1-12-2012

Short Sales, Long Sales, and the Lee-Ready Trade Classification Algorithm Revisited

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Keywords

Lee-Ready algorithm, short sales, classification

Disciplines

Finance and Financial Management | Portfolio and Security Analysis

Comments

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January 12, 2012

forthcoming, Journal of Financial Markets

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Asquith, Oman, and Safaya (2010) conclude that short sales are often misclassified by the Lee-Ready algorithm. The algorithm identifies most short sales as buyer-initiated, whereas the authors posit that short sales should be overwhelmingly seller-initiated. Using order data to identify true trade initiator, we document that short sales are, in fact, predominantly buyer-initiated and that the Lee-Ready algorithm correctly classifies most of them. Misclassification rates for short and long sales are near zero at the daily level. At the trade level, misclassification rates are 31% using contemporaneous quotes and trades and decline to 21% when quotes are lagged one second.

1. Introduction

Research in securities markets relies on trade direction to arrive at inferences on a wide array of subjects, from transaction costs and trading behavior of various investor groups to market efficiency and optimal market structure. Because trading data from many sources, including the NYSE's Trade and Quote (TAQ) database, lack trade direction identifiers, it is impossible to directly determine from these data whether a trade was initiated by a buyer or by a seller. Thus the literature has developed methods that allow for indirect trade classification, commonly referred to as "trade classification algorithms." The ability of such algorithms to correctly identify the trade initiator directly affects the credibility of a large body of empirical research.

The most commonly used trade classification algorithm is that proposed by Lee and Ready (1991).[1] The Lee-Ready algorithm infers trade direction from the trade price position relative to the prevailing quotes and historical prices. Studies using data from the early 1990s find that the Lee-Ready algorithm correctly classifies about 85% of all trades (e.g., Finucane, 2000; Odders-White, 2000), but in recent years questions have arisen about the efficacy of the Lee-Ready algorithm given the significant changes in market structure since the early 1990s.

Most recently, Asquith, Oman, and Safaya (2010) argue conceptually that short sales should be predominantly seller-initiated, yet they find that the Lee-Ready algorithm more often classifies short sales as buyer-initiated. The authors conclude that the algorithm is unreliable when used to classify short sales. Such a conclusion casts a shadow over many recent studies of short selling that use the Lee-Ready algorithm to sign trades. These studies find that short sellers provide liquidity when it is needed, help keep prices in check, and contribute to price discovery and market efficiency (e.g., Alexander and Peterson, 2008; Diether, Lee, and Werner, 2009b;

[1] Although a number of alternative algorithms have been developed (e.g., Ellis, Michaely, and O'Hara, 2000; Chakrabarty, Li, Nguyen, and Van Ness, 2007), the Lee-Ready algorithm remains the most frequently used.

Bailey and Zheng, 2010; Boehmer and Wu, 2010; and Comerton-Forde, Jones, and Putniņš, 2011). These findings are important from a policymaking standpoint, particularly in light of the negative public image of short sellers and recent debates over bringing back short-sale restrictions.[2] Furthermore, even studies that do not focus on short selling would be compromised if short sales were systematically misclassified by the Lee-Ready algorithm, as short sales represent a significant portion of general trading activity (e.g., Diether, Lee, and Werner, 2009a, report that short selling accounts for over 24% of the volume in NYSE stocks and for over 36% of the volume in NASDAQ stocks). Given the importance of understanding short and long sellers' actions for academic research and policymaking, it is imperative to assess the Lee-Ready algorithm's reliability in classifying trades.

In this paper, we use INET[3] order data to examine whether the Lee-Ready algorithm correctly identifies the true trade initiator for short sales. We also examine the Lee-Ready algorithm's accuracy for long sales to see if the performance differs for short versus long sales. The INET order data allow us to match each trade to the orders that constitute it and determine whether the trade is triggered by a sell order or a buy order, without relying on the Lee-Ready (or any other) algorithm. We follow the convention in the market microstructure literature of considering a trade to be "initiated" by the last party to agree to the trade, the party whose decision causes the trade to occur. The initiator is thus the liquidity demander in the trade. For each INET trade, we identify the true trade initiator from the order data and then compare these true initiation statistics with the Lee-Ready estimates.

[2] "There's a Better Way to Prevent 'Bear Raids'" by R. Pozen and Y. Bar-Yam, *The Wall Street Journal*, November 18, 2008; "Restore the Uptick Rule, Restore Confidence" by C. Schwab, *The Wall Street Journal*, December 9, 2008; "Four European Nations to Curtail Short Sales" by L. Story and S. Castle, *The New York Times*, August 11, 2011; "Studies Find Shorting Bans Come Up Short" by J. Armstrong, *Traders Magazine Online News*, October 4, 2011.

[3] Until 2005, when it was acquired by NASDAQ, INET was an independent Electronic Communications Network (ECN). In 2006, INET and NASDAQ were integrated, and INET became NASDAQ's primary trading platform (Hasbrouck and Saar, 2009).

Our study addresses three issues. First, we ask whether Lee-Ready correctly classifies short sales at the daily level, to shed light on Asquith et al.'s (2010) argument regarding short sales. We also analyze long sales to provide a basis for comparing whether Lee-Ready performs relatively worse for short than long sales and address more general concerns about using Lee-Ready to sign trades. Second, we examine the accuracy of the Lee-Ready algorithm at the trade level, comparing the results from our 2005 sample to the trade-level results from the early 1990s (as in Odders-White, 2000). As part of our trade-level analysis, we re-examine the current practice of using contemporaneous quotes to sign trades versus Lee and Ready's (1991) recommendation that quotes should be lagged. Third, we examine the consequences of trade misclassification at the daily and intraday level in the context of studying the aggressiveness of short and long sellers. We ask whether inferences about short- and long-seller aggressiveness based on the true trade initiator are different from those obtained using the Lee-Ready algorithm.

Addressing the first issue, we find that short sales are more often buyer-initiated than seller-initiated, whereas long sales are more often seller-initiated than buyer-initiated. About 43% of short sales are truly seller-initiated in our sample, whereas close to 54% of long sales are truly seller-initiated. In other words, in short sales it is the buyer of securities who usually causes the trade to occur by taking the liquidity provided by a short seller. In contrast, long sellers consume liquidity more often than they provide it. These findings are important on two levels. First, the Lee-Ready algorithm appears to be correct in classifying most short sales as buyer-initiated, in contrast to Asquith et al.'s (2010) conjectures. Second, at the daily level, Lee-Ready classifications match true trade classifications almost perfectly. The differences between true and inferred classifications are insignificant statistically and economically. These results provide support for studies such as Diether et al. (2009b) and Bailey and Zheng (2010) that use daily data to draw inferences.

That the Lee-Ready algorithm performs well at the daily level does not guarantee that it is equally accurate at the trade level, since daily aggregation could obscure offsetting trade misclassifications. To address our second question, we compare the trade initiator estimates of Lee-Ready to the true trade initiator from the order data. Using contemporaneous quotes and trades, Lee-Ready misclassifies up to 32% of all short sales and up to 31% of all long sales. Because misclassification rates are similar for buyer-initiated and seller-initiated trades, they cancel each other out at the daily level, resulting in the high daily success rates reported earlier. Although our results are not directly comparable to those in Odders-White (2000), we note that misclassifications appear to have increased from the early 1990s, when Odders-White finds that about 15% of all trades are misclassified.

We next examine whether the increase in misclassifications is explained by temporal changes in trade or stock characteristics that the earlier literature finds are related to the error rates of the Lee-Ready algorithm. We confirm that trade size, trade price relative to the NBBO, stock trading frequency, and firm size are still important determinants of misclassification rates in our sample, yet none of these characteristics changes enough to explain the overall increase in misclassification rates since the 1990s. We further show that a relatively simple adjustment to the algorithm reduces misclassification rates by about one third: Using a one-second quote lag lowers the incidence of misclassification from 32% to 21% for short sales and from 31% to 22% for long sales. This finding suggests that researchers should consider returning to the practice of lagging quotes in intraday studies. Notably, lagging quotes does not improve Lee-Ready accuracy in the daily aggregates.

Finally, we examine the consequences of trade misclassification for the inferences drawn from studying short sale and long sale aggressiveness in a multivariate framework. Diether et al. (2009b) find that the variation in short selling as a percentage of total volume suggests that short sellers are contrarian, risk-bearing liquidity providers. Extending their argument to trade aggressiveness (the percentage of trades that are seller-initiated), we confirm that short sellers indeed often act as liquidity providers, as do long sellers. Short sellers and long sellers are less aggressive (provide more liquidity) on days when returns and buy-sell order imbalances are positive. On days when returns are negative, short and long sellers demand liquidity. Notably, liquidity supply and demand patterns by short and long sellers are statistically indistinguishable, which is surprising given short sellers' negative reputation. On the intraday level, we find that short sellers (but not long sellers) provide more liquidity when spreads are wider. Using Lee-Ready estimates generally leads to inferences that are similar to those obtained using true trade direction, although some coefficient estimates differ economically. Overall, our findings support the use of the Lee-Ready algorithm in daily studies; however, studies using the Lee-Ready algorithm at the intraday level should be aware of the increase in trade misclassifications since the early 1990s.

The remainder of the paper is organized as follows. Section 2 describes our data and sample. Section 3 presents our results on the performance of the Lee-Ready estimates compared to the true data for short sales and long sales in a univariate setting. Section 4 compares the performance of the Lee-Ready estimates to the true data in a multivariate analysis of trade aggressiveness. Section 5 concludes.

