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# Idiosyncratic Information and the Cost of Equity Capital: A Meta-Analytic Review of the Literature

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This paper provides a quantitative review of the literature on the repercussions of idiosyncratic information on firms' cost of equity (CoE) capital. In total, I reconsider the results of 113 unique studies examining the CoE effects of information *Quantity*, *Precision* and *Asymmetry*. My results suggest that the association between firm-specific information and CoE is subject to moderate effects. First, the link between *Quantity* and CoE is moderated by disclosure types and country-level factors in that firms in comparatively weakly regulated countries tend to enjoy up to four times greater CoE benefits from more expansive disclosure—depending on the type of disclosure—than firms in strongly regulated markets. Second, a negative relationship between *Precision* and CoE is only significant in studies using non-accrual quality proxies for *Precision* and risk factor-based (RFB)/valuation model-based (VMB) proxies for CoE. Third, almost all VMB studies confirm the positive association between *Asymmetry* and CoE, but there is notable variation in the conclusions reached when *ex post* CoE measures are used.

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*Keywords:* meta-analysis; idiosyncratic information; information risk; expected returns; cost of equity capital; implied cost of capital

# Idiosyncratic Information and the Cost of Equity Capital: A Meta-Analytic Review of the Literature

## 1 Introduction

Extensive literature in accounting and finance investigates the extent to which idiosyncratic information affects price formation and return structures in capital markets. This strand of research commonly tests the proposition that firms with high (low) quality information environments should enjoy relatively low (high) cost of equity (CoE) capital. Specifically, it is conjectured that firms can lower their CoE if they disclose more value-relevant information to investors (*Quantity*), provide information of higher accuracy (*Precision*) and disseminate information more widely between investor groups (*Asymmetry*). While analytical works have modelled these propositions elegantly (e.g., Diamond and Verrecchia (1991), Easley and O'Hara (2004), and Lambert, Leuz and Verrecchia (2012)), the empirical evidence regarding their predictions is mixed (e.g., Core, Guay, and Verdi (2008), McInnis (2010), and Mohanram and Rajgopal (2009)).

Given, on the one hand, that the proper measurement of a firm's CoE (*alias* expected rate of returns) is an ongoing debate in itself (e.g., Botosan and Plumlee (2005), and Easton and Monahan (2016)), and, on the other hand, that proxies for the information attributes (i.e., *Quantity*, *Precision*, *Asymmetry*) are large in number, as informed by both accounting and finance research, the empirical literature is voluminous and the conclusions reached vary widely depending on the proxies used by researchers. With that in mind, the main objective of this paper is to offer a systematic review of the extant literature to examine the reasons underlying the variation in results. In particular, this review meta-analyses the associations of *Quantity* and *Precision* with CoE and provides a descriptive summary of extant findings on the link between *Asymmetry* and CoE.<sup>1,2</sup> To the best of my knowledge, this is the first study to quantitatively summarize

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<sup>1</sup> Meta-analysis is a statistical approach that summarizes empirical findings of multiple studies. Meta-analysis techniques require the use of effect size which—in meta-analytic accounting research—is commonly the study's Pearson  $r$  correlation coefficient between the dependent and independent variable of interest (Hunter, Schmidt, and Jackson (1982), Khlif and Chalmers (2015)).

<sup>2</sup> Given vast variation in research designs between studies examining the impact of *Asymmetry* on CoE (e.g., some studies use yearly, others monthly data; some focus on portfolio-level, other on firm-level) a meta-analysis is not feasible; hence, I focus on descriptive statistics only when examining this link.

all the links between idiosyncratic information and CoE within a unified framework. As such, it complements narrative literature reviews on this topic (e.g., Artiach and Clarkson (2011), Beyer, Cohen, Lys, and Walther (2010), Healy and Palepu (2001), and Kothari, So, and Verdi (2016)) and extends Souissi and Khlif (2012) who focus on disclosure (*Quantity*) effects only.<sup>3</sup>

## 2 Theoretical Background and Research Hypotheses

To facilitate the structure of this review, I present a conceptual framework based on which I select the studies in my sample (see Figure 1). The direct links between *Quantity*, *Precision*, *Asymmetry* and CoE are widely consistent with analytical work (e.g., Easley and O'Hara (2004), Clarkson, Guedes, and Thompson (1996), and Lewellen and Shanken (2002)) and substantiated by empirical evidence. Next, I provide a succinct narrative review of some notable studies examining the CoE effects of firm-specific information in order to pinpoint prevailing debates in the extant work, reveal commonly used information proxies, and offer guidance towards the creation of meaningful sub-groups in later analyses.

(Figure 1 about here)

### 2.1 Information Quantity and Cost of Equity

Literature on estimation risk demonstrates that if the amount of information about a firm is low, investors have difficulties to accurately estimate the return and cash flow parameters of this particular firm. This parameter uncertainty makes such firms a riskier investment vis-à-vis otherwise comparable firms, and hence induces higher CoE (e.g., Clarkson et al. (1996), and Lewellen and Shanken (2002)). A significant proportion of the literature examines the association between *Quantity* and firms' CoE, with 56 such papers analyzed in this study. One stream of research uses simple proxies—such as firm age or period of listing—as measures of information quantity and shows that these prox-

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<sup>3</sup> Similar to this study, Souissi and Khlif (2012) also meta-analyze the link between disclosure and CoE; however, my analysis differs from theirs in that it operates a larger sample (56 vs. 22 studies), covers a longer sampling period (1997-2010 vs. 1997-2017) and analyses substantially more firm-years (342,116 vs 9,553). Furthermore, I include both mandatory and voluntary disclosure studies, while Souissi and Khlif (2012) focus on voluntary disclosure only.

ies are negatively correlated with CoE (e.g., Barry and Brown (1984, 1985), Clarkson and Thompson (1990), Kumar, Sorescu, Boehme, and Danielsen (2008), and Zhang (2006)). A second stream uses firms' disclosure levels as proxies for *Quantity* and ample evidence exists confirming a negative association with CoE (e.g., Baginski and Rakow (2012), Botosan (1997), Campbell, Chen, Dhaliwal, Lu, and Steele (2014), Cao, Myers, Tsang, and Yang (2017), Healy, Hutton, and Palepu (1999), Francis, Khurana, and Pereira (2005), Fu, Kraft, and Zhang (2012), Kothari, Li, and Short (2009), and Ng and Rezaee (2015)). Thus, I formulate Hypothesis 1:

**H1:** The larger (smaller) the quantity of available information about a firm, the lower (higher) its CoE.

## 2.2 Information Precision and Cost of Equity

In a seminal paper, Easley and O'Hara (2004) demonstrate that a firm's CoE decreases with the accuracy of available information about the future value of the firm. Essentially, this means that investors demand to be rewarded for bearing uncertainty about a firm's prospects stemming from imprecise information given to them, implying that firms that disclose higher quality information to investors can benefit from reduced CoE. This proposition is thoroughly researched in the literature (e.g., 38 papers are assigned to this link in my analysis) and the extant work can be categorized into two major strands: *accounting/earnings quality* and *security analyst forecast*-based studies.

The first stream is pioneered by Francis, La Fond, Olsson and Shipper (2004, 2005). The authors examine the association between the quality of accounting information and CoE, and demonstrate that firms' CoE decreases as their earnings quality measures increase (e.g., accrual quality, value relevance). However, in an influential paper, Core, Guay and Verdi (2008) strongly question the validity of these early results. Despite continuous evidence for the proposition that earnings/accounting quality is negatively related to CoE (e.g., Aboody, Hughes, and Liu (2005), Barth, Konchitchki, and Landsman (2013), and Hou (2015)), this link is challenged in a number of papers (e.g., Cohen (2008), Khan (2008), and McInnis (2010)).

The second stream of research uses security analyst forecasts to proxy for information precision. Extant literature argues that the less uncertainty exists about the pro-

spects of a firm, the greater the consensus among security analysts and the more precise their forecasts (e.g., Barry and Brown (1985), Barron and Stuerke (1998), and Barron, Kim, Lim, and Stevens (1998)). Botosan and Plumlee (2013) provide evidence that total analyst forecast precision (AFP) is negatively associated with CoE. Botosan et al. (2004) decompose total analyst forecast precision into private and public information components and show that public (private) AFP is negatively (positively) associated with CoE. Interestingly, Barron, Sheng, and Thevenot (2012) find that for firms with limited public information, private AFP is in fact *negatively* associated with CoE. This might be explained by the dual effect of private information precision. On the one hand, more precise private information might increase information asymmetry, which then induces higher CoE (e.g., Diamond and Verrecchia (1991)) but, on the other hand, it might also decrease CoE when the quantity of public information is limited. Simply put, private information is still better than no information at all (Easley and O'Hara (2004), Lambert et al. (2012)). Given this empirical evidence along with the analytical insights from Easley and O'Hara (2004), I formulate Hypothesis 2:

**H2:** The higher (lower) the information precision of a firm, the lower (higher) its CoE.

### 2.3 Information Asymmetry and Cost of Equity

Easley and O'Hara (2004) furthermore show that as the fraction of uninformed investors as well as the number of private signals about the future value of the firm increases, its CoE also increases: uninformed investors—who only have access to public information—require compensation for “losing out” to privately informed investors—who have access to both public and private information—when making investment decisions. The greater these informational disadvantages are, the larger the CoE premium induced by *Asymmetry*. Numerous papers investigate this conjecture empirically (e.g., 22 such papers are included in my analysis) and mainly use market microstructure proxies (e.g., PIN scores, bid-ask spreads) to gauge the degree of informational disparity between investor groups.<sup>4,5</sup> Easley, Hvidkjaer and O'Hara (2002) were the first to doc-

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<sup>4</sup> PIN scores measure the probability that the next trade order is from a privately informed investor; i.e., based on private information, with higher PIN scores signifying greater *Asymmetry*. The notion underlying the PIN model is that while it is impossible to directly observe which trades are based on private

ument a positive association between CoE and PIN scores. Conversely, Mohanram and Rajgopal (2009, p. 241) conclude that “there is not much evidence to support the interpretation that information risk, proxied by PIN, is a source of priced information risk.” However, these authors acknowledge that while their paper suggests “PIN is not priced risk, it is difficult to make more general statements about the pricing of information risk since information risk can [...] be proxied by different empirical variables”. In fact, using spread-based proxies, Amihud and Mendelson (1986), Bhattacharya, Ecker, Olsson, and Schipper (2012), and Levi and Zhang (2015)—among others—document a significantly positive association with CoE. This corroborates Hypothesis 3:

**H3:** The higher (lower) the information asymmetry between investors, the higher (lower) the firm’s CoE.

## 2.4 Summary of Prior Empirical Evidence

The extant empirical evidence may be summarized as follows. First, whenever the link between *Quantity* and CoE is tested, the current research prefers using disclosure instead of simple proxies for information quantity as indicated by 56 studies using the former and only five studies using the latter (i.e., Barry and Brown (1984, 1985), Clarkson and Thompson (1990), Kumar et al. (2008), and Zhang (2006)). However, it should be noted that proxies for disclosure levels tend to measure disclosure along both a quantity and quality dimension, which makes them noisy estimates of *Quantity*.<sup>6</sup> Furthermore, wide variation in research designs, disclosure types examined and disclosure metrics used by researchers all possibly moderate the overall negative relation between disclosure and CoE.<sup>7</sup> Hence, more evidence along the lines of Richardson and Welker

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information, one can use imbalances between buy and sell orders to infer the probability of information-based trading for a given stock (e.g., Brown, Hillegeist, and Lo (2004), Easley, Kiefer, O’Hara, and Paperman (1996), and Easley, Kiefer, and O’Hara (1997)).

<sup>5</sup> Bid-ask spreads are a measure of the adverse selection problem market makers are exposed to and assumed to increase with information asymmetry (Copeland and Galai (1983), Glosten and Milgrom (1985)). Jack Treynor, publishing under his pseudonym Walter Bagehot (1971), gives an intuitive explanation as to why greater bid-ask spreads are associated with greater information asymmetry.

<sup>6</sup> For instance, Cheng, Collins, and Huang (2006, p. 179) state that “while prior empirical research has used the *quantity* of disclosure as a proxy for the *quality* of disclosure quality, in many cases disclosure quantity and quality are not separable information attributes.”

<sup>7</sup> For instance, some studies investigate mandatory disclosure (e.g., Campbell et al. (2014), and Core, Hail, and Verdi (2015)), while others concentrate on voluntary disclosure aspects (e.g., Botosan and



(2001) and Mangena, Li, and Tauringana (2016) on the types of disclosure that are particularly CoE-relevant seems beneficial. Second, accounting quality, and more specifically earnings quality, appears to be an important determinant of firms' information *Precision*. However, since the study of Core et al. (2008), its association with CoE is subject to controversy. Moreover, CoE tends to decrease with total AFP, but results are mixed for its relationship with the private and public components of analysts' information sets. Third, *Asymmetry* is commonly measured by market microstructure-based proxies, and while there is an ongoing debate about the pricing of PIN (e.g., Botosan and Plumlee (2013), and Duarte and Young (2009)), the negative relationship between bid-ask spreads and firms' CoE seems to be widely accepted.

### 3 Cost of Equity Measurement

Firms' CoE capital is the key variable of interest in this paper and its empirical measurement differs across studies. Some researchers use *ex post* returns to proxy for CoE (e.g., Doukas, Kim, and Pantzalis (2006), and Konchitchki, Luo, Ma, and Wu (2016)), while others apply *ex ante* estimates (e.g., Barth et al. (2013), Bhattacharya et al. (2012), Cohen (2008), and Hou (2015)). I classify those studies that conduct asset pricing tests (i.e., regressing realized returns on possible risk factors) or use average realized returns as CoE proxies as *ex post* and refer to them as realized return-based (REAL) in my analyses. I further divide the remaining "non-REAL" papers, which use *ex ante* CoE specifications, into two categories: risk-factor based (RFB) studies, which calculate CoE by multiplying estimated factor loadings from traditional asset pricing models (e.g., CAPM, FF3) with respective factor returns, and valuation-model based (VMB) studies, which reverse-engineer valuation models (such as the dividend discount, resid-

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Plumlee (2002), and Francis, Nanda, and Olsson (2008)); some papers focus on financial disclosure (e.g., Baginski and Rakow (2012), and Evans (2016)), while others examine non-financial disclosure (e.g., Dhaliwal, Li, Tsang, and Yang (2011), and Ng and Rezaee (2012)); and, some authors use self-constructed disclosure scores (e.g., Botosan (1997), and Kothari et al. (2009)), while others rely on commercially available ones (e.g., Healy et al. (1999), and Richardson and Welker (2001)), and yet others use simple dummy variables to distinguish between disclosing and non-disclosing firms (e.g., Ogneva, Subramanyam, and Raghunandan (2007), and Cao et al. (2017)).

ual income or abnormal earnings growth model) to estimate firms' implied cost of capital (ICC).<sup>8,9</sup>

Empirical proxies are, by definition, inherently flawed (Rao, 1973) and so are the aforementioned return measures. For instance, Elton (1999) states: “The use of average realized returns as a proxy for expected returns relies on a belief that information surprises tend to cancel out over the period of a study and realized returns are therefore an unbiased estimate of expected returns. However, I believe that there is ample evidence that this belief is misplaced” (p. 1199). In a similar vein, Fama and French (1997) argue that RFB proxies are “woefully imprecise estimates of the cost of equity” (p. 154) given that these estimates are based on noisy past realized returns. Ultimately, the unexpected news component in realized returns tends to corrupt the reliability of factor loading and factor premia estimates in RFB models. Finally, Easton and Monahan (2005) examine a number of different VMB estimates and conclude that—due to the optimism in analysts' earnings forecasts— “these proxies are unreliable” (p.501). In addition, VMB measures encounter issues arising from firm-specific estimation (e.g., Easton (2009), Wang (2015)) and growth assumptions made by researchers (e.g., Easton (2006)).

Despite these concerns, two major conclusions regarding the empirical validity of the different measures seem justified. First, proxying for CoE by realized returns is problematic in that discount rate and cash-flow news constitute significant impacts on firm-level returns, making realized returns noisy estimates of CoE (e.g., Chen, Da, and Zhao (2013), Ogneva (2012), and Vuolteenaho (2002)). Second, VMB proxies show somewhat greater construct validity than RFB proxies in terms of association with future realized returns, common risk-factors, and predictive power of returns (Botosan and Plumlee (2005), Botosan, Plumlee, and Wen (2011), Lee, So, and Wang (2010, 2015)). Taken together, this suggests that the measurement of CoE might partially explain

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<sup>8</sup> For a step-wise description of how to operationalize RFB estimates see, for instance, Barth et al. (2013), Landsman, Miller, Peasnell, and Yeh (2011), and O'Hanlon and Steele (2000).

<sup>9</sup> The intuition behind the ICC framework is straightforward: use a specific valuation model, accept the current stock price as at least semi-strong efficient and determine the internal rate of return that equates current stock price of the firm with expected future payoffs to shareholders, where future payoffs are commonly proxied by analysts' earnings forecasts. The internal rate of return is then considered the market participants' *ex ante* assessment of the firm's CoE. See Botosan and Plumlee (2002), Claus and Thomas (2001), Easton (2004), Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), Gordon and Gordon (1997), and Ohlson and Juettner-Nauroth (2005) for common ICC measures.

mixed results across studies when analyzing the effects of *Quantity*, *Precision* and *Asymmetry* on firms' CoE.

## 4 Methodology

The main objective of this paper is to provide a meta-analytic review of the literature on idiosyncratic information and firms' CoE capital. However, only for H1 and H2 research designs between studies are homogenous enough to carry out meta-analyses. Studies relating to H3 often lack necessary information and data comparability to conduct a meaningful meta-analysis (e.g., sample size information is inconsistently reported; some studies use yearly data, others use monthly data; some focus on the portfolio-level, others focus on the firm-level). Hence, for H3 I only provide descriptive statistics (e.g., fraction of studies confirming/rejecting the hypothesis; proxies used and proportions thereof).

### 4.1 Data Collection and Sample

In line with research hypotheses H1-H3, I search for different combinations of several keywords (shown in Table 1) in the following databases to identify relevant studies: ISI Web of Science; ScienceDirect; Emerald Management Ejournal; and SSRN. A review of all top-tier journals in accounting and finance as well as the reference list of all identified articles complements my search.<sup>10</sup> I exclude analytical papers (e.g., Bertomeu, Beyer, and Dye (2011), Cheynel (2013), Christensen, de la Rosa, and Feltham (2010), Dutta and Nezlobin (2017), Hughes, Liu, and Liu (2007), Lambert, Leuz, and Verrecchia (2007), and Strobl (2013)) and studies lacking statistical information required for the meta-analysis of H1 and H2 (e.g., Aboody et al. (2005), Beneish, Billings, and Hodder (2008), Chen, Shevlin, and Tong (2007), Clement, Frankel, and Miller (2003), and Hirshleifer, Hou, and Teoh (2012)) during this process.

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<sup>10</sup> *Accounting Journals*: Accounting Review, Accounting, Organizations and Society, Journal of Accounting and Economics, Journal of Accounting Research, Contemporary Accounting Research, and Review of Accounting Studies; *Finance Journals*: Journal of Finance, Journal of Financial Economics, Review of Financial Studies, Journal of Corporate Finance, Journal of Financial and Quantitative Analysis, Journal of Financial Intermediation, Journal of Money, Credit and Banking, and Review of Finance.

(Table 1 about here)

As noted above, the literature applies various measures for *Quantity*, *Precision*, *Asymmetry* and CoE. Based on the most commonly used proxies in the literature, I create several sub-groups for each information attribute and CoE (see Figure 1) and code each study in my sample accordingly. For instance, Francis et al. (2004) examine the impact of seven different earnings quality measures on two implied cost of capital proxies; hence, I classify this study as using “Accounting Quality” proxies for information precision and “VMB” proxies for CoE. The coding of studies requires my judgment as to which category a paper fits best; hence, this may induce sampling bias in that one might arrive at different classifications for some studies.<sup>11</sup> Moreover, I exclude some insightful papers from the sample because the novelty of the proxies applied in these studies hinders their allocation to one of my sub-groups. For example, El Ghouli, Guedhami, Ni, Pittman, and Saadi (2013) put forward firms’ geographic distance from financial centers as a measure of information asymmetry and show that CoE decreases with proximity; Cao, Myers, Myers, and Omer (2015) find that company reputation is negatively related to CoE, and Muino and Trombetta (2009) document a significant impact of distorted graph disclosure on CoE. Furthermore, I focus on firm-level results, so country-level studies are excluded from the analysis (e.g., Bhattacharya, Daouk, and Welker (2003), and Li (2015)).

## 4.2 Meta-Analysis Techniques

### 4.2.1 Effect Size

Meta-analysis techniques require the use of effect size which—in meta-analytic accounting research—is commonly the study’s Pearson  $r$  correlation coefficient between the dependent and independent variable of interest (Hunter, Schmidt, and Jackson

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<sup>11</sup> For example, Baginski and Rakow (2012) examine the CoE effects of management earnings forecast disclosure policy. They measure disclosure policy as the product of three dimensions: Supplier, Frequency and Precision. Given that (1) their proxy is based on two *Quantity* dimensions (Supplier, Frequency) but only one *Precision* dimension and (2) their main contribution relates to voluntary disclosure—“we extend the literature by examining a specific type of voluntary disclosure rather than disclosure in the aggregate” (p. 317)—I classify their paper as a *Quantity* rather than a *Precision* study.

