Information Asymmetry and the Cost of Capital: The Influence of Public and Private Information*

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Abstract

We estimate the level of informed trading stemming from private information, and that which manifests from processed public information, and find risk-adjusted cost of capital is higher in stocks with higher levels of skilled information processing, but not with higher levels of private information trading. A long-short portfolio based on the level of skilled information processing has annualized abnormal returns of 9.75%. When limited to the smallest quintile of stocks, the abnormal returns grow to 29.69%. Consistent with skilled information processing being a product of firms' public information environments, we find that the relation between cost of capital and skilled information processing is weaker in firms with more competition for information. We compute a risk factor based on information asymmetry due to skilled information processing. This factor significantly affects returns in the time series, especially in small stocks. After accounting for this risk factor, abnormal returns are drastically reduced, suggesting that the commonality in informed trading due to skilled information processing is, in fact, a priced risk factor for equity securities.

Keywords: Informed Trading, Commonality, Information Environment, Information Asymmetry

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Abstract

We estimate the level of informed trading stemming from private information, and that which manifests from processed public information, and find risk-adjusted cost of capital is higher in stocks with higher levels of skilled information processing, but not with higher levels of private information trading. A long-short portfolio based on the level of skilled information processing has annualized abnormal returns of 9.75%. When limited to the smallest quintile of stocks, the abnormal returns grow to 29.69%. Consistent with skilled information processing being a product of firms' public information environments, we find that the relation between cost of capital and skilled information processing is weaker in firms with more competition for information. We compute a risk factor based on information asymmetry due to skilled information processing. This factor significantly affects returns in the time series, especially in small stocks. After accounting for this risk factor, abnormal returns are drastically reduced, suggesting that the commonality in informed trading due to skilled information processing is, in fact, a priced risk factor for equity securities.

1. Introduction

A large body of finance 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 cost of equity capital.

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, Liu, and Liu, 2007), or the ability to generate a private informational advantage from skilled analysis of firm-specific or market-wide public information (Kim and Verrecchia, 1994, 1997; Piotroski and Roulstone, 2005; Alldredge and Cicero, 2015). 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, Roll, and Subrahmanyam, 2000; Gilson, Healy, Noe, and Palepu, 2001), or related to the trading environment (Madrigal, 1996; Easley, O'Hara, and Srinivas, 1998) or to the structural characteristics of the firm (Bhushan, 1989; Dennis and Weston, 2001; Odders-White and Ready, 2005). Accordingly, we partition observed information asymmetry into an unpredictable component based on firm-specific conventional private information, and a predictable component based on public information, and arguably dependent not only on the characteristics of the firm, but also on market-wide factors, and thereby exhibiting commonality across stocks.

This study finds that the marginal firm's risk-adjusted cost of capital is higher in when skilled information processing (expected information asymmetry) levels are higher, but not when levels of private, idiosyncratic informed trading is higher, particularly in small stocks. These findings hold in both cross-sectional and time-series pricing tests. We find that the relation between cost of capital and skilled information processing is weaker in firms with more analysts, better accrual quality, and after *Regulation Fair Disclosure* (Reg FD) was adopted, suggesting that the information risk arising from skilled information processing is a product of firms' public information environments.

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 therefore employ the *adverse selection cost* measure widely used to directly proxy for informed trading (Huang and Stoll, 1996; Bessembinder and Kaufman, 1997; and Hansch, Naik, and Viswanathan, 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[1]. 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.

If one takes the conventional view that informed trading arises solely from insiders with firm-specific hard information, then this type of privately informed trading should exhibit no form of persistence within a stock, nor commonality among stocks. However, we find that informed trading for a given stock is determined by both lagged informed trading and market-wide levels of informed trading, as well as other firm-specific and market-wide factors. This suggests that information asymmetry, at least in part, can also result from private information about market-wide risk factors or skilled processing of public information. To our knowledge, this is the first documentation of

[1] While recent literature (Hasbrouck and Saar, 2009; Collin-Dufresne and Fos, 2015; and O'Hara, 2015) suggests that informed traders may use passive limit orders to trade on private information, rather than aggressively crossing the bid-ask spread, since our estimate of informed trading measures relative profits of liquidity demanders vis-à-vis liquidity suppliers, we only have to assume that informed traders use market or marketable limit orders more often than they use limit orders to trade on private information. This is highly likely, especially considering our sample spans 1995-2013.

commonality in informed trading. This finding not only offers further explanation for the phenomenon of the commonality in liquidity as documented by Chordia, et al. (2000), but more importantly, it also further explains why Easley and O'Hara (2004) find that stocks with greater information asymmetry have higher expected returns.

In his arbitrage theory of capital asset pricing, Ross (1976) states that expected returns should be based on non-diversifiable risk factors. As Hughes, et al. (2007) highlight, returns from prototypical informed trading should be idiosyncratic, and therefore not be a determining factor in a firm's cost of capital. If commonality in information asymmetry exists, as we show, then it is not completely diversifiable, so one may expect returns to be based in part on a stock's level of non-diversifiable information asymmetry, or the component of information asymmetry caused by skilled information processing.

As evidence of this, results from two-dimensional portfolio sorts indicate that the risk-adjusted cost of capital increases in stocks with higher levels of skilled information processing. In fact, a long-short portfolio based on the level of skilled information processing has risk-adjusted annualized abnormal returns of 9.75%. While we find evidence of this effect at all firm sizes, we find that these returns are most prominent in small stocks. If the long-short portfolio is limited to only the smallest quintile of stocks, the annualized abnormal returns grow to 29.69%. These results indicate that skilled information processing is not only positively associated with expected returns, but it may also explain part of the small-firm premium phenomenon.

Accordingly, we test the pricing relevance of overall information asymmetry, skilled information processing, and private information trading in the cross-section – and later in the time series. Using Fama and MacBeth (1973) regressions, we find that cost of capital is positively related to the level of skilled information processing in the cross-section, but not the level of private information trading.

Consistent with the pricing of information asymmetry being a product of firms' information environments[2], we find that the cross-sectional relation between the cost of capital and skilled information processing is weaker in firms with more analysts, better accrual quality, and after Reg FD is adopted.

To test the pricing relevance of skilled information processing in the time series, we compute a risk factor based on returns of firms with high and low levels of skilled information processing. We find that this risk factor significantly affects returns in the time series, especially in small stocks. More importantly, after accounting for this risk factor in a Fama and French (1993) multifactor model, we find that abnormal returns (regression intercepts) are drastically reduced, suggesting that the commonality in informed trading due to skilled information processing is in fact a priced risk factor for equity securities.

Our conclusions are consistent with the empirical findings of Easley and O'Hara (2004) in that we show that information asymmetry is a priced risk factor in US equity markets. Moreover, our findings are consistent with the implications of Hughes, et al. (2007) as we show that a firm's cost of equity capital is not a function of idiosyncratic private information held by corporate insiders, but rather it is a function of undiversifiable risk – namely the level of informed trading arising from either skilled processing of public information or private signals about systemic risk factors.

This paper contributes to the literature in four primary ways. First and foremost, we develop two new measures of informed trading, EXIT and RAIN, measuring information asymmetry arising from skilled information processing and prototypical private informed trading, respectively. Second, we document that informed trading exhibits commonality in the cross-section as well as persistence in the time series, suggesting that at least a portion of informed trading is caused by the skilled processing of publicly-available information, rather than the prototypical insider trading on

[2] See Lambert, Leuz, and Verrecchia (2007, 2011), Akins, Ng, and Verdi (2012), and Bhattacharya, Desai, and Venkataraman (2013).

privately-held information. Third, we show that the skilled information processing component of informed trading is a priced in expected returns, both in the cross section, and in the time series. Finally, we show that firms with stronger information environments, and more competition for information exhibit a weaker association between skilled information processing and the cost of capital.

2. Hypothesis Development

Chordia, et al. (2000) document a commonality in quoted spreads, quoted depths, and effective spreads even after controlling for known determinants of liquidity. They suggest that inventory risks and asymmetric information may be influencing market-wide changes in liquidity. Tookes (2008) presents a theory showing that part of this phenomenon could be explained by traders using information to trade in the stocks of competitors. Furthermore, Easley, Engle, O'Hara, and Wu (2008) show that the probability of informed trading (PIN) exhibits correlation across assets and recognizable patterns. This leads us to our first hypothesis:

Hypothesis 1: *Informed trading displays commonality in the cross section and persistence over time.*

Moreover, Engelberg, Reed, and Ringgenberg (2012) find evidence that a considerable portion of short sellers' advantage in trading is derived from their ability to process publicly-available information. In this context, we assert that the commonality and persistence in informed trading arise from the skilled processing of public information of a firm – or private information about public risk factors as suggested by Hughes, et al. (2007).

