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Christopher S. Armstrong
University of Pennsylvania

John E. Core

Daniel J. Taylor
University of Pennsylvania

Robert E. Verrecchia
University of Pennsylvania

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Abstract
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Keywords
information asymmetry, cost of capital, market competition, expected returns

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Christopher S. Armstrong
carms@wharton.upenn.edu

John E. Core
jcore@mit.edu

Daniel J. Taylor
dtayl@wharton.upenn.edu

Robert E. Verrecchia
verrecchia@wharton.upenn.edu

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1. Introduction

The purpose of this paper is to design an empirical test, and then to provide evidence consistent with this test, that enhances discussions as to when information asymmetry among investors affects the cost of capital in excess of standard risk factors. Recent literature emphasizes that information is not a separate factor in determining the cost of capital in perfect competition settings (e.g., Hughes, Liu, and Liu, 2007; Lambert, Leuz, and Verrecchia, 2007). Further, other work shows that once one controls for average precision, information asymmetry has no effect on the cost of capital in perfect competition settings (Lambert, Leuz, and Verrecchia, 2010). What these papers leave unexamined, however, is whether information asymmetry has a separate effect on the cost of capital in settings that are less than perfectly competitive. To study this question, we examine expected returns in a setting where information asymmetry is most likely in evidence, in combination with a circumstance where information asymmetry is likely to exhibit the greatest effect on expected returns, as proxied by the level of competition for a firm's shares.

Perfect competition in a securities market refers to situations in which investors are price takers or, equivalently, when there are "horizontal demand curves for stocks" (Shleifer, 1986). A body of literature beginning with Hellwig (1980, p. 478) points out that the assumption that traders do not affect price implicitly relies on the assumption that the number of traders is very large (countably infinite). When demand curves are flat, demand has no effect on price. Each investor anticipates that neither his or her own trade, nor the trades of others, will have any effect on price. This assumption of flat demand curves implies that investors with any degree of knowledge about firms can trade as much as they wish without affecting prices.

When equity markets are imperfectly competitive, however, information asymmetry can have a separate effect on firms' cost of capital. Imperfect competition is typically characterized as each investor's self-sustaining belief that he or she faces a downward-sloping demand curve or an upward-sloping price curve for firm shares (see, e.g., Kyle, 1989; Lambert and Verrecchia, 2010), and this scenario occurs when the number of traders is finite.[1] When the number of traders is finite, each investor recognizes the effect he or she has on price, and therefore price curves are upwardly sloping in demand. When price curves are upwardly sloping in demand, the curve for investors who are better informed is likely to be steeper than the curve for investors who are less well informed (in equilibrium). This results from the fact that the trades of better informed investors have a greater impact on price because of their superior knowledge. When investors with different levels of knowledge face different price curves, it is likely that information asymmetry, as a reflection of these different levels of knowledge, will manifest in price.[2]

Perhaps consistent with this observation, Easley, Hvidkjaer, and O'Hara (2002), Francis, LaFond, Olsson, and Schipper (2005), Leuz and Verrecchia (2000), and Hail and Leuz (2006), among others, show strong negative relations between proxies for information quality and proxies for the cost of capital. Thus, one way to reconcile the findings of these papers with those of Core, Guay, and Verdi (2008) and Mohanram and Rajgopal (2009) is to suggest that the former speaks to imperfect competition settings while the latter concerns primarily perfect competition settings. Our results provide evidence that the degree of market competition is an important conditioning variable that these and other empirical studies have not considered.

[1] Prices are upward-sloping when the demand curve is downward-sloping because an increase in investor demand shifts the demand curve outward, with the result that price increases. While upward-sloping prices may seem counterintuitive, they manifest in posted bid-ask spreads and depths for a given stock. A buy order for more shares than are offered at the quoted depth will increase the price above the quoted ask (i.e., the greater the demand, the higher the trade price rises in expectation). Shleifer (1986) shows that prices can be upward-sloping in extreme cases even for very large firms: prices increase when firms are first included in the S&P 500 index.

[2] See, for example, the discussion in Lambert and Verrecchia (2010).

In this paper we explore further this possibility by introducing a proxy for the level of competition in a firm's shares. While financial market competition is a well accepted economic concept, it has no natural proxy in market data. This problem notwithstanding, we use the number of investors in a firm as our proxy for the level of competition for a firm's shares. Our rationale for this choice is that empirically we observe a wide range in the number of investors in U.S. firms, with some in the hundreds of thousands, thereby seemingly consistent with assumptions about perfect competition and price-taking behavior, but others in the hundreds, thereby less plausibly associated with perfect competition and price taking. When the number of investors in a firm is small, it is unreasonable for these investors to assume that their demand has no effect on price. Instead, here an investor anticipates that his or her demand will have an unfavorable impact on the prices at which his or her trades are executed. To the extent that better- (worse-) informed investors have a more (less) unfavorable impact on prices because of their superior (inferior) knowledge, levels of information asymmetry should manifest in prices.

To find evidence of whether information asymmetry manifests in expected returns, our research design examines future returns in a setting where information asymmetry is most likely in evidence, in combination with a circumstance where information asymmetry is likely to have the greatest effect. Specifically, we sort firms based on their number of shareholders, as a proxy for the level of competition in their shares, and also sort on a proxy for information asymmetry. We find that when the number of shareholders is low, firms with high information asymmetry earn significantly higher excess returns than do firms with low information asymmetry. We also find that when the number of shareholders is high, there is no difference in returns for firms with high information asymmetry over firms with low information asymmetry. Finally, we present evidence that these findings are robust to different proxies for information asymmetry, different ways of sorting, different proxies for the level of competition, different samples, and different models of expected returns.

The remainder of the paper proceeds as follows. The next section reviews the relevant prior literature. Section 3 describes how we measure key variables and the research design for our empirical tests. Section 4 describes our sample. Section 5 presents our findings and robustness tests, and Section 6 concludes the paper and offers caveats to our conclusions.

2. Summary of Hypothesis and Review of Related Literature

In summary of the foregoing, we expect information asymmetry to affect firms' cost of capital when equity markets are imperfectly competitive. We summarize these predictions in Figure 1. When a firm has high (low) information asymmetry and when markets are imperfect, we predict that this firm has a relatively high (low) cost of capital. We therefore expect positive differences in the cost of capital between high and low information asymmetry firms in imperfect markets. On the other hand, when markets are perfect, regardless of the level of information asymmetry, no market participant affects price when he or she trades. Because no individual investor can affect price, differences in information across investors do not affect the cost of capital. In other words, under perfect competition (bottom row of Figure 1), market risk completely explains the cost of capital both when information asymmetry is low (column 2) and when it is high (column 3), so there is no difference (column 4).

Figure 1

Predicted Excess Cost of Capital by Information Environment and Market Setting
(Cost of Capital in Excess of That Expected, Given Market Risk)

	Information Environment		
Market setting	Low Information Asymmetry	High Information Asymmetry	Predicted COC difference
(1)	(2)	(3)	(4)
Imperfect competition	Low	High	Positive
Perfect competition	Zero	Zero	None

A body of literature beginning with Hellwig (1980, p. 478) points out that the assumption that traders do not affect price implicitly relies on the assumption that the number of traders is very large (countably infinite). When the number of traders is finite, each investor knows that he or she and every other investor pushes the price upward (downward) when buying (selling). When each investor has a self-sustaining belief that he or she faces an upwardly sloping price curve for shares of a firm, the market is imperfectly competitive (Kyle, 1989; Lambert and Verrecchia, 2010). The upwardly sloping nature of price reduces an investor's willingness to trade and increases the cost of capital.[3] If, in addition, there is information asymmetry, it increases the upward slope in price, resulting in adverse selection and a higher cost of capital. Adverse selection is a consequence of the fact that when price is upward-sloping, differences in the quality of information across investors affect the price at which trades are executed. In other words, here an individual investor presumes that when he or she trades in a firm's shares, there is

[3] This cost of capital increase occurs even when there are no information differences (Kyle, 1989, and Lambert and Verrecchia, 2009), although the exact magnitude is an empirical matter.

an additional upward slope in price because others will presume that he or she has superior information. We summarize these predictions in the top row of Figure 1. When markets are imperfect, the cost of capital in excess of market risk factors is low when information asymmetry is low (column 2) and high when it is high (column 3), so that we predict a positive difference (column 4).

As noted above, broadly speaking, a large prior body of literature in accounting and finance examines the *unconditional* relation between information asymmetry and the cost of capital (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Easley et al., 2002; Francis et al., 2005; Leuz and Verrecchia, 2000; Hail and Leuz, 2006; Ogneva, 2008). Our study is most closely related to that of Brennan and Subrahmanyam (1996), who show an unconditional relation between the adverse selection component of the bid-ask spread and realized returns. Like them, we use the adverse component of the bid-ask spread as one of our measures of information asymmetry. The innovation of our paper is that we predict and find that the relation between information asymmetry and cost of capital is *conditional* on the level of market competition, and we demonstrate this relation with a variety of proxies for information asymmetry. In other words, we predict and document that when equity markets are imperfectly competitive, information asymmetry can have a separate effect on firms' cost of capital.[4]

When price is upwardly sloping in demand, a stock is less liquid. Our study is therefore also related the recent empirical literature on liquidity risk, although our assumption for why liquidity effects occur is very different. For example, Acharya and Pedersen (2005) assume perfect competition and predict that liquidity risk arises as the result of the correlation between a firm's liquidity and overall market liquidity. Similarly, Pastor and Stambaugh (2003) define

[4] To the best of our knowledge, ours is the first paper to predict and find this relation. A contemporaneous working paper by Akins, Ng, and Verdi (2010) also predicts and finds an interaction between proxies for market competition and proxies for information asymmetry.

liquidity risk as the covariation between a stock's return and market liquidity. Their predictions are derived in part from Campbell, Grossman, and Wang's (1993) perfect competition model in which time-varying risk aversion by a subset of traders implies that current order flow predicts future return reversals. In contrast to Campbell et al. (1993), we allow for imperfect competition so that a stock price's sensitivity to order flow occurs because of upwardly sloping price curves.

Finally, there is also a smaller body of literature on the unconditional relation between the number of shareholders in the firm and cost of capital (e.g., Merton, 1987).[5] Similar to the theory discussed above, Merton also predicts that a lower number of shareholders is associated with higher expected returns. Merton's intuition is similar to the notion in Kyle (1989) and Lambert and Verrecchia (2010) that as the number of shareholders increases, the impact of demand on price decreases, and the cost of capital declines. Merton's model, however, is "unusual" in that it assumes that price curves are flat (and therefore it assumes that the number of investors is countably infinite), yet it still generates a prediction as to how a decrease in the number of shareholders increases expected returns.[6]

3. Research Design

In this section, we first provide an overview of our research design, then provide details of our hypothesis test, and finally describe how we measure variables.

3.1. Overview of Research Design

To test our hypothesis of a positive (no) relation between information asymmetry and the cost of capital when markets are imperfectly (perfectly) competitive, we first sort firms into five

[5] Bodnaruk and Ostberg (2009) test and find evidence for Merton's (1987) predictions using a sample of Swedish firms.

[6] Hellwig (1980) refers to a circumstance in which investors who are finite in number behave as if they have no effect on prices as the "schizophrenia" problem.

quintiles based on a proxy for the level of market competition. We expect the quintile with the lowest (highest) values of the proxy to most resemble imperfect (perfect) competition. Then we sort firms into five quintiles based on a proxy for the degree of information asymmetry. Although it is difficult to directly observe the level of information asymmetry, we expect the quintile with the lowest (highest) values of the proxy to have the least (most) information asymmetry. As illustrated above in Figure 1, in the quintile that is closest to imperfect competition, we predict that firms with a relatively high degree of information asymmetry have a higher risk-adjusted cost of capital than do firms with a low degree of information asymmetry. In the quintile that is closest to perfect competition, we predict that firms with a relatively high degree of information asymmetry have a risk-adjusted cost of capital that is no different from firms with a low degree of information asymmetry.

As we will discuss in more detail in Section 3.2.3, we use both dependent sorts (in which we rank firms within a market competition quintile into information asymmetry quintiles) and independent sorts (in which we rank firms independently into market competition and information asymmetry quintiles and then take the intersection).

