Investor Competition over Information and the Pricing of Information Asymmetry

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Abstract

Whether the information environment affects the cost of capital is a fundamental question in accounting and finance research. Relying on theories about competition between informed investors as well as the pricing of information asymmetry, we hypothesize a cross-sectional variation in the pricing of information asymmetry that is conditional on competition. We develop and validate empirical proxies for competition using the number and concentration of institutional investor ownership. Using these proxies, we find a lower pricing of information asymmetry when there is more competition. Overall, our results suggest that competition between informed investors has an important effect on how the information environment affects the cost of capital.

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I. Introduction

Whether information asymmetry between investors affects the cost of capital is an important issue in the theoretical (e.g., Diamond and Verrecchia 1991; Easley and O'Hara 2004; Hughes et al. 2007; Christensen et al. 2010; Bloomfield and Fischer 2011) and empirical literature (e.g., Brennan and Subrahmanyam 1996; Easley et al. 2002; Duarte and Young 2009; Mohanram and Rajgopal 2009). In this study, we examine the role of competition, defined as the rivalry among informed investors to acquire and trade profitably on private information, in the pricing of information asymmetry. We define private information as exclusive information received directly from the firm and/or from proprietary insights. Our key hypothesis and finding is that the pricing of information asymmetry decreases when there is more competition. This finding is important because it suggests that, in the presence of information asymmetry, more competition can lower the cost of capital. Furthermore, as we describe below, this finding has implications for a large body of literature that investigates the pricing of information quality (e.g., Botosan 1997; Leuz and Verrecchia 2000; Francis et al. 2004, 2005; Core et al. 2008; Ng 2011).

The intuition for our hypothesis on the role of competition in the pricing of information asymmetry is as follows. Theories show that, for a given level of information asymmetry, the degree of exploitation of private information by informed traders is lower when there is more competition (e.g., Holden and Subrahmanyam 1992, 1994; Foster and Viswanathan 1993, 1994, 1996).[1] This occurs because competition leads private information to be incorporated into prices more quickly (i.e., prices become more informative about fundamental value). This effect has two potential implications for the pricing of information asymmetry. First, in a Kyle (1985) type

[1] We use the terms "investors" and "traders" interchangeably. While this approach is consistent with the literature, we discuss some distinctions in Section 3.

model, competition reduces the need for market makers to price protect because it lowers the extent to which information asymmetry is exploited. Second, in an Easley and O'Hara (2004) type model, competition reduces the risk of information asymmetry to uninformed investors because the collective trades by informed investors lead to greater information being reflected in the equilibrium price.

To the best of our knowledge, while there are theories on competition over information in equity markets, no prior study has attempted to measure such competition. Hence, before we test our hypothesis, we first develop and validate our proxies of competition. To develop the proxies, we rely on two key assumptions: (1) institutional investors are also relatively more informed investors (Arbel and Strebel 1983; Sias and Starks 1997; Bartov et al. 2000; Jiambalvo et al. 2002), and (2) the competition between informed investors captures the competition between informed traders (Lehavy and Sloan 2008). We then construct two measures of competition using data on institutional investors' ownership: (1) the number of total institutional investors, and (2) the Herfindahl index, which measures the distribution of information among these investors (Herfindahl 1950). Recognizing that transient institutional investors are the ones most likely to trade actively on information (Bushee 1998; Ke and Petroni 2004; Ke and Ramalingegowda 2005), we also construct analogous proxies using data on transient institutional investor ownership.

Our empirical proxies are motivated from theories on competition over information in the equity markets and from economic theory. The number of informed investors follows directly from theories that characterize the degree of competition using the number of informed traders (e.g., Admati and Pfleiderer 1988; Holden and Subrahmanyam 1992; Foster and Viswanathan 1993; Easley and O'Hara 2004). The use of the Herfindahl index, on the other hand, is an adaptation of a widely used measure of competition in product markets to competition in capital markets. We use this index to capture the distribution of private information among informed investors, with the notion that a more equal distribution results in greater competition (Foster and Viswanathan 1994). As the distribution of private information is not directly observable or measurable, we construct a proxy that uses the distribution of shares among informed investors. The underlying assumption is that informed investors with higher holdings in a given firm are more likely to have more private information because of greater access to the firm or greater incentives to generate private information; hence, the concentration of shares among informed investors captures, with noise, the concentration of private information.

We begin our analyses by validating our competition proxies. A key prediction from theoretical models is that competition reduces market inefficiency and the rents earned by informed investors. That is, future abnormal returns from trading on market inefficiencies should be lower when there is more competition. We provide evidence that more (less) competition is associated with a smaller (larger) drift in prices after earnings announcements.

We then examine the role of competition in the pricing of information asymmetry. We proxy for information asymmetry using the information asymmetry component of the bid-ask spreads developed by Glosten and Harris (1988). Our sample consists of 83,988 (NYSE, AMEX and NASDAQ) firm-years from 1983 to 2008, which, when matched to monthly returns, yield a sample of 968,250 firm-months from January 1984 to December 2009. Using cross-sectional asset pricing regressions, we find significant evidence that the pricing of information asymmetry is lower when there is more competition. For instance, the difference in the pricing of the information asymmetry component of spread between the least competitive and the most competitive quintile ranges from 0.47 percent to 0.86 percent per month, depending on the competition measure used.

We conduct a series of additional analyses to gauge the robustness of our findings. First, we repeat the analyses with the information asymmetry component of PIN; this component, obtained from Duarte and Young (2009), is available only for NYSE and AMEX firms for the sample period from 1983 to 2004. While we continue to find that the pricing of information asymmetry is lower when there is more competition, the economic and statistical significance is slightly weaker. We show that one reason for these weaker results is that NASDAQ firms are excluded from the analysis. Specifically, we find that the effect of competition on the pricing of information asymmetry of spread is mainly driven by NASDAQ (as opposed to NYSE and AMEX) firms. We also split our sample into two periods—pre- and post-Reg FD—because Reg FD could have had a significant influence on the nature, collection, and dissemination of private information (Mohanram and Sunder 2006). We find that the effect of competition on the pricing of information asymmetry is statistically significant in the pre-Reg FD period but not in the post-Reg FD period. However, the economic magnitude of the effect appears to be larger in the post-Reg FD period. One possible explanation for the lack of statistical significance in the post-Reg FD period is the lack of power due to the shorter time series.

Finally, we examine whether investor competition influences the pricing of information asymmetry using accounting-based measures of information quality to proxy for information asymmetry. An extensive literature argues that information quality is priced because poor information quality is associated with higher information asymmetry, and information asymmetry is priced (e.g., Botosan 1997; Francis et al. 2004, 2005). To measure information quality, we use accruals quality and earnings smoothness because these measures have been recently used to examine the pricing of information quality (Francis et al. 2004, 2005; Core et al. 2008; McInnis 2010; Mashruwala and Mashruwala, 2011). Consistent with our primary results, we find some evidence that the pricing of information quality decreases with competition.

This study contributes to the literature in at least two ways. First, it draws upon the theoretical literature to make predictions about the effect of the competition over information on the pricing of information asymmetry. We show that the pricing of information asymmetry decreases with such competition, and that the effect is economically important. While the idea of competition over information has been discussed in the theoretical literature, to the best of our knowledge, no prior empirical study has investigated the outcomes of such competition. In doing so, one contribution of our study is that we develop empirical proxies for competition over information—the number of informed investors and the Herfindahl index of the concentration of institutional holdings. We show that these proxies behave according to the theoretical prediction that competition reduces market inefficiency and economic rents.

Second, we extend previous literature that has empirically investigated the pricing of information asymmetry and information quality (e.g., Easley et al. 2002; Francis et al. 2004, 2005; Core et al. 2008; Duarte and Young 2009; Mohanram and Rajgopal 2009; McInnis 2010). We show that the extent of the competition over information has an important role in determining whether information asymmetry/quality is priced. Stated differently, information asymmetry/quality is more likely to be priced in trading environments where there is less competition over information. Our study highlights the importance of the nature of competition in the trading environment in determining the pricing of information asymmetry/quality.