(1982), Khlif and Chalmers (2015)).<sup>12</sup> If a study only reports regression results, I convert  $t$ -statistics into  $r$  coefficients as  $\sqrt{t^2/(t^2 + df)}$ , where  $df$  is degrees of freedom. If only  $p$ -values are provided, corresponding  $Z$  scores can be obtained from the standard normal table which I then transfer into  $r$  coefficients by using  $Z/\sqrt{N}$ , where  $N$  is sample size (Rosenthal, 1991).

Whenever a study uses multiple, but similar, measures for a variable (say, different proxies for earnings quality), I record the study's average effect size. Therefore, these studies only appear once in the analysis (Ahmed & Courtis, 1999). However, if a study tests different proxies for different samples (say, one RFB and one VMB CoE sample), I record the effect size for each sub-sample separately. Therefore, these studies appear twice in the analysis. To clarify, 56 studies for the link between *Quantity* and CoE contribute 62 observations to my analysis (*Precision*: 35 studies and 48 observations; *Asymmetry*: 22 studies and 28 observations).

Also, where necessary, I multiply a study's effect size by negative one to ensure consistent interpretation across proxies and to conform to the intuition of the underlying hypotheses of this paper. This is required because the interpretation of results varies depending on which proxies are used: some proxies are constructed such that *higher* values also signal higher information quality, while for others *lower* values indicate higher information quality. For instance, in most studies, higher analyst-based measures signal higher *Precision*—confirming H2 if a negative correlation with CoE is observed. In contrast, lower earnings quality proxies usually indicate higher information precision—confirming H2 if a positive, not negative, correlation with CoE is observed. In such instances, I multiply the effect size (of earnings quality) by negative one to reverse and re-align the interpretation of results with the intuition of the underlying hypothesis (H2).

After the effect size for each study is calculated, I estimate the mean correlation ( $\bar{r}$ ) for the population as shown in Eq. (1), where  $N_i$  is the sample size and  $r_i$  is the Pearson correlation coefficient for study  $i$ .

$$\bar{r} = \frac{\sum(r_i N_i)}{\sum N_i} \quad (1)$$

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<sup>12</sup> I use Spearman correlations, if Pearson correlations are not reported.

The population variance ( $S_p^2$ ) is estimated as the difference between observed variance ( $S_r^2$ ) and the sampling error variance ( $S_e^2$ ) as shown in equations (2) to (4), where  $K$  is the total number of studies included in the analysis.

$$S_p^2 = S_r^2 - S_e^2 \quad (2)$$

$$S_r^2 = \frac{\sum N_i (r_i - \bar{r})^2}{\sum N_i} \quad (3)$$

$$S_e^2 = \frac{(1 - \bar{r}^2)^2 K}{\sum N_i} \quad (4)$$

Eventually, I calculate the 95% confidence interval as follows:

$$[\bar{r} - S_p Z_{0.975}; \bar{r} + S_p Z_{0.975}] = [\bar{r} - S_p (1.96); \bar{r} + S_p (1.96)] \quad (5)$$

#### 4.2.2 Homogeneity Tests

To test for homogeneity in the data—that is, to examine if variation in results is due to sampling errors or moderating effects—two methods are followed. First, I put the sampling error variance into perspective to observed variance ( $S_e^2/S_r^2$ ) to reveal the degree to which the residual variance is trivial: if more than 75 percent of the variation in results can be attributed to sampling error (the suggested cut-off in the literature), then the relation under investigation is considered to be homogenous and unmoderated (Ahmed and Courtis (1999), Khlif and Chalmers (2015), Pearlman, Schmidt, and Hunter (1980)). Second, I calculate the chi-square test statistic shown in equation (6), where high statistical significance rejects the null of homogeneity, indicating that moderating effects might impact upon results across studies ( $K-1$  is the degrees of freedom and  $N = \sum N_i$ ). While statistically powerful, it should be noted that chi-square statistics are directly proportional to sample size (Fan, Thompson, & Wang, 1999), which makes it difficult to accept homogeneity at conventional levels in large sample studies like this one.

$$\chi_{k-1}^2 = \frac{NS_r^2}{(1 - \bar{r}^2)^2} \quad (6)$$

### 4.2.3 Sample Size

Most of the papers analyzed in this study report results for a multi-period sample which poses the question of how to define sample size (i.e.,  $N_i$ ) in equations (1) to (6). Using the number of unique firms appears to be most appealing. However, this information is often missing. Conversely, the number of firm-years (firm-quarters or firm-months) is reported most consistently but might bias meta-analytic results towards studies spanning longer sampling periods without necessarily covering more firms. I address this point as follows: when transforming t-statistics (p-values) from regression results into  $r$  coefficients, I determine the degrees of freedom (sample size) based on the number of observations in the regression (e.g., firm-years). When summarizing among studies (e.g., computing mean effect size, population variance, chi-square statistic), I use the average number of firms (i.e., firm-years divided by number of years) as sample size. This maintains the internal integrity of each study—larger sample studies generate robust results—while ensuring a “sampling-period-independent” impact on the meta-level.

## 5 Results

Fifty-six (56) studies in my sample examine the link between *Quantity* and CoE, 35 examine the link with *Precision* and 22 examine the link with *Asymmetry*. Given that some papers provide findings for multiple sub-categories (for instance, RFB and VMB proxies), subsequent analyses are based on 62 observations for *Quantity*, 48 observations for *Precision* and 28 for *Asymmetry*. Hereafter, I use “observations” and “studies/papers” interchangeably but results always refer to the number of observations. The *Quantity*, *Precision* and *Asymmetry* studies included in my sample are shown in Table 2, Table 3, and Table 4, respectively. Table 5 summarizes this information and reports descriptive statistics across the entire sample.

(Table 2 about here)

(Table 3 about here)

(Table 4 about here)

(Table 5 about here)

## 5.1 Information Quantity and Cost of Equity

Subsequent meta-analysis is limited to the disclosure literature, given that “simple-proxy” studies are sparse (i.e., Barry and Brown (1984, 1985), Clarkson and Thompson (1990), Kumar et al. (2008), and Zhang (2006)). Sixty-two (62) observations in my sample analyze the link between *Quantity* and CoE of which most pertain to published work (n=50; 81%) and appear in higher-tier journals (37; 60%).<sup>13</sup> Ten percent of studies use realized returns to proxy for CoE (n=6), with VMB measures prevailing in the disclosure literature (VMB: 50; 81%; RFB: 6; 10%). Whilst some studies include firms from multiple countries in their sample (13; 21%), the great majority are single-country studies (49; 79%). Interestingly, only 25 observations (40%) relate to US firms—which is exceptionally low compared to the US-bias in *Precision* and *Asymmetry* studies (81 and 86 percent, respectively)—and the remaining 37 studies either focus on non-US countries (29; 47%) or include inseparably both US and non-US firms (8; 13%) in their samples (see Table 5).

In addition, Table 5 reports the type of disclosure examined and the disclosure metric used by researchers. I categorize 11 observations (18%) as having a clear focus on financial disclosure, 22 (35%) as evaluating non-financial disclosure aspects, and the remaining 29 (47%) as partial-financial (i.e. all studies with an emphasis on the general quality of firms’ disclosure). Most studies apply self-constructed indices to measure disclosure levels (38; 61%), followed by thirteen studies (21%) relying on third-party providers (e.g., AIMR, S&P scores) and eleven (18%) observations using simple dummy variables to distinguish between disclosing and non-disclosing firms.

Examining the general conclusion of each paper, about 70 percent of all observations (n=44; 71%) tend to confirm the negative association between *Quantity* and CoE, six studies reject it (10%), and the remaining 12 papers (19%) provide

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<sup>13</sup> I refer to journals that have a score of three or four in the ABS 2015 list as higher-tier outlets and denote journals with a score of two and one as well as unrated and unpublished work as lower-tier.



mixed/conditional results for this link. For instance, Francis et al. (2008) show that the negative relation between disclosure and CoE vanishes after controlling for earnings quality; Evans (2016) and Kim and Shi (2011) suggest that the timeliness and the sign of earnings announcements (good/bad) as well as the degree of market competition are important conditioning variables; and Espinosa and Trombetta (2007) and Gietzmann and Ireland (2005) demonstrate that the impact of disclosure on CoE is extenuated by accounting conservatism (i.e., only firms adopting aggressive accounting policies can reduce their CoE by increased disclosure activity). This qualitative assessment is consistent with meta-analytic results (see Table 6). The mean effect size between *Quantity* and CoE is -0.066 with a 95% confidence interval between -0.190 and 0.058, indicating that findings vary across studies. A highly significant  $\chi^2$  of 241.21 with 61 degrees of freedom along with only 26 percent of observed variance explained by sampling error ( $S_e^2/S_r^2$ ) rejects the null of homogenous data and pinpoints the presence of moderating effects.

(Table 6 about here)

### 5.1.1 Measurement of Cost of Equity

Dividing studies according to CoE measurement yields some interesting insights (Table 6, Row II & III). The first sub-group includes those studies which use *ex post* returns (REAL) as proxies for CoE; the second group (RFB/VMB) contains studies applying either risk factor-based or valuation model-based CoE estimates. Total average effect size for the RFB/VMB group ( $\bar{r}$ :  $-0.075 \pm 0.129$ ) is about three times larger than for the REAL group ( $-0.026 \pm 0.037$ ).<sup>14</sup> However, none of the REAL studies examine the association in a pure financial disclosure setting—where CoE effects are most pronounced—which tends to clarify the difference in effect size (Columns II-IV).<sup>15</sup> More importantly, both effect sizes are insignificantly different from zero (p-value: 0.256 and 0.171), indicating that CoE measurement does *not* explain mixed results in the literature.

<sup>14</sup> Average effect size plus/minus two standard deviations (i.e.,  $\sqrt{Sp^2}$ ) of the mean (i.e., 95% interval).

<sup>15</sup> The effect size for VMB proxies ( $\bar{r}$ :  $-0.084 \pm 0.128$ ) is markedly stronger than for RFB measures ( $\bar{r}$ :  $-0.017 \pm 0.071$ ) which—as in the case of the REAL group—is attributable to the fact that none of the RFB studies focus on financial disclosure.

### 5.1.2 Measurement of Quantity

Table 6 distinguishes studies according to the type of disclosure examined by researchers: financial (FF), partial-financial (PF) and non-financial (NF) disclosure studies. Row IV shows a statistically significant correlation of about 12 percent between CoE and FF studies (p-value: 0.019), but a markedly reduced and statistically insignificant effect size of only five percent for PF and NF studies (p-values: 0.358 and 0.361). This shows that financial disclosure is twice as important to investors than non-financial and partial-financial disclosure. However, this is not to say that non-financial information is irrelevant. For example, a relatively large strand of research within the NF category (n=10; 16%) documents a significantly negative association between corporate social responsibility (CSR) disclosure and CoE ( $\bar{r}$ :  $-0.056 \pm 0.022$ , untabulated).<sup>16</sup> Moreover, findings are robust to researchers' choice of how to measure disclosure levels; irrespective of using self-constructed disclosure indices (SCI) or simple dummy variables to proxy for disclosing and non-disclosing firms, the effect size is always significantly negative for FF studies (SCI:  $-0.101 \pm 0.069$ ; Dummy:  $-0.126 \pm 0.106$ ), but insignificant and much weaker for NF and PF studies (see Table 7).<sup>17</sup>

(Table 7 about here)

Next, I examine if different disclosure requirements across countries moderate results. In doing so, I categorize my sample in three different ways. First, I distinguish between US and non-US studies. Second, I assign each study a disclosure regulation score and allocate studies with a score below the sample average of 0.83 to the LOW group and the remainder to the HIGH group.<sup>18</sup> Third, I follow Souissi and Khelif (2012) and form groups based on countries' transparency culture, where the high disclosure

<sup>16</sup> CSR studies: Bachoo, Tan, and Wilson (2013), Clarkson, Fang, Li, and Richardson (2013), Déjean and Martinez (2009), Dhaliwal et al. (2011), Dhaliwal, Li, Tsang, and Yang (2014), Ng and Rezaee (2015), Plumlee, Brown, Hayes, and Marshall (2015), Reverte (2012), Richardson and Welker (2001), and Wu, Lin, and Wu (2014).

<sup>17</sup> Given that error variances ( $Se^2$ ) for FF and NF studies using externally provided disclosures scores (EXI) are larger than observed variances ( $Sr^2$ ), confidence intervals cannot be calculated and a comparison with PF studies is not meaningful.

<sup>18</sup> Consistent with Core et al. (2015), I measure the level of disclosure regulation by the index of disclosure requirements in securities offerings from La Porta, Lopez-De-Silanes, and Shleifer (2006). In the case of multi-country studies, I report a weighted average per observation (weight: firm-years per country).

environment group (HDE) includes studies conducted in the US, UK and Canada, and the low disclosure environment group (LDE) covers the remaining countries.<sup>19</sup>

Table 8, Column V, shows that total disclosure effects are about 3.5 times larger in non-US studies ( $\bar{r}$ : -0.139) than in US studies (-0.039). Similarly, studies concentrating on less regulated (LOW: -0.126) and less transparent countries (LDE: -0.141) document an approximately 3 times stronger correlation between disclosure and CoE than studies focusing on more regulated and more transparent countries (HIGH: -0.062; HDE: -0.043). However, the magnitude of these differences varies according to disclosure types: the CoE effect of financial disclosure in non-US settings is “only” 2.5 times larger than in US settings, while partial- and non-financial disclosure effects are about 3 and 4.5 times larger (similar patterns can be observed for HIGH and LOW as well as HDE and LDE studies).<sup>20</sup>

Higher mandatory disclosure requirements in the US (and in HIGH/HDE countries) may explain these differences in disclosure effects. Mandatory disclosure replaces and pre-empts benefits from voluntary disclosure, which is least pronounced for financial disclosure where financial reporting quality converges towards a uniform standard across countries (e.g. IFRS/US-GAAP convergence), and most pronounced for non-financial disclosure where the difference in requirements between highly regulated countries (US/HIGH/HDE) and weakly regulated countries (non-US/LOW/LDE) is greatest (e.g., Sarbanes-Oxley Act). Furthermore, within each sub-sample a substantial amount of variation in results is now attributable to sampling error (e.g.,  $S_e^2/S_r^2$  ratios of 0.54 and 0.48 for US and non-US studies vis-à-vis 0.26 for the sample as a whole); together with less significant chi-square statistics, this confirms that disclosure environments across countries do partially moderate results.

(Table 8 about here)

<sup>19</sup> LDE countries: Austria, Bahrain, Belgium, Brazil, Denmark, Egypt, France, Germany, Hong Kong, India, Indonesia, Korea, Kuwait, Malaysia, Netherlands, Oman, Philippines, Qatar, Saudi Arabia, Singapore, Spain, Sweden Switzerland, Taiwan, and United Arab Emirates.

<sup>20</sup> It should be noted that while effect sizes differ markedly in magnitude, only some of them are statistically significant: US-PF, NonUS-PF, HIGH-PF, HDE-PF, LDE-PF. However, as the differences in effect sizes between disclosure environments and disclosure types are all highly significant (minimum t-statistic 13.46, untabulated two-sample T-test), my conclusions remain qualitatively unchanged.

### 5.1.3 Summary of Results

Figure 2 summarizes the key results from meta-analyzing the association between *Quantity* and CoE. Taken together, findings suggest that researchers' choice of CoE measurement does *not* explain mixed results in the disclosure literature, but it is the type of disclosure (financial vs. partial-/non-financial) as well as the disclosure setting (strongly vs. weakly regulated countries) which moderates results: CoE effects emanating from partial-/non-financial disclosure are insignificant (rejecting H1), but economically and statistically material for financial disclosure (confirming H1). Furthermore, in countries where disclosure regulation and requirements are low (non-US/LOW/LDE), investors appreciate firms' disclosure efforts to a much greater extent than in higher regulated environments (US/HIGH/HDE groups).

(Figure 2 about here)

## 5.2 Information Precision and Cost of Equity

Forty-eight (48) observations analyze the CoE effects of *Precision*, most of which relate to published work (n=42; 88%) and appear in higher-tier journals (29; 60%). The sample is strongly tilted towards US firms, with only nine observations (19%) stemming from non-US data. About one-third of observations use realized returns to proxy for CoE (REAL: 16; 33%) and the remaining two-thirds mainly apply VMB estimates (VMB: 26; 54%; RFB: 6; 13%). The vast majority of studies (41; 85%) rely on accounting/earnings quality measures for information precision, with analyst-based proxies (7; 15%) being the exception (see Table 5).

Focusing on the general conclusion of each paper, about half of all observations (n=27; 56%) confirm the negative association between *Precision* and CoE, eight studies tend to reject it (17%), and the remaining papers provide mixed/conditional results for this link (13; 27%). For instance, Ogneva (2012) shows that only after controlling for cash flow shocks in realized returns does a negative association with *Precision* exist; Kim and Qi (2010) confirm H2 after excluding low-priced firms from their sample, and Mashruwala and Mashruwala (2011) document a negative relation only in January. This qualitative assessment is consistent with meta-analytic results (shown in Table 9). The mean effect size between *Precision* and CoE is -0.048 with a 95% confidence interval

between -0.142 and 0.047, illustrating that results are mixed across studies. A highly significant  $\chi^2$  of 177.89 with 47 degrees of freedom along with only 27 percent of observed variance explained by sampling error ( $S_e^2/S_r^2$ ) rejects the null of homogenous data and signposts the presence of moderating effects.

(Table 9 about here)

### 5.2.1 Measurement of Cost of Equity

As before, I divide my sample into two sub-groups according to CoE measurement (Table 9, Row II & III). Total average effect size for the REAL group is -0.014.<sup>21</sup> The effect size for RFB/VMB is about seven times larger ( $\bar{r}$ : -0.082) and almost significant at the 10% level (p-value: 0.111). The difference between the two effect sizes is highly significant (t-statistic: -165.1; untabulated two-sample T-test). Overall, this proves that the measurement of CoE has a moderating effect on results. While there seems to be no relation between *Precision* and a firm's realized returns, the association with RFB and VMB proxies is statistically and economically meaningful.<sup>22</sup>

### 5.2.2 Measurement of Information Precision

In a similar vein, the empirical measurement of *Precision* might explain the overall insignificant correlation with CoE ( $\bar{r}$ : -0.048  $\pm$  0.095). However, irrespective of whether *Precision* is proxied by accounting quality (-0.044  $\pm$  0.085) or analyst forecasts (-0.067  $\pm$  0.139), the relations with CoE remain insignificant (Table 9, Row IV). Moreover, results suggest that data heterogeneity stems from RFB/VMB studies, since variation across REAL results is mainly due to sampling error ( $\chi^2$ : 9.55, df: 15). Therefore, I focus subsequent moderator effect analyses on RFB/VMB studies.

Table 9, Row II, shows that the relation between CoE and analyst-based proxies is twice as strong ( $\bar{r}$ : -0.142 vs. -0.074), considerably more significant (p-value: 0.000 vs. 0.122) and less heterogenous ( $\chi^2$ : 9.03\* vs. 83.21\*\*\*) than for accounting quality-based

<sup>21</sup> As the sampling error variance ( $S_e^2$ ) is larger than the observed variance ( $S_r^2$ ), the population variance ( $S_p^2$ ) is negative; thus, no meaningful confidence interval can be determined.

<sup>22</sup> The effect size between information precision and RFB proxies ( $\bar{r}$ : -0.100  $\pm$  0.084) is slightly stronger than for VMB proxies ( $\bar{r}$ : -0.073  $\pm$  0.103); however, as the number of RFB studies is low (n=6), a separate sub-group is not meaningful.

proxies. This stronger correlation might be explained by the fact that analyst-based proxies are more volatile measures of *Precision* than accounting quality proxies, with greater variance leading to higher correlations coefficients. For instance, Barron et al.'s (1998) AFP measure is perceived to be highly sensitive to outliers and measurement error (Barron et al., 2012, p. 21) which makes it a highly dispersed proxy for *Precision*. In contrast, Dechow and Dichev's (2002) accrual quality (AQ) metric—the most widely used measure of accounting quality—is estimated from a time-series of firm fundamentals that increases its robustness and decreases dispersion. To this extent, accounting quality studies draw a more conservative picture of the relation between *Precision* and CoE.

A sufficiently large number of accounting quality-based studies (n=41) allows for further analysis of this subset of observations.<sup>23</sup> Designated by a significant chi-square statistic ( $\chi^2$ : 83.21\*\*\*, df: 26), the link between accounting quality and RFB/VMB estimates is exposed to moderator effects—REAL results, on the other hand, are unmoderated, but economically weak. As noted before, AQ metrics are a common proxy for accounting quality. Table 10, Row II, sub-samples data accordingly and shows that the relation between the AQ-metric group and CoE remains moderated ( $\chi^2$ : 68.04\*\*\*, df: 14) and insignificant ( $\bar{r}$ :  $-0.082 \pm 0.120$ ), while the opposite is observed for non-AQ metrics—such as earnings value relevance or accounting conservatism ( $\chi^2$ : 13.08, df: 11;  $\bar{r}$ :  $-0.063 \pm 0.020$ ). Differently stated, as the proxies in my sample become more heterogenous, the correlation with CoE becomes less, not more, moderated which is contrary to expectations in that one may assume that studies sharing the same underlying empirical measure would also yield similar results. Therefore, the debate over whether *Precision* impacts upon CoE is in fact a debate over whether accrual quality affects CoE: results for the remaining studies, which at times use very diverse measures, corroborate the hypothesis that firms with higher *Precision* tend to enjoy lower CoE.

(Table 10 about here)

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<sup>23</sup> Given that my sample includes only seven analyst-based studies, further in-depth analysis is not meaningful.

