The Role of Diversification in the Pricing of Accruals Quality

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Abstract

Prior studies suggest that accounting information risk, primarily idiosyncratic in nature, can be diversified away. I show that accounting information risk, proxied by accruals quality, is priced even if it is entirely idiosyncratic. Building on a model developed in the ambiguity literature, I predict that (1) in an under-diversified market, idiosyncratic information risk is priced even if it is diversifiable, and (2) in a well-diversified market, idiosyncratic information risk is priced when information is subject to managers' discretion and thus ambiguous. The empirical results corroborate the predictions from the model. An association is observed between (unambiguous if risky) innate accruals quality and cost of capital. This association can be largely mitigated through diversification. However, diversification has little impact on the association between (ambiguous) discretionary accruals quality and cost of capital.

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1. Introduction

A fundamental question in accounting research is whether accounting information risk (or quality) is priced in the capital market. Prior studies have theoretically and empirically shown a link between information risk and cost of capital (e.g., Easley and O'Hara, 2004; Francis, LaFond, Olsson, and Schipper, 2004, 2005).[1] This link has been contested by a growing number of studies (e.g., Hughes, Liu, and Liu, 2007; Core, Guay, and Verdi, 2008; Caskey, Hughes, and Liu, 2014). The latter studies show that idiosyncratic information risk can be diversified away in the capital market and that no cross-sectional association exists between idiosyncratic information risk and cost of capital.[2] Because accounting information is primarily idiosyncratic in nature, these studies suggest that the link between accounting information risk and cost of capital does not exist in a well-diversified market.[3] Therefore, it is still unclear whether accounting information risk is priced in the capital market.

I aim to shed light on this debate by showing that accounting information risk is priced even if it is entirely idiosyncratic. My initial hypothesis derives from the fact that most investors do not hold well-diversified portfolios (e.g., Levy, 1978; Merton, 1987; Fama and French, 2007). In this case, Merton (1987), among others, predicts a positive relation between idiosyncratic risk and stock returns. Moreover, Merton's model implies that as investor diversification increases, the positive relation between idiosyncratic risk and stock returns is mitigated.

[1]Information risk in these studies is defined as "the likelihood that firm-specific information that is pertinent to investor pricing decisions is of poor quality" (Francis, LaFond, Olsson, and Schipper, 2004, 2005). It is defined in the same way in this paper.

[2]By idiosyncratic risk (or unsystematic risk), I refer to risk that is specific to an asset or a small group of assets. Systematic risk, on the other hand, affects the whole market or economy.

[3]Several recent studies have shown that information risk has a strong association with idiosyncratic volatility, suggesting that a considerable amount of accounting information is idiosyncratic (e.g., Rajgopal and Venkatachalam, 2011; Chen, Huang, and Jha, 2012).

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My further hypotheses are built upon an asset-pricing model derived by Epstein and Schneider (2008), who distinguish between ambiguous and unambiguous information. Following prior literature (e.g., Ellsberg, 1961), I regard risk and ambiguity as two subcategories of uncertainty. All information can be risky but not necessarily ambiguous. The idea of ambiguity initially comes from Knight (1921).[4] He illustrates the concept with an example of two people drawing from an urn containing four balls of two colors: "One man knows that there are red and black balls, but is ignorant of the number of each; another knows that the numbers are three of the former to one of the latter." Ambiguous information refers to the former case, in which the information can be interpreted under multiple probability distributions.[5] In contrast, unambiguous information refers to the latter case, in which information is interpreted under a unique prior distribution.[6] Epstein and Schneider (2008) show that when investors are facing ambiguous information, idiosyncratic risk cannot be fully diversified away by holding a well-diversified portfolio.

I argue that discretionary information is more ambiguous than innate information. This is because innate information, by definition, is driven by past economic fundamentals and it is easier for investors to draw on experience to interpret it. In contrast, discretionary accruals choices give rise to ambiguity.[7] As summarized in Healy and Wahlen (1999), many accounting studies find that managers have both opportunistic and signalling motives when making accruals choices. On the one hand, in applying their discretion, managers can be opportunistic and choose reporting methods and estimates for accruals to maximize their

[4]Knight (1921) calls it "uncertainty" as opposed to "risk". Thus, some later studies use "Knight uncertainty" to refer to ambiguity.

[5]The probability of drawing a red ball is 25% with one red ball and three black balls, or 50% with two red balls and two black balls, or 75% with three red balls and one black ball.

[6]The probability of drawing a red ball is 75%.

[7]In fact, the implications of the Epstein-Schneider model apply to all management disclosures broadly. In this paper, I focus on the specific context in which managers are making accrual choices.

own interests (i.e., opportunistic motive). On the other hand, managers can also use their knowledge about the business to select reporting methods and estimates to signal their private information to investors (i.e., signalling motive).[8] Investors do not know which motive applies (opportunistic vs. signalling). Therefore, discretionary accruals choices give rise to ambiguity. In other words, the distribution of discretionary accruals conditional on an opportunistic motive differs from the distribution conditional on a signalling motive. Investors, similar to the first man in Knight's example who only knows that there are red and black balls, are facing multiple probability distributions and find discretionary information ambiguous.[9] In additional analyses, I show that investors respond more strongly to bad news than good news when discretionary accruals quality is low. However, I do not find a similar pattern for innate accruals quality. These results are consistent with one of the implications of ambiguous versus unambiguous information shown in Epstein and Schneider (2008), i.e., investors react to bad news more strongly than good news when facing ambiguous information. Hence, these results lend further support to the argument that innate information is less unambiguous than discretionary information. Therefore, as implied by Epstein and Schneider (2008), discretionary accruals quality is less likely to be diversified away.

I first empirically examine the extent to which accounting information quality, measured by accruals quality, is priced as diversification increases in an under-diversified market. In particular, I investigate how the relation between the firm's cost of capital and accounting

[8] An example of the dual motives in accruals choices can be illustrated by the valuation allowance for deferred tax assets. While Miller and Skinner (1998) find that this allowance reflects managers' expected future taxable income (i.e., signalling motive), Schrand and Wong (2003) document evidence of earnings management through manipulating this allowance (i.e., opportunistic motive).

[9] Note that relative to innate information, investors' experience is of less help to investors in interpreting discretionary information, and it is difficult to attach a prior probability to the two motives. First, in contrast to economic fundamentals, managers' motives are seldom revealed, making it difficult for investors to judge which motive applies, even *ex post*. Second, each time an estimate is made, it is case-specific and what happened in the past may not apply to the current situation managers face before making estimates.

information quality weakens as the extent of diversification increases. Based on Merton (1987), I hypothesize and find that the pricing of accruals quality decreases as diversification increases. The extent of diversification is gauged by a measure developed in Bushee and Goodman (2010). In particular, using institutional investors' holding information, I estimate the extent to which institutional investors' portfolio returns can be explained by market returns, indicating how closely the institutional investors' holdings resemble the market portfolio. A high explanatory power of the relation between institutional investor portfolio returns and market portfolio returns indicates a high extent of diversification.

I further break down accruals quality into innate and discretionary components. Unlike discretionary accruals, which are ambiguous, innate accruals are primarily unambiguous. Therefore, based on the Epstein and Schneider (2008) model, I hypothesize that while the pricing of accruals quality decreases with diversification for innate accruals, diversification is less salient in the pricing of discretionary accruals quality. The empirical results support my hypotheses. I first show a strong relation between accruals quality metrics and firms' cost of capital. After decomposing accruals quality into two components, I find that diversification has a much stronger impact on the pricing of innate accruals quality than on the pricing of discretionary accruals quality. In particular, as one moves from the bottom to the top diversification decile, approximately 80% of the cost-of-capital effect of the innate accruals quality is diversified away, but little change is observed for the cost-of-capital effect of the discretionary accruals quality. These results hold for a number of accruals quality measures and are robust to controlling for conventional risk factors, analyst forecast bias, and industry effects. Moreover, the inferences remain unchanged in a battery of sensitivity tests. Overall, these findings suggest that, as predicted by the Epstein-Schneider ambiguity model, accounting information risk due to accruals choices cannot be diversified away.

The next section discusses related literature. Section 3 describes the Epstein-Schneider model and presents hypotheses development. Section 4 describes the empirical research design, and Section 5 presents the data and results. Additional analysis and robustness tests are presented in Sections 6 and 7. Section 8 concludes.

2. Related Literature

2.1. Information Risk and Cost of Capital

This paper is closely related to the debate on whether information risk is priced in capital markets (e.g., Beyer, Cohen, Lys, and Walther, 2010; Shevlin, 2013). As discussed in Beyer, Cohen, Lys, and Walther (2010), Easley and O'Hara (2004) provide a link between information risk and cost of capital. Extending Grossman and Stiglitz's (1980) rational expectation model, Easley and O'Hara (2004) demonstrate that more private information increases the risk faced by uninformed investors. Because uninformed investors are not able to adjust their portfolio weights in the same way as informed investors, uninformed investors ask for a higher cost of capital to compensate for this risk. Therefore, information risk is priced. In contrast, Hughes, Liu, and Liu (2007) extend Easley and O'Hara's (2004) model to a large economy in which the full extent of diversification is present. They conclude that information risk is either diversifiable or subsumed by existing risk factors. Therefore, in a large economy, information risk associated with idiosyncratic factors is fully diversifiable and should not affect the cost of capital in a systematic manner.[10] The idea of information risk being diversifiable is not entirely new. In traditional asset-pricing theory (e.g., Fama,

[10] Lambert, Leuz, and Verrecchia (2007, 2012) show that information risk has no effect when the number of traders becomes large. Specifically, information risk is eliminated by perfect competition among investors. However, the mechanism in these papers is conceptually different from diversification.

1991), only systematic, non-diversifiable risks affect the cost of capital. Therefore, accounting information risk, which is primarily idiosyncratic in nature, can be diversified away.

