521)	0.02	509

Table 7. Cumulative Price Change, Trades and Volume by Trade Sizes, Trader Types and Firm Sizes

The LARGE firm sample comprises of the thirty largest firms and the SMALL firm sample comprises of the thirty smallest firms. Firm size is calculated as the closing stock price times the number of shares outstanding as of October 31, 1990, for each stock in our sample. I provide 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 and over). Additionally, within each trade size, trades are identified as initiating from individuals and institutions. I define a stock-price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade. The percentage of cumulative price change, for a given firm, is the sum of all stock price changes occurring on trades in a given size-trader category divided by the total cumulative price change over the sample period. I, then, estimate the weighted cross sectional mean of the cumulative stock price change, reported below, where the weights are the absolute value of the cumulative price change, in a stock, over the sample period. The percentage of trades (volume) is the sum of all transactions (volume) in a given size category divided by the total cumulative trades (volume) over the sample period. The percentage of trades (volume) by a specific trader group recalculates the corresponding percentages within each trader group. These are presented in columns 3, 6 and 9.

Panel A: LARGE Firms

Trade Size (1)	% of Cumulative Price Change (2)	% of Cumulative Price Change by Specific Trader Group (3)	Number of Trades (4)	% of Trades (5)	% of Trades by Specific Trader Group (6)	Volume (7)	% of Volume (8)	% of Volume by Specific Trader Group (9)
Small(100-499 shares)	-39.53		41,303	36.15		8,066,100	2.56	
Medium(500-9999 shares)	91.64		65,095	56.98		142,861,700	45.32	
Large(10000+ shares)	47.89		7,841	6.86		164,307,000	52.12	
Trades Initiated by Individuals								
Small(100-499 shares)	-12.78	48.26	21,432	21.66	68.19	3,854,700	1.44	15.65
Medium(500-9999 shares)	-18.61	70.24	9,624	9.73	30.62	13,761,900	5.13	55.86
Large(10000+ shares)	4.90	-18.50	373	.38	1.19	7,019,100	2.62	28.49
Trades Initiated by Institutions								
Small(100-499 shares)	-25.99	-20.55	17,389	17.57	25.75	3,491,800	1.30	1.43
Medium(500-9999 shares)	107.67	85.12	43,567	44.03	64.52	106,023,500	39.56	43.56
Large(10000+ shares)	44.82	35.43	6,570	6.64	9.73	133,866,500	49.95	55.00

Panel B: SMALL Firms

Trade Size (1)	% of Cumulative Price Change (2)	% of Cumulative Price Change by Specific Trader Group (3)	Number of Trades (4)	% of Trades (5)	% of Trades by Specific Trader Group (6)	Volume (7)	% of Volume (8)	% of Volume by Specific Trader Group (9)
Small(100-499 shares)	-2.50		3,175	39.19		652,600	4.92	
Medium(500-9999 shares)	102.58		4,680	57.76		7,799,200	58.74	
Large(10000+ shares)	-.08		247	3.05		4,825,900	36.35	
Trades Initiated by Individuals								
Small(100-499 shares)	10.34	14.83	2,234	31.94	49.24	448,300	4.19	11.07
Medium(500-9999 shares)	57.98	83.12	2,260	32.31	49.81	2,935,400	27.46	72.51
Large(10000+ shares)	1.43	2.05	43	0.61	0.95	664,500	6.22	16.41
Trades Initiated by Institutions								
Small(100-499 shares)	-12.73	-42.10	825	11.80	33.58	169,400	1.58	2.55
Medium(500-9999 shares)	44.83	148.24	1,460	20.88	59.42	3,150,400	29.47	47.42
Large(10000+ shares)	-1.86	-6.14	172	2.46	7.00	3,323,400	31.08	50.03

Table 8. Cumulative Price Change, Trades and Volume by Trade Size and Trader Types for the Universe of TORQ Stocks

The sample consists of all valid transactions in 144 NYSE firms in the TORQ database. The table includes 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 and over). Additionally, within each trade size, trades are identified as initiating from individuals and institutions. I define a stock-price change that occurs on a given trade as the difference between the trade's price and the price of the previous trade. The percentage of cumulative price change, for a given firm, is the sum of all stock price changes occurring on trades in a given size-trader category divided by the total cumulative price change over the sample period. I, then, estimate the weighted cross sectional mean of the cumulative stock price change, reported below, where the weights are the absolute value of the cumulative price change, in a stock, over the sample period. The percentage of trades (volume) is the sum of all transactions (volume) in a given size category divided by the total cumulative trades (volume) over the sample period. The percentage of trades (volume) by a specific trader group recalculates the corresponding percentages within each trader group. These are presented in columns 3, 6 and 9.