### 5.2.3 Summary of Results

Figure 3 reviews the main meta-analytic findings. Overall, the statistical and economic significance of the relationship between information precision and CoE tends to depend on the measurement of CoE: higher *Precision* leads to lower CoE if measured by RFB/VMB proxies, but this link is trivial in asset pricing tests and when average realized returns are used. Furthermore, a material association between RFB/VMB proxies and analyst-based as well as non-AQ metric-based studies is found. However, this relation is insignificant in studies using AQ metrics as measures of accounting quality; H2 is confirmed when non-AQ and analyst-based proxies are used for information precision and RFB/VMB proxies for CoE but rejected when AQ and REAL proxies are applied.

(Figure 3 about here)

### 5.3 Information Asymmetry and Cost of Equity

Twenty-eight (28) observations in my sample examine the link between *Asymmetry* and CoE of which most relate to published work (n=25; 89%) and appear in higher-tier journals (24; 86%). The sample is strongly tilted towards US studies, with only four observations (14%) relying on non-US data. Three-quarters of observations apply *ex post* estimates for CoE (REAL: 21; 75%) and the remainder exclusively use VMB measures (VMB: 7; 25%). The vast majority of studies (24; 86%) utilize market microstructure proxies (i.e., PIN scores, bid-ask spreads), whereas non-microstructure estimates (e.g., analyst-based proxies) are rarely used (see Table 5).

As noted above, a meaningful meta-analysis for the link between *Asymmetry* and CoE is not possible. Therefore, proceeding analyses focus on the general conclusion of each paper. Figure 4, Panel A, shows that about half of all observations confirm the positive association between *Asymmetry* and CoE (n=16; 57%), four observations (14%) tend to reject it, and eight observations (29%) provide mixed/conditional results. In particular, the level of market competition appears to be an important conditioning variable in empirical settings, given that *Asymmetry* effects tend to vanish as markets become more competitive (e.g., Akins, Jeffrey, and Verdi (2012), Armstrong, Core, Taylor, and Verrecchia (2011), and Luong, Nguyen, and Yin (2011)). Furthermore, findings in

Eleswarapu and Reinganum (1993) and Kang (2010) indicate the existence of January-effects.

(Figure 4 about here)

### 5.3.1 Measurement of Cost of Equity

Sub-sampling observations according to CoE measurement reveals some interesting points (see Figure 4, Panel B and C). First, the literature mainly uses realized returns to proxy for firms' CoE (REAL: 21; 75%), with seven observations (25%) relying on VMB estimates, and none using traditional RFB ones. The fact that risk factor-based models (such as the CAPM) derive from the assumption of homogenous expectations between investor groups and hence, by definition “there is no role for accounting to reduce the information asymmetry” (Shevlin, 2013, p. 466), seems to justify the non-representation of RFB proxies in extant studies. Second—and more importantly—there is notable variation in the conclusions reached by REAL studies (reject: 14%; mixed: 38%; confirm: 48%), but findings are rather uniform when VMB proxies are used (reject: 14%; confirm: 86%). This suggests that researchers' choice of CoE measurement impacts the conclusions reached regarding the CoE effects of *Asymmetry* in that VMB studies generally confirm H3, while REAL studies are more likely to reject it.

Given that realized returns tend to be noisy proxies of CoE (Chen et al. (2013), Fama and French, 1997, and Vuolteenaho (2002)), one might argue that greater weight should be placed on studies applying VMB (i.e., implied cost of capital) estimates. In other words, the reason why “only” 48 percent of REAL studies confirm the positive association between *Asymmetry* and CoE might stem from imprecise CoE estimates, which leads to low power tests (e.g. Wang (2015)). While convincing evidence exists that VMB proxies show greater validity than realized return-based proxies (e.g., Botosan and Plumlee (2005), Botosan et al. (2011), and Lee et al. (2010, 2015)), those estimates are not impeccable either. Beyond the issue of lacking estimates for young, small and financially-distressed firms due to coverage bias by analysts (e.g., Diether, Malloy, and Scherbina (2002), Hong, Lim, and Stein (2000), and La Porta (1996)), it is the problem of upward-biased implied cost of capital (ICC) estimates—due to optimistic analyst forecasts (e.g., Dugar and Nathan (1995), Francis and Philbrick (1993), and



McNichols and O'Brien (1997))—which raises particular concerns. For example, Hwang et al. (2013) conclude that “as long as the [ICC] estimates are derived from analysts’ earnings forecasts, potential measurement errors in [ICC] estimates could remain and influence [...] findings.” Therefore, the authors call for “more efforts to fine-tune [ICC] measures” (p. 165). Model-based ICC estimates might be one remedy to overcome these analyst-related deficiencies in future work (e.g., Hou, van Dijk, and Zhang (2012), and Li and Mohanram (2014)).

### 5.3.2 Measurement of Information Asymmetry

As most studies in my sample rely on market microstructure-based proxies to measure information asymmetry (n=24; 86%), I concentrate subsequent analyses on this subset of observations. Figure 5 shows that PIN scores are most widely used (17; 71%) in the literature, followed by bid/ask spreads operated in some studies (7; 29%). None of the spread-based studies reject the direct link between *Asymmetry* and CoE (Figure 5, Panel C) which suggests that higher bid/ask spreads indicate greater information asymmetry and can induce higher CoE. In contrast, the association between PIN scores and CoE is somewhat debated (reject: 24%, mixed: 18%, confirm: 59%): Mohanram and Rajgopal (2009, p. 241) conclude that “there is not much evidence [that] PIN is a source of priced information risk” and Duarte and Young (2009) argue that it is the illiquidity component of PIN which explains the positive relation with CoE, and not the *Asymmetry* part of it. However, the majority of studies in my sample confirm the negative CoE effects arising from asymmetric information (Figure 5, Panel B). Together with new evidence from longer sampling periods (e.g., Aslan, Easley, Hvidkjaer, and O'Hara (2011), and Brennan, Huh, and Subrahmanyam (2016)) and improved estimation techniques (e.g., Easley, López de Prado, and O'Hara (2012), and Hwang, Lee, Lim, and Park (2013)), this substantiates the proposition of PIN being an important driver of CoE.<sup>24</sup>

(Figure 5 about here)

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<sup>24</sup> See also Boehmer, Grammig, and Theissen (2007), Yan and Zhang (2012), and William Lin and Ke (2011) for a discussion on how to improve PIN score measurement.

### 5.3.3 Summary of Results

Figure 6 summarizes key results from the analysis of information asymmetry with CoE and shows that evidence is strongest for VMB proxies and bid-ask spreads, but somewhat mixed for REAL proxies and PIN scores. Overall, the majority of studies find a positive *Asymmetry*-CoE relation which corroborates the conjecture of informational disparity between investor groups causing an increase in firms' CoE (confirming H3). However, recent analytical and empirical evidence demonstrates that high levels of market competition tend to subdue these *Asymmetry* effects. Specifically, Akins et al. (2012), Armstrong et al. (2011) and Luong et al. (2011) show that—consistent with the analytical model of Lambert et al. (2012)—the significance of *Asymmetry* on CoE declines as market competition increases; that is, in perfectly liquid markets, in which both informed and uninformed investors act as price takers, asymmetric information has no material effect on firms' CoE. These findings put forward market competition as an important conditioning variable in future research.<sup>25</sup>

(Figure 6 about here)

### 5.4 Additional Analysis

To address concerns of publication bias (Møller & Jennions, 2001), I test for differences in meta-analytic results between higher-tier and lower-tier journals. Table 11 reports findings for the link between *Quantity* and CoE and shows that there is no clear pattern regarding the differences in average effect sizes between the two groups: higher-tier journals report a stronger effect size when RFB/VMB proxies are being used (high: -0.081; low: -0.055), while lower-tier journals report a stronger effect size for REAL proxies (-0.020; -0.158). Similarly, higher-tier studies find stronger CoE effects for financial disclosure (-0.119; -0.044), while lower-tier studies report a stronger relation with partial-financial disclosure (-0.038; -0.138)—average effect sizes for non-financial disclosure are alike (-0.061; -0.040). Comparable patterns are observed for the link between *Precision* and CoE (see Table 12). For instance, when measuring CoE by

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<sup>25</sup> Common proxies for market competition include: investor concentration (Akins et al., 2012), institutional ownership (Luong et al., 2011) and number of shareholders (Armstrong et al. (2011), Barron et al. (2012)).

RFB/VMB proxies, total average effect size is larger in higher-tier journals ( $\bar{r}$ : -0.097) than in lower-tier ones (-0.067); in contrast, when focusing on realized return-based studies, total average effect size is larger for lower-tier (-0.019) vis-à-vis higher-tier publications (-0.014). However, for both links results in higher-tier journals are slightly more heterogeneous than in lower-tier ones—which can be inferred from more significant chi-squares, lower  $S_e^2/S_r^2$  ratios and wider confidence intervals—indicating that the CoE effects of *Quantity* and *Precision* are discussed more controversially in higher-tier outlets.

As a further robustness test, I follow Ahmed, Chalmers, and Khelif (2013) and calculate for all significant results a “fail-safe” N statistic that estimates the number of unpublished studies reporting null results required to reduce the mean effect size to a specified criterion.<sup>26</sup> In particular, I am examining how many studies are necessary to reduce observed effect sizes from the meta-analyses to a hypothetical effect size of just below zero. Using a criterion of -0.01, it requires approximately 40 studies to revert the negative association between financial disclosure and CoE and about 73 studies to change the overall negative relation between *Precision* and VMB/RFB proxies, with 23 (18) studies needed to alter results when *Analyst* (non-AQ) proxies are being used. Taken together, these additional tests suggest that my main findings tend to be free of publication bias and unaffected by the file drawer problem.

(Table 11 about here)

(Table 12 about here)

## 6 Discussion of Results and Conclusion

This paper provides a quantitative review of the literature examining the effect of idiosyncratic information on firms’ CoE capital. For the links of *Quantity* and *Precision* with CoE I report meta-analytic results, and for the link with *Asymmetry* I provide de-

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<sup>26</sup> The fail-safe N statistic is calculated as:  $K_0 = K \left[ \frac{\bar{r}_k}{\bar{r}_0} - 1 \right]$  where  $K_0$  is the number of unpublished studies required to affect conclusion reached (i.e., fail-safe N),  $K$  is the total number of studies included in the meta-analysis,  $\bar{r}_k$  is the reported mean effect size,  $\bar{r}_0$  is the criterion effect size specified by the research (Orwin, 1983).

scriptive statistics only due to data constraints. In total, I review the results of 113 unique papers and my findings suggest that the association between firm-specific information and CoE is subject to moderate effects as indicated by insignificant average effect sizes (*Quantity*:  $-0.066 \pm 0.124$ ; *Precision*:  $-0.048 \pm 0.095$ ), and a notable number of studies (29%) that only find conditional results for the link between *Asymmetry* and CoE.

The empirical measurement of both CoE and information attributes partially explains these mixed results. First, findings for the link between *Quantity* and CoE depend on disclosure type (financial vs. partial-/non-financial) and disclosure settings insofar as firms in comparatively weakly regulated countries tend to enjoy two to four times greater CoE benefits from more expansive disclosure—depending on the type of disclosure—than firms in highly regulated countries such as the US or the UK. Second, the conjectured negative relationship between *Precision* and CoE is only significant in studies using analyst-based and non-accrual quality proxies for *Precision* and RFB/VMB proxies for CoE. That is, the link between information precision and CoE seems trivial in asset pricing tests (REAL proxies) or when accrual quality metrics are used. Third, almost all VMB studies confirm the positive association between *Asymmetry* and CoE (86%), but there is notable variation in the conclusions reached by REAL studies (reject: 14%; mixed: 38%; confirm: 48%).

*Impact of Endogeneity.* Endogeneity is a major challenge in the extant literature (e.g., Core (2001)) and offers an alternative explanation for mixed meta-analytic findings. In particular, simultaneity and reverse causality creates difficulties when examining the theoretically negative relation between *Quantity/Precision* and CoE: firms disclose more or better information to lower their CoE (i.e., negative correlation), but only firms with high CoE decide to do so (i.e., positive correlation). Hence, endogeneity can lead to an insignificant relation between information quality and firms' CoE (e.g., Balakrishnan, Billings, Kelly, and Ljungqvist (2014)). To this extent, the insignificance of some results might be explained by the fact that data used in the meta-analyses are typically from correlation matrices and, therefore, not incorporating methods used by the studies in my sample to address endogeneity.

*CoE Measurement.* VMB measures are most frequently used in the literature (e.g., 60 percent of all 138 observations use such proxies in my sample), followed by asset pricing tests and realized returns (REAL) in second place (31%) and RFB estimates in third (9%). Extant findings, therefore, hinge on the validity of the CoE measures applied: results are only as valid as the proxies used to attain them. In other words, the commonly found negative relationship between higher information quality and VMB proxies might be a spurious one (i.e., better information may “simply” reduce optimism in analyst forecasts which lowers VMB estimates mechanically) and noise in realized returns may explain the generally insignificant relationship in REAL studies (e.g., McInnis (2010), and Ogneva (2012)).

These issues of CoE measurement raise the question of how to weigh existing evidence. Given that valuation model-based estimates tend to be more valid measures of CoE than realized return-based proxies (e.g., Botosan and Plumlee (2005), Botosan et al. (2011), and Lee et al. (2010, 2015)), one might place greater weight on the conclusions reached in VMB studies: firms with better corporate information environments are likely to enjoy lower CoE than otherwise identical firms. However, analyst-based ICC estimates tend to be upward-biased, leading to distorted results (e.g., Easton and Monahan (2005, 2016), and Easton and Sommers (2007)). Moreover, young, small and financially-distressed firms are rarely covered by security analysts (e.g., Diether et al. (2002), Hong et al. (2000), and La Porta (1996)), biasing ICC samples towards larger and more established firms.

While analyst forecast bias can be corrected for (e.g., Guay, Kothari, and Shu (2011), Larocque (2013), and Mohanram and Gode (2013)), the problem of sampling bias remains in analyst-based ICC studies. This poses a trade-off for researchers to use either a *less* representative sample with *more* valid CoE proxies (VMB) or a *more* representative sample with *less* valid return estimates (REAL). To this extent, VMB findings are not necessarily generalizable towards smaller and younger firms, and REAL study results may be confounded by cash-flow and discount-rate news. Recent advancements in model-based ICC estimates might help overcome this predicament in future work because these estimates are analyst-independent—removing forecast bias—and calculated from firms’ current accounting information only, thus ensuring representative samples (e.g., Hou et al. (2012), and Li and Mohanram (2014)).

*Information Quality Measurement.* The literature uses several different proxies for firms' information attributes and results vary depending on which proxy is used (e.g., AQ vs. non-AQ; PIN vs. SPREAD-based studies). However, even when identical information proxies are applied, disagreement in the literature remains (see, for example, Core et al. (2008) and Mohanram and Rajgopal (2009) for a discussion on the pricing of accrual quality and PIN scores). Measurement error in the proxies for *Precision*, *Asymmetry* and *Quantity* might cause these inconsistent results and one way to address it is to improve the empirical soundness of the respective proxies (e.g., McNichols (2002) AQ metric modification of the Dechow-Dichev (2002) model; Brown and Hillegeist (2007) and Hwang et al. (2013) PIN score modification of the Easley et al. (1996, 1997) model). However, despite such improvements, no single proxy can be entirely free of measurement error. Thus, another approach to deal with this errors-in-variable problem is to operationalize more elaborate research designs. In this respect, further work along the lines of Verdi (2005), who uses principal component analysis to control for noise in information proxies, seems beneficial to increase empirical robustness of results.

*General Implications of Findings.* Extant evidence is (yet) insufficient to support idiosyncratic information as a separate risk factor in asset pricing models (i.e., rigorous asset pricing test as in Core et al. (2008) and Mohanram and Rajgopal (2009) tend to refute the possibility of an information risk factor). However, evidence is ample enough to confirm the hypothesis of better information quality leading to lower CoE (e.g., Core et al. (2008) themselves find that better accrual quality leads to lower market beta which is equal to lower CoE). While at first glance an antithesis, this conclusion is consistent with economic theory that corroborates a negative relationship between idiosyncratic information and CoE, but questions if it impacts CoE directly (e.g., Easley and O'Hara (2004), and Lambert et al. (2012)) or only indirectly through other risk factors such as market beta (e.g., Hughes et al. (2007), and Lambert et al. (2007)). My findings also suggest important implications for practice: firms can lower their CoE if they release more value-relevant information to investors (e.g., committing to more expansive disclosure), provide information of higher precision (e.g., following stricter reporting standards), and disseminate information more widely between investor groups (e.g., promoting investor relations). However, these benefits are likely to be attenuated in

countries where strong regulation and transparency requirements establish *ex ante* high quality corporate information environments.

It should also be noted that the extant literature is silent on the relative importance of *Precision*, *Asymmetry* and *Quantity* as determinates of firms' CoE; that is, which of the three attributes has comparatively greater CoE relevance remains unanswered by current studies. Therefore, to resolve the debate about the market pricing of idiosyncratic information empirically, it seems necessary to extend prevailing research designs—which examine the impact of one information proxy on one CoE proxy at a time—towards a comprehensive methodology that allows for simultaneously examining the different information attributes and CoE measures within one empirical model. Such an approach might help disentangle the underlying complexity between idiosyncratic information and firms' CoE. A first promising step in this direction has been taken by Bhattacharya et al. (2012).

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## Appendix: Journal Index

Journal	Abbreviation	ABS 2015
Academy of Taiwan Business Management Review	ATBMR	n/a
Accounting in Europe	AIE	2
<b>Accounting Review</b>	<b>TAR</b>	<b>4</b>
<b>Accounting, Organizations and Society</b>	<b>AOS</b>	<b>4</b>
Advanced Science Letters	ASL	n/a
Advances in Accounting, incorporating Advances in International Accounting	AIA	2
Applied Economics	AE	2
Asian Journal of Business and Accounting	AJBA	n/a
Asian Review of Accounting	ARA	2
Asia-Pacific Journal of Accounting & Economics	APJAE	2
Asia-Pacific Journal of Financial Studies	APJFS	n/a
Australian Accounting Review	AAR	2
Australian Journal of Management	AJM	n/a
Business Research	BR	n/a
China Finance Review International	CFRI	1
<b>Contemporary Accounting Research</b>	<b>CAR</b>	<b>4</b>
Corporate Social Responsibility and Environmental Management	CSREM	1
Emerging Markets Finance and Trade	EMFT	n/a
<b>European Accounting Review</b>	<b>EAR</b>	<b>3</b>
European Management Journal	EMJ	2
Global Journal of Business Research	GJBR	n/a
Industrial Management and Data Systems	IMDS	2
<b>International Business Review</b>	<b>IBR</b>	<b>3</b>
<b>International Journal of Accounting</b>	<b>IJA</b>	<b>3</b>
<b>International Journal of Forecasting</b>	<b>IJF</b>	<b>3</b>
International Review of Economics and Finance	IREF	2
<b>International Review of Financial Analysis</b>	<b>IRFA</b>	<b>3</b>
<b>Journal of Accounting and Economics</b>	<b>JAE</b>	<b>4</b>
<b>Journal of Accounting and Public Policy</b>	<b>JAPP</b>	<b>3</b>
<b>Journal of Accounting Research</b>	<b>JAR</b>	<b>4</b>
<b>Journal of Accounting, Auditing and Finance</b>	<b>JAAF</b>	<b>3</b>
Journal of Applied Accounting Research	JAAR	2
<b>Journal of Banking and Finance</b>	<b>JBF</b>	<b>3</b>
Journal of Business	JB	n/a
<b>Journal of Business Finance and Accounting</b>	<b>JBFA</b>	<b>3</b>
Journal of Business, Economics and Finance	JBEF	n/a
<b>Journal of Corporate Finance</b>	<b>JCF</b>	<b>4</b>
Journal of Economics, Finance and Administrative Science	JEFA	n/a
<b>Journal of Empirical Finance</b>	<b>JEF</b>	<b>3</b>

*Table continued next page.*



## Journal Index (cont.)

Journal	Abbreviation	ABS 2015
<b>Journal of Finance</b>	<b>JF</b>	<b>4</b>
<b>Journal of Financial and Quantitative Analysis</b>	<b>JFQA</b>	<b>4</b>
<b>Journal of Financial Economics</b>	<b>JFE</b>	<b>4</b>
Journal of Intellectual Capital	JIC	2
<b>Journal of International Financial Markets, Institutions and Money</b>	<b>JIFMIM</b>	<b>3</b>
Journal of Multinational Financial Management	JMFM	2
<b>Journal of Risk and Insurance</b>	<b>JRI</b>	<b>3</b>
Management Decision	MD	2
<b>Management Science</b>	<b>MS</b>	<b>4</b>
Management Science and Engineering	MSE	n/a
Managerial and Decision Economics	MDE	2
Managerial Finance	MF	1
North American Journal of Economics and Finance	NAJEF	2
Pacific Accounting Review	PAR	1
Quarterly Journal of Finance	QJF	1
Review of Accounting and Finance	RAF	2
<b>Review of Accounting Studies</b>	<b>RAST</b>	<b>4</b>
<b>Review of Finance (European Finance Review)</b>	<b>RF</b>	<b>4</b>
<b>Review of Quantitative Finance and Accounting</b>	<b>RQFA</b>	<b>3</b>
SSRN	SSRN	n/a

Notes: Journals in bold are categorised as high-tier journals in this study. Ranking follows the Academic Journal Guide 2015 (ABS).