Our study is related to Armstrong et al. (2011), as both studies examine the effect of competition on the pricing of information asymmetry. The key difference is the conceptual definition of competition. Armstrong et al. (2011) define competition as the extent to which investors' trades have price impact. Specifically, they argue that when there are more shareholders (their proxy for competition), there is lower price impact. Our study, in contrast, defines competition as the rivalry among informed investors to acquire and trade profitably on private information. Theories about such competition predict that increased competition among informed traders means that their private information gets impounded into prices more quickly, which, in turn, reduces the degree of exploitation of private information by informed traders. Thus, consistent with their different conceptualizations of competition, both studies use different proxies of competition. Armstrong et al. (2011) use the number of total shareholders, whereas we use the number of institutional investors and the concentration of institutional investor ownership. The concentration of ownership is an innovation of our study that borrows from the microeconomic literature on product market competition to capture competition among informed investors in capital markets.

Section II develops our hypothesis. Section III describes our research design. Sections IV and V present our results on the pricing of information asymmetry and information quality, respectively. Section VI concludes.

II. Hypothesis Development

In this section, we develop our hypothesis on how cross-sectional variation in competition affects the pricing of information asymmetry between informed and less informed/uninformed traders. Kyle (1985) shows how an informed trader, with a monopoly over private information, strategically trades to exploit his/her private information. In this model, the informed trader's private information reveals that there is a difference between the current market price and the underlying value of the firm. The informed trader profits by trading against the market makers and liquidity traders (also known as less informed traders). Notably, s/he trades in small quantities over time to camouflage his/her trades and maximize profits.[2] As a result of these trades, private information is gradually incorporated into prices and the market price converges to the underlying value. Market makers price protect in a manner that imposes trading costs on all traders. In particular, the increased price impact of the trades results in traders buying (selling) shares at average higher (lower) prices.[3] To the extent that traders require a return to be compensated for trading costs, the cost of capital is higher for firms with higher trading costs (Amihud and Mendelson 1986). In other words, in this model, information asymmetry is priced.

Admati and Pfleiderer (1988), Holden and Subrahmanyam (1992, 1994), Foster and Viswanathan (1993, 1994, 1996), and many others extend Kyle (1985) to incorporate multiple informed traders, as opposed to a single informed trader. In particular, Holden and Subrahmanyam (1992, 247) note that "Kyle's (1985) assumption of a single informed trader is strong in the sense that in actual financial markets, it is reasonable to expect that at least a few players will have access to private information and trade in the knowledge that they will face competition with other informed agents in the market." A greater number of informed traders causes these traders to compete more aggressively, which, in turn, causes their private information to be revealed more rapidly. As Holden and Subrahmanyam (1992, 248) state, "The contrast in results between the case of a monopolistic informed trader and that of multiple

[2] Prior literature has provided evidence consistent with informed traders selecting trade sizes to camouflage their trades (e.g., Barclay and Warner 1993; Chakravarty 2001; Alexander and Peterson 2007; Anand and Chakravarty 2007).

[3] As shown by Glosten and Milgrom (1985), trading costs can also be imposed on traders through bid-ask spreads (instead of price impact). Greater information asymmetry results in larger spreads, which means that investors have to buy (sell) each unit of shares at a higher ask (lower bid) price.

informed traders is driven by aggressive competition between these traders.… the unique Nash equilibrium is an equilibrium in which imperfect competitors acting noncooperatively choose larger quantities than a monopolist (or collusive agents) would choose." They also demonstrate that, in the limit (in which the number of informed traders extends to infinity), all private information is revealed in the first trade so that profit from informed trading converges to zero.

One implication of these models is that an increase in the number of informed investors results in a more competitive environment, which causes private information to be incorporated into prices more quickly (i.e., prices become informative about fundamental value faster). With more informative prices, there is less need for market makers to price protect. In other words, for a given level of information asymmetry, the degree of exploitation of private information by informed investors is lower when there is more competition. Thus, investors (on average) demand a lower return for that level of information asymmetry, which makes the pricing of information asymmetry smaller.[4]

The discussion thus far has focused on markets with imperfect liquidity; in these markets, information asymmetry is priced because investors demand compensation for trading costs. Competition can influence the pricing of information asymmetry even in markets with perfect liquidity because competition reduces the risk that certain investors face when others have private information. Easley and O'Hara (2004) propose a model in which informed investors use their information advantage to trade with uninformed investors, and hold portfolios more heavily weighted to stocks with positive private information and against stocks with negative private information. The information asymmetry increases the risk to the uninformed investors, who

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[4] Diamond and Verrecchia (1991) show that public disclosure, by bringing private information into the public domain, also affects the cost of capital by reducing information-asymmetry-related trading costs.

cannot adjust their portfolios to account for private information. In equilibrium, information asymmetry is priced to reflect the information risk to uninformed investors.[5]

In this model, competition also reduces the pricing of information asymmetry. Specifically, as shown in Easley and O'Hara (2004, 1572), increasing the number of informed traders serves this purpose. The intuition for this result is similar to the discussion in the previous section. Increasing competition means that informed traders' collective trades are more informative and more information is reflected in the equilibrium price. In particular, Easley and O'Hara note that, if more traders are informed, then their information is revealed to the uninformed investor with greater precision. This makes the stock less risky for uninformed investors, reducing the pricing of information asymmetry.

In light of the above arguments, our hypothesis is that, *ceteris paribus,* more competition reduces the pricing of information asymmetry by reducing the degree of exploitation of private information by informed traders. Hence, our hypothesis, stated in alternative form, is:

Hypothesis: The pricing of information asymmetry decreases with more competition.

Before we proceed, we note that competition in the equity markets is analogous to competition over sales in the product markets (Holden and Subrahmanyam 1992). In product markets, firms with monopoly power over product sales extract rents from consumers; more competition between firms over product sales reduces this exploitation (Samuelson and Nordhaus 2009). In equity markets, informed traders with monopoly power over private information extract rents by trading against less informed traders (e.g., liquidity traders). More competition between informed traders over private information reduces market inefficiency, in

[5] There is a dispute in the theoretical literature as to whether information asymmetry results in priced information risk. Hughes et al. (2007) and Lambert et al. (2011) show that information risk, as modeled in Easley and O'Hara (2004), is diversifiable. In particular, they show that when the number of assets (and the number of investors) extends to infinity, information risk is no longer priced. That is, the analysis in Easley and O'Hara relies on the number of assets being finite.

that it causes prices to reflect private information more quickly and reduces rent extraction. In the next section, we rely on the above analogy in the construction of our measures of competition in equity markets.

III. Measures of Competition

Testing our hypothesis requires a proxy for the degree of competition. While the prior theoretical literature has examined issues related to information-based competition in the equity markets, we are unaware of previous attempts in the empirical literature to measure such competition. Before we proceed to discussing the specific proxies, we highlight two important assumptions underlying them.

First, we assume that institutional investors belong to the class of informed investors - i.e., investors with private information. As discussed by Admati and Pfleiderer (1988, 7), privately informed traders include traders who "observe something about the piece of public information that will be revealed one period later to all traders or who are able to process public information faster or more efficiently than others are." In a similar vein, Kim and Verrecchia (1994, 42) note that some market participants "process earnings announcements into private information…traders capable of informed judgments from public sources can be thought of as market experts who follow a firm closely (e.g., large shareholders, financial analysts, managers at competing firms)." Consistent with these claims, several studies have shown that institutional investors, as opposed to individual retail investors, are more likely to be informed investors (e.g., Arbel and Strebel 1983; Sias and Starks 1997; Bartov et al. 2000; Jiambalvo et al. 2002).

Second, theoretical models of trading (e.g., Kyle 1985) are models about *traders*, as opposed to *investors*. One difference between traders and investors is that traders include both potential investors (i.e., investors who do not currently hold shares in a company) and existing investors. Ideally, we would measure competition between informed *traders* for a stock, but this information is not observable. Thus, we measure competition between informed *investors*, under the assumption that the number of existing investors captures the number of current and potential investors.[6] This assumption is consistent with prior research. For instance, Lehavy and Sloan (2008, 331), when confronting a similar challenge, state the following: "We cannot directly observe how many investors 'know about' a particular security. We can, however, observe the number of institutional investors who own a security. It seems reasonable to argue that the number of investors who know about a security is increasing in the number of investors that own the security."

