Revisiting the Stealth Trading Hypothesis*

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Abstract

The stealth trading hypothesis (STH) states that informed traders concentrate their trades on medium sizes to conceal their information. Supporting empirical evidence for the NYSE case is considerable. In this paper, we question several methodological aspects of previous studies to provide new insights. We show that the STH cannot be rejected under alternative definitions of the trade-size cutoffs, after we control for bid-ask bounce, time between trades, and prevailing spread and depth. When we extract the friction-related component in price changes, we cannot reject the STH for some subsets of medium-sized trades, but we show that most of the disproportionally large role in the cumulative price change previously attributed to medium-sized trades dissipates.

Keywords: Stealth trading, trade size, trade frictions, electronic order-driven markets, trade duration, order aggressiveness, bid-ask spread, price formation, market microstructure.

1. Introduction

In market microstructure research, it is widely accepted that private information is revealed through trading. Endowed with perishable informational advantage, informed investors tend to trade gradually, looking for ways to conceal their trading intentions, in an attempt to delay the full revelation of their information. For example, in the seminal paper by Kyle (1985), informed traders break up their trades and spread them through time in order to camouflage their information. In Admati and Pfleiderer (1988), informed trading occurs when liquidity-motivated trading volume is high. Theoretical studies suggest than informed traders might act as liquidity providers by submitting limit orders rather than market orders when private information is substantial, long-lived, and/or their valuation is close to the current market quotes (Kaniel and Liu, 2006) or when they face wide bid-ask spreads and distant deadlines (Harris, 1988). Supporting evidence of the use of limit orders by informed traders is provided by Anand et al. (2005). In the literature about hidden volume (e.g., Moinas, 2005, Bessembinder et al, 2009), it is argued that informed traders may use hidden limit orders to obscure their positions and minimize the price impact of their trades.

Barclay and Warner (1993) study trade-size choices by informed investors and the implications of these choices for the volatility of prices. They argue that an informed trader can achieve a large change in share position with a remarkably smaller cumulative price concession through several medium-size trades spread over time. A large-size-based trading strategy would be self-revealing, and the cumulative price concession would be too high. A small-size-based trading strategy would be too expensive in terms of transaction costs, therefore limiting the profit potential, and time-to-completion, increasing the risk of the information being publicly revealed. Barclay and Warner's main hypothesis is that "[…] if informed traders concentrate their trades in medium sizes, and stock-price movements are mainly due to private information revealed through these investors' trades, then most of the stocks cumulative price change will take place on medium size trades" (p. 282). This hypothesis is known as the stealth trading hypothesis (henceforth, STH). It is important to emphasize that STH concerns the proportion of cumulative price changes across all trades of a given size. Therefore, to test the STH, we must take into account not only the price concession per trade of a given size, but also the frequency distribution of trade sizes.

Barclay and Warner (1993) (hereafter, BW93) established the basic methodology that has been used in posterior work on this topic. Firstly, one computes the security's cumulative price change over a sample period in each trade size category. The price change that occurs on a given trade is defined as the difference between the trade's price and the price of the previous transaction. The cross-sectional average cumulative price change in each category is then compared with the cross-sectional average proportion of either trades or volume in each category. When we use the proportion of trades as the reference, the hypothesis that is tested is labeled the "Public Information Hypothesis" (hereafter, PIH). The PIH postulates that stock-price volatility is due to public information and that cumulative price changes are directly proportional to the relative frequency of trades. Instead, when we use the proportion of volume as the reference, the alternative hypothesis is called the "Trading Volume Hypothesis" (hereafter, TVH). The TVH claims that cumulative price changes are directly proportional to trading volume. BW93 and several other studies (e.g., Chakravarty, 1991, and Anand, and Chakravarty, 2007) provide supporting evidence to the STH for different financial markets using the same methodology.[1]

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[11] The literature on stealth trading is reviewed in the next section.

Previous studies on the STH share the assumption that the only feature of the trading process that is correlated with the value of the asset is trade size. In the spirit of models such as Easley and O'Hara (1987), strategic informed traders' trading decisions consist merely in fixing the absolute size of their market orders, small, medium, or large. Market microstructure literature, however, has shown that traders learn about the true value of the asset by analyzing trade related and market environment related aspects other than trade size (e.g., Easley et al., 1997). In this paper, we extend BW93 methodology to account for some of those aspects previous studies have found to be relevant in price discovery, allowing for a more complex decision making problem by strategic informed traders. In particular, in addition to trade size, we consider the time between trades (trade duration), and both the relative bid-ask spread (immediacy costs) and the quoted depth at the time of the trade (order aggressiveness).

Easley and O'Hara (1992) proposes a model that highlights the importance of the timing of trades in price discovery, by establishing a link between the existence of information, the time between consecutive trades (trading intensity), and the stochastic process of securities prices. In their model, informed traders only trade when they have information, so that long durations mean no news. On the contrary, a shortening of trade durations signals that new information is arriving, which may result in increased bid-ask spreads, and speeded price adjustments. According to this model, trades of any size executed at short durations should have higher price impact. By breaking up large volume trades into smaller ones, as the STH predicts, informed traders are generating a larger number of information-based trades, increasing the trading rates. Hence, stealth trading may signal the presence of informed traders by increasing the trading intensity, as predicted by Easley and O'Hara (1992). Easley et al. (1997a,b) estimate asymmetric information dynamic models of market-maker behavior based on Easley and O'Hara

(1992). For 1 out of 6 NYSE-listed stocks considered, trade-size adds information content beyond that contained in the underlying transaction process. Engle (2000) observes that longer (shorter) durations lead to lower (higher) volatility. Dufour and Engle (2000) generalize Hasbrouck's (1991) vector autoregressive (VAR) model for trades and quotes by explicitly modeling the process of trade arrival. They find that as trade durations decrease, the price impact of trades, the speed of price adjustment to trade-related information, and the positive autocorrelation of signed trades, all increase.

So far, our discussion has focused on the predicted positive relationship between information asymmetry risk and price impact. However, the extensive theoretical research on the behavior of market makers exposed to informed traders has another major prediction: that information asymmetry risk is positively related to the size of the bid-ask spread.[2] Adverse selection costs models for order-driven markets, also predict that the bid-ask spread of the open limit order book has a component due to information asymmetry risk.[3] Consistently, Hasbrouck (1991) shows that the bid-ask spread plays a role in ascertaining the impact of trades. Using a VAR model for trades and quotes, he finds that trades that occur when the spread is wide have a relatively higher price impact than those that occur when the spread is narrow.

A market order (or a marketable limit order) is classified as aggressive when its size is larger than the available depth at the best quote on the opposite side of the market (e.g., Biais et al., 1995). In most order-driven markets, aggressive buy (sell) orders walk up (down) the book. Hence, *ceteris paribus*, aggressive orders carry on higher price concessions than non-aggressive orders of similar size. In terms of BW93 methodology, aggressive orders are expected to produce, more often than not, non-zero price changes

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[2] Seminal papers supporting this prediction include Bagehot (1971), Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), and Admati and Pfleiderer (1988), among others.
[3] See Glosten (1994), Handa et al. (2003), Foucault et al. (2007), and Goettler et al. (2008).

no matter the direction of the preceding trade. On the contrary, non-aggressive orders are expected to produce non-zero price changes mostly when they are preceded by a trade in the opposite direction. These price changes, however, are likely due to bid-ask bounce. These information unrelated movements (e.g., Roll, 1984) may bias any empirical test of the STH. Ascioglu et al. (2005) provide some evidence that price changes induced by bid-ask bounce downward bias the contribution of small-size trades.

Given the discussion above, we expect that the relative spread and the quoted depth right before a trade is executed, and the time gone since the prior trade, will condition the contribution to the security's cumulative price change in each trade size category. The relevant question is whether, after we control for trade features other than size and for liquidity conditions, the STH can still be confirmed.

Another major assumption of BW93 methodology is that price changes are mainly due to private information. However, one of the cornerstones of market microstructure research is the existence of trading frictions that make prices to temporarily deviate from the efficient price (e.g., Stoll, 2000). Hasbrouck (1996) considers the distinction between information-related and friction-related price changes as one of the two basic dichotomies in microstructure research (the other being trade-related vs. trade-unrelated information).[4] This dichotomy motivates empirical specifications in which the security's price follows a random walk (so-called efficient price) plus transitory disturbances (e.g., Hasbrouck, 2002). For example, Madhavan et al. (1997) use a structural model of price formation to show that between 54% and 65% of the transaction price volatility of a sample of NYSE-listed stocks is attributable to market frictions. Hasbrouck (1993)

[4] Sources of transitory price changes include the bid-ask bounce, price discreteness, market making costs (i.e., inventory holding costs, adverse selection costs, operative costs), limit order traders' exposure risk (i.e., free option risk, non-execution risk), temporary order imbalances, temporary liquidity shortfalls, specific trading rules (such as exchange mandated price smoothing) etc.

employs a reduced-form model to decompose transaction prices into their efficient and transitory components. He proposes to use the standard deviation of the pricing error as a summary measure of the quality of prices. Using a sample of NYSE-listed stocks, he reports that the average lower bound estimate of this measure is about 0.33% of the stock price, but it reaches 0.55% for small-caps.