Much empirical research examines whether accruals quality or, more broadly, information risk, is a priced factor that impacts the cost of capital. Using different research designs, many studies find an economically and statistically significant cost of capital effect associated with accruals quality. These studies include Bhattacharya, Daouk, and Welker (2003); Botosan, Plumlee, and Xie (2004); Francis, LaFond, Olsson, and Schipper (2004, 2005); Aboody, Hughes, and Liu (2005); Kim and Qi (2010); Kravet and Shevlin (2010); Bhattacharya, Ecker, Olsson, and Schipper (2012); Callen, Khan, and Lu (2012); Ogneva (2012); Barth, Konchitchki, and Landsman (2013).[11] However, as pointed out in Francis, Huang, Rajgopal, and Zang (2008), these studies critically rely on the assumption that idiosyncratic risk is priced, which is not uncontroversial. Therefore, it is unclear whether a link exists between information risk and cost of capital.[12]

In summary, a central issue in this debate is whether information risk is diversifiable (Beyer, Cohen, Lys, and Walther, 2010). This paper sheds light on this issue by showing that accounting information risk cannot be diversified away when the information is ambiguous. The ambiguity arises from the dual motives of managers when applying their discretion in accruals quality choices. The findings in this paper thus fill a gap in the literature and enhance our understanding of the link between accounting information quality and cost of capital.

[11] Exceptions include Core, Guay, and Verdi (2008); Mohanram and Rajgopal (2009); Mashruwala and Mashruwala (2011).

[12] Related to this paper, two recent studies document that investor competition has an effect on how the information risk affects the cost of capital (Armstrong, Core, Taylor, and Verrecchia, 2011; Akins, Ng, and Verdi, 2012). Essentially, investor competition differs from the notion of diversification. Untabulated results show that after removing variations related to investor competition from my diversification proxy, the main inferences are unchanged, indicating that results in this paper are not driven by investor competition.

2.2. Ambiguity

This paper introduces ambiguity into the analysis of information risk. In fact, the concept of ambiguity has been widely studied, starting from Keynes (1921) and Knight (1921). In contrast to risk, where objective probability distributions are specified, ambiguity is characterized by the inability of the decision maker to formulate a unique probability distribution or by her lack of trust in any single probability estimate. A classic example of ambiguity is Ellsberg's (1961) paradox. When people make choices that cannot be justified by a unique probability distribution, they are willing to pay a premium to insure against ambiguity. This is the so-called "ambiguity aversion".

While Ellsberg (1961) only considers thought experiments, a large body of experimental studies have found behavioral patterns consistent with ambiguity aversion (see Camerer and Weber (1992) and Halevy (2007) for reviews of these studies). For example, Sarin and Weber (1993) show that ambiguity aversion exists in markets. Specifically, in their experimental markets, subjects including experienced traders seem to regard an ambiguous asset as inferior to an unambiguous asset, and they are thus willing to pay less for it. This is important because the existence of individuals' ambiguity aversion is not necessarily reflected in markets. An implication of Sarin and Weber's (1993) results is that ambiguity aversion potentially impacts how information is priced in the capital market.

A large number of studies in economics and finance have utilized the concept of ambiguity to explain a variety of issues in the capital market (e.g., Epstein and Miao, 2003; Cao, Wang, and Zhang, 2005). However, few studies in accounting have examined the role of ambiguity. Caskey (2009) and Williams (2014) are exceptions. Caskey (2009) shows that aggregate information is likely to benefit investors because it reduces perceived ambiguity. In particular, ambiguity-averse investors may prefer to trade based on aggregate signals

that reduce ambiguity at the cost of a loss in information. This result suggests that easy-to-interpret summary accounting disclosures can mitigate non-participation in the stock market and reduce capital costs. Williams (2014) empirically examines the role of ambiguity in shaping the responses of stock market participants to firm-specific information releases. Using changes in the VIX index as an empirical proxy to capture changes in ambiguity, Williams (2014) shows that following an increase in the VIX there is a significant asymmetric response to earnings news.[13] Specifically, he finds that investors weight bad earnings news more heavily than good earnings news, following an increase in the VIX. The results suggest that ambiguity does matter in capital markets.

In this paper, I argue that ambiguity changes the way investors interpret accounting information and this, in turn, affects how accounting information quality is priced in the capital market. This result is important because it indicates that accounting information is not only risky but also ambiguous. More importantly, while prior literature primarily studies accounting information in the framework of risk, this paper further highlights the importance of considering ambiguity when investigating accounting issues.

3. Hypotheses Development

3.1. The Epstein-Schneider Model

The Ellsberg paradox suggests that people's behavior is different when they are given objective probabilities (i.e., risky situation), compared to when they are not told the probabilities (i.e., ambiguous situation). Epstein and Schneider (2008) extend this idea to a scenario where financial market participants process a large amount of news or signals.

[13]In Williams (2014), the VIX index, constructed by the Chicago Board Options Exchange (CBOE), represents the implied volatility of an at-the-money option for the S&P 100 index with a maturity of one month.

Following Daniel and Titman (2006), they distinguish between "tangible" and "intangible" information. Particularly, while tangible information refers to information associated with past performance, intangible information is information associated with future performance that is unrelated to past performance. Epstein and Schneider (2008) further argue that tangible information is unambiguous because investors can draw on experience to help them interpret this information. In contrast, intangible information is ambiguous because investors do not have complete knowledge about the quality or precision of this information. Therefore, investors do not update beliefs in a standard Bayesian fashion, but behave as if they have multiple likelihoods in mind when processing signals.

I argue that accounting information can be ambiguous. In particular, the ambiguity mainly arises from discretionary accruals choices. Therefore, I classify accounting information into two types: innate information and discretionary information. Innate information, similar to tangible information defined in Daniel and Titman (2006), is driven by economic fundamentals, and investors can draw on experience to interpret this information. Therefore, according to the definition in Epstein and Schneider (2008), innate information is unambiguous. Conversely, discretionary information is driven by management choices and is primarily based on managers' estimates of future performance. As summarized in Healy and Wahlen (1999), managers, in applying their discretion, can be opportunistic and choose reporting methods and estimates to maximize their own interests, i.e., the opportunistic motive. Alternatively, they can use their knowledge about the business to select reporting methods and estimates to provide their private information to investors, i.e., the signalling motive. Because investors do not know which motive applies (opportunistic vs. signaling), they have multiple prior beliefs on the precision of the information and find it hard to interpret. In addition, distinct from innate information, investors' past experiences are of little help and

it is difficult for investors to attach a prior probability to the two motives. First, in contrast to economic fundamentals, managers' motives are seldom revealed, making it difficult for investors to judge which motive applies, even *ex post*. Second, each time an estimate is made, it is case-specific and what happened in the past may not apply to the current situation. Therefore, discretionary information is more ambiguous than innate information.

Epstein and Schneider (2008) point out two key implications of ambiguous information. First, when facing ambiguous information, investors tend to overreact to "bad news" and underreact to "good news." In particular, when given conditional probabilities, investors would assume the worst-case scenario and choose the conditional probability that is most damaging to their interests. Therefore, they would find "bad news" reliable and "good news" unreliable.

Second, Epstein and Schneider (2008) show that when investors expect that ambiguous information about an asset is going to arrive, they require compensation for holding the asset. In fact, under risky situations, investors also require compensation when expecting risky but unambiguous information. However, risk lowers a risk-averse investor's utility by increasing the volatility of her portfolio. With only idiosyncratic risks in the market, the variance of her portfolio decreases as the number of assets in the portfolio becomes large, and tends to zero when she is holding the market portfolio. In other words, as the market portfolio becomes riskless, investors would not price the riskiness of the information since the uncertainty of any portfolio does not affect utility at the margin. Distinct from the risky situation, Epstein and Schneider (2008) demonstrate that ambiguity has a first-order effect and lowers the mean of an asset's expected return. Because the market portfolio does not

become less uncertain as the number of assets increases, ambiguity cannot be diversified away.[14]

The intuition for those predictions can also be stated as follows. When information is risky but unambiguous, according to the law of large numbers, good news and bad news cancel out as the number of assets in a portfolio becomes large. However, when information is ambiguous, investors assume the worst-case scenario (based on the conditional probability that is most damaging to their interests). If ambiguous information conveys good news, the worst-case scenario is that the good news is unreliable. If ambiguous information conveys bad news, the worst-case scenario is that the bad news is reliable. Therefore, good news and bad news are of different perceived precisions and cannot cancel each other out. Because bad news is interpreted by investors to be more precise than good news for all stocks, investors act as if the mean of expected payoff is lower for all stocks. In fact, the mean of the expected portfolio payoff is lower no matter how many stocks are included in the portfolio.

3.2. Hypotheses Development

In the Epstein-Schneider model, investors are assumed to be well diversified. However, as noted by early studies such as Merton (1987), for various reasons investors may not be able to or may not choose to hold well-diversified portfolios. Therefore, to form empirically testable hypotheses, I examine the association between the pricing of information quality and the extent of diversification. Based on the results under risky situations in Epstein and Schneider (2008), as well as those in prior studies (e.g., Hughes, Liu, and Liu, 2007), my first hypothesis, stated in the alternative form, is as follows:

[14]See their Equation (10) on page 209.

Hypothesis 1: The pricing of information risk is negatively associated with the extent of diversification.

When information is decomposed into innate and discretionary components, I argue that discretionary information is more ambiguous than innate information. Therefore, following Epstein and Schneider (2008), the effect of diversification is expected to be weaker on the pricing of ambiguous discretionary information risk in comparison to unambiguous innate information risk. Hence, my second hypothesis, stated in the alternative form, is as follows:

Hypothesis 2: The association between the extent of diversification and the pricing of discretionary information risk is weaker than that between the extent of diversification and the pricing of innate information risk.

4. Research Design

4.1. Measuring Accruals Quality

The analysis in the previous section applies to all management disclosures broadly. In this paper, I focus on a specific context, in which managers are making accruals choices. Therefore, I choose accruals quality as the proxy for information risk. Following the prior literature, I define accruals quality in two ways. First, I define accruals quality as the time-series standard deviation of residuals from regressions of working capital accruals on past, present, and future cash flows from operations, plus the change in revenues and property, plant, and equipment (Dechow and Dichev, 2002; McNichols, 2002). Throughout this paper, this measure is denoted as DD. Second, I define accruals quality as the absolute value of abnormal accruals, $|AA|$, following a modified Jones (1991) approach, as detailed in Francis, LaFond, Olsson, and Schipper (2005). For both variables, larger values indicate poorer ac-

cruals quality. The details of how to construct these two measures are provided in Appendix A.

