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Measuring Private Information in a Specialist Market

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Since the reduced forms of the popular measures of asymmetric information in the price formation process are not nested within larger models we cannot evaluate their fit using standard statistical tools. Furthermore, pairwise correlations amongst the measures are small. We benchmark these measures cross-sectionally to realized specialist loss rates (using alternatively volume and number of trades) in the TORQ data. While five of the six measures are significantly correlated with this benchmark, this is only because they are correlated with the specialist participation rate. We infer that the measures do not measure private information in order flow, even in the setting for which they are designed.

Keywords: Specialist market; Measuring adverse selection

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1. Introduction

Measuring the strategic interactions between agents in financial markets is a central issue in financial economics. The New York Stock Exchange in the 1980s and early 1990s is a canonical example of a specialist market, and provides an ideal setting to analyze this behavior as transactions and quote data is available and the market setting is slower and simpler in many ways than it became in the late 1990s. In Appendix A we provide the salient features of this market as well as how these have changed since 1996. Because of the fairly clean mapping from orders into observed transactions, the specialist market provides an appealing context in which to study the role of private information in price formation. Furthermore, Saar (2010) points out that many exchanges and regulators have recently moved to this format, where a designated market maker has an affirmative obligation. Saar notes that this is especially true for less liquid equity and derivative securities, and documents several cases where the introduction of specialists resulted in improved market quality.¹

There are several measures of the role played by private information in the price formation process. While some of these measures are unified structurally (Huang and Stoll, 1997) their reduced-forms are just-identified so that none is amenable to formal specification tests. For example, the empirical specifications of each of the measures use different market outcomes to proxy for price formation. Empirically, the cross-sectional correlation across these measures is rather low. This means that despite the relative simplicity of the market setting and the availability of relevant data, there is no consensus on the role that private information plays in the price formation process in specialist markets. Stoll (2003 p. 599) summarizes the state of knowledge:

It is not yet clear which – asymmetric information, inventory or order processing costs – are the most important factors in the bid-ask spread. Nor is it clear how

¹Saar's (2010) examples of markets that have introduced designated market makers since 1996 include the Chicago Board of Options Exchange, in 1999, and the Tel Aviv Stock Exchange in 2004. Menkveld and Wang (2013) examine the effect of Euronext allowing small-cap firms to hire a designated market maker in 2001. They find that this agent adds value by increasing the stock's liquidity.

these components vary across stocks or how they are affected by regulation, by market design, and by stock characteristics.

In light of this, several studies have attempted to gauge the efficacy of the alternative measures by benchmarking them to a viable economic measure of private information. However, papers that have evaluated the relationship between measures of private information obtained from high-frequency market data and those pertaining to the firm's cash flows have not had encouraging results.² This is not surprising since the local risks of trading with a privately informed agent, which apply to relatively short time horizons and may vary over time, may differ structurally from informational asymmetries concerning the fundamental risks of an enterprise, as discussed by Callahan, Lee, and Yohn (1997).

Collin-Dufresne and Fos (2014) also cast doubt on the efficacy of empirical measures of private information in price formation. They find that such measures are lower on days when informed traders (identified as Schedule 13D filers) trade than on other days. They attribute this to several phenomena. First, these traders use limit orders—supplying liquidity. Cornell and Sirri (1992) also find that insiders to the Anheuser-Busch acquisition of Campbell-Taggart in 1982 used limit orders, and that liquidity is generally higher on days when these traders were in the market. Second, these traders time their trading to coincide with high levels of liquidity. These results show how much more complicated actual trading is relative to market microstructure models that assume that insiders demand liquidity. This further motivates the need to evaluate the efficacy of the empirical measures of adverse selection in order flow.

We analyze the cross-sectional relationship between specialist participation and loss rates and six popular measures of informational asymmetries in trading activity. We use 137 New York Stock Exchange (NYSE) stocks in the period November 1, 1990 through January 31, 1991. We define the specialist participation rate as the proportion of trading volume in the stock that involves the specialist. Loss conditional on specialist trade is the

 $^{^{2}}$ Examples of papers that evaluate the correlations between the measures of asymmetric information in trading and fundamental cash flows include Van Ness, Van Ness, and Warr (2001), Neal and Wheatley (1998), Clarke and Shastri (2000), Halov (2006), and Lebedeva (2012).

ratio of the specialist volume that entails a loss to total specialist volume. We use three alternative post-transaction (lag) periods to assess a trade's profitability: five-minute, onehour, and one-day. The realized specialist loss rate is the product of these two ratios. We find that most of the measures are statistically significantly positively correlated with the realized specialist loss rate. However, these correlations derive almost entirely from the measures' correlations with the specialist participation rate. There is virtually no link to the outcome of specialist trades. Thus our results are supportive of Collin-Dufresne and Fos (2014). Indeed our results are discouraging since the measures we consider were developed expressly for the specialist market setting of our analysis.

Empirical microstructure specifications are built on the theoretical foundations of the seminal models of Kyle (1985) and Glosten and Milgrom (1985). In these models liquidity providers, or dealers, face an adverse selection problem that does not degenerate into a no-trade result because there are noise traders whose demand to trade is exogenous. The models assume that competition amongst liquidity providers gives rise to a competitive equilibrium in which dealers earn no monopoly rents. The models also assume that informed traders demand liquidity, (and that they do not compete with dealers to provide liquidity). This equilibrium has two important properties. First, a bid-ask spread (or implicit spread in a call market) equates expected losses from trading with informed traders with expected gains from trading with liquidity traders. Second, dealers update their conditional expectation of the asset's value as a function of the order flow.

The popular and widely-used empirical measures of private information rely on the response of posted bid-ask quotes to the order flow, the effect of transactions on transaction prices, or the imbalance between buy and sell orders. In most studies the order flow is unobserved so that in practice each transaction serves as a proxy for an underlying order. In this paper we consider two measures of private information derived from serial covariance spread models: George, Kaul, and Nimalendren (1991) (GKN) and Lin, Sanger, and Booth (1995) (LSB); two derived from trade-indicator models: Glosten and Harris (1988) (GH) and Huang and Stoll (1997) (HS); one derived from an efficient price long-run variance decomposition model: Hasbrouck (1991a, 1991b) (VAR); and one that uses daily order

imbalances only: Easley, Kiefer, O'Hara, and Paperman (1996) (PIN).

Using specialist loss rates to benchmark measures of private information is attractive for at least two reasons. First, as Collin-Dufresne and Fos (2014) and Cornell and Sirri (1992) show, liquidity providers may have private information. Second, limit orders in general, which compete with the specialist in liquidity provision, may become stale. Specialist quotes will always reflect all publicly available information. In equilibrium we expect that specialist losses will be offset by gains. So it is the loss rate that proxies for the realizations of trading with a better informed counterparty.

The remainder of this paper is organized as follows. In the next section we describe the six popular measures of private information that we analyze. Section 3 contains a description of the TORQ data. In Section 4 we characterize the role and profitability of the specialist. Section 5 contains the paper's main results in three subsections. First we consider the sample cross-sectional properties of the measures as well as their small-sample distributions. Second, we conduct the benchmarking analysis, and third we perform a number of robustness checks on these benchmarking results. Section 6 concludes the paper.

2. Informational asymmetries in the specialist market

Roll (1984) shows that an observed efficient price path will exhibit serial correlation as the result of bid-ask bounce. Serial correlation spread models expand on this insight and generally include the dynamics of the quoted bid-ask spread and the direction of trade to decompose the spread into a component that is due to adverse selection and a component that is unrelated to informational asymmetry. Table 1 provides a summary of the six measures of informational asymmetry that we use in this paper. GKN and LSB are popular members of the class of serial correlation spread models. Table 1 shows that both measures project the change in the bid-ask quotes on transaction-specific information so the consequent measure of informational asymmetry is available as a regression coefficient. GKN use change in the trade indicator variable (which equals 1 if the trade is a market order to buy, and -1 if the trade is a market order to sell), as the independent variable. LSB use the effective half-spread (i.e., the transaction price less the midpoint of the quoted spread) as the independent variable.

Huang and Stoll (1997) distinguish the serial correlation models from trade indicator spread models. We consider GH and HS from this class of models. Both are models of the components of the bid-ask spread. As seen in Table 1, GH involves a projection of the price change on trade variables, and HS is a system of equations for both the price change and the change in the trade indicator. Huang and Stoll (1997) show that their theoretical framework generalizes the models of Glosten and Harris (1988) and George, Kaul, and Nimalendren (1991). In particular HS decompose the spread into three components: asymmetric information, inventory control, and order processing costs. In terms of estimating the reduced form specifications of these models, Table 1 shows that they are not nested, as each uses different data in measuring the impact of trades on the price.

Hasbrouck (1991a, 1991b) (VAR) uses the Wold decomposition of a vector autoregression of returns and trade variables to decompose the variance of the efficient stock price into a trade-driven component and a component that is unrelated to the order flow. Easley, Kiefer, O'Hara and Paperman's (1996) PIN (we use the refined version due to Easley, O'Hara, and Hvidkjaer 2002) depends solely on the distribution of buy and sell orders-not the dynamics of transactions prices-which differentiates it from the other models we consider. Details on estimation of PIN (documented problems with estimation are avoided with a simulated annealing algorithm) and VAR are provided in Appendices C and D respectively.³

Neal and Wheatley (1998) estimate GH and GKN on a sample of 17 closed-end funds. They find that the adverse selection component of the spread from GH averages 19% for the closed-end funds and 34% for a matched stock sample. These values from GKN are 52% and 65%, respectively. Neal and Wheatley argue that since these funds are portfolios that are unlikely to have asymmetric information, then high values of an adverse selection component

³A glance at Table 1 reveals that PIN, VAR, and GH are non-linear functions of parameter estimates. This means that these measures are biased in small sample. We account for this small sample bias with the bootstrap for VAR and GH. With the bootstrap we construct the expected value of measure—by integrating over the random parameter estimates. The correction for GH is trivial. It is infeasible to bootstrap PIN since obtaining the estimates requires a non-trivial non-linear optimization.

might indicate that the empirical models are misspecified. Neal and Wheatley document a significant divergence across these two measures, which they attribute to a misspecification in GKN. In particular, they argue that GKN's assumption that the (entire) spread can be bifurcated into an order-processing cost component and an adverse selection component is violated (Neal and Wheatley 1998, p. 141).

Van Ness, Van Ness and Warr (2001) estimate the adverse selection component of the spread using GH, GKN, LSB, HS, and an additional measure from Madhavan, Richardson, and Roomans (1997) (which is similar to GKN). They compare these measures to benchmarks of informational asymmetry that are popular in corporate finance, such as the number of analysts that follow the stock, research and development expenses, and (analysts') earnings forecast errors. They find that for the most part the microstructure-based estimates are not related to their benchmarks. They report that only the HS measure is positively correlated with some of their alternative measures of asymmetric information. As noted in the introduction, the lack of correlation between microstructure measures estimated on high frequency transaction and quote data, and proxies for fundamental informational asymmetries is not surprising. They are measuring fundamentally different sources of risk.

PIN is an extremely popular tool to measure informational asymmetry, and is now widely used as such in a wide array of studies ranging from institutional effects on trading to corporate finance, to traditional asset pricing.⁴ All of the measures rely on the assumption that the order flow can be reconstructed from observed transactions. Boehmer, Grammig, and Theissen (2007) consider the effect of trade misclassification on estimated PIN. They designate trades as buys and sells using the conventional Lee and Ready (1991) algorithm, and estimate PIN. Then they identify buys and sells using system order data from the NYSE for 1,043 stocks in the third quarter of 2002. They obtain a mean PIN estimate of 13.6%

⁴Recent papers that use PIN within a corporate finance context include: Aktas, de Bodt, Declerck, and Van Oppens (2007), Ascioglu, Hegde, and McDermott (2008), Bakke and Whited (2010), Bharath, Pasquariello, and Wu (2009), Brockman and Yan (2009), Chen, Goldstein, and Jiang (2007), Brown and Hillegeist (2007), and Duarte, Han, Harford, and Young (2008). Studies considering PIN and institutional questions include: Barclay and Hendershott (2003), Boulatov, Hatch, Johnson, and Lei (2009), Easley, O'Hara, and Paperman (1998), Easley, O'Hara, and Saar (2001), Ellul and Pagano (2006), Roll, Schwartz, and Subrahmanyam (2009) and Vega (2006). Studies that look at PIN and asset pricing issues include: Easley and O'Hara (2004), Hvidkjaer (2008) and Duarte and Young (2009).

with the Lee and Ready algorithm and 17.2% using the correct trade classification. They argue that misclassification inherent in transactions data will lead to a systematic downward bias in estimated PIN. Further they show that this bias is larger for less frequently traded stocks.

Duarte and Young (2009) provide an example of the specification problem that motivates our analysis. In particular, they argue that PIN is not rich enough to capture the positive correlation between buy and sell orders, which is pervasive in the data. They develop an extended PIN which captures this feature. Using this, they find that the correlation between Easley, Kiefer, O'Hara and Paperman's (1996) PIN measure and expected returns, shown in Easley and O'Hara (2004), is due to PIN's measurement of liquidity-incorrectly identified as private information.

3. Data

The TORQ data cover 144 NYSE stocks in the three-month period, November 1990 through January 1991.⁵ Appendix B describes the filters used on the data, and the reason that we must discard seven stocks. Appendix B.2 lists 18 stocks that we also remove from the sample for robustness checks. These stocks have a small number of transactions and/or a very low price over the three month period. We perform all of our analyses on both the full 137 stock sample as well as the 119 stock sample with these stocks removed.

Hasbrouck (1992) and Lee and Radhakrishna (2000) provide thorough descriptions of the TORQ database. Hasbrouck, Sofianos and Sosebee (1993) provide a comprehensive description of the NYSE at this time. We need the TORQ data because it provides a glimpse into the counterparties to most transactions–something that is not available with the Trade and Quote Database (TAQ), for example. We use the algorithm described in Madhavan and Panchapagesan (2000, esp., p.643–645) to identify all transactions that involve the NYSE specialist.⁶ The TORQ database has been used in many studies of market behavior.

⁵We are grateful to Joel Hasbrouck for making this data available and providing a perspicacious user's guide at his web site: http://people.stern.nyu.edu/jhasbrou/Research/WorkingPaperIndex.htm.

⁶Madhavan and Panchapagesan (2000) credit Edwards (1999) and Panchapagesan (1999) with developing and refining this algorithm, respectively.

Madhavan and Panchapagesan (2000) explore the specialist's strategy at the opening call market on the NYSE. Harris and Panchapagesan (2005) show that specialists use the imbalance in the limit order book to their advantage. Chung, Van Ness and Van Ness (1999) look at the quote formation process and the relative importance of limit orders and the specialist. Kavajecz and Odders-White (2001) investigate the importance of limit orders in the quote formation process. They show that transactions are not the only reason for quote and depth revisions. Chung, Van Ness and Van Ness (2001) isolate specialist spreads (after removing the limit order book) on the TORQ stocks and show that these are generally larger than inside spreads that include the limit order book, but still smaller than spreads on comparable Nasdaq companies.

Lee and Radhakrishna (2000) use the System Order Database file within the TORQ database to show that Lee and Ready's (1991) trade classification algorithm is very accurate on the SuperDOT transactions within the TORQ data. They also find that 94% of market orders in the TORQ database are filled in a single execution. We do not rely on TORQ's System Order Database file (which only contains information on SuperDot orders), instead we identify all transactions involving the specialist by matching transactions (in the transactions file) with TORQ's Audit file.⁷ We use the Lee-Ready algorithm to classify trades as buyer- or seller-initiated. As such we include all transactions on the NYSE, including those involving non-electronic orders.

4. Specialist outcomes

We sort the 137 stock sample into size terciles (with Tercile 1 containing the largest stocks) to describe the data. We measure size as the market capitalization of equity at the beginning of the sample period. The large and medium terciles contain 46 stocks and the small tercile contains 45 stocks. Tables 2.A1 and 2.A2 show the specialist's participation rates in terms of share volume and number of trades, respectively. The data show that specialists play a larger role in the market for smaller stocks. This is consistent with the

⁷The TORQ database comprises four files: the transactions file, the quotations file, the system order database file, and the audit file.

literature (e.g., Madhavan and Sofianos 1998). On average more than 26% of the trading volume in small stocks involves the specialist. By comparing transaction-based participation rates with the volume-based participation rates, it is clear that specialists are more likely to be involved in smaller trades. For the average stock, specialists are involved in 23% of the trading volume and 39% of transactions.