It follows that the transaction price changes computed by BW93 and their followers contain an information-unrelated component. This is a relevant matter since the STH analysis is aimed to infer about the informational content of different trade-size categories through the accumulation of their instantaneous price changes. A standard way to get rid of certain types of trading frictions (such as bid-ask bounce) is to work with quote midpoints rather than transaction prices. As Hasbrouck (1988, 1991) points out, however, trading frictions cause lagged price effects of trades and serial correlation in quote changes, meaning that quote midpoint changes are not friction-free. In this paper, we use both quote midpoint changes and the unexpected component of the quote midpoint changes, extracted using time series techniques, instead of transaction price changes to test the STH.

To perform our empirical analysis, we use data from the electronic trading platform of the Spanish Stock Exchange, an order-driven market. Our database spans from July 2000 to December 2006, and our sample consists of the 55 most active and liquid common stocks during that period.

Using the BW93 methodological approach, we find evidence consistent with previous studies. When price changes are replaced by quote midpoint changes a remarkable portion of the disproportionally large role previous studies attribute to medium-sized trades dissipates. Nonetheless, the STH cannot be rejected, meaning that the STH is robust to bid-ask bounce. When we take out the friction-related dynamics in the quote midpoint changes, however, the role of medium-sized trades in the friction-unrelated cumulative quote midpoint change is virtually proportional to their share of trades and volume. Thus, we conclude that findings in prior studies might be largely biased by the friction-related component in the price changes.

We also show that trade size is not the only feature of the trading process that explains the cumulative price change. Using quote midpoint changes, we find that, *ceteris paribus*: (a) non-aggressive trades of any size play a negligible role, while aggressive trades, specially medium-sized, account for a disproportionate portion of the cumulative quote midpoint change; (b) medium-sized trades play a major role when the prevailing spread is large, and (c) trades of any size, but most notably medium-sized, with short durations have a disproportionally large role in the cumulative quote midpoint change. When all previous features of the trading process are considered together, we cannot reject the STH for some categories of medium-sized trades using either quote midpoint changes of friction-unrelated quote midpoint changes. In general, therefore, our findings qualify but support the STH.

The remaining of the paper is structured as follows. In section 2, we review the literature on the STH. In section 3, we provide market background and describe our database and sample. In section 4, we discuss methodological details. In section 5, we test the STH using quote midpoint changes instead of trade price changes to account for bid-ask bounce. In section 6, we test the STH controlling for order aggressiveness, relative spreads, and trade duration. In section 7, we test the STH using the unexpected component of the quote midpoint changes, as a proxy for the changes in the conditional expectation about the true value of the asset. Finally, in section 8 we conclude.

2. Literature on stealth trading

All the studies we review below analyze stealth trading using the methodological approach originally proposed by BW93, meaning that: (a) they assume that the informational content of a trade is determined, solely, by its size; (b) the same trade-size cutoffs are used for all stocks; (c) accumulated returns for each trade-size category are computed from marginal transaction prices; (d) they assume that price changes are driven by information, so they ignore the friction-related component in price changes.

With a few exceptions, the existing empirical studies about the STH deal with the NYSE case. The evidence supporting the STH in this market is overwhelming. BW93 use a sample of tender-offer target firms and reports that 99% of the cumulative price change occurs on medium-size trades, overcoming the frequency of this trade size category (38%). Chakravarty (2001) uses audit trail data from the TORQ database and a sample of NYSE-listed stocks with at least a 5% stock price variation. He reports that nearly 80% of the cumulative price change occurs from medium-size trades. In addition, he shows that stealth trading is mainly related to trades initiated by institutional investors. Alexander and Peterson (2007) examine trade-size clustering in the NYSE; they conclude that this phenomenon is consistent with the actions of stealth traders. Blau et al. (2009) study which trade sizes drive the well documented U-shaped pattern in intraday price changes. They find that intraday price changes from larger (smaller) trades exhibit a (reverse) U-shaped pattern. They argue that smaller trades are more informative when volume is low (middle of the day) because informed traders engage in stealth trading to disguise their information. Hansh and Choe (2007) perform an investigation of the STH from 1993 to 2003. They find that the distribution of informed trades in the NYSE shifts from medium-size trades to small-size trades around 2000. They argue that this shift towards smaller trades is mostly due to the decline in transaction costs, which has brought down the lower bound of trade sizes for stealth trading. Chakravarty et al. (2008) examine the fragmentation of trades by institutional traders around earnings announcements. For positive earnings surprises, they find evidence of stealth trading in the period immediately after the event, whereas for negative earnings surprises stealth trading happens within a two-day window before the event. Their findings depict the nature of the institutions' informational advantage: superior processing capacity of public information, for positive surprises, and gathering of (and trading on) the information before it becomes public, for negative surprises.

As far as we know, there are two studies about stealth trading for financial markets other than the NYSE. Using BW93 original methodology and data from the Tokyo Stock Exchange (TSE), Ascioglu et al. (2007) provide evidence supporting the STH. However, they show that by combining positive and negative price changes, the true effect of trade size on cumulative price changes is veiled. When they separate positive and negative price changes, small trades make the largest contribution to price changes, and they reject the STH against the PIH. They also show that large trades contribute more to the cumulative price change on high volatility days. Anand and Chakravarty (2007) show that price discovery in the options market primarily occurs through small and medium-sized trades. For a given contract, almost 60% of the price discovery takes place in the market with the highest market share, where informed traders prefer medium sizes and at-the-money calls to execute their trades. For liquid contracts, medium-sized trades account for the largest contribution, while for illiquid contracts, the largest contribution corresponds to small-sized trades.

3. Market background and data

We use trade and quote data from the Spanish Stock Exchange (hereafter, SSE). The World Federation of Exchanges (2006) ranks the SSE as the 9th largest stock exchange in the world in terms of market capitalization (the 4th in Europe), and the 7th in terms of total value of share trading (the 4th in Europe). All the stocks we consider are handled by the electronic order-driven platform of the SSE, called SIBE (*Sistema de Interconexión Bursátil Español*). The SIBE continuous trading session spans from 9:00 a.m. to 5:30 p.m., and it is preceded by a 30-minute opening call market and followed by a 5-minute closing call market. SIBE-listed stocks have no designated market makers or figure alike. Liquidity supply comes exclusively from limit orders stored in the open limit order book (hereafter, LOB) following the usual price-time priority rule. A transaction takes place when a market order or a marketable limit order hits the opposite side of the market. Transactions are easily classified into buyer-initiated and seller initiated since every trade consumes liquidity either at the best ask quote or the best bid quote available at the time of submission. Price improvement is not possible and traditional classification algorithms (e.g., Lee and Ready, 1991) are not necessary. The SIBE is a highly transparent market, with both pre-trade and post-trade information being disseminated in real time through the vendor screens.

Our database extends over six and a half years, from July 2000 to December 2006, being the largest database used so far to test the STH. The database consists of high frequency quote and trade files. Quote files comprise ask and bid quotes and the displayed depth up to the 5 best LOB levels. These files add a new register every time the LOB changes, either because a new order is submitted or an already-stored order is modified or withdrawn. Trade files include price, size, and time stamp of each trade. All files are matched using an algorithm originally developed by Pardo and Pascual (2011).

Our sample is formed by SIBE-listed common stocks that belong to the official market index: the IBEX-35. It includes the 35 most liquid and active stocks of the SIBE. Its composition is revised in an ordinary manner every six months. Extraordinary revisions are also common. During the whole sample period, there were a total of 55 index-constituents. In Table I, we provide some descriptive sample statistics and statistics for five subsamples based on market capitalization. Table I shows that our sample is quote heterogeneous, with remarkable differences in terms of trading activity and liquidity among the stocks in our sample.

[Table I]

4. Methodological details

4.1. *Trade-size cutoffs*

Previous studies about the STH analyzing NYSE data use the same trade-size cutoffs than BW93. Trades within 100-499 shares are small-sized, trades within 500-9,999 shares are medium-sized, and large-sized trades involve 10,000 shares or more. In the SSE, shares are not traded in round lots, as in the NYSE. Therefore, the BW93 cutoffs may not be appropriate. In Table II, we provide some statistics on the trade-size distribution for the 55 SIBE-listed stocks in our sample. There is evidence of trade-size clustering within the intervals [100 200), [500 750), [1000 2000), and [2000, 5000) shares.[5] Using the BW93 cutoffs, small trades in the SSE represent 30.45% of all trades, plus an additional 14.75% for trades below 100 shares. In comparison with BW93 NYSE sample (see Table 1, p.290), small-size trades are less frequent in the SSE, while medium (47.44%) and especially large trades (7.35%) are more frequent.