2. Data and sample selection

Our analysis uses data from TAQ, the Center for Research in Security Prices (CRSP), the short sales data provided by exchanges under the SEC's Reg SHO initiative, and order data from INET. We analyze data from two months (June and December 2005) to replicate the sample period in Asquith et al. (2010).[4] In 2005, under Reg SHO, one third of the stocks in the Russell 3000 index are designated as pilot stocks, for which short sale price tests are suspended. The remaining – non-pilot – stocks are subject to an uptick rule on the NYSE and a bid price test on NASDAQ.[5]

2.1 Sample construction

We construct our sample of pilot stocks as follows. From CRSP, we collect all NASDAQ-listed common stocks (SHRCD = 10 and 11, EXCH = 3) that trade every day during May, June, and December 2005. We exclude NASDAQ small-cap stocks (NMSID = 3) and stocks with prices below $5 per share. We then use the Reg SHO list to separate the stocks into a pilot sample (342 stocks) and a non-pilot sample (1,319 stocks). To form a size-stratified sample of pilot stocks, we rank the pilot stocks by market capitalization as of the end of May 2005 and select every third stock, for a total of 100 stocks.

We construct a matched sample of 100 non-pilot stocks as follows. Using one-to-one matching without replacement, we determine a unique non-pilot match for each stock in our pilot sample based on CRSP market capitalization, closing price, and share volume. We use market

[4] In addition to June and December, Asquith et al. (2010) analyze data from March 2005, finding results similar to the other two months. We exclude March 2005 from our analysis because the Reg SHO pilot program does not formally commence until May 2, 2005 (SEC Release No. 50747 (November 29, 2004)).

[5] Under the uptick rule, a short sale is allowed only on a plus tick or on a zero tick where the most recent price change preceding the zero tick was a plus-tick (called a zero-plus tick). Under the bid price test, a short sale is not allowed at or below the inside bid when the current inside bid is at or below the previous inside bid.

capitalization and price at the end of May 2005 and average daily trading volume in May 2005, which precedes our analysis period. We randomize the order of matching by sorting the pilot stocks alphabetically by ticker symbol. We then calculate the following matching error for each pilot stock *i* and each remaining non-pilot stock *j*:

$$\text{matching error} = \left|\frac{MCAP_i}{MCAP_j} - 1\right| + \left|\frac{PRC_i}{PRC_j} - 1\right| + \left|\frac{VOL_i}{VOL_j} - 1\right|, \qquad (1)$$

where *MCAP* is the stock's market capitalization, *PRC* is the stock's closing price, and *VOL* is the stock's average daily volume. For each pilot stock, we select the non-pilot stock with the lowest matching error and subsequently remove the selected non-pilot stock from the list of potential non-pilot matches for the remaining pilot stocks. Table 1 provides descriptive statistics for the pilot stocks and the matched sample of non-pilot stocks.

[Table 1 Here]

Table 1 shows that the pilot and non-pilot samples are well-matched on market capitalization, price, and volume, with mean and median differences insignificantly different from zero. The pilot and non-pilot samples also exhibit similar volume-based characteristics (i.e., number of trades, number of short sales, number of shorted shares, and proportion of short volume in total volume). We note that a few of the spread differences are statistically significant, yet they are economically small and the differences switch signs among the four measures. For example, the mean percentage quoted spread is higher for pilot stocks, but the median percentage quoted spread is lower. Overall, there are no consistent differences between the two samples.

We note that our sample of stocks differs from that of Asquith et al. (2010). Our sample consists of 200 stocks selected to evenly represent the distribution of market capitalizations of NASDAQ stocks, while the Asquith et al. sample consists of 200 randomly selected stocks, 100 of which are listed on the NYSE and 100 are listed on NASDAQ. We restrict our sample to

NASDAQ stocks because INET accounts for less than one percent of trading in NYSE stocks during our sample period (Shkilko, Van Ness, and Van Ness, 2010). An additional difference between our sample and the Asquith et al. sample is that our pilot stocks are paired to non-pilot stocks in a one-to-one match, whereas Asquith et al. do not match their pilot stocks to non-pilot stocks. Instead, their random sample contains 35 NYSE pilot stocks, 65 NYSE non-pilot stocks, 22 NASDAQ pilot stocks, and 78 non-pilot NASDAQ stocks. We examine pilot and non-pilot stocks separately to make our analysis comparable to that in Asquith et al.; however, we note that INET did not enforce NASDAQ's bid price test for short sales during our sample period (Diether et al., 2009a). Thus, our data may preclude us from detecting the same magnitude of differences between the pilot and non-pilot samples as that reported by Asquith et al. The results from our sample are more likely to be comparable to their pilot sample results.

Our primary motivation for examining June and December 2005 is to replicate the period studied in Asquith et al. (2010). These two months also offer the advantage of capturing a recent, relatively "normal" time in the markets – after decimalization, but before the financial crisis and the scrutiny of short sellers that followed (e.g., Boehmer, Jones, and Zhang, 2009; Beber and Pagano, 2011). Figure 1 demonstrates that prices of the sample stocks generally rise in June 2005 and fall in December 2005. We examine the results for the two months separately as well as jointly in case the accuracy of the Lee-Ready algorithm or the degree of seller initiation is sensitive to market direction.

[Figure 1 Here]

2.2 Determination of trade initiator for INET trades

The heart of this paper is a comparison of the true percentage of short and long sales that are seller-initiated, as determined from the INET order data, and the percentage of short and long sales estimated to be seller-initiated by the Lee-Ready algorithm. In this section, we first examine how much of the trading in NASDAQ stocks occurs on INET and then discuss the identification of trade initiator using order data and the Lee-Ready algorithm.

INET trading in NASDAQ stocks. Since our order data come from the INET trading platform, a natural concern is how much of market-wide trading occurs on INET. Nearly all of the trading in NASDAQ stocks during our sample period occurs on three venues: NASDAQ, INET (which is owned by NASDAQ but at this time operates as a separate market and reports trades separately from NASDAQ), and Arca (which has not yet merged with the NYSE). Table 2 shows that INET is the second-largest trading venue, representing about one quarter of total trading volume in our sample stocks in the month prior to our sample period (Panel A: May 2005) and a similar fraction in the two sample months (Panels B and C: June and December 2005). We note that INET and Arca, which are pure limit order books, have a smaller average trade size than does NASDAQ.[6] Finucane (2000) and Odders-White (2000) find that smaller trades are more often misclassified by the Lee-Ready algorithm, which could bias our study towards finding more misclassification on INET than occurs on NASDAQ at this time. We return to this issue in Section 3.

[6] Shkilko, Van Ness, and Van Ness (2008) find that trades on NASDAQ are about twice as large as trades on the National Stock Exchange (the host market for INET trades during our sample). Since 2005, NASDAQ's average trade size has fallen as NASDAQ has begun to resemble a pure limit-order market. In 2006, INET absorbed NASDAQ's SuperMontage and BRUT systems to become NASDAQ's primary trading platform (Hasbrouck and Saar, 2009). According to Brian Hyndman, Senior Vice President NASDAQ OMX, by September 2010 NASDAQ's average trade size had fallen to 225 shares (http://www.thetradenews.com/asset-classes/equities/5091).

Arca and, to a lesser extent, INET attract a higher percentage of short sales than long sales. This pattern is likely attributable to the less strict enforcement of the bid test by these two venues as compared to NASDAQ (Diether et al., 2009a). The remaining three venues, the Chicago Stock Exchange, FINRA's Alternative Display Facility (ADF), and the American Stock Exchange (AMEX), execute very little volume in our sample.

[Table 2 Here]

Trade initiator from INET order data. For our analysis, we must identify short sales and long sales in the INET dataset. The Reg SHO dataset identifies short sales by the exchange on which they are reported. During our sample period, INET reports all of its trades via the National Stock Exchange (NSX), and INET is the only major market that reports via the NSX.[7] We identify INET short sales by matching the NSX short sales to INET data on executed orders, based on ticker, date, time stamp, price, and traded quantity. We treat the remaining INET executions as long sales. Time stamps in the INET data are in milliseconds, and time stamps in the Reg SHO data are in seconds. Since there may be slippage in reported timestamps, we truncate INET time stamps to seconds and examine a look-ahead/look-back window of up to 10 seconds to find the matching trade. Over 98% of short sales are matched within one second, and 99.5% are matched within five seconds (see Appendix for the frequency distribution of matches). In the remainder of the paper, we use matches based on the one-second window, for consistency with Asquith et al. (2010). We also run a series of robustness checks including all trades for which matches occur within longer look-ahead/look-back windows. The results from these checks are nearly identical to the reported results and are available on request.

[7] When INET switches reporting from NSX to NASDAQ in February 2006, NSX reported volume drops to nearly zero.

The INET data indicate whether each trade executes against a sitting buy or sell order in the limit order book.[8] Following the chronology of order submission logic proposed by Odders-White (2000), we designate trades that execute against a sitting buy order (a buy limit order) as seller-initiated and trades that execute against a sitting sell order (a sell limit order) as buyer-initiated. This procedure produces a dataset of short sales and long sales executed on the INET platform with the true trade initiator identified directly from the order data.