Information risk has been shown by Easley, Hvidkjaer, and O'Hara (2002), Easley and O'Hara (2004), Aslan, Easley, Hvidkjaer, and O'Hara (2011), Hwang, Lee, Lim, and Park (2013), and Brennan, Huh, and Subrahmanyam (2015) to have a positive relation with expected return. Others, such as, Duarte and Young (2009) and Mohanram and Rajgopal (2009) find that information risk is not priced in expected stock returns and is instead an idiosyncratic risk. We contribute to this literature by suggesting that traditional measures of informed trading – whether PIN, adverse selection costs, or other measures – contain components of information risk which are diversifiable and idiosyncratic, and those which are not diversifiable, as evidenced by the commonality in informed trading. Therefore, the expected return of a stock should be positively related to the expected informed trading of the stock, but not with the private informed trading risk. Since we can use the commonality and persistence in informed trading to separate the two, we are able to test this.

Hypothesis 2: *In the cross section, the cost of equity capital should be a function of the level of expected informed trading.*

Lambert, Leuz, and Verrecchia (2007, 2011) show that high-quality disclosure can reduce the cost of capital due to information risk, and that asymmetric information risk should only be priced when competition for information is imperfect. Akins, Ng, and Verdi (2012) thus create empirical measures of information competition and find a lower pricing of informed trading when there is more competition. Consequently, if the cross-sectional pricing of expected informed trading is indeed a function of skilled processing of public information, then in firms with better informational environments – more institutional competition for information, more equity analysts, and higher accrual quality – the cost of capital should be significantly less dependent on the level of skilled information processing.

While Core, Guay, and Verdi (2008) find that accruals quality is not a priced risk factor in stock returns – in contrast to Francis, LaFond, Olsson, and Schipper (2005) – Callen, Khan, and Lu (2013) show that accruals quality has a direct effect on price efficiency while Bhattacharya, Desai, and Venkataraman (2013) show that earnings quality directly affects information asymmetry and Levi and Zhang show that temporary increases in information asymmetry affect the cost of capital. Accrual quality should therefore be representative of the firms' informational environment. Firms with greater information uncertainty (worse accrual quality) should have a worse competition for information, and skilled information processing should therefore have a greater effect on the cost of capital. Similarly, Callen, et al. (2013) use the number of analysts following a stock as a measure of investor attention, suggesting that greater analyst following should lead to greater competition for information, and thus a lower pricing of skilled information processing.

Similarly, since information dissemination became more uniform following Reg FD – in which firms were prohibited by the Securities and Exchange Commission (SEC) from disclosing material information to certain parties unless the information is simultaneously or previously distributed to the public – information environments should have improved uniformly after Reg FD was adopted. This should have ultimately had the effect of improving competition for information and, according to Lambert, et al. (2007, 2011), reducing the effect of information asymmetry on the cost of capital. Akins, et al. (2012) show that following Reg FD, competition for information indeed improved, and the relation between expected returns and information asymmetry was reduced. This leads us to our third hypothesis, that this effect should also be true for the relation between expected returns and skilled information processing.

Hypothesis 3: *The relation between cost of capital and skilled information processing is weaker in firms with better information environments and after Reg FD was adopted.*

In his arbitrage pricing theory, Ross (1976) introduces a model in which a non-diversifiable risk factor other than the market risk premium can be a priced risk factor in expected stock returns. Since, numerous studies, most notably Fama and French (1993) and Carhart (1997) document and test risk factors which may be priced. If informed trading does indeed exhibit commonality and persistence, and this is indeed a product of imperfect competition for information, and skilled processing of publicly-available information, then there should exist a component of information asymmetry, namely skilled information processing, which is not diversifiable, and which could therefore affect the cost of capital, leading us to Hypothesis 4.

Hypothesis 4: *In the time series, cost of equity capital should be a function of non-diversifiable factors, including skilled information processing.*

3. Sample

3.1 Data

We use NYSE Trade and Quote (TAQ) data to calculate all intraday measures in this paper. Our sample covers trading hours from 9:30 am to 4:00 pm, ranging from 1995 to 2013. We calculate the national best bid and offer (NBBO) quotes for each order through the trading day using the quote dataset, and then merge the NBBO quotes into the trade dataset and sign each trade as a buy or sell following the Lee and Ready (1991) algorithm. From this data, we then compute dollar order imbalance, proportional quoted spreads (scaled by mid-quote prices), mid-quote prices, and adverse selection cost for each trade. We aggregate these measures for every stock on every day, summing the number of trades, volume, and dollar order imbalance, averaging the quoted spreads, and computing volume-weighted averages of adverse selection costs. Finally, we calculate the percentage change in quoted spread and compute the order imbalance ratio by scaling dollar order imbalance by dollar volume and taking the absolute value.

We acquire daily returns, closing price, and shares outstanding for each stock from CRSP. Subsequently, we estimate daily volatility as the squared return, tick-size as the reciprocal of the closing price, market capitalization as the product of closing price and shares outstanding. All daily variables are then winsorized at the 1st and 99th percentiles.

We collect annual firm-level accounting data from COMPUSTAT, including assets, operating cash flows, receivables, inventory, payables, current assets, taxes payable, property, plant, and equipment, revenue, and industry. We use this data to compute accrual quality following Dechow and Dichev (2002). We collect the number of analysts following a stock each earning announcement from IBES. Following Akins, et al. (2012), we calculate institutional competition as a Herfindal-Hirshman index of institutional ownership concentration, specifically the negated sum of the squared ratios of number of shares held by an institutional investor divided by the number of shares held by all institutional investors. So, if a firm had only 1 institutional investor, the competition index equals -1, but if there are many institutions, the index approaches 0. Therefore, a higher index value is indicative of more investor competition. We gather institutional holdings data from 13F filings collected by Thomson Reuters.

Market-level measures, including the Fama and French (1993) factors and the VIX index, are collected from Wharton Research Data Services (WRDS). We use the value-weighted market index (including dividend) series from CRSP for market return. We calculate several volume-weighted market-level variables ourselves, including average market order imbalance, average market quoted spread, and average market adverse selection costs using the following formula:

$$X_{-i,t} = \frac{\sum_{j \neq i}(X_{jt}V_{jt})}{\sum_{j \neq i}(V_{jt})}, \tag{1}$$

where X_{jt} is the firm-level variable of interest, V_{jt} is the volume of firm j on day t, and firm i is the firm of interest (this procedure ensures that a firm's own measures don't affect the estimates of the market-wide measures when testing for commonality).

To adjust for skewness, we take the natural logarithm of *quoted spread, volatility, (analysts + 1), tick size, market-average quoted spread,* and *VIX*. The log transformation gives these variables a distribution much closer to normal, making them more suitable for estimating predicted values in a regression setting.

3.2 Information Asymmetry Measures

To the extent that informed traders are demanders of liquidity, at least at the margin, one can discern the level of information asymmetry (or informed trading) in a stock by estimating the average profits of liquidity demanders, vis-à-vis liquidity suppliers. We therefore employ the *adverse selection cost* measure to estimate the level of informed trading in each stock. Similar measures are used by Huang and Stoll (1996), Bessembinder and Kaufman (1997), and Hansch, Naik, and Viswanathan (1999). Specifically, using the NBBO and inferred trade directions in conjunction with the TAQ trades data, we measure the daily adverse selection cost as the average k-minute midpoint return for liquidity demanders:

$$ASC(k)_{i,t} = \frac{1}{N}\sum_{r=1}^{N}\frac{d_{i,r}(m_{i,r+k}-m_{i,r})}{m_{i,r}} \tag{2}$$

where $m_{i,r}$ is the NBBO midpoint of stock i at trade r, $m_{i,r+k}$ is the NBBO midpoint k-minutes after trade r, d is the trade direction where +1 indicates a customer (liquidity demander) buy and -1 indicates a customer sell, and there are N trades on day t. We measure adverse selection costs at the 15-, 30-, and 60-minute levels.

While adverse selection cost (ASC) adequately captures average levels of information asymmetry in a stock on a given day, it fails to capture the source of the asymmetry. To split ASC into two components we use a regression-based methodology. Specifically, we regress ASC on several determinants of skilled information processing as well as commonality and persistence in informed trading. We then take the predicted values from this regression as the level of expected informed trading (EXIT), and the residuals from the regression as the residual asymmetric information (RAIN). While EXIT should capture persistence, commonality, and skilled information processing components of information asymmetry, RAIN should capture the components of ASC *not* associated with those aspects, and therefore, we assume that RAIN represents all the unexpected, or private information trading.