After we sort firms into 25 (=5x5) portfolios each year, for each market competition quintile, we compute future monthly returns to the hedge portfolio that takes a long position in firms with the highest level of information asymmetry, and a short position in firms with the lowest level of information asymmetry. We use the three Fama and French (1993) factors to control for market risk and to describe the behavior of expected returns under the null hypothesis that information asymmetry has no effect on expected returns. This three-factor model of expected returns is widely used in the literature in both finance and accounting (e.g., Pastor and Stambaugh, 2003; Aboody, Hughes, and Liu 2005; Francis et al., 2005; Petkova, 2006).

Specifically, for each market competition quintile, we estimate time-series regressions of the *information asymmetry hedge portfolio* returns on the three Fama-French factors:

$$R_{H,t} = a_{\mathrm{H}} + b_H\, MKTRF + s_H\, SMB_t + h_H\, HML_t + \varepsilon_{p,t}. \quad (1)$$

where *MKTRF*, *SMB*, and *HML* are the Fama and French (1993) factors and R_H is the return on the information asymmetry hedge portfolio for a given market competition quintile. The variable of interest is the estimated intercept a_{H}. If a_{H} is significantly greater than zero, firms with high information asymmetry earn higher risk-adjusted returns than do firms with low information asymmetry.

3.2. Details of research design

In this section, we detail our research design outlined in the previous subsection, introduce our proxies and discuss concerns about them, and discuss how we address these concerns in our tests.

3.2.1. Specification of cost of capital tests

We test our hypotheses about cost of capital by using future excess returns as a proxy for cost of capital. The main alternative to using future returns as a proxy for expected returns is to use an implied cost of capital measure, and we acknowledge that there is an ongoing debate in the literature on the relative merits of future returns versus implied cost of capital as a proxy for expected returns (e.g., Easton and Monahan, 2005; Guay, Kothari, and Shu, 2006; McInnis, 2010). A chief interest of our study, however, is firms with low market competition. Because low-competition firms tend to have little to no analyst following, implied cost of capital estimates (for which analyst forecasts are required) cannot be calculated for most of these firms.[7] One of the drawbacks to using a firm's realized returns to proxy for its expected return is that

[7] Panel C of Table 1 shows that few analysts follow firms in the lowest market competition quintile.

realized returns measure expected returns with noise. However, we attempt to mitigate concerns about noise in future returns by grouping firms into portfolios.

In our tests, we form portfolios by sorting based on the variable(s) of interest and evaluate future excess returns to the portfolio using time-series regressions similar to Equation (1). This "calendar time portfolio" approach is used extensively in the finance literature to test asset pricing models (e.g., Black, Jensen, and Scholes, 1972; Fama and French, 1993; Fama and French, 2008). The primary advantages of this approach are that it does not assume that returns are linear in the variable of interest (i.e., the sort variable) and that it collapses the cross-section of returns (on a given date) into a single time-series observation, thereby alleviating concerns about cross-sectional dependence. This approach stands in contrast to traditional return regressions, where returns are regressed on firm characteristics. Such regressions assume linearity in the underlying firm characteristic, require standard error corrections for cross-sectional dependence, and are known to be prone to outlier problems (e.g., Kraft, Leone, and Wasley, 2006; Fama and French, 2008). The one modification we make, however, to the standard calendar time portfolio approach is to compute the standard error for time-series regressions using heteroskedasticity-robust standard errors, which allow for time-varying volatility.[8]

In work closely related to ours, Brennan and Subrahmanyam (1996) use portfolios sorted on the adverse selection component of the bid-ask spread to examine whether information asymmetry is associated with an increase in expected returns. Similarly, Pastor and Stambaugh (2003) use portfolios sorted on firms' exposure to a liquidity factor as evidence to support their hypothesis that expected returns are higher when liquidity risk is higher. We acknowledge, however, that a significant hedge return in portfolio sorts may also be interpreted as evidence of

[8] We check the residuals of the regression for autocorrelation but find none.

mispricing, as in Sloan (1996) and Daniel, Hirshleifer, and Subrahmanyam (2001). We try to mitigate this alternative interpretation by using the widely used Fama-French model in our primary tests and by showing that our results are robust to a number of alternative specifications of expected returns. To ensure that our results are distinct from findings that liquidity risk may be a priced factor, in sensitivity tests that we describe in Section 5.5, we add Pastor and Stambaugh's (2003) liquidity factor and Sadka's (2006) liquidity factor to the Fama-French factors. Similarly, to ensure that our results are distinct from short-term momentum, we add Carhart's (1997) momentum factor. Nevertheless, as with all asset pricing tests, our tests are joint tests of our hypotheses and of a correctly specified asset pricing model.

A final issue is how to weight firms within each portfolio to calculate a monthly portfolio return. Following prior literature (e.g., Brennan and Subrahmanyam, 1996), we use equal weights because our hypotheses are about the expected returns for a typical or average stock. If we instead used value-weighting, our return results would reflect expected returns for a large stock, not for a typical or average stock. Equal-weighted monthly returns are usually calculated by purchasing an equal-weighted portfolio, holding it for one month, and then rebalancing this portfolio so that it has equal weights at the start of the next month. The concern with this equal-weighted returns calculation, however, is that frequent rebalancing can produce biased estimates of realized returns because of the bid-ask bounce (Blume and Stambaugh, 1983). To ensure that our results are conservative and not subject to this bias, we follow Blume and Stambaugh (1983) and compute returns to an equal-weighted portfolio that is rebalanced annually, or a "buy-and-hold" portfolio. The portfolio is formed on June 30 based on an initial equal weighting, and the monthly "buy-and-hold" return is the portfolio's percentage change in value, with dividends, for the month. This procedure yields monthly returns to an equal-weighted portfolio that is rebalanced once at the beginning of each year.[9] Note that annual rebalancing means that the transaction costs necessary to earn the reported abnormal return are paid only once a year because the portfolio turns over only once a year.

3.2.2. Measures of market competition

We use the number of shareholders as our primary measure of market competition. Specifically, we use the number of shareholders of record as of the fiscal year end, as firms report in their annual 10-K filings (Compustat Data #100). This annual measure is available for a large number of firms beginning in 1975. Among the limitations of this measure are that it is available only once per year and that it may be noisy because the SEC requires firms to "give the approximate number of shareholders of record," a figure that may not include individual shareholders when shares are held in street name (Dyl and Elliott, 2006).

The literature on imperfect competition implicitly assumes that the number of shareholders in a firm is given and that there are economic frictions or restrictions associated with a firm's expansion of its shareholder base. Our theory predicts that if the number of shareholders increases, the slope of the price curve caused by any information asymmetry decreases, and the cost of capital decreases. This is the message that underlies Merton (1987): Firms can reduce their cost of capital by expanding their shareholder base and so have an incentive to do so. Thus, if one assumes that there are no restrictions to expanding the shareholder base, then presumably a firm will increase its shareholder base to the point that it becomes large. So as a practical matter, but consistent with the theory on imperfect competition, we (like Merton, 1987) also assume that there are unstated and/or unspecified reasons that some firms have a small shareholder base despite the benefits of expanding this base. In descriptive

[9] The coefficient on the low competition hedge portfolio is larger if we rebalance our portfolios at the monthly level rather than the annual level. For example, the abnormal returns to the *ASC_spread* hedge portfolio in the low market competition in Panel A of Table 3 (Table 4) increase from 1.04% (0.88%) per month to 1.16% (0.97%) per month.

analysis in Section 5.4, we will attempt to shed light on this issue by comparing characteristics of firms with low and high numbers of shareholders, and with low and high information asymmetry.

The fact that we observe variation in the number of shareholders supports the assumption that there are costs to increasing ownership. Absent such costs, we would expect to observe all firms having similar numbers of shareholders. As Grullon, Kanatas, and Weston (2004) and Bushee and Miller (2007) point out, increasing firm visibility and ownership requires a costly and complex strategy of changes in disclosure, advertising, and media coverage. The tendency of individual investors to suffer from an attention effect, which results in their holding only a few firms in an undiversified portfolio, probably compounds such costs. From the shareholder's perspective, the benefits to the increased share ownership primarily accrue to existing shareholders (in terms of higher prices), whereas new shareholders would bear the costs (e.g., transaction costs of taking a position and costs of being informed about the stock). Accordingly, while we do not seek to explain why some firms have more shareholders than others, variation in the number of shareholders does not seem to be out-of-equilibrium behavior. We take variation in share ownership as a given and examine whether this variation explains the relationship between information asymmetry and cost of capital.

Notwithstanding the foregoing, a potential concern is that the number of shareholders and expected returns may be simultaneously determined. To see this concern, note that we can re-express our hypothesis as the following: We expect information asymmetry to matter in imperfect markets (proxied by a small number of shareholders) because the demand impact on price is larger in these markets. Simultaneity can occur not only if a large number of shareholders cause a lower demand impact, but also if a higher demand impact of price causes a lower number of shareholders (if certain investors are attracted to, say, more liquid stocks). A body of literature that includes Grullon et al. (2004) examines the determinants of the size of the firm's shareholder base. Among other things, Grullon et al. (2004) find that measures of firm size and investor recognition (e.g., advertising expense, market value, and firm age) are positively associated with the number of shareholders, and a proxy for transactions costs (the reciprocal of price) is negatively associated with the number of shareholders. It is not clear whether this potential endogeneity affects our tests, since we are sorting firms into a relatively small number of groups and are primarily interested in the extreme groups. Second, any endogenous relation between the number of shareholders and expected returns will affect our future returns tests only if we have omitted a (correlated) variable from our expected returns model. As we discuss above, we use a number of asset pricing models to ensure that we have not omitted any factor relevant to future returns. In addition, we find that the size of the shareholder base is relatively time invariant. Firms in the lowest quintile in one year remain in the lowest quintile the next year. This finding suggests that a firm's shareholder base is stable over time and, therefore, that firms are not altering their shareholder base in response to variations in the firm's expected return.[10]

Note that the number of shareholders can be a noisy proxy for the degree of market competition, because shares can be dispersed evenly among shareholders or concentrated so that one shareholder holds most of the shares. We acknowledge this limitation, but we note that if shareholders are more concentrated, one would expect more adverse selection if there is information asymmetry. Our information asymmetry proxies should capture this additional adverse selection. Since our hypothesis is related to the interaction between the degree of market

[10] When we use the lagged number of shareholders as an instrument for market competition, across all measures of information asymmetry, we find inferences that are identical to what we find below for both independent and dependent sorts.

competition and information asymmetry, the structure of our research design (i.e., dual portfolio sorts) should mitigate this concern. As another way of addressing concerns about noise in the number of shareholders, we report results below in which we refine our measure of market competition using high (low) trading volume as an additional means of identifying high (low) competition.

3.2.3. Measures of information asymmetry

We use five measures of information asymmetry: two that are market-based and two that are accounting-based, in addition to analyst coverage.

Our market-based measures are (1) the adverse selection component of the bid-ask spread (*ASC_spread*), and (2) the bid-ask spread itself (*Spread*). Previous studies have used both measures to proxy for the degree of information asymmetry (e.g., Brennan and Subrahmanyam, 1996). *ASC_spread* measures the extent to which unexpected order flow affects prices and is increasing in information asymmetry. We estimate *ASC_spread* following Madhavan, Richardson, and Roomans (1997) (described in detail in the Appendix). Because the algorithm is very time-consuming to run, we measure *ASC_spread* for each firm once a year in June, using all intra-day data for that month. Similarly, we measure *Spread* for the month of June as the average bid-ask spread scaled by trade price and weighted by order size. *ASC_spread* is a component of the bid-ask spread. Thus, if *ASC_spread* is estimated accurately (inaccurately), *Spread* will be a more (less) noisy measure of information asymmetry.

