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Informed Trading, Information Asymmetry and Pricing of Information Risk: Empirical Evidence from the NYSE

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by

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Abstract

We investigate and test hypotheses on how informed trading varies with market-wide factors and the structural and trading characteristics of a firm. We find strong evidence of commonality in informed trading, and a systematic dependence of informed trading on firm characteristics that is largely consistent with intuition and earlier theory and empirical evidence, wherever available. We accordingly decompose informed trading into two components: one that reflects information asymmetry with respect to skilled information processors with potentially private information on systematic factors or who generate a private informational advantage using public data; and another unpredictable component that reflects truly private information, potentially of traditional insiders. We test the pricing relevance of both these components and find that it is only the unpredictable component reflecting truly private information that is priced, and is priced more strongly and in a manner more robust than total informed trading. Our pricing-relevance results strongly support Easley and O'Hara (2004) and do not support Hughes, et al. (2007).

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Informed Trading, Information Asymmetry and Pricing of Information Risk: Empirical Evidence from the NYSE

1. Introduction and Motivation

A large body of academic literature has modeled the role of private information in asset markets, examined the inter-relationship between the resultant information asymmetry and the trading actions of investors, investigated a wide range of other issues relevant to information asymmetry, and importantly, provided empirical evidence that information asymmetry is priced in the required rate of return.

This paper is anchored in the notion that information asymmetry need not necessarily arise just from the prototypical “insiders” with firm-specific hard information, i.e. the corporate managers and their affiliates, but could arise from skilled information processors with private information about market-wide systematic return factors (Subrahmanyam (1991); Hughes, et al. (2007)), or the ability to generate a private informational advantage from skilled analysis of firm-specific or market-wide public information (Kim and Verrechia (1994, 1997)). These skilled information processors could be unconnected to a firm but investing resources to acquire price-relevant private information (Grossman and Stiglitz (1980)) that can be specific to the firm or sector-specific, or market-wide (Chordia, et al. (2000); Gilson, et al. (2001)), or related to the trading environment (Madrigal (1996); Easley, et al. (1998)) or to the structural characteristics of the firm (Bhushan (1989b); Dennis and Weston (2001); Odders-White and Ready (2006)). Accordingly, we partition observed information asymmetry into an unpredictable component based on firm-specific (truly) private information, and a predictable component based on public information, and arguably dependent not only on the trading and structural characteristics of the firm, but also on market-wide factors, and thereby exhibiting commonality across stocks.

It is empirically challenging to fully measure all dimensions of private information, but at least a subset of such private information should arguably be revealed periodically to the market through the trading actions of investors with access to private value-relevant information. We empirically investigate information asymmetry through the use of two reasonably direct and most extensively used market microstructure measures – the *PIN* measure developed, tested and used in, for example, Easley and O'Hara (1992), Easley, et al. (1997a, b), and Easley, et al. (2002); and the *adverse selection* measure widely used to directly proxy for informed trading (Huang and Stoll (1996); Bessembinder and Kaufman (1997); and Hansch, et al. (1999)), representing the spread revenue lost, on average, by passive liquidity suppliers to liquidity demanders, the group that arguably includes informed investors demanding immediacy to extract rents from their information before their information becomes fully incorporated into prices (Harris (2003, p. 226)). Throughout this paper, we use the terms "information asymmetry" and "informed trading" quite interchangeably, with the choice depending on the economic context of where they are used.

Our first contribution is to test hypotheses on the systematic relationship between our two information asymmetry measures and the market-wide factors that could be the most likely to impound private information on economy-wide systematic return factors, and most likely to reflect the trading actions of skilled information processors aggregating public information across stocks and sectors[2]. We choose four factors: overall market volatility, aggregate trading volume over all stocks, average bid-ask spread across stocks, and market-wide buy-sell order-imbalance; and thereby investigate the extent of commonality in observed measures of informed trading.

[2] For example, market-wide informed trading can arise as trading by large institutional investors acting in concert to similar information, thereby generating similar order-flow. Information relevant to these investors may, for example, be economic and monetary news and policy announcements. Additionally, Admati and Pfleiderer (2000) show that new information on a small set of dominant firms in a particular industry may be used by investors to enhance their information-set of related firms in the same industry, potentially causing the same trades across many stocks at once. Some types of investors, e.g., hedge funds, may be particularly active in skilled processing of public information, investing expertise and other resources without turnover or trading cost considerations, implementing strategies that call for simultaneous trades of many stocks at the same time (See Malkiel and Saha (2005); Khandani and Lo (2007)).

Our second contribution is to test hypotheses on the systematic relationship between our two information asymmetry measures and firm-specific factors that could be the most likely to impound firm-specific private information inferred by skilled information processors from publicly available data. We choose six stock-level trading characteristics: volatility, trading volume, actual and unexpected bid-ask spread, tick-size and buy-sell order-imbalance; and several information-relevant firm-specific structural characteristics, e.g., size, asset tangibility, growth options, insider and outsider ownership, and the availability of alternative trading mechanisms.

We then use the estimated systematic relationships between informed trading and common market-wide factors, and between informed trading and the structural and trading characteristics of a firm, to calculate the "expected" level of informed trading (*EXIT*), and interpret *EXIT* as a proxy for the asymmetric information content of skilled information processors who have private information about systematic market-wide factors or who use public data to generate a private informational advantage. We label the unexplained part of the observed level of informed trading as *Residual Asymmetric Information* – or *RAIN* for brevity and ease of exposition. *RAIN*, a measure that captures the aggregate net economic effect of the abnormal, unexpected level of informed trading, is interpreted as a measure that represents truly private non-public information that encapsulates within it (potentially informed) trades by traditional insiders. One can think of our decomposition as conceptually creating three information based classes of traders: uninformed traders, skilled information processors without inside private information but with the capacity to generate a private informational advantage through private information on systematic factors or with available public information, and informed traders with truly private information.

Our final contribution is to extend the empirical literature on information asymmetry and cost of capital (e.g., Easley, et al. (2002)) and examine the extent to which the different components of information asymmetry are priced in the cross-section of stock returns. The theoretical models relevant in this context are Easley and O'Hara (2004) (hereafter EO) and Hughes, et al. (2007) (hereafter HLL); both of whom provide valuable insights for the central issue in this paper even though our empirical framework, like others before, is not totally consistent with the rigid structure of their models[3]. The popular intuition is that information risk is priced because uninformed investors need to be compensated for the risk of systematically losing out to privately more-informed investors; and more formally, EO show that firms with a higher fraction of private (relative to public) information exposure have a higher required return. HLL, unlike EO, explicitly incorporate private information about systematic return factors, and, emphasizing diversification, argue that the pricing effect in EO Proposition 2 disappears in a large economy due to diversification, and both informed and uninformed investors exploit liquidity traders in a noisy supply environment. On one hand, HLL argue that, because of diversification, firm-specific information characteristics do not determine expected returns, and, on the other hand, they show that factor risk premiums increase as information asymmetry about systematic factors increases; and importantly, even though firm-level private signals arguably carry more information about idiosyncratic rather than systematic factors, even infinitesimally tiny systematic factor information has a finite effect on factor risk premiums when aggregated.

Based on EO, we would expect that *RAIN*, the informational advantage from fully private non-public information, should clearly be priced in the required rate of return, but based on HLL, we would expect the risk on this account to be fully diversified away: in fact, in an HLL world one could argue that the results in Easley, et al. (2002) could potentially have been driven by *EXIT* not *RAIN*, and the true test of EO will have to based on *RAIN*, and not on total information asymmetry. To resolve this issue empirically, we test the return relevance of *RAIN*.

[3] For example, while HLL are silent on an information asymmetry factor since it does not arise endogenously in their model, they also say that their model is not inconsistent with its existence.

The EO and HLL expectations are also different for the return relevance of *EXIT*, the public-data-based private informational advantage of skilled information processors potentially with private information on systematic factors. Based on HLL, private information on systematic market-wide factors, and hence *EXIT*, should generate a positive risk premium. However, given that *EXIT* is based on public data, and even the processing skills arguably extend across a wide spectrum of traders, one would not expect a positive risk premium for *EXIT* based on EO[4]. Accordingly, we distinguish between these modeling intuitions by exploring this issue empirically by testing the return relevance of *EXIT*.

The empirical analysis of this paper is based on all reasonably liquid stocks traded on the New York Stock Exchange (hereafter NYSE), and covering the eleven-year period between January 1995 and December 2005. Our results on the relationships of information asymmetry with market and firm factors are generally consistent with our *ex-ante* expectations. We find that both information asymmetry measures have a strong and significant positive association with market-wide and firm-level volatilities (consistent with French and Roll (1986)), market-wide and firm-level trading volumes (consistent with Bhushan (1989a) and Admati and Pfleiderer (1988)), market-wide and firm-level bid-ask spreads (consistent with Glosten and Milgrom (1985)), and market-wide and firm-level order-imbalances (consistent with Kyle (1985)). Information asymmetry is also significantly higher for firms with higher growth options (consistent with Matsumoto (2002)), higher asset-tangibility (consistent with Cotter and Richardson (2002) and Kothari et al. (2002)), greater insider ownership (consistent with Aboody, et al. (2005) and Lakonishok and Lee (2001)), lower outsider ownership (consistent with an improvement in

[4] In fact, in EO, as the fraction of traders with private information increases, the required rate of return *decreases*, because the demand for the stock from informed traders increases and the precision with which information is revealed to the uninformed increases. In our view, while private information in EO is idiosyncratic, even if we assume that this idiosyncratic private information has a systematic component, these systematic components will be widely dispersed, and hence reduce rather than increase required returns.

communication with investors as in Bushee and Noe (2000)), less profitable firms, relatively smaller firms (consistent with Bhushan (1989b) and Lakonishok and Lee (2001)), and firms with options trading on it (consistent with Easley, et al. (1998)).

Overall, we find strong evidence of commonality in informed trading and the existence of a core component in information asymmetry related to private information about systematic factors or skilled information analysts who, consistent with Kim and Verrecchia (1994, 1997), generate private information from public data. On average, about 47% of explained variation in informed trading is attributable to market-wide commonality, with the remaining 53% attributable to the firm-level environment captured by firm-specific structural characteristics and the stock-level trading environment. As expected, we find that, consistent with sophisticated investors being more likely to invest in large firms (Chordia and Subrahmanyam (2004); Farrar and Girton (1981)), market-wide commonality in information asymmetry is significantly greater for larger firms. We also find that, in the context of information asymmetry, stock-level trading characteristics are relatively less important for larger firms, and, consistent with investors of smaller firms having lesser public information (Bhushan (1989b)) and being exposed to greater risk because of their less diverse operations (Agmon and Lessard (1997)), firm-level structural and individual asset characteristics are relatively more important in explaining informed trading for smaller firms.

Finally, we find that *RAIN*, the unpredictable component of information asymmetry that represents truly private information, is priced in the asset's required rate of return, and its effect on pricing is stronger and more robust than that of total information asymmetry. At the same time, *EXIT*, the predictable component that potentially represents the economic gain of skilled information processors from "private" information on market-wide factors and other public information, does <u>not</u> have a significantly positive risk premium. Our results strongly support the intuition in

Easley and O'Hara (2004), and do not support the intuition in Hughes, et al. (2007), neither with regard to the effects of diversification, nor with respect to the risk premium for systematic factors.

The remainder of this paper is structured as follows. Section 2 summarizes the hypotheses. Section 3 presents the methodology. Section 4 describes the data. Section 5 documents the empirical results. And finally, Section 6 provides concluding remarks.

2. Hypotheses

2.1 Relationship of Information Asymmetry with Market and Firm Factors

Our first set of hypotheses relate to how information asymmetry, as measured by our two proxies, varies systematically with different market and firm factors. For compactness of exposition, Table 1 lists the measures and variables whose relationship with information asymmetry we investigate. The listing is under three sub-heads: market-wide factors, firm-specific trading characteristics and firm-specific structural characteristics. Table 1 also briefly summarizes what we believe the hypothesized relationship of each of these variables should arguably be with informed trading, and the rationale for the hypothesized relationship, citing the relevant literature wherever possible. Accordingly, on the basis of the arguments and the associated literature cited in Table 1, the hypotheses we test are listed below.