Furthermore, I decompose the accruals quality measures into innate and discretionary components (Francis, LaFond, Olsson, and Schipper, 2004). Innate accruals quality is designed to capture innate information quality, and discretionary accruals quality is designed to capture discretionary information quality. Following Francis, LaFond, Olsson, and Schipper (2005), I use two approaches. The first approach explicitly separates the innate and discretionary components of accruals quality using annual regressions of accruals quality on the innate factors. The regression model is as follows:

$$\begin{aligned} AQ_{j,t} =& \lambda_{0,t} + \lambda_{1,t} Ln(Assets_{j,t}) + \lambda_{2,t}\sigma(CFO)_{j,t} + \lambda_{3,t}\sigma(Sales)_{j,t} + \lambda_{4,t} Ln(OperCycle_{j,t}) \\ &+ \lambda_{5,t} NegEarn_{j,t} + \lambda_{6,t} IntIntensity_{j,t} + \lambda_{7,t} CapIntensity_{j,t} + \mu_{j,t}, \end{aligned} \tag{1}$$

where $AQ_{j,t}$ is the respective accruals quality metric for firm j in year t (DD, $|AA|$), $Assets_{j,t}$ is firm j's total assets, $\sigma(CFO)_{j,t}$ is the standard deviation of firm j's cash flow from operations scaled by total assets, $\sigma(Sales)_{j,t}$ is the standard deviation of firm j's sales scaled by total assets, $OperCycle_{j,t}$ is the length of firm j's operating cycle measured as the sum of days accounts receivable and days inventory, $NegEarn_{j,t}$ is the proportion of years (over the estimation period) for which firm j reported negative net income before extraordinary items, $IntIntensity_{j,t}$ is firm j's average research and development expense plus advertising expense divided by sales, and $CapIntensity_{j,t}$ is firm j's average net PPE scaled by total assets. The predicted value from the regression yields an estimate of the innate portion of firm j's accruals quality in year t, and the prediction error is the estimate of the discretionary component of firm j's accruals quality in year t.

The second approach controls for innate factors affecting accruals quality by including them as independent variables in the costs of capital regression. In these augmented regressions, the coefficient on AQ captures the cost-of-capital effect of the portion of accruals quality that is incremental to the effect captured by the innate factors. This coefficient is interpreted as a measure of the cost-of-capital effect of discretionary accruals quality.

4.2. Measuring the Implied Cost of Capital

In this paper, I employ four accounting-based valuation models to estimate the *ex ante* rate of return implied in contemporaneous stock price and analyst forecast data (Claus and Thomas, 2001; Gebhardt, Lee, and Swaminathan, 2001; Gode and Mohanram, 2003; Easton, 2004). All four models are derived from the discounted dividend valuation model but exploit accounting relations (e.g., the clean surplus relation) to obtain an equivalent valuation equation based on residual income or abnormal earnings. Market price and analyst forecasts are substituted into the valuation equation to obtain the cost of capital as the discount rate that equates current stock price and the sequence of expected future residual incomes or abnormal earnings. The individual models differ with regard to the use of analyst forecast data, the assumptions of short-term and long-term growth, the explicit forecasting horizon, and the incorporation of industry effects. These models are commonly used in the literature and explicitly separate cash-flow effects from cost-of-capital effects. Details of these models are summarized in Appendix B.

The estimates from these four models are labeled as COC_{CT}, COC_{GLS}, COC_{GM}, and COC_{PEG}, respectively. As there is little consensus in the literature regarding which of the models works best (e.g., Botosan, Plumlee, and Wen, 2011), I use the mean of these four proxies (COC_{AVG}) as my primary dependent variable. Averaging should reduce idiosyncratic

measurement error across the models. In robustness checks, I repeat my main test using each of these estimates separately, as well as realized returns.

4.3. Measuring the Extent of Diversification

Prior studies suggest that investors may not be able to or may choose not to hold well-diversified portfolios for various reasons. Many studies document that most individual investors invest in a limited number of stocks. For instance, Goetzmann and Kumar (2008) show that, based on a sample of more than 62,000 household investors in the period from 1991 to 1996, over 25% of the investor portfolios contained only one stock, over half contained no more than three stocks, and less than 10% contained more than ten stocks. Furthermore, institutional investors often deviate from investing in the market portfolio. Studies show that some institutional investors adopt specific investment strategies, such as value or growth strategies (e.g., Bushee, 2001; Abarbanell, Bushee, and Raedy, 2003; **?**). In addition, some institutional investors choose to hold large blocks in certain firms and take an active role in governance (e.g., Smith, 1996). If investors deviate from the market portfolio, prior studies suggest that idiosyncratic risk can be priced (e.g., Levy, 1978; Merton, 1987; Fama and French, 2007). Hence, this evidence raises the possibility that investors might not hold portfolios that are as well diversified as assumed in theory.

While it is widely suggested that investors do not always hold well-diversified portfolios, little guidance has been offered in the prior literature on how to gauge the extent of diversification. One exception is Bushee and Goodman (2010), who develop a diversification measure based on information from a firm's institutional investors. The basic idea comes from CAPM theory, which predicts that the market portfolio is the most diversified portfolio possible as it consists of every asset in the economy held according to its market portfolio

weight.[15] If this is the case, the extent to which an investor's portfolio returns can be explained by market returns indicates how closely the institutional investors' holdings resemble the market portfolio and thereby the extent of diversification. The diversification measure in this paper is built upon this idea. Specifically, I first calculate the return for each individual institution's portfolio in each month based on the ownership disclosed in the preceding calendar quarter filing reported on Thomson Reuters Spectrum (e.g., portfolio weights on March 31 are used to calculate portfolio returns for April, May, and June). Following Bushee and Goodman (2010), I adjust for delisting by assuming that when a portfolio firm delists in the middle of a quarter, the institution re-invests the funds in the CRSP value-weighted index for the remainder of the quarter. The following time-series regression is estimated for each institution in a five-year rolling window:

$$R_{k,t} - r_f = \alpha_{k,t} + \beta_{k,t}(R_{mt} - r_f) + \epsilon_{k,t}, \tag{2}$$

where $R_{k,t}$ is the return for institution k in month t, R_{mt} is the market return in month t, and r_f the risk-free rate. For each institution in month t, this time-series regression is estimated using monthly returns in the previous five years, i.e., t - 60 to t - 1.[16] I further require at least 30 observations in each regression. Therefore, R^2 from Eq.2 is used to measure the extent of diversification for institution k in month t.

[15] Admittedly, holding a market portfolio is not a necessary condition for investors to eliminate exposure to idiosyncratic risk. In a large market, it is possible that holding a portfolio that is sufficiently large but smaller than a market portfolio can be good enough to be well diversified. However, this possibility introduces a conservative bias for my tests. In particular, misclassifying a well-diversified stock to be under-diversified would make it harder to detect variation of the pricing effect of accruals quality under different extents of diversification.

[16] Bushee and Goodman (2010) estimate this regression using the full sample period. In the robustness tests, I use the full period and find that the inferences remain unchanged.

To obtain a firm-level diversification measure, for each firm-quarter, I calculate the average R^2 of all institutions weighted by their ownership of the firm's shares. The average institutional investor is assumed to be representative of the marginal investors.[17] This assumption is based on the findings that (1) institutional investors are expected to have more significant impacts on the stock price due to their larger size and sophistication (Hand, 1990), and (2) higher institutional ownership is associated with a more sophisticated marginal investor (Jiambalvo, Rajgopal, and Venkatachalam, 2002; Piotroski and Roulstone, 2004) and higher efficiency of stock prices (Ali, Hwang, and Trombley, 2003; Collins, Gong, and Hribar, 2003). This procedure results in a firm-quarter diversification measure $R^2_{i,q}$ for firm i in quarter q. It is further averaged over the corresponding year and transformed into a firm-year measure in order to merge with cost of capital and other annual data.

5. Empirical Results

5.1. Sample and Descriptive Statistics

I begin with all non-financial firms from the intersection of COMPUSTAT, CRSP, IBES and Thomson Reuters Spectrum. Because the institutional ownership information in Thomson Reuters Spectrum is only available starting in 1980, and I require at least 30 months of this information to estimate the extent of diversification, my sample is restricted to the 1982 to 2010 period. Following Claus and Thomas (2001) and Gebhardt, Lee, and Swaminathan (2001), implied cost of capital estimates are imputed as of July 1 each year. The sample

[17] Following Bushee and Goodman (2010), I only consider institutional investors in constructing this measure. Williams (2014) shows that ambiguity reversion is less severe for institutional investors than individual investors. In this case, only including institutional investors thus introduces a conservative bias into my analysis and makes it harder to find the results. However, the inferences remain unchanged if I account for individual investors by assuming they are fully under-diversified, i.e., $R^2 = 0$. Specifically, I recalculate the average R^2 and assign an $R^2 = 0$ for individual investors weighted by their ownership.

size is further reduced after requiring each observation to have one-year-ahead and two-year-ahead non-negative earnings forecasts, a long-term growth forecast, and a contemporaneous share price. To align accruals quality measures with the implied cost of capital, I require the fiscal year-end to be at least four months before June in order to assure that financial data are publicly available and reflected in the market price at the time of my computations. In addition, quarterly data are averaged over the four quarters' estimates that precede the end of June in each year.

Table 1 reports summary descriptive statistics for the pooled sample. Because the inclusion of different accruals quality metrics leads to different sample sizes, all variables are reported based on the sample size before requiring the availability of accruals quality metrics. Thus, there are 47,854 firm-year observations in total. To avoid giving extreme observations heavy weight in the return regressions and the effects of potential data-recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or next largest values.[18]

First, I list five implied cost of capital estimates in Panel A of Table 1. COC_{AVG} is the average of all the above four estimates used in the prior literature, which is the main proxy for cost of capital in this paper. The mean of COC_{AVG} is 11.65%, and the median is 10.90%. Second, six accruals quality measures are presented in Panel B. While calculating $|AA|$ requires the information in the past and current fiscal year, calculating DD requires information for the past five years. Thus, $|AA|$ is available for more firm-year observations. Separating accruals quality into innate and discretionary components further reduces the sample size. The mean of DD is 3.84%, and the mean of $|AA|$ is 5.82%. The proxy for

[18]The main inferences remain unchanged after eliminating low-priced stocks (i.e., stocks with price lower than \$5).

diversification, R^2, is reported in Panel B. The mean (median) value of R^2 is 88% (90%), meaning that the market index explains around 90% of the return earned by the average institutional investor.

