Recognition and Disclosure of Intangible Assets — a Meta-Analysis Review

Anne JENY*

ESSEC Business School, Cergy-Pontoise, France

Rucsandra MOLDOVAN

John Molson School of Business, Concordia University, Montréal, Québec, Canada

Abstract

The knowledge- and Internet-based economy demands a re-examination of the accounting treatment for intangibles and a thorough understanding of the results on this topic. We review the literature on internally developed intangible assets using meta-analysis techniques which allow us to highlight the consensus and areas of disagreement in quantitative empirical results. We find relatively robust positive meta-relationships between (1) firm size and intangible-related disclosure, (2) R&D expenses and the firm's stock market returns, and (3) R&D expenses and firm performance volatility. Some relations often cited in the literature do not seem to hold, namely the correlations of R&D expense with analyst earnings forecast errors and with share price. However, we note that after considering over one hundred accounting papers, only 35 percent meet the basic criteria to permit quantitative aggregation of results via meta-analysis. Even when aggregation is possible, the studies are often heterogeneous, therefore denying a reliable interpretation of averages.

Keywords: Intangible assets; Research and development; Capitalization; Disclosure; Quantitative literature review; Meta-analysis; Regression coefficients

*Corresponding Author:
Ave Bernard Hirsch, B.P. 50105, Cergy-Pontoise Cedex, 95021, FRANCE
Tél.: + 331 34432803
Fax: + 331 34432811
jeny@essec.edu

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1. Introduction

The so-called "knowledge economy" (OECD, 1996) and the new Internet-based business models require a better understanding of intangible assets and an examination of the role that accounting and financial reporting could or should play in this newly-created context.[1] The purpose of this survey is (1) to organize and synthesize prior empirical accounting research findings on the recognition and disclosure of intangible assets using meta-analysis, and (2) to identify areas and questions of interest where empirical research would be most useful to address issues on intangible assets raised by current economic and business developments. Meta-analysis enables us to quantitatively summarize the relationships between dependent and independent variables included in prior studies, and to evaluate whether the results of a set of studies represent similar phenomena. We aim to contribute to the ongoing debate on recognition versus disclosure of intangible assets.

In her literature review of value relevance of financial and non-financial information on intangibles, Wyatt (2008) argues that R&D expenditures are value relevant but are less reliable than tangible items and vary in the ability to signal future benefits. Some non-financial measures of brands and customer satisfaction are usually value relevant but do not appear to be reliable indicators of future profitability. Empirical results on recognition and disclosure of intangibles are still inconclusive. We contribute in this direction by expanding the time period of the literature review and by using meta-analysis methodology highlight significant relationships

[1] "Uber, the world's largest taxi company, owns no vehicles. Facebook, the world's most popular media owner, creates no content. Alibaba, the most valuable retailer, has no inventory. And Airbnb, the world's largest accommodation provider, owns no real estate. Something interesting is happening" (Goodwin, 2015).

between information on intangibles and performance measures, either market- or accounting-based.

We organize our review according to a framework based on the recognition versus disclosure of intangible assets debate. The framework is founded on the reasoning that in the case of intangible assets, for which recognition rules are relatively strict and arguably not aligned with the needs of the knowledge economy, "disclosures can bridge the gap between a firm's financial statement numbers and its underlying business fundamentals" (Merkley, 2014). Disclosure on intangible assets encompasses required disclosures under *IAS 38 Intangible Assets* and voluntary disclosures in the notes to financial statements (permitted by IAS 38) or in other public corporate documents.

Financial reporting of intangible assets is the subject of a debate between advocates for an increase in mandatory disclosures and broader recognition of internally-developed intangible assets (Cañibano, Garcia-Ayuso, and Sanchez, 2000; Lev, 2008), and defenders of the present rules which rely mainly on voluntary disclosures with limited recognition of intangible assets (Penman, 2009; Skinner, 2008a, 2008b). At the heart of this debate is the nature of intangibles, which occupy a space "at the center of an information gap that arises from the forward-looking and uncertain nature of economic activity" (Wyatt, 2008).

Disclosure on intangible assets relates mostly to items for which the intrinsic, uncertain nature of intangible assets which makes reliable measurement difficult (Schipper, 2007). In this situation, the purpose of disclosure is to (1) increase predictive ability, (2) provide information to undo un-comparable accounting or create an alternative treatment, and (3) reduce uncertainty (Schipper, 2007). In general, prior empirical disclosure literature suggests that more disclosure is good for users.[2] However, there is also evidence that too much disclosure (EFRAG, 2012) may overwhelm users (André, Filip, and Moldovan, 2016; Lehavy, Li, and Merkley, 2011). Therefore, the recognition versus disclosure debate on intangibles is overlaid by the issues of how much disclosure on intangible assets users find useful, and whether disclosure should be mandatory or left entirely up to management.

Examining recognition and disclosure in the context of intangible assets also allows us to contribute to the discussions on the role of financial statements, which the International Accounting Standards Board (IASB) has been revising as part of its Disclosure Initiative. Before any arguments concerning the failure of the current accounting model (e.g., Lev, 2008) can be made, the role of financial statements in today's knowledge economy should first be clarified. Skinner (2008b) maintains that as long as intangible-intensive firms are able to attract financing even though their accounts do not recognize many of the intangibles, then there are no problems with accounting for intangibles, and therefore no problems with the current accounting model. Ledoux and Cormier (2013) show that voluntary disclosure about intangibles plays an important complementary role on top of financial reporting. Our review summarizes the empirical correlations between intangibles and accounting-based and market-based performance to provide a synthesized perspective on this issue.

We make a number of choices in order to streamline our survey. First, we restrict our focus to all intangible assets except goodwill. Similar to Skinner (2008b), we consider that recognition and measurement of goodwill relates to accounting for business combinations rather

[2] See Healy and Palepu (2001) and Beyer, Cohen, Lys, and Walther (2010) for extensive literature reviews of empirical disclosures studies.

than strictly intangibles.[3] Compared to previous reviews of the literature on intangible assets (e.g., Wyatt, 2008), we take a broader perspective on financial reporting for intangibles, considering both the capitalization and expensing of intangible asset amounts (which we term recognition for ease of referencing), and disclosure of information about intangible assets. Second, our survey only includes papers that have been published in accounting journals or focus on accounting for intangibles. Intangible assets, particularly R&D investments, are studied by researchers across several fields, from biotechnology advancements to strategic and operations management. The point of interest to us, however, is the way companies account for and externally report these investments. Third, we only consider empirical archival papers.[4] Focusing on empirical research allows us to discuss in depth the reporting environment and the role of other stakeholders in the reporting decision, as well as use of meta-analysis to summarize the results.

We conduct a comprehensive keyword search on the widely-used research article databases provided by EBSCO and ProQuest to identify the relevant papers to review. Our initial sample includes 116 papers of which 105 published in accounting and finance journals and focusing on the accounting treatment and reporting of intangible assets other than goodwill. We use meta-analyses to summarize prior findings by testing the variables measuring intangible assets, their determinants and their consequences as identified in prior studies. Out of the 105

[3] "Accounting standard-setters have also devoted a great deal of attention to accounting for goodwill, which is a topic that I leave aside because it is largely separable from the discussion in many of the proposals on intangibles accounting and because its recognition and measurement is related to accounting for business combinations, which I see as taking the discussion too far afield. I would note though that a loose definition of goodwill - as the excess of a business's economic value over its book value – is taken by commentators as evidence of the failure of the current accounting model to correctly recognize intangibles" (Skinner, 2008a).

[4] We believe that modelling-based research necessarily assumes away a lot of the complexities of the environment in which managers decide how to account for intangible assets (Beyer et al., 2010).

papers, 37 unique papers that yield 46 combinations of papers and variable pairs could be included in the meta-analysis (i.e., what meta-analysts refer to as "primary studies").

We observe that out of the 105 published accounting papers we start from, about 35 percent meet the basic assumptions and data requirements for their results to be synthesized via meta-analysis. Many of the studies are "unique" in the sense that their results have not been replicated or reproduced in similar or different settings. Nevertheless, such "unique" papers are often cited in the literature as having shown a particular relation and settled a particular research question. It is unclear whether this mindset allows the accounting research field any claims at policy implications.

We report six meta-analyses, each based on five or more studies. Our results show that the meta-analytic association between firm size and intangible assets disclosure is positive and statistically significant, as well as the relationship between R&D expenses and stock returns. We find a positive statistically-significant meta-analytic relation between R&D expenses and the volatility of future firm profitability, and a weaker positive relation between R&D expenses and the level of future firm profitability. However, we do not find significant meta-analytic relations between R&D expenses and share prices and between R&D expenses and analyst earnings forecast errors. Our results are important since they question the presumed general R&D value relevance and usefulness of R&D expense numbers for financial analysts' forecasts.

Our survey contributes to the literature in several ways. First, our discussion of recognition versus disclosure of internally-developed intangible assets emphasizes a number of areas where more research could shed additional light and advance understanding. Some of the fundamental questions that still remain unanswered are: the role of intangible assets disclosure at large and more specifically for the valuation of new, Internet-based companies at the time of IPO and subsequently; how do analysts use, interpret and discuss the intangible assets numbers and disclosures; who invests in R&D intensive firms; how value-relevant is the mandated disclosure on intangible assets.

Second, by aggregating and summarizing the evidence on recognition and disclosure of intangible assets, we contribute to the ongoing debate between those asking for more recognition and disclosure related to intangible assets (e.g., Lev, 2008) and those who believe that expensing (i.e., the status quo in the U.S.) is perfectly adequate for the accounting treatment of intangibles to achieve its stated purpose (e.g., Skinner, 2008a,b). Some of the empirical evidence seems to favor recognition of certain internally-developed intangibles (development costs) as assets, even though this could be a channel for earnings management (e.g., Cazavan-Jeny and Jeanjean, 2006). This is an expression of the trade-off between reliability and relevance in accounting information, i.e., recognizing more intangible asset would increase the relevance of financial statements, but could impair their reliability. Meta-analysis can inform such debates by synthesizing results, ideally, from a large number of studies.