To split observed ASC into EXIT and RAIN, we regress ASC on several variables with previously documented associations with informed trading. For example, we include stock order imbalance, stock bid-ask spread, and change in the bid-ask spread as Glosten and Milgrom (1985) and Kyle (1985) posit that order imbalance is higher and bid-ask spreads are wider when information asymmetry is higher and decreases in liquidity are associated with informed trades. We include firm volatility and return because French and Roll (1986) show that informed trading is the principle factor behind high variances. We include tick size because Chordia, Roll, and Subrahmanyam (2005) show that lower tick sizes are associated with more efficient prices, and this should display greater levels of informed trading, due to the ease of trading. To capture the commonality in informed trading, we use market-level measures of bid-ask spread, volatility, return, and order imbalance, as well as the market average ASC, since a positive relation between stock- and market-level ASC would be indicative of commonality in informed trading. Similarly, to capture persistence in informed trading, we include the lagged value of the previously mentioned variables (excluding tick size due to its persistence), as well as the lagged value of the stock-level ASC. We also include the percentage of institutional ownership, the institutional competition, and the number of analysts covering the firm as information environment of the firm should play a large role in the level of informed trading, particularly the persistence and expected levels thereof. The results of these regressions are presented in Table 1.

Most notably, we see that adverse selection costs (measured at the 15-, 30- and 60-minute levels) are strongly positively associated with market adverse selection costs, both contemporaneously and in lagged form. We also see that adverse selection costs are strongly and positively autocorrelated. We interpret this as evidence that informed trading is both persistent in the time series and displays commonality in the cross-section. This result, in addition to the significance of other market-wide and lagged variables gives us confidence that the predicted values of these regressions (EXIT) are a representative estimation of expected informed trading, and therefore, the residuals from these regressions (RAIN) proxy for private information trading. Because regression results at the 15-, 30-, and 60-minute interval are similar we henceforth only present results from ASC(15), EXIT(15), and RAIN(15)[3].

3.3 Risk Factor Construction

To test the time-series pricing of the different aspects of information asymmetry, we create three risk factor which captures the return deriving from overall informed trading, skilled information processing, and private information trading. For example, we create the risk factor measuring skilled information processing for each day taking the return of an equally-weighted portfolio in which we

[3] Identical analysis using 30-, and 60- minute ASC measures was also completed. The results are similar to those presented in the remainder of the paper and are available upon request.

sell short the stock-days with the least skilled information processing (in the lowest quintile of EXIT(15)) and go long the stock-days with the most skilled information processing (in the highest quintile of EXIT(15))[4]. We label this factor *asymmetric minus symmetric* (or AMS) in reference to the amount of information asymmetry in the constituent stocks. Since we create three risk factors, we label the variable underlying the given risk factors with subscript (i.e. $AMS_{ASC(15)}$, $AMS_{EXIT(15)}$, $AMS_{RAIN(15)}$).

Descriptive statistics are displayed in Table 2. Panel A contains summary statistics while Panel B contains correlation of information asymmetry measures and Panel C contains correlations of market-level variables and risk factors. In Panel B, we see that ASC is positively correlated with market ASC. This, along with the significance of the market ASC coefficients in Table 1, give support to Hypothesis 1, that there is commonality in informed trading. We also see that the correlation between EXIT and market ASC is stronger than between market ASC and either ASC or RAIN. This suggests that EXIT does indeed capture this commonality in informed trading, and thus gives us a decent estimate of "expected informed trading" (at least relative to ASC and RAIN).

In Panel C, we see that all three forms of AMS are positively correlated with the market risk premium and the SMB factor. Hughes, et al. (2007) suggests that informed trading itself should not be a priced risk factor in expected returns, but private signals about market risk factors may be priced. While we later find evidence that expected informed trading is a priced risk factor, these correlations suggest that we cannot refute this assertion, and that our findings may indeed be influenced by private signals about market risk factors.

Most interestingly, we find that $AMS_{EXIT(15)}$ and $AMS_{RAIN(15)}$ are extremely correlated (0.9941). While both factors are highly correlated with $AMS_{ASC(15)}$ (0.8105, and 0.8247, respectively), this cannot fully explain why returns for stocks with high EXIT are higher than stocks with low EXIT on

[4] Since these portfolios are formed based on ex-post informed trading measures, no real profits could be made from this trading strategy.

the same days that returns for stocks with high RAIN are higher than stocks with low RAIN, when RAIN and EXIT themselves share a very low correlation by construction (in fact, these variables should be orthogonal, but have a very small correlation – see Panel B – due to winsorization). This is likely driven by days when both skilled information trading and private informed trading are a large risk to the marginal trader, for example prior to earnings announcements. While these confounding days may blur inferences about the time series pricing of skilled information processing, it should not influence the cross-sectional pricing results.

4. Empirical Results

To informally inspect the relation between the cost of capital and information asymmetry, we form calendar-time portfolios by sorting all stock-days from 1995-2013 into quintiles based on the previous day's value of market capitalization (size) and average information asymmetry – measured by the 15-minute ASC, EXIT, and RAIN. Once the portfolios are formed, excess returns are regressed on the three Fama and French (1993) factors on a stock-day basis, and the intercept term is collected for each portfolio. This allows us to inspect the excess returns, after controlling for the market, size, and value effects, with respect to information asymmetry. Further sorting by size allows us to inspect the effect firm size has on the information asymmetry effect, and vice versa. These results are presented in Table 3.

In Panel A, we see that stocks in the top quintile of prior day ASC – total information asymmetry – outperform stocks in the bottom quintile by 2.15 basis points (bps) per day (5.56% per year), a finding consistent with Easley and O'Hara (2004). While we also document that smaller stocks earn a premium over large stocks, consistent with the size effect documented by Fama and French (1992), we also find that the effect of information asymmetry is amplified in smaller stocks; for the smallest quintile of stocks, stocks in the top quintile of prior day ASC earned 3.29 bps per day (8.64% per year) more than those in the bottom quintile of prior day ASC. Compare this to 0.77 bps per day (1.95%

per year) for the largest stocks. Again, this is evidence that information asymmetry is associated with higher expected returns.

However, when we divide information asymmetry into skilled two components – skilled processing of public information (estimated by EXIT) and private information trading (RAIN) – we see that these excess returns are driven by the former and not the latter. In Panel B, we show that stocks in the highest quintile of skilled information processing (EXIT(15)) earns 3.70 bps per day (9.76% per year) more than those in the lowest quintile. This effect is magnified in the smallest quintile of stocks, where stocks in the highest quintile of skilled information processing earns 10.32 bps per day (29.69% per year) more than those in the lowest quintile. Moreover, we see a monotonic decrease in average excess returns as skilled information processing decreases. Compare this to Panel C. We see that when portfolios are formed on private information trading (RAIN(15)), the excess returns of the highest RAIN quintile are 0.21 bps per day (0.52% per year) more than the lowest RAIN quintile. In the smallest quintile of stocks, excess returns of the highest RAIN quintile are 4.48 bps per day (11.94% per year) more than the lowest RAIN quintile. Moreover, we observe a U-shaped pattern to excess returns vis-à-vis private information trading, rather than a monotonic increase. This lends preliminary evidence in favor of Hypothesis 2, that cost of capital is a function the level of expected informed trading.

To more rigorously test the cross-sectional pricing of skilled information processing, we perform cross-sectional regressions of excess return on documented risk factors following Fama and MacBeth (1973) and Fama and French (1992). Table 4 presents time-series averages of these cross-sectional regressions using Newey-West (1986) corrected standard errors. We regress excess return on the previous day's estimated beta[5], the natural logarithm of market capitalization, and the natural logarithm of the book-to-market ratio. In Models 2-5, we include lagged measures of information

[5] The firm's beta is estimated based on 3 months of daily returns, then sorted into deciles for each date, then betas for each portfolio are re-estimated over the next 3 months to mitigate measurement error.

asymmetry. In Model 2, we see that total information asymmetry, ASC, is positively associated with excess returns and is marginally statistically significant. However, when we split this variable into skilled information processing (EXIT) and private information trading (RAIN) in Models 3 and 4, we find EXIT is priced in the cross-section (with a t-statistics of 3.98[6]), while RAIN is not. This is confirmed when both EXIT and RAIN are included in the cross-sectional regressions. For example, for a firm with mean RAIN, a 1 basis point increase in previous day EXIT (representing average liquidity demanders 15-minute profit relative to liquidity suppliers, due to skilled information processing) is associated with a 55.64-basis-point increase in *daily* expected return. While this may seem extremely high, consider that the standard deviation of EXIT(15) is .035 bps, so a one standard deviation increase in EXIT equates to a 1.9 basis point increase in expected return (5.03% annualized). Meanwhile, for a firm with mean EXIT, a change in RAIN has no statistically significant effect on expected return. We interpret this as clear evidence that not only is information asymmetry and informed trading a priced factor in the cross-section of stock returns, but consistent with Hypothesis 2, the level of skilled information processing, and not the level of private information trading is the component of information asymmetry which is priced in the cross-section.