Trade Size (1)	% of Cumulative Price Change (2)	% of Cumulative Price Change by Specific Trader Group (3)	Number of Trades (4)	% of Trades (5)	% of Trades by Specific Trader Group (6)	Volume (7)	% of Volume (8)	% of Volume by Specific Trader Group (9)
Small(100-499 shares)	13.31		90,321	41.02		17,852,700	3.41	
Medium(500-9999 shares)	65.46		117,617	53.42		240,022,400	45.84	
Large(10000+ shares)	21.23		12,228	5.55		265,695,000	50.75	
Trades Initiated by Individuals								
Small(100-499 shares)	36.02	105.53	53,301	28.16	66.04	9,904,200	2.24	16.88
Medium(500-9999 shares)	-3.50	-10.25	26,698	14.10	33.08	34,812,200	7.86	59.32
Large(10000+ shares)	1.61	4.72	714	0.38	0.88	13,965,400	3.15	23.80
Trades Initiated by Institutions								
Small(100-499 shares)	-17.61	-26.74	31,437	16.61	28.95	6,329,100	1.43	1.65
Medium(500-9999 shares)	66.73	101.30	66,995	35.39	61.70	160,980,700	36.36	41.92
Large(10000+ shares)	16.76	25.44	10,146	5.36	9.34	216,742,700	48.96	56.44

Appendix

Below I present the 97 stocks in our sample, displaying at least a 5% price increase between January 31, 1991, and November 1, 1990. The price increase in each stock is calculated as the closing price on January 31, 1991, minus the opening price on November 1, 1990, divided by the opening price. The market value of each firm is computed as of October 30, 1990.

Ticker	Number of transactions	Market Value (in units of $1,000)	Opening Price on November 1, 1990	Closing Price on January 31, 1991	Stock price increase (%)
AC	719	371,027	13.000	16.875	29.8
ACN	1678	1,002,907	23.250	29.375	26.3
ACS	233	55,114	16.000	17.000	6.3
ADU	257	2,418	0.172	0.219	27.3
AL	1289	4,622,310	18.625	21.000	12.8
ALX	320	134,352	21.000	24.250	15.5
AMD	2792	441,357	3.875	7.125	83.9
AMN	154	140,829	35.875	40.375	12.5
AR	731	1,072,312	23.375	28.750	23.0
ARX	244	23,862	1.750	1.875	7.1
AYD	296	52,772	10.625	15.750	48.2
BA	8869	15,332,891	44.250	49.250	11.3
BG	543	418,424	21.000	24.500	16.7
BZF	444	96,328	7.250	8.875	22.4
CAL	1834	111,563	2.375	3.875	63.2
CLF	428	270,308	21.250	29.125	37.1
CMH	770	168,258	12.875	14.875	15.5
CMI	272	260,776	16.875	22.125	31.1
CMY	1931	1,170,700	24.625	31.500	27.9
COA	170	31,845	3.875	4.375	12.9
CP	782	4,977,422	15.375	17.750	15.4
CPY	365	398,060	26.000	29.000	11.5
CU	661	387,713	16.500	25.125	52.3
CUE	1578	304,313	10.250	15.375	50.0
CYM	985	779,941	15.000	19.750	31.7
CYR	1236	777,412	23.625	38.750	64.0
DBD	631	468,707	31.000	38.250	23.4
DCN	548	998,424	20.875	31.000	48.5
DI	3741	2,552,175	17.625	23.000	30.5
DP	338	411,514	23.375	34.000	45.5
DSI	735	147,845	10.250	11.000	7.3
EFG	65	619	0.055	0.059	7.1
EHP	231	3,266	0.563	0.625	11.1
EKO	260	34,839	2.250	2.750	22.2
EMC	2317	152,930	6.625	9.875	49.1
FBO	1041	551,458	16.250	22.250	36.9
FDX	1896	1,972,377	33.125	42.750	29.1
FFB	1060	826,200	13.250	19.125	44.3
FLP	246	17,409	1.375	1.750	27.3