The statistics for control variables are reported in Panel C. $BETA$ is the portfolio beta as constructed in Fama and French (1992). I use the previous 24 to 60 months of monthly returns (as available) to estimate firm betas using the market model. Stocks are assigned to 10×10 portfolios on the basis of size and β. I then compute the equal-weighted portfolio returns. For each size-β portfolio, I run the full-period time-series regression of the portfolio return on the current and prior month's value-weighted market returns. The portfolio β is estimated as the sum of the slopes of these two market returns, and the sum is meant to adjust for the effects of non-synchronous trading (Dimson, 1979). The mean (median) of $BETA$ is 1.26 (1.24). ME is the market value of equity, which is the product of the monthly closing price and the number of shares outstanding. Following Fama and French (1992), I construct book-to-market equity ratio (BE/ME) as the fiscal year-end book value of common equity divided by the calendar-year-end market value of equity. The mean and median values of $Ln(ME)$ and $Ln(BE/ME)$ are very close, indicating that the skewness issue has been well taken care of by taking a natural logarithm. Lev is defined as the ratio of long-term debt to total assets with a mean (median) of 22% (22%), and MMT, which captures price momentum, is the logarithm of one plus the compounded returns over the previous 12 months with a mean of 9% and a median of 10%. $FBIAS$ is the one-year-ahead forecast error (forecast minus actual value) deflated by lagged price. The mean (median) value of $FBIAS$ is 0.89% (0.14%). The positive mean suggests that analyst forecasts tend to be optimistic about future earnings. MMT and $FBIAS$ are utilized to control for potential bias in implied cost of capital estimates caused by the optimism in analyst forecasts.

Table 2 presents the time-series means of bilateral correlations. Two observations are worth mentioning. First, the Pearson (Spearman) correlation between diversification (R^2) and firm size ($Ln(ME)$) is 16% (10%). Untabulated results show that R^2 is only moderately correlated with other firm characteristics.[19] This indicates that R^2 is not likely to be driven by firm characteristics. Second, $FBIAS$ is positively correlated with COC_{AVG}. The Pearson (Spearman) correlation is 15% (19%), indicating that analyst forecast optimism can bias upward the implied cost of capital estimate, as suggested by prior studies (e.g., Claus and Thomas, 2001; Easton and Monahan, 2005). Therefore, the correlation highlights the need to control for analyst forecast errors in the analysis.

5.2. The Association Between Accruals Quality and Cost of Capital

I begin the multivariate analysis by exploring the association between accruals quality and cost of capital. I estimate the following regression model:

$$\begin{aligned} COC_{i,t} =& \alpha_t + \gamma_{1,t} BETA_{i,t-1} + \gamma_{2,t} Ln(ME_{i,t-1}) + \gamma_{3,t} Ln(BE_{i,t-1}/ME_{i,t-1}) + \gamma_{4,t} Lev_{i,t-1} \\ &+ \gamma_{5,t} MMT_{i,t-1} + \gamma_{6,t} FBIAS_{i,t+1} + \beta_t AQ_{i,t-1} + \sum IndustryControl + \epsilon_{i,t}, \quad (3) \end{aligned}$$

where the dependent variable is COC_{AVG} , which is the mean of four implied cost of capital estimates imputed from commonly used accounting valuation models. I use each of DD and $|AA|$ as accruals quality proxies, which are estimated based on a modified Dechow and Dichev (2002) model and a modified Jones (1991) model, respectively. These two metrics are further decomposed into innate and discretionary components by two approaches as detailed

[19]For example, the highest correlation among them is the one between R^2 and the number of institutional investors. The Pearson (Spearman) correlation is 13% (10%).

in Section 4.1. My main interest is in the coefficient of AQ (i.e., β), which is predicted to be positive.

Following the prior literature, I include a set of control variables that are likely to affect the cost of capital. First, I control for the portfolio beta (BETA) and expect that $\gamma_1 > 0$. Fama and French (1992) find that stock returns are negatively correlated with firm size and are positively correlated with book-to-market equity. Firm size (MV) is measured as the logarithm of the market value of common equity. Book-to-market equity (BE/ME) is constructed as the logarithm of the ratio of the fiscal-year-end book value of common equity divided by the calendar-year-end market value of equity. I expect that $\gamma_2 < 0$ and $\gamma_3 > 0$. Modigliani and Miller (1958) argue that the cost of equity should increase as leverage increases. I include a leverage ratio (Lev) and expect $\gamma_4 > 0$.

In addition, I note that the implied cost of capital estimates can be affected by forecast bias (Easton and Sommers, 2007). Two variables are included to control for this bias. First, I include price momentum (MMT) to mitigate the bias driven by analysts' sluggishness with respect to information in past stock returns (Guay, Kothari, and Shu, 2011). MMT is defined as the logarithm of one plus the compounded returns over the previous 12 months. I expect that $\gamma_5 < 0$. Second, following Hail and Leuz (2006, 2009), I control for analyst forecast errors. $FBIAS$ is the one-year-ahead forecast error (forecast minus actual value) deflated by lagged price.[20] I expect that $\gamma_6 > 0$. The signs of the coefficients of all control variables are shown to be consistent with expectations.

[20] McInnis (2010) finds that the optimism in analyst forecasts yields implied cost of capital estimates that are systematically too high for firms with volatile earnings. To ensure the results are not driven by earnings volatility, I further control for earnings smoothness as defined in McInnis (2010). Untabulated results show that the inferences remain unchanged after controlling for earnings smoothness.

Finally, I control for industry-fixed effects in my regression model. Cost of capital is shown to vary substantially across industries (Fama and French, 1997). Therefore, I use Fama and French's (1997) 48-industry classification to construct industry indicators.

I use Fama and MacBeth (1973) regressions to control the cross-correlation in residuals.[21] The results are reported in Table 3. First, columns 1 and 4 examine whether the total AQ is priced. The coefficient on DD ($|AA|$) is 0.13 (0.04) and significant at the 1% level. These results are consistent with prior studies that document an association between accruals quality and implied cost of capital (e.g., Francis, LaFond, Olsson, and Schipper, 2004). This indicates that investors charge a high cost of capital when accruals quality is low. In columns 2, 3, 5, and 6, DD and $|AA|$ are separated into innate and discretionary components using two approaches. The first approach explicitly separates these two components by regressing total AQ on innate factors, and the second approach instead controls innate factors in the regression. It appears that the coefficients of both innate and discretionary AQ are significantly positive. For example, in column 2, the coefficient on innate (discretionary) AQ is 0.26 (0.04) and is significant at the 1% level. In column 3, the coefficient on discretionary AQ is 0.05 and is significant at the 1% level. This is consistent with the findings in Francis, LaFond, Olsson, and Schipper (2004, 2005), who also find lower coefficients on discretionary AQ than those on innate AQ. The results are similar when AQ is proxied by $|AA|$.

5.3. The Influence of Diversification on the Pricing of Accruals Quality

Next, I analyze whether the association between accruals quality and cost of capital documented in Table 3 can be mitigated by diversification. To ease the exposition, I rank R^2 into deciles every year and then scale the decile rank so that it ranges from 0 to 1.[22]

[21] The references remain the same when data is pooled and standard errors are clustered by year and firm.
[22] The results are robust to the quintile and percentile ranks.

The decile rank of diversification is denoted as $D(R^2)$ and interacts with the accruals quality metrics. Thus, the regression model augmented with diversification is as follows:

$$\begin{aligned} COC_{i,t} =& \alpha_t + \gamma_{1,t} BETA_{i,t-1} + \gamma_{2,t} Ln(ME_{i,t-1}) + \gamma_{3,t} Ln(BE_{i,t-1}/ME_{i,t-1}) + \gamma_{3,t} Lev_{i,t-1} \\ &+ \gamma_{4,t} MMT_{i,t-1} + \gamma_{5,t} FBIAS_{i,t+1} + \delta_t D(R^2) \\ &+ \sum_{M=Total|(Innate\&Disc)} AQ_M(\beta_M + \theta_M D(R^2)) + \sum IndustryControl + \epsilon_{i,t}. \end{aligned} \quad (4)$$

My main interest is the coefficients of the interaction terms (i.e., θ_M) between AQ metrics and $D(R^2)$. θ_M/β_M reveals how much the information risk can be diversified away as one moves from the bottom to the top diversification decile.

The results are reported in Table 4. Because they are very similar across two accruals quality measures (DD and $|AA|$), I use DD for illustration. Columns 1 and 4 present the results for the total AQ. For example, in column 1 the coefficient on AQ is 0.18 and is significant at the 1% level. More importantly, the coefficient on AQ $\times D(R^2)$ is -0.14 and is significant at the 1% level. These results indicate that investors charge less for bearing information risk when they are well diversified. Regarding the economic significance of this finding, a comparison between the coefficient on AQ and that on the interaction term reveals that as one moves from the bottom to the top decile, approximately 78% (0.14/0.18) of information risk is diversified away. This evidence supports Hypothesis 1 and is consistent with the notion that information risk proxied by accruals quality is diversifiable.

Furthermore, in columns 2, 3, 5, and 6, total AQ is separated into two components: innate and discretionary AQ. In column 2, the coefficient on innate (discretionary) AQ is 0.30 (0.05) and is significant at the 1% (5%) level, meaning that investors charge a higher cost of capital to compensate for both types of information risk. However, the effects of

diversification on these two components are distinct. In particular, the coefficient on innate AQ $\times D(R^2)$ is -0.24 and is significant at the 1% level. This indicates that as one moves from the bottom to the top decile, approximately 80% (0.24/0.30) of information risk is diversified away. On the other hand, the coefficient on discretionary AQ $\times D(R^2)$ is -0.02 and is insignificant. In column 3, when discretionary AQ is separated out under the second approach, the coefficient on discretionary AQ $\times D(R^2)$ is -0.01 and is still insignificant. The insignificant coefficients on discretionary AQ $\times D(R^2)$ suggest that little of the cost of capital effect of discretionary information risk can be mitigated by diversification. Further comparison between the coefficient of innate AQ $\times D(R^2)$ (b1) and discretionary AQ $\times D(R^2)$ (b2) shows that they are significantly different ($t = -3.37$). These results support Hypothesis 2 in that diversification has much less effect on the discretionary information risk than on the innate information risk. Similar results are also observed when accruals quality is proxied by $|AA|$ in columns 5 and 6.

Overall, the results in Table 4 confirm the findings in the portfolio analysis. First, it demonstrates a strong association between the pricing of innate information risk proxied by accruals quality and diversification. This result is consistent with Hypothesis 1 and indicates that (1) innate information risk is diversifiable, and (2) innate information risk is priced because the market is under-diversified.