Our first proxy of competition is the number of informed investors, which we measure as the number of institutional investors holding the firm's stock (*#Inst*). This measure follows directly from the theory models discussed in Section II (e.g., Admati and Pfleiderer 1988; Holden and Subrahmanyam 1992; Foster and Viswanathan 1993). In particular, these models use the number of informed traders to represent the extent of competition between informed traders, such that a greater number of informed traders indicates more competition. As noted in Holden and Subrahmanyam (1992), an extension of Kyle's (1985) model of a single informed investor to a model with two (or more) informed investors is mathematically equivalent to an extension of a model of monopoly pricing to one of duopoly pricing. That is, increased competition from one to

[6] To the best of our knowledge, there is no data available on the number of potential informed investors. In untabulated analyses, we have computed proxies for the number of institutional investors using ownership from the previous five years, independent of whether the institution was still a shareholder at the end of the period. The intention is to capture the potential number of informed investors as opposed to the actual number. These variables are highly correlated with ours (correlations of 0.96 and 0.84 for total and transient institutional investors respectively) and inferences are the same as they are for our variables.

multiple competitors results in a reduction in extracted rents from less informed investors; in the limit of perfect competition, profit equals zero.

Our second measure of competition explores the distribution of information among informed investors. An important idea in the industrial organization literature is that, not only does the number of firms matter, so does the distribution of their market shares (e.g., Herfindahl 1950). In a similar vein, we argue that in addition to the number of informed investors, the *distribution* of private information among informed investors can affect trading behavior and the resulting profits. A more equal distribution of private information implies that information will be more quickly revealed in prices due to more competitive trading among informed investors (Foster and Viswanathan 1994). Hence, the degree of competition increases not only with the number of informed investors, but also with the distribution of private information among them.

Conceptually, the construct of interest is the distribution of private information among informed investors, with the notion that a more equal distribution results in greater competition. However, this distribution is not directly observable or measurable. Hence, we use the distribution of shares to proxy for the distribution of private information. That is, we assume that informed investors with higher holdings on a given firm are likely to have more private information. This could occur for two reasons. First, the larger investor could have more access to the firm (e.g., by appointing directors to sit on corporate boards or by having relatively more exclusive access to management), and therefore would be able to obtain more privileged information. Second, the larger investor, by having a higher investment in the firm, has greater incentives to generate private information about the firm.

We note that, as shown in theories on competition over private information, an increase in the monopoly power over private information enables informed investors to earn economic rents from trading on private information against uninformed investors. Thus, the use of the distribution of institutional holdings (as a proxy for the distribution of private information) in the securities market is analogous to the use of the distribution of size or sales to estimate the distribution of market power in product markets.

Hence, we propose a measure of the amount of competition in stock *i*, *HerfInst*, based on the Herfindahl index. This measure takes into account the number and relative holdings of shares of each institutional investor for a given firm. The computation is as follows:

$$HerfInst_i = -1 \times \sum_{j=1}^{N} \left(\frac{Investor_{i,j}}{Investor_i} \right)^2, \tag{1}$$

where $Investor_{i,j}$ is the number of shares held by institutional investor *j* in stock *i*, $Investors_i$ is the total shares held by all institutional investors of stock *i*, and *N* is the total number of institutional investors in stock *i*. Given that the typical Herfindahl index measures concentration, we multiply the Herfindahl index by minus one so that a higher value of *HerfInst* measures more competition in the trades of stock *i*.

As discussed above, we use institutional investors as a proxy for informed competition. Prior research, however, has shown that certain types of institutional investors are more likely to trade on information (e.g., Grinblatt and Keloharju 2000; Ke and Petroni 2004; Ke and Ramalingegowda 2005). For example, a commonly used institutional investor classification by Bushee (1998) divides institutional investors into transient investors, dedicated investors, and quasi-indexers. Ke and Petroni (2004) and Ke and Ramalingegowda (2005) find that transient institutional investors (i.e., institutional investors who hold small stakes in numerous firms and trade frequently in and out of stocks) trade on information to make profitable trades. Hence, in the same vein as our earlier measures based on total institutional investor ownership, we measure the number of transient institutional investors, *#Trans*, and the Herfindahl index for competition, *HerfTrans*. If a firm does not have any transient institutional investors but has other types of institutional investors, we set *#Trans* is zero and *HerfTrans* to minus one to reflect no competition among transient institutional investors.

We construct the above measures of competition by employing data from the institutional investor database used by Bushee (1998). Briefly, Bushee constructs several variables related to institutional investors using data from the CDA/Spectrum Institutional (13f) Holdings (s34) database available from Thomson Reuters. In particular, his database provides quarterly data on the institutional investors of each firm, as well as the classification of each institutional investor as transient, dedicated, or quasi-indexing. For each year, we compute our proxies of competition using the data for the December quarter.

Validating our Measures of Competition

While we motivate the above proxies based on prior theories that have studied the concept of competition between informed investors, we acknowledge that each proxy is an imperfect measure of competition. We provide some construct validity tests by examining whether these proxies behave according to a key prediction of theories on competition: in the presence of information asymmetry, competition reduces market inefficiency and the economic rents (in terms of abnormal stock returns) of informed investors.

We test this prediction using the post-earnings-announcement drift (PEAD) setting. PEAD is a suitable setting to validate our proxies for two reasons. First, we need to identify an event for which informed investors are more likely to have an information advantage. Earnings announcements are one such event. Lee et al. (1993) document a significant increase in information asymmetry and trades during earnings announcements, consistent with Kim and

Verrecchia's (1994) argument that earnings announcements represent an event in which sophisticated investors convert the information on earnings into private information. Second, the PEAD literature has documented significant evidence of market inefficiency with respect to earnings announcements (e.g., Ball and Brown 1968; Bernard and Thomas 1989, 1990). To the extent that competition reduces market inefficiencies, we would predict that PEAD would be smaller for firms with higher competition.

We first obtain a sample of quarterly earnings announcements from NYSE, AMEX, and NASDAQ firms from 1983 to 2008 (and returns from 1984 to 2009). We define an earnings surprise for firm *i* in fiscal quarter *q*, $UE_{i,q}$, as:

$$UE_{i,q} = \frac{E_{i,q} - E_{i,q-4}}{MV_{i,q-4}}, \qquad (2)$$

where $E_{i,q}$ is the most recent quarterly earnings, $E_{i,q-4}$ is the quarterly earnings four fiscal quarters ago, and $MV_{i,q-4}$ is the market value at the end of the fiscal quarter four fiscal quarters ago.

To examine how PEAD returns vary cross-sectionally with competition, we form five-by-five portfolios by sorting earnings surprises and competition into quintiles within each quarter. Hence, each firm-quarter is assigned to a *UE* quintile (*UE quintile*) and a competition quintile (*Competition Quintile*). To calculate 12-month abnormal returns (*AbRet12*), we collect monthly returns from CRSP for the 12-month period beginning from the month following the announcement month. For each firm-quarter, we compute the size-adjusted return by subtracting the buy-and-hold return in the same CRSP size-matched decile from the buy-and-hold return of the firm, with size measured as the market capitalization at the beginning of the calendar year. If a firm delists during the buy-and-hold period, we include its delisting returns; if the delisting returns are missing, we assume a delisting return of 100 percent if the delisting arises due to performance-related reasons (Sloan 1996; Ng et al. 2008). We then determine the average buy-and-hold return for each portfolio by averaging the buy-and-hold returns of all firm-quarters within the portfolio.

Table 1, Panel A presents the portfolio results. Consistent with the PEAD literature, we find that portfolio abnormal returns are positive (negative) for the top (bottom) quintile of earnings surprise. When we examine the pattern of portfolio returns across the top (bottom) quintile, we find that the magnitude of the positive (negative) returns in the top (bottom) quintile becomes less positive (negative) when competition increases. Thus, the hedge portfolio returns (i.e., returns from buying (shorting) firms in the top (bottom) quintile of earnings surprises) become smaller as competition increases. These results are consistent across all our four proxies of competition. For example, with *HerfInst* (*HerfTrans*) as the proxy for competition, we find that the hedge portfolio returns decrease from 13.55 percent (11.90 percent) in the least competitive quintile to 2.95 percent (2.90 percent) in the most competitive quintile. Overall, the degree of market inefficiency associated with PEAD is smaller when there is higher competition.

Next, in Table 1, Panel B we estimate cross-sectional regressions to control for previously documented determinants of PEAD. In particular, we control for volume and volatility because these variables are likely correlated with our measure of competition and because they have been documented by the prior literature to be determinants of PEAD (e.g., Bhushan 1994; Mendenhall 2004). *Volume* is the average daily dollar trading volume of the firm during the earnings announcement month. *Volatility* is the standard deviation of the residuals of a regression of daily returns on the S&P 500 during the twelve months ending in the announcement month, with the requirement that at least 24 daily returns are available for the regression.