## References

- Aboody, D., Hughes, J., & Liu, J. (2005). Earnings Quality, Insider Trading, and Cost of Capital. *Journal of Accounting Research*, 43(5), 651-673.
- Ahmed, K., Chalmers, K., & Khlif, H. (2013). A Meta-analysis of IFRS Adoption Effects. *The International Journal of Accounting*, 48(2), 173-217.
- Ahmed, K., & Courtis, J. K. (1999). Associations between corporate characteristics and disclosure levels in annual reports: a meta-analysis. *The British Accounting Review*, 31(1), 35-61.
- Akins, B. K., Jeffrey, N., & Verdi, R. S. (2012). Investor Competition over Information and the Pricing of Information Asymmetry. *The Accounting Review*, 87(1), 35-58.
- Al-Hadi, A., Taylor, G., & Hossain, M. (2015). Disaggregation, auditor conservatism and implied cost of equity capital: An international evidence from the GCC. *Journal of Multinational Financial Management*, 29, 66-98.

- Al Guindy, M. (2016). *Corporate Twitter Use and Cost of Capital*. Available at SSRN: <https://ssrn.com/abstract=2824733>.
- Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2), 223-249.
- Armstrong, C. S., Core, J. E., Taylor, D. J., & Verrecchia, R. E. (2011). When Does Information Asymmetry Affect the Cost of Capital? *Journal of Accounting Research*, 49(1), 1-40.
- Artiach, T. C., & Clarkson, P. M. (2011). Disclosure, conservatism and the cost of equity capital: A review of the foundation literature. *Accounting and Finance*, 51(1), 2-49.
- Artiach, T. C., & Clarkson, P. M. (2014). Conservatism, disclosure and the cost of equity capital. *Australian Journal of Management*, 39(2), 293-314.
- Aslan, H., Easley, D., Hvidkjaer, S., & O'Hara, M. (2011). The characteristics of informed trading: Implications for asset pricing. *Journal of Empirical Finance*, 18(5), 782-801.
- Bachoo, K., Tan, R., & Wilson, M. (2013). Firm Value and the Quality of Sustainability Reporting in Australia. *Australian Accounting Review*, 23(1), 67-87.
- Bagehot, W. (1971). The Only Game in Town. *Financial Analysts Journal*, 27(2), 12-22.
- Baginski, S. P., & Rakow, K. C. (2012). Management earnings forecast disclosure policy and the cost of equity capital. *Review of Accounting Studies*, 17(2), 279-321.
- Balakrishnan, K., Billings, M. B., Kelly, B., & Ljungqvist, A. (2014). Shaping Liquidity: On the Causal Effects of Voluntary Disclosure. *Journal of Finance*, 69(5), 2237-2278.
- Barron, O. E., Kim, O., Lim, S. C., & Stevens, D. E. (1998). Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review*, 421-433.
- Barron, O. E., Sheng, X. S., & Thevenot, M. (2012). *The Information Environment and Cost of Capital*. Available at SSRN: <https://ssrn.com/abstract=2099825>.
- Barron, O. E., & Stuerke, P. S. (1998). Dispersion in Analysts' Earnings Forecasts as a Measure of Uncertainty. *Journal of Accounting, Auditing & Finance*, 13(3), 245-270.
- Barry, C. B., & Brown, S. J. (1984). Differential information and the small firm effect. *Journal of Financial Economics*, 13(2), 283-294.

- Barry, C. B., & Brown, S. J. (1985). Differential Information and Security Market Equilibrium. *Journal of Financial and Quantitative Analysis*, 20(4), 407-422.
- Barth, M. E., Konchitchki, Y., & Landsman, W. R. (2013). Cost of capital and earnings transparency. *Journal of Accounting and Economics*, 55(2-3), 206-224.
- Beneish, M. D., Billings, M. B., & Hodder, L. D. (2008). Internal control weaknesses and information uncertainty. *The Accounting Review*, 83(3), 665-703.
- Berger, P. G., Chen, H. J., & Li, F. (2012). *Firm specific information and the cost of equity capital*. Available at SSRN: <https://ssrn.com/abstract=906152>.
- Bertomeu, J., Beyer, A., & Dye, R. A. (2011). Capital Structure, Cost of Capital, and Voluntary Disclosures. *The Accounting Review*, 86(3), 857-886.
- Beyer, A., Cohen, D. A., Lys, T. Z., & Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50(2-3), 296-343.
- Bhattacharya, N., Ecker, F., Olsson, P. M., & Schipper, K. (2012). Direct and Mediated Associations among Earnings Quality, Information Asymmetry, and the Cost of Equity. *The Accounting Review*, 87(2), 449-482.
- Bhattacharya, U., Daouk, H., & Welker, M. (2003). The world price of earnings opacity. *The Accounting Review*, 78(3), 641-678.
- Blanco, B., Garcia Lara, J. M., & Tribo, J. A. (2015). Segment Disclosure and Cost of Capital. *Journal of Business Finance & Accounting*, 42(3-4), 367-411.
- Boehmer, E., Grammig, J., & Theissen, E. (2007). Estimating the probability of informed trading—does trade misclassification matter? *Journal of Financial Markets*, 10(1), 26-47.
- Botosan, C. A. (1997). Disclosure Level and the Cost of Equity Capital. *The Accounting Review*, 72(3), 323-349.
- Botosan, C. A., & Plumlee, M. A. (2002). A Re-examination of Disclosure Level and the Expected Cost of Equity Capital. *Journal of Accounting Research*, 40(1), 21-40.
- Botosan, C. A., & Plumlee, M. A. (2005). Assessing Alternative Proxies for the Expected Risk Premium. *The Accounting Review*, 80(1), 21-53.
- Botosan, C. A., & Plumlee, M. A. (2013). Are Information Attributes Priced? *Journal of Business Finance & Accounting*, 40(9-10), 1045-1067.
- Botosan, C. A., Plumlee, M. A., & Wen, H. E. (2011). The Relation between Expected Returns, Realized Returns, and Firm Risk Characteristics. *Contemporary Accounting Research*, 28(4), 1085-1122.

- Botosan, C. A., Plumlee, M. A., & Xie, Y. (2004). The Role of Information Precision in Determining the Cost of Equity Capital. *Review of Accounting Studies*, 9(2-3), 233-259.
- Boujelbene, M. A., & Affes, H. (2013). The impact of intellectual capital disclosure on cost of equity capital: A case of French firms. *Journal of Economics Finance and Administrative Science*, 18(34), 45-53.
- Brennan, M. J., Huh, S. W., & Subrahmanyam, A. (2016). Asymmetric Effects of Informed Trading on the Cost of Equity Capital. *Management Science*, 62(9), 2460-2480.
- Brown, S., & Hillegeist, S. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies*, 12(2-3), 443-477.
- Brown, S., Hillegeist, S. A., & Lo, K. (2004). Conference calls and information asymmetry. *Journal of Accounting and Economics*, 37(3), 343-366.
- Callen, J. L., Khan, M., & Lu, H. (2013). Accounting Quality, Stock Price Delay, and Future Stock Returns. *Contemporary Accounting Research*, 30(1), 269-295.
- Campbell, J. L., Chen, H., Dhaliwal, D. S., Lu, H.-m., & Steele, L. B. (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, 19(1), 396-455.
- Cao, Y., Myers, J. N., Myers, L. A., & Omer, T. C. (2015). Company reputation and the cost of equity capital. *Review of Accounting Studies*, 20(1), 42-81.
- Cao, Y., Myers, L. A., Tsang, A., & Yang, Y. G. (2017). Management forecasts and the cost of equity capital: international evidence. *Review of Accounting Studies*, 1-48.
- Chan, A. L. C., Lin, S. W. J., & Strong, N. (2009). Accounting conservatism and the cost of equity capital: UK evidence. *Managerial Finance*, 35(4), 325-345.
- Chan, C. Y., Lo, H. C., & Yang, M. J. (2016). The revision frequency of earnings forecasts and firm characteristics. *North American Journal of Economics and Finance*, 35, 116-132.
- Chen, K. C., Wei, K.-C. J., & Chen, Z. (2003). *Disclosure, corporate governance, and the cost of equity capital: evidence from Asia's emerging markets*. Available at SSRN: <https://ssrn.com/abstract=422000>.
- Chen, L., Da, Z., & Zhao, X. (2013). What Drives Stock Price Movements? *Review of Financial Studies*, 26(4), 841-876.
- Chen, L. H., Dhaliwal, D. S., & Trombley, M. A. (2008). The Effect of Fundamental Risk on the Market Pricing of Accruals Quality. *Journal of Accounting, Auditing & Finance*, 23(4), 471-492.

- Chen, S., Shevlin, T., & Tong, Y. H. (2007). Does the Pricing of Financial Reporting Quality Change Around Dividend Changes? *Journal of Accounting Research*, 45(1), 1-40.
- Cheng, C. S. A., Collins, D., & Huang, H. H. (2006). Shareholder rights, financial disclosure and the cost of equity capital. *Review of Quantitative Finance and Accounting*, 27(2), 175-204.
- Cheyne, E. (2013). A theory of voluntary disclosure and cost of capital. *Review of Accounting Studies*, 18(4), 987-1020.
- Chien, Y. T., & Lu, H. M. (2015). Firm websites and the risk of firm. *Industrial Management & Data Systems*, 115(3), 504-520.
- Choi, J. J., Jin, L., & Yan, H. (2016). *Informed trading and expected returns*. Available at SSRN: <https://ssrn.com/abstract=2193733>.
- Christensen, P. O., de la Rosa, L. E., & Feltham, G. A. (2010). Information and the Cost of Capital: An Ex Ante Perspective. *The Accounting Review*, 85(3), 817-848.
- Clarkson, P., Guedes, J., & Thompson, R. (1996). On the diversification, observability, and measurement of estimation risk. *Journal of Financial and Quantitative Analysis*, 31(01), 69-84.
- Clarkson, P. M., Fang, X., Li, Y., & Richardson, G. (2013). The relevance of environmental disclosures: Are such disclosures incrementally informative? *Journal of Accounting and Public Policy*, 32(5), 410-431.
- Clarkson, P. M., & Thompson, R. E. X. (1990). Empirical Estimates of Beta When Investors Face Estimation Risk. *Journal of Finance*, 45(2), 431-453.
- Claus, J., & Thomas, J. (2001). Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets. *Journal of Finance*, 56(5), 1629-1666.
- Clement, M., Frankel, R., & Miller, J. (2003). Confirming Management Earnings Forecasts, Earnings Uncertainty, and Stock Returns. *Journal of Accounting Research*, 41(4), 653-679.
- Cohen, D. A. (2003). *Quality of financial reporting choice: determinants and economic consequences*. Available at SSRN: <https://ssrn.com/abstract=422581>.
- Cohen, D. A. (2008). Does information risk really matter? An analysis of the determinants and economic consequences of financial reporting quality. *Asia-Pacific Journal of Accounting & Economics*, 15(2), 69-90.
- Copeland, T. E., & Galai, D. (1983). Information Effects on the Bid-Ask Spread. *Journal of Finance*, 38(5), 1457-1469.

- Core, J. E. (2001). A review of the empirical disclosure literature: discussion. *Journal of Accounting and Economics*, 31(1-3), 441-456.
- Core, J. E., Guay, W. R., & Verdi, R. (2008). Is accruals quality a priced risk factor? *Journal of Accounting and Economics*, 46(1), 2-22.
- Core, J. E., Hail, L., & Verdi, R. S. (2015). Mandatory disclosure quality, inside ownership, and cost of capital. *European Accounting Review*, 24(1), 1-29.
- Dechow, P. M., & Dichev, I. D. (2002). The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *The Accounting Review*, 77(s-1), 35-59.
- Déjean, F., & Martinez, I. (2009). Environmental Disclosure and the Cost of Equity: The French Case. *Accounting in Europe*, 6(1), 57-80.
- Dhaliwal, D., Li, O. Z., Tsang, A., & Yang, Y. G. (2014). Corporate social responsibility disclosure and the cost of equity capital: The roles of stakeholder orientation and financial transparency. *Journal of Accounting and Public Policy*, 33(4), 328-355.
- Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review*, 86(1), 59-100.
- Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, Liquidity, and the Cost of Capital. *the Journal of Finance*, 46(4), 1325-1359.
- Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of Opinion and the Cross Section of Stock Returns. *Journal of Finance*, 57(5), 2113-2141.
- Doukas, J. A., Kim, C. F., & Pantzalis, C. (2006). Divergence of opinion and equity returns. *Journal of Financial and Quantitative Analysis*, 41(03), 573-606.
- Duarte, J., Han, X., Harford, J., & Young, L. (2008). Information asymmetry, information dissemination and the effect of regulation FD on the cost of capital. *Journal of Financial Economics*, 87(1), 24-44.
- Duarte, J., & Young, L. (2009). Why is PIN priced? *Journal of Financial Economics*, 91(2), 119-138.
- Dugar, A., & Nathan, S. (1995). The Effect of Investment Banking Relationships on Financial Analysts' Earnings Forecasts and Investment Recommendations. *Contemporary Accounting Research*, 12(1), 131-160.
- Dutta, S., & Nezlobin, A. (2017). Information disclosure, firm growth, and the cost of capital. *Journal of Financial Economics*, 123(2), 415-431.
- Easley, D., Hvidkjaer, S., & O'Hara, M. (2010). Factoring Information into Returns. *Journal of Financial and Quantitative Analysis*, 45(2), 293-309.

- Easley, D., Hvidkjaer, S., & O'Hara, M. (2002). Is Information Risk a Determinant of Asset Returns? *Journal of Finance*, 57(5), 2185-2221.
- Easley, D., Kiefer, N. M., & O'Hara, M. (1997). One day in the life of a very common stock. *Review of Financial Studies*, 10(3), 805-835.
- Easley, D., Kiefer, N. M., O'Hara, M., & Paperman, J. B. (1996). Liquidity, Information, and Infrequently Traded Stocks. *Journal of Finance*, 51(4), 1405-1436.
- Easley, D., López de Prado, M. M., & O'Hara, M. (2012). Flow Toxicity and Liquidity in a High-frequency World. *Review of Financial Studies*, 25(5), 1457-1493.
- Easley, D., & O'Hara, M. (2004). Information and the Cost of Capital. *Journal of Finance*, 59(4), 1553-1583.
- Easton, P. (2006). Use of forecasts of earnings to estimate and compare cost of capital across regimes. *Journal of Business Finance & Accounting*, 33(3- 4), 374-394.
- Easton, P. (2009). Estimating the cost of capital implied by market prices and accounting data. *Foundations and Trends® in Accounting*, 2(4), 241-364.
- Easton, P. D. (2004). PE Ratios, PEG Ratios, and Estimating the Implied Expected Rate of Return on Equity Capital. *The Accounting Review*, 79(1), 73-95.
- Easton, P. D., & Monahan, S. J. (2005). An Evaluation of Accounting- Based Measures of Expected Returns. *The Accounting Review*, 80(2), 501-538.
- Easton, P. D., & Monahan, S. J. (2016). Review of Recent Research on Improving Earnings Forecasts and Evaluating Accounting-based Estimates of the Expected Rate of Return on Equity Capital. *Abacus*, 52(1), 35-58.
- Easton, P. D., & Sommers, G. A. (2007). Effect of Analysts' Optimism on Estimates of the Expected Rate of Return Implied by Earnings Forecasts. *Journal of Accounting Research*, 45(5), 983-1015.
- El Ghouli, S., Guedhami, O., Ni, Y., Pittman, J., & Saadi, S. (2013). Does Information Asymmetry Matter to Equity Pricing? Evidence from Firms' Geographic Location\*. *Contemporary Accounting Research*, 30(1), 140-181.
- Eleswarapu, V. R., & Reinganum, M. R. (1993). The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics*, 34(3), 373-386.
- Eliwa, Y., Haslam, J., & Abraham, S. (2016). The association between earnings quality and the cost of equity capital: Evidence from the UK. *International Review of Financial Analysis*, 48, 125-139.
- Elton, E. J. (1999). Presidential Address: Expected Return, Realized Return, and Asset Pricing Tests. *Journal of Finance*, 54(4), 1199-1220.

- Elzahar, H., Hussainey, K., Mazzi, F., & Tsalavoutas, I. (2015). Economic consequences of key performance indicators' disclosure quality. *International Review of Financial Analysis*, 39, 96-112.
- Embong, Z., Mohd- Saleh, N., & Hassan, M. S. (2012). Firm size, disclosure and cost of equity capital. *Asian Review of Accounting*, 20(2), 119-139.
- Espinosa, M., & Trombetta, M. (2007). Disclosure interactions and the cost of equity capital: Evidence from the Spanish continuous market. *Journal of Business Finance & Accounting*, 34(9-10), 1371-1392.
- Eugster, F. (2014). *Endogeneity and the Dynamics of Voluntary Disclosure Quality: Is There Really an Effect on the Cost of Equity Capital?* Available at SSRN: <https://ssrn.com/abstract=2379683>.
- Evans, M. E. (2016). Commitment and Cost of Equity Capital: An Examination of Timely Balance Sheet Disclosure in Earnings Announcements. *Contemporary Accounting Research*, 33(3), 1136-1171.
- Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, 43(2), 153-193.
- Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 56-83.
- Feng, M., Li, C., & Gu, Z. (2009). *Management Forecasts and the Cost of Equity*. Available at SSRN: <https://ssrn.com/abstract=1471058>.
- Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2005a). The market pricing of accruals quality. *Journal of Accounting and Economics*, 39(2), 295-327.
- Francis, J., LaFond, R., Olsson, P. M., & Schipper, K. (2004). Costs of Equity and Earnings Attributes. *The Accounting Review*, 79(4), 967-1010.
- Francis, J., LaFond, R., Olsson, P. M., & Schipper, K. (2005b). The market pricing of accruals quality. *Journal of Accounting and Economics*, 39(2), 295-327.
- Francis, J., Nanda, D., & Olsson, P. E. R. (2008). Voluntary Disclosure, Earnings Quality, and Cost of Capital. *Journal of Accounting Research*, 46(1), 53-99.
- Francis, J., & Philbrick, D. (1993). Analysts' Decisions As Products of a Multi-Task Environment. *Journal of Accounting Research*, 31(2), 216-230.
- Francis, J. R., Khurana, I. K., & Pereira, R. (2005). Disclosure incentives and effects on cost of capital around the world. *The Accounting Review*, 80(4), 1125-1162.
- Fu, R., Kraft, A., & Zhang, H. (2012). Financial reporting frequency, information asymmetry, and the cost of equity. *Journal of Accounting and Economics*, 54(2-3), 132-149.



- García-Sánchez, I.-M., & Noguera-Gámez, L. (2017). Integrated information and the cost of capital. *International Business Review*, 26(5), 959-975.
- Garcia Lara, J. M., Garcia Osma, B., & Penalva, F. (2011). Conditional conservatism and cost of capital. *Review of Accounting Studies*, 16(2), 247-271.
- Gebhardt, W. R., Lee, C. M. C., & Swaminathan, B. (2001). Toward an Implied Cost of Capital. *Journal of Accounting Research*, 39(1), 135-176.
- Gietzmann, M., & Ireland, J. (2005). Cost of capital, strategic disclosures and accounting choice. *Journal of Business Finance & Accounting*, 32(3-4), 599-634.
- Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1), 71-100.
- Gode, D., & Mohanram, P. (2003). Inferring the Cost of Capital Using the Ohlson–Juettner Model. *Review of Accounting Studies*, 8(4), 399-431.
- Gordon, J. R., & Gordon, M., J. . (1997). The Finite Horizon Expected Return Model. *Financial Analysts Journal*, 53(3), 52-61.
- Gray, P., Koh, P.-S., & Tong, Y. H. (2009). Accruals Quality, Information Risk and Cost of Capital: Evidence from Australia. *Journal of Business Finance & Accounting*, 36(1-2), 51-72.
- Grüning, M. (2011). Capital Market Implications of Corporate Disclosure: German Evidence. *Business Research*, 4(1), 48-72.
- Guay, W., Kothari, S., & Shu, S. (2011). Properties of implied cost of capital using analysts' forecasts. *Australian Journal of Management*, 36(2), 125-149.
- Hail, L. (2002). The impact of voluntary corporate disclosures on the ex-ante cost of capital for Swiss firms. *European Accounting Review*, 11(4), 741-773.
- He, W. P., Lepone, A., & Leung, H. (2013). Information asymmetry and the cost of equity capital. *International Review of Economics & Finance*, 27, 611-620.
- Healy, P. M., Hutton, A. P., & Palepu, K. G. (1999). Stock Performance and Intermediation Changes Surrounding Sustained Increases in Disclosure. *Contemporary Accounting Research*, 16(3), 485-520.
- Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1), 405-440.
- Hirshleifer, D., Hou, K., & Teoh, S. H. (2012). The accrual anomaly: risk or mispricing? *Management Science*, 58(2), 320-335.