More importantly, the results reveal that although innate information risk (proxied by innate AQ) can be diversified away, discretionary information risk (proxied by discretionary AQ) cannot. They are consistent with the predictions obtained from the Epstein-Schneider model and support Hypothesis 2. Table 4 also highlights the important effects of diversification on the pricing of information risk.

6. Additional Analysis

As implied in Epstein and Schneider (2008), when investors face ambiguous information, they tend to react more strongly to bad news than good news. In this section, I test whether the asymmetric responses to good and bad news are more pronounced when discretionary information quality (proxied by discretionary AQ) is low. First, following prior literature (e.g., Teoh and Wong, 1993; Skinner and Sloan, 2002; Williams, 2014), I estimate the following regression:

$$CAR_{i,t} = \rho_0 + \rho_1 GoodNews_{i,t} + \rho_2 BadNews_{i,t} + \rho_3 Ln(ME_{i,t}) + \rho_4 Ln(1 + \#Analysts) + \psi_{i,t}, \quad (5)$$

where CAR is the cumulative abnormal return for firm i in year t, continuously compounded between the forecast date and the earnings announcement date. The abnormal return is computed by subtracting the return over the corresponding period on a CRSP size-matched decile from the stock return. Unexpected earnings (UE) are measured as actual earnings minus the median of the most recent analyst forecasts provided by IBES deflated by the stock price on the day prior to the start of the cumulation period for stock return. $GoodNews$ equals UE if UE is positive, and 0 otherwise. Likewise, $BadNews$ equals UE if UE is negative, and 0 otherwise. ME is the market value of equity on the day prior to the start of the cumulation period for stock return. $\#Analysts$ is the number of analysts following over the year. Year-fixed effects are included in the regression and the standard errors are calculated after clustering by firm and year. To minimize the effects of market frictions, I eliminate those observations with prices less than or equal to \$5 prior to the event window (Ball, Kothari, and Shanken, 1995). The observations with more than two consecutive days

of zero trading in the week prior to the event window are excluded to reduce the impact of illiquidity (Chordia and Swaminathan, 2000). In order to reduce the possibility that my results are driven by outliers, I delete observations for which the absolute value of UE or CAR is greater than 100%, as well as observations with book-to-market ratio greater than 1 on day 0 (Conrad, Cornell, and Landsman, 2002). Because it has been shown that earnings response coefficients are essentially zero for firms reporting negative earnings (Hayn, 1995; Lipe, Bryant, and Widener, 1998), observations where firms report negative earnings are eliminated (Conrad, Cornell, and Landsman, 2002). Finally, I restrict all firm year observations to have all required variables available for analysis and end up with 25,862 firm years over the period from 1982 to 2010.

The sample is partitioned into quintiles based on innate AQ and discretionary AQ, respectively. Eq.5 is then estimated for the full sample, as well as for each innate AQ and discretionary AQ quintiles. Then, the coefficients of $GoodNews$ and $BadNews$ are compared based on a Wald test. The results based on DD are reported in Table 5.

In the full sample, the coefficients of $GoodNews$ and $BadNews$ are 0.33 and 0.29, respectively. Although they are both significant at the 1% and 5% levels, the difference between these two coefficients is 0.04 and insignificant. Similarly, when the sample is partitioned into innate AQ quintiles, the differences between the coefficients of $GoodNews$ and $BadNews$ are 0.14 and 0.11 for the lowest and highest quintiles, and neither are significant at the conventional level. In contrast, when the sample is partitioned into discretionary AQ quintiles, the difference between $GoodNews$ and $BadNews$ is 0.13 and insignificant for the lowest quintile. The difference between $GoodNews$ and $BadNews$ is -0.41 and significant at the 1% level for the highest quintile. This indicates that investors react to bad news more strongly than to good news when discretionary AQ quality is low but they are not sensitive to the

level of innate information quality. Therefore, these results are consistent with one of the implications of ambiguous information as shown in Epstein and Schneider (2008) and further corroborate my argument in Section 2 that innate information is less ambiguous than discretionary information.

7. Robustness Checks

This section presents several robustness checks for the main results in Table 4. First, I de-bias the cost of capital estimates using the methodology introduced in two recent studies. Second, I examine whether my findings hold for each estimate from the four implied cost of capital models, for an alternative way to aggregate the four estimates, and for realized returns. Finally, I assess whether my results are sensitive to alternative proxies for diversification.

7.1. De-biased Cost of Capital Estimates

Studies estimating implied cost of capital have expressed concerns that the optimism in analyst forecasts is a potential source of error in cost of capital estimation (Claus and Thomas, 2001; Easton and Monahan, 2005). Recently, two studies have used comprehensive approaches to adjusting forecasts for predictable forecast errors (Larocque, 2013; Mohanram and Gode, 2013). In particular, Mohanram and Gode (2013) remove predictable errors from analyst forecasts using a model based on Hughes, Liu, and Su (2008) and show a much stronger relationship between the de-biased cost of capital estimates and realized returns. To ensure that the main results in this paper are not affected by the optimism in analyst forecasts, I replicate the main tests using the de-biased cost of capital estimates.[23] First, the

[23]The inferences remain unchanged when cost of capital estimates are estimated using the method introduced in Larocque (2013).

following two regressions are estimated for each year:

$$\begin{aligned} SURP_{t+1} =& \eta_{0,t} + \eta_{1,t} TA_{i,t} + \eta_{2,t} \Delta Sales_{i,t} + \eta_{3,t} LTG_{i,t} + \eta_{4,t} \Delta PPE_{i,t} + \eta_{5,t} \Delta OLA_{i,t} \\ &+ \eta_{6,t} RET_{i,t-1} + \eta_{7,t} REV_{i,t-1} + \tau_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} SURP_{t+2} =& \delta_{0,t} + \delta_{1,t} TA_{i,t} + \delta_{2,t} \Delta Sales_{i,t} + \delta_{3,t} LTG_{i,t} + \delta_{4,t} \Delta PPE_{i,t} + \delta_{5,t} \Delta OLA_{i,t} \\ &+ \delta_{6,t} RET_{i,t-1} + \delta_{7,t} REV_{i,t-1} + \psi_{i,t}, \end{aligned} \tag{7}$$

where $SURP_{t+1}(SURP_{t+2})$ is the one- (two-) year analyst forecast error scaled by stock price, TA is total accruals, $\Delta Sales$ is sales growth, LTG is the median analyst long-term growth estimate, ΔPPE is growth in PPE, ΔOLA is growth in other long-term assets, and RET is the annual buy-and-hold returns. A lagged RET is used so that it is known before the forecast is issued. REV is the difference between the consensus analysts' one-year-ahead forecast and the forecast at the start of the year. Untabulated results show that the mean coefficients obtained from these two regressions are similar to those reported in Panel B of Table 6 in Mohanram and Gode (2013).

The coefficients η's and δ's estimated at year t are multiplied with realized values in year $t+1$ to predict the forecast errors for earnings at year $t+1$. For example, I use the η's and δ's estimated in year 2000 to predict the forecast errors $PSURP_{t+1}$ and $PSURP_{t+2}$ in year 2001 and obtain adjusted analyst forecasts $AEPS_{t+1} = EPS_{t+1} + PSURP_{t+1} \times Price$ and $AEPS_{t+2} = EPS_{t+2} + PSURP_{t+2} \times Price$. The de-biased cost of capital estimates are recomputed using the adjusted analyst forecasts.

Table 6 reports the Fama-Macbeth regression results based on the mean of the de-biased cost of capital estimates. The independent variables are the same as those in Table 4. For the sake of brevity, I only report the coefficients of AQ metrics and their interactions with

$D(R^2)$. The coefficients on the interaction terms between innate AQ and $D(R^2)$ continue to be significantly negative (-0.27 and -0.16 and significant at the 1% level for DD and $|AA|$, respectively), indicating a strong mitigating effect of diversification on the pricing of innate AQ. In contrast, the interaction terms between discretionary AQ and $D(R^2)$ continue to be weak (-0.02 and -0.01 and insignificant for DD and $|AA|$, respectively), indicating a limited effect of diversification on the pricing of discretionary AQ. Hence, the results demonstrate that adjusting for analyst optimism does not alter the main results.

7.2. Other Alternative Cost of Capital Estimates

In Table 7, I report results using implied cost of capital estimates from each of the four models, the first principal component of the four individual estimates,[24] and monthly realized returns as alternative proxies for cost of capital.[25] For the sake of brevity, only the results of innate and discretionary AQ proxied by DD are reported here. The results of AQ proxied by $|AA|$ are qualitatively similar. As shown in Table 7, the results for all of these refinements are consistent with those in Table 4 and lead to the same inferences as before. In particular, the coefficients on innate AQ and discretionary AQ remain significantly positive across all cost of capital estimates. More importantly, the coefficients on the interaction between innate AQ and $D(R^2)$ are all significantly positive and the coefficients on interaction between discretionary AQ and $D(R^2)$ remain insignificant. For example, when cost of capital is proxied by COC_{CT}, while the coefficient on innate AQ $\times D(R^2)$ is -0.45 and is significant at the 1% level, the coefficient on innate AQ $\times D(R^2)$ is -0.06 and is insignificant. These

[24]Untabulated results show that the first principal component explains 70% of the total variance.

[25]Realized returns are measured in the same period as the implied cost of capital estimates, i.e., from 1982 to 2010. Following Kim and Qi (2010), I eliminate low-priced stocks (i.e., stocks with price lower than \$5) in the sample.

results indicate that my findings do not depend on the choice of cost of capital estimates or the method of aggregation.

7.3. An Alternative Diversification Proxy

In this subsection, I check whether my main results are sensitive to an alternative diversification measures.[26] The idea is to measure the deviation of the portfolio weight assigned to a firm by an institutional investor from the weight implicit in the market portfolio. For example, stock i consists of $S_{f,i}$ percent of institutional investor f's total holding in stock i. However, if institutional investor f holds the market protfolio, the portfolio weight of stock i should be $\frac{1}{n}$ where n is the number of assets in the market. In the US market, which this paper examines, the number of assets $n \to \infty$ and thus $\frac{1}{n} \to 0$. Therefore, $S_{f,i}$ estimates the deviation of the portfolio weight. For firm i, I calculate the average of this measure across all institutional investors weighted by their ownership of the firm's shares and obtain $Perc_{i,t}$ for firm i in year t. By assuming the average investor represents the marginal investor, $Perc_{i,t}$ gauges the extent of diversification of the investors who set the price for stock i. Similar to my main tests, I rank $Perc_{i,t}$ into deciles every year and then scale the decile rank so that it ranges from 0 to 1.