The dependent variable is *AbRet12*. We sort firms into quintiles on the basis of earnings surprises. *UE quintile* is the quintile portfolio to which a firm-quarter has been assigned based on its unexpected earnings within each quarter. Similarly, we sort firms into quintiles based on competition, trading volume, and return volatility (*Competition, Volume*, and *Volatility*). To facilitate the interpretation of the coefficients on the interaction terms, we rescale the quintile ranks to range from zero to one. Finally, we include beta, size, and book-to-market to control for risk.

Table 1, Panel B presents the results of the regressions. The coefficient of interest is the interaction term between *UE* and *Competition*. Each of the four columns in Panel B has a different competition proxy. In all four columns, we find that the hedge portfolio returns decrease with competition. For example, in Column 2 (Column 4), the competition proxy is *HerfInst* (*HerfTrans*). The coefficient on *UE* × *Competition* of -8.11 (-6.35) indicates that the hedge portfolio returns in the most competitive quintile of *HerfInst* (*HerfTrans*) are smaller than those in the least competitive quintile by 8.11 percent (6.35 percent).

<INSERT TABLE 1 ABOUT HERE>

Overall, we find strong evidence from both portfolio tests and cross-sectional regressions that there is a smaller PEAD (i.e., less market inefficiency) when there is more competition, as measured using our proxies. To the extent that competition reduces market inefficiency as the theory predicts, this evidence suggests that these proxies capture competition.

IV. The Role of Competition in the Pricing of Information Asymmetry

To test our hypothesis, we rely on the following cross-sectional asset pricing regression specification:

$$R_{i,t+1} = \alpha + \Sigma\beta_j \, Risk_{j,i,t} + \lambda_1 \, NIASpread_i + \lambda_2 \, IASpread_{i,t} + \lambda_3 \, Turnover_{i,t} + \lambda_4 \, Competition_{i,t}$$
$$+ \lambda_5 \, Turnover_{i,t} \times NIASpread_{i,t} + \lambda_6 \, Turnover_{i,t} \times IASpread_{i,t}$$
$$+ \lambda_7 \, Competition_{i,t} \times NIASpread_{i,t} + \lambda_8 \, Competition_{i,t} \times IASpread_{i,t} + \varepsilon_{i,t+1}, \quad (3)$$

R_{t+1} is the monthly excess return during the 12-month period, i.e., January to December, in year t+1 (in the event of a delisting, a firm's delisting return, when available from CRSP, is used as the monthly return). *Risk* is a vector consisting of *Beta*, *Size*, and *BTM*. *Beta* is the market beta from the regression of daily excess stock returns on the daily excess market returns in the calendar year, with a minimum requirement of 24 daily returns. *Size* is the natural logarithm of the market value of equity in millions at the end of year t. *BTM* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the fiscal year end at least three months before the end of year t. *IASpread* (*NIASpread*) is the information asymmetry component (non-information asymmetry component) of the bid-ask spread for year t; these components are obtained using the spread decomposition model in Glosten and Harris (1988), details of which are presented in Appendix A.[7] *Turnover* is the monthly share turnover in December of year t. *Competition* is either *#Inst*, *HerfInst*, *#Trans*, or *HerfTrans*, as defined earlier.

We include the *NIASpread,* as well as its interactions with *Competition*, to better isolate the effects of competition on pricing of information asymmetry. The inclusion of *Turnover*, as well as its interactions with *IASpread* and *NIASpread*, is to address the concern that *Competition* could be simply capturing stock liquidity.[8] To mitigate the effect of cross-sectional dependence in the regression residuals, we follow the prior literature and estimate Fama-MacBeth (1973)

[7] In an additional analysis later in the study, we use the information asymmetry component of PIN developed by Duarte and Young (2009) as an alternative proxy for information asymmetry. We also use accruals quality and smoothness which capture, among other things, information asymmetry.

[8] In untabulated analysis, we also have used total trading volume as an alternative proxy for liquidity. We use turnover in the main tests because this variable, which is scaled by total outstanding shares, is likely to better capture differences in stock liquidity across firms in the cross-section. The results with volume yield similar inferences.

regressions. Specifically, we first run cross-sectional regressions for each month in the sample. Each reported coefficient is the average of the monthly coefficients. The t-statistic for each reported coefficient is obtained by dividing the coefficient by the standard error of the monthly coefficients.

In the above regression, the coefficient of interest is the coefficient on the interaction term between *Competition* and *IASpread*, λ_8. To ease exposition, we rank *Competition* and *Turnover* into quintiles every year and then scale the quintile rank so that it ranges from zero to one. As such, λ_8 indicates the incremental pricing of information asymmetry as one moves from the bottom to the top quintile of competition. Based on our hypothesis that the pricing of information asymmetry is decreasing in competition, we expect λ_8 to be negative.

Table 2 presents summary statistics and the correlations for the variables used in our tests of Eq. (3). There are 83,988 firm-years from 1983 to 2008 with data to measure information asymmetry, competition, and control variables. We match each firm-year to monthly returns in the following year, yielding a sample of 968,250 firm-months with monthly returns from January 1984 to December 2009.

Panel A presents the descriptive statistics for our sample. First, we present statistics for our measures of the information-asymmetry and non-information-asymmetry components of the bid-ask spread, *IASpread* and *NIASpread*. *IASpread* and *NIASpread* have a mean of 0.23 percent and 1.13 percent, respectively. Moving on to our competition measures, the mean number of institutional investors (transient institutional investors) is 89.33 (27.10). The mean Herfindahl competition index based on institutional investors (transient institutional investors) is -0.17 (-0.37). The mean market beta is 0.88. The median market capitalization and book-to-market of equity are $257 million (=exp(5.55)) and 0.49 (=exp(-0.71)), respectively. Finally, the mean monthly share turnover is 0.09.

Panel B presents Pearson correlations among the variables. All the correlations are significant at $p<0.01$. The positive correlation between *IASpread* and *NIASpread* indicates that stocks with a higher information asymmetry component of spread have a higher non-information asymmetry component of spread. In addition, consistent with the theories on competition, *IASpread* is negatively correlated with competition. All competition measures are positively and significantly correlated with each other. For example, *#Inst* has pairwise correlations of 0.39, 0.90, and 0.50 with *HerfInst, #Trans,* and *HerfTrans*, respectively. There are also positive pairwise correlations between our competition measures and *Turnover*. One explanation for these correlations is that greater competition increases the extent to which shares turn over among investors.

<INSERT TABLE 2 ABOUT HERE>

Table 3 presents the regression results of the cross-sectional asset pricing tests based on Eq. (3). For comparability across different measures, we assume a one standard deviation difference in *IASpread* when we make inferences about the economic significance of the coefficient on the interaction term between *Competition* and *IASpread*; this standard deviation is 0.33 (see Table 2). We then examine how this difference translates into a difference in the pricing of information asymmetry between the most and least competitive quintiles by multiplying the standard deviation and the coefficient on the interaction term between *IASpread* and each proxy for competition.

The results in Column 1 indicate that neither the information asymmetry nor the non-information asymmetry components of spread are priced, on average. In the remaining columns, we test our hypothesis on the role of competition in the pricing of information asymmetry by examining whether there is a cross-sectional difference in the pricing of the information asymmetry component of spread conditional on competition.

Consistent with our hypothesis, the coefficient on the interaction term between *IASpread* and various proxies of competition is negative and statistically significant in all four columns. For instance, with *#Inst* (*HerfInst*) as the measure of competition, the coefficient is -2.48 (-1.66), which is statistically significant at $p<0.05$. This indicates that the pricing of (a one standard deviation difference in) information asymmetry in the most competitive quintile is 0.79 percent (0.53 percent) per month less than it is in the least competitive quintile. Similarly, with *#Trans* (*HerfTrans*) as the measure of information asymmetry, the pricing of information asymmetry in the most competitive quintile is 0.86 percent (0.47 percent) lower than it is in the least competitive quintile. Finally, we note that there is generally no statistically significant evidence of a difference in the pricing of the non-information asymmetry component of spread that is conditional on competition. This is important because, while one might expect competition to affect the overall pricing of spread, our results indicate that competition among informed investors only affects the pricing of the information asymmetry component of spread. Hence, competition over information appears to be driving our results. Overall, these results are consistent with our prediction that the pricing of information asymmetry decreases with more competition.[9]

<INSERT TABLE 3 ABOUT HERE>

Alternative Measure of Information Asymmetry - *AdjPIN*

[9] In untabulated tests, we find that our results are robust to controlling for the number of shareholders (the proxy for competition used in Armstrong et al. (2011)). Further, in our sample we find no evidence that the number of shareholders affects the pricing of information asymmetry. We note, however, that the differences in samples and research designs between Armstrong et al. and our study could explain the difference in the results.