Table continued

Ticker	Number of transactions	Market Value (in units of $1,000)	Opening Price on November 1, 1990	Closing Price on January 31, 1991	Stock price increase (%)
FMI	174	38,809	6.375	7.625	19.6
FNM	9332	7,077,116	28.500	39.625	39.0
GBE	314	22,704	1.000	1.125	12.5
GE	19274	49,984,706	51.625	64.000	24.0
GLX	7071	21,012,860	29.500	35.625	20.8
HAN	3202	2,768,319	18.000	19.500	8.3
HE	1279	620,368	27.750	32.250	16.2
HF	533	149,758	26.250	32.000	21.9
HFI	346	42,828	7.000	10.125	44.6
HTR	2153	235,676	9.625	10.625	10.4
IBM	17928	62,440,541	105.375	126.875	20.4
ICM	228		3.625	4.125	13.8
IS	197	23,011	1.875	2.250	20.0
KFV	699	202,545	10.500	12.500	19.0
KR	1403	1,082,042	11.250	17.250	53.3
KWD	447	111,796	6.250	14.000	124.0
LOG	575	377,500	20.000	22.000	10.0
LPX	1309	988,229	20.375	30.125	47.9
LUK	139	227,523	19.000	21.875	15.1
MBK	50	1,541	13.250	18.000	35.8
MCC	57	45,522	6.500	8.000	23.1
MDP	310	406,945	21.875	24.500	12.0
MNY	278	70,714	10.250	10.875	6.1
MO	21940	44,140,482	47.125	55.625	18.0
MX	420	298,854	15.250	22.500	47.5
NI	507	1,181,557	17.500	18.750	7.1
NIC	371	48,619	7.500	10.375	38.3
NT	712	5,856,850	26.375	27.750	5.2
OEH	63	24,388	2.375	2.750	15.8
PH	1284	1,167,464	20.000	26.750	33.8
PIM	1201	250,781	6.500	6.875	5.8
PIR	494	154,608	4.125	5.875	42.4
PMI	720	492,080	13.250	18.125	36.8
PRI	950		11.375	14.375	26.4
RDA	904	2,454,433	24.750	29.375	18.7
REC	165	52,147	5.000	5.250	5.0
RPS	476	154,096	4.625	5.375	16.2
SPF	1113	159,277	5.000	7.875	57.5
SWY	819	950,400	11.000	14.500	31.8
TCI	151	15,925	3.125	4.375	40.0
TEK	971	421,225	15.250	19.750	29.5
TUG	242	75,031	6.750	7.500	11.1
TXI	365	181,445	12.000	15.125	26.0
UAM	348	219,305	13.125	17.375	32.4
UMG	214	28,031	2.000	2.125	6.3
URS	97	9,881	2.750	3.625	31.8
USH	624	433,847	23.875	31.625	32.5
UTD	90	625,895	14.875	16.125	8.4

Table continued

Ticker	Number of transactions	Market Value (in units of $1,000)	Opening Price on November 1, 1990	Closing Price on January 31, 1991	Stock price increase (%)
UWR	608	174,090	10.875	13.250	21.8
VCC	82	6,045	1.250	1.500	20.0
W	855	1,595,024	24.750	28.000	13.1
WAE	55	1,853	0.086	0.094	9.1
WBN	2352	164,473	6.000	12.000	100.0
WCS	1113	386,552	17.500	20.750	18.6
WHX	208	17,263	2.625	3.875	47.6
WIN	544	2,655,837	29.875	36.375	21.8
Y	121	526,160	75.500	85.750	13.6
ZNT	213	261,476	10.250	12.500	22.0

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