Trade initiator from the Lee-Ready algorithm. To identify the trade initiator based on the Lee-Ready algorithm, we compare the price of each INET trade to the midpoint of the prevailing National Best Bid and Offer (NBBO) quotes. For our main analyses we use contemporaneous quotes to sign trades. In Section 3, we examine how lagging the quotes affects the accuracy of trade classification. A trade is classified as seller-initiated if it occurs below the NBBO midpoint and as buyer-initiated if it occurs above the midpoint. Trades occurring at the NBBO midpoint are classified as seller-initiated (buyer-initiated) if the trade price is lower (higher) than the price of the previous trade, with the previous trade drawn from the consolidated trade tape.

3. Lee-Ready algorithm versus true trade initiator

We begin this section by examining the seller-initiation percentages for short and long sales at the daily aggregation level. This analysis is comparable to Asquith et al. (2010). To augment this analysis, we then examine the misclassification frequencies at the trade level. The latter, more granular approach allows us to see whether the daily results reflect the true classification accuracy or are driven by trade misclassifications offsetting each other intraday.

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[8] For a detailed description of the INET order book data, see Hasbrouck and Saar (2009).

3.1 Classification at the daily level

Table 3 compares the percentage of short sales (Panel A) and long sales (Panel B) that are truly seller-initiated (True) to the percentage of sales identified as seller-initiated by the Lee-Ready algorithm (LR-estimated). We present the results as the percentage of trades and the percentage of share volume, treating the individual stock as the unit of observation. That is, we compute the seller-initiated percentage for each stock by averaging across sample days and then report the average across stocks.

[Table 3 Here]

The differences between the True and LR-estimated seller-initiated percentages are statistically insignificant in all periods, for both short and long sales, in both the pilot and non-pilot samples. For example, the true proportion of seller-initiated short trades in pilot stocks during the combined period is 42.6%, and the Lee-Ready algorithm estimates this share as 42.8% – a statistically insignificant difference. Similarly, the true share of seller-initiated long trades in pilot stocks is 54.7%, compared to the Lee-Ready estimated 54.8%. We find similar results when we compare the percentage of seller-initiated share volume instead of seller-initiated trades (see columns labeled %Shares in Table 3).

Our order-based analysis indicates that the preponderance of buyer initiation in short sales is true rather than the result of inaccuracies of the Lee-Ready algorithm as Asquith et al. (2010) suggest. Another notable observation from our findings is that short sellers are typically engaged in liquidity provision, as they initiate less than half of the trades they are involved in.[9] Long sellers, on the other hand, more often initiate trades and therefore consume liquidity. The greater

[9] Statistical tests (unreported, but available on request) of the differences between short-sale and long-sale seller-initiation percentages show that the differences are significant at the 1% level.

aggressiveness of long sellers dovetails with recent evidence that long sales depress prices more than short sales (Bailey and Zheng, 2010; and Shkilko et al., 2010) and that short sellers often choose to provide liquidity to impatient buyers (Diether et al., 2009b; and Comerton-Forde et al., 2011).

Our finding that the Lee-Ready algorithm classifies close to 43% of short volume in NASDAQ pilot stocks as seller-initiated is consistent with Asquith et al.'s (2010) finding of 42% to 47% seller initiation in their sample of NASDAQ pilot stocks (their Table 3, page 166). For non-pilot stocks, the Lee-Ready algorithm classifies 43% to 45% of short volume as seller-initiated in our sample, whereas Asquith et al. report 37% to 39% in their sample. As mentioned earlier, we do not expect our estimates for non-pilot stocks to match those in Asquith et al. because our sample is focused on INET trades, and INET did not strictly enforce the bid price test for non-pilot stocks during this period.

Tests of the differences between the pilot and non-pilot seller-initiated percentages show that the differences are statistically insignificant in both sample months and overall.[10] In other words, short sellers in pilot stocks are not more aggressive than short sellers in non-pilot stocks in our sample. Because the two samples yield identical inference, we combine them into one 200-stock sample in the tests that follow.[11]

3.2 Classification at the trade level

That the Lee-Ready algorithm generally classifies short sales and long sales accurately at the daily aggregation level is encouraging, but the daily findings may obscure misclassifications of

[10] For brevity, we do not report the tests of pilot versus non-pilot stock differences in Table 3. These results are available on request from the authors.
[11] In the regression analyses in Section 4, we distinguish between pilot and non-pilot stocks by including a pilot indicator, in case differences become apparent in a multivariate setting.

individual trades if they offset each other. For example, if 25% of true buyer-initiated trades are erroneously classified as seller-initiated, while 25% of true seller-initiated trades are erroneously classified as buyer-initiated, the accuracy of the Lee-Ready estimates would appear high at the daily level even though many individual trades were misclassified. To determine to what extent the Lee-Ready algorithm's high daily accuracy carries through to the more granular level, we examine the frequency of misclassification of individual trades.

In Table 4, we compare the true initiator for each trade with the classification provided by the Lee-Ready algorithm. In this table, we use contemporaneous trades and quotes to make the results comparable to our analysis in Table 3 and to most of the current literature. We conduct a series of robustness checks using lags of quotes later in this section.

Nearly 32% of short sales are misclassified by the Lee-Ready algorithm in our sample: 14.8% of true seller-initiated short trades are misclassified as buyer-initiated by Lee-Ready, and 17% of true buyer-initiated short sales are misclassified as seller-initiated. Similarly, Lee-Ready misclassifies about 31% of long sales, with 15.3% of long seller-initiated trades misclassified as buys and 15.5% of long buyer-initiated trades misclassified as sells. These misclassification rates are about double those found by Finucane (2000) and Odders-White (2000) for NYSE transactions from the early 1990s. Odders-White reports that nearly 15% of trades were misclassified by Lee-Ready: 7.6% of true sells were classified as buys, and 7.4% of true buys were classified as sells (her Table 2, Panel C, page 267).

[Table 4 Here]

Our results may appear surprising to readers who expect that in a fully electronic market like INET, the Lee-Ready algorithm should be able to determine a trade's direction with near-perfect accuracy. Indeed, in a hypothetical purely electronic limit order market, in which (i) all orders are publicly displayed, (ii) the inside quotes always match the NBBO, (iii) time clocks at every NBBO contributor are perfectly synchronized, and (iv) new orders never arrive simultaneously, the Lee-Ready logic should lead to very precise estimates. Every incoming marketable order would execute against either the best bid or the best offer, and comparing the resulting transaction price to the prevailing inside quotes would perfectly identify trade direction.[12]

We note that INET differs from the ideal market assumptions in several ways. First, hidden orders are allowed, and one cannot see hidden orders in the INET data until and unless they are executed. Second, INET traders are not market makers and thus are not obligated to post two-sided quotes at all times.[13] Third, Reg NMS was not in effect in 2005, so INET was not required to abide by the trade-through rule. Fourth, time clocks among NBBO-contributing markets are not perfectly synchronized, and finally, multiple trades can arrive at INET simultaneously. All of these imperfections relative to the ideal market create the environment in which the Lee-Ready algorithm performs less than perfectly.[14]

Given the imperfect performance of the Lee-Ready algorithm on the trade level, we examine whether the trade and firm characteristics that have been shown to affect misclassification rates are disproportionally affecting trade identification in our sample. The results in Table 5 suggest that misclassifications generally follow patterns that are similar to those found by Odders-White (2000). Specifically, misclassifications are highest at the spread midpoint (Panel A), for stocks with more transactions (Panel C), and for larger firms (Panel D). The only notable difference is that our sample exhibits higher misclassification rates for large trades (Panel B), whereas Odders-White finds higher misclassification rates for small trades. We verify our results using

[12] We thank the referee for suggesting this perspective.
[13] Chakrabarty, Corwin, and Panayides (2011) document that INET often does not post two-sided quotes.
[14] Chakrabarty et al. (2007) come to similar conclusions about error rates in classifying INET trades. Holden and Jacobsen (2011) draw attention to issues in determining the NBBO that arise from time stamp differences.

two trade-size cutoffs: 300 shares, which is approximately the mean trade size in our sample (and equal to the cutoff that Odders-White uses), and 100 shares, which is the median trade size in our sample. Both size cutoffs show higher misclassification rates for larger trades. Although this switch to higher misclassification of large rather than small trades is interesting, it cannot explain the overall increase in trade misclassification since the early 1990s, as the proportion of large trades has fallen over time.[15]

A new development since the 1990s is the introduction of hidden orders on ECNs such as INET. The misclassification frequencies for trades executed against hidden orders are between 30% and 32%, and misclassification frequencies for trades executed against displayed orders are between 31% and 32% (Panel E). We note that the difference in misclassification rates between displayed and hidden orders is not large enough to explain the increase in trade misclassification over time. It appears that the significant increase in misclassification frequency since the early 1990s is driven by an increase in misclassifications across the board, rather than a major shift towards the types of trades that are more often misclassified.