Lambert, et al. (2007, 2011) show that information asymmetry should only be priced when competition for information is imperfect. In that context, we next test Hypothesis 3, the relation between expected returns and expected informed trading is weaker in firms with better information environments. We measure a firm's information environment 3 ways: the level of competition between institutional investors, the number of analysts following the stock, and the accrual quality of the firm's financial statements[7]. Separately for each of these measures, we sort each observation

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[6] Harvey, Liu, and Zhu (2016) suggest that due to extensive data mining, that standard p-values may not suffice in judging the statistical significance of a factor in the cross-section of returns, and instead suggest that t-statistics should at least exceed 3.

[7] These three measures have previously been used to measure competition for information (Akins, Ng, and Verdi, 2012), information uncertainty (Jiang, Lee, and Zhang, 2005; Zhang, 2006; Lu, Chen, and Liao, 2010; Bhattacharya, Desai, and Venkataraman, 2013), and investor attention (Callen, Khan, and Lu, 2013).

into deciles based on the previous quarter's values. The deciles are then given values from 0 to 9 and then scaled by 9, so the resulting variable is scaled from 0 to 1, where 0 represents a firm with one of the poorest information environments and 1 represents a firm with one of the best information environments.

We next interact these scaled variables by EXIT and RAIN and regress excess returns on these terms in the cross section. The time-series averages of these regression coefficients are presented in Table 5. In Panel A, we see that skilled information processing is strongly priced in the cross-section of returns of firms in the lowest decile of institutional competition, analysts, and accrual quality. When we analyze the effect of EXIT for companies with strong information environments by summing the coefficients on EXIT and the interaction term, we see that in firms with strong information environments, skilled information processing has less of an effect on expected returns, and moreover this weakened effect is statistically significant when gauging the information environment using the number of analysts and accrual quality. For example, in a firm with poor accrual quality, a one standarddeviation increase in previous day EXIT(15) is associated with a 2.92 basis point increase in daily expected return (7.63% annualized), however for a firm with excellent accrual quality, a one standard deviation increase in EXIT(15) is associated with a 0.10 basis point increase in expected return (statistically indifferent from 0). Conversely, in Panel B we see that RAIN has no statistical effect on the cost of capital, regardless of the information environment of the firm.

We further test Hypothesis 3 by examining a market-wide shock to the information environment and competition for information. Reg FD made information dissemination by firms more uniform. This should have ultimately had the effect of improving competition for information and, according to Lambert, et al. (2007, 2011), should reduce the effect of information asymmetry on the cost of capital. We test this by examining the cross-sectional pricing of ASC, EXIT, and RAIN before and after the adoption of Reg FD. These results, presented in Table 6, indicate that following Reg FD ASC is no longer a priced factor in the cross-section of returns. However, when we split information asymmetry into skilled information processing (EXIT) and private informed trading (RAIN), we once again see that EXIT is associated with higher expected returns both before and after Reg FD while RAIN is not. However, we also see that the relation between EXIT and expected returns is weakened following Reg FD, when competition for information would have increased. Holding RAIN at the mean, prior to Reg FD, a one standard deviation increase in previous day EXIT was associated with a 2.49 basis point increase in expected return (6.47% annualized). After Reg FD, the same change in EXIT was associated with a 1.73 basis point increase in expected return (4.46% annualized). The change in pricing following the adoption of Reg FD, in addition to the weaker EXIT-return for firms with better analyst attention and accrual quality support Hypothesis 3, that the cross-sectional pricing of information asymmetry, particularly skilled information processing, is weaker when firms' information environments are stronger.

We next test Hypothesis 4. Since skilled information processing is not completely diversifiable, according to the arbitrage pricing theory, expected returns should be a function of a risk factor based on the risk premium for stocks with more skilled information processing. In Table 7, we present time-series pricing tests of the Fama and French (1993) model while including our new factor, AMS. In Panel A, Model 1 we regress excess return on the traditional 3-factor model on a stock-day level. Note the statistically significant constant, indicating that the 3-factor model is still leaving a portion of returns unexplained. When we include the version of AMS based on ASC, we see that not only is AMS significantly priced in the time series, but the constant is also reduced, still marginally significant relative to zero. However, wen we replace that version of AMS with one based on EXIT, we see that the constant is reduced to a coefficient statistically indifferent from zero. This indicates that Our 4-factor model, including AMS based on EXIT explains time-series returns better than the traditional 3-factor model. In Model 4, we find that this is also true of the version of AMS based on RAIN. However, due to the extremely high correlation of $AMS_{EXIT(15)}$ and $AMS_{RAIN(15)}$, perhaps this shouldn't be surprising. In Panel B we include the Carhart (1997) momentum factor and find similar results.

The constant term in the traditional 4-factor model, and the 5-factor model including $AMS_{ASC(15)}$ are both statistically different from zero, while the constant term in the 5-factor models including $AMS_{EXIT(15)}$ and $AMS_{RAIN(15)}$ are statistically indifferent from zero, indicating that those two models explain excess returns better than the traditional 4-factor model.

However, when analyzing the cross-sectional pricing of information asymmetry, we found that the size of the firm greatly impacted the excess return due to information asymmetry. Therefore, were perform the time-series pricing tests separately for each quintile of firm size. These regression results are presented in Table 8. In Panel A, we see that the traditional 4-factor model (including the market risk premium, SMB, HML, and UMD factors) has a positive and statistically significant intercept term on every size portfolio. Moreover, when performing an F-test with the null hypothesis that all 5 constants equal 0, we calculate an F-statistic of 116.82, strongly rejecting the null.

When we include $AMS_{ASC(15)}$ in Panel B, only the smallest stocks have a statistically positive constant term, and all 5 constant terms reduced in absolute value relative to Panel A. Also, AMS is significantly priced in every size portfolio, though much less so for the largest 3 quintiles. When we perform an F-test with the null hypothesis that all intercept terms equal 0, we calculate an F-statistic of 33.61, still rejecting the null hypothesis, but with less confidence than in Panel A. Similarly, we calculate an F-statistic that AMS is not priced in any size portfolio. Not surprisingly, we compute an F-statistic of 3,399.52, strongly rejecting that null.

We next test the time-series pricing of $AMS_{EXIT(15)}$ and $AMS_{RAIN(15)}$ by size quintiles in Panels C and D, respectively. In panel C, we again find that all the constant terms were reduced, relative to both Panels A and B, and the adjusted R^2 for all 5 size portfolios increased, suggesting that $AMS_{EXIT(15)}$ explains time-series returns better than $AMS_{ASC(15)}$. However, we still see that a sizable amount of the size puzzle is unexplained, as the smallest stocks still earn a premium, even after controlling for size with the SMB factor and skilled information processing with the $AMS_{EXIT(15)}$ factor. When performing the F-test that all 5 constant terms equal 0, we calculate an F-statistic of 18.83, once again rejecting that the constants are all zero, but with much less confidence than the traditional 4-factor model (F-statistic of 116.82). We also calculate an F-statistic of 11,019.59 that $AMS_{EXIT(15)}$ is *not* a priced risk factor in any size portfolio. In Panel D, we find very similar results for $AMS_{RAIN(15)}$. Taken in conjunction with the cross-sectional pricing results, we conclude that information asymmetry – and particularly information asymmetry due to skilled information processing – is a priced risk factor in the time series, and can explain part, but not all, of the size-return puzzle, supporting Hypothesis 4.

5. Concluding Remarks

We expand our understanding of informed trading to incorporate not just the prototypical insider who trades on privately-held information, but also the valuable trading advantage gleaned from the skilled processing of publicly-available information. We show that there is commonality in informed trading which arises, at least in part, from skilled information processing as the level of expected informed trading is a priced factor in expected stock returns, but less so in firms with quality information environments. We also show that returns are a function of a risk factor based on skilled information processing, and that this factor can partially explain the size effect that is not already accounted for by current asset pricing models.