[Table II]

In Table III, we form 5 equally-sized portfolios based on both average price (Panel A) and trading frequency (Panel B). Panel A shows that as the average transaction price decreases, the median transaction size increases, from 133.51 for portfolio P1 (highest average price) to 406.59 for portfolio P5 (lowest average price). The 95% quantile of

[5] The lower bounds of these intervals concentrate most of the trades.

the trade-size distribution for portfolio P1 is about 1368 shares, whereas for portfolio P5 is about 6654 shares. Hence, the upper bounds in the BW93 cutoffs might be too large for low-priced SSE stocks. In fact, Panel A shows that as we increase transaction price, the percentage of small-sized trades increases while the percentage of both medium and large trades decreases. A possible solution is to redefine the BW93 trade-size cutoffs in terms of € rather than shares. The cross-sectional average transaction price in our sample is about 20€. We can then use the intervals (0 10,000€) for small-sized, [10,000€ 200,000€) for medium-sized, and at or above 200,000€ for large-sized trades. Panel A shows that using these €-based cutoffs, the disparity in the distribution of trade-sizes across portfolios decreases to some extent. Panel B reports similar problems with the activity-based portfolios. The median transaction size increases with trading frequency, from portfolio P5 (least active) to P1 (most active). With the BW93 trade-size cutoffs, the proportion of small-size transactions increases with the average trading activity of the stock. In this case, the use of the €-based cutoffs has the effect of increasing the proportion of small trades across all portfolios by decreasing the proportion of medium and large trades, but the divergence between distributions is barely affected.

We opt for considering stock-specific cutoffs based on the trade-size distribution of each asset. Namely, we compute the 50% (p5) and 95% (p95) percentiles of the trade-size distribution for each stock. Trades below the median trade-size are small-sized; trades at or above the median, but below the 95% percentile, are medium-sized, and trades at or above the 95% percentile are large-sized. The percentiles are revised every month.[6]

4.2. *Cumulative price changes and trading frictions*

[6] We also considered the €-based cutoff in Table III, but our findings do not remarkably differ from those obtained using the other cutoffs. These additional analyses are available upon request from the authors.

BW93 compute the price change as $\Delta p_t = p_t - p_{t-1}$, where p_t is the price of the transaction at time *t*. For aggressive market orders, we have different transaction prices involved in a single trade as they walk up or down the book. We define p_t in this case as the marginal price, that is, the price of the last share transferred. As previously discussed, Δp_t includes a component which is friction-related. We take account of that part due to bid-ask bounce by using quote midpoint changes instead of price changes. We follow Hasbrouck (1991) in fixing our timing convention: the quote midpoint change is $\Delta q_t = q_t - q_{t-1}$, where q_t stands for the average of the best ask and bid quotes set after the trade has occurred at time *t*. The quote midpoint prevailing before the trade at *t* has taken place is q_{t-1}. A $|\Delta p_t| > 0$ fully driven by bid-ask bounce, will have no impact in the quote midpoint change ($\Delta q_t = 0$).

Our method to compute the cumulative price change is as follows. For each of the 55 stocks and for each month between July 2000 and December 2006, we sum all price changes that occur on trades in a given trade-size category. We then divide this sum by the monthly cumulative price change across all trade-size categories. Finally, we compute a weighted average percentage of the monthly cumulative price change (henceforth, WAPCPC) in each trade-size category across all months and stocks, where the weight of each observation is the absolute value of the cumulative monthly price change. Our method differs from BW93 in that we allow the weight of each stock in the cross-sectional summary measure to vary from month to month instead of assuming a fixed weigh over the whole sample period. Given the length of our sample period, we understand this is a proper way to proceed. Following the previous steps, we also compute, for comparative purposes, the weighted average percentage of monthly number of trades (henceforth, WAPT), and the weighted average percentage of the monthly volume in shares (henceforth, WAPV). WAPT and WAPV are computed following the same steps and weights than WAPCPC.

Chakravarty (2001) suggests that stocks with a significant price change are more likely to have experienced informed trading and, hence, stealth trading. He samples stocks with a minimum 5% absolute price change. Following this suggestion, we give a zero weight in the computation of the summary measure to any stock that during a given month reports an absolute cumulated price change below 5%, but only for that month.

In computing accumulated price changes, we exclude quote and trade data from the opening and closing auctions. We eliminate overnight returns by discarding the first trade of each day. Besides, since May 2001 the SIBE incorporates a system of stock-specific intraday price limits and short-lived (5-minute) call auctions directed to handle unusual volatility levels. We exclude quote and trade data from these intraday auctions, and the first trade after each intraday auction too.

4.3. *The unexpected component of the quote midpoint price changes*

We follow Hasbrouck (1991) to obtain the estimate of the unexpected component in the quote midpoint changes, which we take as a proxy for the information-related component of price changes. We assume that the q_t can be decomposed into $q_t = m_t + s_t$. The first RHS term is the efficient price, the expected true value of the asset at some distant future conditional on the public information available right after trade t is completed, say $m_t = E\left[\Im_T \mid \Phi_t\right]$. The second RHS term ($s_t$) is a time dependent transitory component due to market frictions. Since revisions in expectations should be unpredictable, the efficient price satisfies the martingale property. Thus, $E\left[\Delta q_t \mid \Phi_{t-1}\right] = E\left[\Delta s_t \mid \Phi_{t-1}\right]$, and the unexpected component of Δq_t is given by $\Delta m_t = \Delta q_t - E\left[\Delta s_t \mid \Phi_{t-1}\right]$.

As in Hasbrouck (1991), we assume that the relevant information in Φ_{t-1} is the history of quote midpoint revisions and trades up to time *t-1*. We add to this set the history of spreads and trade durations up to time *t-1*. The trading process is summarized by the trade sign (x_t), which equals 1 for buyer-initiated trades and -1 for seller-initiated trades, and the signed trade size (v_t) in shares. We also consider the interaction of {x_t, v_t} with the bid-ask spread (sp_t), and the trade duration (d_t) in seconds. We assume that $E\left[\Delta s_t \mid \Phi_{t-1}\right]$ is a linear function relating trades and quote revisions which is stable over time

$$\begin{aligned}\Delta q_t = &\sum_{j=1}^{r}\left(\alpha_j \Delta q_{t-j} + \beta_j^x x_{t-j} + \beta_j^v v_{t-j}\right) + \sum_{j=1}^{r}\left(\beta_j^{xsp} x_{t-j} sp_{t-j} + \beta_j^{vs} v_{t-j} sp_{t-j}\right) + \\ &+ \sum_{j=1}^{r}\left(\beta_j^{xd} x_{t-j} d_{t-j} + \beta_j^{vd} v_{t-j} d_{t-j}\right) + \Delta m_t\end{aligned} \quad [1]$$

For each stock and month, we estimate model [1] by Ordinary Least Squares with White-robust standard errors of the estimated coefficients. No lag reaches back to the previous day, meaning that we discard the first *r* trades each day.[7] We consider two different options for *r*, 5 and 10 lags, but we report the findings only with *r* = 10 because our conclusions are barely the same with *r* = 5. The residuals of [1] are taken as our estimate of the unexpected and friction-unrelated quote midpoint change.

5. Stealth trading and the bid-ask bounce

In Table IV Panel A, we report the WAPCPC in each trade size category using transaction price changes, as in BW93. In Table IV Panel B, we report the WAPCPC using quote midpoint changes. In both panels, trade-size categories are defined using the BW93 cutoffs and the stock-specific cutoffs. To test the PIH and the TVH, we use

[7] We have analyzed the trade-size distribution of the initial *r* trades per day. We do not find remarkable differences with respect to the whole sample trade-size distribution. Results available upon request.

the non-parametric Wilcoxon (1945) rank-sum test for equality of medians. We compare the monthly series of the percentage cumulative price change in each trade-size category with the corresponding monthly series of the percentage of trades and the percentage of volume in shares, respectively. In the PIH (TVH) column, we report the median difference between the corresponding monthly time series in each trade-size category. Finally, we also report WAPT and WAPV in each trade size category.

[Table IV]

From Panel A, we see that most of the cumulative price change occurs in medium-sized trades. Using BW93 cutoffs, medium-sized trades cause 159.67% (WAPCPC) of the cumulative price change in our sample, while they comprise 36.45% of trades (WAPT) and 57.22% of share volume (WAPV). Large-sized trades cause about 46.87% of the cumulative price change, while they represent only 2% of all trades and 28.33% of the volume traded. Finally, medium-sized trades' contribution to the cumulative price change is -106.57%, much less than their WAPT (61.56%) and their WAPV (14.44%). Using BW93 methodology, our findings are therefore consistent with previous studies about the NYSE. We confirm that in SSE medium-sized trades have a disproportionally large role in the cumulative price change relative to their proportion of volume and trades, therefore supporting the STH. The statistical tests provide no support to the PIH and the TVH: medium-sized trades contribute more than expected given their percentage of trades and volume in the sample, while small-sized trades contribute less than expected. Thus, the PIH and the TVH are rejected in all cases at the 1% level.