[Table 5 Here]

A notable difference between our analysis and earlier studies of trade misclassification, such as Odders-White (2000), is that prior to 1998 most researchers using the Lee-Ready algorithm compare trades to quotes that are in effect a minimum of five seconds before the transaction is reported. In contrast, our Table 4 follows the current convention of a zero-second lag between quotes and trades. To facilitate comparison with the earlier studies, we next calculate misclassification frequencies using one- through five-second lags between quotes and trades.[16]

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[15] More than half of the trades are over 300 shares in Odders-White's (2000) sample, versus less than a quarter of the trades in our sample.
[16] Lee and Ready (1991) propose the five-second quote lag to account for quotes being updated before the trades that triggered them were reported, because at the time of their study quotes were updated on a computer while trades

The results in Table 6 suggest that introducing a quote lag reduces the incidence of misclassification. The total misclassification percentage drops to 21.4% for short sales using a one-second lag (Panel A), then rises monotonically to 23.6% for short sales using a five-second lag (Panel E). A similar pattern obtains for long sales. This analysis suggests that for trade-level classification, lagging quotes by at least one second is better than using contemporaneous quotes in the Lee-Ready algorithm.[17] This result is consistent with the argument in Peterson and Sirri (2003), who note that using the NBBO quotes contemporaneous with the trade instead of the NBBO at order submission will cause the Lee-Ready algorithm to misclassify some trades, and that the degree of misclassification will depend on the time that the order takes to execute.

[Table 6 Here]

Although lagging the quotes reduces the misclassification frequency at the trade level, Table 7 shows that it does not improve Lee-Ready's accuracy once the classifications are aggregated to the daily level, because most of the misclassified buys and misclassified sells offset each other. In our sample, the daily averages are closest to the true values when no lag is used, but most of the Lee-Ready estimates based on one- to five-second quote lags produce daily seller-initiation percentages that are economically similar to the no-lag estimates and the true seller-initiation percentages.

[Table 7 Here]

In summary, analysis of order data suggests that the Lee-Ready algorithm misclassifies more than 30% of trades at the trade level. Because misclassification rates are not biased towards buys

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were entered manually. Bessembinder (2003) finds that by 1998, making no allowance for trade reporting lags is preferred to a five-second lag. Vergote (2005) reports that a two-second delay is optimal, while Piwowar and Wei (2006) suggest that a one-second lag produces superior trade direction estimates.

[17] Analyses of trade misclassification frequencies by characteristics reveal similar relations for the Lee-Ready algorithm using one- to five-second quote lags as for the Lee-Ready algorithm using contemporaneous quotes (as in Table 5). These results are available from the authors on request.

or sells, the misclassified trades cancel each other out at the daily aggregation level. Further, introducing a one-second lag in quotes reduces the trade-level misclassification to less than 22%, while lagging quotes does not result in economically significant changes in the accuracy of daily aggregates.

4. Consequences of trade misclassification in analyzing short and long seller aggressiveness

A natural question is whether trade misclassification at the daily or intraday level affects the inferences drawn from multivariate studies of trader behavior. In the regression models that follow, we use both the true aggressiveness from INET order data and the Lee-Ready estimates. If the Lee-Ready estimates of trade initiation are adequate substitutes for the true trade initiation derived from order data, inference will be similar for models using the true aggressiveness and the Lee-Ready estimates.

The analysis in Section 3.1 indicates that short sellers are less aggressive than long sellers. About 43% of daily short sales are seller-initiated, while about 55% of daily long sales are seller-initiated. Yet short sellers are often vilified in the media. One possible explanation is that although they are less aggressive than long sellers in general, short sellers are particularly aggressive when their activities are most detrimental. To investigate this possibility, we move to a multivariate setting and examine when short sellers and long sellers are most aggressive.

One challenge for our analysis is that the literature lacks a theoretical model of short sellers' day-to-day behavior. In the absence of a theoretical foundation, recent empirical studies have relied on various sets of explanatory variables; however, there is little consensus on the set of covariates to include.[18] The structure and focus of our study suggest that the model of Diether et

[18] For example, Diether et al. (2009b) model short selling as a function of returns, order imbalances, volatility, and spreads; Christophe, Ferri, and Hsieh (2010) include prices, returns, and momentum; and Massoud, Nandi,

al. (2009b) is most suitable for our purposes. The panel structure of their dataset is similar to ours, and our focus on short and long sellers' aggressiveness is compatible with Diether et al.'s focus on short-seller liquidity provision.

We examine how seller aggressiveness, measured by the percentage of trades that are seller-initiated, changes as a function of the variables that Diether et al. (2009b) identify as determinants of short selling activity. One hypothesis is that short and long sellers are less aggressive when returns are positive and when a stock has a positive buy-sell order imbalance because sellers act as voluntary liquidity providers to more aggressive buyers. Conversely, when returns and order imbalances are negative, sellers may switch to liquidity-demanding strategies. This hypothesis implies a negative relation between seller aggressiveness and returns or order imbalances. Another hypothesis consistent with Diether et al. (2009b) is that sellers may act as opportunistic risk bearers during periods of increased uncertainty, when asymmetric information drives spreads wider or when intraday volatility is higher. If so, we would expect to see a negative relation between seller aggressiveness and spreads or volatility, as short sellers would be providing liquidity during periods of increased uncertainty, thus bearing risk.

4.1 Aggressiveness at the daily level

Equation (2) includes our variables of interest and control variables in a panel regression specification:

$$SI_{i,t} = \alpha + \beta_1 Return_{i,t} + \beta_2 Return_{i,t-5,t-1} + \beta_3 OrderImbalance^{+}_{i,t} + \beta_4 OrderImbalance^{+}_{i,t-5,t-1} + \beta_5 Spread_{i,t} + \beta_6 Volatility_{i,t} + \beta_7 Volatility_{i,t-5,t-1} + \beta_8 SI_{i,t-5,t-1} + \beta_9 Turnover_{i,t-5,t-1} + \beta_{10} Pilot_i + \tag{2}$$

Saunders, and Song (2011) use an extended set of variables including returns, sales growth, institutional ownership, and a number of accounting and loan characteristics.

$$\sum_{k=1}^{199} \theta_k StockDummy_{k,i} + \sum_{m=1}^{42} \delta_m DayDummy_{m,t} + \varepsilon_{i,t},$$

where $SI_{i,t}$ is the percentage of sales that are seller-initiated in stock i , $i \in \{1,2, \ldots, 200\}$, on day t, $t \in \{1,2, \ldots, 43\}$, measured using either the true data or the Lee-Ready method.[19] $Return_{i,t}$ is the return on stock i on day t; $Return_{i,t-5,t-1}$ is the cumulative return on stock i over the previous five days. Order imbalance is defined as the buy volume minus sell volume divided by total volume, with buy and sell volumes determined from INET data. $OrderImbalance^{+}_{i,t}$ is equal to the order imbalance in stock i on day t if the order imbalance is greater than zero, else zero. We focus on the positive range of order imbalances to be consistent with Diether et al. (2009b). $OrderImbalance^{+}_{i,t-5,t-1}$ is defined analogously using the previous five-day average of the order imbalance. $Spread_{i,t}$ is the percentage effective spread of stock i on day t, computed as twice the difference between the trade price and the midpoint of the best bid and ask quotes divided by the quote midpoint, times an indicator equal to +1 (-1) for buyer-initiated (seller-initiated) trades, as determined from INET order data. $Volatility_{i,t}$ is the difference between the high and low price of stock i on day t, divided by the high price;[20] $Volatility_{i,t-5,t-1}$ is the average of $Volatility_{i,t}$ over the previous five days. $Turnover_{i,t-5,t-1}$ is the average daily share volume in stock i over the previous five days, included to account for autocorrelation in volume. In addition, we control for the autocorrelation in the dependent variable by including its lag. $Pilot_i$ is equal to one if stock i is a Reg SHO pilot stock, else zero; we include the pilot variable in case the multivariate framework reveals differences in seller aggressiveness that were not observable in our initial tests (Table 3). $StockDummy_{k,i}$ is an indicator variable equal to one if observation $SI_{i,t}$ is for stock k, else zero, to

[19] We present the regression results using the seller-initiated percentage as the dependent variable for ease of economic interpretation. All results are robust to an alternative specification in which the dependent variable is defined as the log odds ratio of the seller-initiation percentage to address the limited nature of the dependent variable. Results of regressions using the log odds ratio are available from the authors on request.

[20] We use this definition of volatility for consistency with Diether et al. (2009b); dividing by the average price or closing price yields identical inference.

implement stock fixed effects. $DayDummy_{m,t}$ is an indicator variable equal to one if observation $SI_{i,t}$ is on day m, else zero, to implement day fixed effects. For estimation purposes, we suppress one stock dummy and one day dummy because the model contains an intercept.

Table 8 contains the results of panel regressions using subsets of explanatory variables in Equation (2). Because returns and order imbalances are positively correlated (correlation of 0.16, significant at the 1% level), including them in the same regression specification may introduce multicollinearity and make the coefficient estimates difficult to interpret. Furthermore, there is likely to be a mechanical relation between order imbalances and seller aggressiveness: A higher positive order imbalance naturally implies that sellers have less need to initiate trades and are more often providing liquidity to eager buyers. To lessen the potential impact of these issues, we estimate two specifications for each dependent variable: without order imbalance variables (odd-numbered specifications in Table 8) and with return variables replaced by order imbalance variables (even-numbered specifications in Table 8). We are concerned about both serial correlation and cross-correlation, so we estimate standard errors that are clustered by both calendar day and stock (Thompson, 2011).