- Hong, H., Lim, T., & Stein, J. C. (2000). Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. *Journal of Finance*, 55(1), 265-295.
- Hou, K., van Dijk, M. A., & Zhang, Y. (2012). The implied cost of capital: A new approach. *Journal of Accounting and Economics*, 53(3), 504-526.
- Hou, Y. (2015). The role of diversification in the pricing of accruals quality. *Review of Accounting Studies*, 20(3), 1059-1092.
- Hughes, J. S., Liu, J., & Liu, J. (2007). Information asymmetry, diversification, and cost of capital. *The Accounting Review*, 82(3), 705-729.
- Hunter, J. E., Schmidt, F. L., & Jackson, G. B. (1982). *Meta-Analysis: Cumulating Research Findings Across Studies*. Beverly Hills: SAGE Publications.
- Hwang, L.-S., Lee, W.-J., Lim, S.-Y., & Park, K.-H. (2013). Does information risk affect the implied cost of equity capital? An analysis of PIN and adjusted PIN. *Journal of Accounting & Economics*, 55(2-3), 148-167.
- Hwang, L.-S., & Lim, S.-Y. (2012). Do Investors Price Accruals Quality? A Reexamination in the Implied Cost of Equity Capital. *Asia-Pacific Journal of Financial Studies*, 41(4), 458-490.
- Kang, M. (2010). Probability of information-based trading and the January effect. *Journal of Banking & Finance*, 34(12), 2985-2994.
- Khan, M. (2008). Are accruals mispriced? Evidence from tests of an Intertemporal Capital Asset Pricing Model. *Journal of Accounting and Economics*, 45(1), 55-77.
- Khelif, H., & Chalmers, K. (2015). A review of meta-analytic research in accounting. *Journal of Accounting Literature*, 35, 1-27.
- Khelif, H., Samaha, K., & Azzam, I. (2015). Disclosure, ownership structure, earnings announcement lag and cost of equity capital in emerging markets: The case of the Egyptian stock exchange. *Journal of Applied Accounting Research*, 16(1), 28-57.
- Kim, D., & Qi, Y. (2010). Accruals quality, stock returns, and macroeconomic conditions. *The Accounting Review*, 85(3), 937-978.
- Kim, J.-B., & Sohn, B. C. (2013). Real earnings management and cost of capital. *Journal of Accounting and Public Policy*, 32(6), 518-543.
- Kim, J. W., & Shi, Y. (2011). Voluntary disclosure and the cost of equity capital: Evidence from management earnings forecasts. *Journal of Accounting and Public Policy*, 30(4), 348-366.

- Konchitchki, Y., Luo, Y., Ma, M. L. Z., & Wu, F. (2016). Accounting-based downside risk, cost of capital, and the macroeconomy. *Review of Accounting Studies*, 21(1), 1-36.
- Kothari, S. P., Li, X., & Short, J. E. (2009). The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis. *The Accounting Review*, 84(5), 1639-1670.
- Kothari, S. P., So, E., & Verdi, R. (2016). Analysts' Forecasts and Asset Pricing: A Survey. In A. W. Lo & R. C. Merton (Eds.), *Annual Review of Financial Economics*, Vol 8 (Vol. 8, pp. 197-219).
- Kristandl, G., & Bontis, N. (2007). The impact of voluntary disclosure on cost of equity capital estimates in a temporal setting. *Journal of Intellectual Capital*, 8(4), 577-594.
- Kumar, P., Sorescu, S. M., Boehme, R. D., & Danielsen, B. R. (2008). Estimation Risk, Information, and the Conditional CAPM: Theory and Evidence. *Review of Financial Studies*, 21(3), 1037-1075.
- La Porta, R. (1996). Expectations and the Cross-Section of Stock Returns. *Journal of Finance*, 51(5), 1715-1742.
- La Porta, R., Lopez-De-Silanes, F., & Shleifer, A. (2006). What Works in Securities Laws? *the Journal of Finance*, 61(1), 1-32.
- La Rosa, F., & Liberatore, G. (2014). Biopharmaceutical and chemical firms' R&D disclosure, and cost of equity: The impact of the regulatory regime. *European Management Journal*, 32(5), 806-820.
- Lambert, R., Leuz, C., & Verrecchia, R. E. (2007). Accounting Information, Disclosure, and the Cost of Capital. *Journal of Accounting Research*, 45(2), 385-420.
- Lambert, R. A., Leuz, C., & Verrecchia, R. E. (2012). Information Asymmetry, Information Precision, and the Cost of Capital. *Review of Finance*, 16(1), 1-29.
- Landsman, W. R., Miller, B. L., Peasnell, K., & Yeh, S. (2011). Do investors understand really dirty surplus? *The Accounting Review*, 86(1), 237-258.
- Larocque, S. (2013). Analysts' earnings forecast errors and cost of equity capital estimates. *Review of Accounting Studies*, 18(1), 135-166.
- Larson, C. R., & Resutak, R. J. (2015). *Sources of investor uncertainty and expected stock returns*. Available at SSRN: <https://ssrn.com/abstract=2318062>.
- Latiff, A. R., & Taib, F. (2011). The Cost of Equity Effect of Accruals Quality and Ownership Structure. *Academy of Taiwan Business Management Review*, 7(1), 1-10.

- Lee, C., So, E. C., & Wang, C. (2010). Evaluating Implied Cost of Capital Estimates. *SSRN eLibrary*.
- Lee, C., So, E. C., & Wang, C. C. (2015). Evaluating firm-level expected-return proxies. *Harvard Business School Accounting & Management Unit Working Paper*(15-022), 15-57.
- Levi, S., & Zhang, X. J. (2015). Do Temporary Increases in Information Asymmetry Affect the Cost of Equity? *Management Science*, *61*(2), 354-371.
- Lewellen, J., & Shanken, J. (2002). Learning, Asset-Pricing Tests, and Market Efficiency. *Journal of Finance*, *57*(3), 1113-1145.
- Li, K., & Mohanram, P. (2014). Evaluating cross-sectional forecasting models for implied cost of capital. *Review of Accounting Studies*, *19*(3), 1152-1185.
- Li, X. (2015). Accounting Conservatism and the Cost of Capital: An International Analysis. *Journal of Business Finance & Accounting*, *42*(5-6), 555-582.
- Liu, M., & Wysocki, P. (2016). Cross-Sectional Determinants of Information Quality Proxies and Cost of Capital Measures. *Quarterly Journal of Finance*, *0*(0), 1650016.
- Lopes, A. B., & de Alencar, R. C. (2010). Disclosure and cost of equity capital in emerging markets: The Brazilian case. *International Journal of Accounting*, *45*(4), 443-464.
- Luong, L. H., Nguyen, L. H., & Yin, X. (2011). *Institutional Investors, Private Information, and the Cost of Capital*. Available at SSRN: <https://ssrn.com/abstract=1972657>.
- Mangena, M., Li, J., & Tauringana, V. (2016). Disentangling the Effects of Corporate Disclosure on the Cost of Equity Capital: A Study of the Role of Intellectual Capital Disclosure. *Journal of Accounting Auditing and Finance*, *31*(1), 3-27.
- Mashruwala, C. A., & Mashruwala, S. D. (2011). The pricing of accruals quality: January versus the rest of the year. *The Accounting Review*, *86*(4), 1349-1381.
- McInnis, J. (2010). Earnings Smoothness, Average Returns, and Implied Cost of Equity Capital. *The Accounting Review*, *85*(1), 315-341.
- McNichols, M., & O'Brien, P. C. (1997). Self-Selection and Analyst Coverage. *Journal of Accounting Research*, *35*, 167-199.
- McNichols, M. F. (2002). The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors: Discussion. *The Accounting Review*, *77*, 61-69.
- Mohanram, P., & Gode, D. (2013). Removing predictable analyst forecast errors to improve implied cost of equity estimates. *Review of Accounting Studies*, *18*(2), 443-478.

- Mohanram, P., & Rajgopal, S. (2009). Is PIN priced risk? *Journal of Accounting and Economics*, 47(3), 226-243.
- Møller, A. P., & Jennions, M. D. (2001). Testing and adjusting for publication bias. *Trends in Ecology & Evolution*, 16(10), 580-586.
- Muino, F., & Trombetta, M. (2009). Does graph disclosure bias reduce the cost of equity capital? *Accounting and Business Research*, 39(2), 83-102.
- Ng, A. C., & Rezaee, Z. (2012). *Sustainability disclosures and cost of capital*. Available at SSRN: <https://ssrn.com/abstract=2038654>.
- Ng, A. C., & Rezaee, Z. (2015). Business sustainability performance and cost of equity capital. *Journal of Corporate Finance*, 34, 128-149.
- O'Hanlon, J., & Steele, A. (2000). Estimating the Equity Risk Premium Using Accounting Fundamentals. *Journal of Business Finance & Accounting*, 27(9-10), 1051-1083.
- Ogneva, M. (2012). Accrual Quality, Realized Returns, and Expected Returns: The Importance of Controlling for Cash Flow Shocks. *The Accounting Review*, 87(4), 1415-1444.
- Ogneva, M., Subramanyam, K. R., & Raghunandan, K. (2007). Internal control weakness and cost of equity: Evidence from SOX section 404 disclosures. *The Accounting Review*, 82(5), 1255-1297.
- Ohlson, J., & Juettner-Nauroth, B. (2005). Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies*, 10(2-3), 349-365.
- Orens, R., Aerts, W., & Cormier, D. (2010). Web-Based Non-Financial Disclosure and Cost of Finance. *Journal of Business Finance & Accounting*, 37(9-10), 1057-1093.
- Orens, R., Aerts, W., & Lybaert, N. (2009). Intellectual capital disclosure, cost of finance and firm value. *Management Decision*, 47(10), 1536-1554.
- Orens, R., Aerts, W., & Lybaert, N. (2013). Customer value disclosure and cost of equity capital. *Review of Accounting and Finance*, 12(2), 130-147.
- Orwin, R. G. (1983). A Fail-SafeN for Effect Size in Meta-Analysis. *Journal of Educational Statistics*, 8(2), 157-159.
- Othman, R. (2012). Impact of financial reporting quality on the implied cost of equity capital: Evidence from the Malaysian listed firms. *Asian Journal of Business and Accounting*, 3(1), 1-25.
- Paugam, L., & Ramond, O. (2015). Effect of Impairment-Testing Disclosures on the Cost of Equity Capital. *Journal of Business Finance & Accounting*, 42(5-6), 583-618.

- Pearlman, K., Schmidt, F. L., & Hunter, J. E. (1980). Validity generalization results for tests used to predict job proficiency and training success in clerical occupations. *Journal of Applied Psychology*, 65(4), 373.
- Plumlee, M., Brown, D., Hayes, R. M., & Marshall, R. S. (2015). Voluntary environmental disclosure quality and firm value: Further evidence. *Journal of Accounting and Public Policy*, 34(4), 336-361.
- Poshakwale, S., & Curtis, J. K. (2005). Disclosure level and cost of equity capital: evidence from the banking industry. *Managerial and Decision Economics*, 26(7), 431-444.
- Rao, P. (1973). Some Notes on the Errors-in-Variables Model. *The American Statistician*, 27(5), 217-218.
- Reverte, C. (2012). The Impact of Better Corporate Social Responsibility Disclosure on the Cost of Equity Capital. *Corporate Social Responsibility and Environmental Management*, 19(5), 253-272.
- Richardson, A. J., & Welker, M. (2001). Social disclosure, financial disclosure and the cost of equity capital. *Accounting, Organizations and Society*, 26(7-8), 597-616.
- Rosenthal, R. (1991). *Meta-analytic procedures for social research* (Vol. 6): Sage.
- Safdar, R., & Yan, C. (2016). Information risk, stock returns, and the cost of capital in China. *China Finance Review International*, 6(1), 77-95.
- Saini, J. S., & Herrmann, D. (2012). *Cost of equity capital, information asymmetry, and segment disclosure*. Available at SSRN: <https://ssrn.com/abstract=1758934>.
- Sheng, X., & Thevenot, M. (2015). Quantifying differential interpretation of public information using financial analysts' earnings forecasts. *International Journal of Forecasting*, 31(2), 515-530.
- Shevlin, T. (2013). Some personal observations on the debate on the link between financial reporting quality and the cost of equity capital. *Australian Journal of Management*, 38(3), 447-473.
- Souissi, M., & Khelif, H. (2012). Meta- analytic review of disclosure level and cost of equity capital. *International Journal of Accounting & Information Management*, 20(1), 49-62.
- Strobl, G. (2013). Earnings Manipulation and the Cost of Capital. *Journal of Accounting Research*, 51(2), 449-473.
- Tohang, V., & Hutagaol-Martowidjojo, Y. R. I. (2015). Corporate Voluntary Disclosure and Cost of Equity in an Emerging Country: Evidence from Indonesia. *Advanced Science Letters*, 21(4), 898-902.

- Verdi, R. S. (2005). *Information environment and the cost of equity capital*. Available at SSRN: <https://ssrn.com/abstract=757966>.
- Vuolteenaho, T. (2002). What Drives Firm-Level Stock Returns? *Journal of Finance*, 57(1), 233-264.
- Wang, C. (2015). Measurement errors of expected-return proxies and the implied cost of capital. *Harvard Business School Accounting & Management Unit Working Paper*(13-098).
- William Lin, H.-W., & Ke, W.-C. (2011). A computing bias in estimating the probability of informed trading. *Journal of Financial Markets*, 14(4), 625-640.
- Wu, S.-w., Lin, F., & Wu, C.-m. (2014). Corporate Social Responsibility and Cost of Capital: An Empirical Study of the Taiwan Stock Market. *Emerging Markets Finance and Trade*, 50, 107-120.
- Xiao-feng, H., Wei-ling, L., & Ming-yi, L. (2006, 5-7 Oct. 2006). *Empirical Study of the Relationship between Voluntary Disclosure and the Cost of Equity Capital*. Paper presented at the Management Science and Engineering.
- Xu, R. Z. (2009). Reexamination of the relationship between disclosure and cost of capital. *Global Journal of Business Research*, 3(1), 15-26.
- Yan, Y., & Zhang, S. (2012). An improved estimation method and empirical properties of the probability of informed trading. *Journal of Banking & Finance*, 36(2), 454-467.
- Yan, Y., & Zhang, S. (2014). Quality of PIN estimates and the PIN-return relationship. *Journal of Banking & Finance*, 43, 137-149.
- Zhang, X. F. (2006). Information Uncertainty and Stock Returns. *Journal of Finance*, 61(1), 105-137.
- Zhao, Y., Davis, M., & Berry, K. T. (2009). Disclosure channel and cost of capital: evidence from open vs closed conference calls. *Review of Accounting and Finance*, 8(3), 253-278.

**Table 1: Attributes and Keywords**

<b>Attributes</b>	<b>Keywords</b>
Information Quantity	<ul style="list-style-type: none"> <li>▪ information quantity/amount</li> <li>▪ information/estimation risk</li> <li>▪ mandatory/voluntary disclosure</li> <li>▪ financial/non-financial disclosure</li> <li>▪ age/listing/operating history</li> <li>▪ media/press coverage</li> <li>▪ firm/company prominence</li> </ul>
Information Precision	<ul style="list-style-type: none"> <li>▪ information precision/accuracy/quality</li> <li>▪ financial reporting quality</li> <li>▪ accounting quality</li> <li>▪ earnings quality/management</li> <li>▪ earnings attributes</li> <li>▪ accrual quality</li> <li>▪ analyst forecast</li> <li>▪ security analyst</li> <li>▪ analyst forecast precision/accuracy/dispersion</li> <li>▪ earnings/analyst characteristic</li> <li>▪ earnings persistence/predictability/smoothness/value relevance/timeliness/conservatism</li> </ul>
Information Asymmetry	<ul style="list-style-type: none"> <li>▪ information asymmetry/dissemination/dispersion</li> <li>▪ informational dis/advantages</li> <li>▪ un/informed investor</li> <li>▪ public/private information</li> <li>▪ probability of informed trading/PIN</li> <li>▪ bid-ask spread</li> <li>▪ investor concentration/competition</li> <li>▪ market liquidity</li> <li>▪ firm-specific information</li> <li>▪ idiosyncratic information</li> </ul>
Cost of Equity	<ul style="list-style-type: none"> <li>▪ cost of equity</li> <li>▪ cost of capital</li> <li>▪ implied cost of capital</li> <li>▪ expected rate of return</li> <li>▪ required rate of return</li> <li>▪ discount rate</li> <li>▪ weighted cost of capital</li> </ul>

*The table shows for each information attribute (and cost of equity) the respective keywords searched for in several databases and journals.*



**Table 2: Information Quantity on CoE – Description of Studies Included in the Meta-Analysis**

Study	Journal*	Country†	US?†	Disc. Env.€	Disc. Reg. Score§	No. of firms§	No. of firm-years‡	Sampling Period	DV: CoE‡	IV: Quantity£	Disc. Type£	Disc. Metric£	Direct Link?	Effect size (Pearson's <i>r</i> coeffi- cient)	Source of Information
Al Guindy (2016)	SSRN	US	Y	HDE	1.00	1,232	8,626	2007-2013	VMB	Disc.	NF	Dummy	Confirm	-0.0870	Table 5, p. 30
Al Guindy (2016)	SSRN	US	Y	HDE	1.00	54	381	2007-2013	VMB	Disc.	FF	Dummy	Confirm	-0.1008	Table 6, p. 31
Al-Hadi, Taylor, and Hossain (2015)	JMFM	6 Count.	N	LDE	n/a	141	705	2007-2011	VMB	Disc.	PF	SCI	Confirm	-0.0160	Table 2, p. 80
Bachoo et al. (2013)	AAR	AUS	N	LDE	0.75	150	450	2003-2005	VMB	Disc.	NF	Dummy	Confirm	-0.0157	Table 3, p. 78
Baginski and Rakow (2012)	RAST	US	Y	HDE	1.00	1,355	1,355	2004	VMB	Disc.	FF	SCI	Confirm	-0.1164	Table 4, p. 299
Blanco, Garcia Lara, and Tribo (2015)	JBFA	US	Y	HDE	1.00	1,667	10,002	2001-2006	VMB	Disc.	PF	SCI	Confirm	-0.1281	Table 6, p. 391
Blanco et al. (2015)	JBFA	US	Y	HDE	1.00	1,667	8,502 <sup>b</sup>	2001-2006	REAL	Disc.	PF	SCI	Confirm	-0.0314	Table 10, p. 398
Botosan (1997)	TAR	US	Y	HDE	1.00	122	122	1990	VMB	Disc.	PF	SCI	Confirm	-0.1430	Table 7, p. 342
Botosan and Plumlee (2002)	JAR	US	Y	HDE	1.00	246	2,706	1986-1996	VMB	Disc.	PF	EXI	Mixed	0.0110	Table 4, p. 34
Boujelbene and Affes (2013)	JEFA	FR	N	LDE	0.75	102	102	2009	RFB	Disc.	NF	SCI	Confirm	-0.2180	Table 4, p. 50
Campbell et al. (2014)	RAST	US	Y	HDE	1.00	2,048	8,193	2005-2008	REAL	Disc.	PF	SCI	Confirm	-0.0292	Table 8, p. 436
Cao et al. (2017)	RAST	31 Count.	B	n/a	0.84	6,309	37,856	2004-2009	VMB	Disc.	FF	Dummy	Confirm	-0.1500	Table 2, p. 14
Chen, Wei, and Chen (2003)	SSRN	9 Count.	N	LDE	0.87	273	545	2000-2001	VMB	Disc.	PF	EXI	Confirm	-0.1400	Table 6, p. 391
Cheng et al. (2006)	RQFA	US	Y	HDE	1.00	348	348	2001-2002	VMB	Disc.	FF	EXI	Confirm	-0.0500	Table 2, p. 193
Chien and Lu (2015)	IMDS	US	Y	HDE	1.00	4,122	16,488	2009-2012	RFB	Disc.	NF	SCI	Confirm	-0.0090	Table 4, p. 515
Clarkson et al. (2013)	JAPP	US	Y	HDE	1.00	98	195	2003, 2006	VMB	Disc.	NF	SCI	Reject	0.1096	Table 4. p. 423
Core et al. (2015)	EAR	35 Count.	B	n/a	0.86	3,347	50,201	1990-2004	VMB	Disc.	PF	SCI	Confirm	-0.0083	Table 3, p. 14
Core et al. (2015)	EAR	35 Count.	B	n/a	0.86	3,347	50,201	1990-2004	REAL	Disc.	PF	SCI	Confirm	-0.0030	Table 4, p. 18
Déjean and Martinez (2009)	AIE	FR	N	LDE	0.75	112	112	2006	RFB	Disc.	NF	SCI	Reject	0.1450	Table 5, p. 73
Dhaliwal et al. (2011)	TAR	US	Y	HDE	1.00	795	11,925	1993-2007	VMB	Disc.	NF	Dummy	Mixed	-0.0297	Table 4, p. 76
Dhaliwal et al. (2014)	JAPP	31 Count.	B	n/a	0.83	6,093	79,212	1995-2007	VMB	Disc.	NF	Dummy	Confirm	-0.0700	Table 3, p. 341
Elzahar, Hussainey, Mazzi, and Tsalavoutas (2015)	IRFA	UK	N	HDE	0.83	90	448	2006-2010	VMB	Disc.	FF	SCI	Confirm	-0.1695	Table 7, p. 106
Elzahar et al. (2015)	IRFA	UK	N	HDE	0.83	90	448	2006-2010	VMB	Disc.	NF	SCI	Reject	-0.0378	Table 7, p. 106
Embong, Mohd- Saleh, and Hassan (2012)	ARA	MY	N	LDE	0.92	135	406	2004-2006	VMB	Disc.	PF	SCI	Mixed	-0.1430	Table 2, p. 126

Table continued next page.