Using the stock specific trade-size cutoffs, small-sized trades' WAPCPC (-124.05%) is still far below their WAPT (61.56%) and WAPV (7.78%). Medium-sized trades cause 157.08% of the cumulative price change and comprise 44% of trades and 45.91% of volume. Large-sized trades cause 67.41% of the cumulative price change, a contribution which is: (a) above those reported in previous studies for the NYSE with the BW93 methodology; (b) above their WAPT (5.07%), and (c) above their WAPV (46.42%). The PIH and the TVH are generally rejected at the 1% level. We can therefore conclude that our findings so far are robust to the different trade-size cutoffs considered.

Panel B in Table IV shows that previous findings remarkably change when we control for bid-ask bounce. Using BW93 trade-size cutoffs, the low and negative WAPCPC for small-sized trades disappears.[8] Trades in this category cause 26.64% of the cumulative quote midpoint change, which is still below their WAPT, but above their WAPV. Compared with their WAPT (36.45%), and to a lesser extent with their WAPV (57.22%), medium-sized trades still account for a disproportionately large percentage of the cumulative quote midpoint change (62.49%). Regarding large-sized trades, they comprise 10.87% of the cumulative quote midpoint change, above their WAPT (2%) but below their WAPV (28.33%). Using the stock specific trade-size cutoffs, the contribution of small-sized trades falls to about 13%, large-sized trades reach a 25.71% WAPCPC, still below their WAPV (46.31%), and medium-sized trades still report a WAPCPC (61.31%) is larger than their proportion of trades (44.06%) and volume (45.91%). As in Panel A, the PIH and the TVH are always rejected.

In summary, we can conclude that the STH is robust to bid-ask bounce. Nonetheless, our findings corroborate Ascioglu et al. (2005) intuition that the friction-related component in price changes largely explains the disproportionally low role in the cumulative price change previous studies have attributed to the small-sized trades. In what follows, we work exclusively with quote midpoint changes.

6. Trade size, order aggressiveness, relative spreads, and trade durations

[8] Negative contributions for small-size trades are common in previous studies.

In this section, we test the STH once we control for determinants of the information content of trades other than size. In particular, we consider order aggressiveness, prevailing immediacy costs, and trade durations. We define a trade as "ex-post" aggressive if it consumes more than is available (both displayed and non-displayed) at the opposite market quote.[9] The relative spread prevailing right before trade t takes place (rs_t) is computed as the ratio between the bid-ask spread and the quote-midpoint. We define three stock-specific levels of relative spread based on the percentiles of the empirical distribution of this variable: small (0, 0.25], medium (0.25, 0.75], and large (0.75, 1]. The duration of trade t is computed as the time in seconds between trade t and trade $t-1$. We also define three stock-specific trade duration levels based on the percentiles of the empirical distribution of this variable: short (0, 0.25], mid (0.25, 0.75], and long (0.75, 1].

Table V summarizes the stealth trading analysis conditional on order aggressiveness. We find negative or near-zero WAPCPC for all non-aggressive trades in all trade-size categories, largely below their corresponding percentages of trades and volume. This is a remarkable finding since non-aggressive orders account for 70% of all trades and 46.7% of all the volume in our sample. Regarding aggressive orders, we find disproportionally large contributions to the cumulated quote midpoint change relative to their proportion of trades for all trade-size categories. Using the BW93 cutoffs, aggressive small trades display a WAPCPC near 38%, a remarkable contribution taken into account that their WAPT is 14.18% and their WAPV is only 4.37%. Aggressive large-sized trades cause 10.81% of the cumulative quote midpoint change, above their

[9] Iceberg orders are allowed in the SIBE, but we can only ex-post infer about their presence. They are revealed once a market order consumes more depth than displayed at the corresponding market quote (see Pardo and Pascual, 2011). Our findings do not vary if we define order aggressiveness in "ex-ante" terms, that is, if we consider exclusively the displayed depth to compare with the size of the upcoming orders. Additional analyses using ex-ante order aggressiveness are available upon request from the authors.

percentage of trades (1.02%) but below their percentage in volume (19.69%). Similar findings are reported when the stock-specific cutoffs are considered. The WAPCPC for aggressive small-sized trades falls to 22.48%; for the aggressive large-sized trades it rises to about 26%, this time above both their WAPT (1%) and their WAPV (20.57%). In line with the STH, however, aggressive medium-sized trades report the largest WAPCPC, about 65% no matter the trade size-cutoffs considered, surpassing by far their proportion of trades (between 14.87% and 16%) and their proportion of volume (about 29%). For all categories considered, both the PIH and the TVH are rejected at the 1% level.

[Table V]

Table V suggests that informed traders concentrate on aggressive trades, most notably on medium-sized aggressive trades. We therefore qualify the STH as formulated by BW93. Informed traders do try to conceal their trading intentions by submitting medium-sized orders. Nonetheless, they fit the size of their orders to the available depth. They tend to submit orders that consume the available depth at the opposite market quote.

Table VI summarizes our analysis of stealth trading conditional on the relative spread. Consistent with earlier studies (e.g., Hasbrouck, 1991), Table VI shows that trades executed when the spread is large tend to be more informative than trades executed when the spread is small. Consider, for example, the small-sized trades case with the stock-specific cutoffs. Small-sized trades executed when the spread is large, which account for 12.28% of all trades and 1.84% of all volume, display a WAPCPC of 5.76%. However, small-sized trades executed when the spread is narrow, which represent 14.7% of all trades and 2.25% of all volume, display a WAPCPC of 1.73%. Besides, for all categories of small trades the PIH is rejected, as they account for a disproportionally low percentage of the cumulative quote midpoint change relative to their proportion of trades. Moreover, the TVH cannot be rejected for small trades happening when spreads are large or midsized. Therefore, Table VI provides scarce support to small-sized trades being information-motivated.

[Table VI]

Medium-sized trades completed when the spread is large display a WAPCPC of 16.5%, above their WAPT (8.3%) and WAPV (8.41%). The PIH and the TVH are rejected in the proper direction. Although medium-sized trades completed when the spread is midsized report the largest WAPCPC (30.22%), above their WAPT (21.29%) and WAPV (22.29%), the TVH cannot be rejected. Regarding medium-sized trades completed when the spread is small, our findings are not consistent with the STH since these trades report a 14.6% WAPCPC, close to or below their WAPT and WAPV. In this case, the PIH (TVH) is rejected because the difference between the monthly percentages of cumulative quote midpoint change and trades (volume) is, in median terms, negative. Finally, Table VI shows that large-sized trades display a WAPCPC above their WAPT but below their WAPV in all spread categories. For these trades, the PIH is rejected when the spread is large or midsized. The TVH is always rejected but against the alternative that, in median terms, the percentage of the monthly cumulative quote midpoint change is below the percentage of the monthly volume in shares.

In a nutshell, Table VI also qualifies the STH as formulated by BW93. *Ceteris paribus*, medium-sized orders executed when the spread is narrow are not information motivated. Only medium-sized trades executed when the spread is large comprise a proportion of the cumulative quote midpoint change statistically above both the proportion of trades and the proportion of volume in that category.

Finally, Table VII summarizes our analysis of stealth trading conditional on trade durations. Consistent with Easley and O'Hara (1992) theoretical predictions, Table VII shows that trades of any size with short (long) durations display a WAPCPC which is largely above (below) their corresponding WAPT and WAPV. Only for trades with short duration, the PIH and the TVH are both rejected against the alternative that the percentage cumulative quote midpoint change is above the percentage of trades and volume, respectively. Consider again the stock-specific cutoffs. Among short-duration trades, medium-sized trades are the ones that comprise the largest proportion of the cumulative quote midpoint change (21.25%), while their proportion of trades is just 2.51% and their proportion of volume is only 2.42%. The monthly median of the difference between the percentage cumulative quote midpoint change and the percentage of trades or volume is above 18%. For mid-durations, only medium-sized trades report a contribution to the cumulative quote midpoint change above their proportion of both trades and volume. In this case, however, median monthly deviations are just 6.18% and 4.54%, respectively.

[Table VII]

Table VII also moderate the STH. Trades of any size with short-duration have a disproportionally large role in the cumulative quote midpoint change relative to their proportion of trades and volume. A way to interpret this finding is that in periods of intense information arrival informed traders trade all sizes, and so trade size is not informative for uninformed liquidity providers. Another interpretation might be that during fast trading periods quotes are more sensitive to trades of any size. The abovementioned disproportion is particularly noticeable for medium-sized trades. This is consistent with informed traders concentrating their trades primarily on medium sizes, and is therefore consistent with the STH.