In this section, we repeat our earlier analyses using the adjusted probability of informed trading, *AdjPIN*, as an alternative measure of information asymmetry. The probability of informed trading, which is commonly known as PIN, is based on the sequential trade model by Easley et al. (1996). Duarte and Young (2009) decompose PIN into an information asymmetry component, adjusted PIN (*AdjPIN*), and a non-information asymmetry component, the probability of a symmetric order flow shock (*PSOS*). They motivate this decomposition by noting that while the sequential trade model underlying PIN attributes abnormal trading to private information, this trading could also result from liquidity shocks.

We obtain the *AdjPIN* and *PSOS* used in Duarte and Young (2009). Since *AdjPIN* and *PSOS* are available only for NYSE and AMEX firms from 1983 to 2004, we present the analysis with *AdjPIN* as an additional analysis—the analysis uses a smaller cross-section (because of the exclusion of NASDAQ firms) and a shorter time-series (because the sample ends in 2004). The sample consists of 470,875 firm-months with monthly returns from January 1984 to December 2005.

In the first column of Table 4, the results indicate that *AdjPIN* is not priced, while *PSOS* is. These results are consistent with Duarte and Young (2009). The remaining columns present the regression results conditional on competition. All coefficients on the interaction term between *AdjPIN* and *Competition* are negative and statistically significant at $p<0.10$. In terms of economic significance, the coefficient on the interaction term between *AdjPIN* and *HerfInst* indicates a monthly differential in the required rate of return of 0.30 percent (=3.30 × 0.09), the latter being the standard deviation for *AdjPIN* in our sample) per month between stocks in the least and most competitive quintiles for a one standard deviation difference in information asymmetry. Finally, we note that there is no evidence of a cross-sectional difference in the pricing of *PSOS* conditional on competition. Thus, competition affects only the pricing of the information asymmetry component of PIN.

<INSERT TABLE 4 ABOUT HERE>

Additional Analyses

Overall, the results in our earlier analyses are consistent with our hypothesis that the pricing of information asymmetry decreases with competition. In this section, we conduct a number of additional analyses. For parsimony, we present results with *HerfInst* and *HerfTrans* as our proxies for competition. To the extent that it is important to take into account the distribution of private information among informed investors when measuring competition, these measures are likely to be better proxies for competition.

NYSE and AMEX versus NASDAQ Firms

The results in Table 4, when compared to Table 3, suggest that the effect of competition on the pricing of *AdjPIN* is not as strong as the effect of competition on the pricing of *IASpread*. One possible explanation is that *AdjPIN* is available only for NYSE and AMEX firms, while *IASpread* is also available for NASDAQ firms. To investigate this explanation, we repeat the analyses in Table 3 after dividing the full sample into a subsample of NYSE and AMEX firms and a subsample of NASDAQ firms. For comparability with the *AdjPIN* results, we restrict the sample period to 1983 to 2004.

Table 5 presents these results. All variables presented in Table 3 are included in the model but, for brevity, we only present the coefficients for our main variables. The first two columns document the results for NYSE and AMEX firms; the next two document the results for NASDAQ firms. The coefficient of interest is the coefficient on the interaction term between *Competition* and *IASpread*.

The effect of competition on the pricing of information asymmetry is stronger (in magnitude and statistical significance) for NASDAQ firms than it is for NYSE and AMEX firms. Specifically, for NYSE and AMEX firms, the coefficients on the interaction term between *Competition* and *IASpread* are -0.90 (0.01) with *HerfInst* (*HerfTrans*) as the measure of competition; these coefficients are not statistically significant. In contrast, for NASDAQ firms, the coefficients are -2.44 and -1.63, which are statistically significant. On one hand, this result provides a possible explanation for the weaker results when *AdjPIN* is used to examine how the pricing of information asymmetry varies with competition. That is, competition has an insignificant effect on the pricing of information asymmetry among NYSE and AMEX firms, possibly because there is less information asymmetry and/or less variation in information asymmetry. On the other hand, this result also highlights the importance of identifying settings in which competition is likely to have a greater role in the pricing of information asymmetry.[10]

<INSERT TABLE 5 ABOUT HERE>

Pre- and Post-Regulation Fair Disclosure

In this section, we provide some exploratory analyses of whether there is a difference in the role of competition in the pricing of information asymmetry before and after 2000, the year in which Regulation Fair Disclosure (Reg FD) was implemented. The motivation for this analysis is that Reg FD could have had a significant influence on the nature of private information and how it is collected and disseminated. For example, Mohanram and Sunder (2006) examine the change in the nature of information available to analysts around Reg FD and find an increase in the precision of idiosyncratic information available to analysts, leading to

[10] In untabulated analyses, we find that the mean and standard deviation of *IASpread* for NASDAQ (NYSE/AMEX) firms are 0.30% and 0.37% (0.20% and 0.30%), respectively. Thus, NASDAQ firms have a higher and wider cross-sectional variation in information asymmetry. This lends support to the evidence that NASDAQ firms might be a more powerful sample for examining how the pricing of information asymmetry varies with competition.

better analyst performance. Thus, we split our sample into two subperiods: (1) during and before August 2000, which is the date when Reg FD was passed, and (2) after August 2000. We then repeat the analyses in Table 3 for each of the two subperiods.

Table 6 reports the results. In the pre-Reg FD sample, the coefficients on *Competition* × *IASpread* with *HerfInst* (*HerfTrans*) are a statistically significant -0.87 (-0.94), providing evidence that more competition is associated with a lower pricing of information asymmetry pre-Reg FD. In the post-Reg FD sample, the coefficients are larger in magnitude but statistically insignificant. Despite the differences in statistical significance, one must be cautious in interpreting the results as evidence that competition has no significant role post-Reg FD. First, the time series is significantly shorter for the post-Reg FD period than for the pre–Reg FD period, and this can affect the power of the statistical tests. Second, confounding events (e.g., the decimalization of stock prices, Sarbanes Oxley, the tech bubble crash) occurred around and after the passage of Reg FD, making it difficult to attribute any difference solely to Reg FD.

<INSERT TABLE 6 ABOUT HERE>

VI. Competition, Information Asymmetry, and Information Quality

Our hypothesis predicts that the pricing of information asymmetry decreases with competition. We test this hypothesis using the information asymmetry component of spread and PIN. Our goal is to provide evidence with empirical proxies that best approximate the economic construct of information asymmetry.

In this section, we examine the implications of our earlier results for a fundamental issue in the accounting literature that has attracted extensive theoretical and empirical research: the pricing of information quality. The general prediction from this literature is that cost of capital is higher when information quality is poorer (e.g., Botosan 1997; Francis et al. 2004, 2005). This argument is based on the idea that higher information quality reduces information asymmetry. To the extent that poorer information quality captures higher information asymmetry, the pricing of information quality should also decrease with more informed competition, given our previous results with information asymmetry. Hence, in this section, we investigate whether the pricing of information quality decreases with competition, under the assumption that information quality proxies for information asymmetry.

To proxy for information quality (*IQ*), we use accruals quality (*AQ*) and earnings smoothness (*Smoothness*). These measures have been recently used in the literature in the context of the cost of capital (Francis et al. 2004, 2005; Core et al. 2008; McInnis 2010). We follow Francis et al. (2005) and estimate *AQ* as the standard deviation of the residuals during the years *t-5* to *t-1* from the Dechow and Dichev (2002) accruals model, as modified by McNichols (2002). The model is a cross-sectional regression of working capital accruals on lagged, current, and future cash flows, plus the change in revenue and PPE. All variables are scaled by average total assets. *Smoothness* is the ratio of a firm's standard deviation of net income before extraordinary items to its standard deviation of cash flows from operations from *t-5* to *t-1*; net income and cash flows are scaled by average total assets.

Table 7 presents the results of cross-sectional asset pricing tests that examine whether the pricing of information quality varies cross-sectionally with competition. The regression specification follows Eq. (3), except that we now replace the information asymmetry measures with measures of information quality. Similar to our earlier regressions, the coefficient on the interaction term of *IQ* and *Competition* is the coefficient of interest in each of the columns. A statistically significant negative coefficient on this interaction term indicates that more competition is associated with the lower pricing of information quality.