**Table 2: Information Quantity on CoE – Description of Studies Included in the Meta-Analysis (cont.)**

Study	Journal <sup>*</sup>	Country <sup>†</sup>	US? <sup>†</sup>	Disc. Env. <sup>‡</sup>	Disc. Reg. Score <sup>§</sup>	No. of firms <sup>§</sup>	No. of firm-years <sup>‡</sup>	Sampling Period	DV: CoE <sup>¶</sup>	IV: Quantity <sup>¶</sup>	Disc. Type <sup>¶</sup>	Disc. Metric <sup>¶</sup>	Direct Link?	Effect size (Pearson's <i>r</i> coefficient)	Source of Information
Espinosa and Trombetta (2007)	JBFA	SP	N	LDE	0.50	50	250	1998-2002	VMB	Disc.	PF	EXI	Mixed	-0.2000	Table 4, p. 1384
Eugster (2014)	SSRN	CH	N	LDE	0.67	104	1,039	1999-2008	VMB	Disc.	PF	EXI	Mixed	-0.2260	Table 4, p. 40
Evans (2016)	CAR	US	Y	HDE	1.00	187	935	2003-2007	VMB	Disc.	FF	SCI	Mixed	0.0440	Table 1, pp.1147-8
Feng, Li, and Gu (2009)	SSRN	US	Y	HDE	1.00	335	4,024	1995-2006	VMB	Disc.	FF	SCI	Mixed	-0.0343	Table 4, pp. 30-1
Francis, Khurana, et al. (2005)	TAR	23 Count.	N	n/a	0.69	137	274	1991, 1993	VMB	Disc.	PF	EXI	Confirm	-0.1450	Table 7, p. 1154
Francis et al. (2008)	JAR	US	Y	HDE	1.00	677	677	2001	VMB	Disc.	PF	SCI	Mixed	-0.0381	Table 4, p. 79
Fu et al. (2012)	JAE	US	Y	HDE	1.00	333	7,654	1951-1973	REAL	Disc.	NF	SCI	Confirm	-0.0600	Table 3, p. 139
Fu et al. (2012)	JAE	US	Y	HDE	1.00	333	7,654	1951-1973	RFB	Disc.	NF	SCI	Confirm	-0.0500	Table 3, p. 139
García-Sánchez and Noguera-Gámez (2017)	IBR	27 Count.	B	n/a	0.72	659	3,294	2009-2013	VMB	Disc.	PF	Dummy	Confirm	-0.0620	Table 5, p. 965
Gietzmann and Ireland (2005)	JBFA	UK	N	HDE	0.83	30	301	1993-2002	VMB	Disc.	PF	SCI	Mixed	-0.1340	Table 2c, p. 625
Grüning (2011)	BR	DE	N	LDE	0.42	361	361	2006	REAL	Disc.	PF	EXI	Confirm	-0.1580	Table 4, p. 58
Hail (2002)	EAR	CH	N	LDE	0.67	73	73	1997	VMB	Disc.	PF	EXI	Confirm	-0.4780	Table 5, p. 761
Healy et al. (1999)	CAR	US	Y	HDE	1.00	37	408	1980-1990	REAL	Disc.	PF	EXI	Confirm	-0.1034	Table 6, p. 504
Khelif, Samaha, and Azzam (2015)	JAAR	EG	N	LDE	0.50	73	292	2006-2009	RFB	Disc.	PF	SCI	Confirm	-0.2730	Table 4, p. 44
Kim and Shi (2011)	JAPP	US	Y	HDE	1.00	1,066	3,198	2003-2005	VMB	Disc.	FF	Dummy	Mixed	0.0148	Table 5, p. 360
Kothari et al. (2009)	TAR	US	Y	HDE	1.00	223	1,338 <sup>a</sup>	1996-2001	RFB	Disc.	PF	SCI	Confirm	-0.0313	Table 3, p. 1658
Kristandl and Bontis (2007)	JIC	4 Count.	N	LDE	0.46	95	95	2004	VMB	Disc.	PF	SCI	Mixed	0.0315	Table 6, p. 587
La Rosa and Liberatore (2014)	EMJ	8 Count.	N	n/a	0.60	62	309	2005-2009	VMB	Disc.	PF	SCI	Reject	0.0560	Table 10, p. 816
Lopes and de Alencar (2010)	IJA	BR	N	LDE	0.25	55	276	1998, 2000/02/04/05	VMB	Disc.	PF	SCI	Confirm	-0.2900	Table 3, p. 454
Mangena et al. (2016)	JAAF	UK	N	HDE	0.83	125	125	2004	VMB	Disc.	FF	SCI	Confirm	-0.2500	Table 3, p. 12
Mangena et al. (2016)	JAAF	UK	N	HDE	0.83	125	125	2004	VMB	Disc.	NF	SCI	Confirm	-0.3440	Table 3, p. 12
Ng and Rezaee (2015)	JCF	Global	B	n/a	n/a	598	13,745	1991-2013	VMB	Disc.	NF	SCI	Confirm	-0.0300	Table 3, pp. 138-9
Ogneva et al. (2007)	TAR	US	Y	HDE	1.00	2,021	2,021	2004	VMB	Disc.	NF	Dummy	Reject	0.0127	Table 2, pp.1268-9

Table continued next page.

**Table 2: Information Quantity on CoE – Description of Studies Included in the Meta-Analysis (cont.)**

Study	Journal <sup>*</sup>	Country <sup>†</sup>	US? <sup>†</sup>	Disc. Env. <sup>‡</sup>	Disc. Reg. Score <sup>§</sup>	No. of firms <sup>§</sup>	No. of firm-years <sup>‡</sup>	Sampling Period	DV: CoE <sup>¥</sup>	IV: Quantity <sup>¥</sup>	Disc. Type <sup>¥</sup>	Disc. Metric <sup>¥</sup>	Direct Link?	Effect size (Pearson's <i>r</i> coefficient)	Source of Information
Orens, Aerts, and Lybaert (2009)	MD	4 Count.	N	LDE	0.55	223	223	2002	VMB	Disc.	NF	SCI	Confirm	-0.1313	Table 4, pp.1547-8
Orens, Aerts, and Cormier (2010)	JBFA	7 Count.	B	n/a	0.84	668	668	2002	VMB	Disc.	NF	SCI	Confirm	-0.2720	Table 5, p. 1076
Orens, Aerts, and Lybaert (2013)	RAF	4 Count.	N	LDE	0.52	217	217	2002	VMB	Disc.	NF	SCI	Confirm	-0.1150	Table 4, p. 139
Paugam and Ramond (2015)	JBFA	FR	N	LDE	0.75	445	445	2009	VMB	Disc.	FF	SCI	Confirm	-0.1112	Table 4, p. 606
Plumlee et al. (2015)	JAPP	US	Y	HDE	1.00	79	474	2000-2005	VMB	Disc.	NF	SCI	Confirm	-0.0150	Table 3, p. 351
Poshakwale and Courtis (2005)	MDE	Global	B	n/a	n/a	27	135	1995-1999	VMB	Disc.	PF	SCI	Confirm	-0.3410	Table 4, p. 438
Reverte (2012)	CSREM	SP	N	LDE	0.50	19	114	2003-2008	VMB	Disc.	NF	EXI	Confirm	-0.2388	Table 4, p. 263
Richardson and Welker (2001)	AOS	CA	N	HDE	0.92	108	324	1990-1992	VMB	Disc.	FF	EXI	Confirm	-0.0460	Table 2, p. 604
Richardson and Welker (2001)	AOS	CA	N	HDE	0.92	108	324	1990-1992	VMB	Disc.	NF	EXI	Reject	0.0110	Table 2, p. 604
Saini and Herrmann (2012)	SSRN	US	Y	HDE	1.00	87	87	2005	VMB	Disc.	PF	SCI	Confirm	-0.0770	Table 2, p. 42
Tohang and Hutagaol-Martowidjojo (2015)	ASL	ID	N	LDE	0.50	29	58	2010-2011	VMB	Disc.	PF	SCI	Confirm	-0.2210	Table 2, p. 901
Wu et al. (2014)	EMFT	TW	N	LDE	0.75	121	482	2007-2010	VMB	Disc.	NF	Dummy	Confirm	-0.0930	Table 3, p. 113
Xiao-feng, Wei-ling, and Ming-yi (2006)	MSE	CH	N	LDE	0.67	102	102	2005	VMB	Disc.	PF	SCI	Confirm	-0.5200	Table 4, p. 1449
Xu (2009)	GJBR	US	Y	HDE	1.00	212	212	1996	VMB	Disc.	PF	EXI	Mixed	-0.0300	Table 3, p. 21
Zhao, Davis, and Berry (2009)	RAF	US	Y	HDE	1.00	255	255	2000	VMB	Disc.	NF	Dummy	Confirm	-0.1529	Table 9, p. 274

Notes: \* Journal names along with their ABS 2015 ranking are shown in the appendix. <sup>†</sup> AU: Australia; BR: Brazil; CH: Switzerland; CA: Canada; DE: Germany; EG: Egypt; FR: France; ID: Indonesia; MY: Malaysia; SP: Spain; TW: Taiwan; UK: United Kingdom; US: United States; Studies focusing on US firms only are denoted (Y), non-US studies (N) and studies using inseparably both US and non-US firms in their sample (B). <sup>‡</sup> Disc. Reg.: Disclosure regulation score from La Porta et al. (2006); in the case of multi-country studies scores are a weighted average by number of firm-years per country. <sup>§</sup> Number of firms is approximated as number of firm-years divided by number of sample years. <sup>¥</sup> When multiple samples are selected for one study, average sample size is reported. <sup>¥</sup> REAL: realised-return, RFB: risk factor-based, VMB: valuation model-based cost of equity proxy. <sup>¥</sup> Disc.: Disclosure; Disclosure Types: Full-financial (FF), part-financial (PF), non-financial (NF) disclosure; Disclosure Metrics: Self-constructed index (SCI), external third-party index (EXI), binary dummy variable (Dummy). <sup>¶</sup> <sup>a</sup> Converted firm-quarters into firm-years. <sup>b</sup> Converted firm-months into firm-years.

**Table 3: Information Precision on CoE – Description of Studies Included in the Meta-Analysis**

Study	Journal*	Country <sup>†</sup>	No. of firms <sup>§</sup>	No. of firm-years <sup>‡</sup>	Sampling Period	DV: CoE <sup>¥</sup>	IV: Precision <sup>£</sup>	Direct Link?	Effect size (Pearson's <i>r</i> coefficient)	Source of Information
Artiach and Clarkson (2014)	AJM	US	196	3,138	1985-2000	VMB	Acc.Qual.	Confirm	-0.0593	Table 3, p. 305
Barron et al. (2012)	SSRN	US	307	8,606 <sup>a</sup>	1983-2010	VMB	Analyst	Confirm	-0.2327	Table 2, p. 29
Barth et al. (2013)	JAE	US	1,985	51,612	1974–2000	RFB	Acc.Qual.	Confirm	-0.1210	Table 1, p. 214
Barth et al. (2013)	JAE	US	1,985	51,612	1974–2000	REAL	Acc.Qual.	Confirm	-0.0380	Table 1, p. 214
Berger, Chen, and Li (2012)	SSRN	US	1,665	41,615	1980-2004	RFB	Acc.Qual.	Confirm	-0.0475	Table 7, p. 33
Berger et al. (2012)	SSRN	US	1,015	25,365	1980-2004	VMB	Acc.Qual.	Confirm	-0.0830	Table 5, p. 29
Bhattacharya et al. (2012)	TAR	US	1,054	12,648	1993-2005	RFB	Acc.Qual.	Confirm	-0.1770	In-text, p. 475
Bhattacharya et al. (2012)	TAR	US	1,054	12,648	1993-2005	VMB	Acc.Qual.	Confirm	-0.2243	Table 2, p. 463
Botosan and Plumlee (2013)	JBFA	US	555	6,656	1993-2004	VMB	Analyst	Mixed	-0.1470	Table 3, p. 1061
Botosan et al. (2004)	RAST	US	312	2,804	1993-2001	VMB	Analyst	Mixed	-0.0930	Table 2, p. 247
Callen, Khan, and Lu (2013)	CAR	US	1,129	29,345	1981-2006	REAL	Acc.Qual.	Confirm	-0.0354	Table 5 & 6, pp. 283-85
Callen et al. (2013)	CAR	US	841	19,336	1984-2006	VMB	Acc.Qual.	Confirm	-0.0416	Table 7, p. 287
Chan, Lin, and Strong (2009)	MF	UK	416	5,403	1987-1999	VMB	Acc.Qual.	Mixed	-0.0190	Table 3, p. 336
Chan et al. (2009)	MF	UK	416	5,403	1987-1999	REAL	Acc.Qual.	Mixed	-0.0288	Table 9, p. 342
Chan, Lo, and Yang (2016)	NAJEF	US	1,828	32,910	1996-2013	RFB	Analyst	Confirm	-0.1203	Table 4, p.125
Chen, Dhaliwal, and Trombley (2008)	JAAF	US	2,122	53,048	1980-2004	REAL	Acc.Qual.	Confirm	-0.0420	Table 2, p. 480
Chen et al. (2008)	JAAF	US	614	15,339	1980-2004	VMB	Acc.Qual.	Confirm	-0.0433	Table 4, p. 489
Cohen (2003)	SSRN	US	1,111	16,664	1987-2001	VMB	Acc.Qual.	Reject	-0.0045	Table 6 & 8, pp. 44-6
Cohen (2008)	APJAE	US	1,074	18,264	1987–2003	VMB	Acc.Qual.	Reject	-0.0068	Table 3, p. 83
Cohen (2008)	APJAE	US	1,074	18,264	1987–2003	RFB	Acc.Qual.	Reject	-0.0052	Table 4, p. 85
Core et al. (2008)	JAE	US	2,909	93,093	1970-2001	REAL	Acc.Qual.	Reject	0.0003	Table 4 & 5, pp. 11-3
Core et al. (2008)	JAE	US	814	21,979	1975-2001	VMB	Acc.Qual.	Reject	-0.0386	Table 8, p. 18
Diether et al. (2002)	JF	US	2,908	66,884	1980-2002	REAL	Analyst	Reject	0.0089	Table 9, p. 2136
Diether et al. (2002)	JFQA	US	1,203	22,854	1983-2001	REAL	Analyst	Confirm	-0.0585	Table 8, p. 597
Eliwa, Haslam, and Abraham (2016)	IRFA	UK	587	4,112	2005–2011	VMB	Acc.Qual.	Confirm	-0.0714	Table 1, p. 131

*Table continued next page.*

**Table 3: Information Precision on CoE – Description of Studies Included in the Meta-Analysis (cont)**

Study	Journal*	Country <sup>†</sup>	No. of firms <sup>§</sup>	No. of firm-years <sup>‡</sup>	Sampling Period	DV: CoE <sup>¥</sup>	IV: Precision <sup>£</sup>	Direct Link?	Effect size (Pearson's <i>r</i> coefficient)	Source of Information
Francis et al. (2004)	TAR	US	790	21,334	1975-2001	VMB	Acc.Qual.	Confirm	-0.0481	Table 5, 6 & 9, pp. 990-1001
Francis, LaFond, Olsson, and Schipper (2005a)	JAE	US	1,722	55,092	1970-2001	VMB	Acc.Qual.	Confirm	-0.0248	Table 2, p. 309
García Lara, García Osma, and Penalva (2011)	RAST	US	1,875	54,389	1975-2003	REAL	Acc.Qual.	Confirm	-0.0139	Table 4 & 6, pp. 261-4
Gray, Koh, and Tong (2009)	JBFA	AU	170	1,362	1998-2005	VMB	Acc.Qual.	Confirm	-0.0676	Table 3, p. 63
Gray et al. (2009)	JBFA	AU	170	1,362	1998-2005	REAL	Acc.Qual.	Confirm	-0.0730	Table 4 & 5, pp. 66-8
Hou (2015)	RAST	US	1,418	41,134	1982-2010	VMB	Acc.Qual.	Confirm	-0.1275	Table 2, p. 1073
Hwang and Lim (2012)	APJFS	US	645	9,672	1993-2007	VMB	Acc.Qual.	Confirm	-0.1640	Table 2, p. 471
Kim and Qi (2010)	TAR	US	2,802	103,682	1970-2006	REAL	Acc.Qual.	Mixed	-0.0040	Table 4, pp. 947-9
Kim and Sohn (2013)	JAPP	US	1,211	30,276	1987-2011	VMB	Acc.Qual.	Confirm	-0.0673	Table 2, p. 529
Konchitchki et al. (2016)	RAST	US	2,567	100,095	1976-2014	REAL	Acc.Qual.	Confirm	-0.0118	Table 5, p. 21
Larson and Resutec (2015)	SSRN	US	79	2,684	1978-2011	REAL	Acc.Qual.	Mixed	-0.0491	Table 6 & 8, p. 42-4
Larson and Resutec (2015)	SSRN	US	49	1,728	1977-2011	VMB	Acc.Qual.	Mixed	-0.1102	Table 9, p. 45
Latiff and Taib (2011)	ATBMR	MY	141	141	2004	VMB	Acc.Qual.	Confirm	-0.1624	Table 4, p. 6
Liu and Wysocki (2016)	QJF	US	1,454	68,348	1960-2006	RFB	Acc.Qual.	Mixed	-0.1200	Table 3, p. 15
Liu and Wysocki (2016)	QJF	US	945	44,392	1960-2006	VMB	Acc.Qual.	Mixed	-0.0700	Table 3, p. 15
Mashruwala and Mashruwala (2011)	TAR	US	2,561	92,187	1971-2006	REAL	Acc.Qual.	Mixed	-0.0048	Table 6, p. 1368
McInnis (2010)	TAR	US	1,777	56,870 <sup>b</sup>	1975-2006	REAL	Acc.Qual.	Reject	-0.0025	Table 1, p. 321
McInnis (2010)	TAR	US	438	14,008	1975-2001	VMB	Acc.Qual.	Reject	-0.0444	Table 4, p. 328
Ogneva (2012)	TAR	US	2,184	80,790	1970-2006	REAL	Acc.Qual.	Mixed	-0.0048	Table 4, pp. 1433-4
Othman (2012)	AJBA	MY	461	3,688	2000-2007	VMB	Acc.Qual.	Confirm	-0.0319	Table 3, p. 17
Safdar and Yan (2016)	CFRI	CN	1,251	8,754	2006-2012	VMB	Acc.Qual.	Mixed	-0.0244	Table 2, p. 87
Safdar and Yan (2016)	CFRI	CN	1,251	8,754	2006-2012	REAL	Acc.Qual.	Mixed	-0.0138	Table 3, 5, & 6, p. 89-92
Sheng and Thevenot (2015)	IJF	US	128	3,583 <sup>a</sup>	1984-2011	VMB	Analyst	Confirm	-0.3300	Table 2, p. 521

Notes: \* Journal names along with their ABS 2015 ranking are shown in the appendix. <sup>†</sup> AU: Australia; CN: China; MY: Malaysia; UK: United Kingdom; US: United States. <sup>§</sup> Number of firms is approximated as number of firm-years divided by number of sample years. <sup>‡</sup> When multiple samples are selected for one study, average sample size is reported. <sup>¥</sup> REAL: realised-return, RFB: risk factor-based, VMB: valuation model-based cost of equity proxy. <sup>£</sup> Acc.Qual: Accounting/Earnings Quality, Analyst: security analyst forecast based proxy. <sup>a</sup> Converted firm-quarters into firm-years. <sup>b</sup> Converted firm-months into firm-years.

**Table 4: Information Asymmetry on CoE – Description of Studies Included in the Analysis**

Study	Journal*	Country <sup>†</sup>	Sampling Period	DV: CoE <sup>‡</sup>	IV: Asymmetry <sup>‡</sup>	Proxy <sup>‡</sup>	Direct Link?	Source of Information <sup>§</sup>
Akins et al. (2012)	TAR	US	1984-2009	REAL	Micro.	B/A	Mixed	Table 3, p. 48
Akins et al. (2012)	TAR	US	1984-2005	REAL	Micro.	PIN	Mixed	Table 4, p. 50
Amihud and Mendelson (1986)	JFE	US	1961-1980	REAL	Micro.	B/A	Confirm	Table 3, p. 236
Armstrong et al. (2011)	JAR	US	1988-2006	REAL	Micro.	B/A	Mixed	Table 3 & 4, pp. 23-8
Armstrong et al. (2011)	JAR	US	1976-2006	REAL	Non-Micro.	Acc.Qual.	Mixed	Table 3 & 4, pp. 23-8
Armstrong et al. (2011)	JAR	US	1976-2006	REAL	Non-Micro.	Analyst	Mixed	Table 3 & 4, pp. 23-8
Aslan et al. (2011)	JEF	US	1965-2009	REAL	Micro.	PIN	Confirm	Table 8, p. 796
Barron et al. (2012)	SSRN	US	1983-2010	VMB	Non-Micro.	Analyst	Confirm	Table 4, p. 32-4
Bhattacharya et al. (2012)	TAR	US	1993-2005	VMB	Micro.	B/A	Confirm	Table 2, p. 463
Bhattacharya et al. (2012)	TAR	US	1993-2005	VMB	Micro.	PIN	Confirm	Table 2, p. 463
Botosan and Plumlee (2013)	JBFA	US	1993-2004	VMB	Micro.	PIN	Confirm	Table 4, p. 1062
Botosan and Plumlee (2013)	JBFA	US	1993-2004	REAL	Micro.	PIN	Reject	Table 4, p. 1062
Brennan et al. (2016)	MS	US	1983-2010	REAL	Micro.	PIN	Confirm	Table 4 & 5, pp. 2469-70
Choi, Jin, and Yan (2016)	SSRN	CN	1996-2007	REAL	Non-Micro.	Comp.	Confirm	Table 6, p. 36
Duarte and Young (2009)	JFE	US	1984-2004	REAL	Micro.	PIN	Reject	Table 10, p. 136
Duarte, Han, Harford, and Young (2008)	JFE	US	1985-2000	REAL	Micro.	PIN	Confirm	Table 5, p. 37
Easley et al. (2002)	JF	US	1984-1998	REAL	Micro.	PIN	Confirm	Table 6, p. 2213
Easley, Hvidkjaer, and O'Hara (2010)	JFQA	US	1983-2001	REAL	Micro.	PIN	Confirm	Table 6, p. 307
Eleswarapu and Reinganum (1993)	JFE	US	1961-1990	REAL	Micro.	B/A	Mixed	Table 2, p. 379
He, Lepone, and Leung (2013)	IREF	AU	2001-2008	VMB	Micro.	B/A	Confirm	Table 4 & 5, p. 617-8
Hwang et al. (2013)	JAE	KR	2000-2004	VMB	Micro.	PIN	Mixed	Table 5, p. 158
Hwang et al. (2013)	JAE	KR	1995-2005	REAL	Micro.	PIN	Mixed	Table 9, p. 162
Kang (2010)	JBF	US	1984-2002	REAL	Micro.	PIN	Mixed	Table 4, p. 2990
Levi and Zhang (2015)	MS	US	1993-2003	REAL	Micro.	B/A	Confirm	Table 3, p. 361

*Table continued next page.*

**Table 4: Information Asymmetry on CoE – Description of Studies Included in the Analysis (cont.)**

Study	Journal*	Country†	Sampling Period	DV: CoE‡	IV: Asymmetry‡	Proxy‡	Direct Link?	Source of Information§
Luong et al. (2011)	SSRN	US	1984-2006	REAL	Micro.	PIN	Mixed	Table 5, pp. 46-7
Mohanram and Rajgopal (2009)	JAE	US	1984-2002	VMB	Micro.	PIN	Reject	Table 7, p. 239
Mohanram and Rajgopal (2009)	JAE	US	1984-2002	REAL	Micro.	PIN	Reject	Table 1, p. 230
Yan and Zhang (2014)	JBF	US	1983-2005	REAL	Micro.	PIN	Confirm	Table 8, p. 147

Notes: \* Journal names along with their ABS 2015 ranking are shown in the appendix. † AU: Australia; CN: China; KR: South Korea; US: United States. ‡ REAL: realised-return, VMB: valuation model-based cost of equity proxy. ‡(Non-)Micro.: (Non-)Microstructure-based proxies. ‡ B/A: Bid/Ask-spreads; PIN: Probability of informed trading scores; Acc.Qual.: Accounting/Earnings Quality, Comp.: market competition, Analyst: security analyst forecast based proxy. § Information used to decide if a study confirms/rejects or finds mixed results regarding the direct link between Asymmetry and CoE.