In Table VIII, we put together all previous analyses by taking into account simultaneously trade size, trade duration, order aggressiveness, and the prevailing bid-ask spread. Given the findings in Table V, we group all non-aggressive orders in each trade-size category. Aggressive orders, however, are split into 9 subcategories, depending on the three levels of the bid-ask spread and the trade duration previously defined. This partitioning results in 30 categories of trades, 10 for each trade-size category. For each of these 30 categories, we compute the same statistics (WAPCPC, WAPT, and WAPV) and perform the same tests (PIH and TVH) than in previous analyses. The categories are not sorted in terms of WAPCPC, but according to how much their percentage of the cumulative quote midpoint change exceeds that expected under the PIH. Thus, Table VIII reports the top ten categories of trades by either the median difference between the monthly percentages of cumulative quote midpoint change and trades (PIH column) or to the difference between WAPCPC and WAPT.[10] Consistent with our previous findings, all top ten categories turn out to include aggressive trades. The findings with the BW93 cutoffs are reported in Panel A and the findings with the stock-specific cutoffs are reported in Panel B.

[Table VIII]

Consider Panel A of Table VIII. The most important finding to highlight is that, independently of the sorting criteria, among the top five categories at least four include medium-sized trades, and three of them always form the top three. Depending on the sorting criteria, there are up to seven categories of medium-sized trades in the top ten. The four top categories of medium-sized trades comprise 40.43% of the cumulative quote midpoint change; the aggregated difference between WAPCPC and WAPT

[10] Our main conclusions are robust to using other sorting criteria, such as the median difference between the monthly percentages of cumulative quote midpoint change and volume (TVH column) or the difference between WAPCPC and WAPV.

(WAPV) is 35.38% (30.58%), and the aggregated median difference between the monthly percentages of cumulative quote midpoint change and trades (volume) is 22.66% (19.12%). For these top four medium-sized categories, the PIH and the TVH are rejected against the alternative that the proportion of cumulative quote midpoint change is greater than the proportion of trades or volume, respectively. The second finding to remark is that among the top ten categories, there are no long-duration trades or trades completed when spreads are small unless they include medium-sized trades (and never among the top five). Small-sized trades or large-sized trades with long durations or with narrow spreads, never appear in the top ten. Panel B reports similar findings. As in previous analyses, when the stock-specific cutoffs are considered, large-sized trades play a major role in detriment of small-sized trades.

In summary, our findings in Table VIII are consistent with the STH in that certain categories of medium-sized trades account for a disproportionally large proportion of the cumulative quote midpoint change, relative to their proportion of trades or volume. It is also consistent with prior literature suggesting that trade characteristics such as order aggressiveness, prevailing immediacy costs, and trade durations have information content beyond trade size. Trades of any size executed when the spread is narrow or much time after the prior trade have a less remarkable role in explaining the cumulative quote midpoint change than other trades of similar size. We qualify the STH by showing that trade size is not the sole determinant of the cumulative quote midpoint change, although we do support the STH in showing that informed traders concentrate more often than not on medium sizes.

7. Stealth trading and the unexpected component of price changes

We have already shown that previous studies on stealth trading are biased by bid-ask bounce, but there are other sources of friction we have not considered yet. Our next goal is to test the STH once we filter the time series of quote midpoint changes to get rid of the serial correlation and the lagged quote effects of trades induced by trading frictions. We use the time series model [1] in Section 4, to obtain an estimate of the unexpected and friction-free component in the quote midpoint changes (Δm_t). Model [1] is estimated for each stock and month. There is limited serial correlation left in Δm_t: the average Durbin Watson statistic across monthly estimates is 1.99 (0.0217 std). Moreover, Δm_t is barely predictable using standard reduced-form or structural time series models of quotes and trades in the literature. All these are desirable properties for an estimate of the efficient price changes.

In Table IX, we test study stealth trading but using Δm_t instead of Δq_t. Table IX should be compared with Panel B of Table IV. Using the BW93 trade-size cutoffs, we find that the WAPCPC of small-sized trades increases from 26.6% (Table IV) to 46.22% (Table IX), but it is still below their WAPT (61.56%). Regarding medium-sized trades, their WAPCPC falls from 62.51% when computed using Δq_t to 47.57% when computed using Δm_t. The role of medium-sized trades in the cumulative Δm_t is still above their WAPT (36.45%), but no longer above their WAPV (57.22%). Finally, the contribution of large-sized trades falls from 10.88% (Table IV) to 6.21% (Table IX), above their WAPT (2%), but far below their WAPV (28.33%). With the stock-specific cutoffs, the WAPCPC of medium-sized trades (45.61%) comes even closer to both their WAPT (44.06%) and their WAPV (45.91%). Table IX therefore shows a dramatic decline in the role medium-sized trades play in the cumulative price change, which is now quite proportional to their portion of trades and volume in the sample. The evidence reported suggests that the evidence supporting the STH in prior studies might be largely explained by the friction-related component in the price changes.

[Table IX]

We have previously shown that certain categories of medium-sized trades account for a larger proportion of the cumulative quote midpoint change than others, depending on the trade duration and the immediacy costs and depth prevailing at the time of completion. Next, we proceed to test the STH using the friction-unrelated quote midpoint changes and controlling for the aggressiveness of orders, the duration of trades, and the prevailing relative spread. Namely, we replicate the analysis summarized in Table VIII but using Δm_t instead of Δq_t. Table X reports our findings.

[Table X]

When the BW93 trade-size cutoffs are considered (Panel A), we find at least four categories of medium-sized trades among the top five. When we sort the trades by the median difference of the monthly percentages of the cumulative Δm_t and trades (PIH column), categories of medium-sized and large-sized trades conform the top ten list. The top five categories of medium-sized trades comprise 20.61% of the cumulative Δm_t, while they represent 8.32% of trades and 16.43% of volume. The top five subsets of large-sized trades, however, display an aggregated WAPCPC of just 3.05%, while they represent 0.35% of trades and 5.87% of volume. The PIH is rejected for the top four medium-sized categories, but with a median monthly difference between the percentages of cumulative Δm_t and trades aggregated across categories of only 5.96%. When we sort trades by the difference between WAPCPC and WAPT, eight of the nine possible categories of aggressive medium-sized trades monopolize the top ten, accounting for 32% of the cumulative Δm_t, 12.79% of trades, and 25.22% of volume. The difference between WAPCPC and WAPT (WAPV) aggregated across categories is 19.33% (6.89%).

Trades with long durations appear in the top ten only when they are medium-sized, and they comprise 4.42% of the cumulative Δm_t when sorted by PIH, and 7.33% when sorted by WAPCPC-WAPT. Trades completed when spreads are narrow now climb to the top ten. Their role, however, largely depends of the trade-size. Medium-sized trades in the top ten executed when the spread is narrow account for 2.17% the cumulative Δm_t when sorted by PIH, and 8.58% when sorted by WAPCPC-WAPT. Small and large-sized trades in the top ten completed when the spread is narrow account for 0.4% of the cumulative Δm_t when sorted by PIH, and 6.07% when sorted by WAPCPC-WAPT.

When the stock-specific cutoffs are considered (Panel B), medium-sized and large-sized trades dominate the top ten. When sorted by the difference between WAPCPC and WAPT, for example, the top five medium-sized categories display a 27.56% WAPCPC, 14.77% more than the WAPT and 12.4% more than the WAPV aggregated across those categories. The top five large-sized categories, in contrast, display a WAPCPC of 6.74%, 5.3% above their WAPT and 6-77% below their WAPV.

In summary, if we are willing to assume that the only feature of trades correlated with the true value of the asset is trade size, and we control for the friction-related component in price changes, the prominent role attributed to medium-sized trades in the cumulated price change disappears. However, if we take into consideration the duration of trades and the prevailing bid-ask spread and depth, the STH is supported for certain categories of medium-sized trades, as they play a disproportionally large role in the cumulative friction-unrelated quote midpoint change, superior to that played by small-sized or the large-sized trades.

8. Conclusions

Previous studies on the stealth trading hypothesis (STH) assume that the only feature of the trading process correlated with the true value of the asset is trade size. Other features such as the time since the prior trade or the prevailing bid-ask spread and depth are purposely ignored, even though existing literature has shown that they may have information content beyond trade size. Previous studies also presume that price changes are information-motivated, ignoring the widely proven existence of a friction-related component in price changes. In this paper, we face this potential limitations. Firstly, we control for bid-ask bounce by using quote midpoint changes rather than transaction price changes. Secondly, we use time series techniques to filter the time series of quote midpoint changes from lagged price effects of trades and series correlation induced by trading frictions. Finally, we consider the aggressiveness of trades, their duration, and the prevailing bid-ask spreads in testing the STH.