The advantage of *ASC_spread* and, to some extent, the *Spread* itself, is that it is a precise measure of the outcome of information asymmetry. In other words, if there is information asymmetry, it manifests as an increase in *ASC_spread.* As mentioned above, a concern with *ASC_spread* is that we expect it to be a function of both market competition (the number of shareholders) and information asymmetry. Our dual sort research design addresses this concern in two ways. First, we use the lag values of *ASC_spread* and *Spread* as instruments for information asymmetry in our analyses. Second, we sort firms on both the number of shareholders and on *ASC_spread*. If *ASC_spread* is a function of both the number of shareholders and information asymmetry, then holding constant the number of shareholders, which is roughly the case within quintiles sorted first on the number of shareholders, any variation in the adverse selection component should be the result of variation in information asymmetry.

A second concern with *ASC_spread* is that our hypothesis predicts that the slope of the price curve, and the effects of information asymmetry, diminish when market competition is high. We therefore expect that *ASC_spread* becomes small as the level of market competition increases. (As discussed below, our descriptive evidence in Table 1, Panel C is consistent with this expectation.) Thus, while we expect *ASC_spread* to have high power to detect information asymmetry when competition is low, it may have low power when competition is high. We address this concern in two ways. First, we use two measures (accrual quality and research and development expense) that capture the potential for information asymmetry but have a low correlation with our measure of market competition (Table 1 Panel B). Table 1, Panel C also shows that these measures retain more of their variation in the high market competition quintile, indicating that they have the potential to be powerful in detecting information asymmetry.

Second, we use dual independent sorts, which assign firms to information asymmetry portfolios *independent* of their level of market competition. The benefit of independent sorts is that they tend to result in similar variation in information asymmetry across the market competition portfolios. The cost is a reduction in power (because of sparsely populated cells) to the extent that the two sorting variables are correlated.

As discussed above, we use two accounting-based measures that capture the potential for information asymmetry. First, *R&D* is the ratio of annual research and development expense to sales. Prior research uses R&D expense to proxy for the presence of intangible assets, which are associated with higher information asymmetry (e.g. Barth and Kasznik, 1999; Barth, Kasznik, and McNichols, 2001). Second, we use scaled accruals quality (*SAQ*) to measure information asymmetry.[11] Ogneva (2008) finds this measure to be superior to unscaled accruals quality in predicting future returns. Accruals quality and scaled accrual quality are both increasing in the unexplained variance of accruals, and prior research (e.g., Aboody et al., 2005; Francis et al., 2005) suggests that when this variance is higher, earnings quality is lower and information asymmetry is higher.

Finally, *Analyst Coverage* is the number of sell-side analysts issuing one-year-ahead earnings-per-share forecasts for the firm during the year according to the I/B/E/S Summary file. Prior research suggests that greater analyst coverage improves the information environment and therefore is associated with lower information asymmetry (e.g., Brennan and Subramanyam, 1995).

3.3. Timing of variable measurement

The timing of our variable measurement is the same as that of Fama and French (1993), who rank firms into portfolios based on market value of equity and the book-to-market ratio. Fama and French (1993) form portfolios once a year at the end of June, compute future returns

[11] Ogneva (2008) estimates accruals quality as the standard deviation of residuals from the regression of total current accruals on lagged, current, and future cash flows plus the change in revenue and property, plant, and equipment. (See Francis et al., 2005, p. 302.) Ogneva (2008) lags this variable one period, to avoid look-ahead bias. *SAQ* is obtained by scaling AQ by the average of the absolute value of total accruals over the previous five years.

for the next 12 months, and then re-form portfolios at the end of the following June. They measure the market value of equity at the end of June of year *t* and compute book value (and all financial statement variables) as of the last fiscal year end in year *t-1*.

Similarly, we form portfolios once a year at the end of June and compute future returns for the next 12 months. Because the number of shareholders, *R&D*, and *SAQ* are calculated from data reported in firms' 10-K filings, we calculate these variables using data as of the last fiscal year end in year *t-1*. The market value of equity, the bid-ask spread (*Spread*), and its adverse selection component (*ASC_spread*) can be observed from market data, and we measure these variables each June. Recall that we use the lagged values of *ASC_spread* and *Spread* in our analyses. Finally, we measure *Analyst Coverage* as the number of sell-side analysts issuing a one-year-ahead earnings forecast during June of year *t*.

4. Sample Selection and Descriptive Statistics

We construct our sample using data from Compustat, CRSP, ISSM, TAQ, and I/B/E/S. To be included in the sample, a firm must trade on a U.S. exchange (CRSP share codes 10, 11, and 12) and must have a non-missing return and market value on the CRSP monthly file in June of year *t*. We begin the sample in June 1976, when the number of shareholders becomes available on Compustat, and conclude in June 2005.[12] This time frame allows for the inclusion of return data from CRSP from June 1976 to June 2006. The first and last columns of Panel A of Table 1 show the number of observations available each year for the number of shareholders from Compustat and for market value from CRSP.

[12] If a firm delists in a given month during the sample period, we follow Beaver, McNichols, and Price (2007) and compute the return by compounding the monthly return and the delisting return. Since we compute delisting returns, we have return observations for all firms in our sample as of June of year *t*.

The remaining columns of Panel A of Table 1 show the number of observations available for the remaining variables. We begin measuring the adverse selection component of the bid-ask spread (*ASC_spread*) and the bid-ask spread (*Spread*) in 1988, which is when intraday data for the NYSE, AMEX, and Nasdaq becomes available from ISSM.[13] *ASC_spread* is available for a smaller number of firms than is the bid-ask spread, because we require signed order flow from the Lee and Ready (1991) algorithm to estimate *ASC_spread*. The TAQ data is available only for firms traded on the NYSE, AMEX, and Nasdaq, so we cannot compute *ASC_spread* for all firms for which we have the number of shareholders.

To have a sample that covers a reasonable number of years and firms, for a given test, we require availability of only the test variables. For example, when we test our hypothesis about market competition and information asymmetry using *Number of Shareholders* and *ASC_spread*, we use all available firm-years for which we have estimates of both the *Number of Shareholders* and *ASC_spread* (i.e., from 1988 to 2005), but when we test the same hypothesis using number of analysts, we extend the sample period to 1976 to 2005 (i.e., we use all available firm-years for which we have estimates of both the *Number of Shareholders* and *Analyst Coverage*).

Panel B of Table 1 presents descriptive statistics and a correlation matrix for our variables. The top half of Panel B presents descriptive statistics for all firm-years in the sample, and the bottom half presents a correlation matrix. We report Spearman (Pearson) correlations above (below) the diagonal. We focus on Spearman correlations because many of our variables are highly skewed and because our portfolios use ranked values. Because of our interest in cross-sectional correlations between variables (e.g., market competition and information asymmetry), we compute annual correlations and report the mean of the annual correlations in the table. We

[13] NYSE and AMEX firms are available starting in 1984, but because these firms are typically much larger in terms of number of shareholders, we could not find a reasonable way to include them in the full time-series.

compute standard errors using the time-series standard deviation of the annual correlations, and we denote significant (at the 5% level, two-sided) correlations in bold.

There is a positive correlation between *ASC_spread* and *Spread*, our two market-based proxies for information asymmetry. This large, positive correlation suggests that the variables capture a similar construct. Consistent with prior research that finds that *Analyst Coverage* is associated with lower information asymmetry, there is a large negative correlation between *Analyst Coverage* and both *ASC_spread* and *Spread*. The correlations between *R&D* and *SAQ* and the two market-based measures of information asymmetry are small, suggesting that the measures may be capturing different aspects of information asymmetry. Also note the negative correlation between the *Number of Shareholders* and *ASC_spread*. This finding is consistent with the predictions of models such as those from Kyle (1989) and Lambert and Verrecchia (2010), which show that as market competition increases, the slope of the demand curve (as proxied by *ASC_spread*) decreases. Finally, it is important to note the large positive correlation (0.54) between market value and the number of shareholders. While this correlation suggests a potential size effect, recall that we control for size by including the *SMB* factor in the factor regressions in all of our tests. We will also describe in sensitivity tests in Section 5.5.1 additional ways in which we ensure that our results are not simply capturing differences in returns that result from differences in firm size.

In the final panel of Table 1, Panel C, we present descriptive statistics for the extreme quintiles (i.e., one and five) for each of the information asymmetry proxies for the extreme quintiles of market competition. In the left-hand columns, we show statistics where the portfolios have been formed by sorting first based on the number of shareholders (“dependent sorts”), and in the right-hand columns we show statistics where the portfolios have been formed by sorting independently on the number of shareholders and on the information asymmetry variable, and intersecting the resulting quintile sorts ("independent sorts"). We sort each information asymmetry variable into five quintiles and report the median of the top and bottom quintiles. We compute these medians each year and then take the time-series average of these medians. The number of observations shown is the average annual number of observations in that portfolio.

Panel C reveals several patterns in the data. First, consistent with our prediction**,** and with the negative correlation shown in Panel B, we find that as market competition increases, the slope of the demand curve (as proxied by *ASC_spread*) decreases. There is a large and economically significant decrease in the median *ASC_spread* in both the low and high information asymmetry quintile when moving from the low competition to the high competition quintile. At the same time, we find that the variation in *ASC_spread* is decreasing in market competition. This decrease can be seen from the decrease in the Q5 - Q1 difference in median *ASC_spread* from 0.0102 in the low competition quintile to 0.0013 in the high competition quintile. *Spread* exhibits similar declines, but of a smaller magnitude.

Although these declines are consistent with our hypothesis that the effects of information asymmetry on demand curves diminish as markets approach perfect competition, they suggest a possible alternative explanation for why we might find that information asymmetry is unrelated to expected returns when market competition is high. It is possible that information asymmetry affects returns when market competition is high, but that our market-based proxies cannot detect this effect because they exhibit little variation when market competition is high. As noted above, we address this concern in two ways. First, we also examine two accounting-based measures of the potential for information asymmetry (*R&D* and *SAQ*) and *Analyst Coverage*. In the case of *SAQ*, Panel C shows that there is *more* variation in *SAQ* when market competition is high. In particular, the Q5 - Q1 difference in median *SAQ increases* from 1.001 in the low competition quintile to 1.258 in the high competition quintile. Second, we repeat our tests using independent sorts. Since *ASC_spread* is correlated with our proxy for market competition, independently sorting firms into portfolios holds constant the variation in information asymmetry within each market competition quintile. Consistent with this approach, Panel C shows that the Q5 - Q1 difference in *ASC_spread* decreases by only 0.0007 when moving from the low competition quintile (0.0075) to the high competition quintile (0.0068).

5. Results

5.1. Information asymmetry and expected returns

In Table 2, we present excess returns for quintile portfolios sorted on each of our information asymmetry proxies. Although our hypothesis predicts a relation conditional on the level of market competition, we provide unconditional results in Table 2 as a benchmark for our later tests, and also to benchmark against prior work such as that of Brennan and Subramanyam (1996) and Ogneva (2008), which predict and find unconditional relations between information asymmetry proxies and expected returns.

Panel A on the left of Table 2 shows results for our market-based measures, and Panel B on the right shows results for our other measures. For each measure, we report excess monthly buy-and-hold returns (a_p) for each quintile of the information asymmetry measure after controlling for market risk using the three Fama and French (1993) factors. We present the estimate of a_p and the associated t-statistic. We also show the coefficient on each of the Fama-French factors, but to conserve space, we do not report t-statistics but instead indicate significance with asterisks. The column marked "hedge" indicates the portfolio difference between the high and low information asymmetry quintiles.

Of note are the results for *ASC_spread* and *SAQ*. For *ASC_spread*, the hedge portfolio difference between the fifth and first quintiles is positive and significant, and the coefficient indicates that this portfolio earns excess returns of 0.50% per month. The magnitude of this 0.50% information asymmetry hedge portfolio return for our sample of NYSE, AMEX, and Nasdaq stocks from 1988 to 2006 is very similar to the 0.55% return reported in Brennan and Subramanyam (Table 4, 1996) for their sample of NYSE stocks from 1984 to 1991.

Second, when we use *SAQ* as the measure of information asymmetry, the 0.12% hedge portfolio difference between the fifth and first quintiles is not significant. This result stands in contrast to Ogneva's (2008) finding of a significant return of 0.19% per month on an equal-weighted *SAQ* hedge portfolio. However, we can replicate her results on our data if we employ equal weights and use the less conservative portfolio formation rule of rebalancing the portfolio each month.