[Table 8 Here]

Specification 1 in Table 8 shows that when returns are positive, short sellers are less aggressive, initiating a smaller percentage of trades, and when returns are negative, short sellers are more aggressive.[21] In terms of economic magnitude, the coefficient on same-day return, $Return_{i,t}$, implies that a one percentage point positive (negative) return results in a 1.45 percentage point drop (increase) in the short-seller aggressiveness. This is consistent with our hypothesis that when prices are rising, buyers are more aggressive, and thus sellers can act as passive liquidity

[21] Dropping lagged returns from the analysis does not affect the coefficient estimates on contemporaneous returns; these results are available on request from authors.

providers, relying on limit orders and leading to a lower seller-initiation percentage. Conversely, when prices are falling, short sellers may rely less on limit orders if they seek speedy executions. In most specifications, short sellers appear less aggressive when spreads are wider, consistent with the hypothesis that they act as opportunistic risk bearers, while the coefficient estimates on volatility are mostly insignificant. Specification 5 in Table 8 shows that like short sellers, long sellers are less aggressive when returns are positive. In contrast to short sellers, long sellers appear more aggressive when spreads are wider, but only when we use true trade initiation (specification 5 in Table 8).

We emphasize that although short sellers demand more liquidity in down markets, our results do not necessarily imply that short sellers deliberately push prices down. Notably, we obtain similar aggressiveness results for long sellers (specification 5). Although the coefficient estimates are smaller for long sales than for short sales, multivariate tests show that the differences between these coefficients are not statistically significant.[22] Thus the data imply that there is no difference between short and long sellers' aggressiveness in up or down markets. In this light, the negative reputation of short sellers remains puzzling.

Specifications 2 and 6 in Table 8 show that replacing returns with positive order imbalances leads to similar inference. When a stock has a large positive order imbalance, short sellers and long sellers are less aggressive. The mechanical link between order imbalance and seller aggressiveness likely explains the higher explanatory power in the order-imbalance regressions (e.g., R-squared of 34.47% in specification 2 versus 13.46% in specification 1).

[22] In these tests, we include short sellers and long sellers together in a multivariate model similar to that in equation (2). To test for significance of differences, we include a dummy variable that indicates observations corresponding to short sales as opposed to long sales. The interaction of this dummy with the return variable has an insignificant coefficient, suggesting that the difference between short and long sellers' aggressiveness is not statistically significant.

Using Lee-Ready estimates for seller initiation percentages leads to similar inferences as using true seller initiation percentages (see specifications 1 and 2 versus 3 and 4, or 5 and 6 versus 7 and 8). Both the True and the Lee-Ready measures imply that positive returns and positive order imbalances have a significantly negative effect on seller aggressiveness for both short and long sales; the main difference is that the coefficient estimates are larger when we use true seller initiation. This difference in the coefficients is statistically significant for both short and long sales. True initiation percentages also result in a better model fit. Using Lee-Ready estimates to determine trade direction appears to add noise but does not change the qualitative inference of our analyses.

4.2 Aggressiveness at the intraday level

Although the results in Table 8 are informative, we recognize that they may be affected by endogeneity. Of particular concern are the relations between trade aggressiveness, returns, and volatility, which may be changing in a systematic way and may not be successfully captured by the daily aggregates in equation (2).[23] One way to alleviate potential endogeneity is to re-estimate equation (2) on the intraday level, relying on short-term lags of the dependent variables. To ensure that all sample stocks have a sufficient number of observations for intraday analysis, we divide each trading day into 30-minute intervals and use explanatory variables from the preceding interval to draw inferences.[24] Correlations between returns and order imbalances and between order imbalances and dependent variables remain high on the intraday level (e.g., correlation between returns and order imbalances is 0.2, significant at 1% level), therefore we

[23] For example, Brunnermeier and Pedersen (2005, 2009) theorize that aggressive selling that causes significant price changes may, under certain conditions, induce even more selling and further price changes, often accompanied by substantial volatility.
[24] We exclude the first 30 minutes of each trading day to avoid using explanatory variables from the prior day. As a result we have twelve 30-minute intraday observations for each stock on each day.

follow the approach adopted in Table 8 and use returns in the odd-numbered specifications and order imbalances in the even-numbered specifications. In addition, we exclude the lagged dependent variable because of its correlation with other explanatory variables. Finally, we use two versions of the Lee-Ready estimates, with one-second and zero-second lags, to see whether lagging the quote improves Lee-Ready results at the half-hourly level of aggregation. Equation (3) includes our variables of interest and control variables in a panel regression specification:

$$SI_{i,t,p} = \alpha + \beta_1 Return_{i,t,p-1} + \beta_2 OrderImbalance^{+}_{i,t,p-1} + \beta_3 Spread_{i,t,p-1} + \beta_4 Volatility_{i,t,p-1} + \beta_5 Turnover_{i,t,p-1} + \beta_6 Pilot_i + \sum_{k=1}^{199} \theta_k\, StockDummy_{k,i} + \sum_{m=1}^{42} \delta_m DayDummy_{m,t} + \sum_{n=1}^{11} \gamma_n\, IntervalDummy_{n,p} + \varepsilon_{i,t,p}, \qquad (3)$$

where *i* refers to the stock, $i \in \{1,2, \ldots, 200\}$, *t* refers to the day, $t \in \{1,2, \ldots, 43\}$, and *p* refers to the 30-minute intraday period, $p \in \{1,2, \ldots, 12\}$. $IntervalDummy_{n,p}$ is an indicator variable equal to one if observation $SI_{i,t,p}$ is in intraday period *n*, else zero, to account for intraday period fixed effects. All other variables are defined similarly to those in equation (2) but are computed over 30-minute intraday intervals. For estimation purposes, we suppress one stock dummy, one day dummy, and one interval dummy because the model contains an intercept. Standard errors are clustered by calendar day and stock.

The results of the intraday analyses, reported in Table 9, generally confirm our earlier findings. Aggressiveness of both short and long sellers declines when lagged intraday returns are positive and increases when lagged returns are negative.[25] Additionally, positive order imbalances reduce aggressiveness of both seller types. Short sellers provide greater liquidity

[25] The differences between return coefficients in the short sale and long sale specifications are statistically insignificant.

when spreads are wider, but this effect does not extend to long sellers. Finally, volatility remains a mostly insignificant factor for short and long sellers' aggressiveness.

[Table 9 Here]

As in the daily analyses, analyses using the true and Lee-Ready dependent variables yield similar inference in terms of the signs of the coefficients, although coefficient values differ. The coefficients from one-second lag estimates are closer to the coefficients of the true estimates than the coefficients from zero-second lag estimates are, confirming our recommendation that researchers should consider using one-second lags when applying the Lee-Ready algorithm to intraday analyses. We caution that the distortions caused by zero-second lags may have larger impact in a more granular trade-by-trade analyses; it is possible that our 30-minute aggregation period is long enough to allow misclassifications on both sides to partly offset each other. In addition, we note that our results are obtained from the INET order data and may apply differently for markets with different structures.

5. Conclusions

This study examines the success rates of the Lee-Ready trade classification algorithm for short and long sales, using true trade initiation data from INET. We show that despite recent criticism, the algorithm performs well and correctly identifies most short sales as buyer-initiated and most long sales as seller-initiated. In daily aggregates, Lee-Ready misclassification rates are near zero. This result validates a number of recent day-level studies that use the algorithm to sign trades.

Despite the success of the algorithm at the daily level, we find that it performs less than ideally at the more granular trade level, misclassifying more than 30% of trades. Because misclassification is evenly split between buyer-initiated and seller-initiated trades, the errors offset each other in daily aggregates. The increase in misclassification in our more recent sample is substantial, compared to the 15% misclassification rate reported in samples from the early 1990s. We further show that determinants of misclassification identified in prior research still matter, yet none of them has changed enough to explain the increase in misclassification rates over time.

In our main results, we follow the current convention of using contemporaneous quotes and trades to determine trade direction. When we instead use a one-second quote lag, the misclassification rate declines by one third, to about 21%. Our results suggest that researchers who use the Lee-Ready algorithm at the trade level in recent samples may benefit from lagging quotes.

Finally, we show that using Lee-Ready estimates leads to similar inferences as using true trade initiation data in a study of short and long sellers' behavior. We show that both long sellers and short sellers provide liquidity in up markets and demand liquidity in down markets. Moreover, short sellers' order aggressiveness is statistically indistinguishable from long sellers' aggressiveness. Our findings are particularly notable in light of media and regulators' attention to short sellers' allegedly aggressive trading practices and suggest that the widespread suspicion of short sellers may not be warranted.

Our results are important on three levels. First, we confirm that using the Lee-Ready algorithm to sign trades results in estimates that are nearly indistinguishable from true initiation rates at the daily level, removing the cloud of suspicion about the algorithm's reliability in day-level studies. Second, we caution that using the Lee-Ready algorithm in intraday studies without lagging quotes may result in misclassification rates that are considerably higher than those obtained in the 1990s. To reduce misclassification in intraday studies, we suggest lagging quotes by one second. Finally, we shed new light on short and long sellers' aggressiveness while showing that both true trade initiation and Lee-Ready estimates of trade initiation lead to similar inference in this setting.

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Table 1: Sample Descriptive Statistics

Descriptive statistics are presented for the sample of 100 Reg SHO pilot stocks and 100 non-pilot stocks matched on price, market capitalization, and share volume. Closing *Price* and *Market capitalization* are as of May 31, 2005; *Share volume* and *Dollar volume* are averages for May 2005; all other statistics are based on the two-month sample period, June and December 2005. *% Shares shorted* is the ratio of the number of shares shorted to total volume. *Quoted spread* is the difference between the best ask and best bid quotes; *Effective spread* is twice the difference of the trade price minus the quote midpoint at the time of the trade, times an indicator equal to +1 (-1) for buyer-initiated (seller-initiated) trades, with trade initiator determined from order data. Percentage spreads are calculated as the effective or quoted spread in cents divided by the quote midpoint. Averages are calculated for each stock across all sample days, and cross-sectional means and medians of the time-series averages are reported in this table. P-values are based on *t*-tests for mean differences and Wilcoxon signed rank tests for median differences. Data are from CRSP, TAQ, and the INET order book.