The first three columns document the results with *AQ* as the proxy for information quality. From the first column, we observe that the coefficient on *AQ* is positive but statistically insignificant. This result is consistent with Core et al. (2008), who find that *AQ* is not priced on average. In the next column, the interaction term between *AQ* and *HerfInst* is a marginally significant -6.71 (p=0.09). This indicates that for a one standard deviation difference in *AQ*, which equals 0.03 in our sample, the monthly difference in the expected return in the most competitive quintile is 0.20 percent less than in the least competitive quintile. In the third column, the coefficient between *AQ* and *HerfTrans* is a statistically insignificant -5.81 (p=0.12).

The next three columns present the results with *Smoothness* as the proxy for information quality. *Smoothness* is not priced on average, consistent with McInnis (2010). However, when we examine the pricing of *Smoothness* conditional on competition, we find some evidence that the pricing of information quality decreases with competition. In particular, the next two columns show the coefficient on the interaction term between *Smoothness* and *HerfInst* (*HerfTrans*) is marginally significant. In terms of economic significance, for a one standard deviation difference in *Smoothness*, which equals 0.52 in our sample, the monthly difference in the expected return in the most competitive quintile is 0.15 percent (0.14 percent) less than it is in the least competitive quintile. Overall, the results in Table 7 indicate some marginal evidence that the pricing of information quality decreases with more competition.

<INSERT TABLE 7 ABOUT HERE>

VII. Conclusion

The issue of whether information asymmetry is priced has been of significant academic interest. We re-examine this question by emphasizing an important aspect of capital markets with information asymmetry—competition among informed investors over private information. While prior research has investigated whether information asymmetry is priced on average, it has not studied whether there is cross-sectional variation in the pricing conditional on the extent of such competition.

We measure competition as the number of total and transient institutional investors, as well as the Herfindahl indices measuring the distribution of information among each type of institutional investor. The implicit assumption underlying these measures is that institutional investors are relatively more informed investors and that the competition between informed investors captures the competition between informed traders. We measure information asymmetry using the information asymmetry components of the bid-ask spread and PIN.

Consistent with our hypothesis, we show that the pricing of information asymmetry decreases with competition, and that this effect is economically important. We then explore the implications of this finding for the accounting literature that examines whether information quality, as a proxy for information asymmetry, is priced. We repeat our analyses by replacing our measures of information asymmetry proxies with measures of information quality, finding similar (albeit weaker) results. That is, our results indicate that the pricing of information quality marginally decreases with competition.

Future research into the effects of the information environment on the equity markets could consider the level of competition between informed investors over private information. A direct implication of our findings is that, in the face of information asymmetry, firms could potentially reduce their cost of capital by encouraging more competition. An indirect implication is that efforts to mitigate information asymmetry such as increased corporate disclosure and transparent financial reporting might have greater cost of capital effects in markets (either within a single country or across different countries) characterized by less competition.

Appendix A. The Decomposition of Bid-Ask Spread

The following regression specification is used to obtain the parameters required to decompose the spread:

$$\Delta Price_{i,s} = C_0 \Delta Trade_{i,s} + C_1 \Delta Trade_{i,s} \times TradeSize_{i,s} + Z_0 Trade_{i,s} + Z_1 Trade_{i,s} \times TradeSize_{i,s} + \varepsilon, \qquad (A1)$$

where, for the trade at time s for firm i, ΔPrice is the change in trade price scaled by the previous trade price, TradeSize is the number of shares traded, and Trade is an indicator that is equal to +1 if the trade is classified as buyer-initiated and -1 if the trade is seller-initiated.

A brief description of the intuition underlying Eq. (A1) is as follows: Glosten and Harris (1988) indicate that for a round-trip transaction, the non-information asymmetry component is obtained by $2(C_0 + C_1 TradeSize)$ and the information asymmetry component of the bid-ask spread is obtained by $2(Z_0 + Z_1 TradeSize)$, with the spread estimated as the sum of the two components. The first component allows market makers to generate revenue from a seemingly random order flow to cover inventory holding and order processing costs, as well as to provide monopoly profits. It is a transitory component because it is unrelated to the underlying value of the securities. The second component assumes that order flows will be correlated with future price changes. It arises because rational market makers in a competitive environment will widen the spread in response to information asymmetry. The scaling of price changes by the previous price - i.e., the use of intraday returns, facilitates cross-sectional comparability of information asymmetry across firms.

Econometrically, it can be observed from Eq. (A1) that the key distinction between the information asymmetry component and the non-information asymmetry component is that the coefficients for the non-information asymmetry component are based on ΔTrade, while the coefficients for the information asymmetry component are based on Trade. The intuition for the difference is as follows. The non-information asymmetry component assumes that market makers generate revenue using random switching between buyer- and seller-initiated trades to "buy low and sell high," on average. ΔTrade captures the idea that, when a buy (sell) order is filled, market makers raise bid and/or ask prices to increase the probability that the next order will be a sell (buy) to maintain inventory. Price changes, which reflect the compensation to the market makers, reverse on average (i.e., the effect of trades on prices is transitory). The information asymmetry component captures the idea that buy orders (i.e., Trade = 1) cause "true" prices to rise by (Z_0 + Z_1TradeSize), while sell orders (i.e., Trade = -1) cause them to fall by (Z_0 + Z_1TradeSize). Buy and sell orders have a permanent effect on prices because they are due to a change in expectations of firm value. Eq. (A1) provides the regression coefficients, Z_0, Z_1, C_0, and C_1. For trade size, we compute the average trade size (AvgTradeSize).

We compute the information asymmetry (*IASpread*) and non-information-asymmetry (*NIASpread*) components of the spread using the intraday data from the Institute for the Study of Security Markets database (ISSM) and the NYSE Trade and Quotes database (TAQ). ISSM provides the data for NYSE and AMEX firms from 1983 to 1992 and for NASDAQ firms from 1987 to 1992. TAQ provides the data for NYSE, AMEX, and NASDAQ firms from 1993 to 2008. Due to the extensive computational requirements, we use only the intraday data from December of each year to estimate the components. The exception is December 1989, due to missing data for NASDAQ firms for November and December 1989; in this case, we use intraday data from October 1989. We then express the components in percentages by multiplying them by 100, and winsorizing at the 1st and 99th percentile.

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TABLE 1: Validation of Competition Proxies: Competition and Market Efficiency

Panel A – Portfolio returns

Competition	*UE* Quintile					
#Inst Quintile	I	II	III	IV	V	Hedge
I	-4.64	-3.07	0.15	6.30	9.12	13.77
II	-1.78	-0.46	3.07	6.28	9.87	11.65
III	-2.66	0.15	1.56	4.46	5.70	8.35
IV	-0.41	0.77	1.35	3.58	4.30	4.71
V	-0.05	0.96	1.01	1.95	2.81	2.86
HerfInst Quintile	I	II	III	IV	V	Hedge
I	-4.40	-3.15	-0.75	5.56	9.16	13.55
II	-1.89	-0.73	3.28	6.16	9.70	11.59
III	-1.82	0.85	2.62	5.87	6.99	8.81
IV	-1.59	1.04	1.10	2.60	3.93	5.52
V	-1.15	0.21	0.69	2.19	1.80	2.95
#Trans Quintile	I	II	III	IV	V	Hedge
I	-4.61	-2.03	0.75	6.45	9.59	14.20
II	-1.75	-0.22	1.97	6.68	9.80	11.54
III	-1.99	-0.18	2.85	4.34	7.09	9.08
IV	-1.57	0.67	0.73	3.36	3.95	5.53
V	-0.27	0.73	1.02	2.03	2.48	2.75
HerfTrans Quintile	I	II	III	IV	V	Hedge
I	-2.96	-2.23	0.32	6.50	8.94	11.90
II	-2.48	-0.96	2.98	5.62	8.63	11.11
III	-3.13	0.18	2.16	5.07	8.04	11.18
IV	-1.92	0.28	1.27	2.96	4.38	6.30
V	-1.15	1.14	0.51	2.38	1.76	2.90

TABLE 1: Validation of Competition Proxies (cont'd)