Third, our review shows that the majority of studies examines intangible assets recognition, and underlines the small number of empirical studies on the disclosure of intangible elements. This is relevant in a context where disclosure is seen as one solution to reduce information asymmetry and signal value creation (Hoogervorst, 2017), at a time when the current accounting model is regarded by some as insufficient and inconsonant with the knowledge-based business models (Lev, 2008). The IASB and the Financial Accounting Standards Board (FASB) are revisiting some of the conceptual underpinnings of the financial statements, giving academics the opportunity to contribute in a direct way to standard setting.[5]

From a research methods perspective, this paper contributes by providing a detailed view of meta-analysis techniques, taking into account the latest developments in the statistical literature. We discuss meta-analysis based on regression coefficients (Becker and Wu, 2007) and apply this in an accounting context. We distinguish between "classic" meta-analysis and meta-regression analysis, MRA, (Stanley and Jarrell, 1989) as used primarily in the Economics literature and only recently in accounting (Hay and Knechel, 2017). We clarify that MRA makes certain assumptions about the scale and distribution of the regression coefficients that are not met in all empirical settings. Obtaining scale-free effect sizes from regression results in the spirit of traditional meta-analysis overcomes this issue. Appendix A illustrates meta-analysis based on regression coefficients in detail.

We continue by describing the institutional background of accounting for intangible assets and our organizing framework for analyzing the empirical accounting literature in section 2. Section 3 presents the meta-analysis methodology and our sample of primary studies. Section 4 describes and discusses our meta-analysis results, and section 6 concludes and proposes avenues for future research.

2. Financial reporting standards on intangible assets and framework of analysis

2.1. Institutional background

[5] http://www.fasb.org/cs/ContentServer?c=FASBContent_C&cid=1176167848789&d=&pagename=FASB%2FFASBContent_C%2FActionAlertPage

Recognition and disclosure of internally-developed intangible assets differs under IFRS and U.S. GAAP, but both sets of standards struggle with the question of how to incorporate the economic properties of intangible assets into the financial reporting system (Powell, 2003).

IAS 38 *Intangible assets* requires most internally-developed intangible assets, such as customer lists, trademarks, brands, mastheads, etc., to be expensed (IASB, 2004). Since their cost cannot be distinguished from the normal cost of doing business (IAS 38 par. 16), reliable measurement is difficult. For R&D projects, however, the standard distinguishes between costs incurred in the research phase and costs incurred in the development phase. While the distinction involves considerable judgment, the general discriminating principle is the probability of future economic benefits. Since the outcomes of the research phase are highly uncertain, the standard requires expensing of research costs. The development phase, however, is an application phase to advance the project to a ready-for-use or sale state, at which point future economic benefits are probable. Development costs must also meet six recognition criteria before they can be capitalized. The identification phase along with the six recognition criteria for development costs constitute a high recognition threshold which means that, although companies applying IFRS capitalize some of the development costs, most R&D costs are expensed.

The disclosure requirements in IAS 38 mainly concern the accounting policies for recognized classes of intangible assets. Required disclosures also include the amount of expensed R&D during the period. Without being mandatory, the standard encourages disclosure about the fully amortized intangible assets still in use and a description of the significant intangible assets controlled by the entity but not recognized as assets because they did not meet the recognition criteria (IAS 38 par. 128).

Under U.S. GAAP, the accounting treatment for internally-developed intangibles is conservative and requires immediate expensing. However, recognition of purchased intangibles is allowed (Ciftci and Darrough, 2015). In the early 2000s, the FASB worked on a project related to "Disclosure of information about intangible assets not recognized in the financial statements" intended to expand note disclosure on internally-developed intangible assets (FASB, 2001). In the AAA comment letter on this project, Skinner et al. (2003) note that "voluntary disclosure of intangibles information is not widespread" suggesting that the costs of measuring intangibles and proprietary costs outweigh the benefits of disclosure.[6]

Chen, Gavious and Lev (2015) show, however, that under the IAS 38 capitalization of development costs requirement, Israeli companies that switched from U.S. GAAP to IFRS disclosed more R&D-related information than previously, and more than companies that continue to apply U.S. GAAP. This finding indicates that when the information is available, managers are more likely to disclose it, which further suggests that the cost of producing this information is probably the highest hurdle against disclosure.

The IASB's Disclosure Initiative Project includes a review of disclosure requirements in the existing financial reporting standards. Although a redraft of the disclosure requirements in IAS 38 is not yet available, if IAS 16 *Property, plant and equipment* is any indication, the IASB is likely to require more details about the business model as related to the particular item being disclosed and the risks associated with that item for the entity, on top of the disclosures of measurement basis and changes during the year already included in most standards (IASB, 2015).

[6] The FASB removed this project from its technical agenda in 2004 stating that any action on this topic will be taken jointly with the IASB.

2.2. Framework for organizing the literature on intangible assets

We organize the literature review in terms of the accounting treatment of internally-developed intangible assets from recognition versus disclosure perspective. The tension between recognition and disclosure arises from the perceived differential in reliability and the question of whether users actually read and understand disclosures.

Advocates for additional mandatory disclosures claim that financial statements fail to reflect key intangible resources; consequently, outsiders do not have sufficient information and this negatively affects investments in such assets (Cañibano et al., 2000; Lev, 2001; Nakamura, 1999). Persistent under-investment could lead to severe adverse consequences, impairing long-term growth potential for companies and economies. Actors on this side of the debate also argue that financial statements are less relevant for capital markets nowadays than in the past, and point to the persistent decrease in the book-to-market ratio and earnings response coefficients over time (Brown, Lo, & Lys, 1999; Chang, 1999; Lev & Zarowin, 1999).

On the other side of the debate, promoters of the status quo argue that the capital markets fulfil their function of providing financial resources to intangible-intensive firms and that such companies do not appear to under-invest in intangibles (Skinner, 2008b). From a valuation standpoint, their argument is that as intangibles generate wealth, revenue streams will eventually flow through the income statement, allowing financial statement users to infer the value of these assets (Penman, 2009). They make the case that more recognition or disclosures are not necessary for market participants to assess intangibles' implications for enterprise values. The gap between book and market values could also be an indication that firms relying on intangible assets, i.e., with a low base of recognized assets, benefit from a high market value. They also point out that mandatory recognition of intangibles has inherent reliability issues, as measurement problems are typically exacerbated for these assets: intangibles are synergistic, many are not separately saleable as their value depends on other assets, and they are not actively traded on a secondary market (Basu and Waymire, 2008). As underlined by this debate, previous empirical papers are still inconclusive on what type of intangible assets could or should be recognized, under which conditions, at what value.

Accounting standards are still incomplete on the topic of intangible assets since they are mostly recognized at fair value if they have been acquired and not recognized if internally developed. Empirical research could help standard setters, preparers and users of financial statements to select intangible assets that could be relevant to recognize and to offer criteria of recognition and rules of valuation. Meta-analysis is useful to map the existing literature and to highlight the robust relationships.

3. Research method for literature synthesis and sample of primary studies

3.1. The meta-analysis research method[7]

<u>*Purpose of meta-analysis techniques*</u>

Meta-analysis is the statistical analysis of a collection of quantitative results from individual studies that examine the effect of an independent variable (say, X_j) on a dependent variable (say, Y) for the purpose of synthesizing and integrating the empirical findings (Glass, 1976, 1977).[8] In order to synthesize comparable metrics, the empirical results from individual studies examining the relation between X_j and Y are transformed into a scale-free index, i.e., effect size. The effect sizes permit an assessment of the magnitude and direction of the relation

[7] Appendix A contains detailed formulas and a worked-through numerical example to illustrate the meta-analysis statistical method with partial correlational data as input and applying the random effects model.
[8] In this paper, we present and interpret five different meta-analyses, meaning that we meta-analyze five pairs of variables that could be represented as (X_{j1}, Y_1), (X_{j2}, Y_2), …, (X_{j5}, Y_5).

between variables that together with the variance or uncertainty in effect sizes summarizes and synthesizes the primary results on the relation between X_j and Y (Glass, 1977).

When individual results from primary studies are contradictory, meta-analysis can be used to provide a coherent, quantitative way of summarizing the findings, thereby overcoming some of the shortcomings of narrative literature reviews (Trotman and Wood, 1991). Even when the individual empirical results go in the same direction, meta-analysis can still be useful since it aggregates the results in separate but comparable studies into one measure of the effect of variable X_j on Y. In fact, this was the initial reasoning for the development and use of meta-analysis in experimental medical and psychological research (O'Rourke, 2007).[9] In social sciences, meta-analysis has been used as a statistical tool for hypothesis testing (Polanin and Pigott, 2015). However, since the assumptions underlying meta-analytic hypothesis testing are unrealistic in the context of social sciences, meta-analysis is increasingly conducted to explore the dispersion of effect sizes (Aloe and Thompson, 2013; Borenstein, Higgins, Hedges, and Rothstein, 2017; Hak, van Rhee, and Suurmond, 2016).

Regression-based effect sizes in meta-analysis

Generally speaking, an effect size is a measure of the relationship between two variables. There are numerous such measures, but traditional meta-analysis uses bivariate correlation coefficients, i.e., zero-order effect sizes (Cohen, 1965; Rosenthal, 1991), such as the Pearson correlation as input for the relation between two variables. This is possible since traditional meta-analysis was developed for primary studies reporting randomized-trial data.