These findings contribute to the literature by defining the difference between skilled information processing and private information trading and establishing empirical estimations of both – EXIT and RAIN – by showing that skilled information processing is associated with higher expected returns, and by establishing that firms with weaker information environments have a higher pricing of skilled information processing in their cost of capital.

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Table 1: Predictability of Informed Trading

The following table presents results of pooled regressions to test the predictability and commonality of informed trading. The dependent variable in all 3 regression models is $ASC(k)_{i,t}$ – the adverse selection component of the bid-ask spread of stock i on day t, where k equals 15, 30, or 60 minutes. $ASC(k)_{i,t}$ is regressed on market variables, stock characteristics, ownership characteristics, and 1-day lagged determinants. The sample includes all stocks from 1995-2013. Coefficients have been scaled for ease of presentation. Robust standard errors are clustered by firm. The corresponding T-statistics are presented to the right of the corresponding coefficients. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

		Coef. Scale	$ASC(15)_{i,t}$	t-stat	$ASC(30)_{i,t}$	t-stat	$ASC(60)_{i,t}$	t-stat
Market Variables	$ASC(k)_{-i,t}$	÷1,000	486.30***	10.78	892.57***	11.08	1295.5***	11.23
	$\ln(spread_{-i,t})$	x1,000	-0.242***	-8.13	-0.216***	-6.16	-0.222***	-4.98
	$\ln(VIX_t)$	x1,000	-0.038	-0.90	-0.038	-0.74	0.003	0.04
	Order $Imb._{-i,t}$	x1,000	-0.045	-0.52	-0.094	-0.88	-0.132	-1.00
	Mkt. $Ret._t$	x1,000	-1.243***	-4.41	-1.325***	-3.76	-1.869***	-3.99
Stock Characteristics	$\ln(spread_{i,t})$	x1,000	0.291***	65.23	0.288***	64.28	0.267***	62.59
	$\ln(volatility_{i,t})$	x1,000,000	18.10***	40.74	22.60***	36.67	28.00***	34.19
	Order $Imb._{i,t}$	x1,000,000	127.50***	16.28	193.90***	18.55	323.90***	24.54
	Δ $spread_{i,t}$	x1,000,000	1.970***	30.04	1.940***	27.53	1.800***	23.83
	$Return_{i,t}$	x1,000	1.128***	15.59	1.681***	17.52	2.542***	20.02
	$\ln(Tick\ Size_{i,t})$	x1,000,000	0.842	0.38	-1.570	-0.65	-1.980	-0.73
Lagged Determinants	$ASC(k)_{i,t-1}$		0.054***	47.90	0.036***	36.67	0.025***	27.62
	$ASC(k)_{-i,t-1}$	÷1,000	321.33***	8.07	198.06***	3.18	15.16	0.17
	$\ln(spread_{-i,t-1})$	x1,000	-0.097***	-3.25	-0.130***	-3.68	-0.121***	-2.65
	$\ln(VIX_{t-1})$	x1,000	0.133***	3.18	0.132***	2.57	0.101	1.55
	Order $Imb._{-i,t-1}$	x1,000	-0.263***	-4.96	-0.368***	-5.52	-0.376***	-4.55
	Mkt. $Ret._{t-1}$	x1,000	-0.101	-0.58	0.080	0.39	0.209	0.90
	$\ln(spread_{i,t-1})$	x1,000	18.121***	16.35	17.705***	16.58	16.999***	17.66
	$\ln(volatility_{i,t-1})$	x1,000,000	3.830***	11.21	3.470***	8.33	2.880***	5.60
	Order $Imb._{i,t-1}$	x1,000,000	-35.80***	-5.52	-45.20***	-6.01	-75.10***	-8.59
	Δ $spread_{i,t-1}$	x1,000,000	0.351***	7.67	0.391***	7.44	0.400***	6.74
	$Return_{i,t-1}$	x1,000	0.023	0.44	-0.105*	-1.67	-0.146**	-1.99
Owner-ship	$\ln(analysts_{i,t})$	x1,000	0.069***	35.85	0.072***	34.32	0.073***	30.83
	% Inst. $Holdings_{i,t}$		-6.95E-08	-1.08	-1.53E-08	-0.25	3.18E-08	0.48
	Inst. $Comp._{i,t}$	x1,000	0.231***	9.48	0.269***	9.48	0.265***	7.96
	Constant	x1,000	-0.518***	-7.17	-0.562***	-6.53	-0.684***	-6.54
	Adj. R^2		0.075		0.050		0.034	
	Observations		3,934,665		3,907,443		3,864,681	

Table 2: Descriptive Statistics

The following tables present summary statistics (Panel A) of the sample used in this study on the bond-day level and correlations of information asymmetry variables on the bond-day level (Panel B) and of market-level variables on the day level (Panel C).

Panel A: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
ASC(15)	12,623,134	0.00046	0.00175	-0.00471	0.00982
ASC(30)	12,390,332	0.00044	0.00198	-0.00589	0.01049
ASC(60)	12,104,097	0.00041	0.00225	-0.00715	0.01132
EXIT(15)	5,028,020	0.00034	0.00035	-0.00022	0.00163
EXIT(30)	4,994,007	0.00034	0.00035	-0.00023	0.00157
EXIT(60)	4,941,042	0.00032	0.00033	-0.00023	0.00150
RAIN(15)	5,028,020	-0.00001	0.00113	-0.00417	0.00503
RAIN(30)	4,994,007	-0.00001	0.00141	-0.00526	0.00605
RAIN(60)	4,941,042	-0.00001	0.00170	-0.00632	0.00706
Market ASC(15)	11,104,010	7.8E-11	6.8E-11	7.9E-12	4.2E-10
Market ASC(30)	10,943,520	7.0E-11	5.7E-11	6.6E-12	3.3E-10
Market ASC(60)	10,723,667	6.2E-11	5.0E-11	4.9E-12	2.9E-10
ln($spread_{-i}$)	14,323,093	-6.615	0.748	-7.714	-4.945
ln(VIX)	21,130,639	2.978	0.358	2.292	4.393
Mkt. Order Imb.	14,226,286	0.140	0.061	0.042	0.599
Mkt. Ret.	15,689,458	0.000	0.012	-0.090	0.115
ln(spread)	21,091,065	-5.066	1.347	-9.970	0.693
ln(volatility)	14,290,106	-9.088	2.340	-48.783	-4.159
Order Imb.	14,226,286	0.350	0.323	0.001	1.021
% Δ spread	21,021,506	4.653	33.353	-58.732	147.366
Ret.	15,680,847	0.001	0.034	-0.972	16.929
ln(Tick Size)	15,684,823	-2.743	1.076	-4.743	0.799
ln(analysts)	10,245,188	2.092	0.795	0.693	4.043
% Inst. Holdings	10,035,696	2.162	16.159	0.000	97.986
Inst. Comp.	10,103,599	-0.050	0.087	-1.000	-0.003
β	15,299,009	0.730	0.679	-25.991	15.962
ln(Firm Size)	9,967,703	6.692	2.050	-4.927	13.348
ln(Book-to-Mkt.)	7,554,504	-0.775	0.903	-10.711	12.449
Accrual Quality	5,039,532	-0.047	0.040	-0.524	-0.007
Reg FD Dummy	21,139,648	0.692	0.462	0.000	1.000
$AMS_{ASC(15)}$	21,139,648	0.000	0.003	-0.026	0.019
$AMS_{EXIT(15)}$	21,139,648	0.001	0.007	-0.055	0.095
$AMS_{RAIN(15)}$	21,139,648	0.000	0.007	-0.053	0.093
MRP	21,139,648	0.000	0.012	-0.090	0.114
SMB	21,139,648	0.000	0.006	-0.049	0.044
HML	21,139,648	0.000	0.007	-0.051	0.040
UMD	21,139,648	0.000	0.010	-0.082	0.070