We measure a transaction's profitability by comparing the midpoint of the bid-ask spread after each interval (five minutes, one hour, and one day) to the transaction price. Table 2.A3 provides summary statistics for the loss rate conditional on specialist trade in volume terms, and Table 2.A4 provides summary statistics for the loss rate conditional on specialist trade in trade terms. These loss rates are very similar whether measured by volume or number of trades. The rate increases in the lag length used to measure the trade's profitability. This rate is significantly less than 50% and its scale is of a similar magnitude to that of the specialist participation rate. The fact that specialists tend to trade in a profitable manner is consistent with the facts that specialists have private information about the state of the limit order book, local demand and supply conditions, and the identities of some counterparties.⁸

The NYSE specialist in 1991 had both positive and negative obligations which may affect market outcomes. The specialist's positive obligation was to maintain an orderly market-to enable transactions when only one side of the market is present without large price swings from transaction to transaction.⁹ The negative obligations require the specialist to yield in situations where both a willing buyer and seller are present.

Tables 2.A5 and 2.A6 provide details on the realized specialist loss rate, by volume and by trade, respectively. Recall that this is defined as the product of the specialist participation rate and loss conditional on specialist trade. The volume-based loss rates tend to decrease

⁸Benveniste, Marcus, and Wilhelm (1992) and Battalio, Ellul, and Jennings (2007) discuss the lack of anonymity in a specialist market. Harris and Panchapagesan (2005) show that specialists can exploit their private information about the state of the limit order book to trade profitably.

⁹Specialists did have the discretion to seek a trading halt as a means of avoiding this obligation. There are no trading halts in any of the stocks in the TORQ sample. Furthermore, Lamoureux and Wang (2013) demonstrate that, following a public information shock, the specialist can maintain desired price continuity without putting his or her own capital at risk, at the expense of limit orders rendered stale by the shock.

with market capitalization. The exceptions to this are: when one day is used to identify losing trades, the mean loss rate on medium stocks exceeds that on small stocks; and when one hour is used to identify losing trades, the median loss rate on medium stocks exceeds that on small stocks. Small stocks exhibit the most heterogeneity in volume-based and trade-based loss rates. Comparing Tables 2.A5 and 2.A6 shows that the transactions-based loss rates are much larger than those based on volume, confirming the phenomenon noted above that specialists are more heavily involved in smaller trades. Also the trade-based loss rates do not exhibit the same relationships with stock size as the volume-based loss rates. At all three horizons the smallest tercile has the smallest median transactions-based loss rate.

Table 2.B provides summary statistics of our three control variables. The first control variable is the logarithm of the company's equity market capitalization at the start of the sample period. The second variable is the annualized daily return standard deviation from the three month period just prior to our sample period. This is very skewed, as one-half of the stocks in our sample have return standard deviations between 3 and 6%; however, 5% of the return standard deviations exceed 16%. The time-weighted proportional bid-ask spread is measured using all intra-day quotes (from the Institute for the Study of Security Markets (ISSM) data) from the three-month period just prior to the start of the sample period. In this pre-decimalization period, the mean spread on the NYSE exceeds 2%. The spreads are also positively skewed as 5% of the stocks' spreads exceed 6.5%.

Table 2.C shows the correlations between the two multiplicands of the realized specialist loss rate. We report Pearson correlations in the upper triangle and Spearman (rank) correlations in the lower triangle. Statistical significance (rejecting the null hypothesis that the correlation is zero) is indicated with one, two, and three asterisks at the 10, 5, and 1% levels of significance, respectively. When the loss rate is measured with volume there is a small negative correlation between the specialist participation rate and the loss conditional on specialist trade. When the loss rate is measured with number of trades this correlation is essentially zero. Thus as we consider the realized specialist loss rate we see that roughly equal parts of its variance come from its two components. This table also shows that loss rates measured with the number of transactions are less sensitive to the lag length than the rates measured with volume. The volume-based loss rates from 5-minute and 1-hour lags have correlations with the loss rate from the 1-day lag that are less than 50%.

We report specialist (dollar) profitability summed over the 63 trading days, equallyweighted across stocks, using all three trade classification horizons in Table 3.A. Table 3.B provides summary statistics of realized specialist profits and losses over the three-month interval. In this panel we evaluate the actual sequence of specialist trades in each stock and mark to market the specialist's inventory on January 31, 1991 at the midpoint of the closing spread. We equally weight these to produce the average dollar profits and losses under the heading "Absolute profit." We also scale the profit or loss in each stock by the total trading volume in the stock over the 3-month interval in computing the averages under the heading "Scaled realized specialist profit" in Table 3.C. Table 3.D shows the average specialist profit rates scaled by the specialist trade in the stock.

Tables 3.A and 3.B show that time diminishes large stock specialist profitability much more than that of specialists in medium and small stocks. Tables 3.C and 3.D show that the choice of scale has a significant effect on the averages. For example when we first scale the specialist profit by the total volume in the stock and then average these ratios (Table 3.C), the equally-weighted average across the 137 stocks is a loss. By contrast, when we first scale each specialist's profit by the specialist volume (Table 3.D), the average is a gain.

While the average large stock specialist is well-positioned to profit from local liquidity imbalances he does not in practice. If the average large stock specialist reversed each trade after five minutes he would have earned \$77,373 in trading profits over the three month period. In fact he lost \$194,969 over this period. Overall, the average dollar profit/loss is a loss of \$64,889. The fact that specialists lose money on average–despite profitable trading opportunities is consistent with the findings of Madhavan and Smidt (1991), Hasbrouck and Sofianos (1993), and Madhavan and Sofianos (1998): On average, specialists do not attempt to maintain a flat inventory, instead their behavior is consistent with speculation over several months. Our measure of specialist performance will be biased downward by the Exchange's orderly market requirement. However, the losses documented in Table 3 cannot be attributed to this constraint-especially since there are profitable trading opportunities at higher frequencies. In contrast to the larger stocks, the average specialist in the smallest stocks made a profit, despite the fact that the fixed period trading rules shown in Panel A result in much smaller profits for these stocks than for the larger stocks. This suggests that the small stock specialists do strategically control inventory more than the specialists in larger stocks. Further only specialists in small stocks, on average, exploit the opportunity to profit from knowledge of the local liquidity conditions.

Specialist profitability is negatively skewed in all three terciles-evinced by the fact that median profits are all positive, whereas the means are all negative. The largest loss (over \$13 million) is for IBM's specialist. IBM's price was \$105.375 at the beginning of the period, and \$126.875 at the end of the period. The second largest loss was for Sonat, Incorporated, where the specialist lost \$1,507,750 over the three month period. Sonat's price fell from \$51.125 at the beginning of the period to \$41.375 at the end. GE's specialist lost the third most, \$1,477,294, while GE's price rose from \$51.625 to \$63.875. The largest profits (over \$3.5 million) went to the specialist of Fannie Mae, whose price rose from \$28.50 to \$39.625 over the three months. In the medium size tercile, CUC International's specialist had the highest profit of \$328,362, as CU rose from \$16.5 to \$25.125 over the three months. AMD's specialist lost over \$779,000 while the stock rose from \$3.875 to \$7.25. In the small tercile, Monarch Capital Corporation's share price fell from \$5.625 to \$0.40625, and its specialist made \$57,922. Aydin Corporation's share price grew from \$10.625 to \$15.75, while its specialist lost \$36,962. Clearly the high level of trading volume in the largest stocks creates the most opportunity for specialist profitability and losses.

5. Efficacy of private information measures

5.1 Properties of the measures

Tables 4, 5 and 6 provide summary statistics of the six empirical estimators that we consider. In all cases, for GH, GKN, HS, and LSB (which are standard method of moment estimators), we truncate the estimate of the percentage of the spread due to private information to lie between 0 and 1, by censoring the estimates. Table 4 provides the equally-weighted sample properties–overall and for each size tercile–of each estimator, along with the number of truncations from above and below. The four spread decomposition estimators are directly comparable–they measure the percentage of the bid-ask spread due to adverse selection. Consistent with Huang and Stoll (1997, esp., footnote 6), we find that 69% of the HS estimates are less than 0. As in Neal and Wheatley (1998), the average GKN estimate of 71% is much higher than the average GH estimate of 23%.¹⁰ Bharath, Pasquariello, and Wu (2009) estimate GKN using daily return data, and report an average of 85%. LSB, with a mean of 39%, lies between GH and GKN. PIN is an estimate of the percentage of trades (not volume) containing private information. Bharath, Pasquariello, and Wu report an average PIN of 20% (obtained from Easley, Hvidkjaer, and O'Hara 2005), which is close to our mean PIN of 23%.

PIN, HS and VAR diminish monotonically in size across the three terciles. In the case of HS, this is simply because there are fewer truncations at 0 in the smallest tercile. Huang and Stoll (1997) suggest that the source of the problem with their estimator is that the order flow variable (measured from transaction data) is not negatively serially correlated, as it would be if a risk-averse specialist were actively managing her inventory, (i.e., estimates of π in Table 1, are less than 0.5). Of 137 estimates, we have only three estimates of π that are greater than 0.5. All of these cases are for stocks in the smallest tercile. The average value of π in our sample is 0.18. So whereas Huang and Stoll's estimator is designed specifically to separate inventory from adverse selection costs, market buys and sells do not exhibit the negative serial correlation that they would in their equilibrium. Furthermore, Madhavan

¹⁰George, Kaul, and Nimalendran (1991) estimate their model on daily and weekly data from 1963–1985. They note that their estimate of the percentage of the spread due to adverse selection (8 - 13%) is much lower than previous estimates (40%).

and Sofianos (1998, p.189) show that to the (limited) extent that these NYSE specialists manage their inventories they do so, not by adjusting their quotes, but by "selectively timing the magnitude and direction of their trading, participating more actively as sellers (buyers) when holding long (short) positions." This behavior is why the pattern of buy and sell executions is not serially correlated as it is in the equilibrium described by Huang and Stoll.

GKN increases monotonically in size, while the mean LSB estimator of the largest stocks is higher at 39% than the mean of the smallest stocks, 37%; although LSB exhibits very little variation along the size dimension. Within size terciles, each estimator exhibits significant variability. With the exception of LSB, the highest cross-sectional variation in the estimators occurs within the smallest tercile.

Table 5 provides small-sample bootstrapped distribution properties (including the standard deviations) of each estimator for the tenth and thirty-ninth largest firms in each size tercile. For the four spread component estimators as well as Hasbrouck's VAR, we bootstrap from the estimated residuals and use the estimated model parameters to construct each pseudo-sample. Following Hasbrouck (1991b), as shown in Appendix D, the VAR measure that we use in all of our analyses is the mean of 100,000 bootstrapped pseudo-samples. For PIN, we bootstrap from the pairs of number of buys and number of sells recorded on each day in the sample. We use 100,000 bootstrap pseudo-samples in this table.

Not surprisingly, in light of boundary condition problems, HS's small sample precision is very low: the 95% ile sampling interval is the entire support of the parameter's distribution for the three smallest firms considered in this table. GKN tends to be the most precise estimate (under the null that it is the correct model). At the individual stock level, with three months of daily data, the precision with which PIN is estimated is similar to that of GH and VAR. The sampling distributions are quite skewed in some cases. For example for DSI, the maximum likelihood estimate of PIN is 5%, and the bootstrapped mean (median) is 9% (7%). The bootstrapped 95% sampling band is 2% - 33%. For the smallest individual stock considered (WDG), the 95% sampling band is 12% - 71%. The sampling distribution of WDG's VAR is even more dramatically skewed. The VAR estimate is 30%, and the 95% sampling band is 4% - 74%.

Table 6 shows the Pearson and Spearman (rank) correlation matrices in the upper and lower triangles respectively, for our six measures of private information. Since five of these measures are estimated with high frequency, tick-by-tick data, and purport to isolate the role of private information in the price formation process, we expect them to be highly correlated, cross-sectionally. When we use all trades and look across the size terciles (the rows designated All, of 15 pairwise correlations, the significantly positive correlations are GH with: GKN, HS, LSB, and VAR; and VAR with: HS, LSB, and PIN. These patterns are robust over the correlation measure, although the Spearman correlations are generally lower than their Pearson counterparts. For example, GH and PIN are significantly positively correlated according to the Pearson measure, but not according to the Spearman measure. The highest correlations are between GH and LSB–especially for medium and small stocks. As we saw in Table 4, medium-sized stocks have the highest estimates of private information from GH and LSB. However, the average LSB estimate for small stocks is very close to that of large stocks, whereas for GH the estimate for large stocks is much smaller than that of small stocks. Across the entire sample, the highest pairwise correlations are: GH and LSB, 70%, PIN and VAR, 52%, and GH and VAR, 48%. Thirteen of the fifteen pairwise correlations are less than 50%.

As discussed above, the (reduced-form) estimators of private information are not subject to traditional specification tests of over-identifying restrictions. Table 5 shows that each of the reduced form estimators appears to be estimated with a high degree of precision. However the low correlations between the measures belie this result. As noted in the introduction, the efficacy of these measures depends on assumptions that link empirical market processes with theoretical constructs. The mapping from demand and supply into measured orders is also subject to strategic manipulation and data distortions. All of these issues are concerns for the models, but they do not affect our benchmark measure of private information, since the realized specialist loss rate is a "model-free" measure.

5.2 Benchmarking the measures

For these reasons, we now turn to gauging the efficacy of the measures by benchmarking them to the realized specialist loss rates and their two components. We project the benchmark on the measure(s) and three pre-determined control variables (reported in Table 2.B): stock volatility from the three months preceding the sample period, firm size at the beginning of the sample period, and the average proportional bid-ask spread from the three months preceding the sample period. Table 7 reports the results of these cross-sectional regressions where the volume-based realized specialist loss rate is the benchmark. The last column in each panel is an in-sample encompassing regression that includes all six measures as regressors. The purpose of the encompassing regression (following e.g., Fair and Shiller 1990), is to ascertain the degree to which each of the six measures contains information that is incremental to the other measures (and the control variables).

The table shows that there are relationships between this benchmark and several of these variables that are robust across the three lag lengths used to identify a trade's profitability. The realized specialist loss rate is decreasing in both firm size and the (prior period) proportional bid-ask spread. Volatility is significantly positively related to the benchmark, when 5 minutes and 1 hour lags are used to measure profitability. However volatility is not related to the benchmark when a trade's profitability is measured with a 1-day lag. In addition, three of the measures, GH, GKN, and LSB are correlated with the volume-based loss rate at all three lags, at the 1% significance level. This effect is incremental to that from the three pre-determined variables. When added one at a time to the control variables, the R^2 values in the table show that GH and GKN are much more correlated with the benchmark than the other measures. The three encompassing regressions, show that GKN has the most independent information in explaining the benchmark at all three lags.

While this result is necessary for GKN and GH to be efficacious in measuring the extent of private information in the order flow it may be that the measures are correlated with that portion of the realized specialist loss rate that is unrelated to private information–namely the specialist participation rate. Recall from Table 2.C that the two multiplicands of this benchmark are of roughly equal scale, and they are negatively correlated. It may be that the measures and control variables can explain the specialist participation rate, but not the realization of adverse selection risk. To investigate this Table 8 shows the results of the same type of cross-sectional regressions and control variables as in Table 7, where the dependent variable is the specialist participation rate in Panel A, and the loss conditional on specialist trade using the three lag lengths, in Panels B - D, respectively. Looking across the four panels, it is clear that the correlation between GKN, or GH, and the realized specialist loss rate from Table 7, is driven by the correlation between these measures and the specialist participation rate.

The results in Table 8.A are very similar to those in Table 7. The specialist participation rate is decreasing in both (lagged) firm size and the lagged proportional bid-ask spread. As noted above, the size effect is documented in the literature. Volatility is not related to the specialist participation rate. GH, GKN, and VAR are all significantly positively correlated with the specialist participation rate at the 1% level, and incremental to the three predetermined variables. Furthermore, as with the realized specialist loss rate, GKN is the only measure that contains unique information about the specialist participation rate, beyond that contained in the controls, using a significance level of 1%.