Hypotheses H_1 (Market-wide factors) - Information asymmetry is related:
H_{1A}: *Positively with market-wide bid-ask spread.*
H_{1B}: *Positively with market-wide trading volume.*
H_{1C}: *Positively with market-wide volatility.*
H_{1D}: *Positively with market-wide order-balance.*

Hypotheses H_2 (Stock trading characteristics) - Information asymmetry is related:
H_{2A}: *Positively with stock bid-ask spread.*
H_{2B}: *Positively with stock trading volume.*
H_{2C}: *Positively with stock volatility.*

H_{2D}: Positively with stock order-balance.
H_{2E}: Positively with stock tick-size.
H_{2F}: Positively with unexpected changes in stock bid-ask spreads.

Hypotheses H_3 (Stock structural characteristics) - Information asymmetry is related:
H_{3A}: Negatively with firm size.
H_{3B}: Negatively with Book-to-Market Ratio (proxying for lack of growth options).
H_{3C}: Negatively with firm profitability.
H_{3D}: Negatively with ratio of R&D Expenses to sales (proxying for asset intangibility).
H_{3E}: Positively with ratio of Capital Expenses to sales (proxying for asset tangibility).
H_{3F}: Positively with insider ownership.
H_{3G}: Negatively with outsider ownership.
H_{3H}: Negatively with the existence of options trading on the stock.

2.2 Proportion of Informed Trading Explained by Public Information

In this context, we have three specific expectations. First, institutions are more likely to be sophisticated investors and more likely to invest in large firms (Chordia and Subrahmanyam (2004); Farrar and Girton (1981)), which, following the argument of the sophisticated investor generating private-information from public data, implies that, those "informed" trades by institutions that are based on skilled analysis of public data, should increase in relative importance with firm size; and therefore, market-wide commonality in information asymmetry is likely to be relatively greater for larger firms. Second, large-firm stocks are more liquid and price-efficient, and should arguably provide less opportunities to informed traders to exploit their private information; and hence, information asymmetry based on trading characteristics should be less important to informed traders for relatively larger firms. And finally, since investors of smaller firms have lesser public information (Bhushan (1989b)) and are exposed to greater risk because of their less diverse operations (Agmon and Lessard (1997)), private information about firm-level structural and individual asset characteristics should be relatively more important in explaining informed trading for smaller firms. Accordingly, we test the following hypotheses:

H_{4A}: Market-wide commonality in informed trading is greater for larger stocks.
H_{4B}: Informed trading driven by stock trading characteristics is less for larger stocks.
H_{4C}: Informed trading driven by stock structural characteristics is less for larger stocks.

2.3 Price Relevance of Information Asymmetry

Referring to the discussion of this issue in the introduction, we note that EO predict an information risk premium based on the fraction of private (relative to public) information exposure. HLL, unlike EO, argue that, because of diversification, firm-specific private information will not generate a risk premium in the cross-section of expected returns. Hence, *RAIN* should be priced based on EO but not on HLL. On the other hand, HLL show that factor risk premiums increase as information asymmetry about systematic factors increases, and hence *EXIT* should generate a positive risk premium based on HLL. However, since *EXIT* is based on publicly-available data, one would not expect a positive risk premium for *EXIT* based on EO. In fact, one may even see an *EXIT*-related reduction in required returns in EO. This is because, even if we assume that this idiosyncratic private information in EO has a systematic component, these systematic components will be widely dispersed, and EO predict that the required rate of return *decreases* as the dispersion of private information across traders increases. Hence, our hypotheses on the price relevance of information asymmetry are the following:

H_{5A}: RAIN is a positively priced risk factor as per Easley & O'Hara (2004).
Alternative H_{5B}: RAIN is not priced as per Hughes, et al. (2007).
H_{6A}: EXIT is a positively priced risk factor as per Hughes, et al. (2007).
Alternative H_{6B}: RAIN is not priced as per Easley and O'Hara (2004).

3. Methodology

3.1 Measuring Informed Trading

We use two measures of informed trading: *PIN* (labeled PIN_1 hereafter), and *adverse selection* losses of liquidity suppliers to liquidity demanders (labeled IA_1 hereafter). The *PIN* measure assumes that investors are either informed or uninformed, and private information is revealed to the informed investor at the beginning of each trading session; hence, informed trades reflect this private information by being either exclusively buys or sales, but the trade direction of uninformed investors fluctuates randomly between buys and sells. The resulting daily number of buys and sells serves as the empirical input enabling maximum likelihood estimates of the model, and of PIN_1 over a set of *T* trading days. Empirical studies that use PIN_1 (e.g., Easley, et al. (2002); Odders-White and Ready (2006); Vega (2006) and others), show that the measure is well behaved and yields intuitive results. However, PIN_1 is estimated over a large number of trading sessions, and is relatively difficult to use for identifying short-lived changes in the information environment. One could potentially estimate PIN_1 is with higher frequency data, but there are well-documented computational difficulties[5]. In this paper, we use publicly available PIN_1 data estimated over a one-year horizon.

Our second measure of informed trading is the daily average adverse selection loss of liquidity suppliers to traders demanding liquidity. Assuming that informed investors demand immediacy to extract rents from their information before their information becomes fully incorporated into prices, and that liquidity suppliers' profits come not from private information but extraction of rents from supplying immediacy (through a difference between bid and ask prices), this loss should, on average, be zero in the absence of informed trading. IA_1, this direct measure

[5] These problems, documented by Easley, et al. (2008), Easley, et al. (2004), and Vega (2006), reflect a truncation error that arises because the software used for maximum likelihood estimation reaches its numerical limit, and occur when the number of transactions is high or when the imputed level of informed order flow is large relative to the uninformed order flow.

of adverse selection, provides transaction-level estimates of informed trading that can be aggregated over any chosen frequency or class of traders. Daily averages of this variable are robust and provide estimates at a sufficiently high frequency in the context of this paper. At a transaction level, we define IA_1 as[6]:

$$IA_{1,t} = D_t \left(M_T - M_t \right) / M_t \, , \tag{1}$$

where D_t is a trade direction indicator taking a value of +1 for a buy trade and –1 for a sell trade, M_t and M_T are the quote mid-points at the time of the transaction, t, and some time, T, later. To account for variation in the time horizon that private new information is impounded into prices, IA_1 is estimated over 15 minutes, 30 minutes, 60 minutes, and over 24 hours (hereafter one day)[7]. The comparison of estimates of this information asymmetry variable with similarly defined variables used in previous studies and some simple time-series diagnostics show that IA_1 values are reasonable, intuitive and consistent[8].

3.2 Systematic Variation of Informed Trading

To capture variation of informed trading related to market-wide commonality, stock trading characteristics, and firm structural characteristics, the level of informed trading is regressed on the set of explanatory variables identified in the hypotheses section above. First, we estimate a single regression with all variables together. Second, we divide the regression analysis into three parts, examining how the step-wise removal of explained variance of informed trading due to market-

[6] Following Hasbrouck and Sofianos (1993) and Naik and Yadav (2006), and slightly differently from Huang and Stoll (1996) and Bessembinder and Kaufman (1997), we use quote mid-points rather than transaction prices to mitigate problems related to bid-ask bounce and unequally spaced transaction times (see, e.g., Lease, et. al (1991)).

[7] Following Bessembinder and Kaufman (1997), we use quotes posted at least five seconds before the trade. Outliers are handled by excluding the first half-hour of the trading day, IA_1 observations larger than ten percent (Huang and Stoll (1996)), and those eight standard deviations away from the daily stock-level average. In addition, the daily top and bottom 0.1 percentiles are deleted to minimize the influence of extreme observations.

[8] The 29.7 basis points reported by Bessembinder and Kaufman (1997) for an equally-weighted average over 24 hours is close to our 22.8 basis points of the average IA_1 calculated the same way. The values reported in Huang and Stoll (1996) and Bessembinder (2003a, b) are also very similar if appropriate adjustments, such as dividing by the average quote mid-point, are made.

wide commonality, the stock-level trading environment, and the firm-specific structural characteristics, affects excess returns. Both specifications provide similar results.

For the three-step analysis, informed trading alternatively captured by PIN_1 or IA_1, is first regressed on the set of market-wide commonality variables and variation explained by these variables is subsequently removed. This procedure is repeated using stock-level trading characteristics and firm-level structural characteristics until all the three sources of common variation of informed trading are taken out of informed trading. Each regression has a firm-specific intercept[9]. Accordingly, the first regression, used to investigate the presence of common market-wide components in informed trading, is specified as:

$$InfoTrade_{1,i,t} = \beta_{i,0} + \beta_1 MBA + \beta_2 MVOL + \beta_3 MVLA + \beta_4 MOIB + \varepsilon_{i,t}, \tag{2}$$

where $InfoTrade_{1,i,t}$ alternatively denotes PIN_1 or IA_1 of stock i on day t and the variables *MBA*, *MVOL*, *MVLA*, and *MOIB* are the daily market-level bid-ask spread, dollar trading volume, volatility, and order-imbalance, respectively. The market-wide component is subsequently taken out of $InfoTrade_{1,i,t}$ by calculating $InfoTrade_{2,i,t}$ defined as:

$$InfoTrade_{2,i,t} = InfoTrade_{1,t} - \left(\hat{\beta}_1 MBA + \hat{\beta}_2 MVOL + \hat{\beta}_3 MVLA + \hat{\beta}_4 MOIB\right). \tag{3}$$

$InfoTrade_{2,i,t}$ is subsequently related to firm-level variables. The relationship between stock-level trading characteristics and informed trading is investigated by the following regression:

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[9] It appears reasonable to us to go from the general (market-wide variation) to the specific (stock-level trading or structural characteristics), but otherwise, the order in which regressions (2) to (6) are estimated is arguably arbitrary. In this context, we use step-wise regressions to empirically verify whether our order of the regressions corresponds roughly to the explanatory power of the variables. We find that variables relating to market-wide and stock-level trading characteristics always dominate, except that firm-size occasionally features as the third or fourth most important variable. However, since stock-level trading variables are at least as important as market-wide trading variables in explaining information asymmetry, we also, for robustness, run estimations in which we first regress on stock-level trading characteristics, then on market-wide factors, and then on firm-level structural characteristics. The estimated regression coefficients of these regressions are not qualitatively different from what we report in Table 5.

$$InfoTrade_{2,i,t} = \gamma_{i,0} + \gamma_1 VLA_{i,t} + \gamma_2 BA_{i,t} + \gamma_3 OIB_{i,t} + \gamma_4 TIC_{i,t} + \gamma_5 UEDSpread_{i,t} + \gamma_6 VOL_{i,t} + \eta_{i,t}, \tag{4}$$

where *VLA*, *BA*, *OIB*, *TIC*, *UEDSpread*, and *VOL* are stock-level volatility, bid-ask spread, order-imbalance, tick size, unexpected changes in the bid-ask spread, and trading volume, respectively. Variation attributable to stock-level trading characteristics is taken out by calculating:

$$InfoTrade_{3,i,t} = InfoTrade_{2,i,t} - \left(\hat{\gamma}_1 VLA_{i,t} + \hat{\gamma}_2 BA_{i,t} + \hat{\gamma}_3 OIB_{i,t} + \hat{\gamma}_4 TIC_{i,t} + \hat{\gamma}_5 UEDSpread_{i,t} + \hat{\gamma}_6 VOL_{i,t}\right). \tag{5}$$

$InfoTrade_{3,i,t}$ is used to investigate the relationship between structural characteristics and information environment:

$$InfoTrade_{3,i,t} = \delta_{i,0} + \delta_1 Insider_{i,t} + \delta_2 Outsider_{i,t} + \delta_3 Capex_{i,t} + \delta_4 R\&D_{i,t} + \delta_5 BTM_{i,t} + \delta_6 Profit_{i,t} + \delta_7 Options_{i,t} + \delta_8 Size_{i,t} + \xi_{i,t}, \tag{6}$$

where *Insider*, *Outsider*, *Capex*, *R&D*, *BTM*, *Profit*, *Options*, and *Size* denote the fraction of common stocks held by corporate insiders and outsiders, capital expenditures, R&D expenses, the book to market ratio, the profit margin, and an indicator for the availability of exchange-traded options on stock *i*. We calculate the *Residual Asymmetric Information*, *RAIN*, as:

$$RAIN_{i,t} = InfoTrade_{3,i,t} - \left(\hat{\delta}_1 Insider_{i,t} + \hat{\delta}_2 Outsider_{i,t} + \hat{\delta}_3 Capex_{i,t} + \hat{\delta}_4 R\&D_{i,t} + \hat{\delta}_5 BTM_{i,t} + \hat{\delta}_6 Profit_{i,t} + \hat{\delta}_7 Options_{i,t} + \hat{\delta}_8 Size_{i,t}\right), \tag{7}$$

where $RAIN_{i,t}$ denotes the unexplained residual part of informed trading of firm *i* on day *t*, and represents the observed level of informed trading that deviates from what the public investor expects given the market environment, the stock-level trading environment, and features that characterize each particular firm. As informed trades based on inside private information should not show co-variation across stocks, *RAIN* is likely to capture informed trading that is associated with truly private information trades. Finally, we define *EXIT* as the difference between total informed trading and *RAIN*.