	Means			Medians		
	Pilot	Non-Pilot	*p-value*	Pilot	Non-Pilot	*p-value*
Price ($)	26.98	27.78	*0.1341*	23.81	25.94	*0.1933*
Market capitalization ($millions)	2040.47	2861.81	*0.1887*	730.17	713.19	*0.7644*
Share volume (thousands)	1087.50	1353.76	*0.2298*	260.12	251.26	*0.7642*
Dollar volume ($millions)	18.82	28.51	*0.1825*	4.78	4.65	*0.4841*
Number of trades	878	1,079	*0.1063*	405	423	*0.9204*
Number of short-sale trades	309	388	*0.1206*	146	133	*0.4841*
Number of shares shorted	96,586	138,592	*0.0840*	22,658	21,041	*1.0000*
% Shares shorted	28.0%	28.1%	*0.9146*	28.8%	28.7%	*0.7644*
Quoted spread (cents)	7.01	7.13	*0.1449*	4.42	4.76	*0.2056*
% Quoted spread (bps)	18.22	17.64	*0.0150*	12.14	12.24	*0.0073*
Effective Spread (cents)	2.92	2.86	*0.3483*	1.40	1.47	*0.9878*
% Effective Spread (bps)	7.72	7.10	*0.0482*	4.18	3.96	*0.0169*

Table 2: INET's Share of Trading Volume for Sample Stocks

Total Volume , *Short Sale Volume* , *Average Short Sale Trade Size, Long Sale Volume* , and *Average Long Sale Trade Size* are calculated for each stock/month/exchange. Each exchange's volume percentage is calculated as the ratio of its volume to marketwide volume per stock. Cross-sectional series averages for each period are reported in the table below for the 100 Reg SHO pilot stocks (left panel) and 100 non-pilot stocks (right panel) matched on price, market capitalization, and share volume. For exchanges that do not trade all 100 stocks, we report the mean percentage across the subsets of pilot and non-pilot stocks traded on that exchange; because not all exchanges trade all sample stocks, percentages do not sum to 100% across exchanges. Panel A contains the means for May 2005, the pre-period used for creating the matched sample; panels B and C present the means for June and December 2005, the sample months used for analysis. *ADF* is FINRA's Alternative Display Facility. Data are from the Reg SHO database and TAQ.

	Pilot						Non-Pilot					
	% of Total Volume	% of Short Sale Volume	Average Short Sale Trade Size*	% of Long Sale Volume	Average Long Sale Trade Size*	Number of Sample Stocks Traded	% of Total Volume	% of Short Sale Volume	Average Short Sale Trade Size*	% of Long Sale Volume	Average Long Sale Trade Size*	Number of Sample Stocks Traded
Panel A: May 2005												
NASDAQ	53.8%	48.0%	288	57.4%	328	100	54.8%	47.8%	317	59.1%	315	100
INET	**25.6%**	**27.9%**	**175**	**24.3%**	**179**	**100**	**24.8%**	**27.4%**	**181**	**23.3%**	**182**	**100**
ARCA	20.4%	24.1%	181	18.0%	188	100	20.3%	24.8%	187	17.5%	192	100
CHICAGO	0.8%	0.0%	123	1.2%	18,632	16	0.3%	0.0%	113	0.5%	6,458	15
ADF	0.3%	0.3%	197	0.3%	368	14	0.1%	0.1%	114	0.1%	181	22
AMEX	0.0%	0.0%	1,291	0.1%	7,218	8	0.1%	0.1%	947	0.0%	1,013	9
Panel B: June 2005												
NASDAQ	54.9%	48.5%	298	59.0%	339	100	55.0%	48.0%	335	59.6%	344	100
INET	**23.8%**	**26.1%**	**178**	**22.6%**	**180**	**100**	**24.0%**	**26.4%**	**186**	**22.4%**	**184**	**100**
ARCA	21.1%	25.3%	181	18.2%	186	100	21.0%	25.5%	191	17.9%	192	100
CHICAGO	0.4%	0.0%	62	0.7%	7,441	12	0.2%	0.0%	0	0.3%	8,695	14
ADF	0.2%	0.3%	262	0.2%	233	21	0.2%	0.1%	182	0.2%	271	25
AMEX	0.0%	0.0%	1,017	0.0%	788	8	0.1%	0.1%	1,103	0.1%	435	10
Panel C: December 2005												
NASDAQ	55.7%	50.1%	281	59.4%	314	100	56.9%	49.5%	311	61.7%	322	100
INET	**24.6%**	**26.4%**	**175**	**23.4%**	**169**	**100**	**24.0%**	**26.4%**	**184**	**22.7%**	**174**	**100**
ARCA	19.5%	23.4%	184	16.9%	184	100	18.8%	24.0%	193	15.4%	189	100
CHICAGO	0.2%	0.0%	10	0.4%	9,890	36	0.2%	0.0%	54	0.4%	17,602	26
ADF	0.6%	0.5%	317	0.6%	402	24	0.8%	0.3%	374	1.0%	510	19
AMEX	0.0%	0.0%	426	0.0%	311	8	0.0%	0.0%	267	0.0%	396	10

* The large average trade sizes on Chicago and AMEX are driven by a few outlier trades reported on exchanges that attract little trading volume overall in the sample stocks.

Table 3: Seller-initiated Sales Determined from Order Data versus the Lee-Ready Algorithm

This table reports the percentage of short sales (Panel A) and long sales (Panel B) that are seller-initiated, based on the order data associated with each trade (*True*) and based on the Lee-Ready algorithm (*LR-estimated*), for the 100 Reg SHO pilot stocks (left panel) and 100 non-pilot stocks (right panel) matched on price, market capitalization, and share volume. Averages are calculated for each stock over the time period, and cross-sectional means are reported in the table. P-values for the *True-LR Difference* are based on double-sided t-tests of the differences. The analysis periods are June 2005, December 2005, and the two months combined. Data are from the Reg SHO database, TAQ, and INET order book.

	Pilot						Non-Pilot					
	True		LR-estimated		True - LR Estimated p-value of difference		True		LR-estimated		True - LR Estimated p-value of difference	
	%Trades	%Shares	%Trades	%Shares	%Trades	%Shares	%Trades	%Shares	%Trades	%Shares	%Trades	%Shares
Panel A: Short Sales												
June	41.7%	42.7%	42.2%	42.8%	*0.3104*	*0.7999*	42.4%	42.9%	42.7%	43.1%	*0.6431*	*0.7631*
December	43.6%	43.8%	43.4%	43.8%	*0.8340*	*0.9538*	44.6%	44.4%	44.8%	44.8%	*0.9666*	*0.4068*
Combined Period	42.6%	43.3%	42.8%	43.3%	*0.6675*	*0.9279*	43.0%	43.6%	43.5%	43.9%	*0.3978*	*0.3868*
Panel B: Long Sales												
June	54.9%	56.2%	55.1%	56.2%	*0.4883*	*0.9789*	53.9%	54.7%	54.6%	55.3%	*0.1566*	*0.1495*
December	54.4%	55.0%	54.4%	55.2%	*0.8912*	*0.7415*	53.6%	54.3%	53.9%	54.5%	*0.4458*	*0.7681*
Combined Period	54.7%	55.6%	54.8%	55.7%	*0.7366*	*0.8372*	53.8%	54.4%	54.3%	54.9%	*0.1774*	*0.1340*

Table 4: Trade-by-Trade Classification Performance of Lee-Ready Algorithm with No Quote Lag

This table presents a comparison of the true classification (buy or sell, determined from order data) to the classification from the Lee-Ready algorithm, based on contemporaneous trades and quotes, on a trade-by-trade basis for the sample of 200 stocks. Each entry contains the number and percentage of transactions in the sample that fall into the respective category. *Total Misclassification %* for each sample equals the percentage of true sells classified as buys plus the percentage of true buys classified as sells. Sample period is June and December 2005. Data are from the Reg SHO database, TAQ, and INET order book.

		True Buy		True Sell		Total
		Number	Percent	Number	Percent	Misclassification %
Short Sales	Lee-Ready method: Buy	1,159,336	38.9	439,885	14.8	31.8
	Lee-Ready method: Sell	505,973	17.0	875,463	29.4	
Long Sales	Lee-Ready method: Buy	1,661,988	30.9	822,834	15.3	30.8
	Lee-Ready method: Sell	837,237	15.5	2,064,639	38.3	

Table 5: Trade-by-Trade Performance of Lee-Ready Algorithm by Characteristics

This table contains a breakdown of the accuracy of the Lee-Ready algorithm (based on contemporaneous trades and quotes) by trade and firm characteristics for the 200 sample stocks. Each row presents the number and percentage of transactions *in that category* that are correctly and incorrectly classified. Summing along each row provides the total number of transactions falling into the respective category. (Percentages sum to 100% along each row.) Summing down a "Number" column within a category (e.g., trade size) yields the total number of correctly classified and incorrectly classified transactions in the sample. Chi-square statistics test the hypothesis that the frequency of misclassification is independent of the characteristic. Sample months are June and December 2005. Data are from the Reg SHO database, TAQ, and INET order book.