By contrast, the results in Tables 8.B, 8.C, and 8.D show that the measures are largely uncorrelated with the loss conditional on specialist participation. Volatility is significantly positively correlated with this metric when trade profitability is measured with a 5-minute or 1-hour lag, but not a 1-day lag. None of the measures are significantly correlated with this conditional loss rate at all three lags.

5.3 Robustness Checks

Our robustness checks proceed along three dimensions in terms of defining the metrics and the sample. All of the results above use share volume to measure the specialist participation rate and loss rate. As a robustness check we use number of trades instead of volume in the cross-sectional benchmarking regressions. The second dimension is the exclusion of 18 low-priced and infrequently traded stocks as described in Appendix B.2. This leaves us with a sample of 119 stocks. The third modification is that we replace the sample estimate of GH with its bias-corrected bootstrap estimator using 1 million pseudo-samples. We find that this estimator's small sample bias is virtually nil.

The results of all of the robustness checks are reported in Tables 9 - 14, which report the same regressions as in Tables 7 and 8. Tables 9 and 10 use the 119-stock sample and the bootstrapped GH estimator. Comparing Table 9 with Table 7 shows that removing the smallest stocks reduces the statistical importance of firm size in explaining the crosssectional variation in the realized specialist loss rates. The results on the reduced sample are otherwise qualitatively similar to those reported in Table 7. Table 10.A shows that the relationship between specialist participation and the control variables and measures is not affected by removing the smallest stocks from the sample. Panels B – D of Table 10 show that as with the full sample, none of the measures is correlated with the specialist loss rate–conditional on participating at all three lag-lengths used to measure trade profitability. However, both stock volatility and GH are significantly positively correlated with this benchmark when trade profitability is assessed using one hour and one day lags.

Tables 11 and 12 use the entire sample and trade-weighting instead of volume. Comparing Table 11 with Table 7 shows that lagged volatility and GKN have a statistically larger correlation with the trade-based specialist loss rate than with the volume-based measure at all three lag lengths used to measure trades' profitability. Table 12 shows that the reason for the higher correlation with the pre-period return volatility is due to both components of the benchmark. Table 12.A shows that trade-based specialist participation is significantly related to volatility, whereas Table 8 shows that volume-based specialist participation is not. Similarly GKN is more strongly correlated with participation based on trades than on volume. The R^2 on the regression with the three control variables and GKN is 35% in the volume-based regression and 58% in the trade-based regression. Panels B, C, and D of Table 12 also show that GH is significantly correlated with the trade-based specialist loss rate-conditional on specialist trade. Whereas in Table 8, this relationship only holds when we use a one hour lag to establish a trade's profitability. Tables 13 and 14 use the 119-stock sample, the bootstrapped GH estimator, and tradeweighting. Comparing Table 13 with Table 11 shows the effect of removing the smallest stocks and bootstrapped GH estimator on the trade-based benchmark regressions. This is similar to the effect of removing the smallest stocks on the volume-based measures. In particular, size and volatility become less important, but both GH and GKN have positive, significant coefficients in the encompassing regressions at all three lags. Table 14 shows that this is because both GH and GKN have significant, unique information about the trade-based specialist participation rate. Table 14 Panels B, C, and D show that GH is significantly positively related to the trade-based conditional specialist loss rate on the reduced sample when this is established using 5-minute and 1-hour lags. However, as in the base cases, none of the measures is significant when one day is used to define the tradeprofitability.

Table 14 shows that when trades are used to measure loss rates instead of volume (as in Table 10), volatility is significantly positively related to the conditional specialist loss rate-measured with all three lag lengths. GH is also significantly positively correlated with this conditional loss rate at both the five-minute and one-hour lag lengths. But as in Table 10, none of the measures is significantly correlated with this benchmark at all three lags.

6. Conclusion

The substantive question that motivates this paper is whether any of the statistical tools developed to measure adverse selection in specialist markets can explain the cross-section of realized specialist losses in that setting. Collin-Dufresne and Fos (2014) suggest that markets are more complex than the theory underpinning these measures. Their results suggest that the measures may not be related to adverse selection. We focus on a small subset of the markets that Collin-Dufresne and Fos consider with two objectives in mind. First Collin-Dufresne and Fos' sample includes very heterogeneous market regimes. The measures of private information developed in the 1980's and 90's were developed with the specialist market in mind. Especially important for the measures we consider is that there is a close mapping between orders and observed transactions. Subsequent to decimalization this is no longer the case. Secondly, by focusing on the specialist's realized losses, we are able to develop a benchmark that is not affected by stale limit orders or an informed liquidity provider. The importance of the latter concern is demonstrated by Cornell and Sirri (1992) and Collin-Dufresne and Fos.

Our empirical results largely support Collin-Dufresne and Fos' (2014) pessimistic conclusions. The measures developed by Glosten and Harris (1988) and George, Kaul, and Nimalendran (1991) correlate positively with the realized specialist loss rate. For the most part, this is due to their correlation with the specialist's participation rate. This participation rate is generally decreasing in firm size, and bid-ask spread, and increasing in volatility. After conditioning on these controls, and one another, each of these two measures (GH and GKN) contains unique information about the specialist participation rate. The reason for this is that they measure the price impact of a trade. GKN measures the response of the price and spread to a trade whereas GH measures the effect of volume on the transaction price. The other four measures that we consider are either unrelated to specialist participation rates (HS and PIN) or are encompassed by GH and GKN (LSB and VAR). Attaching economic meaning to the specialist's participation rate requires an equilibrium model. If liquidity provision is competitive then this reflects the fixed and inventory costs of making a market. To the extent that it is not, then this is a reflection of the specialist's monopoly power. In either case, quotes are more responsive to trades when this factor is higher.

However, none of the measures is consistently able to explain the cross-section of specialist loss rates-conditional on (specialist) trade. The failure of the measures is anticipated by Huang and Stoll (1997, p.997) who note that, "inventory and adverse selection components are difficult to distinguish because quotes react to trades in the same manner under both."

Appendices.

A. Institutional Details

While US stock markets of the 1980s and early 1990s bear little resemblance to markets in the 2010s they do provide a laboratory in which to study a wide array of issues in the area of market microstructure. This is due to the availability of trade and quote data from ISSM starting in 1982 and TAQ starting in 1993, as well as the technological, institutional and regulatory structure of the market. This environment includes a centralized exchange, relatively large minimum tick size, and a fairly clean mapping from (largely unobservable) orders into (observable) trades.

This environment has changed dramatically since 1996 (see, for example Angel, Harris and Spatt, 2011). Important changes include Regulation ATS (promulgated in 2000), which opened the door to alternative trading venues giving rise to heightened competition for the NYSE from electronic clearing networks. In the face of this increased fragmentation, Regulation NMS (promulgated in 2005) strengthened the national market system for equity trading, to ensure optimal execution. Recognizing the enormous cumulative effect of all of this on its business, in October 2008, the NYSE transformed specialists into designated market makers on a regulatory parity with floor brokers. The classification of trades based on which side demands immediate liquidity (which is required of five of the six estimators we consider) is much more complicated in this new post-decimalization, highly decentralized trading era.

All of the statistics that were developed to study and measure the importance of private information in a specialist market work with dealer quotes and transactions, but are based on order flow. Therefore a key feature of the market is the ability to reconstruct the order flow from observed transactions. Thus, an integral part of *all* of the measures that we consider is the Lee and Ready (1991) algorithm, which is used to identify which side of a transaction demanded liquidity, and the empirical mapping from orders into transactions. This aspect of markets has changed dramatically over the past two decades. Hvidkjaer (2008, esp., p.1131), and GAO (2005) suggest that this is a consequence of decimalization. Angel, Harris and Spatt (2011) note that from 2004 through 2009, daily equity trading volume in the US doubled, while average trade size halved. They discuss that the decoupling of transactions from underlying supply and demand conditions is the result of automation, market segmentation, and algorithmic trading.

It is this decoupling of supply and demand conditions from submitted orders, which in turn are decoupled from individual transactions (and even venues) that renders the Lee and Ready (1991) algorithm and the measures of private information based on transactions and quotes inappropriate for "fast" computerized markets. Huang and Stoll (1997, esp., p.1018), are explicit on this point. Their estimate of the adverse selection component of the spread is negative for 18 of the 19 stocks studied. They note that split orders can give rise to a spurious positive serial correlation in the measured order flow, and suggest that this may be distorting their estimates.

So the analyses in this paper apply to relatively "slow" markets (by 2013 NYSE standards), where the Lee and Ready (1991) algorithm can be reasonably applied to *transactions* in order to identify the underlying *orders*. As noted in footnote 1, thinly-traded stocks on Euronext, with a designated market maker are a modern example of such a setting.

B. Data filters

1. Base case

We only include all quotes and all NYSE transactions that take place between 9:30 and 16:00 Eastern time. We exclude the opening (call market) transaction in all cases. For all transactions, we require that the transaction price and size both be greater than zero. For quotes, we require that the bid be positive, the ask be positive, and the ask be greater than the bid. We also require that the bid and offer sizes be positive. Finally, we add five seconds to the quotes clock to temporally align quotes with trades.¹¹

¹¹This is a standard adjustment on data from this period, see, e.g., Chordia, Roll, and Subrahmanyam (2011), esp. fn.12.

While there are 144 stocks in the TORQ database, and we may obtain the other five estimators in all cases, we lose seven stocks in estimating VAR. Five of these have less than 85 transactions that survive the filters described above, (one, GFB, has only three transactions over the entire three-month period). The largest of these, LUK, has the appearance of a unit root in signed volume (and just 192 transactions). Finally, one, EHP, has a maximum price of \$0.46875, 226 trades, and only 29 buyer-initiated trades. The ticker symbols of the seven discarded stocks (and their size rank of the original 144 TORQ stocks) are: GFB (144), EFG (142), EHP (139), VCC (134), MCC (109), MTR (101), and LUK (68).

2. Robustness check subsample

Of the remaining 137 stocks, 18 have very low prices and/or a small number of transactions. To ensure that our results are not overly influenced by these stocks we repeat all analysis using a subsample of 119 stocks that exclude these 18. The 18 excluded stocks (with maximum price and number of transactions reported in parentheses are: DLT (0.875, 88), FLP (1.875, 217), GBE (1.75, 367), ICM (4.00, 187), IS (2.50, 146), ITG (0.4375, 88), MBK (18.25, 30), NSO (0.5469, 59), OEH (3.25, 21), PIM¹² (6.875, 1259), SLT (2.375, 101), TCI (4.25, 154), UMG (2.375, 166), URS (3.625, 57), WAE (0.50, 43), WDG (1.125, 130), Y (86.50, 96), and ZIF (5.00, 113).

C. Estimating PIN

As shown in Table 1, PIN is estimated using maximum likelihood, under the assumption that the number of buy and sell orders on each day are independently distributed according to the product of Poisson processes that govern buying and selling by liquidity tradersindependent of information flow, the arrival of private information, and the behavior of informed traders-conditional on an information shock. This implies that the econometrician observes *orders*. Prior to 2000, trades closely parallel orders, but decimalization and open limit order books have driven a large wedge between orders and trades, so that trade data post 2000 is a poorer proxy for quotes (see, for example, GAO 2005). Aktas, de Bodt,

¹²This stock exhibits virtually no price change over the three-month period. Its minimum transaction price is \$6.50, and it maximum is \$6.875.

Declerck, and Van Oppens (2007) report a difficulty in obtaining convergence for between 13 and 19% of their cases. We initially experienced similar difficulties using gradient-based non-linear optimization methods. By switching to simulated annealing we are able to obtain convergence in all cases. We use the algorithm of Goffe, Ferrier, and Rogers (1994). The procedure is more time-consuming than gradient-based methods, but much more robust. In all instances, we use multiple starting conditions to ensure global optimization.

D. Estimating VAR

Our VAR estimation follows Hasbrouck (1991b) exactly. That is, the VAR has four equations: r_t , X_t , $X_t ext{V}_t$, and $X_t ext{V}_t^2$, where: r_t is the return on transaction t -based on the midpoint of the bid-ask spread at the time of the transactions, X_t is the trade indicator for trade t: 1 if the trade is a (market) buy, 0 if it cannot be classified, and -1 if the trade is a (market) sell. We use Hasbrouck's triangularization. That is, we assume that $\Psi_t = [X_t, X_t ext{V}_t, X_t ext{V}_t^2]$ is exogenous with respect to r_t . Let $\mathbf{Y}_t = [r_t, \Psi_t]$. Following Hasbrouck (1991b), the time-series is re-seeded each day, so that at the start of each trading day, $r_0 = \mathbf{Y}_j = 0$, $j = -1, \dots, P-1$. P is the lag length of the VAR. We follow Hasbrouck and set P = 5. There are several cases, with insufficient data to estimate this large of a system with five lags (in which case there are 93 free parameters in this VAR). In these cases, we reduce P by 1 until stationarity (and identification) is obtained.

As shown in Table 1, after estimating VAR, we obtain the impulse response coefficients and follow Hasbrouck in using these to decompose the variance of permanent shocks to rinto components that depend on the transactions process, and those that do not. Hasbrouck uses 30 lags of the moving average coefficients to compute the variance components. We use 100 lags. Hasbrouck also notes that the VAR may be subject to small sample bias, and uses a bootstrap to deal with this. He uses 100 pseudo-samples from a bootstrap and evaluates the mean. We also bootstrap–and use 100,000 pseudo-samples. We report the means of these 100,000 bootstrapped samples.¹³

¹³If we were interested in inference on the impulse response coefficients, we would also have to adjust the VAR estimates, as in Sims and Zha (1999).

To construct the bootstrap pseudo-samples, we retain the daily structure of the original data, so that each day is seeded with the actual Ψ_0 on that day, and:

$$r_i = \Psi_j = 0, i = 0, \dots - P + 1, \text{ and } j = -1, \dots, -P + 1.$$

The number of transactions on each day is fixed, as is the number of days with at least two transactions. We use the same P to estimate the VAR on each bootstrapped pseudo-sample as we used to estimate the VAR on the sample data. We impose stationarity on the pseudo-samples using a rejection method.

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Table 1Estimators of private information

This table summarizes the six estimators of informational asymmetry considered in the paper. P_t is the transaction price. M_T is the midpoint of the bid and ask quotes immediately following the transaction at time t. $RD_t = (P_{t+1} - P_t)/P_t - (M_{T+1} - M_T)/M_T$. Γ_T is the spread immediately following the transaction at time t. ΔX_t is the change in the trade indicator, where $X_t = 1$ if the trade is buyer initiated and -1 if the trade is seller initiated. M_t is the midpoint of the prevailing bid and ask quotes when the transaction at time t occurs, $m_t = ln(M_t)$, $p_t = ln(P_t)$. V_t is the number of shares traded. \overline{V} is the average trading volume per transaction over the sample period in the stock. Γ_t is the prevailing spread when the transaction at time t occurs. π is the probability that the trade at time t is opposite in sign to the trade at t-1. Hasbrouck's (1991b) trade informativeness estimator is derived from the Wold decomposition of the following vector autoregression:

 $r_t = h_1 r_{t-1} + h_2 r_{t-2} + \dots + l_0 \Psi_t + l_1 \Psi_{t-1} + \dots + \nu_{1,t}$, $\Psi_t = j_1 r_{t-1} + j_2 r_{t-2} + \dots + k_1 \Psi_{t-1} + k_2 \Psi_{t-2} + \dots + \nu_{2,t}$. $r_t = m_t - m_{t-1}$. $\Psi_t = [X_t, X_t \cdot V_t, X_t \cdot V_t^2]'$. $\Omega_{3\times3} = Var(v_{2,t})$. Following Hasbrouck, we assign 0 to X_t if trade t cannot be classified as buyer- or seller- initiated and include it in estimating the VAR. We exclude unclassified trades in estimating all other estimators. The parameters in PIN are: α , the probability of an information event occurring at the beginning of each day, γ , the probability of bad news conditional on an information event occurring, μ , the arrival rate of informed trades, ε_b , the rate of uninformed buy trade arrivals, and ε_s , the rate of uninformed sell trade arrivals. In deriving PIN, it is assumed that if an information shock occurs, it occurs in the morning and is fully reflected in price by day's end. Then the log-likelihood on day *i* is:

$$L_i((B_i, S_i)|(\alpha, \gamma, \mu, \varepsilon_b, \varepsilon_s)) = [-\varepsilon_b - \varepsilon_s + Z_i(lnQ_b + lnQ_s) + B_i\ln(\mu + \varepsilon_b) + S_i\ln(\mu + \varepsilon_s)] + \ln[\alpha(1 - \gamma)e^{-\mu}Q_Q^{S_i - Z_i}Q_b^{-Z_i} + \alpha\gamma e^{-\mu}Q_b^{B_i - Z_i}Q_s^{-Z_i} + (1 - \alpha)Q_s^{S_i - Z_i}Q_b^{B_i - Z_i}]$$

 B_i and S_i are the number of buys and sells on date *i*, respectively. $Z_i = (B_i + S_i)/2$. $Q_s = \varepsilon_s/(\mu + \varepsilon_s)$. $Q_b = \varepsilon_b/(\mu + \varepsilon_b)$. Maximizing $\sum_{i=1}^{l} L(B_i, S_i | (\alpha, \gamma, \mu, \varepsilon_b, \varepsilon_s))$ across *I* independent (by assumption) trading days yields maximum likelihood estimates of the five parameters.