[9] "By the middle of the 20th century, the sheer volume of research reports [in social, educational, and medical interventions] forced researchers to consider how to develop and apply methods to synthesize the results produced" (O'Rourke, 2007).

Much of contemporary primary research, however, uses complex, theoretically-driven multivariate regression models. In addition, primary studies meta-analyzed in economics, accounting, or other social sciences are based on observational data analyzed via multivariate regression analysis that aims to remove potential confounding effects (more or less successfully). The implication is that "the results of complex models should not be cumulated using simple, or zero-order, effect sizes" (Cooper and Hedges, 1994).

Therefore, the switch to using regression results as input for meta-analysis means that the meta-analytic effect size relies not on bivariate correlations but on partial correlations that show the relation between X_j and Y *after* controlling for the effect of other variables included in the model (Aloe and Thompson, 2013).[10]

While common meta-analysis techniques can be used to synthesize partial effect sizes (Cooper, Hedges, and Valentine, 2009; Hedges and Olkin, 1985), certain regression-specific features must be considered.[11] Probably the most important feature relates to model specification in primary studies. If the primary regressions include different sets of control variables, which happens more often than not (Aloe, 2014), then each observed partial correlation between X_j and Y could be estimating a different population parameter. This has two implications. First, the random effects model may be more appropriate than a fixed-effects approach for computing an overall meta-analytic effect size from partial effects (Aloe and Thompson, 2013). Second, when analyzing a collection of partial correlations, the differences in model complexity that are likely to influence the size of the partial correlation should be taken into account, i.e., included as

[10] Bivariate effects and partial effects represent different parameters and thus should not be treated as the same, should not be expected to have exactly the same properties, nor should they be combined within the same dataset (Becker and Wu, 2007; Keef and Roberts, 2004; Williams, 2012).
[11] For example, see (Hak et al., 2016) for a discussion of particularities related to regression data input to meta-analysis.

predictors in a regression model with partial correlations as dependent variables (Aloe, Tanner-Smith, Becker, and Wilson, 2016). We discuss each of these implications in turn.

Random effects model

Related to the first implication, the random effects model accounts for the possibility that there is variability in the population of effect sizes, an appropriate assumption in studies that use real-world data (Field, 2003). It does this by incorporating between-studies heterogeneity into the combined effect size (DerSimonian and Laird, 1986), on top of within-study variability due to sampling error. Specifically, the combined effect size is obtained after weighting the partial effect size from each study by the inverse of each *within*-study variance plus the observed variance of effect sizes *between*-studies, also called the DerSimonian-Laird estimator and denoted as τ^2 (Borenstein et al., 2017; DerSimonian and Laird, 1986). As such, under the random effects models, the threshold for the combined effect size to be statistically different from 0, for example, is much higher compared to a combined effect size computed under the assumption of fixed effects model which takes into account only within-study variability.

Heterogeneity of primary studies

One of the fundamental assumptions of meta-analysis is that the primary studies synthesized are comparable. Comparability refers to studies that examine samples drawn from the same population, specify the same type of model, examine the same two variables etc. Such features are perhaps realistic for experimental studies, but not for empirical archival studies using observational data, as is the case in accounting. Statisticians explain that the combined effect size is not a useful outcome of the meta-analysis if the samples analysed in the meta-analysis are heterogeneous; in that case, each sub-population has its own true effect size (Hak et al., 2016).

Following the recommendations in Hak et al. (2016) and Borenstein et al. (2017) we estimate two statistics that depict different aspects of heterogeneity.

First, the I^2 is a relative measure of the proportion of studies with observed variance that reflects real differences in effect size. Put simply, the numerator of this proportion is the between-studies variability τ^2, and the denominator is the total variability, i.e., the sum of τ^2 and the within-study variability due to error sampling. If I^2 percentage is low, then observed heterogeneity is mainly due to within-study error sampling, so the studies included in the meta-analysis can be considered homogeneous. If I^2 is large, then the total heterogeneity is mainly due to between-studies heterogeneity so the primary studies cannot be considered as examining the same population. If the studies are heterogeneous, the combined effect size is not meaningful and the *range* of the effect sizes should be examined.[12] Borenstein et al. (2017) caution that I^2 provides a relative measure of *whether or not* there is heterogeneity in the sample of studies, but does not inform on the *how much* heterogeneity there is.

The prediction interval provides a measure for the range of heterogeneity. It gives an approximate range in which the effect size of about 95 percent of studies will fall, assuming the true effect sizes are normally distributed through the domain. In essence, the prediction interval describes the range of observed effect sizes and gives a view of the dispersion of effect sizes from the studies included.[13] Therefore, a large prediction interval means that there is a large

[12] The threshold for "small" and "large" I^2 is arbitrary. Borenstein et al. (2017) refer to 25%, 50% and 75% as thresholds that could guide the researcher.

[13] Borenstein et al. (2017) notes that while the confidence interval around the combined effect size and the prediction interval may seem similar, they are not. The former is a measure of *precision* of the combined effect size, while the latter is a measure of *dispersion* of the individual effect sizes.

amount of heterogeneity in the sample and the source of heterogeneity should be examined. However, a large prediction interval can also be due to the small number of studies included in the meta-analysis (Borenstein et al., 2017).

Recently, statisticians have recommended that observed heterogeneity be examined using regression analysis, where the independent variables are potential reasons for heterogeneity, e.g., differences in model specification, differences in variable scaling etc. (Aloe et al., 2016; Schmidt, Oh, and Hayes, 2009). This appears similar to the MRA (Stanley and Jarrell, 1989) literature in economics; the terminology is quite deceitful. Williams (2012) notes that MRA is different from meta-analysis regression. The former generally uses the regression coefficients from primary studies as dependent variables which makes sense if the variables have the same scale across all primary studies included and if the distribution of beta coefficients is the same across all studies, whereas the latter first produces metric-free effect sizes with a known distribution.

Publication bias

The fact that the publication process in social sciences is biased against null results was recognized early on, e.g., Sterling (1959). The literature on the meta-analysis method has developed several measures that assess the robustness of the results to null results in "file drawers" (Orwin, 1983; Rosenthal, 1979). While "file drawer" measures are a feature of traditional meta-analysis, most of the meta-regression (Stanley and Jarrell, 1989) literature, including Hay and Knechel (2017) in accounting, uses MRA to examine a broader notion of publication bias where sources of heterogeneity of *published* studies are (also) searched for among variables that relate to the publishing process, e.g., the type of university where the researches are employed, the quality of the journal, the country or geographical region from which the sample is drawn etc.[14]

When the sample of primary studies is small, running regression analysis to test the publication bias is not feasible. The alternative is then to follow traditional meta-analysis and report file drawer measures, such as Rosenthal's Fail-safe N (Rosenthal, 1979) and Fisher's Fail-safe N (Fisher, 1935). Rosenthal's FSN determines the number of studies with non-significant or negative results needed to reverse conclusions about a significant combined effect size with a 95 percent confidence level (Rosenthal, 1979). There is no statistical significance test associated with this FSN, but Rosenthal (1979) proposed comparing the estimated FSN number with a critical number of studies ($5 \times k + 10$) to decide whether the FSN number estimated is small or large. If FSN is larger than the critical number of studies, the combined effect size is considered robust to the possibility of publication bias.

Fisher's Fail-safe N is based on Fisher's test, which is a test of the combined significance relying on the sum of the natural logarithm of the significance level of the effect size in the primary studies included in the meta-analysis (Fisher, 1935). Fisher's test follows a chi-square distribution with $2 \times k$ degrees of freedom, hence its statistical significance can be determined by looking up the corresponding values in the chi-square distribution table. A highly significant Fisher's test means that it would take a large number of studies with non-significant p-values to render the combined effect size non-significant (Fisher, 1935). An iterative procedure as

[14] Stanley (2005) tried to re-position MRA "beyond publication bias" towards the broader investigation of heterogeneity.

described by Becker (2005) can be used to estimate the actual number of studies with p-values of 0.50 necessary to bring Fisher's test to non-significance.[15]

Number of primary studies necessary for meta-analysis

We wrap up the description of the meta-analysis research method with a discussion of the number of studies necessary as input and the choice we made in this paper.

The number of primary studies necessary as input so that the meta-analysis results are reliable is not clarified in the statistical literature. Theoretically, two studies are enough to compute the meta-analysis statistics (Valentine, Pigott, and Rothstein, 2010). However, as Borenstein et al. (2017) put it, one "cannot obtain a useful estimate of the standard deviation in a meta-analysis with three studies, any more than [one] can obtain a precise estimate of the standard deviation in a primary study with three subjects." In more practical terms, statistical academic papers that contain simulations of meta-analysis results generally view a sample of ten studies as small (Aloe, 2014; Tipton, 2015).

3.2. Sample of studies included in meta-analyses

We begin our review of the literature on intangible assets by conducting a keyword search on *EBSCO* and *ProQuest*, the two largest databases for published academic articles.[16] We limit the search to journals in accounting and finance. The keywords used are "intangible", "intangible asset", "research and development", "R&D", "intellectual capital", "IAS 38", "software development" and derivations of these words. We retain only papers using empirical

[15] Note that Becker (2005) further argues that the large differences in various measures of FSN (e.g., Rosenthal, Fisher, Orwin etc.) are due to the power of each of the tests and that other ways should be used to assess the robustness of the meta-analysis to publication bias, i.e., meta-analysis regression.

[16] Database searches was conducted at two points in time, in October 2015 and in November 2017.

archival research methods and eliminate studies on goodwill (as per our discussion above) and on the tax effects of R&D since two comprehensive meta-regression reviews were recently published on this topic (Belz, Hagen, and Steffens, 2017; Castellacci and Lie, 2015). The search query includes the title, abstract, and keywords of published articles in these databases. We also check the list of references in previous literature reviews on intangibles (Wyatt, 2008), to include any relevant papers that may not have appeared in our database search.