Panel B: Correlation of Information Asymmetry Variables

	ASC(15)	ASC(30)	ASC(60)	EXIT(15)	EXIT(30)	EXIT(60)	RAIN(15)	RAIN(30)	RAIN(60)	Market ASC(15)	Market ASC(30)	Market ASC(60)
ASC(15)	1	0.5728	0.4398	0.2828	0.2803	0.2753	0.9394	0.5119	0.3863	0.0181	0.0238	0.0258
ASC(30)	0.5728	1	0.5513	0.2298	0.2291	0.2266	0.5246	0.9601	0.5105	0.0133	0.0199	0.0229
ASC(60)	0.4398	0.5513	1	0.1852	0.1865	0.1871	0.4023	0.5200	0.9723	0.0097	0.0166	0.0216
EXIT(15)	0.2828	0.2298	0.1852	1	0.9823	0.9654	-0.0044	0.0019	0.0017	0.0456	0.0491	0.0561
EXIT(30)	0.2803	0.2291	0.1865	0.9823	1	0.9811	-0.0017	-0.0027	0.0003	0.0409	0.0718	0.0682
EXIT(60)	0.2753	0.2266	0.1871	0.9654	0.9811	1	-0.0020	-0.0007	-0.0023	0.0439	0.0656	0.1064
RAIN(15)	0.9394	0.5246	0.4023	-0.0044	-0.0017	-0.002	1	0.5407	0.4083	0.0048	0.010	0.0102
RAIN(30)	0.5119	0.9601	0.5200	0.0019	-0.0027	-0.0007	0.5407	1	0.5300	0.0035	0.0029	0.0072
RAIN(60)	0.3863	0.5105	0.9723	0.0017	0.0003	-0.0023	0.4083	0.5300	1	0.0005	0.0035	0.0010
Market ASC(15)	0.0181	0.0133	0.0097	0.0456	0.0409	0.0439	0.0048	0.0035	0.0005	1	0.8673	0.8159
Market ASC(30)	0.0238	0.0199	0.0166	0.0491	0.0718	0.0656	0.0100	0.0029	0.0035	0.8673	1	0.8504
Market ASC(60)	0.0258	0.0229	0.0216	0.0561	0.0682	0.1064	0.0102	0.0072	0.0010	0.8159	0.8504	1

Panel C: Correlation of Market Variables

	VIX	MRP	SMB	HML	UMD	$AMS_{ASC(15)}$	$AMS_{EXIT(15)}$	$AMS_{RAIN(15)}$
VIX	1	-0.1253	-0.0365	-0.0351	-0.001	-0.1583	-0.1457	-0.1531
MRP	-0.1253	1	0.0495	-0.1313	-0.2669	0.6191	0.8632	0.8751
SMB	-0.0365	0.0495	1	-0.144	0.0727	0.225	0.2431	0.1961
HML	-0.0351	-0.1313	-0.144	1	-0.278	-0.1482	0.0539	0.0238
UMD	-0.001	-0.2669	0.0727	-0.278	1	-0.2078	-0.352	-0.321
$AMS_{ASC(15)}$	-0.1583	0.6191	0.225	-0.1482	-0.2078	1	0.8105	0.8247
$AMS_{EXIT(15)}$	-0.1457	0.8632	0.2431	0.0539	-0.352	0.8105	1	0.9941
$AMS_{RAIN(15)}$	-0.1531	0.8751	0.1961	0.0238	-0.321	0.8247	0.9941	1

Table 3: Excess Return by Sorted Portfolios

The following tables present the excess daily return (α) from calendar-time portfolios that are formed by sorting all stocks from 1995-2013 into quintiles based on the previous day's value of market capitalization and average information asymmetry – measured by the 15-minute adverse selection component (ASC –Panel A) of the bid-ask spread, expected informed trading (EXIT – Panel B), and residual asymmetric information (RAIN – Panel C), as defined in Section 3.2. Once the portfolios are formed, excess returns are regressed on the three Fama and French (1993) factors on a stock-day basis, and the intercept term (α) is collected from the below equation for each portfolio. Excess returns are scaled such that the reported α is in basis points per day.

$$\left(r_{it} - r_f\right) = \alpha + \beta_M MRP_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_{it}$$

Panel A: Excess Return by ASC(15)

α(bps)		Size Portfolio						
		All	1	2	3	4	5	5-1
	All		4.9233	1.8177	0.8173	0.7516	0.7112	-4.2121
ASC(15) Portfolio	1	1.8640	6.0629	2.7212	2.2617	0.8231	0.3125	-5.7504
	2	1.8958	6.2456	2.5629	1.3219	1.4684	0.8813	-5.3644
	3	1.3553	4.9647	2.7065	1.0092	1.0318	0.8052	-4.1595
	4	1.4533	5.9556	1.5260	1.3526	0.5757	1.3840	-4.5716
	5	4.0116	9.3514	4.2223	1.6181	2.4600	1.0804	-8.2710
	5-1	2.1476	3.2885	1.5011	-0.6436	1.6369	0.7680	

Panel B: Excess Return by EXIT(15)

α(bps)		Size Portfolio						
		All	1	2	3	4	5	5-1
	All		4.9233	1.8177	0.8173	0.7516	0.7112	-4.2121
EXIT(15) Portfolio	1	0.9437	1.5176	1.0653	1.3263	1.4299	0.7414	-0.7762
	2	0.8546	2.2903	-0.3090	1.6773	1.0925	0.2951	-1.9952
	3	1.4438	8.4683	1.9278	0.9483	1.4776	1.8488	-6.6195
	4	1.6321	8.1687	2.5325	1.3904	0.9558	1.4206	-6.7481
	5	4.6393	11.839	4.1935	2.7208	2.6012	2.8597	-8.9797
	5-1	3.6956	10.322	3.1281	1.3946	1.1713	2.1183	

Panel C: Excess Return by RAIN(15)

α(bps)		Size Portfolio						
		All	1	2	3	4	5	5-1
	All		4.9233	1.8177	0.8173	0.7516	0.7112	-4.2121
RAIN(15) Portfolio	1	2.6710	10.156	3.7444	2.0616	1.3853	0.3800	-9.7758
	2	1.5745	4.9845	2.9997	1.6743	1.3746	1.2195	-3.7650
	3	1.0725	8.2380	1.6363	0.8762	1.1810	0.7883	-7.4497
	4	1.3215	9.9008	1.1750	1.5771	1.3250	1.0642	-8.8366
	5	2.8775	14.633	4.5213	1.7455	1.7999	1.1078	-13.525
	5-1	0.2064	4.4772	0.7769	-0.3161	0.4147	0.7277	

Table 4: Cost of Capital and Information Asymmetry in the Cross-Section
The following table presents results of time series averages of cross-sectional regressions following Fama and MacBeth (1973), using Newey-West (1986) corrected standard errors. All regressions of the following form are run each day:

$$(r_{it} - r_f) = \lambda_{0t} + \lambda_{1t}\beta_{p,t-1} + \lambda_{2t}\ln(Size_{i,t-1}) + \lambda_{3t}\ln(BTM_{i,t-1}) + \boldsymbol{\Lambda}'\boldsymbol{X} + \varepsilon_{it}$$

where $(r_{it} - r_f)$ is the return of stock i on day t, less the risk free rate, β_p is the beta of the portfolio to which the stock belongs (the firm's beta is estimated, then sorted into 10 portfolios by beta each date, then betas for each portfolio are re-estimated to mitigate measurement error), *Size* is the market value of equity of the firm, *BTM* is the book to market ratio of the firm, and $\boldsymbol{X}$ is a vector of information asymmetry variables - the 15-minute adverse selection component (ASC) of the bid-ask spread, expected informed trading (EXIT), and residual asymmetric information (RAIN), as defined in Section 3.2. The sample includes all stocks from 1995-2013. Two-tailed p-values, based on the Newey-West (1986) standard errors, are in parenthesis below the corresponding coefficients. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Constant	0.0884	0.1688**	0.0622**	0.1364***	0.0648**
	(0.151)	(0.027)	(0.013)	(<.001)	(0.010)
$\beta_{p,t-1}$	0.0094	-0.0070	-0.0010	0.0031	-0.0020
	(0.776)	(0.839)	(0.962)	(0.889)	(0.941)
$\ln(Size_{i,t-1})$	-0.0030	-0.0100	-0.0030	-0.0100***	-0.0040
	(0.572)	(0.148)	(0.196)	(<.001)	(0.173)
$\ln(BTM_{i,t-1})$	0.0111	0.0212*	0.0004	0.0023	0.0006
	(0.170)	(0.087)	(0.899)	(0.522)	(0.868)
$ASC(15)_{i,t-1}$		7.0671*			
		(0.092)			
$EXIT(15)_{i,t-1}$			57.245***		55.641***
			(<.001)		(<.001)
$RAIN(15)_{i,t-1}$				2.096	2.3977
				(0.255)	(0.196)
Periods	4,491	4,491	4,458	4,458	4,458

Table 5: Information Environment and Cross-Sectional Pricing of Information Asymmetry