Estimator name	Estimator specification	Estimator of private information
	Panel A: Serial covariance spread estimator	
George-Kaul-Nimalendran (GKN)	$2RD_t = a_0 + a_1(\Gamma_T/M_T) \bigtriangleup X_t + \xi_t$	$1 - a_1$
Lin-Sanger-Booth (LSB)	$\Delta m_{t+1} = c_0(p_t - m_t) + \zeta_t$	<i>C</i> ₀
	Panel B: Trade-indicator estimator	
		$2(b_2 + b_3 \overline{V})$
Glosten-Harris (GH)	$\Delta P_t = b_0 \Delta X_t + b_1 \Delta X_t V_t + b_2 X_t + b_3 X_t V_t + \eta_t$	$\overline{2(b_0+b_1ar{V})+2(b_2+b_3ar{V})}$
Huang-Stoll (HS)	$\Delta M_t = (d_0 + d_1) \frac{\Gamma_{t-1}}{2} X_{t-1} - d_0 (1 - 2\pi) \frac{\Gamma_{t-2}}{2} X_{t-2} + \varsigma_t$	d_0
	$E(X_{t-1} X_{t-2}) = (1-2\pi)X_{t-2}$	
	Panel C: Variance decomposition estimator	
Hasbrouck (VAR)	$r_t = v_{1,t} + h_1^* v_{1,t-1} + h_2^* v_{1,t-2} + \dots + l_0^* v_{2,t} + l_1^* v_{2,t-1} + \dots$	$(\sum_{i=0}^{\infty}l_i^*)\Omega(\sum_{i=0}^{\infty}l_i^{*'})$
	$\Psi_t = j_1^* v_{1,t-1} + j_2^* v_{1,t-2} + \dots + v_{2,t} + k_1^* v_{2,t-1} + k_2^* v_{2,t-2} + \dots$	$\overline{(\sum_{i=0}^{\infty} l_i^*) \Omega(\sum_{i=0}^{\infty} l_i^{*'}) + (1 + \sum_{i=1}^{\infty} h_i^*)^2 \sigma^2(v_1)}$
	Panel D: Probability of informed trading	
	$\sum_{i=1}^{I} L(B_i, S_i (\alpha, \gamma, \mu, \varepsilon_h, \varepsilon_c))$	αμ
Easley-Kiefer-O'Hara-Paperman (PIN)	$\underline{\frown}_{i=1}^{i=1}$	$\alpha\mu + \varepsilon_b + \varepsilon_s$

Table 2Summary statistics

The sample is 137 stocks in the Trades, Orders, Reports, and Quotes (TORQ) database, over the period November 1, 1990 - January 31, 1991. Panel A reports summary statistics of specialist variables by firm size. The 137 stocks are sorted into terciles by size. The specialist participation rate by volume is the ratio of the specialist share volume to the total volume in that stock. The specialist participation rate by trades is the ratio of the number of specialist trades to the total number of trades in that stock. The loss rate conditional on specialist volume is the ratio of unprofitable specialist share purchases and sales to the specialist share volume in that stock. The loss rate conditional on specialist trade is the ratio of unprofitable number of specialist trades to the number of specialist trades in that stock. The realized specialist loss rate by volume is the ratio of unprofitable specialist share purchases and sales to the total volume in that stock. The realized specialist loss rate by trades is the ratio of the unprofitable number of specialist trades to the total number of trades in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. The realized specialist loss rate by volume is the product of the specialist participation rate by volume and the loss rate conditional on specialist volume. The realized specialist loss rate by trades is the product of the specialist participation rate by trades and the loss rate conditional on specialist trade. Panel B reports summary statistics of control variables used in the paper. Firm size at the start of sample period is the natural logarithm of the market value of the firm's equity in thousands as of November 1, 1990. Annualized stock volatility prior to sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Time weighted proportional spread prior to sample is the bid ask spread divided by the midpoint of the bid ask spread, weighted by the elapsed time before it is updated from August 1, 1990 through October 31, 1990 using quote data from the Institute for the Study of Security Markets (ISSM) database. Panel C reports pairwise Pearson (upper triangle) and Spearman (rank) (lower triangle) correlations of the specialist outcomes. ***, **, and * denote significantly different from zero at the 1%, 5%, and 10% significance levels, respectively. All specialist and spread variables are multiplied by 100.

		Std.					
	Mean	Dev.	5 th Pctl	25 th Pctl	Median	75 th Pctl	95 th Pctl
		Panel A: Sur	<u>nmary statisti</u>	cs of specialist v	ariables by firm	size	
		Panel A1:	Realized spec	cialist participati	on rate by volur	ne	
All	22.86	10.79	7.88	15.31	21.69	28.24	42.19
Large	18.84	7.10	9.73	15.09	17.50	22.89	29.58
Medium	23.46	11.94	3.27	16.15	22.80	30.14	41.25
Small	26.20	11.48	9.62	19.52	25.20	33.28	47.84
		Panel A2	: Realized spe	cialist participat	ion rate by trade	es	
All	39.39	17.86	14.56	28.83	38.47	47.34	59.36
Large	35.35	9.11	19.95	28.15	36.87	40.11	49.03
Medium	38.76	15.69	5.45	30.99	40.49	50.03	59.15
Small	43.99	24.47	15.68	30.04	41.79	51.43	57.22
		Panel A	3: Loss rate c	conditional on sp	ecialist volume		
		Eval	uating trade p	rofitability after	five minutes		
All	24.13	10.55	8.39	17.62	22.86	29.70	45.75
Large	23.70	5.69	14.96	20.08	23.04	28.15	32.10
Medium	24.41	11.80	8.39	17.62	22.71	28.49	46.06
Small	24.27	12.85	6.70	14.15	22.68	32.12	48.00
		Ev	aluating trade	profitability after	er one hour		
All	26.76	9.27	11.21	21.06	25.77	31.89	43.88
Large	28.65	5.53	19.71	24.64	28.85	32.58	36.56
Medium	25.79	8.96	11.21	20.91	23.75	32.20	41.83
Small	25.87	12.01	8.01	19.02	23.39	30.18	52.12
		Ev	aluating trade	e profitability aft	er one day		
All	29.96	8.41	13.25	24.94	30.28	34.48	43.72
Large	32.41	4.75	23.98	29.37	32.63	35.54	39.17
Medium	30.83	7.17	20.37	25.61	31.84	34.33	43.72
Small	26.69	11.09	11.11	20.37	26.80	30.54	44.96

			Tabl	e 2 – Continued			
	Moon	Std.	5 th Dot1	25 th Dot1	Madian	75 th Dot1	05 th Datl
	Mean	Dev. Panel	A4. Loss rate	<u>conditional on s</u>	pecialist trade	75 FCI	93 FCI
		<u> </u>	<u>114. Loss face</u>	rofitability after	five minutes		
A11	24.26	8 57	9 37	18 69	24.00	29.56	39.62
Large	26.20	5.45	18.54	21.41	25.53	30.47	35.50
Medium	23.94	7.30	11.34	18.87	24.20	27.59	35.56
Small	22.67	11.55	6.35	14.86	20.78	30.12	44.55
		Ev	aluating trade	profitability afte	er one hour		
All	26.64	7.32	13.02	22.27	27.77	31.79	37.38
Large	29.52	4.69	22.38	25.95	29.98	32.94	36.93
Medium	26.56	5.68	15.77	22.81	27.98	30.41	33.60
Small	23.92	9.62	8.40	17.80	23.41	30.41	40.10
		E	valuating trade	e profitability aft	er one day		
All	30.58	6.28	17.65	27.02	31.40	34.89	39.95
Large	32.87	3.40	26.11	31.03	33.25	35.25	37.64
Medium	32.01	5.21	24.23	28.68	31.93	36.13	40.00
Small	26.92	7.72	13.89	21.97	26.87	33.00	40.63
		Panel	A5: Realized	specialist loss ra	ate by volume		
		Eva	luating trade p	rofitability after	five minutes		
All	5.28	3.45	1.43	2.94	4.39	6.67	13.31
Large	4.42	1.88	2.13	3.12	3.96	5.60	7.78
Medium	4.94	2.61	1.38	2.94	4.52	6.55	8.93
Small	6.45	4.84	1.43	2.52	4.89	9.00	14.88
		Ev	aluating trade	profitability after	er one hour	= 10	12 10
All	5.96	3.59	1.46	3.86	5.27	7.13	12.49
Large	5.29	1.78	2.97	3.98	5.10	6.76	8.62
Medium	5.79	3.19	1.10	3.58	5.44	1.33	11.57
Small	6.79	4.95 E	1.40	3.52 maafitahilita aft	4.95 an ana day	8.65	16.75
A 11	6 70	2 75			$\epsilon 07$	0 27	14 97
All	6.00	3.73	1.07	4.55	0.07 5.80	8.37 7.10	14.87
Large	0.09	2.29	5.50	4.38	5.80	/.10	10.30
Small	6.86	4.40	1.03	4.05	0.24	0.09 8 50	17.04
Sillali	0.80	4.10 Ponc	1.70	4.27	0.31	0.39	12.55
		<u> </u>	luating trade n	<u>a specialist 1088 i</u> rofitability after	five minutes		
A11	9.87	8.05	2 79	5 90	8 42	12.09	22.67
Large	9.24	3.16	5.22	6.61	9.04	10.86	14 57
Medium	8.83	4 25	1 47	5 91	8 58	11.90	15.17
Small	11.52	12.79	2.79	3 74	677	13.12	43.01
	11102	Ev	valuating trade	profitability afte	er one hour	10112	10101
All	10.73	7.28	2.80	6.31	9.84	13.23	22.49
Large	10.43	3.21	5.49	8.39	9.84	12.88	15.23
Medium	10.15	4.75	1.41	6.60	10.36	13.74	18.40
Small	11.60	11.24	3.06	4.75	8.22	14.12	41.86
		E	valuating trade	e profitability aft	er one day		
All	12.00	6.15	3.96	8.03	11.55	14.64	23.49
Large	11.58	3.14	6.80	9.27	11.76	13.47	16.24
Medium	12.30	5.60	1.65	9.06	12.23	15.38	23.14
Small	12.11	8.54	4.27	5.92	9.71	14.64	31.40

	commutu						
Panel B: Summary stat	istics of contro	ol variał	oles				
		Std.					
Variable	Mean	Dev.	5 th Pctl	25 th Pctl	Median	75 th Pctl	95 th Pctl
Firm size at the start of sample period	12.47	2.27	8.53	11.04	12.51	13.88	16.42
Annualized Stock Volatility prior to sample period	0.07	0.09	0.02	0.03	0.05	0.06	0.16
Time Weighted Proportional Spread prior to sample	2.12	1.73	0.54	0.99	1.48	2.88	6.57
Panel C: Correlations	of specialist	outcome	es				
				(1)	(2)	(3)	(4)
Realized specialist participation rate by volume (1)				100%	-21%**	-16%*	-14%*
Loss rate conditional on specialist volume with trade profitability evaluated after	er five minutes	(2)		-19%*	* 100%	62%***	36%***
Loss rate conditional on specialist volume with trade profitability evaluated after	er one hour (3))		-22%**	** 58%***	· 100%	49%***
Loss rate conditional on specialist volume with trade profitability evaluated after	er one day (4)			-17%*	* 34%***	48%***	100%
				(5)	(6)	(7)	(8)
Realized specialist participation rate by Trades (5)				100%	-3%	0%	-7%
Loss rate conditional on specialist trade with trade profitability evaluated after five minutes (6) 0% 100% 84%***							62%***
Loss rate conditional on specialist trade with trade profitability evaluated after one hour (7) 1% 82%*** 100% 75%							75%***
Loss rate conditional on specialist trade with trade profitability evaluated after of	one day (8)			-4%	61%***	* 71%***	100%

 Table 2 – Continued

Table 3 Specialist trading performance (\$)

Summary statistics of specialist trading performance using 137 stocks in the Trades, Orders, Reports, and Quotes (TORQ) database over the period November 1, 1990 – January 31, 1991. We compute each performance measure for each trade and sum these to get the profitability at the stock level. These are equally-weighted to obtain the reported means. We measure performance by multiplying the transaction size by the difference between the quote midpoint after the trade and the trade price. We report this for three alternative post-trade intervals: five minutes, one hour, and one (trading) day. Absolute specialist realized profit is the total profit of the specialist trades over the whole sample period. Scaled specialist realized profit is the absolute specialist realized profit divided by the total trading volume in the stock over the whole sample period. Scaled conditional specialist realized profit is the absolute specialist realized profit divided by the total specialist trading volume over the whole sample period. Size is the market value of the firm's equity on October 31, 1990. The 137 stocks are sorted into terciles by size. Panel A reports summary statistics of specialist profitability – evaluated at each of the three post-trade intervals. Panel B provides summary statistics of the absolute realized profitability of the specialist' transactions over the three-month period. Remaining inventory at the end of the period is marked to market at the midpoint of the closing bid-ask spread on Thursday, January 31, 1991. Panel C provides summary statistics of the scaled conditional realized specialist profit.

		Std.					
	Mean	Dev.	5 th Pctl	25 th Pctl	Median	75 th Pctl	95 th Pctl
		Panel	A: Specialist tra	ding performan	ce (in \$)		
		Evalu	ating trade profita	ability after five	e minutes		
All	28,608.11	76,413.43	-1,762.50	257.22	3,882.81	20,065.63	78,575.00
Large	77,372.92	120,289.48	-1,731.25	13,281.25	29,581.25	62,328.13	374,206.25
Medium	8,744.16	8,919.16	-981.25	1,593.75	5,240.63	13,293.75	22,562.50
Small	767.36	2,109.19	-1,888.29	-212.50	257.22	1,540.63	3,890.63
		Eval	luating trade prof	itability after of	ne hour		
All	19,192.57	51,187.25	-7,237.50	425.00	5,225.00	17,828.13	75,337.50
Large	48,748.19	81,506.16	-32,906.25	10,193.75	24,112.50	44,053.13	300,000.00
Medium	8,512.70	10,519.01	-7,237.50	1,862.50	6,568.75	12,809.38	30,406.25
Small	959.32	3,763.63	-5,381.25	-273.44	746.88	1,987.50	6,325.00
		Eva	luating trade prof	fitability after o	ne day		
All	4,382.42	104,027.13	-43,800.00	-2,006.25	1,751.56	14,184.38	80,412.50
Large	6,286.94	180,105.65	-278,381.25	-12,046.88	13,381.25	48,025.00	289,337.50
Medium	7,241.20	21,048.95	-29,268.75	-5,312.50	2,906.25	15,253.13	39,825.00
Small	-339.48	4,910.30	-5,137.50	-875.00	478.13	1,971.88	6,068.75
		Panel I	B: Realized specia	alist absolute pr	ofit (in \$)		
All	-64,889.38	1,228,145.51	-551,912.50	-5,946.39	6,275.00	40,300.00	516,125.00
Large	-194,968.61	2,145,721.93	-1,477,293.75	-59,693.75	34,625.00	110,087.50	1,115,700.00
Medium	-4,789.40	176,855.34	-192,812.50	-12,493.75	8,462.50	38,756.25	302,012.50
Small	2,262.07	15,293.45	-20,137.50	-3,050.00	1,728.13	7,125.00	24,587.50
		Panel C: Sca	aled realized spec	<u>ialist profit (in</u>	\$0.001 / share))	
All	-1.85	73.15	-179.76	-4.56	5.22	18.11	72.41
Large	-4.48	60.18	-156.25	-8.29	5.67	18.63	63.74
Medium	-4.69	94.08	-207.30	-14.53	7.50	25.27	137.90
Small	3.56	61.09	-70.90	-3.64	3.93	13.37	41.57
	Pa	anel D: Scaled co	onditional realize	d specialist pro	fit (in \$0.001 /	share)	
All	1.42	283.32	-493.49	-42.56	33.85	92.41	364.70
Large	-12.36	305.66	-843.66	-56.43	45.15	113.14	364.70
Medium	1.91	352.82	-516.92	-82.97	34.51	113.27	447.48
Small	14.41	162.47	-261.03	-18.65	16.96	59.62	121.90

Table 4 Sample properties of the statistical estimators of private information

Summary statistics for the six estimators of private information using 137 stocks in the Trades, Orders, Reports, and Quotes (TORQ) database, over the period November 1, 1990 – January 31, 1991. Moment estimators are censored to lie within their theoretical support. We obtain estimates using the entire sample, and report the cross-sectional sample statistics of the censored estimates, as well as the number of uncensored estimates less than 0, and the number of uncensored estimates greater than 1. All estimates are reported in percentages. Size is the market value of the firm's equity as of November 1, 1990. The 137 stocks are sorted into terciles by size. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Table 1 for definitions of the estimators.