Table 1 Panel A summarizes the paper sample construction procedure. The search yielded 116 different papers, of which two are unpublished working papers, nine discuss intangible assets but not from an accounting perspective, leaving us with 105 published accounting papers. Of these, 16 do not have the necessary data to compute partial effect sizes (e.g., the studies do not report *t*-values, or the empirical models used are not among the common types of regression models used in accounting research).[17] We eliminate 38 other papers that examine unique combinations of variables. That leaves 51 papers (49 percent of the 105) that could potentially be included in meta-analyses (i.e., there are at least two studies examining the relation between 2 variables).

The larger the sample of studies included in a meta-analysis, the more reliable the inferences based on the meta-analytic results. However, for the meta-analytic results to be meaningful, the studies must be comparable to a high degree. To balance these opposing requirements, we opt for an ad-hoc threshold of five primary studies necessary in a meta-analysis. We assume that meta-analyses based on five or more studies allow us to analyze the literature of interest with some degree of confidence in the reliability of the results. Where the

[17] Following prior literature (Hay, Knechel, and Wong, 2006), we include only published papers in the sample for meta-analysis, since unpublished manuscripts have not yet received the vetting of the review process and not all unpublished manuscripts are publicly available, which introduces another type of sample selection bias.

number of studies that examine the relation between two variables is lower than 5, we refrain from interpreting the meta-analysis results. This choice eliminates another 14 papers.

There are 37 unique papers in the final sample of papers included in our meta-analyses on intangible assets. Note that one paper can be included in more than one meta-analysis if the paper examines several pairs of variables related to intangible assets. For example, if the regression model in a paper has *Future Profitability* as dependent variable and *R&D expenses* and *Advertising expenses* as independent variables, the paper will appear as input into two of our meta-analyses. Additionally, a paper could report regression models with different dependent or independent variables. Again, that means the paper could be input into two or more of the meta-analyses we run. The 37 unique papers included in the final sample yield 46 combinations of paper and variable pairs.

Table 1 Panel B presents the distribution of the 37 papers by publication outlet. About 38 percent are published in high-quality accounting journals (i.e., The Accounting Review, Journal of Accounting Research, Journal of Accounting and Economics, Contemporary Accounting Research and Review of Accounting Studies).[18] Table 1 Panel C presents the sample distribution by the country or geographic region from which the study sample is drawn. Most studies examine U.S. companies (26 papers, 70 percent). Three papers use samples of firms based in the UK. The other studies are based on samples from Australia, France, Malaysia, South Korea, and Spain. Two papers use large international samples. Non-U.S. geographical regions are, therefore, severely under-represented in the intangible assets accounting literature with enough data to meet the meta-analysis requirements.

[TABLE 1 ABOUT HERE]

[18] According to usual academic journal rankings.

Table 2 lists the 37 papers included in meta-analyses. We provide the year of publication, the journal, the country or geographical region, sample period and the sample size, as well as the source of the information we use in the meta-analysis was collected (table, model, page number).

[TABLE 2 ABOUT HERE]

Given the small number of studies included in each of our meta-analyses, regression analysis would likely result in biased standard errors for the meta-regression coefficients (Hedges, Tipton, and Johnson, 2010; Tipton, 2015). This is a limitation for our review and means that while we can pinpoint heterogeneity, we cannot explore the sources of heterogeneity.

4. Meta-analysis results

Table 3 reports the results for the six meta-analyses that are based on five or more studies. Each meta-analysis is based on a random effects model, meaning that we assume heterogeneity in the sample of observed studies and add it to within-study variability due to sampling error in the estimation of the standard error of the combined effect size. The combined effect size is inverse-weighted with the sum of within-study variability as well as between-study variability that should account for the heterogeneity of effect sizes that could be observed in the population. The meta-analyses test the relationship between (1) intangible disclosures and firm size, (2) analyst earnings forecast error and R&D expense, (3) future firm's profitability and R&D expense, (4) volatility of future firm's profitability and R&D expense, (5) share price and R&D expenses, and (6) stock return and R&D expenses. We discuss each of the meta-analyses in turn.

[TABLE 3 ABOUT HERE]

4.1. Firm size and disclosure about intangible assets

In the context of intangible assets, where recognition rules are relatively strict, and perhaps out of step with the knowledge economy, "disclosures can bridge the gap between a firm's financial statement numbers and its underlying business fundamentals" (Merkley, 2014). We are able to meta-analyze the relation between firm size (as independent variable in regressions) and the firm's disclosure on intangible assets (dependent variable in regressions) based on five studies (García-meca, Parra, Larrán, and Martínez, 2005; Jones, 2007; Kamardin, Abu Bakar, and Ishak, 2015; Kang and Gray, 2011; Merkley, 2014). While the disclosure scores are not defined precisely the same across the five studies, broadly they all measure the amount of information that firms provide about intellectual capital, research and development projects, patents, human resources etc. The size of the firm is generally measured based on the natural logarithm of market value or of total assets. In each of the five studies, the partial effect size is computed based on the *t*-value associated to the regression coefficient of interest and the degrees of freedom in the regression.

On average, the effect size for the relation between firm size and disclosure is 0.067 (i.e., the combined effect size). Taking into account variability from two sources, i.e., within-study and between-studies, the *z*-statistic for testing that the combined effect size equals to zero is 4.80, significant at 1 percent. This means that, on average, across the studies we synthesize, the relation between firm size and the amount of disclosure on intangible assets is positive and statistically significant.

Effect sizes of the relation between firm size and disclosure scores can vary from study to study due to within-study sampling error. However, if the "true" effect sizes also vary widely, then the studies we include in the meta-analysis are too heterogeneous to be synthesized. The I^2

statistic helps in this respect; it tells us how much of the total variability observed would still remain if we somehow removed the within-study variability (Borenstein et al., 2017). We find a percentage of 5.09 of the total variability is due to between-studies variability, meaning that there is likely no heterogeneity between the studies included in the meta-analysis. The prediction interval complements this assessment by showing that the range of potential heterogeneity in about 95 percent of studies that examine the influence of firm size on intangible disclosure scores is between 0.0213 and 0.1126. It is noteworthy that both bounds of the prediction interval are positive. This strengthens the reliability of the positive combined effect size between firm size and intangible disclosure scores.

The fail-safe N “file-drawer” measures estimate that 25 (*Fisher’s FSN*) or 33 (*Rosenthal’s FSN*) studies with null results are necessary to overturn this synthesized average result for the relation between firm size and disclosure scores. These are not exactly large numbers and in fact, Rosenthal’s ad hoc test shows that the FSN is lower than the critical FSN of 35, so at least in theory it is possible that another 30 studies showing null or negative results between firm size and disclosure scores are lying around in file drawers. A larger sample of studies examining this relation would allow a better assessment of the combined effect and its robustness to publication bias.

To summarize, we find that on average, the studies that examine the relation between firm size and disclosure about intangible assets find that larger firms disclose more about their intangible assets, intellectual capital, R&D etc. While this is in line with the predicted hypothesis and the intuitive expectation, the relative robustness of the meta-analysis result lends additional reliability to the relation. The low heterogeneity between the meta-analyzed studies provides some assurance that the synthesized relation is reflecting the “true” relation.

4.2. Financial analysts' earnings forecasts errors and R&D expenses

We meta-analyze the relation between R&D expenses and analyst earnings forecast errors based on results from six primary studies (Anagnostopoulou, 2010; Barron, Byard, Kile, and Riedl, 2002; Ciftci, Lev, and Radhakrishnan, 2011; Gu and Wang, 2005; Jones, 2007; Rajgopal, Venkatachalam, and Kotha, 2003). Except for Anagnostopoulou (2010) who examines the UK setting, the other studies focus on the U.S. and cover parts of the pre-Regulation Fair Disclosure period. On average, R&D expenses and financial analysts' forecast errors are negatively related, but the combined effect size of −0.018 is not significant at conventional levels (z-statistic is −0.53). Gu and Wang (2005) argue that significant levels of intangible assets are inherently accompanied by high information complexity which makes it difficult for analysts to assimilate and process information, and thus increases the forecast error. Anagnostopoulou (2010) argues that R&D expensing, versus capitalizing, is uninformative for financial analysts and ends up hurting their forecasting accuracy. Barron et al. (2002), however, argue that when R&D expenses are high, analysts will supplement the public information with their own private information to try to make sense of the complex situation of the firm.

The percentage of total variability due to between-studies variability is large, 89 percent, which means that the meta-analytic result cannot be interpreted reliably since the studies are too heterogeneous. The prediction interval ranges from −0.1521 to 0.1155 which means that the results of about 95 percent of studies will probably fall within this wide range, with both negative and positive value possible.

Overall, a better understanding of how financial analysts perform their job, especially in relation to high-technology and intangible-intensive firms in contexts where R&D is capitalized versus expensed would contribute to this stream of literature. We believe this requires more empirical research as well as analytical theoretical models.

4.3. Firm profitability and R&D expenses

We run two meta-analyses related to firm profitability. The first looks at the relation between R&D expense and the level of future firm profitability and relies on five studies (Anagnostopoulou and Levis, 2008; Brown and Kimbrough, 2011; Ciftci and Cready, 2011; Pandit, Wasley, and Zach, 2011; Sougiannis, 1994). The resource-based view of the firm posits that investment in R&D and intangibles in general is a source of competitive advantage and economic differentiation (Mauri and Michaels, 1998). We find a positive and marginally significant meta-relation between R&D expenses and future firm profitability, with a combined effect size at 0.014 (z-statistic 1.63). Based on *Rosenthal's FSN*, it would take 17 file-drawer studies with opposite or insignificant results to overturn this meta-result, a number smaller than the critical FSN of 35 studies. *Fisher's FSN* indicates that 14 studies with insignificant results would be required to overturn the meta-result.