Category		Correct		Incorrect		Chi-Square Stat
		Number	Percent	Number	Percent	(p-value)
Panel A: Transaction price in relation to quotes						
Short Sales	At or outside the quotes	1,558,070	71.2	629,602	28.8	46243.78
	Inside the spread but non-midpoint	373,338	63.7	212,992	36.3	(<.0001)
	At the spread midpoint	103,391	50.0	103,264	50.0	
Long Sales	At or outside the quotes	2,862,793	72.7	1,073,075	27.3	107540.00
	Inside the spread but non-midpoint	681,022	62.8	404,037	37.2	(<.0001)
	At the spread midpoint	182,812	50.0	182,959	50.0	
Panel B: Trade size						
Short Sales	300 shares or less	1,529,112	69.8	662,978	30.2	8481.18
	301 shares or more	505,687	64.1	282,880	35.9	(<.0001)
	100 shares or less	1,038,612	69.9	448,094	30.1	3475.29
	101 shares or more	996,187	66.7	497,764	33.3	(<.0001)
Long Sales	300 shares or less	2,975,542	70.7	1,234,995	29.3	19592.07
	301 shares or more	751,085	63.9	425,076	36.1	(<.0001)
	100 shares or less	2,273,509	71.0	930,511	29.0	11679.95
	101 shares or more	1,453,118	66.6	729,560	33.4	(<.0001)
Panel C: Trading frequency (number of transactions)						
Short Sales	4000 or fewer	88,644	71.3	35,702	28.7	1648.66
	4001 - 10,000	249,636	70.6	104,123	29.4	(<.0001)
	over 10,000	1,696,519	67.8	806,033	32.2	
Long Sales	4000 or fewer	68,734	75.5	22,337	24.5	2601.92
	4001 - 10,000	234,481	71.4	93,962	28.6	(<.0001)
	over 10,000	3,423,412	68.9	1,543,772	31.1	
Panel D: Firm size						
Short Sales	Large (deciles 1-5)	1,702,705	68.0	802,956	32.1	708.66
	Small (deciles 6-10)	332,094	69.9	142,902	30.1	(<.0001)
Long Sales	Large (deciles 1-5)	3,132,221	68.9	1,414,132	31.1	1124.20
	Small (deciles 6-10)	594,406	70.7	245,939	29.3	(<.0001)
Panel E: Order visibility						
Short Sales	Displayed	1,894,772	68.3	880,293	31.7	2.53
	Hidden	140,027	68.1	65,565	31.9	(0.1115)
Long Sales	Displayed	3,428,843	69.1	1,531,655	30.9	102.61
	Hidden	297,784	69.9	128,416	30.1	(<.0001)

Table 6: Trade-by-Trade Classification Performance of Lee-Ready Algorithm with Different Quote Lags

This table presents a comparison of the true classification (buy or sell, determined from order data) to the classification from the Lee-Ready algorithm on a trade-by-trade basis for the sample of 200 stocks. Each panel calculates the Lee-Ready classifications using a different quote lag, from one to five seconds. Each entry contains the number and percentage of transactions in the sample that fall into the respective category. *Total Misclassification %* for each sample equals the percentage of true sells classified as buys plus the percentage of true buys classified as sells. Sample period is June and December 2005. Data are from the Reg SHO database, TAQ, and INET order book.

		True Buy		True Sell		Total
		Number	Percent	Number	Percent	Misclassification %
Panel A: Lee-Ready with 1-second lag between trade and quotes						
Short Sales	Lee-Ready method: Buy	1,331,885	44.7	305,067	10.2	21.4
	Lee-Ready method: Sell	333,029	11.2	1,010,075	33.9	
Long Sales	Lee-Ready method: Buy	1,893,007	35.2	564,494	10.5	21.8
	Lee-Ready method: Sell	605,747	11.3	2,322,337	43.1	
Panel B: Lee-Ready with 2-second lag between trade and quotes						
Short Sales	Lee-Ready method: Buy	1,320,120	44.3	312,164	10.5	22.1
	Lee-Ready method: Sell	344,609	11.6	1,002,808	33.7	
Long Sales	Lee-Ready method: Buy	1,885,785	35.0	581,780	10.8	22.2
	Lee-Ready method: Sell	612,642	11.4	2,304,500	42.8	
Panel C: Lee-Ready with 3-second lag between trade and quotes						
Short Sales	Lee-Ready method: Buy	1,309,308	44.0	317,265	10.7	22.6
	Lee-Ready method: Sell	355,217	11.9	997,628	33.5	
Long Sales	Lee-Ready method: Buy	1,877,014	34.9	593,747	11.0	22.5
	Lee-Ready method: Sell	621,179	11.5	2,292,255	42.6	
Panel D: Lee-Ready with 4-second lag between trade and quotes						
Short Sales	Lee-Ready method: Buy	1,300,136	43.6	324,811	10.9	23.1
	Lee-Ready method: Sell	364,219	12.2	990,009	33.2	
Long Sales	Lee-Ready method: Buy	1,868,845	34.7	607,682	11.3	23.0
	Lee-Ready method: Sell	629,130	11.7	2,278,091	42.3	
Panel E: Lee-Ready with 5-second lag between trade and quotes						
Short Sales	Lee-Ready method: Buy	1,290,460	43.3	330,199	11.1	23.7
	Lee-Ready method: Sell	373,723	12.6	984,541	33.1	
Long Sales	Lee-Ready method: Buy	1,859,485	34.5	617,411	11.5	23.4
	Lee-Ready method: Sell	638,244	11.9	2,268,104	42.1	

Table 7: Comparison of Daily Seller-initiated Percentages, True and Lee-Ready with 0- to 5-second Quote Lags

This table presents a comparison of the true seller-initiation percentages to those estimated from the Lee-Ready algorithm, based on quote lags from zero to five seconds. Averages are calculated for each stock over the time period, and cross-sectional means are reported in the table. P-values for the *True-LR Difference* are based on double-sided t-tests of the differences. Sample period is June and December 2005. Data are from the Reg SHO database, TAQ, and INET order book.

				True - LR Estimated		True - LR Estimated p-value of difference	
		%Trades	%Shares	%Trades	%Shares	%Trades	%Shares
Short Sales	True	42.9%	43.4%				
	Lee-Ready estimated with 0-second lag	43.8%	43.6%	-0.9%	-0.2%	*0.4906*	*0.7822*
	Lee-Ready estimated with 1-second lag	41.8%	42.2%	1.1%	1.2%	*0.2342*	*0.1613*
	Lee-Ready estimated with 2-second lag	41.8%	42.2%	1.1%	1.2%	*0.2693*	*0.1971*
	Lee-Ready estimated with 3-second lag	42.1%	42.5%	0.8%	0.9%	*0.5005*	*0.4772*
	Lee-Ready estimated with 4-second lag	42.1%	42.5%	0.8%	0.9%	*0.5268*	*0.4762*
	Lee-Ready estimated with 5-second lag	42.3%	42.6%	0.6%	0.8%	*0.6645*	*0.5169*
Long Sales	True	54.2%	55.0%				
	Lee-Ready estimated with 0-second lag	54.5%	55.3%	-0.3%	-0.3%	*0.7512*	*0.7147*
	Lee-Ready estimated with 1-second lag	55.4%	56.3%	-1.2%	-1.3%	*0.1937*	*0.1205*
	Lee-Ready estimated with 2-second lag	55.0%	55.9%	-0.8%	-0.9%	*0.5610*	*0.5919*
	Lee-Ready estimated with 3-second lag	55.1%	56.0%	-0.9%	-1.0%	*0.4769*	*0.3413*
	Lee-Ready estimated with 4-second lag	54.9%	55.8%	-0.7%	-0.8%	*0.5351*	*0.5236*
	Lee-Ready estimated with 5-second lag	54.9%	55.8%	-0.7%	-0.8%	*0.5521*	*0.5242*

Table 8: Daily Regressions of Seller-Initiated Percentages of Short and Long Sales

The dependent variable is the *True* (order-based) or *Lee-Ready Estimated Seller-Initiated %*, as indicated at the top of each column, for day *t*. *Return* $_t$ is the stock's return on day *t*; *Return* $_{t-5,t-1}$ is the stock's return over the previous five days. *Order imbalance* ^+_t is equal to the daily buy-sell order imbalance (as a % of daily volume) of the stock on day *t* if the imbalance is greater than 0, else zero; *Order imbalance* $^+_{t-5,t-1}$ is defined analogously based on the average order imbalance over the prior five days. *Spread* $_t$ is the percentage effective spread for the stock on day *t*. *Volatility* $_t$ is the difference between the stock's high and low price on day *t*, divided by the high price; *Volatility* $_{t-5,t-1}$ is the average volatility over the previous five days. *Turnover* $_{t-5,t-1}$ is the log of the average daily share turnover of the stock over the previous five days. *Seller-initiated %* $_{t-5,t-1}$ is the average of the dependent variable over the previous five days. *Pilot* is an indicator variable equal to one if the stock is a Reg SHO pilot stock, else zero. Reported values of the *Turnover* and *Pilot* coefficient estimates are scaled by 100 for ease of reading. Regressions also include stock fixed effects and day fixed effects. Sample comprises 100 Reg SHO pilot stocks and 100 non-pilot stocks matched on price, market capitalization, and volume; analysis period is June and December 2005. T-statistics, reported in parentheses below coefficient estimates, are robust to time-series and cross-sectional correlation. $R^2_{demeaned}$ is the reported R-squared from a regression that demeans the data to implement the fixed effects, and R^2 is the reported R-squared from a regression that explicitly includes the dummy variables to implement the fixed effects.