Finally, the bottom right of the table shows that *R&D Expense to Sales* produces a positive and marginally significant (t-stat = 1.77; two-sided p-value = 0.08) hedge portfolio return. *Spread* and *Analyst Coverage* do not exhibit significant hedge portfolio returns. These results serve as a benchmark for the information asymmetry hedge portfolios partitioned on market competition in Panel B.

Also noteworthy in this table is that the Fama-French factors are significant in every portfolio. The R^2s decrease across the information asymmetry portfolios, a finding consistent with the returns to high information asymmetry portfolios not being solely explained by the market factor, or size and book-to-market. Also of note, the *SMB* factor loadings display a nearly monotonic increase in the level of information asymmetry. Since the *SMB* factor is constructed using a hedge portfolio that captures the return differential between small and large firms, this pattern in the factor loadings is consistent with our finding in Table 1, Panel B that information asymmetry is correlated with firm size.[14] Moreover, to the extent that the *SMB* factor captures differences in returns of small versus large firms, allowing the *SMB* factor loadings to vary across information asymmetry portfolios ensures that our tests are not simply capturing differences in firm size.

5.2. Relation between market competition, information asymmetry, and cost of capital

In Tables 3 and 4, we present results of our portfolio tests of our predictions summarized in Figure 1. Tables 3 and 4 present the results when portfolios are formed using dependent and independent sorts, respectively. In each table, we show results for each of five alternative proxies for the degree of information asymmetry.

To conduct the dependent sorts in Table 3, we first sort firm-years into five groups based on the number of shareholders, as a proxy for market competition, and then we further subdivide each of these groups into five groups by sorting on the given proxy for information asymmetry. The resulting 25 market competition-information asymmetry portfolios are approximately equal-sized. The number of observations in the high and low portfolios for each proxy is shown in the left-hand side of Panel C of Table 1, as are the median values for the proxy.

Table 3 shows the results of the information asymmetry hedge portfolio for each information asymmetry proxy. Recall that we expect a positive hedge return for the low competition portfolio. Consistent with this prediction, the hedge portfolio return for the lowest

[14] Note that this finding is consistent with, and similar to, the one that Aboody, Hughes, and Liu (2005) report in their Table 2. In particular, they find that hedge portfolios that take a long (short) position in firms with low (high) earnings quality have significantly positive *SMB* factor and R^2s as low as 5%.

market competition quintile is positive and significant for *ASC_spread*, *Spread*, *SAQ*, *R&D,* and *Number of Analysts.*

Of the significant coefficients for the low competition portfolios, the magnitude ranges from 0.42% per month (5.08% per year) for *SAQ* to 1.04% per month (12.48% per year) for *ASC_spread*. While the magnitude of the *ASC_spread* coefficient in particular appears large, we note that Brennan and Subramanyam (1996) use essentially the same method and report a similar magnitude in their Table 3. For the smallest firms, they report a difference in monthly risk-adjusted returns between firms with the highest and lowest adverse selection component of the bid-ask spread of 1.65%, which amounts to 19.80% on an annual basis. Because their focus is different from ours, Brennan and Subramanyam provide no formal test of this difference. Further, we address the robustness of the *ASC_spread* findings in sensitivity tests below.[15]

Turning to the information asymmetry hedge portfolio in the high market competition quintile, we find that none of the hedge portfolios earn abnormal returns. In other words, there is no difference in risk-adjusted returns between firms with high and low information asymmetry when markets approximate perfect competition. Also of note, the factor loadings vary significantly between extreme portfolios, a finding that emphasizes the importance of computing risk-adjusting hedge portfolio returns.

To conduct the independent sorts in Table 4, we independently sort firm-years into five groups based on the number of shareholders, as a proxy for market competition, and into five groups by sorting on the given proxy for information asymmetry. As shown in the right-hand columns of Table 1, Panel C, the resulting 25 market competition-information asymmetry portfolios differ in size. The number of observations in the high and low portfolios for each

[15] The SAS portfolio sort code that we used to generate the results in Tables 3 and 4 is available from the authors upon request.

proxy is shown in the right-hand side of Panel C of Table 1, as are the median values for the proxy.

Results of the independent sorts in Table 4 are in general similar to those in Table 3. Of the significant coefficients for the low competition portfolios, the magnitude ranges from 0.43% per month (5.12% per year) for *SAQ* to 0.88% per month (10.56% per year) for *ASC_spread*. The one difference is the *Analyst Coverage* hedge portfolio, which does not earn positive risk-adjusted returns, regardless of the level of market competition. Further, note that the factor loadings for proxies in Table 4, Panel B are similar to the corresponding loadings in Table 3, Panel B. For example, in the low competition portfolios formed on *SAQ*, because the factor loadings are similar for the high and low information asymmetry portfolios, they have very little explanatory power for the hedge portfolio.

Collectively, the results in Tables 3 and 4 strongly support our hypothesis that information asymmetry affects (does not affect) the cost of capital in the least (most) competitive markets.

5.3 Refinement of proxy for market competition

Although the number of shareholders is the measure of market competition identified in theoretical market microstructure models such as those from Kyle (1989) and Lambert and Verrecchia (2010), an empirical concern is that this proxy does not distinguish between investors who actively trade in the stock, and thus supply liquidity to the market, and passive investors who buy and hold. To address this concern, we refine our market competition proxy to account not only for differences in the number of shareholders, but also for differences in the level of trading activity in firms' shares. We measure trading activity as share turnover, calculated as annual volume in year t divided by average shares outstanding. If greater turnover is associated with a more competitive market, then firms that have a high (low) number of shareholders *and* high (low) turnover are relatively the most (least) competitive. To capture this idea, we adapt our portfolio sort procedure by introducing an additional sort based on turnover. As before, we first sort firm-years into five quintiles based on the number of shareholders, but now within each market competition quintile, we sort firms into two groups based on turnover.[16] This process produces 10 market competition quintiles, which we then sort into five information asymmetry portfolios, for a total of 50 (= 5 x 2 x 5) portfolios.

Table 5 presents the results of the information asymmetry hedge portfolio according to whether the number of shareholders and trading volume are low and high. For parsimony, we show only the lowest and highest shareholder quintiles. To indicate the lower (higher) competition portfolios, we shade the low shareholder, low turnover (high shareholder, high turnover) portfolios. For all five proxies for information asymmetry, the dependent sort results in Panel A show significant excess returns for the information asymmetry hedge portfolio when both the number of shareholders is low *and* trading volume is low. The magnitude of these returns ranges from 0.57% for *SAQ* to 1.01% for *Analyst Coverage*. In contrast, when the number of shareholders is low but trading volume is high, only the two accounting-based proxies for information asymmetry (*SAQ* and *R&D*) produce significant abnormal returns. We find similar results when we independently sort firms into market competition and information asymmetry portfolios in Panel B of Table 5.

As in our previous tests, the information asymmetry hedge portfolios generally do not produce significant abnormal returns when the level of market competition is high, regardless of the level of trading in the firm's shares. The one exception is *R&D*, which produces a positive information asymmetry hedge portfolio when both the number of shareholders and trading

[16] We thank the referee for suggesting this test.

volume are high. The significant hedge portfolio return for *R&D* in the highest competition portfolio (i.e., the high shareholder, high turnover portfolio) is the one piece of evidence we find that is inconsistent with the hypothesis that information asymmetry does not manifest in high competition settings.

5.4. Comparison of high and low information asymmetry firms

The results so far support our prediction that when market competition is low, firms with high information asymmetry have a higher cost of capital – in fact, roughly 12.5% higher when information asymmetry is measured using a dependent sort on *ASC_spread* as shown in Table 3. Although we predict that these firms will have a higher cost of capital, it is natural to wonder whether the behavior of these firms is consistent with their higher cost of capital. To shed light on this question, in Table 6 we compare proxies for these firms' size and risk, valuation, trading costs, uses of capital, sources of capital, and disclosure/visibility. As we do this, however, we emphasize that the theory we test in this paper takes information asymmetry and market competition as a given and is not a corporate finance or disclosure theory that predicts how firms optimize their investments and capital costs. Therefore, our analysis in Table 6 should be viewed as descriptive.

Since both our theory and our evidence suggest that differences in cost of capital manifest when market competition is low, in Table 6 we focus on the low and high information asymmetry portfolios within the low market competition quintile (first three columns). For parsimony, and because the magnitude of the hedge portfolio return for this proxy is largest, we focus on portfolios formed using dependent sorts on *ASC_spread* (Table 3).[17] As a benchmark, we also show the high market competition quintile (last three columns). For each competition quintile, the first column shows values for the low information asymmetry ("LIA") quintile and

[17] We obtain consistent results with the other information asymmetry measures and when we use independent sorts.

the second column for the high information asymmetry ("HIA") quintile, while the third column shows the difference and significance level. We present in the table a mixture of *ex ante* (i.e., for the year ended June 30 of year *t*) and *ex post* (i.e., for the year ended June 30 of year *t+1*) results. As in prior tables, for the variables shown, we compute the quintile median for each variable for each year and then compute the average annual median.

The first row reports the excess return from Panel B of Table 3 and annualizes it as a reminder that the HIA firms have a 12.5% excess cost of capital. The next three rows compare size and risk. Consistent with the factor loadings in Table 3, Panel B, firms in the HIA quintile are smaller and have lower beta and higher book-to-market. Consistent with the evidence that these firms face a higher cost of capital, the next row shows that HIA stocks have a significantly lower valuation than LIA stocks when the market is least competitive. The market-to-book asset ratio, a common proxy for the valuation measure Tobin's Q (e.g., Gompers, Ishii, and Metrick, 2003), is 33% lower for the HIA group. By contrast, there is no difference in valuation when the market is most competitive. The following rows show that investors who buy or sell HIA stocks pay much higher trading costs as proxied by the *ASC_spread* and *bid-ask spread*. Indeed, simply paying the round-trip spread costs 4% of the 12.5% excess return associated with the firms in the low competition quintile.

The higher book-to-market ratio and lower Tobin's Q of HIA firms suggest lower growth opportunities for the HIA firms (e.g., Smith and Watts, 1992). Consistent with lower growth opportunities and higher capital costs, the HIA firms undertake significantly less new investment and pay lower dividends (as proxied by *Dividend Yield*) than do their low market competition counterparts with low levels of information asymmetry. Consistent with differences in information asymmetry affecting capital costs only in low competition stocks, we find that HIA firms spend significantly less on new investment than LIA firms do when the market is least competitive, and we find no difference in new investment when the market is most competitive. We also find that when the market is least competitive, HIA firms issue significantly *less* debt and equity in than LIA firms do, but that when the market is most competitive, HIA firms issue significantly *more* equity than LIA firms do.[18] Collectively, these differences suggest that in imperfect markets, high information asymmetry firms face higher costs of capital and scarcer financing.

The bottom rows of Table 6 show that the HIA firms issue significantly *fewer* management forecasts both contemporaneously and during the next year. At first, it seems puzzling that managers would not seek to minimize their cost of capital by providing more information in the form of earnings forecasts. But perhaps it should not be viewed as such: Disclosure is costly, and firms with low growth options may rationally choose not to incur the costs associated with reducing information asymmetry. In other words, this finding may suggest that the difference in cost of capital across high and low information asymmetry firms when market competition is low is, in fact, an equilibrium result: Firms may choose to have high information asymmetry because the costs of reducing this asymmetry are greater than the benefits in terms of reducing the cost of capital.