**Table 5: Descriptive Statistics of Quantity, Precision and Asymmetry Studies**

	Quantity		Precision		Asymmetry		Total	
<b>Sample</b>								
Observations	62	100%	48	100%	28	100%	138	100%
Studies	56	90%	35	73%	22	79%	113	82%
<b>Direct Link</b>								
Accept	44	71%	27	56%	16	57%	87	63%
Reject	6	10%	8	17%	4	14%	18	13%
Mixed	12	19%	13	27%	8	29%	33	24%
<b>Published Work</b>								
Yes	50	81%	42	88%	25	89%	117	85%
No	12	19%	6	13%	3	11%	21	15%
<b>Publ. Quality</b>								
Higher-Tier	37	60%	29	60%	24	86%	90	65%
Lower-Tier	25	40%	19	40%	4	14%	48	35%
<b>Country</b>								
US	25	40%	41	85%	24	86%	90	65%
Non-US	37	60%	7	15%	4	14%	48	35%
<b>CoE Proxy</b>								
REAL	6	10%	16	33%	21	75%	43	31%
VMB	50	81%	26	54%	7	25%	83	60%
RFB	6	10%	6	13%	0	0%	12	9%
<b>Quantity Proxy</b>								
Disclosure	62	100%					62	45%
thereof: FF/PF/NF	11/29/22	18/47/35%					62	45%
thereof: SCI/EXI/Dummy	38/13/11	61/21/18%					62	45%
<b>Precision Proxy</b>								
Acc. Quality			41	85%			41	30%
Analyst			7	15%			7	5%
<b>Asymmetry Proxy</b>								
Micro.					24	86%	24	17%
Non-Micro.					4	14%	4	3%

*Notes: This table reports descriptive statistics of the Quantity, Precision and Asymmetry studies included in the literature review for several sample characteristics: (i) Sample: number of studies and observations included; (ii) Direct Link: number of observations (no. of obs.) accepting, rejecting, and finding mixed results for the link with CoE; (iii) Published Work: no. of obs. which are published and unpublished; (iv): Publication Quality: no. of obs. appearing in higher-tier journals (4 & 3 rated journals in ABS 2015 list) and lower-tier journals (ABS 2015 2 & 1 rated, unranked and unpublished work); (v) Country: no. of obs. focusing on US and non-US firms; (vi) CoE Proxy: no. of obs. using realised-return (REAL), risk factor-based (RFB) and valuation model-based (VMB) cost of equity proxies; (vii): Quantity Proxy: no. of obs. focusing on full-financial (FF), part-financial (PF), non-financial (NF) disclosure and using self-constructed indices (SCI), external third-party indices (EXI) and binary dummy variables (Dummy) to measures quantity; (viii) Precision Proxy: no. of obs. applying accounting quality (Acc. Quality) and analyst-based (Analyst) proxies; (ix) Asymmetry Proxy: no. of obs. using microstructure (Micro.) and non- microstructure-based proxies;*



**Table 6: Results by Disclosure Types and CoE Measures**

	<b>Full-Financial (FF)</b>	<b>Partial-Financial (PF)</b>	<b>Non-Financial (NF)</b>	<b>Total</b>
<b>RFB/VMB</b>				
r:	-0.117**	-0.069	-0.053	-0.075
95% CI:	[-0.215; -0.018]	[-0.215; 0.078]	[-0.167; 0.060]	[-0.204; 0.054]
$\frac{S_e^2}{S_r^2}$ :	0.288	0.331	0.263	0.258
$\chi_{K-1}^2$ :	38.14***	72.55***	79.85***	217.38***
K:	11	24	21	56
Sample:	10,423	8,625	17,560	36,607
<b>REAL</b>				
r:	-	-0.025	-0.060	-0.026
95% CI:	-	[-0.066; 0.017]	[-0.060; -0.060]#	[-0.063; 0.011]
$\frac{S_e^2}{S_r^2}$ :	-	0.599	-	0.686
$\chi_{K-1}^2$ :	-	8.34	-	8.75
K:	-	5	1	6
Sample:	-	7,460	333	7,793
<b>Total</b>				
r:	-0.117**	-0.048	-0.054	-0.066
95% CI:	[-0.215; -0.018]	[-0.167; 0.071]	[-0.165; 0.058]	[-0.190; 0.058]
$\frac{S_e^2}{S_r^2}$ :	0.288	0.328	0.275	0.257
$\chi_{K-1}^2$ :	38.14***	88.42***	79.86***	241.21***
K:	11	29	22	62
Sample:	10,423	16,085	17,892	44,400

Notes: This contingency table reports average effect size ( $r$ ), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi_{K-1}^2$ ), number of studies ( $K$ ) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure. # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.

**Table 7: Results by Disclosure Types and Disclosure Metrics**

	<b>Full-Financial (FF)</b>	<b>Partial-Financial (PF)</b>	<b>Non-Financial (NF)</b>	<b>Total</b>
<b>SCI</b>				
r:	-0.101***	-0.039	-0.052	-0.050
95% CI:	[-0.215; -0.018]	[-0.145; 0.067]	[-0.217; 0.12]	[-0.179; 0.079]
$\frac{S_e^2}{S_r^2}$ :	0.654	0.317	0.205	0.270
$\chi_{K-1}^2$ :	9.17*	60.00***	63.36***	140.89***
K:	6	19	13	38
Sample:	2,537	13,934	7,098	23,569
<b>EXI</b>				
r:	-0.049	-0.128*	-0.026	-0.104
95% CI:	[-0.049; -0.049]#	[-0.278; 0.022]	[-0.026; -0.026]#	[-0.231; 0.023]
$\frac{S_e^2}{S_r^2}$ :	1509.313	0.500	1.980	0.594
$\chi_{K-1}^2$ :	0.00	18.00**	1.01	21.89**
K:	2	9	2	13
Sample:	456	1,492	127	2,075
<b>Dummy</b>				
r:	-0.126**	-0.062	-0.055*	-0.083
95% CI:	[-0.232; -0.020]	[-0.062; -0.062]#	[-0.109; 0.00]	[-0.186; 0.020]
$\frac{S_e^2}{S_r^2}$ :	0.117	-	0.456	0.173
$\chi_{K-1}^2$ :	25.60***	-	15.36**	63.47***
K:	3	1	7	11
Sample:	7,430	659	10,667	18,756
<b>Total</b>				
r:	-0.117**	-0.048	-0.054	-0.066
95% CI:	[-0.215; -0.018]	[-0.167; 0.071]	[-0.165; 0.058]	[-0.190; 0.058]
$\frac{S_e^2}{S_r^2}$ :	0.288	0.328	0.275	0.257
$\chi_{K-1}^2$ :	38.14***	88.42***	79.86***	241.21***
K:	11	29	22	62
Sample:	10,423	16,085	17,892	44,400

Notes: This contingency table reports average effect size ( $r$ ), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi_{K-1}^2$ ), number of studies ( $K$ ) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. Distinction is made between type of disclosures—studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure—and disclosure metrics—studies using self-constructed disclosure indexes (SCI), externally provided third-party indices (EXI) or simple dummy variables to distinguish between disclosing and non-disclosing firms (Dummy). # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.

**Table 8: Results by Disclosure Types and Disclosure Regimes**

<i>Panel A: US and Non-US Firms</i>				
	<b>Full-Financial (FF)</b>	<b>Partial-Financial (PF)</b>	<b>Non-Financial (NF)</b>	Total
<b>US</b>				
r:	-0.050	-0.056**	-0.022	-0.039
95% CI:	[-0.136; 0.035]	[-0.102; -0.010]	[-0.073; 0.028]	[-0.104; 0.026]
$\frac{S_e^2}{S_r^2}$ :	0.484	0.720	0.592	0.539
$\chi^2_{K-1}$ :	12.39*	13.88	15.20*	46.38***
K:	6	10	9	25
Sample:	3,346	6,986	9,267	19,599
<b>Non-US</b>				
r:	-0.131	-0.173*	-0.098	-0.139
95% CI:	[-0.131; -0.131]#	[-0.375; 0.028]	[-0.264; 0.069]	[-0.361; 0.037]
$\frac{S_e^2}{S_r^2}$ :	1.352	0.437	0.517	0.478
$\chi^2_{K-1}$ :	2.96	34.33***	19.33**	60.68***
K:	4	15	10	29
Sample:	768	1,720	1,266	3,754
<i>Panel B: High and Low Disclosure Regulation</i>				
<b>HIGH</b>				
r:	-0.117**	-0.035	-0.053	-0.062
95% CI:	[-0.220; -0.014]	[-0.093; 0.024]	[-0.166; 0.061]	[-0.176; 0.052]
$\frac{S_e^2}{S_r^2}$ :	0.262	0.544	0.203	0.221
$\chi^2_{K-1}$ :	38.13***	27.58**	69.05***	176.65***
K:	10	15	14	39
Sample:	9,978	14,118	16,351	40,446
<b>LOW</b>				
r:	-0.111	-0.153	-0.083	-0.126
95% CI:	[-0.111; -0.111]#	[-0.381; 0.075]	[-0.187; 0.021]	[-0.314; 0.061]
$\frac{S_e^2}{S_r^2}$ :	-	0.320	0.721	0.400
$\chi^2_{K-1}$ :	-	37.47***	9.71	50.04***
K:	1	12	7	20
Sample:	445	1,800	944	3,188

Table continued next page.

**Table 8: Results by Disclosure Types and Disclosure Regimes (cont.)**

<i>Panel C: High (HDE) and Low Disclosure Environments (LDE)</i>				
	<b>Full-Financial (FF)</b>	<b>Partial-Financial (PF)</b>	<b>Non-Financial (NF)</b>	<b>Total</b>
<b>HDE</b>				
r:	-0.060	-0.056***	-0.026	-0.043
95% CI:	[-0.159; 0.039]	[-0.097; -0.015]	[-0.107; 0.054]	[-0.122; 0.037]
$\frac{S_e^2}{S_r^2}$ :	0.490	0.782	0.426	0.489
$\chi^2_{K-1}$ :	18.38**	14.07	28.14***	65.46***
K:	9	11	12	32
Sample:	3,668	7,016	9,590	20,275
<b>LDE</b>				
r:	-0.111	-0.186*	-0.083	-0.141
95% CI:	[-0.111; -0.111]#	[-0.398; 0.026]	[-0.187; 0.021]	[-0.326; 0.044]
$\frac{S_e^2}{S_r^2}$ :	-	0.390	0.721	0.429
$\chi^2_{K-1}$ :	-	30.74***	9.71	46.66***
K:	1	12	7	20
Sample:	445	1,491	944	2,879
<b>Total</b>				
r:	-0.117**	-0.048	-0.054	-0.066
95% CI:	[-0.215; -0.018]	[-0.167; 0.071]	[-0.165; 0.058]	[-0.190; 0.058]
$\frac{S_e^2}{S_r^2}$ :	0.288	0.328	0.275	0.257
$\chi^2_{K-1}$ :	38.14***	88.42***	79.86***	241.21***
K:	11	29	22	62
Sample:	10,423	16,085	17,892	44,400

Notes: This contingency table reports average effect size ( $r$ ), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi^2_{K-1}$ ), number of studies ( $K$ ) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. Distinction is made between types of disclosures (i.e., studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure) and the following disclosure regimes: Panel A reports results for US and non-US firms, Panel B categorises studies according to their disclosure regulation scores, with studies below the sample average of 0.83 being assigned to the LOW group and the remainder to the HIGH group; Panel C distinguishes between high disclosure environments (HDE: US, CA, UK) and a low disclosure environments (LDE: AUS, BR, CH, DE, EG, FR, ID, MY, SP, TW) with the respective countries assigned to each group in parentheses. # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.

**Table 9: Results by Information Precision and CoE Measures**

	Acc.Qual.	Analyst	Total
<b>RFB/VMB</b>			
r:	-0.074	-0.142***	-0.082
95% CI:	[-0.168; 0.020]	[-0.211; -0.073]	[-0.183; 0.019]
$\frac{S_e^2}{S_r^2}$ :	0.324	0.554	0.304
$\chi_{K-1}^2$ :	83.21***	9.03*	105.13***
K:	27	5	32
Sample:	24,194	3,130	27,324
<b>REAL</b>			
r:	-0.014	-0.011	-0.014
95% CI:	[-0.014; -0.014]#	[-0.053; 0.031]	[-0.014; -0.014]#
$\frac{S_e^2}{S_r^2}$ :	2.484	0.517	1.675
$\chi_{K-1}^2$ :	5.63	3.87	9.55
K:	14	2	16
Sample:	23,826	4,111	27,937
<b>Total</b>			
r:	-0.044	-0.067	-0.048
95% CI:	[-0.129; 0.040]	[-0.206; 0.071]	[-0.142; 0.047]
$\frac{S_e^2}{S_r^2}$ :	0.313	0.161	0.270
$\chi_{K-1}^2$ :	131.18***	43.50***	177.89***
K:	41	7	48
Sample:	48,020	7,241	55,261

Notes: This contingency table reports average effect size ( $r$ ), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi_{K-1}^2$ ), number of studies ( $K$ ) and sample size as the average number of firms per year (sample) for the association between Information Precision and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies applying accounting quality (Acc.Qual.) and analyst-based (Analyst) proxies for Precision. # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.

**Table 10: Results by Accounting Quality and CoE Measures**

	AQ-Metric	Non-AQ-Metric	Total
<b>RFB/VMB</b>			
r:	-0.082	-0.063***	-0.074
95% CI:	[-0.203; 0.038]	[-0.083; -0.043]	[-0.168; 0.020]
$\frac{S_e^2}{S_r^2}$ :	0.220	0.918	0.324
$\chi^2_{K-1}$ :	68.04***	13.08	83.21***
K:	15	12	27
Sample:	13,891	10,303	24,194
<b>REAL</b>			
r:	-0.011	-0.020	-0.014
95% CI:	[-0.011; -0.011]#	[-0.020; -0.020]#	[-0.014; -0.014]#
$\frac{S_e^2}{S_r^2}$ :	2.060	3.889	1.675
$\chi^2_{K-1}$ :	3.40	1.80	5.63
K:	7	7	14
Sample:	13,998	9,827	23,826
<b>Total</b>			
r:	-0.046	-0.042**	-0.044
95% CI:	[-0.154; 0.061]	[-0.074; -0.010]	[-0.129; 0.040]
$\frac{S_e^2}{S_r^2}$ :	0.206	0.780	0.313
$\chi^2_{K-1}$ :	106.59***	24.37	131.18***
K:	22	19	41
Sample:	27,889	20,131	48,020

Notes: This contingency table reports average effect size ( $r$ ), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi^2_{K-1}$ ), number of studies ( $K$ ) and sample size as the average number of firms per year (sample) for the association between Accounting Quality and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies applying an accrual quality metric (AQ-Metric) and those alternative accounting quality measures (Non-AQ-Metric). # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.

**Table 11: Results by Disclosure Types, CoE Measures and Publication Quality**

	Full-Financial (FF)		Partial-Financial (PF)		Non-Financial (NF)		Total	
	Higher-Tier	Lower-Tier	Higher-Tier	Lower-Tier	Higher-Tier	Lower-Tier	Higher-Tier	Lower-Tier
<b>RFB/VMB</b>								
r:	-0.119**	-0.044	-0.057	-0.133	-0.061	-0.040	-0.081	-0.055
95% CI:	[-0.219; -0.020]	[-0.044; -0.044]	[-0.172; 0.058]	[-0.352; 0.085]	[-0.187; 0.064]	[-0.121; 0.041]	[-0.208; 0.047]	[-0.184; 0.073]
$\frac{S_e^2}{S_r^2}$ :	0.252	9.654	0.322	0.410	0.194	0.469	0.209	0.401
$\chi^2_{K-1}$ :	35.8***	0.2	37.3***	29.3***	56.7***	21.3**	153.3***	59.8***
K:	9	2	12	12	11	10	32	24
Sample:	10,033	390	7,286	1,340	11,007	6,553	28,325	8,282
<b>REAL</b>								
r:	-	-	-0.018	-0.158	-0.060	-	-0.020	-0.158
95% CI:	-	-	[-0.018; -0.018]#	[-0.158; -0.158]#	[-0.060; -0.060]#	-	[-0.020; -0.020]#	[-0.158; -0.158]#
$\frac{S_e^2}{S_r^2}$ :	-	-	2.534	-	-	-	2.329	-
$\chi^2_{K-1}$ :	-	-	1.6	-	-	-	2.2	-
K:	-	-	4	1	1	-	5	1
Sample:	-	-	7,099	361	333	-	7,432	361
<b>Total</b>								
r:	-0.119**	-0.044	-0.038	-0.138	-0.061	-0.040	-0.068	-0.059
95% CI:	[-0.219; -0.020]	[-0.044; -0.044]#	[-0.124; 0.049]	[-0.328; 0.051]	[-0.184; 0.061]	[-0.121; 0.041]	[-0.170; 0.034]	[-0.190; 0.071]
$\frac{S_e^2}{S_r^2}$ :	0.252	9.654	0.362	0.440	0.212	0.469	0.209	0.393
$\chi^2_{K-1}$ :	35.8***	0.2	44.2***	29.6***	56.7***	21.3**	177.1***	63.6***
K:	9	2	16	13	12	10	37	25
Sample:	10,033	390	14,385	1,701	11,340	6,553	35,757	8,643

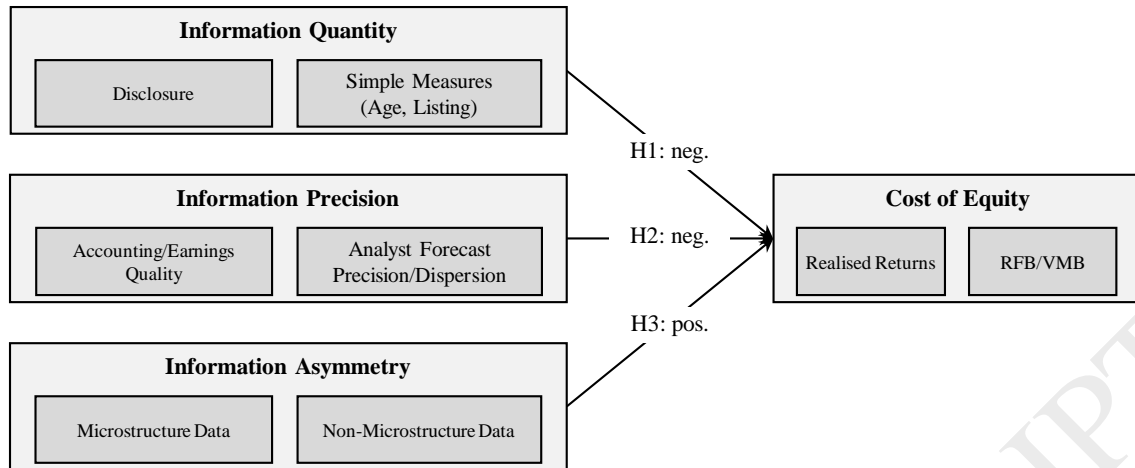
Notes: This contingency table reports average effect size ( $r$ ), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi^2_{K-1}$ ), number of studies ( $K$ ) and sample size as the average number of firms per year (sample) for the association between information quantity and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies focusing fully (FF), partially (PF) or not at all (NF) on financial disclosure. Higher-Tier: 4 & 3 rated journals in ABS2015; Lower-Tier: 2 & 1 rated journals in ABS 2015, unranked and unpublished work. # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.