In general, our main findings qualify but support the STH. Using the traditional methodological approach introduced by Barclay and Warner (1993), we find evidence supporting stealth trading in the Spanish Stock Exchange between 2001 to 2006 for a sample of 55 stocks. When we use quote midpoint changes, however, we observe that a remarkable portion of the disproportionally large role previous studies attribute to medium-sized trades disappears, but the STH is still corroborated. Thus, we conclude that the STH is robust to bid-ask bounce.

We show that non-aggressive orders role in the cumulated quote midpoint change is negligible, independently of their size. In contrast, aggressive orders of any size, but most notably medium-sized trades, account for a disproportionally percentage of the cumulative quote midpoint change. We qualify the STH by showing that, *ceteris paribus*, *aggressive* medium-sized trades are the ones that are likely to be information-motivated. We also moderate the STH by showing that, *ceteris paribus*, medium-sized trades executed when the spread is relatively narrow are not information-motivated. Only medium-sized trades completed when the spread is relatively large cause a percentage of the cumulative quote midpoint change statistically above both their proportion of trades and volume. Finally, we show that trade durations play a major role in the cumulative quote midpoint change. Trades of any size, but most notably medium-sized trades, with short durations have a disproportionally large role in the cumulative quote midpoint change. When order aggressiveness, bid-ask spreads, and durations are considered altogether, we provide support to the STH, but we confirm that all medium-sized trades are not equally informative.

Once quote midpoint changes are filtered to take out the friction-related dynamics, the traditional stealth trading analysis based exclusively on trade sizes provides limited support to the STH. The disproportionally large role attributed by previous studies to medium-sized dissipates. Thus, we conclude that the evidence supporting the STH in prior studies might be largely explained by the friction-related component in the price changes. Nonetheless, once we control for order aggressiveness, trade durations, and the prevailing relative spread, we cannot reject the STH for some categories of medium-sized trades, as they play a disproportionally large role in the cumulative friction-unrelated quote midpoint change, superior to that played by small-sized or the large-sized trades.

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Table II
Trade-size distribution

This table provides summary statistics on the trade size distribution of our sample. The sample comprises 55 stocks traded in the SSE from June 2000 to December 2006

Period Jul. 2000 - Dec. 2006	Total trades*	Mean number of trades per day	Percent of trades	Mean share volume per day*	Percent of share volume
(0,10)	1063.60	3.60	2.12	0.01	0.00
[10,50)	2632.80	7.42	5.26	0.21	0.04
[50,100)	3692.28	10.67	7.37	0.77	0.16
[100,200)	6215.33	18.35	12.41	2.47	0.51
[200,300)	4013.67	11.27	8.01	2.65	0.57
[300,400)	2907.48	8.15	5.80	2.72	0.59
[400,500)	2117.19	5.88	4.23	2.56	0.56
[500,750)	4728.59	13.17	9.44	7.66	1.67
[750,1000)	2299.41	6.36	4.59	5.47	1.20
[1000,2000)	6788.35	18.78	13.55	24.58	5.41
[2000,5000)	6485.15	17.92	12.95	54.14	11.92
[5000,10000)	3461.33	9.57	6.91	61.90	13.63
[10000,15000)	1482.08	4.10	2.96	46.07	10.14
[15000,20000)	591.99	1.63	1.18	27.10	5.98
[20000,∞)	1607.14	4.43	3.21	215.97	47.59
Barclay and Warner (1993) trade-size cutoffs					
Small-sized:					
(0 500)	22642.36	65.34	45.21	11.39	2.44
Medium-sized:					
[500 10000)	23762.82	65.80	47.44	153.76	33.84
Large-sized:					
[10000 ∞)	3681.20	10.17	7.35	289.14	63.71
Total	50086.39	141.30	100.00	454.29	100.00

* Divided by 1000

Table III
Trade-size distribution, stock price, and trading frequency

This table provides summary statistics on the distribution of trade size using alternative cutoffs. Our sample comprises 55 stocks traded in the SSE from June 2000 to December 2006. We sort the stocks into portfolios conditional on the average price (Panel A) and the average trading activity (Panel B).

Panel A. Price-based portfolios

		Quantiles			BW93 cutoffs (%)			BW93 cutoffs in € (%)		
	Average price	0.25	0.5	0.95	(0 500)	[500 10000)	[10000 ∞)	(0 10000)	[10000 200000)	[200000 ∞)
P1	34.90	53.19	133.51	1368.82	69.89	29.12	0.99	60.09	38.67	1.23
P2	22.23	83.10	201.15	2010.49	57.01	41.44	1.55	56.61	41.79	1.60
P3	16.30	105.39	285.51	2808.41	50.20	47.22	2.58	57.29	40.94	1.77
P4	12.38	106.10	319.19	4254.87	48.60	46.81	4.59	61.31	36.44	2.25
P5	6.68	156.82	406.59	6654.83	40.48	52.82	6.70	73.78	24.79	1.42
Avg.										

Panel B. Activity-based portfolios

		Quantiles			BW93 cutoffs (%)			BW93 cutoffs in € (%)		
	Avg. n^{er} of trades*	0.25	0.5	0.95	(0 500)	[500 10000)	[10000 ∞)	(0 10000)	[10000 200000)	[200000 ∞)
P1	2663.55	113.75	426.52	6124.00	43.18	49.72	7.10	48.50	47.22	4.28
P2	775.99	104.51	250.23	2464.35	50.65	47.18	2.17	60.03	38.96	1.02
P3	551.31	108.23	258.04	3846.60	56.88	40.40	2.72	64.95	34.06	0.99
P4	377.73	103.10	254.12	2945.65	53.72	43.89	2.40	64.05	35.04	0.91
P5	127.55	82.52	172.74	1888.51	63.89	34.55	1.56	71.34	27.62	1.04

* Divided by 1000

Table IV
Stealth trading and bid-ask bounce

This table summarizes a traditional analysis of stealth trading using price changes (Panel A) and quote midpoint changes (Panel B). We provide the weighted average of the monthly proportion of the cumulative price change (WAPCPC), of the monthly proportion of trades (WAPT), and of the volume in shares (WAPV) for trades of different size. We consider two alternative trade-size cutoffs. The first one was proposed by Barclay and Warner (1993): (0 499] small-sized, [500 9999) medium-sized, [10000 ∞) large-sized. The second one is based on the stock-specific percentiles of the empirical distribution of trade sizes: (0 50%] small-sized, [50% 95%) medium-sized, [95% ∞) large-sized. PIH stands for "Public Information Hypothesis". The PIH postulates that stock-price volatility is due to public information and that cumulative price changes are directly proportional to the relative frequency of trades. In the PIH column, we report the median of the monthly difference between the percentage of cumulative quote midpoint change and the percentage of trades in each trade-size category. TVH stands for "Trading Volume Hypothesis". The TVH claims that cumulative price changes are directly proportional to trading volume. In the TVH column, we report the median of the monthly difference between the percentage of cumulative quote midpoint change and the percentage of volume (in shares) in each trade-size category.

Panel A: WAPCPC with Barclay and Warner (1993) price changes

Cutoff criteria	Category	WAPCPC	WAPT	WAPV	PIH	TVH
BW93	(0 499]	-106.54	61.56	14.44	-104.94 *	-61.75 †
	[500 9999)	159.67	36.45	57.22	82.22 *	70.06 †
	[10000 ∞)	46.87	2.00	28.33	16.55 *	-12.10 †
Stock-specific	(0% 50%)	-124.05	50.88	7.78	-128.92 *	-85.98 †
	[50% 95%)	157.08	44.06	45.91	75.49 *	72.04 †
	[95% 100%]	66.97	5.07	46.31	48.80 *	9.27

Panel B: WAPCPC with quote midpoint changes (bid-ask bounce correction)

Cutoff criteria	Category	WAPCPC	WAPT	WAPV	PIH	TVH
Trade	(0 499]	26.64	61.56	14.44	-32.98 *	10.40 †
	[500 9999)	62.49	36.45	57.22	17.55 *	5.36 †
	[10000 ∞)	10.87	2.00	28.33	5.67 *	-23.06 †
Stock-specific	(0% 50%)	12.98	50.88	7.78	-39.13 *	3.82 †
	[50% 95%)	61.31	44.06	45.91	15.00 *	11.49 †
	[95% 100%]	25.71	5.07	46.31	18.98 *	-20.53 †

* Public Information Hypothesis (PIH) rejected at the 1% level

† Traded Volume Hypothesis (TVH) rejected at the 1% level

Table V
Stealth trading and aggressiveness

This table summarizes an analysis of stealth trading using quote midpoint changes conditional on the prevailing quoted depth. A trade is classified as aggressive if it consumes more depth (both displayed and hidden) than available at the opposite market quote. The other table contents are the same as in Table IV.