	Short Sales				Long Sales			
Dependent Variable	True Seller-Initiated %		L-R Estimated Seller-Initiated %		True Seller-Initiated %		L-R Estimated Seller-Initiated %	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Return_t$	-1.45		-0.88		-1.19		-0.56	
	(-9.0)		*(-9.3)*		*(-8.4)*		*(-6.6)*	
$Return_{t-5,t-1}$	-0.03		0.14		-0.03		0.05	
	(-0.5)		*(3.4)*		*(-0.9)*		*(1.6)*	
Order $imbalance^+_t$		-0.56		-0.15		-0.68		-0.20
		(-35.7)		*(-10.5)*		*(-69.2)*		*(-12.9)*
Order $imbalance^+_{t-5,t-1}$		0.12		0.05		0.18		0.06
		(3.9)		*(2.3)*		*(8.7)*		*(3.6)*
$Spread_t$	-4.62	-6.76	-6.85	-7.20	5.64	2.76	2.66	1.98
	(-1.8)	*(-3.6)*	*(-3.0)*	*(-3.2)*	*(2.5)*	*(1.6)*	*(1.0)*	*(0.8)*
$Volatility_t$	-0.03	-0.33	0.18	0.02	-0.02	-0.31	0.06	-0.06
	(-0.2)	*(-2.8)*	*(1.6)*	*(0.2)*	*(-0.2)*	*(-5.1)*	*(0.6)*	*(-0.8)*
$Volatility_{t-5,t-1}$	0.05	0.49	0.02	0.24	-0.04	0.40	-0.31	-0.13
	(0.3)	*(3.0)*	*(0.1)*	*(1.8)*	*(-0.3)*	*(3.1)*	*(-2.4)*	*(-1.1)*
$Turnover_{t-5,t-1}$	-0.42	-1.33	-0.41	-0.62	0.30	-0.91	0.13	-0.20
	(-2.1)	*(-7.4)*	*(-4.1)*	*(-6.3)*	*(2.3)*	*(-7.1)*	*(1.2)*	*(-1.9)*
Seller-initiated $\%_{t-5,t-1}$	0.17	0.15	0.08	0.08	0.20	0.13	0.05	0.03
	(7.4)	*(5.9)*	*(3.7)*	*(3.3)*	*(9.2)*	*(6.2)*	*(2.2)*	*(1.3)*
Pilot	-0.43	-1.01	0.06	-0.10	-0.26	-0.86	-0.06	-0.25
	(-1.6)	*(-2.7)*	*(0.1)*	*(-0.5)*	*(-1.4)*	*(-2.3)*	*(-0.4)*	*(-1.5)*
Stock fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Day fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	8600	8600	8600	8600	8600	8600	8600	8600
$R^2_{demeaned}$	0.0495	0.2640	0.0245	0.0359	0.0547	0.5431	0.0595	0.1237
R^2	0.1346	0.3447	0.1051	0.1168	0.1249	0.6052	0.1189	0.1820

Table 9: Intraday Regressions of Seller-Initiated Percentages of Short and Long Sales

The table presents intraday regression results for short sales and long sales, using three different dependent variables. The dependent variable is the *True* (order-based) or *Lee-Ready Estimated Seller-Initiated %*, using a 1-second or 0-second lag between quotes and trades, as indicated at the top of each column, for half-hour interval *t*. *Return* $_{t-1}$ is the stock's return over the previous interval. *Order imbalance* $^{+}_{t-1}$ is equal to the buy-sell order imbalance (as a % of interval volume) of the stock in the previous interval if the imbalance is greater than 0, else zero. *Spread* $_{t-1}$ is the percentage effective spread for the stock in the previous interval. *Volatility* $_{t-1}$ is the difference between the stock's high and low price in the previous interval, divided by the high price. *Turnover* $_{t-1}$ is the log of the interval share turnover of the stock over the previous interval. *Pilot* is an indicator variable equal to one if the stock is a Reg SHO pilot stock, else zero. Reported values of the *Turnover* and *Pilot* coefficient estimates are scaled by 100 for ease of reading. Regressions also include stock fixed effects, day fixed effects, and interval fixed effects. Sample comprises 100 Reg SHO pilot stocks and 100 non-pilot stocks matched on price, market capitalization, and volume; analysis period is June and December 2005. T-statistics, reported in parentheses below coefficient estimates, are robust to time-series and cross-sectional correlation. $R^2_{demeaned}$ is the reported R-squared from a regression that demeans the data to implement the fixed effects, and R^2 is the reported R-squared from a regression that explicitly includes the dummy variables to implement the fixed effects.

	Short Sales						Long Sales					
Dependent Variable	True Seller-Initiated %		L-R Estimated Seller-Initiated %, with 1-second Lag		L-R Estimated Seller-Initiated %, with 0-second Lag		True Seller-Initiated %		L-R Estimated Seller-Initiated %, with 1-second Lag		L-R Estimated Seller-Initiated %, with 0-second Lag	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Return_{t-1}$	-0.98		-1.13		-1.25		-0.92		-1.02		-1.16	
	(-4.3)		*(-5.9)*		*(-6.7)*		*(-4.5)*		*(-5.2)*		*(-5.7)*	
$Order\ imbalance^{+}_{t-1}$		-0.17		-0.07		-0.04		-0.18		-0.08		-0.04
		(-24.4)		*(-13.7)*		*(-7.7)*		*(-27.0)*		*(-13.9)*		*(-8.8)*
$Spread_{t-1}$	-4.11	-3.88	-3.48	-3.37	-2.66	-2.60	1.19	1.02	-0.67	-0.74	-0.08	-0.10
	(-2.8)	*(-2.7)*	*(-2.2)*	*(-2.1)*	*(-2.1)*	*(-2.1)*	*(1.1)*	*(1.1)*	*(-0.6)*	*(-0.6)*	*(-0.1)*	*(-0.1)*
$Volatility_{t-1}$	-0.38	-0.60	-0.17	-0.30	0.21	0.12	0.00	-0.31	0.07	-0.09	0.27	0.16
	(-1.7)	*(-2.5)*	*(-0.7)*	*(-1.2)*	*(1.0)*	*(0.6)*	*(0.0)*	*(-1.3)*	*(0.3)*	*(-0.4)*	*(1.3)*	*(0.8)*
$Turnover_{t-1}$	0.05	-0.43	0.04	-0.18	0.09	-0.02	-0.07	-0.55	-0.10	-0.31	-0.12	-0.23
	(0.6)	*(-5.4)*	*(0.6)*	*(-2.9)*	*(1.7)*	*(-0.4)*	*(-0.7)*	*(-6.2)*	*(-1.2)*	*(-4.0)*	*(-1.8)*	*(-3.4)*
Pilot	0.06	-0.21	0.06	-0.06	0.04	-0.02	0.07	-0.17	0.02	-0.08	0.01	-0.05
	(0.3)	*(-1.1)*	*(0.4)*	*(-0.4)*	*(0.8)*	*(-0.4)*	*(1.1)*	*(-1.5)*	*(0.3)*	*(-0.9)*	*(0.1)*	*(-0.5)*
Stock fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Day fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Interval fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	85790	85790	85790	85790	85790	85790	96127	96127	96127	96127	96127	96127
$R^2_{demeaned}$	0.0064	0.0289	0.0042	0.0086	0.0042	0.0052	0.0052	0.0399	0.0092	0.0163	0.0118	0.0134
R^2	0.0341	0.0570	0.0251	0.0297	0.0235	0.0246	0.0228	0.0577	0.0209	0.0281	0.0231	0.0246

Appendix: Percentage of Short Sales Matched to Order Data, by Look-ahead/Look-back Window

This table reports the match frequency of NSX short sales reported under Reg SHO to INET order data using a look-ahead/look-back windows from 0 seconds to +/- 10 seconds relative to the the time of the trade. Statistics are aggregated for 200 sample stocks in June and December 2005. Cumulative percentage for 10-second window is less than 100% because some short sales cannot be matched even with a 10-second window. Data are from Reg SHO short sales database and INET order database.

Look-ahead/Look-back Window in Seconds	Number of trades	Cumulative Percentage of Trades	Number of Shares	Cumulative Percentage of Shares
0	1,931,936	63.4%	661,629,954	64.5%
1	1,063,873	98.3%	349,322,163	98.5%
2	24,565	99.1%	6,823,601	99.2%
3	5,549	99.3%	1,875,787	99.3%
4	3,257	99.4%	1,017,027	99.4%
5	2,290	99.5%	764,346	99.5%
6	1,334	99.6%	400,841	99.6%
7	870	99.6%	327,443	99.6%
8	613	99.6%	184,019	99.6%
9	613	99.6%	213,062	99.6%
10	501	99.6%	155,037	99.6%

Figure 1: Average Price of Sample Stocks

This figure displays the average daily closing price of the 200 sample stocks from May 2, 2005 through December 30, 2005. Shaded boxes indicate the sample months of June and December. Data are from CRSP.