A potential weakness of the three-step approach (relative to the one-step approach of putting all variables into the same regression) is that the estimates may suffer from an omitted variable bias, at least to a larger degree than if the regression was estimated including all explanatory variables together[10]. Hence, we also undertake all computations by relating informed trading to its explanatory variables in one single regression. Such a single regression specification does not enable examining how the step-wise incorporation or removal of explained variation of informed trading affects excess returns, but does provide coefficient estimates, and their significance, for each variable, and also provides an estimate of *RAIN*. We find that the single regression specification used does not qualitatively affect the sign, magnitude, and significance of most of the estimated regression coefficients, and hence the resultant inferences.

4 Data

We use intra-day data from TAQ covering the eleven-year period from January 2, 1995 to December 30, 2005[11]. Our sample is confined to stocks traded on the NYSE as primary market. Daily time-weighted averages of the best bid and offer (hereafter BBO) quotes are calculated using NYSE data only, since data from regional exchanges can be unreliable for stocks that have their primary listing on the NYSE (Odders-White and Ready (2006)). Trade direction is inferred

[10] In view of the immediately preceding footnote, since the order in which the regressions are run corresponds roughly to the empirical importance of the variables, the potential effects of omitted variable bias from estimating the regression in three steps rather than one are very limited.

[11] REITs, ADRs, ADSs, closed-end funds, convertibles, preference shares, multiple classes of shares, warrants, rights issues, certificates, and stocks with less than 60 days of quotes or trades per calendar year, are excluded. Stocks trading below $1 are also excluded to ensure minimal liquidity and avoid undue influence of discrete prices. Trades at market open, trades out of sequence, trades with special settlement conditions, trades outside market opening hours, or corrected trades, are all purged, as are quotes posted during market open, negative quotes, or quotes that lead to a bid-ask spread that is either negative, above $5, or larger than 40 percent of the transaction price. These "cleaning" procedures are common for these data (see, e.g., Chordia, et al. (2000)).

using the Lee and Ready (1991)-algorithm, and trades are matched with quotes posted at least five seconds before the trade is executed[12].

Monthly and daily stock returns, closing stock prices, value-weighted market-returns, the number of shares outstanding, four-digit SIC codes, and the daily share volume are retrieved from CRSP. Using these data, stock-level volatility is based on the squared daily return, and tick size is proxied by the inverse of the closing stock price. Dollar volume is the product of the closing stock price and share volume, and firm size is the daily product of the closing stock price and the number of shares outstanding. The Fama and French (1995)-factors *SMB* and *HML*, and the one-month Treasury bill rate, are from the Fama-French data-base on WRDS. The Blockholders data of Dlugosz, et al. (2006) on WRDS is used to calculate corporate insider ownership as the sum of the percentage of common stock held by executives, directors, and affiliated entities. Ownership by corporate outsiders is defined as the fraction of common stock held by anyone who is neither affiliated nor employed by the respective firm. Values of PIN_1 were downloaded from Soeren Hvidkjaer's homepage[13]. Data used to calculate profit margins, the ratios of book value to market value, R&D expenses to sales, and capital expenditures to sales, are from COMPUSTAT, where COMPUSTAT data are winsorized at the first top and bottom percentile[14].

Order-imbalance is defined as the sum of the intercept and the residual of a regression of the ratio of absolute daily raw dollar imbalance to daily dollar volume on dollar trading volume. The volume data that are further used in the empirical analysis are defined as the residuals of a

[12] The Lee and Ready (1991)-algorithm may be potentially correlated with the error of IA_1 used to measure informed trading, but remains the most robust and popular way to infer trade-direction. See e.g., Ellis, et. al (2000) for a discussion of commonly used trade-direction algorithms.

[13] We thank Soeren Hvidkjaer on our acknowledgements page for making the PIN_1 data available on his website.

[14] These variables are operating profits (item 13), total sales (item 12), the necessary items to calculate book value excluding preference shares (items 60, 74, and 208 less items 56, 175, and 130), R&D expenses (item 46), and capital expenditures (item 128). Firms with negative book values are excluded. Missing values from COMPUSTAT and the Blockholders database are set to zero. Results are insensitive to these data cleaning procedures.

regression of changes in dollar volume on market volume, stock-level volatility, and market returns (Chordia, et al. (2000) follows a similar set-up):

$$\$Volume_t = \vartheta_0 + \vartheta_1 MVolme_t + \vartheta_2 MVolume_{t-1} + \vartheta_3 r_{m,t} + \vartheta_4 r_{m,t-1} + \vartheta_5 r_{i,t}^2 + \tau_t, \quad (8)$$

where $\$Volume_t$ is the percentage change in dollar volume from the previous trading day to day *t*, $r_{m,t}$ and $r_{i,t}$ are the return on the market and on stock *i* over the same period, and $MVolume_t$ is the equally-weighted market average of stock-level percentage changes in dollar volume from the previous day to day *t*. Defining volume in this way improves the comparability of volume across stocks and removes the time-trend in dollar volume. Similarly, regression (8) is estimated by replacing *Volume* and *MVolume* by the daily percentage changes in bid-ask percentage spreads and the market average of changes therein. The residual of this regression is *UEDSpread*, and represents the unexpected change in bid-ask spreads, our proxy for large changes in bid-ask spreads[15].

Market-level bid-ask spread, trading volume, and order-imbalance are defined as value-weighted averages of the stock-level values. The new methodology VIX index is used to measure market-volatility[16]. The merged data set contains 2,407 individual firms that have valid observations for all data-items, with different years having between 1,287 and 1,641 individual firms.

For ready reference, Table 2 summarizes the definitions of the empirical measurements used in this study. Summary statistics of the data are shown in Table 3. The mean book-to-market ratio is very close to that documented by, for example, Easley, et al. (2002). It is important to note that most variables exhibit significant skewness and a strong size-effect. The value-weighted market average of bid-ask spreads, for instance, is much smaller than the simple mean of the stock-level equivalent, showing that small firms have a much larger bid-ask spread than large

[15] The estimated coefficients of this regression are very close to what Chordia, et. al (2000) report with and without a lead-term. Intercepts are insignificant (average p-values 0.23 and 0.38 for volume and bid-ask spread respectively).
[16] The new methodology VIX index is downloaded from the CBOE website. Based on a portfolio of options on the S&P 500 index, it provides an *ex ante* forecast of expected future volatility, and is best suited to our intention of capturing the markets' information environment, clearly preferable to backward looking past realizations of volatility.

firms. Accordingly, as is common in empirical market microstructure, we rescale input data to improve their distributional characteristics, and to make cross-sectional comparisons more meaningful (Naik and Yadav (2003))[17]. We rescale in two ways: by standardizing parametrically to a mean of zero and a standard deviation of one, as in Hansch, et al. (1999) and Brennan, et al. (1998); and rescaling non-parametrically, as in Llorente, et al. (2001)) but through the method of normal scores by replacing the variable value by its ranking scaled by a factor that fits a unit normal distribution to the data. Our results are not sensitive to the choice of rescaling. Our reported results are based on non-parametric rescaling, since it is explicitly free from any postulated relationship between informed trading and the explanatory variables. Variables capturing market-wide commonality, stock-level trading characteristics, and firm-specific structural characteristics are rescaled within each time-series individually, and the time-specific structural variables are rescaled daily across the cross-section.

5 Discussion of Results

5.1 Univariate Analysis

The correlation matrix in Table 4 provides the first picture of the co-variation between informed trading and our set of explanatory variables. All values are statistically significant. Virtually all our hypotheses in the H_1, H_2, and H_3 groups are supported even in simple univariate analyses. There are just two variables – market trading volume and book-to-market ratio - for which the relationship is in a direction opposite to the corresponding hypothesis for both PIN_1 and IA_1; and there are just two variables – market volatility and unexpected bid-ask spread – for which the relationship of PIN_1 with the explanatory variables is different from that of IA_1. Overall, both measures of informed trading appear to be capturing the same underlying economic phenomenon.

[17] Taking logarithms instead of rescaling is also common, but requires the data to be strictly positive, and additionally implies an exponential relationship between information asymmetry and the explanatory variables that cannot be motivated *a priori* in the current context.

5.2 Multivariate Analysis

Using the methodological set-up outlined in the methodology section, IA_1 and PIN_1 are regressed separately on our set of explanatory variables. Comparability in the estimated relationships of IA_1 and PIN_1 with our explanatory variables can serve as a consistency check to verify that both variables are capturing the same underlying economic phenomenon. To ensure such comparability, daily IA_1 is first expressed as a yearly average since PIN_1 is available only at a yearly frequency. The results in Table 5 are accordingly based on yearly estimates of each of the variables involved. Panel A reports results from a one-step decomposition, while Panels B and C report a three-step decomposition. The IA_1 regressions are estimated over 15, 30, and 60 minutes, and 24 hours, but, since the results are very similar, we only present results for the 60 minutes horizon in Panel C. Overall, we find that our results are largely consistent, whether we use one-step decomposition (Panel A) or three-step decomposition (Panels B and C), and whether we use PIN_1 (Panels A and B) or IA_1 (Panels A and C).

5.2.1 Market-wide Factors and Commonality in Informed Trading

The results in Table 5 show that the hypotheses in the H_1 group are strongly and significantly supported for market-wide spread, market-wide order-imbalance; and particularly for IA_1, also for market-wide volatility. Higher levels of informed trading are related to significantly higher market-wide bid-ask spreads (consistent with Glosten and Milgrom (1985)), significantly higher market-wide order-imbalances (consistent with Kyle (1985)), and significantly higher market volatility (consistent with French and Roll (1986)); and each of these is also consistent with the corresponding univariate results. The association with market volume is significantly negative for PIN_1 and significantly positive for IA_1. The significantly positive relation of volume with IA_1 is consistent with Bhushan (1989a) and Admati and Pfleiderer (1988), and hence, hypothesis H_{1B}.

Irrespective, our results show a strong degree of commonality in informed trading, and imply that a significant proportion of the observed level of informed trading is related to public, market-wide signals. These results are consistent with private information on systematic factors, and with the information analysts in Kim and Verrecchia (1994, 1997) who generate private information, and consequently undertake informed trading, by interpreting publicly available data quicker and more effectively than the marginal investor; and also support the Hasbrouck and Seppi (2001) argument that commonality in trading may be caused by informed investors acting on the same market-wide information.

5.2.2 Stock-level Trading Environment

In the second step, a modified informed trading variable that has been duly purged of market-wide variables, is regressed on stock-level trading characteristics. The results in this context in Table 5 are again consistent with the univariate results. All hypotheses in the H_2 group are strongly and significantly supported except that hypothesis H_{2F} relating to unexpected bid-ask spreads is strongly and significantly supported only for IA_1 but not for PIN_1. Higher levels of firm-level volatility and firm-level bid-ask spreads are both associated with significantly higher levels of informed trading, consistent with French and Roll (1986) and Glosten and Milgrom (1985) respectively. Higher volume is also associated with significantly greater informed trading, consistent with Admati and Pfleiderer (1988) and the empirical findings of Bhushan (1989a) and Llorente, et al. (2001). The positive coefficient of tick size implies that there is less information asymmetry when the tick-size is smaller, and this is consistent with prices converging faster to fundamental values when tick size is smaller, similar to the improvement in price efficiency observed by Chordia, et al. (2005) when NYSE switched to decimal pricing. Greater order imbalance is associated with significantly greater informed trading, and the stronger association of

PIN_1 with order-imbalance (relative to IA_1) likely reflects the fact that PIN_1 estimation is more directly based on order-imbalance.