The following tables present results of time series averages of cross-sectional regressions following Fama and MacBeth (1973), using Newey-West (1986) corrected standard errors. All regressions of the following form are run each day:

$$(r_{it} - r_f) = \lambda_{0t} + \lambda_{1t}\beta_{p,t-1} + \lambda_{2t}\ln(Size_{i,t-1}) + \lambda_{3t}\ln(BTM_{i,t-1}) + \lambda_{4t}IA_{i,t-1} + \lambda_{5t}X_{i,t-1} + \lambda_{6t}(IA_{i,t-1}X_{i,t-1}) + \varepsilon_{it}$$

where $(r_{it} - r_f)$ is the return of stock i on day t, less the risk free rate, β_p is the beta of the portfolio to which the stock belongs (the firm's beta is estimated, then sorted into 10 portfolios by beta each date, then betas for each portfolio are re-estimated to mitigate measurement error), *Size* is the market value of equity of the firm, *BTM* is the book to market ratio of the firm, *IA* is a measure of information asymmetry – either expected informed trading (EXIT – Panel A), and residual asymmetric information (RAIN – Panel B), as defined in Section 3.2 – and *X* is an information environment variable (institutional competition, the number of analysts, and accrual quality) scaled from 0 to 1, 0 corresponding to the firm belonging to the lowest decile of that variable and 1 corresponding to the firm belonging to the highest. The sample includes all stocks from 1995-2013. Two-tailed p-values, based on the Newey-West (1986) standard errors, are in parenthesis below the corresponding coefficients. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Cross-Sectional Pricing of Processed Public Information

	(1)	(2)	(3)
X Variable (Scaled)	Inst. Comp.	Analysts	Accrual Quality
Constant	0.0192	0.0572**	0.0653**
	(0.449)	(0.023)	(0.024)
$\beta_{p,t-1}$	-0.0050	-0.0020	-0.0050
	(0.811)	(0.941)	(0.822)
$\ln(Size_{i,t-1})$	-0.0030	-0.0040	-0.0040
	(0.216)	(0.187)	(0.210)
$\ln(BTM_{i,t-1})$	0.0027	0.0002	0.0044
	(0.448)	(0.959)	(0.341)
$EXIT(15)_{i,t-1}$	83.382***	84.610***	83.390***
	(0.005)	(<.001)	(<.001)
$X_{i,t-1}$	0.0571***	0.0103	0.0180*
	(<.001)	(0.479)	(0.088)
$EXIT(15)_{i,t-1} \times X_{i,t-1}$	-14.371	-57.253*	-80.584***
	(0.720)	(0.087)	(0.005)
Periods	4,458	4,458	4,457

Panel B: Cross-sectional Pricing of Private Information

	(1)	(2)	(3)
X Variable (Scaled)	Inst. Comp.	Analysts	Accrual Quality
Constant	0.1261***	0.1319***	0.2065***
	(<.001)	(<.001)	(0.005)
$\beta_{p,t-1}$	0.0032	0.0038	-0.0120
	(0.888)	(0.866)	(0.647)
$\ln(Size_{i,t-1})$	-0.0110***	-0.0090***	-0.0150**
	(<.001)	(<.001)	(0.015)
$\ln(BTM_{i,t-1})$	0.0015	0.0018	-0.0030
	(0.679)	(0.611)	(0.676)
$RAIN(15)_{i,t-1}$	6.0987	2.7338	-5.9790
	(0.376)	(0.617)	(0.572)
$X_{i,t-1}$	0.0266**	-0.0060	-0.0360
	(0.018)	(0.597)	(0.167)
$RAIN(15)_{i,t-1} \times X_{i,t-1}$	-4.2090	0.1588	-1.1350
	(0.655)	(0.984)	(0.866)
Periods	4,458	4,458	4,457

Table 6: Cross-Sectional Pricing of Information Asymmetry after Change in Information Environment

The following table presents results of time series averages of cross-sectional regressions following Fama and MacBeth (1973), using Newey-West (1986) corrected standard errors. All regressions of the following form are run each day:

$$\left(r_{it}-r_f\right)=\lambda_{0t}+\lambda_{1t}\beta_{p,t-1}+\lambda_{2t}\ln\left(Size_{i,t-1}\right)+\lambda_{3t}\ln\left(BTM_{i,t-1}\right)+\boldsymbol{\Lambda}'\boldsymbol{X}+\varepsilon_{it}$$

where *(r_{it} – r_f)* is the return of stock i on day t, less the risk free rate, β_p is the beta of the portfolio to which the stock belongs (the firm's beta is estimated, then sorted into 10 portfolios by beta each date, then betas for each portfolio are re-estimated to mitigate measurement error), *Size* is the market value of equity of the firm, *BTM* is the book to market ratio of the firm, and ***X*** is a vector of information asymmetry variables - the 15-minute adverse selection component (ASC) of the bid-ask spread, expected informed trading (EXIT), and residual asymmetric information (RAIN), as defined in Section 3.2. The sample includes all stocks from 1995-2013. Regression models 1-4 include observations prior to the adoption of Reg FD (Aug. 21, 2000), while models 5-8 include observations after adoption. Two-tailed p-values, based on the Newey-West (1986) standard errors, are in parenthesis below the corresponding coefficients. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Sample	Pre Reg FD				Post Reg FD			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.0959**	-0.0060	0.0816*	-0.0030	0.1976*	0.0892***	0.1582***	0.0918***
	(0.012)	(0.896)	(0.071)	(0.942)	(0.060)	(0.003)	(<.001)	(0.002)
$\beta_{p,t-1}$	0.0544	0.0281	0.0305	0.0272	-0.0320	-0.0130	-0.0080	-0.0130
	(0.181)	(0.529)	(0.497)	(0.542)	(0.504)	(0.620)	(0.766)	(0.607)
$\ln(Size_{i,t-1})$	-0.0080*	0.0022	-0.0050	0.0020	-0.0110	-0.0060*	-0.0120***	-0.0060*
	(0.099)	(0.678)	(0.353)	(0.698)	(0.253)	(0.065)	(<.001)	(0.056)
$\ln(BTM_{i,t-1})$	-0.0030	-0.0160*	-0.0140*	-0.0150*	0.0309*	0.0069*	0.0087**	0.0069**
	(0.660)	(0.061)	(0.096)	(0.067)	(0.070)	(0.054)	(0.015)	(0.050)
$ASC(15)_{i,t-1}$	9.6575***				6.0439			
	(0.003)				(0.289)			
$EXIT(15)_{i,t-1}$		72.807**		71.109**		51.061***		49.494***
		(0.022)		(0.025)		(0.001)		(0.002)
$RAIN(15)_{i,t-1}$			3.2652	3.2397			1.6314	2.0632
			(0.423)	(0.421)			(0.415)	(0.312)
Periods	1,271	1,267	1,267	1,267	3,219	3,190	3,190	3,190

Table 7: Cost of Capital and Information Asymmetry in the Time Series

The following tables display pooled regressions testing the pricing of asymmetric information in the time series. Observed daily excess returns, *(r_{it} - r_f)*, are regressed on the three Fama-French (1993) factors in Panel A, as well as the Carhart (1997) momentum factor in Panel B, and a fifth factor, AMS, for each stock-day, using the following form:

$$\left(\mathrm{r}_{it} - r_f\right) = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 AMS_t + \varepsilon_{it}$$

The AMS (asymmetric minus symmetric) factor is calculated by sorting all stocks based on their 1-day-lagged value of information asymmetry, (measured by the 15-minute adverse selection component (ASC) of the bid-ask spread, expected informed trading (EXIT), and residual asymmetric information (RAIN), as defined in Section 3.2.), and forming an equally-weighted portfolio which is long the most asymmetric quintile, and short the least asymmetric quintile. The portfolio is then reformed each day. Daily returns from the portfolio are taken as the AMS factor values for each day, *t*. Standard errors are clustered by stock and day, following Petersen (2009). P-values are in parentheses below their respective coefficient estimates. Intercept terms have been multiplied by 1,000 for ease of interpretation. Statistical significance at the 10%, 5%, and 1% levels are represented by *, **, and ***, respectively.