Measure			Std.							
name		Mean	Dev.	5 th Pctl	25 th Pctl	Median	75 th Pctl	95 th Pctl	#(<0)	#(>1)
GH	All	23.25	18.65	0.98	9.90	20.60	31.42	55.03	2	2
	Large	16.35	10.11	2.79	8.28	15.11	23.14	33.60	0	0
	Medium	29.17	19.61	1.93	16.78	25.13	38.39	55.03	0	1
	Small	24.09	21.97	0.00	8.16	21.11	30.74	69.77	2	1
GKN	All	71.43	15.91	35.85	68.03	75.39	81.49	88.37	1	0
	Large	76.90	12.87	62.01	72.53	78.11	83.82	88.31	0	0
	Medium	72.28	15.17	26.29	70.76	75.82	80.92	86.93	0	0
	Small	65.24	17.41	35.85	56.04	68.83	75.55	89.46	1	0
HS	All	1.68	5.34	0.00	0.00	0.00	0.46	8.73	95	0
	Large	0.14	0.57	0.00	0.00	0.00	0.00	1.41	42	0
	Medium	1.64	3.77	0.00	0.00	0.00	0.32	10.11	31	0
	Small	3.22	8.18	0.00	0.00	0.17	3.82	10.56	22	0
LSB	All	38.95	15.57	16.72	30.56	38.48	46.37	66.30	0	1
	Large	38.82	11.45	22.17	33.15	38.43	43.61	51.77	0	0
	Medium	40.89	17.35	5.68	34.03	40.25	49.76	60.87	0	0
	Small	37.14	17.20	17.05	23.87	33.61	46.72	67.52	0	1
PIN	All	22.72	10.42	11.17	16.22	20.78	25.23	48.14	0	0
	Large	17.24	4.85	9.74	14.01	16.65	20.00	25.23	0	0
	Medium	20.71	6.65	12.51	16.89	20.07	24.41	31.54	0	0
	Small	30.08	13.10	14.35	21.10	27.06	36.49	59.04	0	0
VAR	All	26.61	13.19	8.87	16.98	24.67	31.86	54.01	0	0
	Large	18.25	9.69	5.94	12.64	16.94	22.77	31.35	0	0
	Medium	27.33	11.16	12.57	20.25	25.40	32.59	51.87	0	0
	Small	34.08	13.48	15.85	25.76	30.15	40.04	58.87	0	0

Table 5 Summary statistics of bootstrapped parameter and measure estimates

Properties of the small-sample distributions of measure estimates constructed using 100,000 bootstrap draws for six stocks (size rank in the sample of 137 stocks, with 1 being the largest): CPC (10), ACN (39), AC (58), DSI (86), ALL (104), and WDG (131). Moment estimators are censored to lie within their theoretical support. All estimates are reported in percentages. See Table 1 for definitions of the estimators.

Estimator	Parameter or	Stock		Std.			
name	function of parameter(s)	symbol	Mean	Dev.	2.5%ile	Median	97.5%ile
GH	$2(h + h \overline{V})$	CPC	29.75	2.57	24.62	29.79	34.73
	$\frac{2(b_2 + b_3 v_i)}{2(b_2 + b_3 v_i)}$	ACN	35.16	3.83	27.33	35.24	42.44
	$2(b_0 + b_1V_i) + 2(b_2 + b_3V_i)$	AC	33.25	4.06	25.03	33.31	41.03
		DSI	2.33	2.02	0.00	2.07	6.78
		ALL	11.13	3.93	3.16	11.20	18.61
		WDG	24.63	10.86	0.88	25.11	44.72
GKN	$1 - a_1$	CPC	81.92	0.72	80.50	81.91	83.34
	1	ACN	82.43	1.24	80.01	82.43	84.85
		AC	71.02	1.64	67.82	71.00	74.29
		DSI	51.81	1.94	48.13	51.76	55.86
		ALL	36.02	2.83	30.53	36.01	41.67
		WDG	62.59	5.53	51.62	62.60	73.48
HS	d_0	CPC	0.00	0.00	0.00	0.00	0.00
	Ŭ	ACN	1.12	5.93	0.00	0.00	17.43
		AC	0.00	0.17	0.00	0.00	0.00
		DSI	11.05	28.60	0.00	0.00	100.00
		ALL	8.48	25.12	0.00	0.00	100.00
		WDG	12.35	27.95	0.00	0.00	100.00
LSB	c_0	CPC	49.20	1.64	45.88	49.24	52.28
	Ū	ACN	39.76	2.19	35.44	39.78	43.95
		AC	39.89	3.18	33.45	39.96	45.97
		DSI	12.02	1.81	8.45	12.04	15.53
		ALL	21.87	3.21	15.62	21.88	28.14
		WDG	21.14	6.05	9.28	21.14	33.17
PIN	αμ	CPC	17.86	5.51	8.70	17.52	29.14
	$\alpha\mu + \varepsilon$ -buy + ε -sell	ACN	18.71	3.52	11.51	18.91	25.17
		AC	16.75	4.46	9.21	16.40	26.16
		DSI	8.84	7.50	1.83	6.67	32.91
		ALL	25.08	8.27	11.79	23.96	45.24
		WDG	47.25	16.08	11.90	49.59	71.04
VAR		CPC	19.48	3.11	13.63	19.39	25.81
		ACN	31.35	5.37	21.19	31.23	42.13
	$(\sum_{i=0}^{\infty} l_i^*) \Omega(\sum_{i=0}^{\infty} l_i^*)$	AC	37.37	7.50	23.00	37.27	52.34
	$(\sum_{i=0}^{\infty} l_i^*) \Omega(\sum_{i=0}^{\infty} l_i^*) + (1 + \sum_{i=1}^{\infty} h_i^*)^2 \sigma^2(v_1)$	DSI	9.05	5.38	1.36	8.19	21.61
		ALL	30.49	11.94	10.29	29.48	56.18
		WDG	29.83	19.00	3.70	25.94	73.66

Table 6Correlations of measure estimates

Pairwise Pearson (upper triangle) and Spearman (rank) (lower triangle) correlations of the six estimators of private information using 137 stocks in the Trades, Orders, Reports, and Quotes (TORQ) database, covering the period November 1, 1990 – January 31, 1991. Moment estimators are censored to lie within their theoretical support. We report correlations of the estimates obtained with the entire sample. Size is the market value of the firm's equity as of November 1, 1990. The 137 stocks are sorted into terciles by size. ***, **, and * denote significantly different from zero at the 1%, 5%, and 10% levels, respectively. See Table 1 for definitions of the estimators.

		GH	GKN	HS	LSB	PIN	VAR
GH	All	100%	38%***	26%***	70%***	22%***	48%***
	Large	100%	42%***	-7%	46%***	24%	65%***
	Medium	100%	52%***	61%***	74%***	42%***	56%***
	Small	100%	45%***	12%	78%***	11%	36%**
GKN	All	41%***	100%	-4%	46%***	-6%	-5%
	Large	47%***	100%	-2%	32%**	14%	16%
	Medium	46%***	100%	16%	58%***	36%**	24%
	Small	47%***	100%	0%	45%***	1%	0%
HS	All	15%*	-15%*	100%	15%*	9%	30%***
	Large	0%	-3%	100%	-1%	26%*	-17%
	Medium	33%**	11%	100%	56%***	36%**	43%***
	Small	0%	-12%	100%	2%	-14%	21%
LSB	All	70%***	48%***	9%	100%	10%	22%***
	Large	68%***	50%***	2%	100%	4%	13%
	Medium	69%***	44%***	32%**	100%	39%***	51%***
	Small	74%***	43%***	2%	100%	9%	17%
PIN	All	13%	-7%	31%***	8%	100%	52%***
	Large	19%	0%	29%*	15%	100%	39%***
	Medium	16%	30%**	17%	10%	100%	48%***
	Small	3%	0%	0%	22%	100%	34%**
VAR	All	40%***	-11%	31%***	18%**	47%***	100%
	Large	66%***	11%	-16%	24%	14%	100%
	Medium	38%***	14%	11%	22%	33%**	100%
	Small	22%	-8%	21%	13%	25%*	100%

Table 7

Benchmarking estimates of private information to realized specialist loss rates by volume with three pre-sample period control variables

We regress the realized specialist loss rate by volume on the estimates of private information and three pre-sample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period. The realized specialist loss rate by volume is the ratio of unprofitable specialist share purchases and sales to the total volume in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. Annualized stock volatility prior to the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We obtain the estimates of private information described in Table 1 using the entire TORQ database for each of the 137 stocks. Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticity-consistent standard errors are in parentheses.

Independent		Depe	endent varial	ole: Realized	specialist lo	ss rate by vo	lume	
variables	Panel A: Using the five-minute post-trade interval to classify specialist trade profitability							
Intercept	0.15***	0.06**	0.08***	0.15***	0.11***	0.12***	0.12***	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Firm Size	-0.68***	-0.21	-0.68***	-0.68***	-0.56***	-0.53***	-0.52***	-0.26
	(0.16)	(0.17)	(0.15)	(0.17)	(0.16)	(0.17)	(0.19)	(0.19)
Prior Stock Volatility	1.39***	1.48***	1.69***	1.39***	1.51***	1.34***	1.38***	1.61***
	(0.32)	(0.30)	(0.30)	(0.32)	(0.31)	(0.32)	(0.32)	(0.29)
Prior Prop Spread	-0.99***	-0.35	-0.75***	-0.98***	-0.77***	-0.95***	-0.89***	-0.37*
	(0.19)	(0.21)	(0.18)	(0.19)	(0.19)	(0.19)	(0.19)	(0.21)
GH		0.08***						0.06***
		(0.01)						(0.02)
GKN			0.08***					0.06***
			(0.02)					(0.02)
HS				0.01				-0.00
				(0.05)				(0.04)
LSB					0.06***			-0.02
					(0.02)			(0.02)
PIN						0.06**		0.04
						(0.03)		(0.03)
VAR							0.04	0.00
							(0.02)	(0.02)
$R^{2}(\%)$	33.90	45.05	46.59	33.91	39.48	36.31	35.50	51.77
Adj. $R^{2}(\%)$	32.41	43.38	44.98	31.91	37.65	34.38	33.54	48.35

			Table 7 –	Continued					
Independent		Depe	endent variał	ole: Realized	specialist lo	ss rate by vo	lume		
variables	Panel	Panel B: Using the one-hour post-trade interval to classify specialist trade profitability							
Intercept	0.14***	0.03	0.06**	0.13***	0.09***	0.10***	0.10***	-0.01	
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	
Firm Size	-0.53***	0.02	-0.53***	-0.50***	-0.40**	-0.38**	-0.33*	-0.01	
	(0.17)	(0.18)	(0.16)	(0.18)	(0.17)	(0.19)	(0.20)	(0.20)	
Prior Stock Volatility	1.57***	1.68***	1.90***	1.59***	1.70***	1.52***	1.57***	1.82***	
	(0.35)	(0.31)	(0.32)	(0.35)	(0.33)	(0.34)	(0.34)	(0.30)	
Prior Prop Spread	-0.97***	-0.23	-0.72***	-0.95***	-0.74***	-0.94***	-0.86***	-0.23	
	(0.20)	(0.22)	(0.19)	(0.21)	(0.21)	(0.20)	(0.21)	(0.22)	
GH		0.09***	. ,		. ,		. ,	0.08***	
		(0.02)						(0.02)	
GKN			0.09***					0.07***	
			(0.02)					(0.02)	
HS				0.03				0.01	
				(0.05)				(0.05)	
LSB				(0100)	0.06***			-0.03	
250					(0.02)			(0.02)	
PIN					(0.02)	0.06**		0.04	
						(0.03)		(0.03)	
VAP						(0.05)	0.05**	0.00	
VAR							(0.03)	(0.02)	
$\mathbf{P}^2(0)$	20.94	44.01	12 (9	20.00	25.04	22.02	(0.02)	(0.02)	
K(%)	29.84	44.01	45.08	30.00	55.84	32.02	31.93	50.72	
Adj. $R^2(\%)$	28.26	42.31	41.98	27.87	33.89	29.96	29.88	47.22	
	Panel	C: Using th	e one-day po	ost-trade inte	rval to classi	fy specialist	trade profita	bility	
Intercept	0.19***	0.10***	0.12***	0.18***	0.15***	0.16***	0.15***	0.06	
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	
Firm Size	-0.78***	-0.30	-0.77***	-0.72***	-0.65***	-0.66***	-0.57**	-0.33	
	(0.20)	(0.22)	(0.19)	(0.21)	(0.20)	(0.22)	(0.23)	(0.25)	
Prior Stock Volatility	-0.34	-0.25	-0.04	-0.30	-0.22	-0.38	-0.34	-0.07	
	(0.40)	(0.38)	(0.38)	(0.40)	(0.39)	(0.40)	(0.39)	(0.38)	
Prior Prop Spread	-1.08***	-0.44	-0.85***	-1.03***	-0.87***	-1.06***	-0.96***	-0.44	
	(0.23)	(0.27)	(0.23)	(0.24)	(0.24)	(0.23)	(0.24)	(0.27)	
GH		0.08***						0.06*	
		(0.02)						(0.03)	
GKN			0.08***					0.06***	
			(0.02)					(0.02)	
HS			(010_)	0.06				0.05	
110				(0.06)				(0.06)	
LSB				(0100)	0.05***			-0.02	
LOD					(0.02)			(0.02)	
DIN					(0.02)	0.05		0.02	
T TTA						(0.03)		(0.02)	
VAD						(0.03)	0.05*	0.03)	
V AK							(0.03^{*})	(0.01)	
$\mathbf{p}^2(\mathbf{o}(\mathbf{r}))$	14.02	24.47	05 40	15 57	10 70	16.00	(0.03)	(0.03)	
K (%)	14.93	24.47	25.43	15.57	19.50	16.08	16.93	29.92	
Adj. $R^2(\%)$	13.01	22.19	23.17	13.01	17.06	13.54	14.42	24.95	

Table 8

Benchmarking estimates of private information to *two components* of realized specialist loss rates by volume with three pre-sample period control variables

The realized specialist loss rate by volume is the ratio of unprofitable specialist share purchases and sales to the total volume in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. The realized specialist loss rate by volume is the product of the realized specialist participation rate by volume and the loss rate conditional on specialist volume. The realized specialist participation rate by volume is the ratio of the specialist share volume to the total volume in that stock. The loss rate conditional on specialist trade is the ratio of unprofitable specialist share purchases and sales to the specialist share volume in that stock. We regress each of the two components of the realized specialist loss rate by volume on the estimates of private information and three presample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period. Annualized stock volatility prior to the sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We obtain the estimates of private information described in Table 1 using the entire TORO database for each of the 137 stocks. Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticity-consistent standard errors are in parentheses.