Cutoffs criteria	Category	Agressiveness	WAPCPC	WAPT	WAPV	PIH	TVH
BW93	(0 499]	Non-Agr.	-11.29	47.40	10.08	-23.42 *	-6.56 †
		Agr.	37.93	14.18	4.37	8.00 *	12.13 †
	[500 9999)	Non-Agr.	-2.39	21.56	27.95	-16.51 *	-17.51 †
		Agr.	64.88	14.87	29.28	25.65 *	19.86 †
	[10000 ∞)	Non-Agr.	0.06	0.97	8.63	-0.28 *	-4.25 †
		Agr.	10.81	1.02	19.69	3.23 *	-6.28 †
Stock-specific	(0% 50%)	Non-Agr.	-9.50	46.37	8.89	-23.96 *	-6.43 †
		Agr.	22.48	12.50	3.11	6.25 *	10.22 †
	[50% 95%)	Non-Agr.	-3.86	22.94	30.00	-17.26 *	-17.34 †
		Agr.	65.17	16.55	29.67	23.66 *	22.17 †
	[95% 100%]	Non-Agr.	-0.27	0.62	7.77	-1.01 *	-7.48 †
		Agr.	25.98	1.01	20.57	10.77 *	-1.32 †

* Public Information Hypothesis (PIH) is rejected at 1%
† Traded Volume Hypothesis (TVH) is rejected at 1%

Table VI
Stealth trading and the relative spread

This table summarizes an analysis of stealth trading using quote midpoint changes conditional on the prevailing relative spread. Based on the stock specific empirical distribution of the relative spread, we define three levels of immediacy costs: small (0, 0.25], medium (0.25, 0.75], and large (0.75, 1]. The other table contents are the same as in Table IV.

Cutoffs criteria	Category	R.Spread	WAPCPC	WAPT	WAPV	PIH	TVH
BW93	(0 499]	Large	8.78	14.27	3.11	-7.36 *	1.85
		Medium	12.70	29.33	6.97	-22.03 *	-0.30
		Small	5.16	17.96	4.36	-16.17 *	-2.28 †
	[500 9999)	Large	17.50	6.75	10.11	8.42 *	6.25 †
		Medium	30.39	17.57	28.45	7.92 *	-1.76
		Small	14.61	12.12	18.66	-8.61 *	-15.28 †
	[10000 ∞)	Large	3.52	0.46	5.09	0.52	-3.18 †
		Medium	4.02	0.82	13.16	0.92	-10.62 †
		Small	3.33	0.71	10.08	-0.29 *	-7.57 †
Stock-specific	(0% 50%)	Large	5.76	12.28	1.84	-8.26 *	0.93
		Medium	5.49	23.91	3.69	-20.94 *	-0.86
		Small	1.73	14.69	2.25	-13.54 *	-1.92 †
	[50% 95%)	Large	16.49	8.30	8.41	6.18 *	6.06 †
		Medium	30.22	21.29	22.29	4.13 *	3.77
		Small	14.60	14.47	15.21	-12.07 *	-12.21 †
	[95% 100%]	Large	7.54	0.90	8.06	3.74 *	-1.80 †
		Medium	11.40	2.53	22.60	4.99 *	-14.08 †
		Small	6.77	1.64	15.65	-1.43	-14.07 †

* Public Information Hypothesis (PIH) is rejected at 1%

† Traded Volume Hypothesis (TVH) is rejected at 1%

Table VII
Stealth trading and trade durations

This table summarizes an analysis of stealth trading using quote midpoint changes conditional on the trade duration (time since the preceding trade). Based on the stock specific empirical distribution of the trade duration, we define three levels: short (0, 0.25], mid (0.25, 0.75], and long (0.75, 1]. The other table contents are the same as in Table IV.

Cutoffs criteria	Category	Duration	WAPCPC	WAPT	WAPV	PIH	TVH
BW93	(0 499]	Long	4.75	29.87	6.84	-23.87 *	-1.98 †
		Mid	9.54	28.07	6.73	-15.08 *	3.81
		Short	12.35	3.62	0.87	5.26 *	7.52 †
	[500 9999)	Long	11.21	16.80	26.75	-12.34 *	-18.63 †
		Mid	30.69	17.70	27.76	7.98 *	2.06
		Short	20.59	1.94	2.72	19.99 *	19.76 †
	[10000 ∞)	Long	1.77	0.94	14.99	0.20	-14.62 †
		Mid	5.68	0.97	12.07	2.80 *	-8.78 †
		Short	3.42	0.09	1.27	1.07 *	0.23
Stock-specific	(0% 50%)	Long	1.65	24.95	3.73	-24.65 *	-2.78 †
		Mid	4.19	22.99	3.58	-17.82 *	0.90
		Short	7.14	2.93	0.47	4.94 *	7.15 †
	[50% 95%)	Long	12.07	20.26	21.27	-11.76 *	-13.22 †
		Mid	28.00	21.29	22.22	6.18 *	4.54 †
		Short	21.25	2.51	2.42	18.16 *	18.16 †
	[95% 100%]	Long	4.02	2.40	23.59	1.15 *	-18.74 †
		Mid	13.71	2.46	20.75	10.25 *	-6.41 †
		Short	7.98	0.21	1.97	6.98 *	5.76 †

* Public Information Hypothesis (PIH) is rejected at 1%
† Traded Volume Hypothesis (TVH) is rejected at 1%

Table VIII
Top ten: quote midpoint changes

This table summarizes an analysis of stealth trading using quote midpoint changes conditional on the trade duration (time since the preceding trade), trade aggressiveness, and the prevailing relative spread. We consider two different criteria to classify trades by size: The first one was proposed by Barclay and Warner (1993) (Panel A): (0 499] small-sized, [500 9999) medium-sized, [10000 ∞) large-sized. The second one is based on the stock-specific percentiles of the empirical distribution of trade sizes (Panel B): (0 50%] small-sized, [50% 95%) medium-sized, [95% ∞) large-sized. A trade is classified as aggressive if it consumes more depth (both displayed and hidden) than available at the opposite market quote. Based on the stock specific empirical distribution of the trade duration, we define three levels: short (0, 0.25], mid (0.25, 0.75], and long (0.75, 1]. Based on the stock specific empirical distribution of the relative spread, we define three levels of immediacy costs: small (0, 0.25], medium (0.25, 0.75], and large (0.75, 1]. We form 10 subcategories of trades for each trade-size category: 1 category for non-aggressive orders and 9 categories for aggressive orders, resulting for combining the three levels of relative-spread with the 3 levels of trade-durations. The other table contents are described in Table IV.

Panel A: BW93 cutoffs

Sorted by: PIH

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	15.6822	7.35 *	4.71 †	12.27	9.02
Medium	Mid	Short	8.4436	5.24 *	5.08 †	8.15	7.93
Medium	Large	Mid	8.6266	5.16 *	4.45 †	7.39	6.12
Medium	Large	Short	7.6792	4.91 *	4.88 †	7.58	7.50
Small	Large	Short	5.6485	1.41 *	1.46 †	5.53	5.61
Small	Large	Mid	3.7030	0.83	1.32 †	2.58	3.34
Small	Mid	Short	5.0959	0.57	0.76	4.73	4.99
Medium	Large	Long	2.9441	0.08	-0.73	1.66	0.25
Large	Large	Short	1.2608	0.04	0.01 †	1.25	1.13
Large	Mid	Mid	2.1297	0.03	-2.84 †	1.92	-1.46

Sorted by: WAPCPC - WAPT

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	15.6822	7.35 *	4.71 †	12.27	9.02
Medium	Mid	Short	8.4436	5.24 *	5.08 †	8.15	7.93
Medium	Large	Short	7.6792	4.91 *	4.88 †	7.58	7.50
Medium	Large	Mid	8.6266	5.16 *	4.45 †	7.39	6.12
Small	Large	Short	5.6485	1.41 *	1.46 †	5.53	5.61
Medium	Small	Mid	8.0488	-2.40 *	-4.27 †	5.48	3.28
Small	Mid	Mid	8.1902	-1.07	0.73	5.11	7.24
Small	Mid	Short	5.0959	0.57	0.76	4.73	4.99
Medium	Small	Short	4.6597	-0.22	-0.33	4.39	4.20
Medium	Mid	Long	6.6354	-0.64	-3.84 †	3.02	-0.81

* Public Information Hypothesis (PIH) is rejected at 1%

† Traded Volume Hypothesis (TVH) is rejected at 1%

Table VIII (Cont.)
Top ten: quote midpoint changes

Panel B: Stock specific cutoffs

Sorted by: PIH

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	15.7076	7.35 *	6.78 †	11.93	11.22
Medium	Mid	Short	9.1878	5.33 *	5.31 †	8.84	8.80
Medium	Large	Short	7.9059	5.13 *	5.12 †	7.78	7.77
Medium	Large	Mid	7.2850	3.76 *	3.55 †	5.89	5.59
Large	Large	Mid	4.2325	2.17 *	0.63	3.96	1.72
Large	Mid	Mid	5.9020	2.00 *	-2.73 †	5.21	-0.42
Large	Mid	Short	3.1654	1.51 *	1.30 †	3.12	2.63
Small	Large	Short	4.0724	1.43 *	1.49 †	3.98	4.06
Small	Large	Mid	2.5757	0.66	1.14	1.77	2.43
Large	Large	Short	2.6102	0.56 *	0.52 †	2.59	2.42