The relationship of unexpected changes in bid-ask spreads with informed trading measured by PIN_1 is opposite to that measured by IA_1. This may potentially reflect estimation-related issues. PIN_1 values are estimated by aggregating data over a full year, and can therefore pick up long-term effects; for example, the strategic cost-minimizing trading behavior of informed traders (as in Kyle (1985)) generated by informed trading being lower when spreads are unexpectedly high. IA_1, by contrast, is estimated over a much shorter horizon, and is likely to pick up the short-term relationship between bid-ask spreads and informed trading that is also found in the univariate setting, i.e., that higher informed trading causes market makers to widen bid-ask spreads (Glosten and Milgrom (1985)).

5.2.3 Firm-specific Structural Characteristics

In the third step, a modified informed trading variable that has been purged of both market-wide variables and stock-level trading characteristics, is regressed on firm-specific structural characteristics. The results, reported in Table 5, again confirm virtually all the findings from the univariate analysis and, after taking into account all the Panels, provide reasonable support to all the hypotheses in the H_3 group. Consistent with Bhushan (1989b) and Lakonishok and Lee (2001), informed-trading declines significantly with firm size as anticipated. Informed trading also increases significantly as the relative size of the ownership stake of insiders increases, consistent with corporate insiders exploiting their informational advantage (Aboody, et al. (2005); Lakonishok and Lee (2001)). However, outsiders significantly reduce information asymmetry and improve the information environment, in line with the findings of Bushee and Noe (2000) and not consistent with Maug (2002). The significantly negative sign of the coefficient of the book-to-market ratio (for PIN_1 and for 15-minute IA_1) is now opposite to that for the univariate results, and supports hypothesis H_{3B} that growth firms expose investors to greater informed trading, consistent with Matsumoto (2002), who find that growth firms bias the information communicated to the public more than others. Interestingly, more profitable firms also have significantly less informed trading consistent with uninformed investors flocking to profitable companies, leaving less profitable companies with relatively greater informed trading. We continue to find a negative association between informed trading and R&D expenses, and a positive association with capital expenses over sales, indicating that informed traders focus on firms with greater asset tangibility, consistent with intangible assets being difficult to value (Cotter and Richardson (2002) and with uncertain economic benefit (Kothari, et al. (2002)). Finally, the availability of options is associated with a lower level of informed trading: this is consistent with Easley, et al. (1998), and with informed traders preferring to trade in the options market, and consequently, uninformed investors in the market for stocks with options being less exposed to informed trades than investors in comparable stocks without options.

Richer analysis of the potential determinants of the time-series variation in informed trading needs higher frequency measurement of the informed trading variable. We accordingly next investigate daily variation in informed trading levels. Since PIN_1 is available only at a yearly frequency, this daily analysis has to be undertaken using only IA_1 data. However, we note that, in Table 5, both measures of informed trading - PIN_1 and IA_1 - show very similar associations with our set of explanatory variables, and hence, conditional on the occasional estimation-related specificity highlighted above, appear to be capturing the same underlying economic phenomenon. Hence, we are perfectly comfortable with drawing general conclusions about informed trading from the IA_1–based analysis that follows.

5.3 Daily Analysis of Informed Trading

This section reports the results of re-estimating the regressions specified in the methodology section at daily frequency, and to account for the strong size effect in the data, the regressions are estimated individually by firm size deciles. The results are presented in Table 6. As before, we report only results based on IA_1 estimated over 60 minutes, since the results for IA_1 estimated over different intraday horizons, or over 24 hours, are very similar.

The sign of the regression coefficients capturing the relationship between informed trading and market-wide commonality on a daily level are completely consistent with what we found using yearly data (Panel A of Table 6), but the use of daily data enables us to also make other inferences. In relation to market-wide commonality in daily informed trading, we note that the magnitude of the influence of market-level bid-ask spread, market-level volume, and market-wide volatility on firm-level informed trading decreases monotonically in firm size. Since we are conditioning here on market-wide variables separately for each size decile, we are capturing *time-series* (rather than cross-sectional) innovations in these variables; and each of these variables is related to the information environment: liquidity suppliers increase spreads on days with greater information asymmetry, higher volume days correspond to days when the rate of information flow is arguably greater, and higher volatility days are days on which a greater quantum of information gets incorporated into prices. Our IA_1 results imply that, for a given rate of market-wide information flow, market-wide magnitude of information, and overall information asymmetry, the trade-conditioned return of (potentially informed) liquidity demanders is greater for smaller firms relative to larger firms; and this is consistent with Kim and Verrechia (1994, 1997) skilled information processors being able to analyze market-wide data to extract greater informational rents for relatively smaller companies that have correspondingly lower analyst following. On the other hand, the size of the regression coefficients of market-level order-imbalance decrease in firm size, reflecting the lower contemporaneous correlation of market-level changes with firm-level changes for relatively smaller firms, since such smaller, less actively traded stocks need relatively more time to fully incorporate the new information contained in market-wide changes in order-imbalance (Hasbrouck (1991)) since sophisticated skilled information processors are arguably likely to be institutional investors (Lee, et al. (1991)) and focus preferentially on larger firms (Chordia and Subrahmanyam (2004); Farrar and Girton (1981)). The delayed response does not affect the contemporaneous dependence of volatility, volume and spreads to the same extent since these variables exhibit strong time-series persistence, while, on the other hand, the order imbalance variable is mean-reverting.

The dependence of daily informed trading on stock-level trading characteristics is completely consistent with the results based on yearly averages, except for the result relating to tick-size. The inconsistency in the tick-size results is perhaps not surprising since our size-conditioned results in Table 6 essentially represent the effect of time-series variation for the same stock, rather than the cross-sectional variation across stocks captured by yearly data analyses. For yearly data, i.e. essentially across the cross-section, relative tick size captures differences in the efficiency with which information was incorporated into prices, but it is not clear what time-series differences in (the inverse of) price levels for the same stock proxy for. That said, we note that the smallest decile shows a relationship opposite to the rest of the sample, consistent with the finding of Kairys, et al. (2000) that the quality of the price-discovery process deteriorates for the least liquid stocks as the trading process becomes more efficient through a switch from a daily batch auction to continuous pricing.

Use of the daily informed trading variable again enables us to make inferences across size deciles. The influence of firm-level bid-ask spread, firm-level volume, and firm-level order-imbalance on informed trading decreases monotonically in firm size. Again, our IA_1 results imply that, for a given rate of firm-specific information flow, firm-specific information captured by order-imbalance, and firm-specific information asymmetry, the trade-conditioned return of (firm-level informed) liquidity demanders is greater for smaller firms relative to larger firms; and this is consistent with Lakonishok and Lee (2001), who find that private information about firm-level issues is greatest for the smallest stocks. However, the coefficient for firm-level volatility does not vary significantly across firm-size.

Since many of the firm-specific structural variables are observed only on an annual frequency, we consider the relationships between daily informed trading and firm-specific structural characteristics documented in Table 6 Panel C to be indicative rather than definitive. That said, it is clear that, as with yearly data, informed trading is much greater for relatively smaller stocks; firm profit margins are lower for firms with greater informed trading; and the options availability indicator is significant only for larger firms. Outside ownership, which on a yearly frequency is associated with a lower level of informed trading, now shows the opposite relationship. This is consistent with the empirical findings by Yan and Zhang (2007), who find that "short-term institutions" exploit their information advantage whereas "long-term" institutions do not. The results using yearly IA_1 may therefore pick up the relationship between informed trading and long-horizon investors and the relationship found for daily IA_1 likely captures the relationship between informed trading and short-horizon investors.

5.4 Analysis of Explained and Unexplained Informed Trading

To test the H_4 group of hypotheses, we calculate how much of the explained variation in information asymmetry corresponds to market-wide commonality, stock trading characteristics, and firm structural characteristics; and whether the relative proportions depend on the features of the firm.

Table 7 shows the results of decomposing the relative explanatory power of market-wide variables, firm-specific trading characteristics, and firm-specific structural characteristics for different size deciles as per the regression specifications outlined in the explanatory notes to the table. On average, about 47% of *explained variation* of informed trading is associated with the market-wide component, about 46% is attributable to the stock-level trading environment, and about 7% of explained variation is attributable to firm-specific structural characteristics. Thus, almost half the explained variation of informed trading is related to market-wide commonality and factors other than firm-specific characteristics. This is an interesting finding given that empirical studies typically consider informed trading to be a firm-specific phenomenon. Alternative specifications do not change the results qualitatively. Estimating the regression across the entire data panel by firm-size decile, market-wide factors capture between 14% (Decile 1) and 65% (Decile 10) of the explained variance, and stock-level trading characteristics account for between 55% (Decile 1) and 19% (Decile 10). Importantly, ranking the relative explanatory power by other characteristics such as the book-to-market ratio or spreads does <u>not</u> show any significant variation in relative explanatory power across ranks, and is hence not reported.

Importantly, each of the hypotheses H_{4A}, H_{4B}, and H_{4C} are strongly supported. Market-wide commonality in information asymmetry is relatively greater for larger firms; information asymmetry based on trading characteristics is less important for relatively larger firms; and unexplained variation of informed trading becomes more important as we move from larger to smaller firms, reflecting the importance of private information in smaller firms (Lakonishok and Lee (2001)) where investors have lesser public information (Bhushan (1989b)) and are exposed to greater risk because of their less diverse operations (Agmon and Lessard (1997)).

5.5 Informed Trading and Stock Returns

This section tests the H_5 and the H_6 group of hypotheses, i.e., whether *RAIN* and *EXIT* are positively priced risk factors, and hence whether the Easley and O'Hara (2004) model or the Hughes, et al. (2007) model is supported by the data. We test the relationship between returns and informed trading in the cross-section by using a Fama and MacBeth (1973) set-up. The time-period covered by the data includes the period after 2000, which is characterized by a prolonged period of negative market returns. According to Potential and Sundaram (1995), negative excess market returns make the estimated loading on the beta-coefficient insignificant unless negative and positive market returns are separately considered in the cross-sectional regression. For this purpose, up-market (down-market) market betas are defined as being equal to the stock-level beta if the realized market return in excess of the risk-free rate is positive (negative) and zero otherwise. To implement the regression, fifty portfolios are formed based on the average level of informed trading of the previous month. Stock returns in excess of the risk-free rate are averaged within each portfolio and regressed on the portfolio averages of beta, the logarithm of the book-to-market ratio, and the logarithm of firm size. The book-to-market ratio, firm size, and beta are measured as of the previous year. The relevant value of informed trading is the level during the previous calendar year if PIN_1 is used and the average level during the previous month if IA_1 is used as measure of informed trading. This results in the following regression that is estimated every month:

$$R_p^e = \kappa_0 + \kappa_1 BETA_{up,p} + \kappa_2 BETA_{down,p} + \kappa_3 Size_p + \kappa_4 BTM_{up} + \kappa_5 InfoTrade_{k,p} + \zeta_t, \quad (9)$$

where R_p^e is the average portfolio return in excess of the risk-free rate of portfolio p. The variables $BETA_{up,p}$ and $BETA_{down,p}$ are up-market and down-market betas of portfolio p, $Size_p$ is the logarithm of firm size of portfolio p, and BTM_p is the logarithm of the book-to-market ratio of portfolio p. $InfoTrade_{k,p}$ refers to the average level of informed trading-measure k of portfolio p. The monthly effective spread is used as an alternative to $InfoTrade_k$ to verify whether the relationship between informed trading and stock returns does not pick up liquidity effects that, as Brennan and Subrahmanyam (1996) find, may also be priced. Our results are presented in Table 8 using Litzenberger and Ramaswamy (1979)-adjusted *t*-statistics, a weighed least square estimate using the parameter precision as weight. Our results are robust to the choice of the horizon over which IA_1 is estimated.

Intercepts are sometimes insignificant, and the model specified in regression (9) captures cross-sectional returns fairly well. Firm size is hardly significant though the negative regression coefficients reveal the size effect in stock returns, discussed in Fama and French (1992). The lack of statistical significance reflects the results of Kim (1995), who also finds firm size to be of little importance in explaining cross-sectional returns if data covering more recent time periods are used. The inclusion of the up-market and down-market betas turns out to be useful as the loadings are significant and signed, as Potential and Sundaram (1995) suggest, while the (unreported) use of one single beta variable leads to insignificant coefficients. Consistent with Easley, et al. (2002), the total unadjusted level of informed trading is priced in the cross-section. Most importantly, however, the association between excess returns and information risk gets economically and statistically stronger as one moves from total information asymmetry to *RAIN*. This relationship weakens, however, the longer the horizon IA_1 is estimated over. Loadings on *EXIT* are <u>not</u> statistically significant. The result is robust to whether *RAIN* is estimated in three steps as outlined in equations (2) to (7) or whether it is estimated in one go (referred to as *RAIN2* in Table 8).