5.5. Sensitivity analysis

In this section we describe sensitivity analyses. Here as well for parsimony, and because the magnitude of the result is largest, we focus on portfolios formed using dependent and

[18] Following Chen and Zhang (2010), we measure equity offerings as the percentage change in split-adjusted shares outstanding over the next fiscal year. Similarly, we measure debt offerings as the percentage change in long-term debt over the next fiscal year.

independent sorts on *ASC_spread*. We emphasize, however, that all of the results for our other proxies are robust to these sensitivity tests.[19]

5.5.1. Alternative samples

Panels A and B of Table 7 present sensitivity analyses of our primary results where we calculate the returns to dual dependent and independent sorts. The first column of each panel replicates the information asymmetry hedge on *ASC_spread* from Tables 3 and 4 for comparison. The second column presents portfolio returns excluding all stocks with a price of less than $5. This is another way, in addition to our use of buy-and-hold returns, of ensuring that microstructure effects of thinly traded firms do not drive our results, and it provides some comfort that microcap firms that are not representative of the population of investable shares also do not drive our results. Results in both Panels A and B are consistent: The hedge portfolio return for the lowest market competition quintile is positive and significant, and the hedge portfolio return for the highest quintile of market competition is not significantly greater than zero. The third column shows hedge portfolio returns when we restrict the sample to the period after June 2001, when the decimalization of share prices was instituted on the NYSE. We again find that the hedge portfolio return for the low market competition quintile is positive and significant, and that the hedge portfolio return in the high market competition quintile is indistinguishable from zero. Both findings are consistent with our predictions. Moreover, these results are important because this more recent period, during which bid-ask spreads fell and trading practices changed greatly, is likely to be more similar to U.S. capital markets going forward, and shows that our results are not an artifact of the pre-decimalization period.

[19] The one exception is the post-decimalization tests below, which are not applicable to *SAQ*, *R&D*, and *Analyst Coverage*.

In the final two columns of both panels of Table 7, we attempt to address the potential concern that computing portfolio returns relative to the Fama-French factors does not adequately control for the size effect. Our primary proxy for market competition (i.e., number of shareholders) is strongly positively correlated with market value, and some of our proxies for information asymmetry (e.g., *ASC_spread*) are strongly negatively correlated with market value. A potential concern is that sorting firms according to the number of shareholders is simply capturing a size effect. As a first approach, we begin with the same sort of firms on number of shareholders and *ASC_spread* as shown in the first column. Then we sort firms on market value and delete the smallest and largest 20% of firms in the sample (i.e., the top and bottom quintile when ranked on market value). If the market competition hedge portfolio returns are induced by an implicit sort on size, removing the extreme size portfolios should eliminate the excess returns between the quintile portfolios with the largest and the smallest number of shareholders. The fourth column shows that the information asymmetry hedge portfolio in the low market competition quintile remains significant. In the high market competition quintile, we find that the information asymmetry hedge portfolio is not different from zero. Both results are consistent with our predictions and suggest that our dual sort procedure is not simply capturing a size effect.[20]

A related concern is that our dual sorts on *ASC_spread* may effectively sort firms within a given market competition quintile by size. To address this concern, in the fifth column we

[20] As another way of controlling for a potential omitted size effect, we measure the excess return on a stock by subtracting the return of a matching portfolio formed on size and book-to-market equity. The matching portfolios are the updated 25 VW size-B/M portfolios of Fama and French (1993). Using the size and book-to-market matching technique is potentially more robust to nonlinearities in the relation between size and book-to-market and returns (Daniel, Grinblatt, Titman, and Wermers, 1997). However, a weakness of the approach is that it does not control for the exposure to the market factor, which is significant in explaining the low competition information asymmetry hedge portfolios as shown in Panel B of Tables 3 and 4. We therefore use the matched excess returns and also control for the three Fama-French factors. Using this method, we find that information asymmetry hedge portfolio returns remain positive and significant in the low market competition quintile and are not different from zero in the high market competition quintile.

follow a similar approach as we did in the fourth column. We again begin with the same sort of firms on number of shareholders and *ASC_spread* as shown in the first column. Then *within each market competition quintile*, we sort firms on market value and delete the smallest and largest firms in each market competition quintile. If the adverse-selection hedge portfolios returns are induced by an implicit sort on size within market competition quintile, removing the extreme-size portfolios should eliminate the excess returns. But Column 5 shows that the results are consistent in the low market competition quintile (as compared with Column 1) when we make this change. In addition, the information asymmetry hedge portfolio is again indistinguishable from zero in the high market competition quintile. Overall, the results in Table 7 show that our results are robust to a number of alternative samples.

5.5.2. Alternative models of expected returns

Although the Fama and French (1993) model is widely used as a model of expected returns, recent research has uncovered a number of other potential risk factors that appear to be useful in explaining the cross-section of stock returns. Table 8 presents the results from using three augmented versions of the Fama and French (1993) model, where each of the three columns augment the three-factor Fama and French (1993) model with either the Pastor and Stambaugh (2003) liquidity factor, the Sadka (2006) liquidity factor, or Carhart's (1997) momentum factor. The results are all similar to those in the first column, in which we replicate the information asymmetry hedge on *ASC_spread* from Tables 3 and 4 for comparison. In particular, for all three expected return models, we find that the information asymmetry hedge in the lowest market competition quintile is positive and significant and that the information asymmetry hedge in the highest market competition quintile is not significantly different from zero. All three columns are thus consistent with our predictions. The fact that our results are robust to the inclusion of two alternative liquidity factors in the third and fourth columns suggests that our results are not due to the omission of known liquidity risk factors.

5.5.3. Is idiosyncratic risk an alternative explanation?

In this paper, we focus on how information asymmetry affects the cost of capital in imperfect markets. Theory also suggests that as the number of shareholders becomes small, idiosyncratic risk can also affect the cost of capital, because idiosyncratic risk is not diversified away when there are small numbers of shareholders (e.g., Hughes et al., 2007; Lambert et al, 2007). Lambert and Verrecchia (2010) show that the effects of idiosyncratic risk are not linear and are bundled together with those of adverse selection; hence, it may be difficult to empirically separate the two effects.

We conduct two sensitivity analyses to ensure that the fact that we do not control for idiosyncratic risk in our main tests does not affect our findings on information asymmetry. We first conduct tests analogous to our Table 3 and 4 sorts on information asymmetry. We form five quintiles based on the level of market competition and then sort into five quintiles based on idiosyncratic risk, where idiosyncratic risk is computed as in Ang et al. (2006). The returns to the idiosyncratic risk hedge portfolio for the low market competition quintile are not significantly different from zero. These results are inconsistent with idiosyncratic risk being an explanation for our information asymmetry results. Second, we take a similar approach as in the fifth column of Table 7. We again sort firms on the level of market competition and *ASC_spread* as shown in the first column of Table 7. Then within each market competition quintile, we sort firms on idiosyncratic risk and delete the 20% of firms with the smallest and largest values of idiosyncratic risk in each market competition quintile. If the information asymmetry hedge portfolio's returns are induced by an implicit sort on idiosyncratic risk, removing the extreme idiosyncratic risk portfolios should eliminate the excess returns. But we find that the risk-adjusted returns to the information asymmetry hedge portfolio continue to be significant and consistent with our hypothesis. Overall, these sensitivity tests show no evidence that idiosyncratic risk is an explanation for our results on the relation between imperfect competition and information asymmetry.

Collectively, the results in Tables 7 and 8 show that the results in Tables 3 and 4 are robust to alternative samples, restricted time periods, and alternative ways of calculating abnormal returns.

6. Conclusion

This paper examines when information asymmetry among investors affects the cost of capital. When markets are characterized by perfect competition, information asymmetry has no separate effect on the cost of capital. When markets are less than perfectly competitive, however, as in Kyle (1989) and Lambert and Verrecchia (2010), market competition and information asymmetry affect the cost of capital beyond their effect on market risk. We test these predictions and find evidence supporting our predictions. In particular, we find an incremental effect of information asymmetry (beyond market risk) on the cost of capital when the degree of market competition is low and no effect of information asymmetry on the cost of capital when the degree of market competition is high. Collectively, our results suggest that future studies investigating the role of information asymmetry on the cost of capital should include the degree of market competition, which we show is an important conditioning variable in the relationship.

We caveat our results as follows. As to some extent illustrated by our study, at present our empirical and theoretical understanding of the cost of capital is still early. Our empirical tests are based on realized returns. We calculate expected returns using the widely used Fama-French model in our primary tests and show that our results are robust to a number of alternative specifications of expected returns. Nevertheless, as with all asset-pricing tests, our tests are joint tests of our hypotheses and of a correctly specified asset pricing model. Implied cost of capital measures are an alternative proxy for expected returns, and there is an ongoing debate in the literature about the use of future returns versus implied cost of capital as a proxy for expected returns (e.g., Easton and Monahan, 2005; Guay, Kothari, and Shu, 2006; McInnis, 2010). A chief interest of our study, however, is firms with low market competition. Because low-competition firms tend to have little to no analyst following, implied cost of capital estimates (for which analyst forecasts are required) cannot be calculated for most of these firms. Finally, we find that when market competition is low, firms with high information asymmetry have a cost of capital that is from 5.08% to 12.48% higher than firms with low information asymmetry. Although we predict that these firms will have a higher cost of capital, this is an economically large difference in the cost of capital. We suggest that firms may choose to have high information asymmetry because the costs of reducing this asymmetry are greater than the benefits in terms of reducing their cost of capital. Understanding the magnitude and determinants of this trade-off is an important topic for future research.

Appendix

Estimation of the adverse selection component of the bid-ask spread

We estimate the adverse selection component of the bid-ask spread, *ASC_spread*, following Madhavan, Richardson, and Roomans (1997). Prior literature (e.g., Greene and Smart, 1999) uses this method to estimate the adverse selection component of the bid-ask spread. To estimate *ASC_spread*, we gather trade-by-trade and quote data from the Institute for the Study of Security Markets (ISSM) and the Trades and Automated Quotes (TAQ) database provided by the NYSE. We match trades and quotes using the Lee and Ready (1991) algorithm with a five-second lag to determine the direction of the trade (i.e., buy or sell). We clean trades and quotes using the algorithm described in Appendix B of Ng, Rusticus, and Verdi (2008). Once trades are classified as either buyer- or seller-initiated, we estimate the following firm-specific regression:

$$\Delta p_t/p_{t-1} = \psi\, \Delta D_t + \lambda\, (D_t - \rho D_{t-1}) + u_t\ , \qquad (1)$$

where p_t is the transaction price, D_t is the sign of trade (+1 if buy and -1 if sell), and ρ is the AR(1) coefficient for D_t. The fitted λ in the above is *ASC_spread*. The advantage of the Madhavan et al. (1997) model is that it does not assume that price changes are monotonically increasing in signed transaction size, as do other models such as Glosten and Harris (1988). We are reluctant to make this assumption, because prior empirical work generally finds that the assumption is violated (e.g., Barclay and Warner, 1993; Chakravarty, 2001).[21] Note that the only difference between the estimation procedure shown in Equation (1) and the one described in Madhavan et al. (1997) is that we have deflated the dependent variable by lagged price to allow

[21] Nevertheless, we also estimate the Glosten and Harris (1988) measure of the adverse selection component of the bid-ask spread. This measure has a 0.77 (Spearman) correlation with the Madhavan et al. (1997) measure and produces similar inferences. For example, the abnormal returns to the *ASC_spread* hedge portfolio in the low market competition in Panel A of Table 3 are 0.61% per month (t-stat of 2.25).

for cross-sectional comparability.[22] Because the Madhavan et al. (1997) model describes the evolution of transaction prices in a single firm, it was not intended to directly apply to a cross-sectional setting where the price level varies across firms.[23]

[22] Absent this scaling, λ would depend on Δp_t, the change in price, and, hence, the price level of the firm. As a simple example, consider two firms, both with unexpected order flow $(D_t - \rho D_{t-1})$ equal to c (ignoring for the moment ΔD_t). In the first firm, price moves from 10 to 11, and in the second from 100 to 110. Despite identical changes in order flow, λ for the first firm is 1/c and λ for the second firm is 10/c. This example illustrates that, *ceteris paribus*, estimates of λ will differ by a factor of 10 because the price levels of the firms differ by a factor of 10.

[23] This concern about scaling also applies to other microstructure models and measures of *ASC_spread* (e.g., Glosten and Harris, 1988).