Sorted by: WAPCPC - WAPT

Medium	Mid	Mid	15.7076	7.35 *	6.78 †	11.93	11.2211
Medium	Mid	Short	9.1878	5.33 *	5.31 †	8.84	8.7972
Medium	Large	Short	7.9059	5.13 *	5.12 †	7.78	7.7705
Medium	Large	Mid	7.2850	3.76 *	3.55 †	5.89	5.5923
Large	Mid	Mid	5.9020	2.00 *	-2.73 †	5.21	-0.4198
Medium	Small	Mid	7.4875	-2.95 *	-3.27 †	4.51	4.0691
Medium	Small	Short	4.3854	-0.26 *	-0.28 †	4.05	4.0237
Small	Large	Short	4.0724	1.43 *	1.49 †	3.98	4.0559
Large	Large	Mid	4.2325	2.17 *	0.63	3.96	1.7245
Large	Small	Mid	3.7171	-0.40 *	-3.65 †	3.24	-0.9675

* Public Information Hypothesis (PIH) is rejected at 1%

† Traded Volume Hypothesis (TVH) is rejected at 1%

Table IX
Stealth trading and friction-unrelated quote midpoint changes

This table summarizes a traditional analysis of stealth trading using friction-unrelated quote midpoint changes. Using the time series model,

$$\Delta q_t = \sum_{j=1}^{r}\left(\alpha_j \Delta q_{t-j} + \beta_j^x x_{t-j} + \beta_j^v v_{t-j}\right) + \sum_{j=1}^{r}\left(\beta_j^{xsp} x_{t-j} sp_{t-j} + \beta_j^{vs} v_{t-j} sp_{t-j}\right) + \sum_{j=1}^{r}\left(\beta_j^{xd} x_{t-j} d_{t-j} + \beta_j^{vd} v_{t-j} d_{t-j}\right) + \Delta m_t$$

we extract from the quote midpoint changes (LHS) the dynamics caused by trading frictions. In the RHS of the model, *x* is the trade indicator (1 for buyer-initiated trades, -1 for seller-initiated trades); *v* is the signed trade size; *sp* is the bid-ask spread; *d* is the trade duration (time between trades), and Δm is our estimated of the friction-unrelated quote midpoint change. The findings reported are obtained with $r = 10$. The model is estimated for each stock and month by OLS with White-robust standard errors. The contents of the table are the same as in Table IV.

Cutoffs criteria	Category	WAPCPC	WAPT	WAPV	PIH	TVH
BW93	(0 499]	46.22	61.56	14.44	-9.53 *	33.42 †
	[500 9999)	47.57	36.45	57.22	3.27 *	-8.51 †
	[10000 ∞)	6.21	2.00	28.33	2.28 *	-26.57 †
Stock-specific	(0% 50%)	41.65	50.88	7.78	-9.15 *	33.84 †
	[50% 95%)	45.61	44.06	45.91	1.23 *	-2.28 †
	[95% 100%]	12.74	5.07	46.31	6.59 *	-32.95 †

* Public Information Hypothesis (PIH) is rejected at 1%

† Traded Volume Hypothesis (TVH) is rejected at 1%

Table X
Top ten: friction-unrelated quote midpoint changes

This table summarizes a traditional analysis of stealth trading using friction-unrelated quote midpoint changes conditional on the trade duration (time since the preceding trade), trade aggressiveness, and the prevailing relative spread. We consider two different criteria to classify trades by size: The first one was proposed by Barclay and Warner (1993) (Panel A): (0 499] small-sized, [500 9999) medium-sized, [10000 ∞) large-sized. The second one is based on the stock-specific percentiles of the empirical distribution of trade sizes (Panel B): (0 50%] small-sized, [50% 95%) medium-sized, [95% ∞) large-sized. A trade is classified as aggressive if it consumes more depth (both displayed and hidden) than available at the opposite market quote. Based on the stock specific empirical distribution of the trade duration, we define three levels: short (0, 0.25], mid (0.25, 0.75], and long (0.75, 1]. Based on the stock specific empirical distribution of the relative spread, we define three levels of immediacy costs: small (0, 0.25], medium (0.25, 0.75], and large (0.75, 1]. We form 10 subcategories of trades for each trade-size category: 1 category for non-aggressive orders and 9 categories for aggressive orders, resulting for combining the three levels of relative-spread with the 3 levels of trade-durations. See Table IX for details on the estimation of the friction-unrelated quote midpoint changes. The contents of the table are the same as in Table IV.

Panel A: BW93 cutoffs

Sorted by: PIH

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	9.8022	3.32 *	0.70	6.39	3.14
Medium	Large	Mid	3.6410	0.96 *	0.25	2.40	1.13
Medium	Mid	Short	2.7524	0.92 *	0.76 †	2.46	2.24
Medium	Small	Long	2.1759	0.76 *	-3.63 †	0.09	-1.88
Large	Mid	Mid	1.0809	0.06	-2.82 †	0.87	-2.51
Medium	Large	Long	2.2477	0.02	-0.79 †	0.96	-0.45
Large	Large	Short	0.2489	0.00 *	0.00 †	0.24	0.12
Large	Small	Short	0.4047	0.00 *	0.00 †	0.39	0.09
Large	Mid	Short	0.4409	-0.01	-0.09 †	0.42	0.09
Large	Large	Mid	0.8748	-0.07 *	-1.05 †	0.77	-0.61

Sorted by: WAPCPC - WAPT

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	9.8022	3.32 *	0.70	6.39	3.14
Medium	Small	Mid	5.2525	-1.69 *	-3.55 †	2.68	0.48
Medium	Mid	Short	2.7524	0.92 *	0.76 †	2.46	2.24
Medium	Large	Mid	3.6410	0.96 *	0.25	2.40	1.13
Medium	Small	Short	2.0345	-0.22 *	-0.33 †	1.77	1.58
Small	Small	Short	2.0640	-0.19 *	-0.03 †	1.70	1.96
Medium	Mid	Long	5.0830	-0.44	-3.59 †	1.47	-2.36
Small	Small	Mid	4.0112	-1.93 *	-0.29 †	1.29	3.20
Medium	Small	Short	1.3009	-0.09	-0.12	1.20	1.13
Medium	Large	Long	2.2477	0.02	-0.79 †	0.96	-0.45

* Public Information Hypothesis (PIH) is rejected at 1%

† Traded Volume Hypothesis (TVH) is rejected at 1%

Table X (Cont.)
Top ten: friction-unrelated quote midpoint changes

Panel B: Stock specific cutoffs

Sorted by: PIH

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	9.2910	2.95 *	2.40 †	5.52	4.80
Large	Large	Mid	3.0373	1.15 *	-3.60 †	2.35	-3.28
Medium	Mid	Short	2.9995	0.53	0.32	1.61	1.31
Medium	Small	Long	2.5441	0.46	0.43	2.19	2.15
Large	Mid	Mid	1.6631	0.45 *	-1.10 †	1.39	-0.84
Large	Large	Long	1.0819	0.23 *	0.01	1.03	0.55
Large	Large	Short	0.8117	0.08 *	0.03	0.79	0.62
Large	Small	Short	0.9346	-0.02	-0.17 †	0.89	0.46
Medium	Mid	Short	1.6845	-0.07	-0.33 †	0.25	-0.11
Medium	Large	Mid	1.1070	-0.09	-0.10	0.98	0.97

Sorted by: WAPCPC - WAPT

Trade size	Spread	Trade duration	WAPCPC	PIH	TVH	WAPCPC-WAPT	WAPCPC-WAPV
Medium	Mid	Mid	9.2910	2.95 *	2.40 †	5.52	4.80
Medium	Small	Mid	5.3323	-2.35 *	-2.67 †	2.35	1.91
Large	Large	Mid	3.0373	1.15 *	-3.60 †	2.35	-3.28
Medium	Small	Long	2.5441	0.46	0.43	2.19	2.15
Medium	Small	Short	2.2430	-0.26 *	-0.28 †	1.91	1.88
Medium	Mid	Short	2.9995	0.53	0.32	1.61	1.31
Large	Small	Mid	2.0427	-0.40 *	-3.67 †	1.56	-2.64
Large	Mid	Mid	1.6631	0.45 *	-1.10 †	1.39	-0.84
Medium	Small	Long	5.1510	-0.94	-1.66 †	1.19	0.34
Small	Small	Short	1.3256	-0.17 *	-0.02 †	1.05	1.28

* Public Information Hypothesis (PIH) is rejected at 1%

† Traded Volume Hypothesis (TVH) is rejected at 1%