The I^2 is 79 percent, indicating that the set of five primary studies is heterogeneous. The prediction interval ranges between −0.0160 and 0.0444, with a larger range in positive values than in negative values. This indicates that the probable relation between R&D expenses and firm profitability is more likely going to be positive than negative. This further implies that the association with firm profitability is likely dependent on the context of the firm, the industry, and the nature of the intangibles themselves (Lippman and Rumelt, 1982).

The second meta-analysis includes five studies that examine the relation between the volatility (i.e., standard deviation) of future firm profitability with R&D expenses (Amir, Guan, and Livne, 2007; Ciftci and Cready, 2011; Ciftci et al., 2011; Pandit et al., 2011; Weiss, Falk, and Zion, 2013). We find a positive combined effect size of 0.071 significant at 1 percent (*z*-statistic is 5.74).[19] This suggests that the higher the R&D expense, the higher the uncertainty of future profits. This result corresponds to the idea that the result of R&D activities is uncertain and that there is a fine line between projects that are successful and projects that fail. The studies included are likely to be heterogeneous since the I^2 statistic shows that more than 94 percent of total variability is due to between-study variability. While the prediction interval is relatively large, ranging between 0.0043 and 0.1386, it is firmly situated above zero, strengthening our confidence that the combined effect size is indeed positive and can be interpreted. The *FSN* numbers are 52 (Rosenthal's) and 36 (Fisher's), respectively, which means that a large number of studies with insignificant results is necessary to overturn the meta-analytic result.

4.4. R&D expenses and share price

Eleven studies examine the relation between share price and R&D expenses (Ali Shah and Akbar, 2008; Cazavan-Jeny and Jeanjean, 2006; K. M. Ely, Simkof, Thomas, Simko, and Thomas, 2003; Gong and Wang, 2016; Hirschey and Richardson, 2004; Hirschey and Weygandt, 1985; Rajgopal et al., 2003; Shah, Stark, and Akbar, 2009; Shevlin, 1991; Shortridge, 2004; Tutticci, Krishnan, and Percy, 2007; Zhao, 2002). These are "association studies" that examine the contemporaneous relation between a firm's stock price and its R&D activity. The reasoning behind studying the value relevance of R&D expenses is that although the expensing treatment is required by the accounting standards (particularly under U.S. GAAP and if certain criteria is not met under IFRS), these expenses can be viewed as investments into intangible assets. Therefore,

[19] Note that when the combined effect size is not statistically significant, the fail-safe N is zero and reporting it is meaningless.

the goal of the R&D value relevance literature is to assess whether investors view R&D expense as a piece of relevant information useful for deciding whether to buy, hold, or sell a firm's stock (Barth, Beaver, and Landsman, 2001).

A meta-analysis of the primary partial effect sizes results in a combined effect size of 0.057, with a *z*-statistic of 0.73, not significant at conventional levels. Heterogeneity is a concern, i.e., I^2 is 97 percent. Six out of the 11 studies are focused on U.S. samples, while the rest are focused on international samples (Australia France, the UK). However, there does not seem to be a clear separation between R&D value relevance along the geographical lines. Even in the U.S., the value relevance of R&D expense is negative in certain settings, e.g., firms with R&D limited partnerships (Shevlin, 1991).

The prediction interval is −0.1929 to 0.3060, with a range of about 0.5, almost ten times the combined effect size. This indicates that the approximate estimated effect size of the relation between the amount of R&D expenses and subsequent share price in about 95 percent of studies is likely to fall in this wide range. Due to the large variability between studies, drawing too strong conclusions based on the average effect size should be avoided. Nevertheless, a heterogeneous and small association between R&D expenses and share price casts doubt on the presumed generalized value relevance of R&D expenses.

4.5. R&D expenses and stock returns

Fourteen studies examine the relation between R&D expenses and stock returns (Aboody and Lev, 1998; Ali, Ciftci, and Cready, 2012; Boone and Raman, 2004; Brown and Kimbrough, 2011; Bublitz and Ettredge, 1989; Cazavan-Jeny and Jeanjean, 2006; Chambers, Jennings, and Thompson, 2002; Chan, Martin, and Kensinger, 1990; Ciftci and Cready, 2011; Donelson and

Resutek, 2012; Gong and Wang, 2016; Gu and Li, 2010; Han and Manry, 2004; Palmon and Yezegel, 2012). We find a positive combined effect size of 0.044, statistically different from 0 with a z-statistic of 3.66 and a corresponding p-value < 0.01. This indicates that, on average, empirical studies find a positive relation between the amount of R&D expenses and future stock returns. Based on *Rosenthal's FSN*, it would take about 126 null-results studies to overturn the significance of the combined effect size, and about 54 null-results studies to render the Fisher's test insignificant at 95 percent confidence level.

However, the I^2 statistic of 96 percent indicates that a large proportion of variability is due to observed effect sizes varying between studies. We get a better view of the range of heterogeneity from the prediction interval. The interval is between −0.0103 and 0.0993, so we would expect that in about 95 percent of the population of studies, the effect size for the relation between R&D expenses and stock returns will probably fall in this range. Since the prediction interval includes 0, chances are the "true" effect size will be negative in some situations. Nevertheless, about 90 percent of the prediction interval is positive, so we would expect a higher proportion of the effect sizes of this relation to be positive. This high degree of heterogeneity also means that the interpretation of the average, combined effect size may not be reliable since the studies do not seem to be comparable and homogeneous.

In summary, while we find a positive and statistically significant combined effect size from 14 studies on the relation between R&D expenses and stock returns, the studies are too heterogeneous to be aggregated in a meaningful way. This suggests that in some sub-samples the relation between R&D investment and stock returns is not necessarily positive.

4.6. Meta-analyses based on small samples of primary studies

Finally, we present separately the meta-analyses based on four or fewer studies. Given the small sample of studies, the combined effect sizes from these meta-analyses cannot be interpreted with a reasonable degree of reliability. We believe this situation calls for more research on these relationships. We note below some of the surprising meta-analytic relations.

We find a positive meta-analytic relation between R&D expenses and analyst earnings forecast dispersion, suggesting R&D relates to more pronounced disagreement between analysts and more uncertainty in their forecasts. This result is based on two papers that report a positive association (Barron et al., 2002; Jones, 2007) and one that reports a negative association between R&D expenses and analyst forecast dispersion (Ciftci et al., 2011).

There appears to be a positive relation between advertising expenses and analyst earnings forecast errors. This seems counter to the general intuition that advertising expenses are value-enhancing (Pandit et al., 2011) and that advertising contributes to the overall reputation of the firm, making it difficult for customers to switch to competitors (Rajgopal et al., 2003). The meta-analytic results on the relation between advertising expense and R&D expenses, respectively, and future firm profitability are important since it is often argued in a general sense that higher levels of advertising expenses and of R&D expenses lead to higher future firm profitability.

Based on only two studies, capitalized R&D appears to be positively related to the volatility of future firm profitability (Amir et al., 2007; Weiss et al., 2013) and negatively related to share price (Cazavan-Jeny and Jeanjean, 2006; Zhao, 2002). This implies that R&D capitalization is surrounded by increased uncertainty which leads to concerns from an investor perspective (Cazavan-Jeny and Jeanjean, 2006). More research is needed to improve our understanding of these issues.

[TABLE 4 ABOUT HERE]

5. Conclusions and avenues for future research

Overall, the meta-analysis results synthesize the robust empirical relations between variables related to intangible assets in the accounting literature, but also point out areas where more research is needed to improve our understanding on the effects and determinants of recognition and disclosure of intangible assets. We review the empirical archival literature on internally-developed intangible assets, focusing on their accounting treatment. By using meta-analyses to summarize the effects uncovered in this literature, we contribute to the ongoing debate on recognition versus disclosure of intangible assets. A number of observations and potential future research questions arise.

First, the majority of studies reviewed deal with recognition of intangibles in the accounts, either as an asset on the balance sheet or as an expense on the income statement. There are fewer studies on disclosure of intangibles, although the criteria for accounting recognition is so strict (especially in the U.S.) that if managers of intangible-intensive firms want or need to reduce the information asymmetry relative to outsiders, voluntary disclosure about intangibles is the only solution.

Second, we observe that most papers examine the U.S. setting. The European and international settings could yield additional insights into the role of recognition and disclosure of intangibles, given the differences in standards and the fact that capitalization of development costs is allowed by IAS 38. Taking into consideration the various types of listing (i.e., foreign listed companies, domestic companies, companies cross-listed in the U.S. but applying IFRS etc.), future research could address questions related to country-level influences (i.e., investor protection, legal tradition, enforcement etc.) on the recognition and disclosure of intangible assets.

Our meta-analysis tests provide five main results that allow us to highlight the consensus in previous empirical work and the areas of disagreement. First the only robust association of intangible-related disclosures is with firm size, which is not different from other types of voluntary disclosures. The relation between R&D expenses and financial analyst earnings forecast error is not significant and the evidence is mixed which calls for more research on the use of intangible related information by financial analysts. Future firm profitability seems to be positively driven by R&D expenses. Nevertheless, the volatility of future firm profitability is positively correlated with R&D expenses, underlying the risk and uncertainty associated with intangible investments. Finally, our meta-analysis results on value relevance research are in contrast. The return specification of R&D value relevance provides a positive association, but the price specification of R&D value relevance is not significant. Therefore, we cannot conclude on the value relevance of R&D expenses. Studies on advertising expenses, capitalized R&D, or analysts forecast dispersion are too rare to allow for meta-analysis. This situation calls for more research on these topics.