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Table 1. Descriptive Statistics

This table presents descriptive statistics for measures of market competition and information asymmetry. Panel A reports the annual number of observations available for each variable. Panel B reports the distribution of the variables used in the analysis, and their correlations. Bold indicates statistical significance at the 5% level (or lower). Panel C presents descriptive statistics for the extreme quintiles (i.e., one and five) for each of the information asymmetry proxies for the extreme quintiles of market competition. In the left-hand columns, we show statistics where the portfolios have been formed by sorting first based on the number of shareholders ("dependent sorts"), and in the right-hand columns we show statistics where the portfolios have been formed by sorting independently on the number of shareholders and on the information asymmetry variable, and intersecting the resulting quintile sorts ("independent sorts"). We sort each information asymmetry variable into five quintiles and report the median of the top and bottom quintiles. We compute these medians each year and then take the time-series average of these medians. The number of observations shown is the average annual number of observations in that portfolio. *Year* is the year of portfolio formation. *Number of Shareholders* (data #100) is the number of shareholders of record measured as of the firm's fiscal year end. *ASC_spread* is the modified Madhavan, Richardson, and Roomans (1997) measure of the information asymmetry component of the bid-ask spread, estimated over the month of June. *Spread* is the average bid-ask spread scaled by trade price, quoted on TAQ or ISSM and weighted by order size for the month of June. We use the lagged values of *ASC_spread* and *Spread* in our analyses. *Analyst Coverage* is the number of analysts issuing one-year-ahead earnings forecasts for the firm during the year according to the I/B/E/S Summary file. *SAQ* is scaled accruals quality calculated as the Dechow and Dichev (2002) measure of accruals quality scaled by the average of the absolute value of total accruals over the previous five years. *R&D* is the ratio of research and development expense (data #46) to sales (data #12). *Market Value* is the market capitalization (in millions of dollars) measured at the end of June.

Panel A. Number of Observations by Year

Year	*Number of Shareholders*	*ASC_spread*	*Spread*	*Analyst Coverage*	*SAQ*	*R&D*	*Market Value*
1976	3,239	-	-	4,103	2,081	4,056	4,103
1977	4,018	-	-	4,177	2,177	4,120	4,177
1978	3,959	-	-	4,098	2,136	4,046	4,098
1979	3,988	-	-	4,106	2,139	4,041	4,106
1980	3,972	-	-	4,105	2,192	4,017	4,105
1981	4,037	-	-	4,356	2,320	4,236	4,356
1982	4,229	-	-	4,574	2,773	4,436	4,574
1983	4,364	-	-	4,822	2,730	4,592	4,822
1984	4,646	-	-	5,337	2,632	4,986	5,337
1985	4,811	-	-	5,418	2,489	5,050	5,418
1986	4,806	-	-	5,568	2,358	5,077	5,568
1987	5,041	-	-	6,060	2,251	5,439	6,060
1988	5,214	3,451	4,006	6,239	2,204	5,485	6,239
1989	5,139	3,258	3,950	6,172	2,178	5,333	6,172
1990	5,080	3,231	3,911	6,190	2,251	5,299	6,190
1991	5,038	3,200	3,926	6,202	2,374	5,296	6,202
1992	5,102	1,748	1,912	6,507	2,448	5,522	6,507
1993	5,307	3,992	4,964	6,928	2,627	5,777	6,928
1994	5,850	1,958	2,054	7,785	2,881	7,026	7,785
1995	6,076	5,012	5,912	7,936	2,933	7,234	7,936
1996	6,208	5,220	6,016	8,352	2,954	7,609	8,352
1997	6,670	5,760	6,496	8,631	2,914	7,924	8,631
1998	6,623	5,914	6,558	8,522	2,868	7,838	8,522
1999	6,177	6,121	6,490	8,111	2,791	7,396	8,111
2000	5,986	5,847	6,149	8,054	2,802	7,411	8,054
2001	5,560	5,582	5,891	7,505	2,765	6,901	7,505
2002	5,092	5,262	5,536	7,023	2,845	6,377	7,023
2003	4,665	4,926	5,119	6,563	3,040	5,901	6,563
2004	4,528	4,760	4,846	6,469	3,118	5,719	6,469
2005	4,528	4,713	4,781	6,511	3,043	5,693	6,511

Table 1. Descriptive Statistics (Cont'd)

Panel B. Distribution of Variables and Correlation Matrix

Statistic	Mean	Std. Dev.	P10	Median	P90
Number of Shareholders	17.54	1,274.36	0.238	1.651	17.869
ASC_spread	0.004	0.089	0.000	0.001	0.007
Spread	0.024	0.022	0.005	0.016	0.053
Analyst Coverage	3.777	5.974	0.000	1.000	11.000
SAQ	0.925	1.261	0.313	0.776	1.610
R&D	0.765	33.477	0.000	0.000	0.128
Market Value	1,058.510	7,419.770	6.504	80.400	1,425.570

Spearman Correlations

Pearson Correlations

	Number of Shareholders	*ASC_spread*	*Spread*	*Analyst Coverage*	*SAQ*	*R&D*	*Market Value*
Number of Shareholders		**–0.48**	**–0.31**	**0.47**	**0.07**	**–0.07**	**0.54**
ASC_spread	**–0.17**		**0.66**	**–0.67**	**–0.03**	0.00	**–0.76**
Spread	**–0.20**	**0.51**		**–0.60**	**0.01**	–0.01	**–0.66**
Analyst Coverage	**0.49**	**–0.36**	**–0.43**		**–0.03**	**0.04**	**0.70**
SAQ	**0.07**	**–0.01**	**0.03**	0.00		**–0.05**	0.01
R&D	**–0.03**	–0.01	**0.03**	**–0.04**	0.02		0.00
Market Value	**0.62**	**–0.21**	**–0.27**	**0.70**	**0.04**	**–0.02**	

Table 1. Descriptive Statistics (Cont'd)

Panel C. Distribution of Information Asymmetry Variables by Market Competition Quintile

Quintile of Number of Shareholders	Correlation With Number of Shareholders	*ASC_spread* Dependent Sort					*ASC_spread* Independent Sort				
		Quintile 1		Quintile 5		Diff.	Quintile 1		Quintile 5		Diff.
		N	Median	N	Median	Q5–Q1	N	Median	N	Median	Q5–Q1
1	–0.03	156	0.0007	156	0.0109	0.0102	44	0.0003	227	0.0078	0.0075
5	–0.57	156	0.0002	156	0.0015	0.0013	444	0.0003	21	0.0071	0.0068

Quintile of Number of Shareholders	Correlation With Number of Shareholders	*Spread* Dependent Sort					*Spread* Independent Sort				
		Quintile 1		Quintile 5		Diff.	Quintile 1		Quintile 5		Diff.
		N	Median	N	Median	Q5–Q1	N	Median	N	Median	Q5–Q1
1	0.00	169	0.0078	169	0.0586	0.0508	101	0.0058	209	0.0537	0.0479
5	–0.36	169	0.0044	169	0.0266	0.0222	362	0.0057	49	0.0562	0.0505

Quintile of Number of Shareholders	Correlation With Number of Shareholders	*SAQ* Dependent Sort					*SAQ* Independent Sort				
		Quintile 1		Quintile 5		Diff.	Quintile 1		Quintile 5		Diff.
		N	Median	N	Median	Q5–Q1	N	Median	N	Median	Q5–Q1
1	0.00	98	0.356	98	1.357	1.001	104	0.364	82	1.442	1.079
5	0.08	98	0.384	98	1.642	1.258	86	0.363	118	1.524	1.161

Quintile of Number of Shareholders	Correlation With Number of Shareholders	*R&D* Dependent Sort					*R&D* Independent Sort				
		Quintile 1		Quintile 3		Diff.	Quintile 1		Quintile 3		Diff.
		N	Median	N	Median	Q3–Q1	N	Median	N	Median	Q3–Q1
1	0.07	573	0.000	328	0.131	0.131	573	0.000	369	0.103	0.103
5	0.05	608	0.000	328	0.038	0.038	608	0.000	297	0.051	0.051

Quintile of Number of Shareholders	Correlation With Number of Shareholders	*Analyst Coverage* Dependent Sort					*Analyst Coverage* Independent Sort				
		Quintile 1		Quintile 3		Diff.	Quintile 1		Quintile 3		Diff.
		N	Median	N	Median	Q3–Q1	N	Median	N	Median	Q3–Q1
1	0.03	552	0.000	283	3.917	3.917	552	0.000	143	6.233	6.233
5	0.41	328	1.967	335	19.700	17.733	122	0.000	723	12.517	12.517

Table 2. Information Asymmetry Portfolios

We form five equal-weighted portfolios at the end of June of year *t* and compute monthly buy-and-hold returns for each portfolio. We rank firms into quintiles in June of year *t* based on one of five measures of information asymmetry: *ASC_spread*, *Spread*, *SAQ*, *R&D*, and *Analyst Coverage*. All variables are as defined in Table 1. Because of the large number of zero values for *Analyst Coverage* and *R&D*, these measures are ranked into terciles. To be included in a portfolio, the firm must have a non-missing return and market value on the CRSP monthly file in June of year *t*. α is the intercept from a Fama-French three-factor model estimated on monthly portfolio returns, and β^{MKTRF}, β^{SMB}, and β^{HML} are the coefficients on the respective Fama-French factors. The *ASC_spread* and *Spread* portfolios span July 1988-June 2006 and contain, on average, 841 and 930 firms per portfolio per month, respectively. The *Analyst Coverage*, *SAQ*, and *R&D* portfolios span July 1976-June 2006 and contain, on average, 1,970, 503, and 1,792 firms per portfolio per month, respectively. *, **, and *** denote the significance of the factor loadings at the 10%, 5%, and 1% levels (two-tailed), respectively.

Panel A. Market-Based Measures

	Quintile of Information Asymmetry 1	2	3	4	5	Hedge
ASC_spread						
α	–0.09	–0.13	0.01	0.16	0.41	0.50
$t(\alpha)$	(–1.33)	(–1.96)	(0.07)	(1.11)	(1.98)	(2.29)
β^{MKTRF}	1.07***	1.10***	1.02***	0.95***	0.81***	–0.26***
β^{SMB}	0.34***	0.82***	1.13***	1.19***	1.20***	0.86***
β^{HML}	0.31***	0.30***	0.15***	0.20***	0.21**	–0.10
R^2	95.0%	97.07%	95.56%	90.46%	78.82%	51.10%
Spread						
α	–0.07	0.00	0.13	0.26	0.24	0.31
$t(\alpha)$	(–0.72)	(0.03)	(1.35)	(1.64)	(1.04)	(1.17)
β^{MKTRF}	1.08***	0.99***	0.94***	0.90***	0.85***	–0.23***
β^{SMB}	0.47***	0.76***	1.03***	1.23***	1.21***	0.74***
β^{HML}	0.29***	0.29***	0.22***	0.17**	0.28**	–0.01
R^2	91.11%	97.24%	94.59%	88.91%	74.80%	33.92%

Panel B. Other Measures

	Quintile of Information Asymmetry 1	2	3	4	5	Hedge
SAQ						
α	0.04	0.03	0.09	0.04	0.16	0.12
$t(\alpha)$	(0.55)	(0.40)	(1.24)	(0.55)	(1.60)	(1.37)
β^{MKTF}	0.94***	0.97***	0.95***	0.96***	0.92***	–0.02
β^{SMB}	0.87***	0.75***	0.87***	0.90***	0.94***	0.07
β^{HML}	0.21***	0.32***	0.26***	0.26***	0.20***	–0.01
R^2	95.02%	92.98%	93.74%	93.27%	91.06%	2.25%
R&D						
α	–0.11	–0.05	0.13	.	.	0.24
$t(\alpha)$	(–1.45)	(–0.33)	(1.16)	.	.	(1.77)
β^{MKTRF}	0.92***	1.02***	1.01***	.	.	0.09**
β^{SMB}	0.69***	0.76***	1.22***	.	.	0.53***
β^{HML}	0.45***	0.42***	–0.26***	.	.	–0.71***
R^2	91.80%	79.17%	91.65%	.	.	67.08%
Analyst Coverage						
α	0.03	–0.01	–0.09	.	.	–0.12
$t(\alpha)$	(0.21)	(–0.11)	(–2.41)	.	.	(–0.86)
β^{MKTRF}	0.79***	0.96***	1.07***	.	.	0.28***
β^{SMB}	1.01***	1.02***	0.63***	.	.	–0.38***
β^{HML}	0.20***	0.16***	0.22***	.	.	0.02
R^2	82.49%	95.21%	98.06%	.	.	26.63%

Table 3. Information Asymmetry Portfolios Partitioned by Market Competition — Dependent Sorts

We form 25 equal-weighted portfolios at the end of June of year *t* based on two-dimensional dependent sorts and compute monthly buy-and-hold returns for each portfolio. Firms are first ranked into quintiles based on *Number of Shareholders* (data #100), which is the number of shareholders of record measured as of the firm's fiscal year end. Then, within each number of shareholder quintile, firms are ranked into five portfolios based on one of five measures of information asymmetry: *ASC_spread*, *Spread*, *SAQ*, *R&D*, and *Analyst Coverage*. Because of the large number of zero values for *Analyst Coverage* and *R&D*, these measures are ranked into terciles. All variables are as defined in Table 1. To be included in a portfolio, the firm must have a non-missing return and market value on the CRSP monthly file in June of year *t.* Panel A reports the Fama-French α for the information asymmetry hedge portfolio for each market competition quintile. Panel B reports Fama-French α and factor loadings for the extreme portfolios. α is the intercept from a Fama-French three-factor model estimated on monthly portfolio returns, and β^{MKTRF}, β^{SMB}, and β^{HML} are the coefficients on the respective Fama-French factors. The *ASC_spread* and *Spread* portfolios span July 1988-June 2006 and contain, on average, 128 and 160 firms per portfolio per month, respectively. The *Analyst Coverage*, *SAQ*, and *R&D* portfolios span July 1976-June 2006 and contain, on average, 336, 96, and 326 firms per portfolio per month, respectively. *, **, and *** denote the significance of the factor loadings at the 10%, 5%, and 1% levels (two-tailed), respectively.