To further reinforce these results, and to give more weight to the time-series relationship between returns and informed trading, a second asset-pricing test is conducted. Cochrane (2001) discusses the trade-off between the empirical robustness of ordinarily least-squares and the statistical efficiency of generalized least-squares (henceforth referred to as GLS) in asset pricing. Testing the return relevance of the components of the information environment in a GLS framework potentially improves the validity of the results, as it is the most efficient way to adjust Fama-MacBeth regressions for biases and the errors-in-variables problem (Ferson and Harvey (1999)).

Following Brennan and Subrahmanyam (1996), we use a random intercept GLS regression model. In particular, we use a three-way sort on size, book-to-market, and informed trading. Equally-weighted average portfolio excess returns are regressed on market returns in excess of the risk-free rate, the Fama and French (1993)-factors SMB and HML, and the rank of each portfolio based on its level of informed trading. The GLS regressions are run on the full data panel, whereby every portfolio has individual factor loadings for the market factor, the HML factor, and the SMB factor. The coefficient on the level of informed trading, however, is estimated across all portfolios. This procedure results in a large number of explanatory variables, which therefore necessitates adequate time-series observations for a statistically valid estimation. The low sampling frequency of PIN_1 results in relatively few time-series observations of this variable. Therefore, this particular asset-pricing test is done using only the monthly observations of IA_1.

The slope coefficients of *RAIN* in Table 9 again show that it is a positive and significant priced factor. In addition, the loadings on the ranking variable mostly increase in economic terms as one successively removes market-wide commonality, stock-level trading characteristics, and firm-specific structural characteristics of informed trading. And once again, *EXIT* is not related to returns, confirming the associations of the cross-sectional set-up presented in Table 8.

Finally, we do a robustness test to see whether *RAIN* really constitutes a true residual as is claimed in the analysis. For this purpose, we do a principal component analysis on the complete set of stock-level *RAIN* series[18]. If *RAIN* truly represents a residual, one would expect not to find a principal component that captures significant variance across individual stocks. PIN_1 has too few time-series observations to qualify for this test, which is why this test is only conducted using IA_1. Our results, shown in Table 10, do reasonably confirm our residual characterization for

[18] To ensure a sufficiently large time-series, only stocks that have observations at least 97.5 percent of time during the sample period are used.

RAIN. The first principal component does not capture more than 7 percent of the observed variance and the first three principal components together capture less than 12 percent of the observed variance. Thus, *RAIN* seems to be mainly driven by firm-specific events and the filtering approach in the paper appears to have been reasonably successful in removing commonality in variation across stocks.

Overall, our results show, quite unequivocally, that *RAIN*, the unpredictable component of information asymmetry that represents truly private information, is priced in the asset's required rate of return, and its effect on pricing is stronger and more robust than that of total information asymmetry. At the same time, *EXIT*, the predictable component that potentially represents the economic gain of skilled information processors from "private" information on market-wide factors and other public information, does not have a significantly positive risk premium. Accordingly, our results support Easley and O'Hara (2004), and do not support Hughes, et al. (2007).

5.6 Other Robustness Checks

We have highlighted several robustness checks in our discussion of empirical results in the preceding sub-sections. In this sub-section, we further highlight other robustness checks we do to further test the validity of our results. First, regressions (2) to (6) on daily IA_1 data are re-estimated within firm size quintiles and including day-of-the-week dummies. Using firm size quintiles instead of deciles results in the same sign of the associations between the set of explanatory variables and informed trading. While the inclusion of day-of-the-week dummies does not affect the sign or significance of the other explanatory variables, informed trading appears to be higher at the beginning of the week. The Chordia, et al. (2002) finding that the highest level of trading activity is at the beginning of the week, is true also for informed-trading.

Second, as informed trading is proxied by order-imbalance in many theories about the information flow in financial markets (e.g., Easley, et al. (2002); Kyle (1985); Lyons (2001)), several alternative specifications of order-imbalance are tested (in addition to that used in the tables above): specifically, lagged order-imbalance, dummies that account for the sign of order imbalance, and dummies that classify each daily stock-level order-imbalance observation into deciles. Our results are not qualitatively different[19]. We also do the analysis also by conditioning on trade direction. The average information content of order-imbalance seems to differ by trade direction. Buying pressure tends to be positively related to informed-trading, while selling pressure is related to a lower level of informed trading. According to Aboody, et al. (2005) and Lakonishok and Lee (2001), this asymmetry could be due to buys involving a deliberate choice, potentially based on private information; while sales also contain liquidity trades by employees that intend to divest stocks that are part of their compensation package (Aboody, et al. (2005); Lakonishok and Lee (2001)). Consistent with theory (e.g., Kyle (1985)), the size of the daily order-imbalance position has a positive relationship with the level of informed trading.

Third, to investigate the stability of the coefficient estimates, regressions (2) to (6) are re-estimated within sub-periods of the sample by slicing the time-series into two, three, and four partitions. Running the regression in different sub-periods shows estimates largely consistent with Table 6. However, regression coefficients of market-level volatility are mostly negative between 1995 and 1997 as are the coefficients of stock-level bid-ask spreads for the regressions estimated between 2003 and 2005. Both variables exhibit a consistent time-trend during these sub-periods, which the sub-period regression estimates seem to pick-up.

Fourth, noting that IA_1 is a measure of a fixed-interval return *conditional on a trade*, we test whether IA_1 does actually captures the level of informed trading rather than simply proxy for

[19] A noteworthy result is that the order-imbalance variable lagged by one day is positively related to informed trading if IA_1 is estimated over horizons shorter than one day. The coefficient of lagged order-imbalance is negative for larger firms and positive but insignificant for smaller ones if IA_1 is estimated over one day. This suggests that the information contained in order-imbalance is impounded into prices within about one day.

daily unconditional returns. Thus, we construct a return measure that is otherwise identical but excludes the information contained in the timing of a transaction. In particular, we assume that a hypothetical trader observes the daily realization of the explanatory variables. If this realization deviates from the historical (or cross-sectional) average, the trader takes a position of unit size that has the same direction as the deviation of the explanatory variable from its mean value and keeps this position for one day. Alternatively, the amplitude of the deviation from the historical or cross-sectional average is also made to reflect in the size of the position. The resulting stock-level return-series is subsequently regressed on the explanatory variables using the same methodology and sectioning into size groups. Regardless of how this alterative return series is specified, the explanatory power of the regressions remains very low (the R-square is between 0.004 and 0.022). The associations with the explanatory variables are also usually insignificant.

Finally, in the same spirit, another concern related to the use of IA_1 is how strongly IA_1 is influenced by return momentum. Therefore a time-series of daily 15-minutes unconditional quote returns is constructed. This return variable has the same set-up as IA_1 except for explicitly not accounting for the information content of the timing of a trade. This variable should therefore mechanically pick up return momentum. If the relationship between this quote-return variable and the set of explanatory variables is weaker than what is found for IA_1, one could conclude that IA_1 contains more information than simply daily returns. We again find extremely low explanatory power (the average R-square across all size deciles is 3.2 percent). In addition, the signs and the significance of some explanatory variables are not consistent across size decile. These tests show that IA_1 cannot be replicated either using environmental variables observed in the recent past or mechanically by supplying returns over fixed intervals. Therefore, we believe that IA_1 does reflect private economic information that arguably gets transmitted to the market by means of informed trades.

6 Summary and Conclusions

This paper analyses informed trading in about 1,500 reasonably liquid stocks traded on the NYSE between January 1995 and December 2005. Our first major contribution is to investigate and test hypotheses on the relationship between informed trading and market-wide commonality, stock-level trading characteristics, and firm-specific structural characteristics. We find strong support for virtually all of our hypotheses. We find that the relationships between our microstructure-based informed-trading measures, and our set of explanatory variables, are consistent with economic theory, intuition, and, where available, prior theory and empirical evidence obtained using other measures and other empirical approaches.

Our results demonstrate strong market-wide commonality in informed trading with market-level volatility, trading volume, bid-ask spreads, and order-imbalance all significantly related to the level of informed trading; and strong evidence of association between individual firm-specific factors and informed trading. On average, almost half of the observed informed trading can be attributed to commonality, and relatively more so for larger firms. Our results are consistent with Kim and Verrecchia (1994, 1997) type skilled information analysts generating “private” information from public data, and potentially private information on systematic factors.

Given the estimated systematic relationships between informed trading and common market-wide and firm-specific factors, we calculate the “expected” level of informed trading (*EXIT*), and interpret *EXIT* as a proxy for the asymmetric information content of skilled information processors who have private information about systematic market-wide factors or who use public data to generate a private informational advantage. We label the unexplained part of the observed level of informed trading as *Residual Asymmetric Information* – or *RAIN*, and interpret *RAIN* as a measure that represents truly private non-public information encapsulating, for example, trades by traditional insiders.

Finally, we test whether *RAIN* and *EXIT* are priced information factors, and find that *RAIN* is a significant priced information factor, but *EXIT* is not. The Easley and O'Hara (2004) and Hughes, et al. (2007) models have opposite implications for both *RAIN* and *EXIT*; and both our results provide strong support for Easley and O'Hara (2004) but not for Hughes, et al. (2007).

We recognize that we use measures of informed-trading that are not only potentially noisy, but also fairly different in their perspective, underlying assumptions, and even sampling frequency. However, the consistency of our results across such different measures generates more confidence in the conclusions. We also recognize that eleven years of data may be a fairly short time horizon from an asset pricing point of view. But once again, the strength and consistency of the results across different specifications, and across our extensive robustness checks, generate confidence that the results are sufficiently robust to provide useful insights into the nature and the pricing relevance of information asymmetry.

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Table 1 – Hypothesized Relationship of Variables with Informed Trading

This table shows the hypothesized relationships between our explanatory variables and informed trading. The columns "Measure" and "Variable Name" indicate the explanatory variables. The columns "Sign" and "Hypothesis" list respectively the expected sign of the relationship of the variable with informed trading, and the rationale for the hypothesis based on the literature. The symbols "+" and "–" in the column Sign indicate that increases in the particular variable are expected to be related to a higher or lower level of informed trading, respectively.

	Measure	Variable Name	Rationale for Relationship	Sign
Market-wide commonality	Bid-ask spread	MBA	Bid-ask spreads are higher the higher the level of informed trades (Glosten and Milgrom (1985)).	+
	Trading volume	MVOL	Higher trading volume should lead to more informed trades: first, because the resulting more noisy prices increase the relative advantage of private information (Bhushan (1989a)); second, because informed traders hide among liquidity traders (Admati and Pfleiderer (1988)); and third, because the higher trading volume could be arising from greater information flow.	+
	Volatility	MVLA	Private information drives returns' volatility (French and Roll (1986)).	+
	Order imbalance	MOIB	Private information is expressed via order-imbalance (Kyle (1985)).	+
Stock-level trading characteristics	Bid-ask spread	BA	Bid-ask spreads are higher when the level of informed trades is higher (Kyle (1985)).	+
	Unexpected changes in bid-ask spread	UEDSpread	If informed trading is unexpectedly high because of some exogenous factors, market makers increase spreads to protect themselves from losses (Glosten and Milgrom (1985)). That said, as bid-ask spreads unexpectedly increase, there is an unanticipated drop in liquidity, and the number of informed trades decreases since informed traders are strategic (Kyle (1985)).	+
	Trading volume	VOL	Higher trading volume should lead to more informed trades: first, because the resulting more noisy prices increase the relative advantage of private information (Bhushan (1989a)); second, because informed traders hide among liquidity traders (Admati and Pfleiderer (1988)); and third, because the higher trading volume could be arising from greater information flow.	+
	Tick size	TIC	When tick size is lower, prices converge quicker to fundamental values and become more "efficient" (Chordia, et al. (2005)), and hence, relatively more information is impounded into prices over a given time interval, which should arguably result in a higher observed level of the informed trading variable.	–
	Order imbalance	OIB	Private information is expressed via order-imbalance (Kyle (1985)).	+
Firm-specific structural characteristics	Public exposure	Size	Public investors in large firms have more sources of information that get more frequently updated than investors of smaller firms (Bhushan (1989b)). Small firms suffer more from insider trading (Lakonishok and Lee (2001)).	–
	Active management of investor perceptions	BTM	Small firms with growth options (i.e., a lower book-to-market ratio, or BTM) bias investor communication to a greater extent (Matsumoto (2002)). If public information is biased, informed investors are advantaged. Therefore, growth options are positively associated with informed trading.	–
	Profitability	Profit	Uninformed investors flock to profitable companies, implying that less profitable companies have relatively greater informed trading.	–
	Asset tangibility	R&D Capex	Intangibles are difficult to value for outsiders (Cotter and Richardson (2002)) and their economic benefits are more uncertain (Kothari, et al. (2002)). Therefore, higher asset tangibility, as measured by the ratio of R&D-expenses to sales and capital expenses over sales, or Capex, should be associated with a higher level of informed trading.	– +
	Ownership structure	Insider	Corporate insiders exploit their information advantage (Aboody, et al. (2005); Lakonishok and Lee (2001)).	+
		Outsider	Outside ownership by institutional investors should be associated with better investor communication (Bushee and Noe (2000)), decreasing information asymmetry. That said, it is alternatively conceivable that outsiders are able to exploit their information advantage (Maug (2002)), thereby increasing informed trading, though we do not state that as our hypothesis.	–
	Alternative trading instrument	Options	Informed traders also use options (Easley, et al. (1998)). This could lead to a lower level of informed trading as some informed traders exploit their information via the options market.	–

Table 2 – Variable Definitions

This table lists the names of the variables used in this paper in column *Variable Name* and the definition used to construct the respective variable in the column *Definition*.