Independent				Pane	el A:					
variables		Dependent variable being realized specialist participation rate by volume								
Intercept	0.73***	0.53***	0.56***	0.68***	0.68***	0.66***	0.53***	0.32***		
	(0.08)	(0.10)	(0.09)	(0.08)	(0.09)	(0.09)	(0.10)	(0.10)		
Firm Size	-3.38***	-2.30***	-3.37***	-3.05***	-3.21***	-3.02***	-2.36***	-1.90***		
	(0.53)	(0.60)	(0.50)	(0.55)	(0.55)	(0.58)	(0.59)	(0.63)		
Prior Stock Volatility	-1.04	-0.83	-0.26	-0.84	-0.88	-1.15	-1.06	-0.29		
	(1.06)	(1.02)	(1.02)	(1.05)	(1.06)	(1.06)	(1.02)	(0.98)		
Prior Prop Spread	-3.63***	-2.19***	-3.03***	-3.37***	-3.35***	-3.56***	-3.04***	-1.97***		
	(0.62)	(0.73)	(0.60)	(0.63)	(0.66)	(0.62)	(0.62)	(0.70)		
GH		0.18***						0.11		
		(0.05)						(0.07)		
GKN			0.22***					0.22***		
			(0.05)					(0.06)		
HS				0.32**				0.27*		
				(0.16)				(0.14)		
LSB					0.07			-0.14**		
					(0.05)			(0.07)		
PIN						0.14		0.04		
						(0.09)		(0.09)		
VAR							0.24***	0.17**		
							(0.07)	(0.08)		
$R^{2}(\%)$	26.57	32.44	35.44	28.87	27.59	27.86	32.67	43.90		
Adj. $R^2(\%)$	24.91	30.40	33.48	26.72	25.39	25.68	30.62	39.92		

			Table 8 –	Continued					
Independent		Depende	nt variable b	being loss rat	te conditiona	al on special	ist volume		
variables	Panel B: Using the five-minute post-trade interval to classify specialist trade profitability								
Intercept	0.18**	0.11	0.20**	0.21**	0.13	0.17*	0.30***	0.23*	
	(0.09)	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)	(0.11)	(0.12)	
Firm Size	0.31	0.69	0.31	0.11	0.45	0.35	-0.30	0.35	
	(0.58)	(0.68)	(0.58)	(0.60)	(0.59)	(0.63)	(0.66)	(0.75)	
Prior Stock Volatility	4.34***	4.42***	4.27***	4.22***	4.47***	4.33***	4.35***	4.08***	
	(1.14)	(1.14)	(1.17)	(1.15)	(1.15)	(1.15)	(1.13)	(1.15)	
Prior Prop Spread	-0.28	0.22	-0.34	-0.44	-0.05	-0.27	-0.63	0.11	
	(0.67)	(0.82)	(0.69)	(0.68)	(0.71)	(0.67)	(0.69)	(0.82)	
GH		0.06						0.14	
		(0.06)						(0.09)	
GKN			-0.02					-0.10	
			(0.06)					(0.07)	
HS			· /	-0.20				-0.18	
				(0.17)				(0.17)	
LSB				(****)	0.06			0.04	
100					(0.06)			(0.08)	
PIN					(0.00)	0.02		0.09	
						(0.02)		(0.10)	
VAR						(0.10)	-0.15*	-0.23**	
VAR							(0.08)	(0.00)	
$\mathbf{p}^2(0/0)$	11.02	11 75	11 11	11.00	11.70	11.02	(0.08)	(0.09)	
K(%)	11.02	11.75	11.11	11.98	11.72	11.05	15.50	18.01	
Adj. $R^2(\%)$	9.01	9.08	8.41	9.32	9.04	8.34	10.67	12.20	
	Panel	C: Using the	e one-hour p	ost-trade int	erval to clas	sify speciali	st trade profi	tability	
Intercept	0.04	-0.12	-0.05	0.06	-0.07	0.00	0.12	-0.05	
	(0.07)	(0.09)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.10)	
Firm Size	1.48***	2.29***	1.49***	1.33***	1.81***	1.65***	1.08*	1.72***	
	(0.48)	(0.54)	(0.47)	(0.50)	(0.47)	(0.52)	(0.55)	(0.60)	
Prior Stock Volatility	5.66***	5.82***	6.03***	5.57***	5.97***	5.60***	5.66***	5.90***	
	(0.94)	(0.92)	(0.95)	(0.95)	(0.92)	(0.95)	(0.94)	(0.92)	
Prior Prop Spread	0.24	1.32**	0.53	0.12	0.81	0.28	0.01	1.08	
	(0.55)	(0.66)	(0.56)	(0.57)	(0.57)	(0.56)	(0.57)	(0.65)	
GH		0.13***						0.12*	
		(0.05)						(0.07)	
GKN		~ /	0.11**					0.02	
			(0.05)					(0.05)	
HS			(0.00)	-0.14				-0.12	
				(0.14)				(0.14)	
I SB				(0.11)	0 15***			0.08	
LOD					(0.05)			(0.07)	
DIN					(0.05)	0.07		(0.07)	
1 11 1						(0.07		(0.00)	
VAD						(0.08)	0.10	(0.00)	
VAN							-0.10	$-0.20^{-0.2}$	
$\mathbf{P}^{2}(0)$	01.00	35 7 0	24.07	01.04	2674	01.70	(0.07)	(0.07)	
K (%)	21.52	25.78	24.07	21.94	26.74	21.73	22.59	32.66	
Adj. $R^2(\%)$	19.54	23.53	21.77	19.57	24.52	19.36	20.24	27.89	

			Table 8 – C	Continued				
Independent		Dependen	t variable be	eing loss rate	e conditional of	on specialist	volume	
variables	Panel	D: Using the	one-day pos	st-trade inter	rval to classify	y specialist t	rade profital	oility
Intercept	0.16**	0.07	0.17**	0.19**	0.08	0.17**	0.23**	0.18*
	(0.07)	(0.09)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.10)
Firm Size	1.06**	1.53***	1.06**	0.91*	1.31***	1.00*	0.74	1.09*
	(0.47)	(0.55)	(0.47)	(0.49)	(0.47)	(0.51)	(0.54)	(0.61)
Prior Stock Volatility	1.31	1.41	1.30	1.22	1.55*	1.33	1.32	1.27
	(0.93)	(0.93)	(0.95)	(0.94)	(0.92)	(0.94)	(0.93)	(0.94)
Prior Prop Spread	-0.18	0.45	-0.19	-0.30	0.25	-0.19	-0.36	0.21
	(0.55)	(0.67)	(0.56)	(0.56)	(0.57)	(0.55)	(0.57)	(0.67)
GH		0.08						0.07
		(0.05)						(0.07)
GKN			-0.01					-0.08
			(0.05)					(0.05)
HS				-0.15				-0.16
				(0.14)				(0.14)
LSB					0.11**			0.12*
					(0.05)			(0.07)
PIN						-0.02		0.00
						(0.08)		(0.08)
VAR							-0.08	-0.12*
							(0.06)	(0.07)
$R^{2}(\%)$	6.94	8.75	6.95	7.72	10.62	7.00	7.93	15.27
Adj. $R^{2}(\%)$	4.84	5.98	4.13	4.92	7.91	4.18	5.14	9.27

Table 9 Benchmarking estimates of private information to realized specialist loss rates by volume with three pre-sample period control variables using alternative sample and GH estimates

We regress the realized specialist loss rate by volume on the estimates of private information and three pre-sample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period using alternative sample and GH estimates. The realized specialist loss rate by volume is the ratio of unprofitable specialist share purchases and sales to the total volume in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. Annualized stock volatility prior to the sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We replace sample estimates of GH (as used in Table 7) with bootstrapped GH in these regressions. We obtain the estimates of private information described in Table 1 using the entire TORO database for each of the 119 stocks (18 out of the 137 stocks are discarded due to data issues, as described in Appendix B.2). Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticity-consistent standard errors are in parentheses.

Independent	Dependent variable: Realized specialist loss rate by volume								
variables	Panel A	: Using the	five-minute	post-trade in	terval to clas	sify specialis	st trade profi	tability	
Intercept	0.14***	0.02	0.08***	0.15***	0.10***	0.11***	0.10***	-0.01	
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	
Firm Size	-0.01***	0.00	-0.01***	-0.01***	-0.01***	-0.00**	-0.00**	-0.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Prior Stock Volatility	0.24**	0.17	0.09	0.24**	0.17	0.24**	0.28**	0.09	
	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	
Prior Prop Spread	-1.15***	-0.09	-0.74**	-1.16***	-0.81**	-1.08***	-1.06***	0.02	
	(0.33)	(0.34)	(0.32)	(0.33)	(0.33)	(0.33)	(0.33)	(0.34)	
GH		0.11***						0.10***	
		(0.02)						(0.02)	
GKN			0.08***					0.04**	
			(0.02)					(0.02)	
HS				-0.00				-0.03	
				(0.05)				(0.04)	
LSB					0.06***			-0.01	
					(0.02)			(0.02)	
PIN						0.06**		0.05	
						(0.03)		(0.03)	
VAR							0.05**	-0.02	
							(0.02)	(0.02)	
$R^{2}(\%)$	13.43	34.03	26.31	13.43	21.25	16.50	16.48	39.72	
Adj. $R^2(\%)$	11.17	31.71	23.72	10.40	18.49	13.57	13.55	34.75	

Table 9 – Continued								
Independent		Depe	endent variał	ole: Realized	specialist lo	ss rate by vo	lume	
variables	Panel	B: Using the	e one-hour p	ost-trade inte	erval to class	ify specialist	trade profita	bility
Intercept	0.15***	-0.00	0.08***	0.15***	0.10***	0.12***	0.10***	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Firm Size	-0.01***	0.00	-0.01***	-0.01***	-0.01***	-0.01**	-0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prior Stock Volatility	0.31**	0.22**	0.14	0.31**	0.23*	0.30**	0.35***	0.15
	(0.13)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.11)
Prior Prop Spread	-1.34***	-0.08	-0.87**	-1.32***	-0.96***	-1.28***	-1.23***	0.02
	(0.35)	(0.34)	(0.33)	(0.35)	(0.35)	(0.35)	(0.35)	(0.34)
GH		0.13***						0.12***
		(0.02)						(0.03)
GKN			0.09***					0.05**
			(0.02)					(0.02)
HS				0.02				-0.01
				(0.05)				(0.05)
LSB					0.07***			-0.02
					(0.02)			(0.02)
PIN						0.05		0.03
						(0.03)		(0.03)
VAR							0.06**	-0.01
							(0.02)	(0.03)
$R^{2}(\%)$	13 53	39.25	27.81	13 64	21.63	15.00	17.28	43 72
A di $P^2(0/4)$	11.28	37.10	27.01	10.61	19.99	12.00	1/.20	30.07
Auj. N (70)		C. Using th	23.20	10.01		fr emocialist	trada profita	59.07
Test and the			0.11***			a 10***		
Intercept	0.19^{***}	0.03	0.11^{***}	0.19^{***}	0.14^{***}	0.18^{***}	0.12^{***}	0.01
T ' G '	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Firm Size	-0.01***	0.00	-0.01***	-0.01***	-0.01***	-0.01***	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prior Stock Volatility	0.14	0.05	-0.05	0.14	0.06	0.13	0.19	-0.02
	(0.14)	(0.13)	(0.14)	(0.15)	(0.14)	(0.15)	(0.14)	(0.13)
Prior Prop Spread	-1.55***	-0.22	-1.03***	-1.54***	-1.21***	-1.54***	-1.40***	-0.22
CU .	(0.40)	(0.41)	(0.38)	(0.40)	(0.41)	(0.40)	(0.39)	(0.40)
GH		0.14^{***}						0.12***
CUDI		(0.02)	0.10444					(0.03)
GKN			0.10^{***}					0.0/***
			(0.02)	0.00				(0.02)
HS				0.02				-0.04
				(0.06)				(0.05)
LSB					0.06***			-0.03
					(0.02)			(0.03)
PIN						0.01		-0.03
						(0.04)	0	(0.04)
VAR							0.08***	0.03
							(0.03)	(0.03)
$R^{2}(\%)$	14.71	36.35	28.22	14.78	19.96	14.78	20.02	41.75
Adj. $R^{2}(\%)$	12.49	34.12	25.70	11.79	17.16	11.79	17.22	36.94

Table 10 Benchmarking estimates of private information to two components of realized specialist loss rates by volume with three pre-sample period control variables using alternative sample and GH estimates

The realized specialist loss rate by volume is the ratio of unprofitable specialist share purchases and sales to the total volume in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. The realized specialist loss rate by volume is the product of the realized specialist participation rate by volume and the loss rate conditional on specialist volume. The realized specialist participation rate by volume is the ratio of the specialist share volume to the total volume in that stock. The loss rate conditional on specialist trade is the ratio of unprofitable specialist share purchases and sales to the specialist share volume in that stock. We regress each of the two components of the realized specialist loss rate by volume on the estimates of private information and three presample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period. Annualized stock volatility prior to the sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We replace sample estimates of GH (as used in Table 7) with bootstrapped GH in these regressions. We obtain the estimates of private information described in Table 1 using the entire TORQ database for each of the 119 stocks (18 out of the 137 stocks are discarded due to data issues, as described in Appendix B.2). Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticityconsistent standard errors are in parentheses.

Independent	Panel A:									
variables		Dependent	variable beir	ng realized sp	pecialist part	icipation rate	by volume			
Intercept	0.77***	0.42***	0.58***	0.73***	0.70***	0.74***	0.58***	0.31**		
	(0.09)	(0.11)	(0.09)	(0.09)	(0.10)	(0.11)	(0.11)	(0.12)		
Firm Size	-3.57***	-1.69**	-3.55***	-3.32***	-3.35***	-3.43***	-2.62***	-1.73**		
	(0.58)	(0.66)	(0.54)	(0.60)	(0.59)	(0.64)	(0.66)	(0.73)		
Prior Stock Volatility	-2.48	-4.36	-7.13*	-1.86	-3.74	-2.50	-0.88	-5.10		
	(3.96)	(3.65)	(3.86)	(3.96)	(4.00)	(3.97)	(3.89)	(3.75)		
Prior Prop Spread	-4.17***	-1.23	-2.86***	-3.98***	-3.58***	-4.10***	-3.75***	-1.15		
	(1.09)	(1.17)	(1.06)	(1.09)	(1.13)	(1.10)	(1.07)	(1.15)		
GH		0.30***						0.25***		
		(0.06)						(0.08)		
GKN			0.26***					0.22***		
			(0.06)					(0.07)		
HS				0.24				0.16		
				(0.16)				(0.15)		
LSB					0.11*			-0.14*		
					(0.06)			(0.07)		
PIN						0.06		-0.01		
						(0.11)		(0.11)		
VAR							0.21***	0.09		
							(0.08)	(0.08)		
$R^{2}(\%)$	26.61	38.81	36.39	28.06	28.36	26.79	31.23	45.49		
Adj. $R^{2}(\%)$	24.69	36.67	34.16	25.54	25.84	24.22	28.81	40.99		