The results presented in Table 8 are similar to those in Table 4. For example, when AQ is proxied by DD, the coefficient on innate AQ $\times D(R^2_{RES})$ is -0.37 and is significant at the 1% level. However, the coefficient on innate AQ $\times D(R^2)$ is 0.01 and is insignificant. Thus, this research design choice does not alter my main findings.

[26] I thank the discussant for suggesting this measure.

8. Conclusion

This paper examines whether accounting information risk can be diversified away in the capital market. I find that accounting information risk is priced even if it is entirely idiosyncratic. In particular, when the capital market is under-diversified, accounting information risk is priced though it is diversifiable. Furthermore, even if the capital market is well diversified, accounting information risk cannot be diversified away when the information is subject to managers' discretion and is thus ambiguous. These results are supported by a model from the ambiguity literature and empirical evidence.

Taken together, this paper sheds light on the fundamental question of whether accounting information risk is priced. Contrary to a growing body of studies showing that idiosyncratic information risk can be diversified away, I show that accounting information is associated with a non-diversifiable risk and cannot be eliminated. The findings in this paper stress a fundamental role of accounting information in the capital market and strengthen our understanding of accounting information. Moreover, the findings in this paper emphasize the importance of distinguishing between innate and discretionary information. While both information components are priced in an under-diversified market, only the latter is shown to be non-diversifiable.

In addition, by showing that discretionary accruals quality cannot be diversified away, I suggest that accounting information is not only risky but also ambiguous. While ambiguity has been widely studied in the economics and finance literatures, it has drawn little attention in the accounting literature. Since most prior analyses of accounting information ignores the possibility that accounting information can be ambiguous, taking ambiguity into consideration offers the potential to improve our understanding of the role of accounting information in capital markets.

The findings are of potential interest to practitioners and regulators. Regulators have put considerable effort into improving accounting information quality. I show that information risk matters more for stocks held by under-diversified investors. The results suggest that investors are more likely to take information risk into account when they have difficulty in diversifying their portfolios. Therefore, improving information quality appears to be more important for these investors.[27]

Finally, two caveats are in order. First, although the main findings survive a battery of robustness checks, I acknowledge that the measures in the analysis could suffer from measurement errors. My evidence should therefore be interpreted with caution. In addition, my results may be subject to sample truncation bias. For example, the data requirements of implied cost of capital models screen out lesser-known firms with little or no analyst coverage. If these firms tend to have low accruals quality and high cost of capital, it is unclear how truncating these firms would affect my results.

[27]On average, individual investors are less capable of diversifying their portfolios. The findings in this paper are consistent with an emerging literature suggesting that information risk has a bigger impact on individual investors' investment decisions than on institutional investors (Miller, 2010; Lawrence, 2011).

Appendix A Earnings Quality Models

This appendix describes two commonly used models to estimate accruals quality. The first model is a **modified Dechow and Dichev (2002)** model as follows:

$$TCA_{j,t} = \phi_{0,j} + \phi_{1,j}CFO_{j,t-1} + \phi_{2,j}CFO_{j,t} + \phi_{3,j}CFO_{j,t+1} + \phi_{4,j}\Delta Rev_{j,t} + \phi_{5,j}PPE_{j,t} + v_{j,t}, \quad (8)$$

$where:$

$$TCA = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STDEBT)$$

$$TA = TCA - Dep$$

$\Delta CA =$ change in current assets

$\Delta Cash =$ change in cash/cash equivalents

$\Delta CL =$ change in current liabilities

$\Delta STDEBT =$ change in short-term debt

$\Delta Dep =$ depreciation and amortization expense

$NIBE =$ net income before extraordinary items

$CFO = NIBE - TA$

$\Delta Rev =$ change in revenue

$PPE =$ gross property, plant, and equipment.

All variables are scaled by average total assets. Eq.8 is estimated for each of Fama and French's (1997) 48 industry groups with at least 20 firms in year t. Annual cross-sectional estimations yield firm- and year-specific residuals. $DD_{j,t} = \sigma(v_j)_t$ is the standard deviation

of firm j's residuals, $v_{j,t}$, calculated over years t - 4 through t. Larger standard deviations of residuals indicate poorer accruals quality.

The second model is a **modified Jones (1991)** model as follows:

$$\frac{TA_{j,t}}{Asset_{j,t-1}} = \kappa_1 \frac{1}{Asset_{j,t-1}} + \kappa_2 \frac{(\Delta Rev_{j,t} - \Delta AR_{j,t})}{Asset_{j,t-1}} + \kappa_3 \frac{PPE_{j,t}}{Asset_{j,t-1}} + \epsilon_{j,t}. \tag{9}$$

where $\Delta AR_{j,t}$ is firm j's change in accounts receivable between year t - 1 and year t. Eq.9 is estimated for each of Fama and French's (1997) 48 industry groups with at least 20 firms in year t. The resulting measures of normal accruals and abnormal accruals are: $NA_{j,t} = \hat{\kappa_1} \frac{1}{Asset_{j,t-1}} + \hat{\kappa_2} \frac{(\Delta Rev_{j,t} - \Delta AR_{j,t})}{Asset_{j,t-1}} + \hat{\kappa_3} \frac{PPE_{j,t}}{Asset_{j,t-1}}$, and $AA_{j,t} = TA_{j,t} - NA_{j,t}$. $|AA_{j,t}|$ is the absolute value of $AA_{j,t}$ with a greater number indicating poorer accruals quality.

Appendix B Implied Cost of Capital Models

This appendix describes five accounting valuation models that are used to estimate the implied cost of capital in this paper.

Claus and Thomas (2001):

$$P_{i,t} = bps_{i,t} + \sum_{\tau=1}^{4} \frac{(ROE_{i,t+\tau} - r) \times bps_{i,t+\tau-1}}{(1+r)^{\tau}} + \frac{(ROE_{i,t+5} - r) \times bps_{i,t+4} \times (1+\gamma)}{(r-\gamma) \times (1+r)^4}. \tag{10}$$

This is a special case of the residual income valuation model. It is assumed that residual income grows at rate γ after $T = 5$. bps is book value per share, $ROE_{i,t+\tau} = eps_{i,t+\tau}/bps_{i,t+\tau-1}$, $eps_{i,t+\tau} = eps_{i,t+2} \times (1 + ltg_i)^{\tau-2}$ for $\forall \tau > 2$, ltg_i is IBES consensus long term growth rate, $bps_{i,t+\tau} = bps_{i,t+\tau-1} + eps_{i,t+\tau} \times (1-K)$, K is the payout ratio, and γ is the 10-year government bond rate less 3%. r or COC_{CT} is solved via an iterative procedure.

Gebhardt, Lee, and Swaminathan (2001):

$$P_{i,t} = bps_{i,t} + \sum_{\tau=1}^{11} \frac{(ROE_{i,t+\tau} - r) \times bps_{i,t+\tau-1}}{(1+r)^{\tau}} + \frac{(ROE_{i,t+12} - r) \times bps_{i,t+11}}{(r-\gamma) \times (1+r)^{1}1}. \tag{11}$$

This is a special case of the residual income valuation model. It is assumed that residual income converges to industry-specific median return from $T = 3$ to $T = 12$. From $T = 12$ on, residual income is assumed to remain constant. $ROE_{i,t+\tau} = eps_{i,t+\tau}/bps_{i,t+\tau-1}$ for $\tau = 1, 2$, $ROE_{i,t+\tau} = ROE_{i,t+\tau} - fade \forall \tau > 2$, $fade = (ROE_{i,t-2} - HIROE_t)$, $HIROE$ is the industry median from ROE t - 4 to t, $bps_{i,t+\tau} = bps_{i,t+\tau-1} + eps_{i,t+\tau} \times (1-K)$, and K is the payout ratio. r or COC_{GLS} is solved via an iterative procedure.

Gode and Mohanram (2003):

$$P_{i,t} = \frac{eps_{i,t+1}}{r} + \frac{eps_{i,t+2} + r \times dps_{i,t} - (1+r) \times eps_{i,t+1}}{r \times (r - \Delta agr)}. \tag{12}$$

This model uses one-year-ahead forecasted earnings and dividends per share as well as forecasts of short- and long-term abnormal earnings growth. It is assumed that dividends (dps) are a constant fraction of forecasted earnings. Long-term growth rate Δagr is set to be the 10-year government bond rate less 3 percent. Solving r in this equation yields COC_{GM}.

Easton (2004):

$$P_{i,t} = \frac{eps_{i,t+2} - eps_{i,t+1}}{r^2}. \tag{13}$$

This model is a special case of the Gode and Mohanram (2003) model when $T = 2$ and $\gamma = 0$. It embeds the assumption that growth in abnormal earnings persists in perpetuity after the initial period. Solving for r in this equation yields COC_{PEG}.

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Table 1: **Variable Descriptive Statistics for the Pooled Sample**
This table reports the pooled descriptive statistics of non-financial firms traded on the NYSE, Amex, or Nasdaq exchanges during the period 1982 to 2010. COC_{CT} – COC_{GM} are implied cost of capital estimates imputed from four commonly used accounting valuation models. COC_{AVG} is the average of the above four estimates used in the prior literature. DD and $|AA|$ are accruals quality metrics based on a modified Dechow and Dichev (2002) model and a modified Jones (1991) model, respectively. These two metrics are further decomposed into innate and discretionary components. R^2 is the proxy for diversification, estimated using institutional information over five-year rolling windows. The procedure is described in Section 4.3. $BETA$ is the portfolio beta as constructed in Fama and French (1992). ME is the market value of equity, i.e., the product of monthly closing price and outstanding share numbers in June of the previous year. Book-to-market equity (BE/ME) is constructed as the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. Lev is the ratio of long-term debt to total assets. MMT is the logarithm of one plus the compounded returns over the previous 12 months. $FBIAS$ is the one-year-ahead forecast error (forecast minus the actual value) deflated by the lagged price. To avoid giving extreme observations heavy weight in the return regressions and potential data-recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or largest values.