Variable Name	Definition
IA_1	The daily trade size-weighted average of the difference between the quote mid-point right before a transaction and the quote mid-point 15 minutes, 30 minutes, 60 minutes, or one day later scaled by the first quote mid-point.
IA_2	This variable is defined as IA_1 less market-wide commonality.
IA_3	This variable is defined as IA_2 less stock-level trading characteristics.
IA_{RAIN}	This variable is defined as IA_3 less firm-specific structural characteristics.
IA_{EXIT}	This variable is defined as the difference between IA_1 and IA_{RAIN}.
PIN_1	The probability of information-based trades provided on a yearly frequency on Soeren Hvidkjaer's website.
PIN_2	This variable is defined as PIN_1 purged from market-wide commonality.
PIN_3	This variable is defined as PIN_2 purged from stock-level trading characteristics.
PIN_{RAIN}	This variable is defined as PIN_3 less firms-level structural characteristics.
PIN_{EXIT}	This variable is defined as the difference between PIN_1 and PIN_{RAIN}.
Market-level	The value-weighted daily average of the stock-level variables (except for volatility).
Volatility	Market-level volatility is measured by the VIX index and by squared daily returns for individual stocks.
Bid-ask spread	The time-weighted daily average of the individual BBO percentage spread.
Order-imbalance	The absolute daily dollar-imbalance scaled by dollar trading volume orthogonalized to dollar trading volume.
Unexpected changes in bid-ask spread	The residual of a market-model fitted to stock-level quoted percentage bid-ask spreads.
Unexpected changes in trading volume	The residuals of a market-model fitted to stock-level dollar volume
Tick size	The inverse of the stock price.
Firm size	The stock-market capitalization. If used in return regressions, the natural logarithm of the last observation in the previous calendar year is used.
Book value-to-market value	The firm-level book-value divided by firm size. If used in return regressions, the natural logarithm of this measure is used.
Operating profit margin	The ratio of operating profit to sales.
Research and develop-ment-to-sales	The ratio of research and development expenses to sales.
Capital expenditures-to-sales	The ratio of capital expenditures to sales.
Block-ownership - insider	The total fraction of large stakes in common stock held by corporate insiders.
Block-ownership – out-sider	The total fraction of large stakes in common stock held by corporate outsiders.
Options availability	This variable is equal to one if the respective firm has exchange traded options on its common stock and zero other-wise.
Excess returns on the market	The monthly returns on the market in excess of the risk-free rate.
SMB	The monthly returns on the Fama and French (1995)-factor portfolio SMB.
HML	The monthly returns on the Fama and French (1995)-factor portfolio HML.
Excess stock returns	The individual monthly stock returns in excess of the risk-free rate.
Beta	The stock-level beta coefficient calculated as in Fama and French (1992).
Effective spread	The trade size-weighted daily average of the difference between the transaction price and the mid-point of the con-current primary market BBO quotes.
$BETA_{up}$	This variable is an up-market beta based on the definition of Pattengill and Sundaram (1995) and is equal to the estimated beta if excess market returns are positive and zero otherwise.
$BETA_{down}$	This variable is a down-market beta based on the definition of Pattengill and Sundaram (1995) and is equal to the estimated beta if excess market returns are negative and zero otherwise.

Table 3 – Summary Statistics

This table reports the summary statistics of the firm-level means of the variables listed in column *Name* calculated over the period between January 1995 and December 2005. The column *Observations* shows the total number of daily observations and the columns *Mean*, *Q1*, *Median*, *Q3*, and *IQ Range* report the mean, the first quartile, the median, the third quartile, and the difference between *Q3* and *Q1*. The unit of measurement is given by the symbols *bp*, *%*, and *$*, which refer to basis points, percentages, and dollar values respectively (see Table 2 for variable definitions).

	Measure	Observations	Mean	Q1	Median	Q3	IQ Range
Informed trading	IA_1 over 15 minutes (bp)	3,829,045	24.01	10.74	17.93	29.99	19.25
	IA_1 over 30 minutes (bp)	3,828,167	24.12	10.79	18.22	30.09	19.30
	IA_1 over 60 minutes (bp)	3,827,750	24.18	10.79	18.16	30.14	19.35
	IA_1 over 1 day (bp)	3,543,002	28.05	12.15	20.72	35.11	22.95
	PIN_1 (%)	22,164	16.39	12.34	15.58	19.67	7.34
Market-wide commonality	Market-level bid-ask spread (bp)	2,770	22.28	8.74	25.02	30.43	21.69
	Market-level trading volume (millions of $)	2,770	186.16	97.80	200.54	250.17	152.37
	Market-level volatility	2,770	20.70	15.40	20.11	24.44	9.04
	Market-level order-imbalance (%)	2,770	26.81	22.64	25.70	29.47	6.83
Stock-level trading characteristics	Company-level bid-ask spread (bp)	3,829,045	84.50	31.02	53.80	99.99	68.97
	Unexpected changes in bid-ask spread (bp)	3,829,045	0.17	-0.07	0.00	0.02	0.10
	Stock-level trading volume (bp)	3,829,045	85.27	-2.38	0.00	47.88	50.26
	Stock-level volatility (bp)	3,829,045	8.75	3.67	5.84	10.06	6.38
	Stock-level order-imbalance (%)	3,829,045	53.40	19.93	24.86	33.30	13.36
	Stock-level tick size (%)	3,829,045	7.10	3.06	4.62	7.83	4.77
Firm-specific structural characteristics	Firm size (10 millions of $)	3,829,045	401.19	37.17	92.87	258.48	221.31
	Operating profit margin (%)	3,829,045	17.00	7.19	13.72	24.07	16.88
	Book value-to-market value (%)	3,829,045	54.35	26.03	47.83	74.99	48.96
	Research and development-to-sales (%)	3,829,045	1.15	0.00	0.00	0.55	0.55
	Capital expenditures-to-sales (%)	3,829,045	8.32	1.22	3.72	7.64	6.42
	Block-ownership - insiders (%)	3,829,045	3.90	0.00	0.00	1.22	1.22
	Block-ownership - outsiders (%)	3,829,045	9.69	0.00	0.52	17.11	17.11
	Option availability (%)	3,829,045	62.48	0.00	100.00	100.00	100.00
Data used in return regressions	Excess return on the market (%)	132	0.70	-2.25	1.53	3.77	6.01
	SMB (%)	132	0.22	-2.47	-0.14	2.63	5.10
	HML (%)	132	0.43	-1.65	0.45	2.20	3.85
	Excess stock returns (%)	174,611	1.07	0.47	1.09	1.84	1.37
	Beta	3,629,560	0.97	0.76	0.91	1.15	0.39
	Effective spread (%)	3,829,045	0.68	0.26	0.44	0.79	0.53

Table 4 – Correlation of Informed Trading with Explanatory Variables

This table reports the correlation coefficients of the informed trading measures with our explanatory variables (see Table 2 for variable definitions). All values are statistically significant.

	Informed Trading				
	IA_1				
	15 min	30 min	60 min	1 day	PIN_1
IA_1 over 30 minutes	0.92				
IA_1 over 60 minutes	0.83	0.90			
IA_1 over 1 day	0.33	0.36	0.40		
PIN_1	0.27	0.26	0.24	0.11	
Market bid-ask spread	0.23	0.22	0.20	0.10	0.10
Market trading volume	-0.08	-0.08	-0.07	-0.04	-0.15
Market volatility	0.07	0.06	0.06	0.02	-0.06
Market order-imbalance	0.01	0.02	0.02	0.01	0.04
Stock bid-ask spread	0.56	0.56	0.51	0.23	0.38
Unexp. changes in B/A	0.24	0.24	0.21	0.08	-0.03
Stock trading volume	0.08	0.07	0.07	0.03	0.01
Stock volatility	0.07	0.07	0.08	0.06	0.01
Stock order-imbalance	-0.01	0.00	0.00	0.00	0.04
Stock tick size	0.42	0.41	0.37	0.16	0.26
Firm size	-0.12	-0.11	-0.11	-0.05	-0.27
Profit margin	-0.12	-0.12	-0.11	-0.05	-0.15
Book-to-market	0.14	0.15	0.13	0.06	0.21
Research and development	-0.04	-0.04	-0.04	-0.01	-0.12
Capital expenditures	0.02	0.02	0.01	0.01	0.02
Ownership - insider	0.01	0.01	0.01	0.00	0.06
Ownership - outsider	-0.03	-0.03	-0.03	-0.01	-0.02
Option availability	-0.16	-0.17	-0.15	-0.07	-0.46

Table 5 – Decomposition of Yearly Informed Trading

This table shows the results of regressing yearly informed trading, $InfoTrade_1$, on a firm-specific intercept and a set of explanatory variables. The results of estimating the following regression at once is shown in Panel A:

$$\begin{aligned} InfoTrade_{1,i,t} = {} & \beta_{i,0} + \beta_1 MBA + \beta_2 MVOL + \beta_3 MVLA + \beta_4 MOIB \\ & + \gamma_1 VLA_{i,t} + \gamma_2 BA_{i,t} + \gamma_3 OIB_{i,t} + \gamma_4 TIC_{i,t} + \gamma_5 UEDSpread_{i,t} + \gamma_6 VOL_{i,t} \\ & + \delta_1 Insider_{i,t} + \delta_2 Outsider_{i,t} + \delta_3 Capex_{i,t} + \delta_4 R\&D_{i,t} + \delta_5 BTM_{i,t} + \delta_6 Profit_{i,t} + \delta_7 Options_{i,t} + \delta_8 Size_{i,t} + \varsigma_{i,t}, \end{aligned}$$

whereas Panels B and C show the same regression estimated in three steps according to:

$$\begin{aligned} InfoTrade_{1,i,t} &= \beta_{i,0} + \beta_1 MBA + \beta_2 MVOL + \beta_3 MVLA + \beta_4 MOIB + \varepsilon_{i,t}, \\ InfoTrade_{2,i,t} &= \gamma_{i,0} + \gamma_1 VLA_{i,t} + \gamma_2 BA_{i,t} + \gamma_3 OIB_{i,t} + \gamma_4 TIC_{i,t} + \gamma_5 UEDSpread_{i,t} + \gamma_6 VOL_{i,t} + \eta_{i,t}, \\ InfoTrade_{3,i,t} &= \delta_{i,0} + \delta_1 Insider_{i,t} + \delta_2 Outsider_{i,t} + \delta_3 Capex_{i,t} + \delta_4 R\&D_{i,t} + \delta_5 BTM_{i,t} + \delta_6 Profit_{i,t} + \delta_7 Options_{i,t} + \delta_8 Size_{i,t} + \xi_{i,t}, \end{aligned}$$

where $InfoTrade_1$ is alternatively represented by PIN_1 or yearly averages of daily IA_1. The hypotheses associated with the individual explanatory variables are shown in Table 1 and the variable definitions are shown in Table 2. The regression coefficients associated with PIN_1 are in percentages and the coefficients associated with IA_1 are in basis points. *P*-values of a two-sided *t*-test of the coefficient being equal to zero are below (Panel A) or to the right (Panels B and C) of the respective coefficients in parentheses. The R^2, based on the derivation by Nagelkerke (1991), is in percentages. The variables in Panels B and C are presented in decreasing order of their contribution to the R^2.