Table 10 – Continued									
Independent		Depende	nt variable b	eing loss rate	e conditional	l on specialis	st volume		
variables	Panel H	B: Using the	five-minute	post-trade in	terval to clas	sify speciali	st trade profi	itability	
Intercept	0.12	0.02	0.12	0.14	0.06	0.06	0.18	0.05	
	(0.09)	(0.12)	(0.10)	(0.09)	(0.10)	(0.11)	(0.11)	(0.14)	
Firm Size	0.58	1.11	0.58	0.42	0.74	0.84	0.25	1.14	
	(0.58)	(0.73)	(0.59)	(0.61)	(0.60)	(0.65)	(0.69)	(0.82)	
Prior Stock Volatility	9.81**	9.28**	9.74**	9.42**	8.89**	9.78**	9.26**	7.83*	
	(3.99)	(4.01)	(4.19)	(4.02)	(4.06)	(3.99)	(4.04)	(4.23)	
Prior Prop Spread	-0.36	0.47	-0.34	-0.48	0.07	-0.24	-0.50	0.83	
	(1.10)	(1.29)	(1.15)	(1.10)	(1.15)	(1.10)	(1.11)	(1.30)	
GH		0.09						0.16	
		(0.07)						(0.10)	
GKN			0.00					-0.08	
			(0.07)					(0.08)	
HS				-0.15				-0.14	
				(0.16)				(0.17)	
LSB				. ,	0.08			0.06	
					(0.06)			(0.08)	
PIN					· · /	0.10		0.17	
						(0.11)		(0.12)	
VAR							-0.07	-0.19*	
							(0.08)	(0.09)	
$R^{2}(\%)$	673	7 96	674	7 43	7 90	7 50	7 40	13 47	
$A \stackrel{(1)}{=} P^2(0/2)$	4.20	1.70	2.46	1 19	1.50	1.50	1 15	6.22	
Auj. K (%)	4.30	4.75	3.40	4.10	4.07	4.23	4.13	0.55	
	Panel	C: Using the	e one-hour p	ost-trade inte	erval to class	ity specialis	t trade profit	ability	
Intercept	0.05	-0.13	-0.02	0.07	-0.04	-0.00	0.06	-0.12	
	(0.07)	(0.10)	(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.11)	
Firm Size	1.23**	2.19***	1.24**	1.13**	1.49***	1.47***	1.19**	1.98***	
	(0.49)	(0.60)	(0.49)	(0.51)	(0.50)	(0.54)	(0.58)	(0.68)	
Prior Stock Volatility	15.94***	14.98***	14.13***	15.71***	14.45***	15.92***	15.88***	12.75***	
	(3.37)	(3.30)	(3.48)	(3.39)	(3.36)	(3.37)	(3.42)	(3.50)	
Prior Prop Spread	-1.33	0.18	-0.82	-1.40	-0.63	-1.22	-1.35	0.47	
	(0.92)	(1.06)	(0.96)	(0.93)	(0.95)	(0.93)	(0.94)	(1.07)	
GH		0.16***						0.17*	
		(0.06)						(0.08)	
GKN			0.10*					0.01	
			(0.06)					(0.06)	
HS				-0.09				-0.12	
				(0.14)				(0.14)	
LSB					0.13**			0.05	
					(0.05)			(0.07)	
PIN						0.09		0.11	
						(0.09)		(0.10)	
VAR							-0.01	-0.13	
							(0.07)	(0.08)	
$R^{2}(\%)$	20.86	25.67	23.07	21.17	24.58	21.61	20.87	29.40	
Adj. $R^{2}(\%)$	18.79	23.06	20.38	18.40	21.93	18.86	18.09	23.57	

			Table 10 –	Continued				
Independent		Depende	ent variable b	eing loss rat	e conditional	on specialis	t volume	
variables	Pane	el D: Using th	ne one-day po	ost-trade inte	rval to classi	fy specialist	trade profital	bility
Intercept	0.13**	-0.03	0.07	0.16**	0.07	0.16**	0.08	0.03
	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.10)
Firm Size	1.18***	2.04***	1.19***	1.02**	1.36***	1.06**	1.47***	1.56***
	(0.42)	(0.51)	(0.42)	(0.44)	(0.43)	(0.47)	(0.50)	(0.58)
Prior Stock Volatility	8.13***	7.27**	6.58**	7.74***	7.10**	8.14***	8.62***	6.11**
	(2.90)	(2.83)	(2.99)	(2.90)	(2.92)	(2.90)	(2.92)	(2.99)
Prior Prop Spread	-1.49*	-0.14	-1.05	-1.61**	-1.00	-1.54*	-1.36*	-0.30
	(0.80)	(0.91)	(0.82)	(0.80)	(0.83)	(0.80)	(0.80)	(0.92)
GH		0.14***						0.11
		(0.05)						(0.07)
GKN			0.09*					0.04
			(0.05)					(0.05)
HS				-0.15				-0.26**
				(0.12)				(0.12)
LSB					0.09*			0.04
					(0.05)			(0.06)
PIN						-0.05		-0.13
						(0.08)		(0.09)
VAR							0.06	0.05
							(0.06)	(0.07)
$R^{2}(\%)$	18.11	23.45	20.39	19.30	20.58	18.35	18.99	27.69
Adj. $R^{2}(\%)$	15.97	20.76	17.59	16.47	17.80	15.48	16.15	21.71

Table 11

Benchmarking estimates of private information to realized specialist loss rates by trades with three pre-sample period control variables

We regress the realized specialist loss rate by trades on the estimates of private information and three pre-sample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period. The realized specialist loss rate by trades is the ratio of the number of unprofitable specialist trades to the total number of trades in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. Annualized stock volatility prior to the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We obtain the estimates of private information described in Table 1 using the entire TORQ database for each of the 137 stocks. Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Independent		Dep	pendent varia	ble: Realized	l specialist lo	ss rate by tra	des	
variables	Panel	A: Using the	five-minute	post-trade in	terval to class	sify specialis	t trade profit	ability
Intercept	0.19***	0.08	0.08	0.18***	0.12**	0.14**	0.15***	0.02
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Firm Size	-0.69**	-0.16	-0.68**	-0.65**	-0.50	-0.47	-0.53	-0.33
	(0.31)	(0.35)	(0.29)	(0.32)	(0.31)	(0.34)	(0.36)	(0.39)
Prior Stock Volatility	6.30***	6.40***	6.77***	6.32***	6.47***	6.23***	6.30***	6.73***
	(0.62)	(0.60)	(0.59)	(0.62)	(0.61)	(0.61)	(0.62)	(0.60)
Prior Prop Spread	-2.06***	-1.36***	-1.70***	-2.03***	-1.75***	-2.01***	-1.97***	-1.44***
	(0.36)	(0.43)	(0.35)	(0.37)	(0.37)	(0.36)	(0.38)	(0.43)
GH		0.09***						0.03
		(0.03)						(0.04)
GKN			0.13***					0.11***
			(0.03)					(0.03)
HS				0.04				0.05
				(0.09)				(0.09)
LSB					0.08***			0.01
					(0.03)			(0.04)
PIN						0.09		0.06
						(0.05)		(0.05)
VAR							0.04	-0.01
							(0.04)	(0.05)
$R^{2}(\%)$	55.69	58.22	61.46	55.75	57.90	56.58	55.95	62.31
Adj. $R^{2}(\%)$	54.69	56.96	60.30	54.41	56.63	55.26	54.62	59.64