Panel A: Three-Factor Fama-French Model

	(1) (r_{it} - r_f)	(2) (r_{it} - r_f)	(3) (r_{it} - r_f)	(4) (r_{it} - r_f)
MRP_t	0.8038***	0.7287***	0.4148***	0.4296***
	(0.000)	(0.000)	(0.000)	(0.000)
SMB_t	0.3180***	0.2748***	0.1287***	0.1874***
	(0.000)	(0.000)	(0.000)	(0.000)
HML_t	0.4060***	0.4156***	0.2443***	0.2823***
	(0.000)	(0.000)	(0.000)	(0.000)
$AMS_{ASC(15),t}$		0.5653***		
		(0.000)		
$AMS_{EXIT(15),t}$			0.7611***	
			(0.000)	
$AMS_{RAIN(15),t}$				0.7822***
				(0.000)
Constant (×1,000)	0.1807***	0.0787*	-0.0261	-0.0125
	(0.000)	(0.059)	(0.309)	(0.646)
Adj. R^2	0.1468	0.1487	0.1541	0.1536
Observations	9,859,384	9,859,384	9,859,384	9,859,384

Panel B: Four-Factor Fama-French Model

	(1) $(r_{it} - r_f)$	(2) $(r_{it} - r_f)$	(3) $(r_{it} - r_f)$	(4) $(r_{it} - r_f)$
MRP_t	0.7908***	0.7214***	0.4148***	0.4273***
	(0.000)	(0.000)	(0.000)	(0.000)
SMB_t	0.3224***	0.2793***	0.1295***	0.1908***
	(0.000)	(0.000)	(0.000)	(0.000)
HML_t	0.3802***	0.3965***	0.2430***	0.2713***
	(0.000)	(0.000)	(0.000)	(0.000)
UMD_t	-0.0532***	-0.0389***	-0.0036	-0.0252***
	(0.000)	(0.000)	(0.609)	(0.000)
$AMS_{ASC(15),t}$		0.5485***		
		(0.000)		
$AMS_{EXIT(15),t}$			0.7592***	
			(0.000)	
$AMS_{RAIN(15),t}$				0.7741***
				(0.000)
Constant (×1,000)	0.2000***	0.0959**	-0.0243	-0.00135
	(0.000)	(0.024)	(0.357)	(0.961)
Adj. R^2	0.1471	0.1489	0.1541	0.1537
Observations	9,859,384	9,859,384	9,859,384	9,859,384

Table 8: Information Asymmetry and the Size Effect

The following tables display pooled regressions testing the pricing of different measures of asymmetric information in the time series by market capitalization quintile. Observed daily excess returns, *(r_{it} - r_f)*, are regressed on the three Fama-French (1993) factors and as the Carhart (1997) momentum factor in Panel A. A fifth factor, AMS, is added for the following panels for each stock-day, using the following form:

$$(\mathrm{r}_{it} - r_f) = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 AMS_t + \varepsilon_{it}$$

The AMS (asymmetric minus symmetric) factor is calculated by sorting all stocks based on their 1-day-lagged value of information asymmetry, (measured by the 15-minute adverse selection component (ASC) of the bid-ask spread in Panel B, expected informed trading (EXIT) in Panel C, and residual asymmetric information (RAIN) in Panel D, all as defined in Section 3.2.), and forming an equally-weighted portfolio which is long the most asymmetric quintile, and short the least asymmetric quintile. The portfolio is then reformed each day. Daily returns from the portfolio are taken as the AMS factor values for each day, *t*. Standard errors are clustered by stock and day, following Petersen (2009). P-values are in parentheses below their respective coefficient estimates. Intercept terms have been multiplied by 1,000 for ease of interpretation. *F* statistics testing that all constant terms = 0, and that AMS_t is not priced are provided. Statistical significance at the 10%, 5%, and 1% levels are represented by *, **, and ***, respectively.

Panel A: Base Four-Factor Model, by Size Quintile

F-test (all $\alpha = 0$) = 116.8238***

Size Quintile	1	2	3	4	5
	(r_{it} - r_f)	(r_{it} - r_f)	(r_{it} - r_f)	(r_{it} - r_f)	(r_{it} - r_f)
MRP_t	0.4133***	0.6946***	0.9051***	0.9488***	0.9942***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB_t	0.2083***	0.4374***	0.5972***	0.3725***	-0.0031
	(0.000)	(0.000)	(0.000)	(0.000)	(0.875)
HML_t	0.2110***	0.4386***	0.5077***	0.4325***	0.3133***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UMD_t	-0.0315**	-0.0608***	-0.0670***	-0.0713***	-0.0352***
	(0.020)	(0.000)	(0.000)	(0.000)	(0.007)
Constant (×1,000)	0.4923***	0.1818***	0.0817**	0.0752**	0.0711*
	(0.000)	(0.001)	(0.037)	(0.050)	(0.068)
Adj. R^2	0.0298	0.1291	0.2133	0.2410	0.2661
Observations	1,976,491	1,974,128	1,971,854	1,967,376	1,969,535

Panel B: Pricing of Total Information Asymmetry, by Size Quintile

F-test (all $\alpha = 0$) = 33.6161*** F-test (all $\beta_5 = 0$) = 3,399.52***

Size Quintile	1	2	3	4	5
	(r_{it} - r_f)	(r_{it} - r_f)	(r_{it} - r_f)	(r_{it} - r_f)	(r_{it} - r_f)
MRP_t	0.2691***	0.6126***	0.8699***	0.9067***	0.9516***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB_t	0.1187***	0.3865***	0.5754***	0.3463***	-0.0296
	(0.000)	(0.000)	(0.000)	(0.000)	(0.128)
HML_t	0.2448***	0.4579***	0.5160***	0.4423***	0.3232***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UMD_t	-0.0018	-0.0439***	-0.0597***	-0.0627***	-0.0265**
	(0.879)	(0.001)	(0.000)	(0.000)	(0.042)
$AMS_{ASC(15),t}$	1.1416***	0.6493***	0.2786***	0.3331***	0.3368***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant (×1,000)	0.2874***	0.0809	0.0532	0.0377	0.0198
	(0.000)	(0.178)	(0.299)	(0.465)	(0.668)
Adj. R^2	0.0353	0.1320	0.2142	0.2423	0.2671
Observations	1,976,491	1,974,128	1,971,854	1,967,376	1,969,535

Panel C: Pricing of Processed, Public Information, by Size Quintile

F-test (all $\alpha = 0$) = 18.8251*** F-test (all $\beta_5 = 0$) = 11,019.59***

Size Quintile	1	2	3	4	5
	$(r_{it} - r_f)$	$(r_{it} - r_f)$	$(r_{it} - r_f)$	$(r_{it} - r_f)$	$(r_{it} - r_f)$
MRP_t	-0.1386***	0.2175***	0.5963***	0.6672***	0.7350***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB_t	-0.0747***	0.1927***	0.4389***	0.2279***	-0.1363***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HML_t	0.0095	0.2645***	0.3952***	0.3297***	0.2184***
	(0.555)	(0.000)	(0.000)	(0.000)	(0.000)
UMD_t	0.0414***	0.0022	-0.0262**	-0.0342***	-0.0011
	(0.000)	(0.844)	(0.027)	(0.003)	(0.933)
$AMS_{EXIT(15),t}$	1.1146***	0.9636***	0.6237***	0.5687***	0.5235***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant (×1,000)	0.1743***	-0.0802*	-0.0780*	-0.0672	-0.0711*
	(0.000)	(0.051)	(0.063)	(0.135)	(0.084)
Adj. R^2	0.0407	0.1412	0.2186	0.2461	0.2704
Observations	1,976,491	1,974,128	1,971,854	1,967,376	1,969,535

Panel D: Pricing of Private Information, by Size Quintile

F-test (all $\alpha = 0$) = 19.4827*** F-test (all $\beta_5 = 0$) = 10,338.82***

Size Quintile	1	2	3	4	5
	$(r_{it} - r_f)$	$(r_{it} - r_f)$	$(r_{it} - r_f)$	$(r_{it} - r_f)$	$(r_{it} - r_f)$
MRP_t	-0.1232***	0.2445***	0.6118***	0.6709***	0.7355***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB_t	0.0143	0.2746***	0.4912***	0.2718***	-0.0970***
	(0.389)	(0.000)	(0.000)	(0.000)	(0.000)
HML_t	0.0503***	0.3038***	0.4201***	0.3492***	0.2355***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
UMD_t	0.0098	-0.0261**	-0.0444***	-0.0499***	-0.0153
	(0.247)	(0.019)	(0.000)	(0.000)	(0.213)
$AMS_{Rain(15),t}$	1.1426***	0.9587***	0.6247***	0.5919***	0.5512***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant (×1,000)	0.2065***	-0.0436	-0.0562	-0.0531	-0.0598
	(0.000)	(0.304)	(0.189)	(0.239)	(0.145)
Adj. R^2	0.0402	0.1400	0.2182	0.2460	0.2705
Observations	1,976,491	1,974,128	1,971,854	1,967,376	1,969,535