Panel A – One-step Decomposition of the Information Environment

	Variables Capturing Features of the Information Environment of Investors																		
Information	Market-wide Commonality				Stock-level Trading Characteristics						Firm-specific Structural Characteristics								
Asymmetry											Ownership Struc.		Asset Tangibility		Window-dressing		Options as	Firm-	
Captured by	BA Spread	VOL	Vola	OIB	BA Spread	VOL	Vola	OIB	Tick Size	UED Spread	Insider	Outsider	Capex	R&D	BTM	Profit	Alternative	size	R^2
PIN_1	1.01	-1.35	-0.10	0.33	0.80	2.10	50.42	0.63	0.33	-0.51	0.24	-0.73	-0.11	-0.89	-0.24	-0.03	-1.50	-1.37	46.5
	(0.00)	(0.00)	(0.85)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.14)	(0.00)	(0.00)	(0.68)	(0.00)	(0.00)	
$IA_{1,15\ min}$	9.62	2.13	1.81	2.49	2.52	25.70	22.00	1.30	0.71	1.16	-0.17	-0.63	0.67	-1.03	-0.24	-0.35	-1.42	-10.55	44.3
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.68)	(0.56)	(0.00)	(0.55)	(0.00)	(0.00)	(0.05)	(0.12)	(0.05)	(0.00)	(0.00)	
$IA_{1,30\ min}$	8.74	1.91	1.89	2.56	2.54	25.17	24.57	0.83	1.43	1.12	-0.24	-0.62	0.65	-1.14	0.18	-0.30	-1.31	-10.62	44.1
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.90)	(0.24)	(0.00)	(0.42)	(0.00)	(0.00)	(0.03)	(0.23)	(0.10)	(0.00)	(0.00)	
$IA_{1,60\ min}$	9.32	1.83	1.90	2.60	2.46	21.97	23.68	0.92	1.32	1.07	-0.13	-0.54	0.61	-1.31	0.15	-0.44	-1.22	-10.34	48.6
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.25)	(0.00)	(0.63)	(0.01)	(0.00)	(0.01)	(0.31)	(0.01)	(0.00)	(0.00)	
$IA_{1,1\ day}$	10.60	1.27	1.81	3.64	5.86	0.99	36.30	1.08	0.32	1.11	0.44	0.10	0.57	-1.88	-0.22	-1.55	-1.25	-10.94	31.9
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.64)	(0.00)	(0.05)	(0.13)	(0.00)	(0.39)	(0.78)	(0.11)	(0.04)	(0.42)	(0.00)	(0.00)	(0.00)	

(continued)

Table 5 – Decomposition of Yearly Informed Trading (continued)
Panel B – Three-step Decomposition of the Information Environment Captured by PIN_1

	Variable	Coeff	p-value	R^2
Market-wide commonality	Volume	-1.31	(0.00)	39.7
	Order-imbalance	0.54	(0.00)	
	Volatility	0.14	(0.00)	
	Bid-ask spread	0.37	(0.00)	
Stock-level trading characteristics	Order-imbalance	0.34	(0.00)	43.5
	UED Spread	-0.28	(0.00)	
	Volume	1.87	(0.00)	
	Bid-ask spread	0.13	(0.00)	
	Volatility	54.00	(0.08)	
	Tick size	0.04	(0.35)	
Firm-specific structural characteristics	Firm size	-1.15	(0.00)	34.8
	Ownership - corporate outsiders	-0.77	(0.00)	
	Research and development	-0.92	(0.00)	
	Option availability	-2.47	(0.00)	
	Book-to-market	-0.29	(0.00)	
	Ownership - corporate insiders	0.27	(0.01)	
	Capital expenditures	-0.14	(0.07)	
	Profit margin	-0.05	(0.42)	

Panel C – Three-step Decomposition of the Information Environment Captured by IA_1

Variable		Coeff	p-value	R^2
Market-wide commonality	Bid-ask spread	9.01	(0.00)	16.0
	Volatility	2.31	(0.00)	
	Volume	3.97	(0.00)	
	Order-imbalance	2.49	(0.00)	
Stock-level trading characteristics	Volatility	29.47	(0.00)	30.7
	UED Spread	2.98	(0.00)	
	Bid-ask spread	1.83	(0.00)	
	Volume	26.50	(0.00)	
	Tick size	2.61	(0.00)	
	Order-imbalance	1.24	(0.00)	
Firm-specific structural characteristics	Firm size	-9.27	(0.00)	21.2
	Profit margin	-0.64	(0.00)	
	Option availability	-1.15	(0.00)	
	Capital expenditures	0.50	(0.02)	
	Research and development	-1.29	(0.01)	
	Ownership - corporate outsiders	-0.21	(0.34)	
	Book-to-market	-0.14	(0.35)	
	Ownership - corporate insiders	-0.06	(0.63)	

Table 6 – Time-series and Cross-sectional Associations in Daily Informed Trading

This table shows the results of regressing daily values of informed trading measured by IA_1 on a firm-specific intercept and a set of explanatory variables by firm size decile according to:

$$IA_{1,i,t} = \beta_{i,0} + \beta_1 MBA + \beta_2 MVOL + \beta_3 MVLA + \beta_4 MOIB + \varepsilon_{i,t},$$
$$IA_{2,i,t} = \gamma_{i,0} + \gamma_1 VLA_{i,t} + \gamma_2 BA_{i,t} + \gamma_3 OIB_{i,t} + \gamma_4 TIC_{i,t} + \gamma_5 UEDSpread_{i,t} + \gamma_6 VOL_{i,t} + \eta_{i,t},$$
$$IA_{3,i,t} = \delta_{i,0} + \delta_1 Insider_{i,t} + \delta_2 Outsider_{i,t} + \delta_3 Capex_{i,t} + \delta_4 R\&D_{i,t} + \delta_5 BTM_{i,t} + \delta_6 Profit_{i,t} + \delta_7 Options_{i,t} + \delta_8 Size_{i,t} + \xi_{i,t},$$

where IA_1 is estimated over 60 minutes. The hypotheses associated with the individual explanatory variables are shown in Table 1 and the variable definitions are shown in Table 2. Panel A presents the results of regressing IA_1 on variables that capture market-wide commonality. Panel B presents the results of regressing IA_2 on stock-level trading characteristics, and Panel C shows the results of regressing IA_3 on firm-specific structural characteristics. In the table below, the column *Decile* shows the size group with *Decile 10* referring to the largest size group. Regression coefficients shown in column *Coeff* are in basis points, p-values are to the right of the respective coefficients in parentheses and the R^2 is in percentages (based on the derivation by Nagelkerke (1991)). The variables are presented in decreasing order of their contribution to the average explanatory power going from the left to the right.

Panel A – Market-wide Commonality in Daily Informed Trading

	Bid-ask spread		Volume		Volatility		Order-imbalance		
Decile	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	R^2
1	14.08	(0.00)	5.99	(0.00)	4.13	(0.00)	0.16	(0.32)	37.2
2	11.26	(0.00)	2.81	(0.00)	2.75	(0.00)	0.43	(0.00)	40.7
3	10.38	(0.00)	2.64	(0.00)	1.65	(0.00)	0.36	(0.00)	41.3
4	8.76	(0.00)	1.73	(0.00)	1.27	(0.00)	0.69	(0.00)	40.6
5	7.80	(0.00)	1.46	(0.00)	1.13	(0.00)	0.92	(0.00)	40.1
6	7.02	(0.00)	1.40	(0.00)	0.91	(0.00)	1.18	(0.00)	39.7
7	6.05	(0.00)	0.97	(0.00)	0.61	(0.00)	1.12	(0.00)	39.2
8	5.26	(0.00)	0.80	(0.00)	0.59	(0.00)	1.21	(0.00)	38.5
9	4.26	(0.00)	0.55	(0.00)	0.32	(0.00)	1.25	(0.00)	37.8
10	3.24	(0.00)	0.50	(0.00)	0.39	(0.00)	1.34	(0.00)	38.1

Panel B – Informed Trading and Stock-level Trading Characteristics

	Volatility		UED Spread		Bid-ask spread		Volume		Tick size		Order-imbalance		
Decile	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	R^2
1	5.09	(0.00)	3.08	(0.00)	12.60	(0.00)	7.16	(0.00)	3.09	(0.00)	4.06	(0.00)	39.1
2	5.81	(0.00)	3.12	(0.00)	4.98	(0.00)	3.41	(0.00)	-1.30	(0.00)	3.00	(0.00)	39.6
3	5.64	(0.00)	2.90	(0.00)	3.56	(0.00)	2.44	(0.00)	-1.06	(0.00)	2.73	(0.00)	39.4
4	7.47	(0.00)	2.82	(0.00)	2.50	(0.00)	1.89	(0.00)	-1.04	(0.00)	2.38	(0.00)	39.2
5	4.30	(0.00)	2.34	(0.00)	2.02	(0.00)	1.68	(0.00)	-0.62	(0.00)	2.08	(0.00)	37.8
6	6.60	(0.00)	2.16	(0.00)	1.54	(0.00)	1.44	(0.00)	-0.65	(0.00)	1.87	(0.00)	37.3
7	5.49	(0.00)	1.56	(0.00)	1.17	(0.00)	1.15	(0.00)	-0.28	(0.00)	1.71	(0.00)	36.3
8	8.84	(0.00)	1.43	(0.00)	0.69	(0.00)	1.03	(0.00)	-0.28	(0.00)	1.68	(0.00)	36.2
9	8.08	(0.00)	1.12	(0.00)	0.44	(0.00)	0.88	(0.00)	-0.23	(0.00)	1.64	(0.00)	35.2
10	12.32	(0.00)	0.91	(0.00)	0.11	(0.00)	0.81	(0.00)	-0.04	(0.04)	1.68	(0.00)	37.4

(continued)

Table 6 – Time-series and Cross-sectional Associations in Daily Informed Trading (continued)

Panel C – Informed Trading and Firm-specific Structural Characteristics

	Firm Size		Profit		BTM		Outsider		Insider		R&D		Capex		Options		
Decile	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	R^2
1	-21.67	(0.00)	-2.24	(0.00)	-1.11	(0.00)	9.00	(0.00)	6.57	(0.00)	-2.24	(0.01)	1.26	(0.00)	5.46	(0.00)	32.9
2	-18.95	(0.00)	-2.53	(0.00)	-0.31	(0.05)	1.19	(0.00)	-1.79	(0.00)	-2.74	(0.00)	-0.01	(0.98)	4.50	(0.00)	37.9
3	-9.83	(0.00)	-2.26	(0.00)	-0.03	(0.82)	0.58	(0.01)	0.12	(0.67)	-1.65	(0.00)	-1.29	(0.00)	1.79	(0.00)	37.9
4	-9.23	(0.00)	-1.31	(0.00)	0.55	(0.00)	0.51	(0.00)	1.73	(0.00)	0.13	(0.73)	-0.79	(0.00)	1.11	(0.00)	35.9
5	-4.35	(0.00)	-1.39	(0.00)	0.13	(0.27)	0.52	(0.00)	1.38	(0.00)	0.60	(0.17)	-0.02	(0.91)	-0.31	(0.00)	35.7
6	-6.20	(0.00)	-0.87	(0.00)	0.04	(0.68)	1.03	(0.00)	0.30	(0.07)	0.43	(0.23)	-1.11	(0.00)	-1.66	(0.00)	34.6
7	-3.87	(0.00)	-0.89	(0.00)	0.51	(0.00)	0.86	(0.00)	0.35	(0.01)	-0.11	(0.65)	-0.21	(0.05)	-0.87	(0.00)	33.9
8	-2.82	(0.00)	-0.40	(0.00)	0.91	(0.00)	0.25	(0.00)	-0.19	(0.10)	-1.55	(0.00)	0.20	(0.05)	-1.09	(0.00)	32.3
9	-2.26	(0.00)	-0.35	(0.00)	0.27	(0.00)	-0.17	(0.00)	-0.66	(0.00)	-0.61	(0.00)	-0.13	(0.13)	-0.62	(0.00)	31.3
10	-1.31	(0.00)	0.16	(0.00)	0.38	(0.00)	0.14	(0.00)	0.35	(0.00)	0.66	(0.00)	-0.23	(0.00)	-0.31	(0.00)	30.7