Table 11 – Continued									
Independent		Dep	endent varia	ble: Realized	a specialist lo	oss rate by tra	ades		
variables	Pane	B: Using th	e one-hour p	ost-trade inte	erval to class	ify specialist	trade profita	bility	
Intercept	0.17***	0.05	0.05	0.17***	0.10**	0.14***	0.13**	-0.00	
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	
Firm Size	-0.50*	0.14	-0.50*	-0.49*	-0.30	-0.34	-0.31	-0.10	
	(0.28)	(0.31)	(0.25)	(0.29)	(0.28)	(0.31)	(0.32)	(0.34)	
Prior Stock Volatility	5.78***	5.91***	6.30***	5.79***	5.98***	5.73***	5.78***	6.26***	
	(0.56)	(0.53)	(0.51)	(0.56)	(0.54)	(0.56)	(0.56)	(0.52)	
Prior Prop Spread	-1.95***	-1.09***	-1.55***	-1.94***	-1.60***	-1.92***	-1.84***	-1.17***	
~~~	(0.33)	(0.38)	(0.30)	(0.34)	(0.33)	(0.33)	(0.34)	(0.37)	
GH		0.11***						0.05	
ant		(0.03)						(0.04)	
GKN			0.15***					0.12***	
110			(0.03)	0.01				(0.03)	
HS				0.01				0.00	
LCD				(0.08)	0 00***			(0.08)	
LSB					$(0.09^{****})$			0.00	
DIN					(0.05)	0.06		(0.04)	
PIIN						(0.00)		(0.05)	
VAD						(0.03)	0.05	(0.03)	
VAK							(0.03)	(0.00)	
$P^{2}(0/2)$	55 35	50.07	64.00	55 36	58 67	55.02	(0.04)	(0.04)	
$A = \frac{1}{2} \frac{D^2(0)}{1}$	55.55	59.71	(2.01	54.01	57.41	53.92	54.50	(2.50	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$									
Intercent	0.24***	0 10**	0 12***	0.25***	0 17***	0.22***	0 10***	0.06	
Intercept	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	
<b>D</b> ' <b>C</b> '	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	
Firm Size	-0.79***	-0.05	-0.78***	-0.83***	-0.58**	-0.69**	-0.57*	-0.35	
<b>D</b>	(0.26)	(0.29)	(0.23)	(0.28)	(0.26)	(0.29)	(0.30)	(0.30)	
Prior Stock Volatility	3.65***	3.80***	4.18***	3.63***	3.85***	3.62***	3.65***	4.11***	
	(0.52)	(0.48)	(0.47)	(0.53)	(0.50)	(0.53)	(0.52)	(0.47)	
Prior Prop Spread	-2.13***	-1.15***	-1./2***	-2.16***	-1./8***	-2.11***	-2.00***	-1.23***	
CII	(0.31)	(0.35)	(0.28)	(0.31)	(0.31)	(0.31)	(0.32)	(0.33)	
GH		$0.12^{****}$						0.08***	
CVN		(0.02)	0 15***					(0.03)	
UNIN			(0.02)					(0.02)	
ЦС			(0.02)	0.04				(0.03)	
пр				-0.04				-0.00	
ISB				(0.08)	0 00***			(0.07)	
LSD					(0.03)			-0.01	
PIN					(0.03)	0.04		-0.01	
1 110						(0.04)		(0.04)	
VAR						(0.05)	0.05	(0.04)	
							(0.04)	(0.01)	
$R^{2}(\%)$	45 09	53 52	57 56	45 19	49 85	45 35	45 96	60.20	
$\Delta di R^2(\%)$	13.05	52.52	56.28	13.17	18 33	43 70	1/1 37	57 38	
Auj. Λ (%)	43.83	32.11	30.28	43.33	40.33	45.70	44.32	57.58	

### Table 12

# Benchmarking estimates of private information to *two components* of realized specialist loss rates by trades with three pre-sample period control variables

The realized specialist loss rate by trades is the ratio of the number of unprofitable specialist trades to the total number of trades in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. The realized specialist loss rate by trades is the product of the realized specialist participation rate by trades and the loss rate conditional on specialist trade. The realized specialist participation rate by trade is the ratio of the number of specialist trades to the total number of trades in that stock. The loss rate conditional on specialist trade is the ratio of unprofitable number of specialist trades to the number of specialist trades in that stock. We regress each of the two components of the realized specialist loss rate by trades on the estimates of private information and three pre-sample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period. Annualized stock volatility prior to the sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We obtain the estimates of private information described in Table 1 using the entire TORO database for each of the 137 stocks. Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticity-consistent standard errors are in parentheses.

Independent	Panel A:								
variables		Dependen	t variable bei	ing realized s	pecialist parti	icipation rate	by trades		
Intercept	0.87***	0.62***	0.56***	0.85***	0.75***	0.77***	0.66***	0.36**	
	(0.11)	(0.14)	(0.11)	(0.12)	(0.12)	(0.13)	(0.14)	(0.15)	
Firm Size	-3.42***	-2.09**	-3.40***	-3.26***	-3.06***	-2.93***	-2.35***	-2.28**	
	(0.75)	(0.85)	(0.67)	(0.78)	(0.76)	(0.81)	(0.84)	(0.89)	
Prior Stock Volatility	9.98***	10.25***	11.36***	10.08***	10.32***	9.83***	9.97***	11.29***	
	(1.48)	(1.44)	(1.36)	(1.49)	(1.47)	(1.48)	(1.45)	(1.37)	
Prior Prop Spread	-5.69***	-3.91***	-4.63***	-5.56***	-5.08***	-5.59***	-5.07***	-3.99***	
	(0.87)	(1.04)	(0.81)	(0.89)	(0.91)	(0.87)	(0.89)	(0.97)	
GH		0.22***						0.04	
		(0.07)						(0.10)	
GKN			0.39***					0.39***	
			(0.07)					(0.08)	
HS				0.16				0.12	
				(0.22)				(0.20)	
LSB					0.16**			-0.07	
					(0.08)			(0.10)	
PIN						0.19		0.04	
						(0.13)		(0.12)	
VAR							0.25**	0.20*	
							(0.10)	(0.11)	
$R^{2}(\%)$	47.84	51.09	57.83	48.04	49.55	48.70	50.26	59.91	
Adj. $R^{2}(\%)$	46.66	49.61	56.55	46.47	48.02	47.14	48.76	57.07	

Panel	Depend B: Using the	lent variable five-minute	being loss ra	te conditionation	al on speciali	st trade	
Panel	B: Using the	five-minute	nost-trade in	torrial to alac	.: <b>.</b>	1	
0 1 4 4			post trade in	tervar to cras	sity specialis	st trade profit	ability
$0.14^{**}$	0.01	0.10	0.15**	0.06	0.14*	0.21**	0.10
(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.10)
0.75*	1.41***	0.76*	0.66	0.99**	0.77	0.40	1.01*
(0.45)	(0.52)	(0.45)	(0.47)	(0.46)	(0.50)	(0.52)	(0.58)
4.21***	4.34***	4.38***	4.16***	4.44***	4.21***	4.22***	4.30***
(0.90)	(0.88)	(0.91)	(0.90)	(0.89)	(0.90)	(0.90)	(0.90)
-0.93*	-0.05	-0.81	-1.00*	-0.53	-0.93*	-1.14**	-0.18
(0.53)	(0.63)	(0.54)	(0.54)	(0.55)	(0.53)	(0.55)	(0.64)
	0.11**						0.13*
	(0.04)						(0.07)
		0.05					-0.03
		(0.05)					(0.05)
			-0.09				-0.08
			(0.13)				(0.13)
				0.10**			0.05
				(0.05)			(0.06)
					0.01		0.04
					(0.08)		(0.08)
						-0.08	-0.17**
						(0.06)	(0.07)
16.79	20.26	17.40	17.06	19.94	16.80	17.96	24.76
14.92	17.85	14.89	14.54	17.51	14.28	15.48	19.43
Pane	l C: Using th	e one-hour p	ost-trade inte	erval to class	ify specialist	trade profita	bility
0.07	-0.07	0.00	0.09	-0.02	0.08	0.11*	-0.00
(0.05)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)
1.41***	2.15***	1.42***	1.33***	1.67***	1.37***	1.20***	1.64***
(0.36)	(0.41)	(0.36)	(0.38)	(0.36)	(0.40)	(0.42)	(0.46)
4.30***	4.45***	4.61***	4.25***	4.55***	4.32***	4.30***	4.57***
(0.72)	(0.70)	(0.72)	(0.73)	(0.71)	(0.73)	(0.72)	(0.71)
-0.49	0.50	-0.26	-0.56	-0.05	-0.50	-0.62	0.34
(0.42)	(0.50)	(0.43)	(0.43)	(0.43)	(0.43)	(0.44)	(0.50)
	0.12***						0.12*
	(0.04)						(0.05)
		0.09**					0.02
		(0.04)					(0.04)
			-0.08				-0.09
			(0.11)				(0.11)
				0.11***			0.05
				(0.04)			(0.05)
					-0.02		-0.01
					(0.06)		(0.06)
					()	-0.05	-0.11**
						(0.05)	(0.06)
						<pre></pre>	······////////////////////////////////
25.75	31.77	28.71	26.08	31.04	25.80	26.33	36.10
-	(0.07) 0.75* (0.45) 4.21*** (0.90) -0.93* (0.53) 16.79 14.92 Pane 0.07 (0.05) 1.41*** (0.36) 4.30*** (0.72) -0.49 (0.42)	$\begin{array}{ccccccc} (0.07) & (0.08) \\ 0.75^{*} & 1.41^{***} \\ (0.45) & (0.52) \\ 4.21^{***} & 4.34^{***} \\ (0.90) & (0.88) \\ -0.93^{*} & -0.05 \\ (0.53) & (0.63) \\ & 0.11^{**} \\ & (0.04) \end{array}$ $\begin{array}{c} 16.79 & 20.26 \\ 14.92 & 17.85 \\ \hline \end{array}$ $\begin{array}{c} 16.79 & 20.26 \\ 14.92 & 17.85 \\ \hline \end{array}$ $\begin{array}{c} 0.07 & -0.07 \\ (0.04) \\ \hline \end{array}$ $\begin{array}{c} 0.07 & -0.07 \\ (0.05) & (0.07) \\ 1.41^{***} & 2.15^{***} \\ (0.36) & (0.41) \\ 4.30^{***} & 4.45^{***} \\ (0.72) & (0.70) \\ -0.49 & 0.50 \\ (0.42) & (0.50) \\ 0.12^{***} \\ & (0.04) \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Independent		Deper	ndent variable	e being loss ra	ate condition	al on speciali	ist trade	
variables	Pan	el D: Using	the one-day p	oost-trade inte	erval to classi	fy specialist	trade profitab	oility
Intercept	0.21***	0.11*	0.18***	0.24***	0.15***	0.27***	0.29***	0.24***
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)
Firm Size	0.82**	1.37***	0.82**	0.62*	0.99***	0.53	0.45	0.72*
	(0.33)	(0.38)	(0.33)	(0.34)	(0.33)	(0.36)	(0.38)	(0.40)
Prior Stock Volatility	1.41**	1.52**	1.55**	1.30**	1.58**	1.50**	1.42**	1.51**
	(0.65)	(0.64)	(0.66)	(0.65)	(0.65)	(0.65)	(0.65)	(0.62)
Prior Prop Spread	-0.86**	-0.11	-0.75*	-1.01***	-0.56	-0.92**	-1.07***	-0.26
	(0.38)	(0.46)	(0.39)	(0.39)	(0.40)	(0.38)	(0.39)	(0.44)
GH		0.09***						0.13*
		(0.03)						(0.05)
GKN			0.04					-0.02
			(0.03)					(0.04)
HS				-0.19**				-0.21**
				(0.10)				(0.09)
LSB					0.08**			0.03
					(0.03)			(0.04)
PIN						-0.11**		-0.09*
						(0.06)		(0.06)
VAR							-0.09*	-0.11**
							(0.04)	(0.05)
$R^{2}(\%)$	17.86	22.46	18.65	20.30	21.02	20.25	20.19	32.81
Adj. $R^2(\%)$	16.01	20.11	16.19	17.88	18.63	17.83	17.77	28.05

# Table 13 Benchmarking estimates of private information to realized specialist loss rates by trades with three pre-sample period control variables using alternative sample and GH estimates

We regress the realized specialist loss rate by trades on the estimates of private information and three pre-sample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period using alternative sample and GH estimates. The realized specialist loss rate by trades is the ratio of the number of unprofitable specialist trades to the total number of trades in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. Annualized stock volatility prior to the sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We replace sample estimates of GH (as used in Table 7) with bootstrapped GH in these regressions. We obtain the estimates of private information described in Table 1 using the entire TORQ database for each of the 119 stocks (18 out of the 137 stocks are discarded due to data issues, as described in Appendix B.2). Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticity-consistent standard errors are in parentheses.

Independent		De	pendent varia	able: Realized	l specialist lo	ss rate by trac	les	
variables	Panel	A: Using the	e five-minute	post-trade in	terval to class	sify specialist	trade profita	bility
Intercept	0.18***	-0.04	0.05	0.18***	0.10*	0.11*	0.10*	-0.10
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Firm Size	-0.01**	0.00	-0.01***	-0.01**	-0.01*	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prior Stock Volatility	1.33***	1.21***	1.03***	1.32***	1.20***	1.33***	1.39***	1.02***
	(0.21)	(0.19)	(0.20)	(0.21)	(0.21)	(0.21)	(0.21)	(0.19)
Prior Prop Spread	-2.98***	-1.15*	-2.12***	-3.01***	-2.35***	-2.83***	-2.82***	-0.94
	(0.58)	(0.61)	(0.55)	(0.59)	(0.59)	(0.58)	(0.58)	(0.59)
GH		0.19***						0.16***
		(0.03)						(0.04)
GKN			0.17***					0.10***
			(0.03)					(0.03)
HS				-0.04				-0.07
				(0.09)				(0.08)
LSB					0.11***			-0.01
					(0.03)			(0.04)
PIN						0.12**		0.09
						(0.06)		(0.05)
VAR							0.08*	-0.02
							(0.04)	(0.04)
$R^{2}(\%)$	27.39	43.49	41.82	27.51	34.34	30.40	29.71	51.07
Adj. $R^2(\%)$	25.50	41.51	39.78	24.96	32.04	27.96	27.24	47.03

Independent	Dependent variable: Realized specialist loss rate by trades							
variables	Panel B: Using the one-hour post-trade interval to classify specialist trade profitability							
variables								
Intercept	0.20***	-0.04	0.07	0.20***	0.12**	0.15***	0.11**	-0.08
1	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Firm Size	-0.01***	0.00	-0.01***	-0.01***	-0.01*	-0.01*	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prior Stock Volatility	1.36***	1.23***	1.04***	1.35***	1.22***	1.35***	1.43***	1.04***
	(0.20)	(0.17)	(0.18)	(0.20)	(0.19)	(0.20)	(0.20)	(0.17)
Prior Prop Spread	-3.28***	-1.30**	-2.39***	-3.31***	-2.62***	-3.17***	-3.10***	-1.15**
1 1	(0.55)	(0.54)	(0.50)	(0.55)	(0.54)	(0.55)	(0.54)	(0.52)
GH		0.20***						0.17***
		(0.03)						(0.04)
GKN			0.18***					0.11***
			(0.03)					(0.03)
HS				-0.04				-0.09
				(0.08)				(0.07)
LSB					0.12***			-0.02
					(0.03)			(0.03)
PIN						0.09*		0.04
						(0.05)		(0.05)
VAR							0.09**	-0.00
							(0.04)	(0.04)
$R^{2}(\%)$	31.36	51.74	48.30	31.48	39.42	33.20	34.69	59.28
Adj. $R^2(\%)$	29.57	50.05	46.49	29.08	37.29	30.85	32.40	55.92
	Panel	C: Using the	e one-day po	st-trade inte	rval to class	ify specialist	t trade profit	ability
Intercept	0.26***	0.03	0.12***	0.28***	0.20***	0.24***	0.19***	0.01
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Firm Size	-0.01***	0.00	-0.01***	-0.01***	-0.01***	-0.01***	-0.01**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Prior Stock Volatility	0.95***	0.82***	0.60***	0.92***	0.84***	0.94***	1.01***	0.60***
	(0.20)	(0.17)	(0.17)	(0.20)	(0.19)	(0.20)	(0.20)	(0.16)
Prior Prop Spread	-3.19***	-1.28**	-2.22***	-3.25***	-2.67***	-3.14***	-3.03***	-1.16**
	(0.54)	(0.54)	(0.47)	(0.54)	(0.55)	(0.54)	(0.54)	(0.49)
GH		0.20***						0.17***
		(0.03)						(0.04)
GKN			0.19***					0.15***
			(0.03)					(0.03)
HS				-0.08				-0.14**
				(0.08)				(0.06)
LSB					0.09***			-0.05
					(0.03)			(0.03)
PIN						0.04		-0.02
						(0.05)		(0.05)
VAR							0.08**	0.01
							(0.04)	(0.04)
$R^{2}(\%)$	25.02	46.28	47.35	25.75	30.57	25.44	27.81	59.19
Adj. $R^{2}(\%)$	23.06	44.39	45.50	23.15	28.14	22.82	25.28	55.82
J ( ) /								

# Table 14 Benchmarking estimates of private information to two components of realized specialist loss rates by trades with three pre-sample period control variables using alternative sample and GH estimates

The realized specialist loss rate by trades is the ratio of the unprofitable number of specialist trades to the total number of trades in that stock. If the spread midpoint after a specialist purchase is lower than the transaction price it is classified as an unprofitable buy trade. If the spread midpoint after a specialist sale is higher than the trade price it is classified as an unprofitable sell trade. We classify trades using three alternative post-trade intervals: five minutes, one hour, and one (trading) day. The realized specialist loss rate by trades is the product of the realized specialist participation rate by trades and the loss rate conditional on specialist trade. The realized specialist participation rate by trade is the ratio of the number of specialist trades to the total number of trades in that stock. The loss rate conditional on specialist trade is the ratio of unprofitable number of specialist trades to the number of specialist trades in that stock. We regress each of the two components of the realized specialist loss rate by trades on the estimates of private information and three pre-sample period control variables including annualized stock volatility prior to the sample period, firm size at the start of sample period, and time weighted proportional spread prior to the sample period. Annualized stock volatility prior to the sample period is the annualized standard deviation of daily stock returns during the three months prior to the start of the sample period, (August 1, 1990 -- October 31, 1990). Firm size is the natural logarithm of the market value of the firm's equity in thousands on November 1, 1990. Proportional spread is the bid ask spread divided by midpoint of the bid ask spread weighted by the elapsed time before it is updated from August 1, 1990 to October 31, 1990. We replace sample estimates of GH (as used in Table 7) with bootstrapped GH in these regressions. We obtain the estimates of private information described in Table 1 using the entire TORO database for each of the 119 stocks (18 out of the 137 stocks are discarded due to data issues, as described in Appendix B.2). Moment estimators are censored to lie within their theoretical support. The coefficients on stock volatility and firm size are multiplied by 10 and 100, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding heteroskedasticity-consistent standard errors are in parentheses.

Independent				Pane	el A:			
variables		Dependent	t variable bei	ing realized s	pecialist part	icipation rate	by trades	
Intercept	0.96***	0.39***	0.56***	0.96***	0.79***	0.89***	0.74***	0.28*
	(0.12)	(0.15)	(0.12)	(0.13)	(0.13)	(0.15)	(0.15)	(0.15)
Firm Size	-4.14***	-1.13	-4.08***	-4.14***	-3.65***	-3.82***	-3.07***	-2.04**
	(0.80)	(0.89)	(0.68)	(0.84)	(0.80)	(0.89)	(0.93)	(0.92)
Prior Stock Volatility	19.36***	16.36***	9.86**	19.34***	16.60***	19.33***	21.15***	10.89**
	(5.49)	(4.90)	(4.85)	(5.55)	(5.45)	(5.50)	(5.47)	(4.74)
Prior Prop Spread	-7.76***	-3.05*	-5.09***	-7.76***	-6.46***	-7.61***	-7.29***	-2.72*
	(1.51)	(1.57)	(1.34)	(1.53)	(1.55)	(1.52)	(1.50)	(1.45)
GH		0.49***						0.37***
		(0.09)						(0.11)
GKN			0.53***					0.44***
			(0.08)					(0.09)
HS				-0.01				-0.13
				(0.22)				(0.19)
LSB					0.23***			-0.14
					(0.09)			(0.09)
PIN						0.12		-0.03
						(0.15)		(0.13)
VAR							0.23**	0.06
							(0.11)	(0.11)
$R^{2}(\%)$	24.37	41.04	46.29	24.37	28.93	24.83	27.43	53.42
Adj. $R^{2}(\%)$	22.39	38.97	44.40	21.71	26.43	22.19	24.89	49.57

			Table 14 -	- Continued					
Independent	Dependent variable being loss rate conditional on specialist trade Panel B: Using the five-minute post-trade interval to classify specialist trade profitability								
variables									
Intercept	0.07	-0.10	0.03	0.08	0.00	0.02	0.07	-0.08	
	(0.07)	(0.09)	(0.08)	(0.07)	(0.07)	(0.08)	(0.09)	(0.10)	
Firm Size	1.09**	1.97***	1.09**	1.01**	1.29***	1.31***	1.08**	1.97***	
	(0.44)	(0.54)	(0.44)	(0.46)	(0.45)	(0.49)	(0.52)	(0.61)	
Prior Stock Volatility	12.33***	11.46***	11.46***	12.14***	11.23***	12.31***	12.32***	10.34***	
	(3.04)	(2.97)	(3.17)	(3.06)	(3.05)	(3.03)	(3.08)	(3.16)	
Prior Prop Spread	-1.73**	-0.36	-1.49*	-1.79**	-1.21	-1.63*	-1.73**	-0.12	
	(0.83)	(0.95)	(0.87)	(0.84)	(0.87)	(0.84)	(0.85)	(0.97)	
GH		0.14***						0.19	
		(0.05)						(0.11)	
GKN			0.05					-0.04	
			(0.05)					(0.06)	
HS				-0.08				-0.10	
				(0.12)				(0.13)	
LSB					0.09*			0.03	
					(0.05)			(0.06)	
PIN						0.09		0.11	
						(0.08)		(0.09)	
VAR							-0.00	-0.12	
							(0.06)	(0.07)	
$R^{2}(\%)$	19.04	24.01	19.69	19.31	21.60	19.85	19.04	27.39	
Adj. $R^{2}(\%)$	16.93	21.35	16.87	16.48	18.85	17.04	16.20	21.39	
<b>`</b> ````	Pane	el C: Using th	e one-hour p	ost-trade inte	erval to classi	fy specialist	trade profital	oility	
Intercept	0.09*	-0.10	0.02	0.10*	0.01	0.06	0.05	-0.08	
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	
Firm Size	1.14***	2.13***	1.15***	1.07***	1.38***	1.26***	1.34***	1.93***	
	(0.34)	(0.40)	(0.33)	(0.35)	(0.34)	(0.38)	(0.40)	(0.45)	
Prior Stock Volatility	16.03***	15.04***	14.53***	15.86***	14.67***	16.02***	16.38***	13.80***	
-	(2.32)	(2.18)	(2.38)	(2.34)	(2.28)	(2.33)	(2.35)	(2.33)	
Prior Prop Spread	-2.65***	-1.10	-2.23***	-2.70***	-2.01***	-2.59***	-2.56***	-1.03	
	(0.64)	(0.70)	(0.66)	(0.64)	(0.65)	(0.64)	(0.64)	(0.71)	
GH		0.16***						0.15	
		(0.04)						(0.90)	
GKN			0.08**					0.00	
			(0.04)					(0.04)	
HS				-0.07				-0.14	
				(0.09)				(0.09)	
LSB					0.11***			0.05	
					(0.04)			(0.04)	
PIN					` '	0.05		0.02	
						(0.06)		(0.07)	
VAR						· · /	0.05	-0.04	
							(0.05)	(0.05)	
$R^{2}(\%)$	38.89	47.10	41.37	39.17	43.89	39.21	39.40	49.23	
Adi. $R^2(\%)$	37 30	45 24	39 31	37.04	41.92	37.08	37.28	45.03	
1 mj. n (/0)	51.50	73.24	57.51	57.04	71.72	51.00	51.20	-J.UJ	

Independent		Dependent variable being loss rate conditional on specialist trade								
variables	Panel D: Using the one-day post-trade interval to classify specialist trade profitability									
Intercept	0.20***	0.12*	0.15***	0.23***	0.18***	0.24***	0.22***	0.19***		
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)		
Firm Size	0.77**	1.20***	0.78**	0.59*	0.84***	0.61*	0.66*	0.68		
	(0.31)	(0.38)	(0.31)	(0.32)	(0.32)	(0.34)	(0.36)	(0.42)		
Prior Stock Volatility	8.98***	8.55***	7.85***	8.53***	8.58***	8.99***	8.78***	6.90***		
	(2.12)	(2.10)	(2.19)	(2.10)	(2.15)	(2.11)	(2.15)	(2.18)		
Prior Prop Spread	-2.04***	-1.37**	-1.72***	-2.17***	-1.85***	-2.11***	-2.09***	-1.35**		
	(0.58)	(0.68)	(0.60)	(0.58)	(0.61)	(0.58)	(0.59)	(0.67)		
GH		0.07*						0.08		
		(0.04)						(0.05)		
GKN			0.06*					0.04		
			(0.03)					(0.04)		
HS				-0.17**				-0.22**		
				(0.08)				(0.09)		
LSB					0.03			0.00		
					(0.03)			(0.04)		
PIN						-0.06		-0.10		
						(0.06)		(0.06)		
VAR							-0.03	-0.03		
							(0.04)	(0.05)		
$R^{2}(\%)$	26.80	29.00	28.82	29.43	27.39	27.61	27.03	35.68		
Adi. $R^2(\%)$	24.89	26.51	26.32	26.95	24.85	25.07	24.47	30.37		