Panel B – Fama-MacBeth regressions

	Competition			
	#Inst	*HerfInst*	*#Trans*	*HerfTrans*
	I	II	III	IV
Intercept	-1.41	-1.95	-1.21	-1.50
	(-0.42)	(-0.57)	(-0.36)	(-0.44)
Beta	0.06	0.17	0.10	0.19
	(0.05)	(0.13)	(0.08)	(0.14)
Size	-0.96**	-0.77*	-0.88**	-0.75*
	(-2.42)	(-1.86)	(-2.20)	(-1.83)
BTM	3.69***	3.88***	3.82***	3.92***
	(3.74)	(3.75)	(3.77)	(3.78)
Volume	-0.38	5.11*	2.95	6.05**
	(-0.11)	(1.77)	(0.86)	(2.07)
Volatility	-0.02	0.22	-0.39	-0.07
	(-0.01)	(0.07)	(-0.12)	(-0.02)
Competition	12.02***	5.61***	8.01***	3.96**
	(3.55)	(3.20)	(2.87)	(2.35)
UE	15.12***	15.11***	14.56***	14.37***
	(8.84)	(8.85)	(8.60)	(8.55)
UE x Volume	2.22	-3.47	-1.53	-4.35**
	(0.73)	(-1.60)	(-0.58)	(-1.96)
UE x Volatility	0.43	0.27	0.98	0.79
	(0.20)	(0.13)	(0.45)	(0.36)
UE x Competition	**-13.67*** **	**-8.11*** **	**-9.47*** **	**-6.35*** **
	(-4.56)	**(-3.84)**	**(-3.48)**	**(-3.00)**
Adj-R^2 (%)	4.59	4.59	4.53	4.54

This table presents the results of tests that validate our proxies for competition: *#Inst*, *HerfInst*, *#Trans*, and *HerfTrans*. The sample consists of 411,032 firm-quarter earnings announcements from January 1983 through December 2008 with 12-month size-adjusted (i.e., abnormal) post-earnings-announcement buy-and-hold returns from 1984 to 2009. Panel A provides the returns of five-by-five portfolios formed by independent sorts of earnings surprises and competition within each quarter. Panel B provides the results of Fama-MacBeth regressions that examine how the returns associated with earnings surprises vary cross-sectionally with our competition proxies. *#Inst* (*#Trans*) is the number of institutional (transient institutional) investors before the earnings announcement. *HerfInst* (*HerfTrans*) is the Herfindahl measure of the concentration of institutional (transient institutional) investor holdings before the earnings announcement; this measure is multiplied by -1 so that it is increasing in competition. *UE* is the quintile rank of the earnings surprise and is increasing from Quintiles I to V. *Competition* is the quintile rank of each of the competition proxies and is increasing from Quintiles I to V. *Volume* is the quintile rank of the average daily dollar trading volume of the firm during the earnings announcement month. *Volatility* is the quintile rank of the standard deviation of the residuals of a regression of daily returns on the S&P500 index during the twelve months ending in the earnings announcement month, with the requirement that at least 24 daily returns are available for the regression. To ease exposition, all the quintile ranks are re-scaled to range from zero to one. *Beta* is the market beta from the regression of daily excess returns on daily market excess returns in the year ending in the month before the earnings announcement month, with the requirement that at least 24 daily returns are available for the regression. *Size* is the natural logarithm of the market value of equity at the end of the previous fiscal quarter. *BTM* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the end of the previous fiscal quarter. The t-statistics are below the coefficients, in parentheses. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels, respectively.

TABLE 2: Summary Statistics

Panel A: Descriptive statistics

Variable	Mean	STD	P25	Median	P75
Return	0.80	19.01	-7.47	-0.20	7.32
IASpread (%)	0.23	0.33	0.05	0.12	0.28
NIASpread (%)	1.13	1.71	0.14	0.46	1.40
#Inst	89.33	125.45	17.00	46.00	110.00
HerfInst	-0.17	0.19	-0.20	-0.09	-0.05
#Trans	27.10	39.37	4.00	13.00	35.00
HerfTrans	-0.37	0.32	-0.54	-0.24	-0.12
Beta	0.88	0.60	0.46	0.81	1.23
Size	5.64	1.97	4.23	5.55	6.94
BTM	-0.80	0.84	-1.25	-0.71	-0.27
Turnover	0.09	0.14	0.03	0.06	0.10

Panel B: Correlation matrix

	Return	*IASpread*	*NIASpread*	*#Inst*	*HerfInst*	*#Trans*	*HerfTrans*	*Turnover*
Return	---	0.02	0.02	-0.01	-0.01	-0.01	-0.01	-0.01
IASpread		---	0.45	-0.33	-0.47	-0.33	-0.50	-0.12
NIASpread			---	-0.33	-0.49	-0.33	-0.54	-0.08
#Inst				---	0.39	0.90	0.50	0.09
HerfInst					---	0.38	0.73	0.06
#Trans						---	0.52	0.14
HerfTrans							---	0.12
Turnover								---

Panel A (B) presents the descriptive statistics (Pearson correlations) for the main variables. The sample consists of 968,250 firm-months with monthly returns from January 1984 to December 2009. *Return* is the monthly returns in excess of the risk-free rate for the firm in year t+1. *IASpread* (*NIASpread*) is the information asymmetry (non-information asymmetry) component of bid-ask spread; the components are obtained by decomposing the intraday spreads in December of year t. *#Inst* (*#Trans*) is the number of institutional investors (transient institutional investors) at the end of year t. *HerfInst* (*HerfTrans*) is the Herfindahl measure of the concentration of institutional investor holdings (transient institutional investor holdings) at the end of year t; this measure is multiplied by -1 so that it is increasing in competition. *Beta* is the market beta from the regression of daily excess stock returns on daily excess market returns in year t, with a minimum requirement of 24 daily returns. *Size* is the natural logarithm of the market value of equity in millions at the end of year t. *BTM* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the fiscal year end at least three months before the end of year t. *Turnover* is the share turnover in December of year t. All correlations are significant at the 1% level.

TABLE 3: Pricing of Information Asymmetry– *IASpread*

		Competition Proxy			
		#Inst	*HerfInst*	*#Trans*	*HerfTrans*
Intercept	0.37	1.75***	1.12***	1.66***	1.15***
	(0.78)	(4.48)	(2.89)	(4.14)	(2.92)
Beta	-0.01	0.03	0.05	0.00	0.03
	(-0.06)	(0.17)	(0.26)	(0.02)	(0.16)
Size	0.06	-0.31***	-0.12**	-0.26***	-0.12**
	(0.89)	(-5.09)	(-2.35)	(-4.37)	(-2.19)
BTM	0.26***	0.22***	0.25***	0.23***	0.26***
	(3.30)	(3.03)	(3.47)	(3.24)	(3.48)
NIASpread	0.12	0.12**	0.13**	0.12**	0.14**
	(1.62)	(2.02)	(2.24)	(2.06)	(2.29)
IASpread	0.02	0.07	0.13	0.05	0.10
	(0.12)	(0.49)	(0.82)	(0.35)	(0.68)
Turnover		-0.64***	-0.42*	-0.68***	-0.43*
		(-2.73)	(-1.73)	(-2.97)	(-1.84)
Competition		2.26***	1.10***	2.01***	1.07***
		(6.72)	(5.16)	(6.87)	(5.63)
Turnover x NIASpread		0.00	-0.00	-0.03	-0.03
		(0.02)	(-0.02)	(-0.17)	(-0.14)
Turnover x IASpread		-0.18	-0.33	-0.06	-0.29
		(-0.43)	(-0.73)	(-0.14)	(-0.68)
Competition x NIASpread		-0.66	-0.84**	-0.38	-0.33
		(-1.40)	(-2.26)	(-0.89)	(-1.04)
Competition x IASpread		**-2.48****	**-1.66****	**-2.70*****	**-1.48****
		(-2.46)	**(-2.22)**	**(-2.73)**	**(-2.19)**
Adj-R^2 (%)	3.89	4.82	4.74	4.81	4.72

This table presents the results of Fama-MacBeth regressions that examine how the pricing of information asymmetry, as proxied by *IASpread*, varies with *Competition*, as proxied by either *Inst*, *HerfInst*, *#Trans* or *HerfTrans*. The dependent variable is the monthly returns for a firm in year t+1, each of which is then matched to independent variables measured in year t. *IASpread* (*NIASpread*) is the information asymmetry (non-information asymmetry) component of bid-ask spread; the components are obtained by decomposing the intraday spreads in December of year t. *#Inst* (*#Trans*) is the number of institutional investors (transient institutional investors) at the end of year t. *HerfInst* (*HerfTrans*) is the Herfindahl measure of the concentration of institutional investor holdings (transient institutional investor holdings) at the end of year t; this measure is multiplied by -1 so that it is increasing in competition. *Beta* is the market beta from the regression of daily excess stock returns on daily excess market returns in year t, with a minimum requirement of 24 daily returns. *Size* is the natural logarithm of the market value of equity in millions at the end of year t. *BTM* is the natural logarithm of the ratio of the book value of equity to the market value of equity at the fiscal year end at least three months before the end of year t. *Turnover* is the monthly share turnover in December of year t. *Competition* and *Turnover* are converted into quintile ranks within each year and these quintile ranks are then scaled to range from zero to one. The sample consists of 968,250 firm-months with monthly returns from January 1984 to December 2009. The Fama-MacBeth t-statistics are below the coefficients, in parentheses. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 4: Pricing of Information Asymmetry – *AdjPIN*