Panel A. Information Asymmetry Hedge Portfolios Partitioned by Market Competition

		Measure of Information Asymmetry (hedge α)				
		ASC_spread (Q5-Q1)	*Spread* (Q5 – Q1)	*SAQ* (Q5 – Q1)	*R&D* (Q3 – Q1)	*Analyst Coverage* (Q1 – Q3)
Market Competition Quintile	1	1.04	0.65	0.42	0.51	0.38
		(2.83)	(1.93)	(2.88)	(2.85)	(1.94)
	2	0.49	0.29	0.06	0.29	0.17
		(1.96)	(0.98)	(0.39)	(1.55)	(1.09)
	3	0.53	0.41	–0.01	0.24	0.03
		(1.89)	(1.37)	(–0.07)	(1.68)	(0.17)
	4	0.23	0.00	0.17	0.34	–0.05
		(0.79)	(0.01)	(0.98)	(2.48)	(–0.25)
	5	0.03	–0.19	0.11	0.08	–0.09
		(0.13)	(–0.82)	(0.89)	(0.58)	(–0.84)

Table 3. Information Asymmetry Portfolios Partitioned by Market Competition (Cont'd)

Panel B. Detailed Estimates of Extreme Portfolio Returns

ASC_spread

Market Competition Quintile		Q1	Q5	Hedge
1	α	–0.36	0.68	1.04
	t(α)	(–2.51)	(2.00)	(2.83)
	β^{MKTRF}	1.26***	0.80***	-0.46***
	β^{SMB}	0.87***	1.53***	0.66***
	β^{HML}	–0.04	–0.08	-0.04
	R^2	91.13%	71.13%	23.19%
5	α	–0.06	–0.03	0.03
	t(α)	(–0.83)	(–0.16)	(0.13)
	β^{MKTRF}	0.99***	1.04***	0.05
	β^{SMB}	–0.06***	1.24***	1.31***
	β^{HML}	0.29***	0.15*	-0.13
	R^2	92.17%	82.36%	72.82%

SAQ

Market Competition Quintile		Q1	Q5	Hedge
1	α	0.04	0.47	0.42
	t(α)	(0.39)	(3.09)	(2.88)
	β^{MKTRF}	0.82***	0.85***	0.03
	β^{SMB}	1.10***	1.25***	0.15*
	β^{HML}	0.18***	0.09	–0.10
	R^2	86.84%	82.35%	5.82%
5	α	–0.06	–0.16	–0.11
	t(α)	(–0.67)	(–1.74)	(–0.89)
	β^{MKTRF}	0.95***	1.03***	0.08*
	β^{SMB}	0.37***	0.30***	–0.07
	β^{HML}	0.24***	0.41***	0.17***
	R^2	89.81%	86.97%	6.49%

Spread

Market Competition Quintile		Q1	Q5	Hedge
1	α	–0.22	0.43	0.65
	t(α)	(–1.34)	(1.43)	(1.93)
	β^{MKTRF}	1.20***	0.85***	–0.36***
	β^{SMB}	0.86***	1.40***	0.54***
	β^{HML}	–0.03	0.08	0.11
	R^2	88.20%	70.16%	17.37%
5	α	–0.08	–0.27	–0.19
	t(α)	(–0.78)	(–1.42)	(–0.82)
	β^{MKTRF}	1.08***	1.09***	0.01
	β^{SMB}	0.04	1.19***	1.15***
	β^{HML}	0.35***	0.34***	–0.01
	R^2	86.87%	83.86%	62.94%

R&D

Market Competition Quintile		Q1	Q3	Hedge
1	α	–0.12	0.39	0.51
	t(α)	(–1.04)	(2.07)	(2.85)
	β^{MKTRF}	0.89***	0.98***	0.09
	β^{SMB}	0.97***	1.54***	0.57***
	β^{HML}	0.26***	–0.61***	–0.87***
	R^2	86.19%	86.26%	61.82%
5	α	–0.16	–0.08	0.08
	t(α)	–2.86	–0.76	0.58
	β^{MKTRF}	0.97***	1.06***	0.09*
	β^{SMB}	0.28***	0.67***	0.39***
	β^{HML}	0.57***	–0.05	–0.62***
	R^2	93.75%	89.60%	58.81%

Analyst Coverage

Market Competition Quintile		Q1	Q3	Hedge
1	α	0.28	–0.10	0.38
	t(α)	(1.46)	(–1.10)	(1.94)
	β^{MKTRF}	0.76***	1.07***	–0.31***
	β^{SMB}	1.39***	1.08***	0.31**
	β^{HML}	–0.11	–0.16***	0.05
	R^2	76.82%	94.59%	14.87%
5	α	–0.18	–0.09	–0.09
	t(α)	(–1.83)	(–1.56)	(–0.84)
	β^{MKTRF}	0.89***	1.03***	–0.14***
	β^{SMB}	0.94***	0.00	0.94***
	β^{HML}	0.29***	0.35***	–0.06
	R^2	88.95%	94.32%	68.18%

Table 4. Information Asymmetry Portfolios Partitioned by Market Competition — Independent Sorts

We form 25 equal-weighted portfolios at the end of June of year *t* based on two-dimensional dependent sorts and compute monthly buy-and-hold returns for each portfolio. Firms are first ranked into quintiles based on *Number of Shareholders* (data #100), which is the number of shareholders of record measured as of the firm's fiscal year end. Then, independent of this ranking, firms are ranked into five portfolios based on one of six measures of information asymmetry: *ASC_spread*, *Spread*, *SAQ*, *R&D*, and *Analyst Coverage*. Because of the large number of zero values for *Analyst Coverage* and *R&D*, these measures are ranked into terciles. All variables are as defined in Table 1. To be included in a portfolio, the firm must have a non-missing return and market value on the CRSP monthly file in June of year *t.* Panel A reports the Fama-French α for the information asymmetry hedge portfolio for each market competition quintile. Panel B reports Fama-French α and factor loadings for the extreme portfolios. α is the intercept from a Fama-French three-factor model estimated on monthly portfolio returns, and β^{MKTRF}, β^{SMB}, and β^{HML} are the coefficients on the respective Fama-French factors. *, **, and *** denote the significance of the factor loadings at the 10%, 5%, and 1% levels (two-tailed), respectively.

Panel A. Information Asymmetry Hedge Portfolios Partitioned by Market Competition

		Measure of Information Asymmetry (hedge α)				
		ASC_spread (Q5-Q1)	*Spread* (Q5 – Q1)	*SAQ* (Q5 – Q1)	*R&D* (Q3 – Q1)	*Analyst Coverage* (Q1 – Q3)
Market Competition Quintile	1	0.88	0.74	0.43	0.51	0.24
		(2.31)	(2.06)	(2.93)	(3.15)	(1.06)
	2	0.46	0.21	0.09	0.28	0.13
		(1.70)	(0.65)	(0.55)	(1.64)	(0.70)
	3	0.49	0.46	0.03	0.25	0.06
		(1.71)	(1.50)	(0.18)	(1.51)	(0.31)
	4	0.37	–0.11	0.21	0.33	–0.10
		(1.12)	(–0.36)	(1.24)	(2.31)	(–0.54)
	5	–0.10	–0.48	–0.16	0.13	–0.18
		(–0.24)	(–1.33)	(–1.33)	(0.81)	(–1.18)

Table 4. Information Asymmetry Portfolios Partitioned by Market Competition (Cont'd)

Panel B. Detailed Estimates of Extreme Portfolio Returns

Market Competition Quintile		*ASC_spread* 1	*ASC_spread* 5	Hedge
1	α	–0.22	0.66	0.88
	t(α)	(–0.86)	(2.21)	(2.31)
	β^{MKTRF}	1.14***	0.82***	–0.32***
	β^{SMB}	0.92***	1.51***	0.59***
	β^{HML}	0.04	–0.11	–0.15
	R^2	72.59	76.05	16.23
5	α	–0.06	–0.16	0.10
	t(α)	(–1.06)	(–0.40)	(0.24)
	β^{MKTRF}	1.01***	0.97***	–0.04
	β^{SMB}	0.10***	1.26***	1.16***
	β^{HML}	0.43***	0.35**	–0.08
	R^2	94.39%	47.14%	29.91%

Market Competition Quintile		*SAQ* Quintile 1	*SAQ* Quintile 5	Hedge
1	α	0.08	0.51	0.43
	t(α)	(0.73)	(3.25)	(2.93)
	β^{MKTRF}	0.80***	0.85***	0.05
	β^{SMB}	1.20***	1.23***	0.03
	β^{HML}	0.09	0.08	–0.01
	R^2	87.52%	80.53%	0.20%
5	α	–0.01	–0.17	–0.06
	t(α)	(–0.06)	(–1.87)	(–1.33)
	β^{MKTRF}	0.94***	1.04***	0.10**
	β^{SMB}	0.41***	0.30***	–0.11**
	β^{HML}	0.21***	0.41***	0.20***
	R^2	88.30%	88.49%	11.21%

Market Competition Quintile		*Spread* Quintile 1	*Spread* Quintile 5	Hedge
1	α	–0.26	0.48	0.74
	t(α)	(–1.32)	(1.62)	(2.06)
	β^{MKTRF}	1.20***	0.84***	–0.36***
	β^{SMB}	0.85***	1.46***	0.61***
	β^{HML}	–0.06	0.02	0.08
	R^2	84.20	73.51	18.87
5	α	–0.11	–0.59	–0.48
	t(α)	(–1.36)	(–1.76)	(–1.33)
	β^{MKTRF}	1.07***	1.11***	0.04
	β^{SMB}	0.12***	1.29***	1.17***
	β^{HML}	0.43***	0.46***	0.03
	R^2	90.87%	62.39%	38.38%

Market Competition Quintile		*R&D* Quintile 1	*R&D* Quintile 5	Hedge
1	α	–0.11	0.40	0.51
	t(α)	(–1.04)	(2.31)	(3.16)
	β^{MKTRF}	0.89***	0.95***	0.06
	β^{SMB}	0.97***	1.50***	0.53***
	β^{HML}	0.26***	–0.54***	–0.80***
	R^2	86.19%	87.54%	62.04%
5	α	–0.16	–0.03	0.13
	t(α)	(–2.86)	(–0.26)	(0.81)
	β^{MKTRF}	0.97***	1.07***	0.10**
	β^{SMB}	0.28***	0.74***	0.46***
	β^{HML}	0.57***	–0.16**	–0.73***
	R^2	93.75%	87.27%	58.96%