A limitation of the current literature, and implicitly of our review, is the small number of studies on each topic that does not allow a systematic investigation of the sources of heterogeneity between studies. Another limitation could be due to the classification of dependent and independent variables in broader categories that can be matched for the purpose of the meta-analysis. This classification is done manually and reflects our interpretation which may not be the same as the interpretation that other researchers have.

Researchers could also focus on certain Internet-based industries where intangibles are prevalent, such as the entertainment industry. What do managers of companies in these sectors disclose? What questions about intangibles do analysts ask the managers during conference calls? What intangible-related variables are value-relevant for these companies? How does intangibles' disclosure affect the costs and benefits of disclosure? Looking at the IPO prospectus intangible-related disclosures by "unicorn" tech companies could shed light on the current relationship between intangibles, information asymmetry, and the uncommonly-high market valuation for such companies.

Intangible-related disclosure is essential for financial analysts covering R&D-intensive firms. Some of the papers reviewed above use the discussion about intangibles in analyst reports as anecdotal evidence to support earnings forecast and recommendation analyses (Xu, Magnan, and André, 2007). Future research could more directly examine analysts' reports on this topic to assess analysts' assessments of intangibles disclosure (for example, remarks about the quantity of disclosure).

Beyond evaluating the robustness of results from prior literature, we have highlighted a number of areas where additional research would improve our understanding and inform standard setters and practitioners. Overall, we believe that academic research on accounting for intangible assets has considerable potential to inform standard setters and practitioners as they navigate their way through the “knowledge economy.”

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Appendix A: Description of random-effects model meta-analysis using partial correlational effect sizes[20]

I. Formulas and description of meta-analysis

General setup

The primary studies sampled for the meta-analysis report results from multivariate regression models. Assume that a general multivariate regression model reported in study i, out of the k studies included in the meta-analysis, is:

$$Y_i = \beta_{0i} + \beta_{1i}X_{1i} + \beta_{2i}X_{2i} + \cdots \beta_{pi}X_{pi} + \varepsilon$$

The model contains p independent variables and is run on a sample of size n.

Assume further that the goal of our meta-analysis is to synthesize the relation between variables Y and X_j. The main input to this synthesis is based on the regression coefficient β_j that expresses the relation between the dependent variable Y and the independent variable X_j, and related statistics (e.g., t-statistic) from each of the k primary studies sampled.

Since primary studies report multivariate regression models, usually with several control variables, the regression coefficient β_j is a partial correlation between X_j and Y obtained after the bivariate correlation between X_j and Y is controlled for other variables that are likely correlated with either one or both.

Partial effect size based on regression data

For each study i, we compute the partial effect size (*PES*) between Y and X_j, an index that describes the magnitude of an effect after controlling for the influence of other variables in the model (Aloe and Thompson, 2013). Subscript i is omitted for brevity.

$$PES_i = \frac{t_{ji}}{\sqrt{t_{ji}^2 + (n_i - p_i - 1)}}$$

Where t_j is the t-statistic of the regression coefficient β_j, n and p are as defined above.

Note that if the primary study does not report the t-statistic, the coefficient and the standard error are used to compute the t-statistic as $t_{ji} = \beta_{ji}/SE_{ji}$

[20] This appendix provides detailed descriptions of the computation of meta-analysis results reported in this paper. The code that generates our results was written in SAS, but draws heavily from the *Meta-essentials* Excel™ software developed by Suurmond, van Rhee, and Hak (2017) and available online at https://www.erim.eur.nl/research-facilities/meta-essentials/. We appreciate these authors' commitment to open science.

We estimate the variance of the partial effect size as DerSimonian and Laird (1986):

$$Variance\ PES_i = \frac{(1 - PES_i^2)^2}{n_i - p_i - 1}$$

This re-computation of the effect size between X_j and Y is necessary to ensure that the measures synthesized in the meta-analysis have the same metric. The use of the β_j or t_j has been criticized in prior literature (DerSimonian and Laird, 1986). The *PES* is a unit-free index of the relation between X_j and Y. The *PES* and associated statistics are inputs to the meta-analysis statistics that follow.

Combined effect size under the random effects model

Real-world data is very likely to be heterogeneous, so using the fixed-effects model, which accounts for within-study sampling error only, would lead to biased meta-analytic results (Borenstein et al., 2017). The random effects model incorporates two sources of variation,

(1) within-study sampling error, which is the variance of the partial effect size computed above (*Variance PES*), and

(2) between-studies variability, which is the variance of true effects (tau-squared, noted as τ^2).[21]

As proposed by Aloe (2014), between-study variability τ^2 is computed as follows, summing up over all k studies included in the meta-analysis of the relation between variables X_j and Y:

$$\tau^2 = \frac{Q - (k-1)}{\sum_{i=1}^{k}\left(\frac{1}{Variance\ PES_i}\right) - \frac{\sum_{i=1}^{k}\left(\frac{1}{Variance\ PES_i}\right)^2}{\sum_{i=1}^{k}\left(\frac{1}{Variance\ PES_i}\right)}}$$

Where

$$Q = \sum_{i=1}^{k}\left(\frac{PES_i^2}{Variance\ PES_i}\right) - \frac{\left(\sum_{i=1}^{k}\left(\frac{PES_i}{Variance\ PES_i}\right)\right)^2}{\sum_{i=1}^{k}\left(\frac{1}{Variance\ PES_i}\right)}$$

According to Aloe (2014), Q refers to the distribution of observed effects, and is the sum of squared deviations of all effects around the mean, standardized using fixed effect weights (i.e., the inverse of each effect's variance). Q follows the chi-squared distribution with k – 1 degrees of freedom.

[21] An broader issue, beyond the scope of our paper, is whether the random-effects model leads to meaningful results considering that the variability of "true" effects is "derived from the extent of variability of the effect sizes of the underlying studies" (see for example, Professor Suhail Doi's reply dated April 29, 2011 to Riley et al. (2011), available online at http://www.bmj.com/content/342/bmj.d549/rapid-responses).

The square root of τ^2 is an absolute value that tells us how the true effects are distributed (Borenstein et al., 2017).

The random effects model requires that each partial effect size be inverse-weighted by its variance, a measure of within-study variability, plus the between-study variability τ^2

$$Weight_i = \frac{1}{(Variance\ PES_i + \tau^2)}$$

In the absence of between-study heterogeneity, $\tau^2 = 0$, and the random effects model reduces to the fixed-effects model with one source of variation, within-study sampling error (Borenstein et al., 2017; Higgins, Thompson, and Spiegelhalter, 2009; Riley, Higgins, and Deeks, 2011).

The z-score for the partial effect size (*PES*) that takes into account both sources of heterogeneity is then:

$$Z_i = \frac{PES_i}{\sqrt{Variance\ PES_i + T^2}}$$

The weighted mean partial effect size between variables X_j and Y combined across k studies (*CES*) is then:

$$CES = \frac{\sum_{i=1}^{k}(Weight_i \times PES_i)}{\sum_{i=1}^{k} Weight_i}$$

With a standard error:

$$StdErr = \sqrt{\frac{\sum_{i=1}^{k}(Weight_i \times (PES_i - CES)^2)}{(k-1) \times \sum_{i=1}^{k} Weight_i}}$$

Computing the Z-statistic for *CES* will allow to assess the statistical significance of the combined effect size, under the assumption that the Z-statistic follows the normal distribution.

$$Z = \frac{CES}{StdErr}$$

Measures of heterogeneity

1. Proportion of variation in observed effects due to variation in true effects (I^2)

$$I^2 = \frac{Q - (k-1)}{Q}$$

A number of meta-analysis theoretical papers (Borenstein et al., 2017; Higgins, Thompson, and Spiegelhalter, 2009; Riley, Higgins, and Deeks, 2011) explain that in the numerator, difference between Q, the total sum of squares, and the degrees of freedom (k – 1), the sum of squares attributed to sampling error, gives the sum of squares due to variance in true effects. Hence, the percentage I^2, ranging from 0 – 100%, is a measure of true to total variance in the observed effects that shows “what proportion of the observed variance would remain if we could somehow observe the true effect size for all studies in the meta-analysis” (Borenstein et al., 2017; Higgins, Thompson, and Spiegelhalter, 2009; Riley, Higgins, and Deeks, 2011).

To emphasize this point, consider the following very simple illustration inspired by Borenstein et al. (2017):

Constant within-study variability and increasing between-study heterogeneity								
τ^2	1	2	3	4	5	10	100	1000
Within-study variability	5	5	5	5	5	5	5	5
I^2	17%	29%	38%	44%	50%	67%	95%	100%

Constant between-study heterogeneity and increasing within-study variability								
τ^2	5	5	5	5	5	5	5	5
Within-study variability	1	2	3	4	5	10	100	1000
I^2	83%	71%	63%	56%	50%	33%	5%	0%

While I^2 provides a relative measure of the degree to which the studies are heterogeneous, it does not provide any intuition about *how much* the observed effect sizes vary.

2. Prediction interval

The prediction interval provides an approximate range that will probably contain the effect size for about 95% of all population. We compute the prediction interval around the combined effect size as (Rosenthal, 1979):

$$Prediction\ Interval = CES\ \pm t_{(\alpha,df)}\sqrt{StdErr^2 + \tau^2}$$

Where $df = k - 2$ is the number of degrees of freedom and $t_{(\alpha,df)}$ is the critical one-tail t-value for a value of α and df degrees of freedom, and accounts for the fact that the standard deviation is being estimated.[22] The prediction interval uses the variance of *CES* (the square of *StdErr*), as an adjustment for the fact that the true combined effect size may be lower or higher than the estimated *CES*, and τ^2 to account for the heterogeneity of the studies included in the meta-analysis. Rosenthal (1979) notes that when the number of studies k is small, the adjustment has a substantial impact and the interval will likely be very wide.