		Competition Proxy			
		#Inst	*HerfInst*	*#Trans*	*HerfTrans*
Intercept	0.44	1.13*	0.69	1.17*	0.78
	(0.70)	(1.85)	(1.18)	(1.92)	(1.32)
Beta	-0.12	-0.02	-0.01	-0.06	-0.03
	(-0.47)	(-0.09)	(-0.02)	(-0.26)	(-0.12)
Size	0.06	-0.19**	-0.04	-0.18**	-0.05
	(0.72)	(-2.05)	(-0.53)	(-2.08)	(-0.65)
BTM	0.28***	0.25***	0.28***	0.25***	0.27***
	(3.89)	(3.63)	(4.08)	(3.63)	(3.96)
PSOS	0.42*	0.65**	0.75**	0.62*	0.71**
	(1.73)	(1.99)	(2.24)	(1.89)	(2.17)
AdjPIN	0.52	0.64	0.55	0.64	0.51
	(0.91)	(1.30)	(1.10)	(1.29)	(1.03)
Turnover		-0.77**	-0.61**	-0.89***	-0.60**
		(-2.54)	(-2.06)	(-2.88)	(-2.04)
Competition		2.22***	1.40***	2.34***	1.42***
		(4.41)	(4.35)	(4.83)	(4.07)
Turnover x PSOS		-0.47	-0.42	-0.42	-0.60
		(-0.65)	(-0.59)	(-0.57)	(-0.81)
Turnover x AdjPIN		1.74	1.27	1.90	1.43
		(1.24)	(0.93)	(1.31)	(1.03)
Competition x PSOS		-0.02	-0.85	-0.42	-0.65
		(-0.03)	(-1.22)	(-0.57)	(-0.90)
Competition x AdjPIN		**-3.53***	**-3.30***	**-3.59***	**-3.31***
		(-1.71)	**(-1.75)**	**(-1.72)**	**(-1.85)**
Adj-R^2 (%)	3.24	3.99	3.93	3.97	3.91

This table presents the results of Fama-MacBeth regressions that examine how the pricing of information asymmetry, as proxied by *AdjPIN*, varies with *Competition*, as proxied by either *Inst*, *HerfInst*, *#Trans* or *HerfTrans*. The dependent variable is the monthly returns for a firm in year t+1, each of which is then matched to independent variables measured in year t. *AdjPIN* (*PSOS*) is the information asymmetry (probability of symmetric order flow shock) component of PIN from Duarte and Young (2009). All the other variables are defined in Table 3. The sample consists of 470,875 firm-months with monthly returns from January 1984 to December 2005. The Fama-MacBeth t-statistics are below the coefficients, in parentheses. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5: NYSE and AMEX versus NASDAQ Firms

	NYSE and *AMEX*		*NASDAQ*	
	HerfInst	*HerfTrans*	*HerfInst*	*HerfTrans*
IASpread	-0.01	0.03	0.10	0.03
	(-0.02)	(0.12)	(0.51)	(0.16)
Competition	0.69***	0.84***	1.75***	1.75***
	(3.59)	(4.37)	(4.46)	(4.95)
Competition x IASpread	**-0.90**	**0.01**	**-2.44*****	**-1.63****
	(-1.04)	**(0.01)**	**(-2.68)**	**(-2.02)**

This table presents the results of Fama-MacBeth regressions that examine how the pricing of information asymmetry, as proxied by *IASpread*, varies with competition, as proxied by *HerfInst* and *HerfTrans*, for two sub-samples: (i) NYSE and AMEX firms and (ii) NASDAQ firms. As the sample period for the analyses with *AdjPIN* in Table 4 is from 1983 to 2004, we use this period for the analyses in this table. The sample for the NYSE and AMEX (NASDAQ) firms consists of 369,312 (427,633) firm-months with monthly returns from January 1984 to December 2005. The regression specification in this table is the same as that in Table 3. For parsimony, only the coefficients on the key independent variables are reported. The Fama-MacBeth t-statistics are below the coefficients, in parentheses. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6: Analysis of the Pre- and Post-Regulation Fair Disclosure Periods

	Pre-Reg FD		*Post-Reg FD*	
	HerfInst	*HerfTrans*	*HerfInst*	*HerfTrans*
IASpread	0.10	0.11	0.17	0.09
	(0.61)	(0.65)	(0.56)	(0.31)
Competition	0.96***	1.04***	1.35***	1.11***
	(3.82)	(4.36)	(3.47)	(3.55)
Competition x IASpread	**-0.87***	**-0.94***	**-3.07**	**-2.45**
	(-1.79)	**(-1.85)**	**(-1.62)**	**(-1.48)**

This table presents the results of Fama-MacBeth regressions that examine how the pricing of information asymmetry, as proxied by *IASpread*, varies with competition, as proxied by *HerfInst* and *HerfTrans*, for two sub-periods: (i) in and before August 2000, which is the date when Regulation Fair Disclosure (Reg FD) was passed, and (ii) after August 2000. The regression specification in this table is the same as that in Table 3. For parsimony, only the coefficients on the key independent variables are reported. The Fama-MacBeth t-statistics are below the coefficients, in parentheses. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE 7: Pricing of Information Quality

	IQ = AQ			*IQ = Smoothness*		
		HerfInst	*HerfTrans*		*HerfInst*	*HerfTrans*
Intercept	1.54***	1.35***	1.45***	1.41***	1.47***	1.55***
	(4.15)	(3.63)	(3.85)	(3.42)	(3.74)	(3.88)
Beta	-0.03	-0.01	-0.03	-0.04	-0.03	-0.05
	(-0.13)	(-0.05)	(-0.14)	(-0.16)	(-0.15)	(-0.25)
Size	-0.09	-0.16***	-0.18***	-0.08	-0.16**	-0.18***
	(-1.60)	(-2.70)	(-2.93)	(-1.29)	(-2.56)	(-2.72)
BTM	0.22***	0.22***	0.21***	0.26***	0.25***	0.25***
	(3.46)	(3.49)	(3.30)	(3.93)	(3.94)	(3.90)
IQ	-1.72	5.65***	5.07**	0.06	0.21**	0.19**
	(-1.07)	(2.73)	(2.48)	(0.84)	(2.05)	(1.99)
Turnover		0.28	0.23		-0.21	-0.25
		(1.24)	(1.07)		(-0.99)	(-1.26)
Competition		0.74***	0.88***		0.81***	0.94***
		(3.84)	(4.92)		(4.14)	(5.58)
IQ x Turnover		-8.75***	-8.35**		0.03	0.03
		(-2.64)	(-2.51)		(0.17)	(0.19)
IQ x Competition		**-6.71***	**-5.81**		**-0.29***	**-0.27***
		(-1.71)	**(-1.56)**		**(-1.78)**	**(-1.68)**
Adj-R^2 (%)	3.22	3.82	3.78	2.93	3.42	3.38

This table presents the results of Fama-MacBeth regressions that examine how the pricing of information quality (*IQ*), as proxied by *AQ* and *Smoothness*, varies with competition, as proxied by *HerfInst* and *HerfTrans*. *AQ*, which is a measure of a lack of accruals quality, is the standard deviation of the residuals from regressions of the total current accruals on cash flow from operations in the prior, current, and following years; change in revenues; and gross plant, property, and equipment. *Smoothness,* which is a measure of a lack of earnings smoothness, is the ratio of a firm's standard deviation of net income before extraordinary items divided by beginning total assets to its standard deviation of cash flows from operations divided by beginning total assets. All the other variables are defined in Table 3. The sample for *AQ* (*Smoothness*) consists of 576,060 (747,223) firm-months with monthly returns from January 1984 to December 2009. The Fama-MacBeth t-statistics are below the coefficients, in parentheses. Significance levels are based on two-tailed tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.