Market Competition Quintile		*Analyst Coverage* Quintile 1	*Analyst Coverage* Quintile 5	Hedge
1	α	0.29	0.05	0.24
	t(α)	(1.46)	(0.36)	(1.06)
	β^{MKTRF}	0.75***	1.07***	–0.32***
	β^{SMB}	1.39***	0.95***	0.44***
	β^{HML}	–0.11	–0.17***	0.06
	R^2	76.82%	89.40%	15.10%
5	α	–0.30	–0.12	0.18
	t(α)	(–2.08)	(–2.77)	(1.19)
	β^{MKTRF}	0.87***	1.05***	0.18***
	β^{SMB}	0.95***	0.22***	–0.73***
	β^{HML}	0.31***	0.40***	0.09
	R^2	76.42%	96.17%	29.91%

Table 5. Turnover-Based Refinement of Market Competition Measure

This table presents results from using a turnover-base refinement of the market competition measure. We form 50 equal-weighted portfolios at the end of June of year *t* based on three-dimensional sorts (5 x 2 x 5) and compute monthly buy-and-hold returns for each portfolio. In Panel A, firms are first ranked into quintiles based on *Number of Shareholders*. Then, within each quintile, firms are ranked into two groups based on average share turnover over the 12 months ended June of year *t*, and five groups based on each of the five proxies for information asymmetry: *ASC_spread*, *Spread*, *SAQ*, *R&D*, and *Analyst Coverage*. Because of the large number of zero values for *Analyst Coverage* and *R&D*, these measures are ranked into terciles. All variables are as defined in Table 1. As indicated by the shaded cells, firms that have a high (low) number of shareholders and high (low) turnover are relatively most (least) competitive. We compute the *Fama-French* α for the information asymmetry hedge portfolio for the extreme number of shareholder and turnover portfolios. Panel A (Panel B) presents results from dependent (independent) sorts on the five information asymmetry proxies. *Fama-French* α is the intercept from a Fama-French three-factor model estimated on monthly portfolio returns.

Panel A. Turnover-Based Refinement — Dependent Sorts

		ASC_spread (Q5 – Q1)		*Spread* (Q5 – Q1)		*SAQ* (Q5 – Q1)		*R&D* (Q3-Q1)		*Analyst Coverage* (Q1 – Q3)	
		Turnover		Turnover		Turnover		Turnover		Turnover	
Number of Shareholders		High	Low	High	Low	High	Low	High	Low	High	Low
	Low	0.93	0.77	0.19	0.67	0.43	0.57	0.75	0.97	0.20	1.01
		(1.61)	(2.33)	(0.45)	(1.71)	(1.70)	(2.09)	(3.35)	(2.61)	(0.50)	(3.58)
	High	0.02	–0.13	–0.33	–0.21	–0.19	–0.13	0.51	0.02	–0.27	–0.03
		(0.05)	(–0.69)	(–1.01)	(–1.07)	(–1.11)	(–0.94)	(2.33)	(0.10)	(–1.31)	(–0.22)

Table 5. Alternative Measures of Market Competition (Cont'd)

Panel B. Turnover-Based Refinement — Independent Sorts

Number of Shareholders		*ASC_spread* (Q5 – Q1)		*Spread* (Q5 – Q1)		*SAQ* (Q5 – Q1)		*R&D* (Q3-Q1)		*Analyst Coverage* (Q1 – Q3)	
		Turnover		Turnover		Turnover		Turnover		Turnover	
		High	Low	High	Low	High	Low	High	Low	High	Low
Low		0.72	0.92	0.39	0.93	0.39	0.44	0.73	0.88	0.10	0.88
		(1.35)	(2.17)	(0.88)	(2.17)	(1.43)	(1.71)	(3.39)	(2.76)	(0.26)	(2.72)
High		–0.32	–0.02	–1.09	–0.21	–0.26	–0.12	0.55	0.09	–0.45	0.01
		(–0.37)	(–0.05)	(–1.87)	(–0.56)	(–1.40)	(–0.93)	(2.40)	(0.51)	(–1.32)	(0.07)

Table 6. Comparison of Proxies for Size and Risk, Valuation, Trading Costs, Uses of Capital, Sources of Capital, and Disclosure for High and Low Information Asymmetry Portfolios

This table presents firm characteristics of the extreme portfolios formed using dependent sorts on *ASC_spread* partitioned by market competition. We show both the low market competition quintile (first and second columns) and the high competition quintile (fourth and fifth columns). We also present the differences between the *ASC_spread* quintiles (columns three and six) and denote the significance of the difference at the 10%, 5%, and 1% levels (two-tailed) with *, **, and ***, respectively. Portfolio level characteristics are computed as the mean of the annual median values for each portfolio (except for the variables *Market Competition Portfolio*$_{t+1}$ and *Adverse Selection Portfolio*$_{t+1}$). *Annualized excess return*$_t$ is the annualized abnormal return (or alpha) from a regression of monthly portfolio returns in excess of the market on the three Fama-French factors. *Beta* is the slope coefficient from a market model of monthly returns estimated over the previous 60 months. *MVE* is the market value of equity. *B/M* is the book-to-market ratio. The market-to-book assets ratio is the ratio of the market value of assets to book value of assets. *ASC_spread* is the modified Madhavan, Richardson, and Roomans (1997) measure of the information asymmetry component of the bid-ask spread, estimated over the month of June. *Spread* is the average bid-ask spread scaled by trade price, quoted on TAQ or ISSM and weighted by order size for the month of June. *Dividend Yield* is annual dividends scaled by market value of equity. *New Investment* is the Richardson (2006) measure of new investment. *%Change in Debt* is the percentage change in long-term debt over the next fiscal year. *%Change in Equity* is calculated following Chen and Zhang (2010) as the percentage change in split-adjusted shares outstanding over the next fiscal year. *%Issued Management Forecast*$_t$ is the percentage of firms for which management issues an earnings forecast or earnings guidance according to First Call over the fiscal year. *%Issued Management Forecast*$_{t+1}$ is the percentage of firms at which management issues an earnings forecast or earnings guidance according to First Call during the next fiscal year.

	Market Competition Quintile 1			Market Competition Quintile 5		
	ASC_spread Quintile 1	*ASC_spread* Quintile 5	Diff.	*ASC_spread* Quintile 1	*ASC_spread* Quintile 5	Diff.
Cost of capital:						
Annualized excess return	–4.32%	8.16%	12.48%***	–0.72%	–0.36%	0.36%
Size and Risk:						
Beta$_t$	1.19	0.91	-0.28***	0.77	1.10	0.33***
MVE$_t$	343	19	-324***	11658	373	-11285***
B/M$_t$	0.45	0.91	0.46***	0.63	0.77	0.14*
Valuation:						
Market-to-book assets ratio $_t$	1.74	1.16	-0.58***	1.38	1.24	-0.14
Trading costs:						
ASC_spread$_t$	0.001	0.011	0.010***	0.000	0.001	0.001***
Spread$_t$	0.012	0.040	0.028***	0.010	0.018	0.008***
Uses of Capital:						
Dividend Yield$_{t+1}$	0.20%	0.00%	-0.20%*	3.00%	1.40%	-1.60%***
New Investment $_{t+1}$	0.08	0.01	-0.07***	0.040	0.043	0.003
Sources of Capital:						
% Change in Debt$_{t+1}$	4.00%	–5.16%	-9.16%***	4.00%	–0.20%	-4.20%***
% Change in Equity$_{t+1}$	1.40%	0.67%	-0.73%***	0.00%	1.10%	1.10%***
Disclosure:						
%Issue Mgt. Forecast$_t$	23.90%	5.76%	-18.14%**	28.00%	11.90%	-16.10%*
%Issue Mgt. Forecast$_{t+1}$	24.50%	5.84%	-18.66%***	30.00%	13.00%	-17.00%**

Table 7. Robustness to Alternative Samples

This table reports sensitivity analyses of the results presented in Panel A of Tables 3 and 4. We form 25 equal-weighted portfolios at the end of June of year *t* based on two-dimensional sorts on *Number of Shareholders* and *ASC_spread* and compute monthly buy-and-hold returns for each portfolio. Firms are first ranked into quintiles based on *Number of Shareholders* (data #100) and then into quintiles based on *ASC_spread*. All variables are as defined in Table 1. Panel A (Panel B) presents results from dependent (independent sorts) on *ASC_spread*. We present the *Fama-French α* for the *ASC_spread* hedge portfolio for the extreme market competition quintiles. The first column in Panel A (Panel B) replicates the *ASC_spread* hedge portfolio results presented in Table 3 (Table 4). The second column presents results excluding those stocks with price less than $5 per share at the end of June of year *t*. The third column presents alphas for the period following the decimalization of stock prices by the NYSE (i.e., after June of 2001). In the fourth column, we delete the smallest and largest 20% of firms in the sample (i.e., the top and bottom quintile when ranked on market value). In the fifth column, *within each market competition quintile*, we delete the smallest and largest 20% of firms.

Panel A. Hedge Portfolio Returns — Dependent Sorts

		(1)	(2)	(3)	(4)	(5)
		Table 3 Panel A *ASC_spread* hedge α	Excluding Stocks With Price < $5	Post-Decimalization (6/2001)	Excluding Q1 and Q5 MV	Excluding Q1 and Q5 MV by Num. of Sh. Quintile
Market Competition Quintile	1	1.04	1.05	1.55	1.34	1.17
		(2.83)	(2.50)	(2.86)	(3.01)	(2.66)
	5	0.03	-0.34	0.02	0.36	-0.28
		(0.13)	(-2.60)	(0.05)	(0.70)	(-1.46)

Panel B. Hedge Portfolio Returns — Independent Sorts

		(1)	(2)	(3)	(4)	(5)
		Table 3 Panel A *ASC_spread* hedge α	Excluding Stocks With Price < $5	Post-Decimalization (6/2001)	Excluding Q1 and Q5 MV	Excluding Q1 and Q5 MV by Num. of Sh. Quintile
Market Competition Quintile	1	0.88	1.05	1.16	1.30	1.03
		(2.31)	(2.72)	(1.91)	(2.62)	(1.80)
	5	–0.10	-0.50	-0.20	0.47	0.34
		(–0.24)	(-0.97)	(-0.21)	(1.00)	(0.42)

Table 8. Robustness to Alternative Measures of Expected Returns

This table reports sensitivity analyses of the results presented in Panel A of Tables 3 and 4. We form 25 equal-weighted portfolios at the end of June of year *t* based on two-dimensional sorts on *Number of Shareholders* and *ASC_spread* and compute monthly buy-and-hold returns for each portfolio. Firms are first ranked into quintiles based on *Number of Shareholders* (data #100) and then into quintiles based on *ASC_spread*. All variables are as defined in Table 1. Panel A (Panel B) presents results from dependent (independent sorts) on *ASC_spread*. We present the *Fama-French α* for the *ASC_spread* hedge portfolio for the extreme market competition quintiles. The first column in Panel A (Panel B) replicates the *ASC_spread* hedge portfolio *α* using the Fama-French three-factor model presented in Table 3 (Table 4). The second, third, and fourth columns present *α* from the Fama-French three-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor, the Sadka (2006) liquidity factor, and the Carhart (1997) momentum factor, respectively.

Panel A. Hedge Portfolio Returns — Dependent Sorts

		(1)	(2)	(3)	(4)
		Three Factor α	Four Factor α	Four Factor α	Four Factor α
		Table 3 Panel A	Liquidity Pastor-Stambaugh	Liquidity Sadka	Momentum
Market Competition Quintile	1	1.04	1.02	1.00	0.93
		(2.83)	(2.78)	(2.65)	(2.69)
	5	0.03	0.001	0.03	0.02
		(0.13)	(0.00)	(0.15)	(0.05)

Panel B. Hedge Portfolio Returns — Independent Sorts

		(1)	(2)	(3)	(4)
		Three Factor α	Four Factor α	Four Factor α	Four Factor α
		Table 4 Panel A	Liquidity Pastor-Stambaugh	Liquidity Sadka	Momentum
Market Competition Quintile	1	0.88	0.87	0.83	0.67
		(2.31)	(2.27)	(2.12)	(1.83)
	5	–0.10	–0.02	–0.11	–0.06
		(–0.24)	(–0.04)	(–0.26)	(–0.14)