[22] Note that for computing the prediction interval, the *Meta-Essentials* software computes the degrees of freedom as $df = k - 1$. We follow Borenstein et al. (2017) instead and compute the degrees of freedom as $df = k - 2$.

Becker (2005) explains that the prediction interval is not the same as the confidence interval. The confidence interval for the combined effect size is a property of the sample that shows how precisely the mean effect size is estimated (i.e., based on the standard error). In contract, the prediction interval is an index of dispersion, i.e., based on the standard deviation, that shows how widely the effects vary across populations.

Measures of meta-analysis robustness to publication bias

The meta-analytic literature recognized early on that studies with statistically significant results are more likely to be published than those with null results (Becker, 2005). This so-called "file drawer" problem implies that the published studies are but a fraction of the population of studies and may not be representative of the population, which would mean meta-analytic results are biased.

Stouffer, DeVinney, and Suchmen (1949) proposed a relatively simple way of measuring the "tolerance for null results" and other measures have been developed since. Since the various fail-safe N measures developed after Rosenthal give very different results, using FSN measures is seen as problematic from a statistician's perspective (Stouffer, DeVinney, and Suchmen, 1949). Nevertheless, we (and many other empirical researchers) decided to rely on them since the number of studies in the meta-analyses we run is too small to lead to meaningful results in regressions with variables associated with publication bias as predictors, the alternative to FSN proposed in the statistical literature.

1. Rosenthal's Fail-safe N

Rosenthal's FSN answers the following question: "given a significant result for an overall test of combined significance in meta-analysis, how many additional results would it take to reduce the overall test to non-significance?" (Becker, 2005).

$$Rosenthal's\ FSN = k \times \left(\frac{\frac{\sum_{i=1}^{k} Z_i}{\sqrt{k}}}{Z_\alpha} \right)^2 - k$$

Where Z_α equals the one-tailed z-statistic corresponding to the desired confidence level. For example, for $\alpha = 0.05$, $Z_\alpha = 1.645$, and so $Z_\alpha^2 = 2.706$.

Rosenthal's *FSN* relies on the test of combined significance, also known as the "sum of Zs", suggested by (Becker, 2005):

$$Z_S = \frac{\sum_{i=1}^{k} Z_i}{\sqrt{k}}$$

Z_S is a standard normal deviate and testing the null hypothesis is done by comparing Z_S to a table of values from the normal distribution.

Rosenthal's *FSN* is considered robust if it is larger than $5 \times k + 10$. Note, however, that this is an ad-hoc rule and there is no statistical significance testing attached to it (Summond et al. 2017).

2. Fisher's Fail-safe N

Fisher's test is another test of combined significance based on the sum of natural logarithms of observed p-values (Becker, 2005):

$$Fisher's\ test = \sum_{i=1}^{k} -2\ln(p_i)$$

which is distributed as chi-square with $2 \times k$ degrees of freedom under the null hypothesis (Becker, 2005). This means that a p-value can be used to assess whether Fisher's test is significant.

This test can also be used to generate a fail-safe N. In other words, how many studies with p-values equal to 0.50 added to those observed does it take to bring Fisher's test to non-significance? A highly significant Fisher's test means that it would take many studies in "file drawers" to counterbalance the results of the meta-analysis, suggesting that the results can be interpreted as robust.

Following Becker (2005), we use an iterative loop to find the number of studies reporting a p-value of 0.5 that should be added to the meta-analysis to render the Fisher's test non-significant.

Becker explains that adding a study with $p\text{-}value_i = 0.5$ is equivalent to adding a term of $-2\ln(p\text{-}value_i) = 1.386$ to the Fisher test statistic, and increasing the degrees of freedom by 2×1 study. In other words, we are searching for the number of studies reporting insignificant results that would make the p-value for the Fisher's test larger than the α based on the confidence interval, i.e., p-value > 0.05 if the confidence interval is 95%.

II. Numerical example[23]

We illustrate the step-by-step computation of our meta-analysis results with the meta-analysis of the effect size of *Intangible assets* as independent variable (i.e., X_j from the general setup above) on the *Share Price* as dependent variable (i.e., Y from the general setup above).

[23] Note that results change slightly depending on the number of decimals used. In this appendix, we generally limit the number of decimals to 3 for ease of reading, but the results were obtained using 8 decimals in SAS.

We found three studies that examined the relation between these two variables (i.e., k = 3). Table A.1 shows the data collected from each of these studies. The *PaperID* column represents the unique identifier we attributed to each study in the dataset we collected for meta-analysis.

Table A.1: Input data

Paper ID	Authors	Sample size (n)	Beta (β)	t-value (t)	Number of predictors (p)	Source
8	Ritter and Wells (2006)	1078	1.02	7.715	4	Table 2 Panel B, model 1, pg. 855
51	Aboody and Lev (1998)	778	0.57	2.06	3	Table 4 Panel A, pg.176
66	Ely and Waymire (1999)	146	0.0944	1.12	3	Table 3, model 1, pg. 32

We use the regression data collected above to compute the partial correlation effect size for each study and its variance (and implicitly, its standard error). These computations are shown in Table A.2.

Table A.2: Partial effect size based on regression data

Paper ID	Authors	PES	Variance PES
8	Ritter and Wells (2006)	$\frac{7.715}{\sqrt{(7.715)^2 + 1078 - 4 - 1}} = 0.229$	$\frac{(1 - 0.229^2)^2}{1078 - 4 - 1} = 0.000837$
51	Aboody and Lev (1998)	$\frac{2.06}{\sqrt{(2.06)^2 + 778 - 3 - 1}} = 0.074$	$\frac{(1 - 0.074^2)^2}{778 - 3 - 1} = 0.001278$
66	Ely and Waymire (1999)	$\frac{1.12}{\sqrt{(1.12)^2 + 146 - 3 - 1}} = 0.094$	$\frac{(1 - 0.094^2)^2}{146 - 3 - 1} = 0.006919$

Summing over these three studies (k = 3), we find Q, the distribution of observed effect sizes, and τ^2, the between-study heterogeneity, both of which are useful to compute other statistics.

$$Q = \left(\frac{0.229^2}{0.000837} + \frac{0.074^2}{0.001278} + \frac{0.094^2}{0.006919}\right) - \frac{\left(\frac{0.229}{0.000837} + \frac{0.074}{0.001278} + \frac{0.094}{0.006919}\right)^2}{\left(\frac{1}{0.000837} + \frac{1}{0.001278} + \frac{1}{0.006919}\right)} = 12.163$$

$$\tau^2 = \frac{12.163 - (3 - 1)}{\left(\frac{1}{0.000837} + \frac{1}{0.001278} + \frac{1}{0.006919}\right) - \frac{\frac{1}{0.000837^2} + \frac{1}{0.001278^2} + \frac{1}{0.006919^2}}{\left(\frac{1}{0.000837} + \frac{1}{0.001278} + \frac{1}{0.006919}\right)}} = 0.00883$$

In particular, τ^2 is used as adjustment for the weight of each study in the random-effects model approach. The computation of the random-effect model weight and the associated z-statistic for the partial effect size in each study is presented in Table A.3.

Table A.3: Random-effect weight and z-statistic for each study

Paper ID	Authors	PES	Variance PES	Weight	Z
8	Ritter and Wells (2006)	0.229	0.000837	$\frac{1}{0.000837+0.00883}=103.433$	$\frac{0.229}{\sqrt{0.000837+0.00883}}=2.33$
51	Aboody and Lev (1998)	0.074	0.001278	$\frac{1}{0.001278+0.00883}=98.917$	$\frac{0.074}{\sqrt{0.001278+0.00883}}=0.73$
66	Ely and Waymire (1999)	0.094	0.006919	$\frac{1}{0.006919+0.00883}=63.488$	$\frac{0.094}{\sqrt{0.006919+0.00883}}=0.75$

Now that we found the *PES* and the random-effect weight of each study, we can compute the combined effect size, *CES*.

$$CES = \frac{0.229 \times 103.433 + 0.074 \times 98.917 + 0.094 \times 63.488}{103.433 + 98.917 + 63.488} = 0.139$$

With a standard error of:

$$StdErr = \sqrt{\frac{103.433 \times (0.229 - 0.139)^2 + 98.917 \times (0.074 - 0.139)^2 + 63.488 \times (0.094 - 0.139)^2}{(3-1) \times (103.433 + 98.917 + 63.488)}} = 0.049$$

The estimated combined effect size has a z-statistic of:

$$Z = \frac{0.139}{0.049} = 2.84$$

Assuming *CES* follows a normal distribution, a z-statistic of 2.84 means that *CES* is significant at one-tail p-value = 0.0022, and two-tail p-value = 0.0045.

To examine the heterogeneity of the studies included in the meta-analysis, we first compute I^2.

$$I^2 = \frac{12.163 - (3-1)}{12.163} = 0.8355$$

An I^2 of 83.55% is considered large (i.e., close to 100%), so most of the observed dispersion in effect sizes of the relation between *Share Price* and *Intangible assets* is due to variation in “true” effect sizes. Put differently, most of the observed dispersion in effect sizes would remain even if we could somehow remove the within-study variance, i.e., the within-study sampling error. This further implies that interpreting the combined effect size of 0.139 is not useful, and that the focus should be on the range of heterogeneity as shown by the prediction interval.

A small I^2 (i.e., closer to 0%) would mean that there is little variation in “true” effect sizes, so most of the observed dispersion is due to within-study sampling error. Therefore, the population of studies examining the relation between the two variables would be considered homogeneous.