**Table 12: Results by Accounting Quality, CoE Measures and Publication Quality**

	Acc.Qual.		Analyst		Total	
	Higher-Tier	Lower-Tier	Higher-Tier	Lower-Tier	Higher-Tier	Lower-Tier
<b>RFB/VMB</b>						
r:	-0.092*	-0.054	-0.154***	-0.136***	-0.097*	-0.067
95% CI:	[-0.194; 0.009]	[-0.119; 0.011]	[-0.248; -0.060]	[-0.187; -0.086]	[-0.202; 0.009]	[-0.153; 0.019]
$\frac{S_e^2}{S_r^2}$ :	0.273	0.523	0.555	0.580	0.283	0.376
$\chi^2_{K-1}$ :	47.6***	26.8**	5.4*	3.4*	56.5***	42.6***
K:	13	14	3	2	16	16
Sample:	12,698	11,496	994	2,136	13,692	13,632
<b>REAL</b>						
r:	-0.014	-0.019	-0.011	-	-0.014	-0.019
95% CI:	[-0.014; -0.014]#	[-0.019; -0.019]#	[-0.053; 0.031]	-	[-0.014; -0.014]#	[-0.019; -0.019]#
$\frac{S_e^2}{S_r^2}$ :	2.019	20.503	0.517	-	1.389	20.503
$\chi^2_{K-1}$ :	5.4	0.1	3.9	-	9.4	0.1
K:	11	3	2	-	13	3
Sample:	22,081	1,745	4,111	-	26,192	1,745
<b>Total</b>						
r:	-0.043	-0.049*	-0.039	-0.136***	-0.042	-0.061
95% CI:	[-0.135; 0.050]	[-0.108; 0.009]	[-0.162; 0.085]	[-0.187; 0.086]	[-0.139; 0.055]	[-0.144; 0.021]
$\frac{S_e^2}{S_r^2}$ :	0.235	0.591	0.197	0.580	0.283	0.411
$\chi^2_{K-1}$ :	102.0***	28.8**	25.4***	3.4*	127.5***	46.3***
K:	24	17	5	2	29	19
Sample:	34,779	13,241	5,105	2,136	39,884	15,377

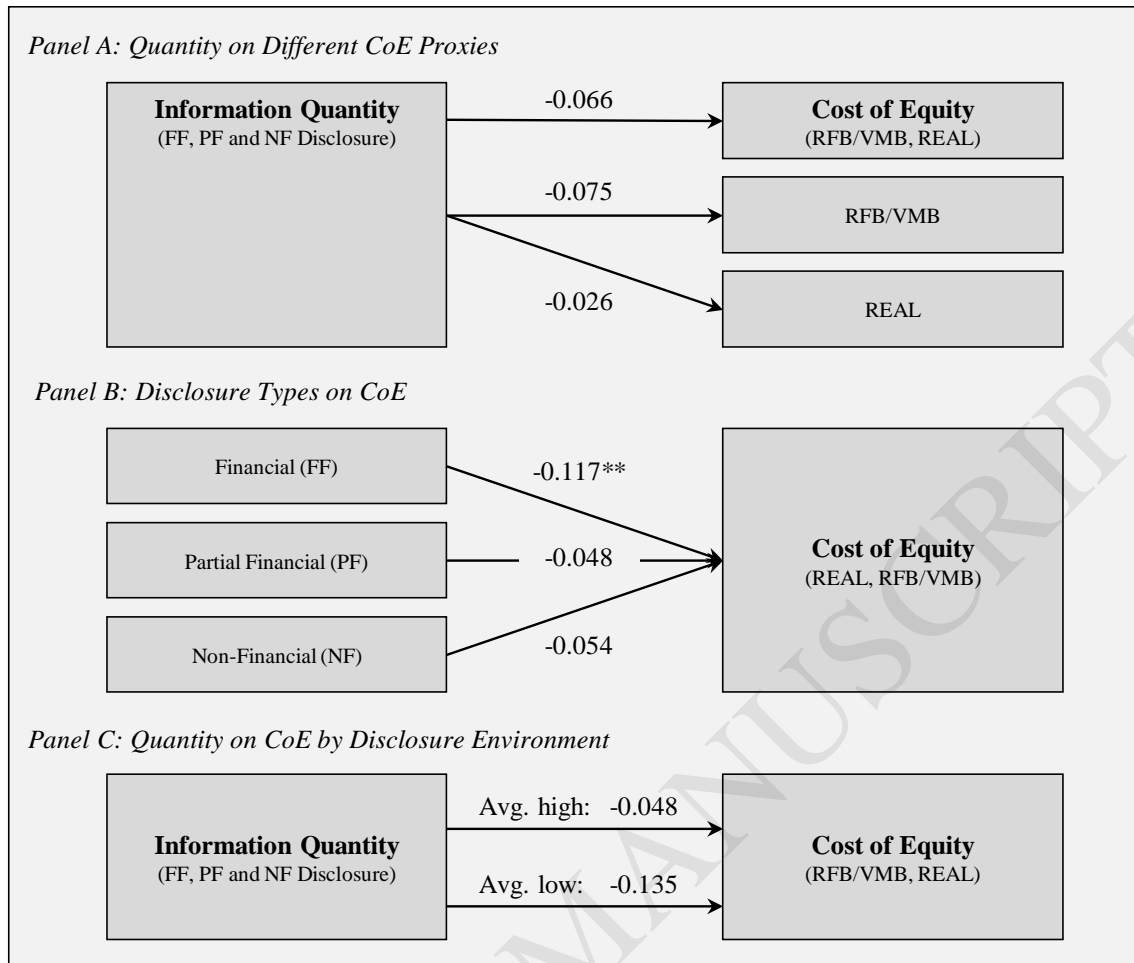
Notes: This contingency table reports average effect size (r), the 95 percent confidence interval (95% CI), the sampling-error explained percentage of observed variance ( $S_e^2/S_r^2$ ), the chi-square statistic ( $\chi^2_{K-1}$ ), number of studies (K) and sample size as the average number of firms per year (sample) for the association between Information Precision and CoE. RFB/VMB contains studies using risk factor-based and/or valuation model-based CoE measures; REAL subsumes studies using realised returns as CoE proxy. Distinction is made between studies applying accounting quality (Acc.Qual.) and analyst-based (Analyst) proxies for Precision. Higher-Tier: 4 & 3 rated journals in ABS2015; Lower-Tier: 2 & 1 rated journals in ABS 2015, unranked and unpublished work. # zero residual variance is used for CI calculation, given the error variance ( $Se^2$ ) being larger than the observed variance ( $Sr^2$ ) resulting in a negative population variance ( $Sp^2$ ). \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.





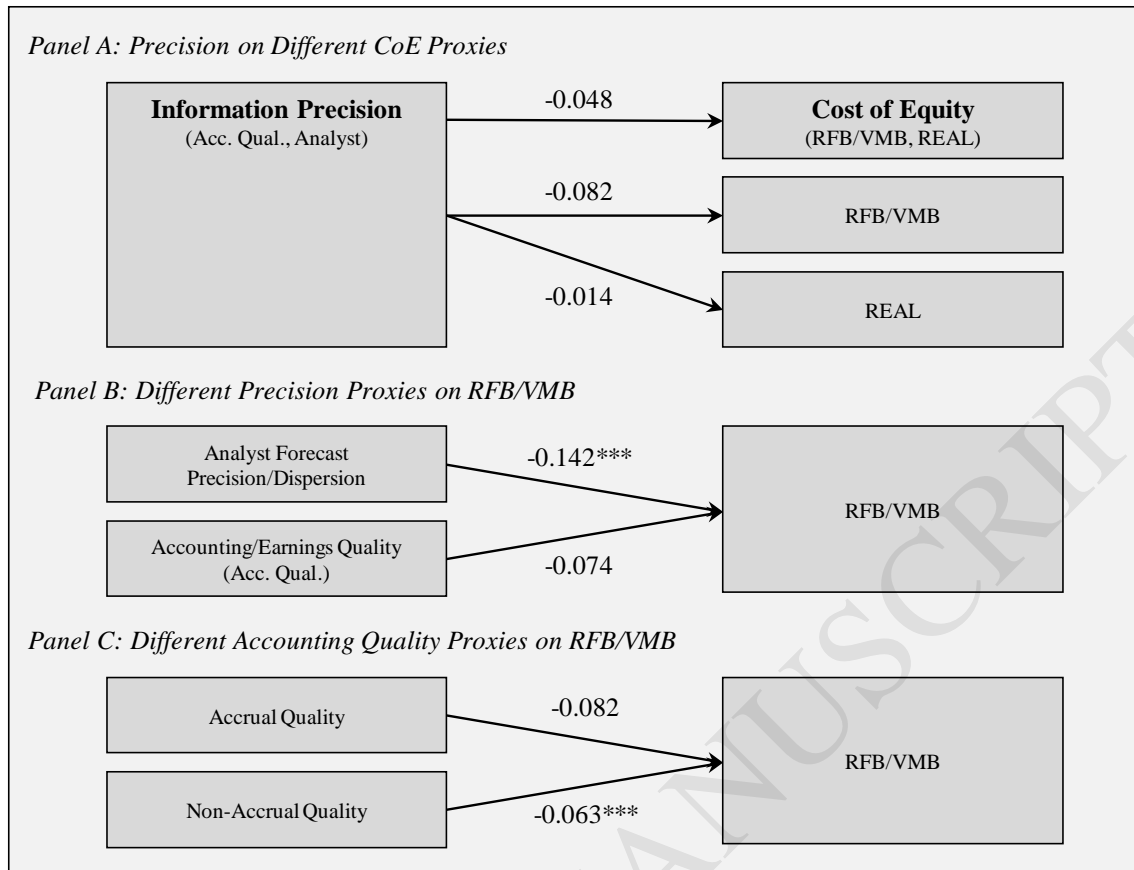
**Figure 1: Conceptual Framework**

*This figure illustrates the direct links between the information attributes and CoE. For each attribute, the most commonly used empirical measures are indicated. VMB (RFB) Valuation model-based (Risk factor-based) cost of equity proxies.*



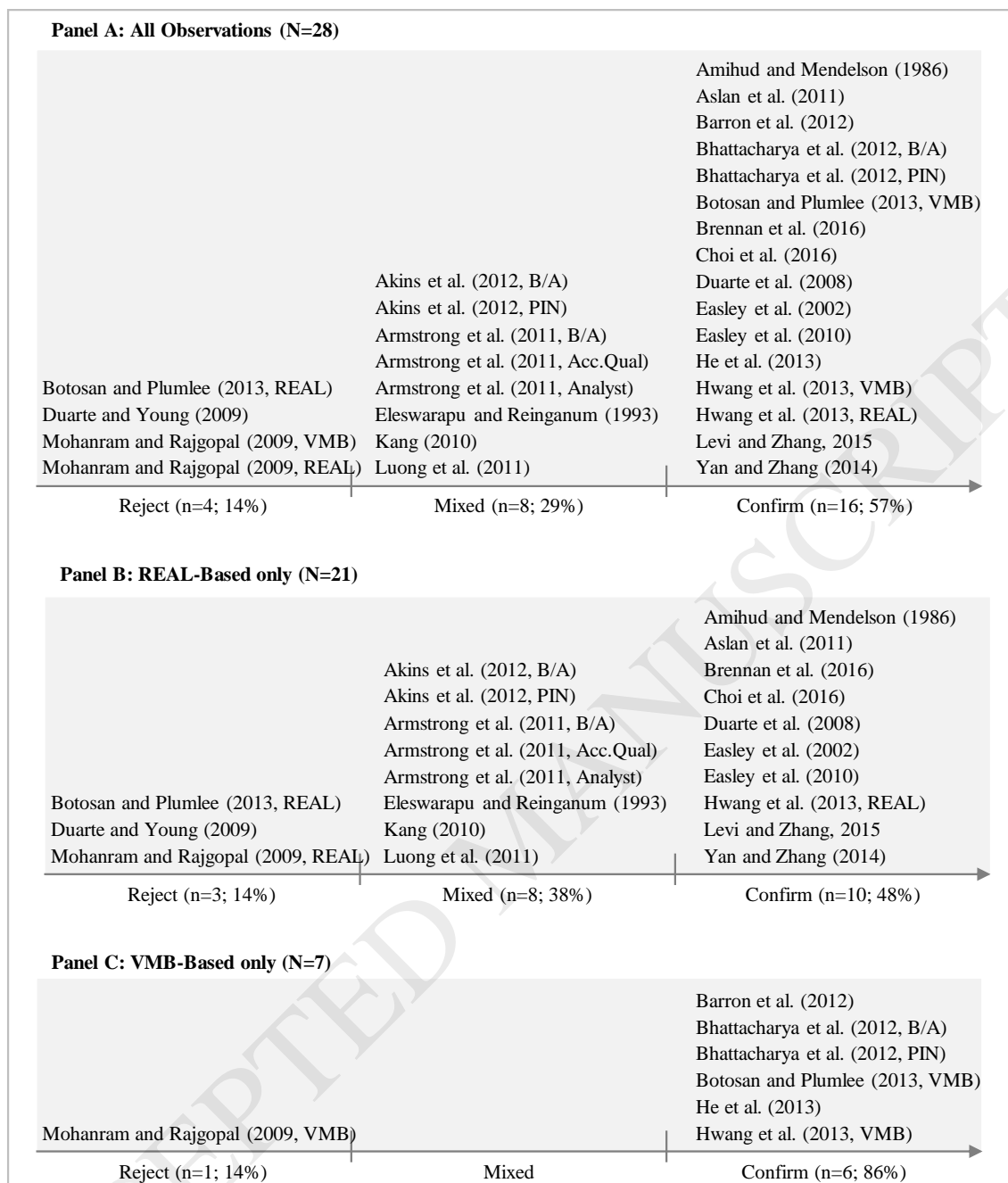
**Figure 2: Information Quantity on CoE – Main Findings**

This figure summarises key findings from the meta-analysis of information quantity with CoE. Panel A shows average effect sizes for different measures of CoE, while Panel B distinguishes between disclosure types. Panel C reports average effect sizes between Quantity and CoE where average high (low) equals the mean effect size of US, HIGH, HDE (Non-US, LOW, LDE) as defined in Table 8. \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.



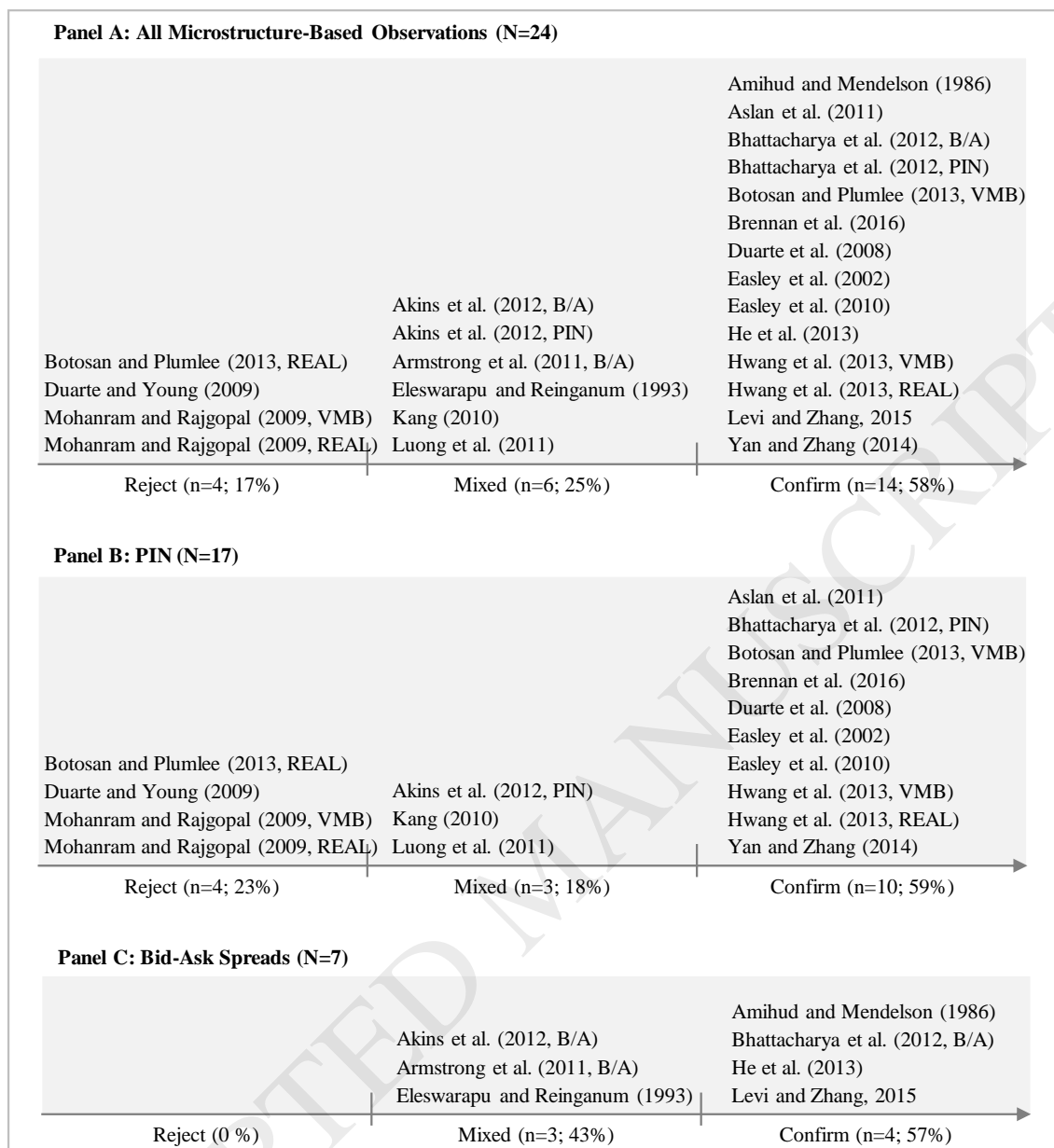
### Figure 3: Information Precision on CoE – Main Findings

This figure summarises key findings from the meta-analysis of information precision with CoE. Panel A shows average effect sizes for different measures of CoE. Panel B (Panel C) reports average effect sizes between different proxies for Precision (Accounting Quality) and RFB/VMB CoE proxies. \*\*\*, \*\*, \* denotes significance at the 0.01, 0.05, 0.10 level.



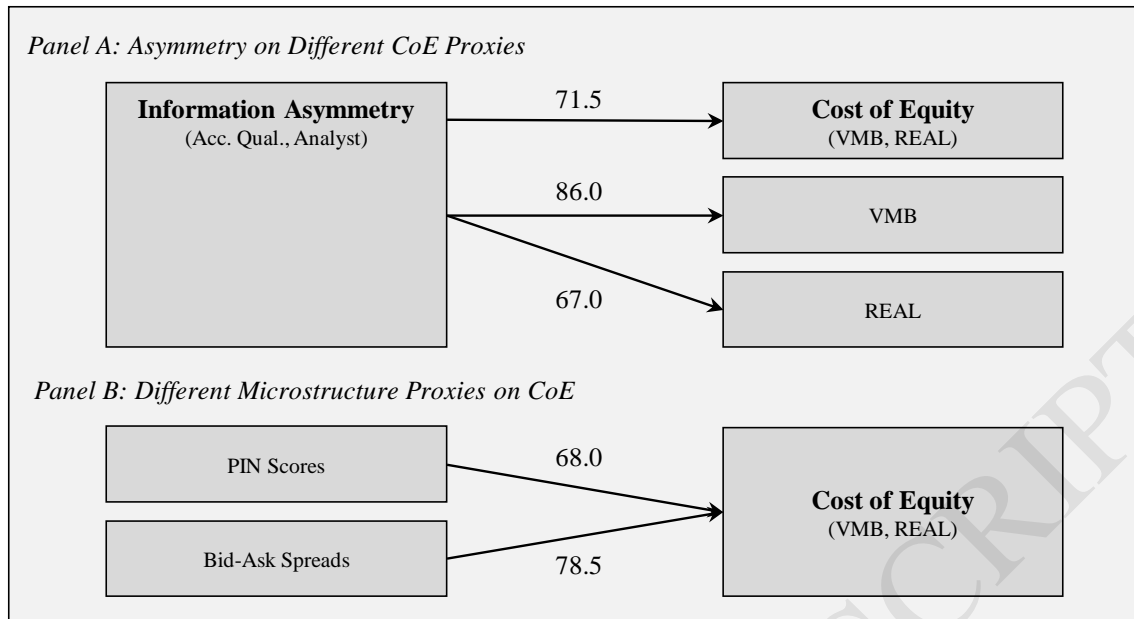
**Figure 4: Information Asymmetry on CoE – Measurement of Cost of Equity**

The figure categorises the sample observations in respect to their general conclusion reached regarding Hypothesis 2. Panel A shows results for all observations. Panel B and Panel C for REAL-based and VMB-Based observations, respectively.



**Figure 5: Information Asymmetry on CoE – Measurement of Information Asymmetry**

The figure categorises the sample observations in respect to their general conclusion reached regarding Hypothesis 2: The higher (lower) the information asymmetry between investors, the higher (lower) the firm's CoE. Panel A shows results for all microstructure-based observations. Panel B and Panel C for PIN-based and Bid/Ask-Spread-Based observations, respectively.



**Figure 6: Information Asymmetry on CoE – Main Findings**

*This figure summarises key findings from the analysis of information asymmetry with CoE. For each link, the figure reports a weighted average score of association across studies (weighting: number of observations), with studies rejecting (confirming) the association being assigned zero (100) points and those finding mixed results given 50 points. Panel A (Panel B) shows average scores for different CoE (Microstructure) proxies.*