Table 7 – Analysis of Common Variation and Idiosyncratic Informed Trading

The table below shows a decomposition of explained variation in informed trading, $\mathrm{Var}\left(\widehat{IA}_1\right)$, into three components by estimating the following regression for every stock individually:

$$IA_{1,t} = \alpha_0 + \sum_{i=1} \beta_i Commonality_{i,t} + \sum_{j=1} \gamma_j Trading_{j,t} + \sum_{k=1} \delta_k Structural_{k,t} + \varepsilon_t .$$

Thereafter, the following statistics are calculated:

$$\mathrm{REP_{Commonality}} = \frac{\mathrm{Var}\left(\sum_{i=1} \hat{\beta}_i \mathrm{Commonality}_i\right)}{\mathrm{Var}\left(\widehat{IA}_1\right)},\ \mathrm{REP_{Trading}} = \frac{\mathrm{Var}\left(\sum_{j=1} \hat{\gamma}_j \mathrm{Trading}_j\right)}{\mathrm{Var}\left(\widehat{IA}_1\right)},\ \mathrm{REP_{Structural}} = \frac{\mathrm{Var}\left(\sum_{k=1} \hat{\delta}_k \mathrm{Structural}_k\right)}{\mathrm{Var}\left(\widehat{IA}_1\right)},$$

where *REP* denotes the relative explanatory power related to *i* market-wide *Commonality* components, to *j* stock-level *Trading* characteristics and to *k Structural* characteristics. Numbers below are averages of the firm-level $REP_{Commonality}$, $REP_{Trading}$, and $REP_{Structural}$ calculated by regressing IA_1 estimated over 60 minutes for each stock individually on all explanatory variables and summing up the ratios of explained to total variance by commonality, trading, and structural components. *Unexplained Informed Trading* is the average of one minus the R-square from the stock-level ordinary least-square regressions. Results are shown by firm size decile, where *Size Decile* is calculated based on the average market capitalization a firm has over the entire sample period. Numbers in the table below are in percentages.

	Average Relative Explanatory Power of (in %)			Unexplained Informed Trading (in %)
Size Decile	Market-wide Commonality	Stock-level Trading Characteristics	Firm-specific Structural Characteristics	
1	27.7	64.4	7.9	78.1
2	32.8	59.6	7.6	75.7
3	40.8	52.3	6.9	73.7
4	43.7	49.3	7.0	73.8
5	47.1	45.3	7.6	73.1
6	47.6	44.8	7.6	71.8
7	53.4	39.7	6.9	72.1
8	57.7	36.1	6.2	70.9
9	62.4	31.0	6.6	69.3
10	60.9	33.6	5.4	68.0

Table 8 – Cross-sectional Returns and Components of Informed Trading

This table shows the results of a Fama and MacBeth (1973)-type cross-sectional regression of monthly portfolio returns in excess of the one-month Treasury bill rate on a set of explanatory variables and the average level of informed trading during the previous month. The regression is estimated monthly January 1995 and December 2005:

$$R_p^e = \kappa_0 + \kappa_1 BETA_{up,p} + \kappa_2 BETA_{down,p} + \kappa_3 Size_p + \kappa_4 BTM_{up} + \kappa_5 InfoTrade_{k,p} + \zeta_t,$$

where $BETA_{up}$ and $BETA_{down}$ are up-market and down-market betas, respectively, the subscript p denotes portfolio p, and $InfoTrade_k$ refers to the measure k of informed trading or the average level of daily effective spread during the previous month (see Table 2 for variable definitions). Panel A shows the results when the regressions are estimated using the monthly excess returns of 50 portfolios formed on the average level of $InfoTrade_k$ during the previous year, whereby $InfoTrade_k$ is captured by PIN_1, PIN_2, PIN_3, PIN_{RAIN}, or PIN_{EXIT}. Panel B shows the results when the regressions are estimated using the monthly excess returns of 50 portfolios formed on the average level of $InfoTrade_k$ during the previous month, whereby $InfoTrade_k$ is captured by the effective spread, IA_1, IA_2, IA_3, IA_{RAIN}, or IA_{EXIT}. IA_{RAIN2} or PIN_{RAIN2} is calculated by regressing all explanatory variables on IA_1. Portfolios are based on IA_{RAIN} or PIN_{RAIN} if $InfoTrade_k$ is not included in the regression. IA_1 is estimated over 60 minutes. *T*-values are based on the Litzenberger and Ramaswamy (1979)-adjustment. The coefficients, shown in columns *Coeff*, are in percentages with *p*-values based on a two-sided *t*-test of the coefficient being equal to zero in parentheses to the right of the respective coefficients. The column R^2 shows the average adjusted R-square from the individual cross-sectional regressions.

Panel A – Cross-sectional Return-Association of PIN_1

PIN_1		PIN_2		PIN_3		PIN_{RAIN}		PIN_{EXIT}		PIN_{RAIN2}		Book-to-Market		Firm Size		Beta: Down-market		Beta: Up-market		Intercept		
Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	R^2
												-0.69	(0.00)	-0.37	(0.00)	-6.73	(0.00)	3.42	(0.00)	3.27	(0.01)	23.2
2.38	(0.06)											-0.78	(0.00)	-0.23	(0.08)	-6.99	(0.00)	2.59	(0.00)	2.59	(0.10)	29.9
		2.23	(0.04)									-0.76	(0.00)	-0.25	(0.06)	-7.00	(0.00)	2.50	(0.00)	2.81	(0.07)	29.9
				1.92	(0.04)							-0.56	(0.00)	-0.16	(0.24)	-6.78	(0.00)	3.33	(0.00)	1.61	(0.33)	29.5
						2.52	(0.03)					-0.72	(0.00)	-0.26	(0.05)	-5.96	(0.00)	3.21	(0.00)	2.00	(0.18)	26.5
								-6.11	(0.34)			-0.55	(0.00)	-0.82	(0.00)	-5.81	(0.00)	3.05	(0.00)	6.76	(0.00)	27.5
										2.08	(0.03)	-0.56	(0.00)	-0.25	(0.04)	-7.19	(0.00)	3.02	(0.00)	2.64	(0.06)	26.2

(continued)

Panel B – Cross-sectional Return-Association of IA_1

Effective Spread		IA_1		IA_2		IA_3		IA_{RAIN}		IA_{EXIT}		IA_{RAIN2}		Book-to-Market		Firm Size		Beta: Down-market		Beta: Up-market		Intercept		
Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	R^2
-96.72	(0.00)													-0.04	(0.98)	0.20	(0.04)	-1.26	(0.00)	1.98	(0.00)	-2.02	(0.21)	27.4
														-0.50	(0.16)	0.17	(0.01)	-1.19	(0.00)	1.78	(0.00)	-2.37	(0.20)	22.6
		326.68	(0.00)											0.00	(0.77)	-0.07	(0.08)	-1.32	(0.00)	1.38	(0.00)	2.62	(0.28)	29.7
				329.68	(0.00)									-0.19	(0.70)	-0.08	(0.05)	-1.43	(0.00)	1.42	(0.00)	2.71	(0.12)	32.6
						221.50	(0.00)							0.08	(0.47)	-0.24	(0.08)	-1.75	(0.00)	1.28	(0.00)	5.36	(0.02)	33.8
								369.09	(0.00)					-0.10	(0.99)	-0.26	(0.01)	-1.18	(0.00)	1.35	(0.00)	-3.37	(0.03)	34.7
										-608.68	(0.00)			-0.09	(0.59)	0.00	(0.88)	-1.46	(0.00)	2.29	(0.00)	0.48	(0.71)	36.6
												62.69	(0.00)	-2.00	(0.00)	-0.10	(0.02)	-1.63	(0.00)	1.29	(0.02)	-1.94	(0.59)	43.1

Table 9 – Pooled Time-series Cross-sectional Association of Informed Trading and Returns

This table shows the results of fitting a pooled time-series cross-sectional generalized least square regression of monthly portfolio excess returns on monthly factor returns and the average level of informed trading during the previous month:

$$R^e_{s,j,t} = \alpha + \sum_{s=1}^{5}\sum_{j=1}^{5}\left(\psi_{s,j} R^m_{s,j,t} + \phi_{s,j} SMB_{s,j,t} + \lambda_{s,j} HML_{s,j,t}\right) + \theta Rank_{s,j,t} + \chi_{s,j} + \upsilon_{s,j,t},$$

$$R^e_{s,p,j,t} = \rho + \sum_{s=1}^{5}\sum_{p=1}^{5}\sum_{j=1}^{5}\left(\mu_{s,p,j} R^m_{s,p,j,t} + \vartheta_{s,p,j} SMB_{s,p,j,t} + \tau_{s,p,j} HML_{s,p,j,t}\right) + \varpi Rank_{s,p,j,t} + \sigma_{s,p,i} + o_{s,p,j,t}.$$

Subscript *s* denotes the firm size group, subscript *p* indicates the book-to-market group, subscript *j* the rank of the level of informed trading, and *t* is the time-index. Five monthly firm size groups and book-to-market groups are formed based on firm size and the book-to-market ratio at the end of the previous year. Similarly, the average level of informed trading of every stock during the previous month is used to calculate informed trading quintiles. The lowest level of informed trading is assigned informed trading quintile rank 1 and the highest level of informed trading is assigned quintile rank 5. Portfolio excess returns, R^e, are calculated as the equally-weighted cross-sectional mean of monthly stock returns in excess of the one-month Treasury bill rate of all stocks that are in the same firm size group and have the same informed trading quintile rank (to calculate $R^e_{s,j,t}$) or that are in the same firm size group, are in the same book-to-market group, and have the same informed trading quintile rank (to calculate $R^e_{s,p,j,t}$). $R^m_{s,j,t}$, $SMB_{s,j,t}$, and $HML_{s,j,t}$ are equal to the market excess returns, and the returns on the SMB and HML factor portfolios, if the respective portfolio belongs to firm size group *s* and to informed trading quintile rank *j* and zero otherwise. $R^m_{s,p,j,t}$, $SMB_{s,p,j,t}$, and $HML_{s,p,j,t}$ are equal to the market excess returns, and the returns on the SMB and HML factor portfolios if the respective portfolio belongs to firm size group *s*, to book-to-market group *p*, and to informed trading quintile rank *j* and zero otherwise. Informed trading is captured by IA_1 estimated over 60 minutes. The estimation uses a generalized least square regression with a random intercept model to account for potential correlation within portfolios. The column *Portfolio Sort* shows that the portfolios are formed based on size, book-to-market, and informed trading (*Size*, *BTM*, *and IA*). The portfolio-specific coefficients of R^m, *SMB*, and *HML* are suppressed for clarity of exposition. Coefficients (*Coeff*) are in percentages and the associated *p-value* is in parentheses to the right.

	IA_1		IA_2		IA_3		IA_{RAIN}		IA_{EXIT}	
Portfolio Sort	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
Size, BTM, and IA	–1.1	(0.68)	42.2	(1.00)	0.8	(0.80)	3.0	(0.01)	1.3	(0.56)

Table 10

Principal Component Analysis on *RAIN*

This table reports the results of a principal component analysis on the *RAIN* time-series. Only stocks that have observations for at least 97.5% of the sample period are used. The column *"RAIN Based on"* shows the horizon over which IA_1 used to construct *RAIN* is estimated, the column *Number of Days* shows the number of days of the sample period included in the estimation, whereas *Number of Firms* shows how many individual firms are included. *Sample Variance Explained (%)* shows the percentage of the total *RAIN*-variance explained by the first, second, and third principal component (*PC*), whereby the second row shows the cumulative variance explained.

			Sample Variance Explained (%)		
RAIN Based on	Number of Days	Number of Stocks	1^{st} PC	2^{nd} PC	3^{rd} PC
IA_1 over 15 minutes	1,235.00	656.00	7.05	3.77	1.08
			7.05	10.82	11.90
IA_1 over 30 minutes	1,244.00	655.00	5.17	2.78	0.96
			5.17	7.95	8.92
IA_1 over 60 minutes	1,224.00	656.00	4.20	2.00	0.93
			4.20	6.20	7.13
IA_1 over 1 day	1,253.00	574.00	3.41	1.02	0.89
			3.41	4.43	5.32

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