Variable	Mean	Median	S.D.	Q1	Q3	N
Panel A						
$COC_{CT}(\%)$	11.45	10.39	5.47	8.46	12.79	47854
$COC_{GLS}(\%)$	11.13	10.86	3.36	9.09	12.85	47854
$COC_{PEG}(\%)$	11.81	11.09	4.08	9.30	13.41	47854
$COC_{GM}(\%)$	12.29	11.06	5.25	8.86	14.56	47854
$COC_{AVG}(\%)$	11.65	10.90	3.61	9.28	13.10	47854
Panel B						
$DD(\%)$	3.84	3.05	2.97	1.79	4.96	36540
$InnateDD(\%)$	3.78	3.30	2.41	2.06	4.95	32410
$DiscDD(\%)$	-0.04	-0.14	1.89	-1.02	0.77	32410
$\|AA\|(\%)$	5.82	3.88	6.47	1.68	7.55	45727
$Innate\|AA\|(\%)$	5.61	4.92	3.78	2.97	7.41	39810
$Disc\|AA\|(\%)$	0.11	-0.54	5.54	-2.92	2.25	39810
R^2	0.88	0.90	0.06	0.86	0.93	47854
Panel C						
$BETA$	1.26	1.24	0.35	1.01	1.48	47854
$Ln(ME)$	6.25	6.18	1.74	4.97	7.41	47854
$Ln(BE/ME)$	-0.62	-0.64	0.96	-1.15	-0.18	47854
Lev	0.22	0.22	0.17	0.07	0.34	47854
MMT	0.09	0.10	0.39	-0.13	0.32	47854
$FBIAS(\%)$	0.89	0.14	6.62	-0.32	1.52	47854

Table 2: **Time-series Means of Bivariate Correlations**
This table contains the time-series means of bivariate correlations of the variables. The sample period is from 1982 to 2012. The correlations above the diagonal are non-parametric Spearman correlations, while the correlations below the diagonal are Pearson correlations. Variables are defined in Table 1.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	COC_{AVG}	1.000	0.097	0.119	-0.012	0.129	0.235	-0.031	0.121	0.228	-0.423	0.221	0.064	-0.200	0.182
2	DD	0.115	1.000	0.760	0.425	0.300	0.530	-0.084	-0.272	0.388	-0.227	-0.200	-0.255	-0.021	0.081
3	$InnateDD$	0.134	0.753	1.000	-0.180	0.321	0.648	-0.153	-0.350	0.466	-0.345	-0.208	-0.302	-0.018	0.097
4	$DiscDD$	0.005	0.553	-0.117	1.000	0.015	-0.072	0.081	0.061	-0.057	0.104	-0.001	0.046	0.000	-0.006
5	$\|AA\|$	0.140	0.309	0.323	0.060	1.000	0.421	0.665	-0.098	0.212	-0.179	-0.101	-0.130	-0.002	0.057
6	$Innate\|AA\|$	0.221	0.528	0.649	-0.021	0.469	1.000	-0.288	-0.171	0.371	-0.389	-0.125	-0.217	-0.010	0.097
7	$Disc\|AA\|$	0.006	-0.013	-0.080	0.082	0.793	-0.159	1.000	0.030	-0.062	0.095	-0.008	0.041	0.006	-0.012
8	R^2	0.023	-0.258	-0.343	0.038	-0.102	-0.185	0.010	1.000	-0.078	0.101	-0.023	0.093	-0.016	0.003
9	$BETA$	0.207	0.342	0.439	-0.033	0.191	0.342	-0.018	-0.085	1.000	-0.314	-0.077	-0.213	-0.034	0.078
10	$Ln(ME)$	-0.406	-0.222	-0.332	0.083	-0.181	-0.363	0.047	0.160	-0.307	1.000	-0.294	0.050	-0.064	-0.099
11	$Ln(BE/ME)$	0.142	-0.168	-0.199	0.000	-0.096	-0.135	-0.016	-0.050	-0.059	-0.293	1.000	0.236	0.137	-0.013
12	Lev	0.084	-0.200	-0.259	0.022	-0.078	-0.171	0.027	0.065	-0.195	0.024	0.167	1.000	-0.026	0.027
13	MMT	-0.212	-0.003	0.005	-0.010	0.003	0.008	-0.003	-0.027	-0.021	-0.090	0.120	-0.041	1.000	-0.157
14	$FBIAS$	0.142	0.116	0.131	0.009	0.069	0.097	0.011	-0.064	0.076	-0.097	0.024	0.070	-0.135	1.000

Table 3: **Fama-MacBeth Regressions of Implied Cost of Capital on Accruals Quality Metrics**

This table presents the time-series averages of the slopes in cross-sectional regressions using the standard Fama and MacBeth (1973) methodology. The sample period is from 1982 to 2010. The dependent variable (COC_{AVG}) is the average of implied cost of capital imputed from four commonly used accounting-valuation models. DD and $|AA|$ are accruals quality metrics based on a modified Dechow and Dichev (2002) model and a modified Jones (1991) model, respectively. These two metrics are further decomposed into innate and discretionary components by two approaches. The first approach explicitly separates the innate and discretionary components of accruals quality using annual regressions of AQ on the innate factors. The second approach controls for innate factors affecting accruals quality by including them in the regression. Innate factors are defined in Eq.1 following Francis, LaFond, Olsson, and Schipper (2005). Their coefficients in the regressions are not tabulated but are available upon request. $BETA$ is the portfolio beta as constructed in Fama and French (1992). ME is the market value of equity, i.e., the product of monthly closing price and outstanding share numbers in June of the previous year. Book-to-market equity (BE/ME) is constructed as the fiscal-year-end book value of common equity divided by the calendar year-end market value of equity. MMT is the logarithm of one plus the compounded returns over the previous 12 months. $FBIAS$ is the one-year-ahead forecast error (forecast minus actual value) deflated by lagged price. To avoid giving extreme observations heavy weight in the return regressions and potential data-recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or largest values. Newey and West (1987) robust t-statistics are reported in parentheses. *, **, and *** indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = COC_{AVG}		AQ = DD				AQ = $\|AA\|$			
$BETA$		0.78***	0.67***	0.57***		0.79***	0.72***	0.58***	
		[8.57]	[6.82]	[5.75]		[9.24]	[8.11]	[5.64]	
$Ln(ME)$		-0.48***	-0.39***	-0.41***		-0.55***	-0.49***	-0.44***	
		[-15.55]	[-12.54]	[-6.12]		[-17.33]	[-16.15]	[-6.97]	
$Ln(BE/ME)$		0.19**	0.26***	0.22***		0.12*	0.17**	0.20***	
		[2.59]	[3.33]	[2.91]		[1.78]	[2.54]	[2.90]	
Lev		2.19***	2.22***	1.90***		2.05***	2.19***	1.85***	
		[13.85]	[13.43]	[9.72]		[14.28]	[14.91]	[11.07]	
MMT		-1.55***	-1.53***	-1.55***		-1.61***	-1.58***	-1.58***	
		[-10.61]	[-9.95]	[-10.66]		[-11.09]	[-10.70]	[-10.86]	
$FBIAS$		0.11***	0.12***	0.11***		0.11***	0.11***	0.11***	
			[9.31]	[8.92]	[8.69]		[9.99]	[9.50]	[8.84]
AQ	**Total**	**0.13*** **				**0.04*** **			
		[12.69]				**[11.26]**			
Method 1	**Innate**		**0.26*** **				**0.11*** **		
			[12.02]				**[10.24]**		
	Disc		**0.04*** **				**0.03*** **		
			[3.70]				**[7.04]**		
Method 2	**Disc**			**0.05*** **				**0.02*** **	
				[4.14]				**[5.39]**	
	Innate Factors	No	No	Yes		No	No	Yes	
Industry Fixed Effects		Yes	Yes	Yes		Yes	Yes	Yes	
$\bar{R}^2$		0.34	0.36	0.37		0.33	0.35	0.37	

Table 4: **The Influence of Diversification on the Pricing of Accruals Quality**
This table presents the time-series averages of the slopes in cross-sectional regressions using the standard Fama and MacBeth (1973) methodology. The dependent variable (COC_{AVG}) is the average of four implied cost of capital estimates imputed from commonly used accounting-valuation models. DD and $|AA|$ are accruals quality metrics based on a modified Dechow and Dichev (2002) model and a modified Jones (1991) model, respectively. These two metrics are further decomposed into innate and discretionary components by two approaches. The first approach explicitly separates the innate and discretionary components of accruals quality using annual regressions of AQ on the innate factors. The second approach controls for innate factors affecting accruals quality by including them in the regression. Innate factors are defined in Eq.1 following Francis, LaFond, Olsson, and Schipper (2005). Their coefficients in the regressions are not tabulated but are available upon request. $D(R^2)$ is the decile rank of $D(R^2)$, proxying for the extent of diversification. R^2 is estimated using institutional information over five-year rolling windows. The procedure is described in Section 4.3. $BETA$ is the portfolio beta as constructed in Fama and French (1992). ME is the market value of equity, i.e., the product of monthly closing price and outstanding share numbers in June of the previous year. Book-to-market equity (BE/ME) is constructed as the fiscal-year-end book value of common equity divided by the calendar year-end market value of equity. Lev is the ratio of long-term debt to total assets. MMT is the logarithm of one plus the compounded returns over the previous 12 months. $FBIAS$ is the one-year-ahead forecast error (forecast minus actual value) deflated by lagged price. To avoid giving extreme observations heavy weight in the return regressions and potential data-recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or largest values. Newey and West (1987) robust t-statistics are reported in parentheses. *, **, and *** indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = COC_{AVG}		AQ = DD			AQ = $\|AA\|$		
$BETA$		0.77***	0.69***	0.60***	0.78***	0.73***	0.61***
		[8.44]	[7.08]	[6.16]	[9.18]	[8.22]	[6.11]
$Ln(ME)$		-0.46***	-0.38***	-0.41***	-0.54***	-0.48***	-0.44***
		[-15.62]	[-13.04]	[-6.94]	[-16.64]	[-16.14]	[-8.05]
$Ln(BE/ME)$		0.19**	0.25***	0.22***	0.12*	0.17**	0.20***
		[2.58]	[3.27]	[3.00]	[1.85]	[2.57]	[3.08]
Lev		2.19***	2.24***	1.98***	2.05***	2.20***	1.92***
		[14.18]	[13.82]	[11.15]	[14.41]	[15.28]	[12.28]
MMT		-1.57***	-1.56***	-1.60***	-1.63***	-1.61***	-1.64***
		[-10.92]	[-10.40]	[-11.09]	[-11.28]	[-11.14]	[-11.33]
$FBIAS$		0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
		[9.31]	[8.84]	[8.65]	[10.00]	[9.47]	[8.77]
$D(R^2)$		0.23**	0.62***	-2.69***	-0.03	0.49***	-2.48***
		[2.59]	[5.56]	[-5.74]	[-0.44]	[4.09]	[-4.68]
AQ		0.18***			0.05***		
			[12.27]			[7.70]	
AQ×$D(R^2)$		**-0.14*** **			**-0.04*** **		
		[-6.68]			**[-2.96]**		
Method 1	Innate		0.30***			0.16***	
			[12.31]			[9.22]	
	Disc		0.05**			0.02***	
			[2.27]			[3.73]	
	b1 : Innate ×$D(R^2)$		**-0.24*** **			**-0.14*** **	
			[-6.44]			**[-5.17]**	
	b2 : Disc ×$D(R^2)$		**-0.02**			**0.00**	
			[-0.59]			**[0.15]**	
Method 2	Disc			0.05**			0.02***
				[2.17]			[4.02]
	Disc ×$D(R^2)$			**-0.01**			**-0.00**
				[-0.20]			**[-0.17]**
	Innate Factors	No	No	Yes	No	No	Yes
	Innate Factors ×$D(R^2)$	No	No	Yes	No	No	Yes
	b1 - b2		**-0.22*** **			**-0.13*** **	
			[-3.37]			**[-5.39]**	
Industry Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$		0.35	0.36	0.38	0.33	0.35	0.37

Table 5: **Additional Analysis – Investor Responses to Earnings Surprise**
This table presents the descriptive statistics and results of OLS regressions on investors' responses to earnings surprise. CAR is the cumulative abnormal return, continuously compounded between the forecast date and the earnings announcement date. Unexpected earnings (UE) are measured as actual earnings minus the median of the most recent analyst forecasts deflated by the stock price on the day prior to the start of the cumulation period for stock return. $GoodNews$ equals UE if UE is positive, and 0 otherwise. $BadNews$ equals UE if UE is negative, and 0 otherwise. ME is the market value of equity on the day prior to the start of the cumulation period for stock return. $\#Analysts$ is the number of analysts following over the year. Panel A reports the descriptive statistics. The sample is then partitioned into quintiles by innate AQ and discretionary AQ. Panel B reports the results of OLS regressions for the whole sample as well as the highest and lowest innate AQ and discretionary AQ, respectively. t-statistics based on standard errors clustered by firm and year are reported in parentheses. *, **, and *** indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = CAR	Full Sample	Innate AQ		Disc AQ	
		High Quality	Low Quality	High Quality	Low Quality
GoodNews	0.33***	0.76***	0.23**	0.28***	0.26**
	[2.76]	[2.99]	[2.24]	[2.70]	[2.38]
BadNews	0.29**	0.62***	0.12*	0.16*	0.67**
	[2.51]	[3.29]	[1.90]	[2.06]	[2.36]
Ln(ME)	0.00	0.00	0.00	0.00	0.00
	[1.18]	[0.23]	[0.95]	[1.41]	[0.48]
Ln(1+#Analysts)	-0.00***	-0.00***	-0.01***	-0.01***	-0.01***
	[-3.00]	[-2.87]	[-3.30]	[-3.70]	[-4.50]
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
GoodNews - BadNews	0.04	0.14	0.11	0.13	-0.41***
(F-stat)	[0.23]	[0.61]	[0.62]	[0.69]	[-2.66]
Adj.R2	0.01	0.03	0.01	0.01	0.01

Table 6: **Robustness Test – De-biased Implied Cost of Capital Estimates**
This table presents the time-series averages of the slopes in cross-sectional regressions using the standard Fama and MacBeth (1973) methodology. The dependent variable (MG_{AVG}) is the average of four de-biased implied cost of capital estimates using the methodology introduced in Mohanram and Gode (2013). The independent variables are the same as those in Table 4. For the sake of brevity, only the coefficients of AQ metrics and their interactions with $D(R^2)$ are reported. To avoid giving extreme observations heavy weight in the return regressions and potential data-recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or largest values. Newey and West (1987) robust t-statistics are reported in parentheses. *, **, and *** indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = MG_{AVG}		AQ = DD			AQ = $\|AA\|$		
AQ		0.21***			0.06***		
		[13.44]			[8.16]		
AQ×$D(R^2)$		**-0.16*** **			**-0.04*** **		
		[-6.83]			**[-3.34]**		
Method 1	Innate		0.40***			0.19***	
			[14.12]			[10.52]	
	Disc		0.07***			0.03***	
			[2.95]			[3.85]	
	Innate ×$D(R^2)$		**-0.27*** **			**-0.16*** **	
			[-6.28]			**[-5.66]**	
	Disc ×$D(R^2)$		**-0.02**			**0.00**	
			[-1.21]			**[-0.30]**	
Method 2	Disc			0.06**			0.03***
				[2.54]			[3.87]
	Disc ×$D(R^2)$			**-0.02**			**-0.01**
				[-0.48]			**[-1.28]**
	Innate Factors	No	No	Yes	No	No	Yes
	Innate Factors ×$D(R^2)$	No	No	Yes	No	No	Yes
	b1 - b2		**-0.25*** **			**-0.16*** **	
			[-5.92]			**[-5.16]**	
Control Variables		Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$		0.32	0.34	0.36	0.31	0.33	0.36

Table 7: **Robustness Test – Alternative Implied Cost of Capital Estimates**
This table presents the time-series averages of the slopes in cross-sectional regressions using the standard Fama and MacBeth (1973) methodology. COC_{CT}, COC_{GLS}, COC_{GM}, and COC_{PEG} are cost of capital estimates from four commonly used accounting valuation models in the literature (Claus and Thomas, 2001; Gebhardt, Lee, and Swaminathan, 2001; Gode and Mohanram, 2003; Easton, 2004). COC_{PC1} is the first principal component of four implied cost of capital estimates. RET is the monthly realized return. Following Kim and Qi (2010), low-priced stocks (i.e., stocks with price lower than \$5) are eliminated when RET is the dependent variable. Accruals quality is estimated from a modified Dechow and Dichev (2002) model. The independent variables are the same as those in Table 4. For the sake of brevity, only the coefficients of AQ metrics and their interactions with $D(R^2)$ are reported. To avoid giving extreme observations heavy weight in the return regressions and potential data-recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or largest values. Newey and West (1987) robust t-statistics are reported in parentheses. *, **, and *** indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	COC_{CT}	COC_{GLS}	COC_{PEG}	COC_{GM}	COC_{PC1}	RET_{t+1}
InnateAQ	0.53***	0.17***	0.36***	0.26***	0.52***	0.13***
	[11.49]	[7.51]	[12.58]	[8.35]	[12.47]	[5.83]
DiscAQ	0.09**	0.04**	0.05**	0.05**	0.05**	0.03**
	[2.06]	[2.53]	[2.38]	[2.49]	[2.66]	[2.49]
b1 : InnateAQ $\times D(R^2)$	**-0.45*** **	**-0.09** **	**-0.24*** **	**-0.27*** **	**-0.26*** **	**-0.08** **
	[-6.69]	**[-2.60]**	**[-6.04]**	**[-5.32]**	**[-5.80]**	**[-2.34]**
b2 : DiscAQ $\times D(R^2)$	**-0.06**	**-0.01**	**-0.03**	**-0.04**	**-0.04**	**-0.04**
	[-0.87]	**[-0.41]**	**[-0.80]**	**[-0.84]**	**[-0.84]**	**[-1.01]**
b1 - b2	**-0.39*** **	**-0.08** **	**-0.22*** **	**-0.23*** **	**-0.22*** **	**-0.04***
	[-3.66]	**[-2.17]**	**[-2.84]**	**[-2.84]**	**[-3.36]**	**[-1.81]**
Control Variables	Yes	Yes	Yes		Yes	Yes
$\bar{R}^2$	0.17	0.41	0.37	0.16	0.41	0.09

Table 8: **Robustness Test – An Alternative Diversification Proxy**
This table presents the time-series averages of the slopes in cross-sectional regressions using the standard Fama and MacBeth (1973) methodology. The extent of diversification is measured an alternative proxy $Perc_{i,t}$. It builds on the deviation of the portfolio weight assigned to a firm by an institutional investor from the weight implicit in the market portfolio. The deviation is captured by the weight of stock i in institutional investor f's portfolio in year t, $S_{f,i,t}$. $Perc_{i,t}$ equals the average $S_{f,i,t}$ across all institutional investors that hold stock i weighted by their ownership in stock i ($Own_{f,i,t}$). That is, $Perc_{i,t} = \Sigma S_{f,i,t} * Own_{f,i,t}$. $D(Perc_{i,t})$ is the decile ranking of $Perc_{i,t}$ scaled into a range between 0 and 1. Other variables are the same as those in Table 4. For the sake of brevity, only the coefficients of AQ metrics and their interactions with $D(Perc)$ are reported. To avoid giving extreme observations heavy weight in the return regressions and potential data recording errors, the smallest and largest 1% of the observations in each year for all variables are set equal to the next smallest or largest values. Newey and West (1987) robust t-statistics are reported in parentheses. *, **, and *** indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = COC_{AVG}		AQ = DD			AQ = $\|AA\|$		
AQ		0.32***		0.06**	0.10***		
		[11.29]		[2.30]	[8.39]		
AQ×D(*Perc*)		-0.24***		-0.01	-0.07***		
		[-7.41]		[-0.34]	[-5.40]		
Method 1	Innate		0.41***			0.19***	
			[13.08]			[10.87]	
	Disc		0.04**			0.04***	
			[2.39]			[4.18]	
	Innate ×$D(Perc)$		-0.37***			-0.21***	
			[-8.05]			[-8.48]	
	Disc ×$D(Perc)$		0.01			-0.01	
			[0.24]			[-0.24]	
Method 2	Disc			0.06**			0.03***
				[2.30]			[3.12]
	Disc ×$D(Perc)$			-0.01			-0.00
				[-0.34]			[-0.13]
Control Variables		Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$		0.36	0.37	0.40	0.36	0.36	0.40