The <u>prediction interval</u> provides an approximation of the range of true effect sizes. Assuming that the confidence level we aim for is 95%, the absolute value of one-tail (or right-tail) t-value for a probability level of α = 0.05 and *df* = 3 – 2 = 1 is 6.31375, so we obtain the prediction interval as follows:

$$Prediction\ Interval = 0.139 \pm t_{\alpha,df=1} \times \sqrt{0.049^2 + 0.00883} = 0.139 \pm 6.31375 \times 0.106$$
$$= 0.139 \pm 0.669$$

Therefore, the interval $[-0.537; 0.815]$ is the approximate range within which the effect size in 95% of the population of studies on *Share Price* and *Intangible assets* will probably be found.

The prediction interval contains the value 0 which means that the true effect size could be either negative or positive. The prediction interval is relatively wide (i.e., the width is almost ten times the combined effect size), meaning that there likely is significant heterogeneity in the population (consistent with the interpretation of I^2). However, since wide prediction intervals are also a reflection of the small number of studies included in the meta-analysis, we cannot interpret it reliably.

We compute two versions of <u>fail-safe N</u>: *Rosenthal's FSN* and *Fisher's FSN*.

The computation of *Rosenthal's FSN* is straightforward:

$$Rosenthal's\ FSN = 3 \times \left(\frac{\frac{2.33 + 0.73 + 0.75}{\sqrt{3}}}{1.645} \right)^2 - 3 = 2.36$$

Where the z-statistic for a confidence level of 95% is 1.645.

We round up Rosenthal's FSN to 3, which means that it would take only 3 studies with a null result to overturn the significant combined effect size we find based on the observed studies included in the meta-analysis. Rosenthal (1979) proposed comparing the FSN to a critical value computed as 5 × 3 + 10 = 25. The FSN = 3 is much lower than the critical FSN of 25 studies, suggesting that the combined effect size and significance are sensitive to publication bias.

Our second way of computing a fail-safe N relies on Fisher's (1935) test of combined significance levels.

$$Fisher's\ test\ statistic = (-2) \times (\ln(0.009) + \ln(0.231) + \ln(0.228)) = 15.309$$

Fisher's test statistic follows a chi-square distribution with 2 × 3 degrees of freedom, so significant at a 0.018 (two-tail p-value).

We use an iterative addition process to find the Fisher FSN, knowing that adding one study with a p-value of 0.5 is equivalent to adding $(-2) \times \ln(0.5) = 1.386$ to the Fisher's test statistic. We add one-by-one hypothetical studies with p-values of 0.5, which also increases the number of degrees of freedom, and stop when the significance level of the re-computed Fisher's test statistic goes above α = 0.05. The number of iterations necessary to render the Fisher's test statistic insignificant gives the fail-safe N based on Fisher's test.

Table A.4: Iterations to find fail-safe N based on Fisher's test

Iteration #0	Fisher's test statistic	15.309
	df	6
	p-value for $\chi^2_{15.309;6}$	0.018
Iteration #1	Fisher's test statistic	15.309 + 1.386 = 16.695
	df	2 × (3 + 1) = 8
	p-value for $\chi^2_{16.695;8}$	0.033
Iteration #2	Fisher's test statistic	15.309 + 2×1.386 = 18.081
	df	2 × (3 + 2) = 10
	p-value for $\chi^2_{18.081;10}$	**0.054**

Consistent with *Rosenthal's FSN*, *Fisher's FSN* shows that it takes only two studies with null-results to overturn the significance of the Fisher's test statistic. This number is very low so it is conceivable that two unpublished studies with insignificant results exist out there, indicating once again that the meta-analysis results are very sensitive to potential publication bias.

Table 1. Composition of the sample of studies included in the meta-analyses

Panel A: Sample selection for meta-analyses

	Number of studies	**Percent**
Initial sample of studies considered for meta-analyses	116	
(−) Unpublished papers	−2	
(−) Not related to accounting of intangible assets	−9	
(=) Published accounting studies	**105**	**100%**
(−) Missing data to compute statistics for meta-analysis	−16	
(−) Only one study to examine the relation between two variables	−38	
	51	48.57%
Sample of studies for meta-analyses (at least 5 primary studies)	**37**	**35.24%**

This table describes the sample selection for the studies included in the meta-analyses. We include a study in the final sample when there are at least five studies that can be included in the meta-analysis. The final sample of studies represents 46 observations at the study-variable pair level.

Panel B: Sample by journal

Journal name and abbreviation	Frequency	Percent
Accounting and Finance (AF)	1	2.70
Asian Review of Accounting (ARA)	1	2.70
Advances in Accounting (AinA)	1	2.70
Contemporary Accounting Research (CAR)	**2**	**5.41**
European Accounting Review (EAR)	2	5.41
Journal of Accounting Research (JAR)	**4**	**10.81**
Journal of Accounting and Economics (JAE)	**1**	**2.70**
Journal of Accounting, Auditing and Finance (JAAF)	5	13.51
Journal of Business, Finance and Accounting (JBFA)	4	10.81
Journal of Empirical Finance (JEF)	1	2.70
Journal of Financial Economics (JFE)	1	2.70
Journal of International Accounting Research (JIAR)	1	2.70
Journal of International Financial Management and Accounting (JIFMA)	2	5.41
Review of Accounting Studies (RAST)	**3**	**8.11**
The Accounting Review (TAR)	**4**	**10.81**
The International Journal of Accounting (TIJA)	4	10.81
TOTAL	**37**	**100%**
Papers in high-quality journals	14	37.84

This table presents the distribution of the final sample of papers included in the meta-analyses by publication journal. Journals in boldface font are considered high-quality.

Panel C: Sample by country

Country or region	Frequency	Percent
Australia	1	2.70
France	1	2.70
International	2	5.41
International (including US)	1	2.70
Malaysia	1	2.70
South Korea	1	2.70
Spain	1	2.70
U.S.	26	70.27
United Kingdom	3	8.11
TOTAL	**37**	**100%**

This table presents the distribution of the final sample of papers included in the meta-analyses by country or region from which the sample of companies is drawn.

Table 2. List of papers in the sample of studies included in meta-analyses

Authors	Year	Journal	Country	Sample period	Sample size	Source of information
Aboody and Lev	1998	JAR	U.S.	1987–1995	778	Table 4 Panel A, pg.176
Ali, Ciftci, and Cready	2012	JBFA	U.S.	1975–2006	38853	Table 2, model 1, pg. 297
Amir, Guan, and Livne	2007	JBFA	U.S.	1972–2002	37263	Table 5, Equation 1 full sample, pg. 238
Anagnostopoulou	2010	JIFMA	UK	1990–2003	6274	Table 3 Panel A, pg. 73
Anagnostopoulou and Levis	2008	TIJA	UK	1990–2003	15488	Table 6, pg.310
Barron, Byard, Kile, and Riedl	2002	JAR	U.S.	1986–1998	1103	Table 4 pg. 306
Boone and Raman	2004	JAAF	U.S.	1994–1997	52	Table 3, model "0-12", pg. 203
Brown and Kimbrough	2011	RAST	U.S.	1980–2006	119436	Table 4, model 1, pg. 559
Bublitz and Ettredge	1989	TAR	U.S.	1974–1983	2832	Table 4, model 1, pg. 118
Cazavan-Jeny and Jeanjean	2006	EAR	France	1993–2002	770	Table 5, model 4, pg. 52
Chambers, Jennings, and Thompson	2002	RAST	U.S.	1979–1998	89419	Equation 1, pg. 151
Chan, Martin, and Kensinger	1990	JFE	U.S.	1979–1985	79	Table 6, model 1, pg. 272
Ciftci and Cready	2011	JAE	U.S.	1975–2003	122636	Table 3 Panel A, model 2 All firms, pg. 72
Ciftci, Lev, and Radhakrishnan	2011	JAAF	U.S.	1979–1997	7591	Table 3 Panel B, model 2, pg. 96
Donelson and Resutek	2012	RAST	U.S.	1973–2008	56145	Table 2 Panel A, pg. 860
Ely, Simko, and Thomas	2003	JAAF	U.S.	1988–1998	193	Table 3, pg. 177
García-meca, Parra, Larrán, and Martínez	2005	EAR	Spain	2000–2001	257	Table 10, model 1, pg. 84
Gong and Wang	2016	AinA	Intl.	1997–2012	7613	Table 5, model 2, Page 54
Gu and Li	2010	JAAF	U.S.	1995–2004	4966	Table 5 Panel A, pg. 105
Gu and Wang	2005	JBFA	U.S.	1981–1998	6167	Table 3, model 5, pg. 1690
Han and Manry	2004	TIJA	South Korea	1988–1998	3191	Table 4 Panel A, pg. 167
Hirschey and Richardson	2004	JEF	U.S.	1989–1995	1720	Table 3, OLS model, pg. 103
Hirschey and Weygandt	1985	JAR	U.S.	1977–1977	390	Table 1, model 3, pg. 330
Jones	2007	CAR	U.S.	1997–1997	119	Table 3, model 3, pg. 506
Kamardin, Abu Bakar, and Ishak	2015	ARA	Malaysia	2006–2006	64	Table VI, model 1, pg. 288
Kang and Gray	2011	TIJA	Intl.	2002–2002	181	Table 5, pg. 418
Merkley	2014	TAR	U.S.	1996–2007	22482	Table 8, model 3, pg. 750
Palmon and Yezegel	2012	CAR	U.S.	1993–2004	8620	Table 7, pg. 649
Pandit, Wasley, and Zach	2011	JAAF	U.S.	1972–2000	20391	Table 3 Panel A, model 4, pg. 135
Rajgopal, Venkatachalam, and Kotha	2003	JAR	U.S.	1999–2000	434	Table 7, model 1, pg. 159
Shah, Stark, and Akbar	2009	TIJA	UK	1990–1998	9752	Table 3, model 1, pg. 199
Shevlin	1991	TAR	U.S.	1980–1985	145	Table 4, model 1, pg.15
Shortridge	2004	JBFA	U.S.	1985–1996	172	Table 3, model 1, pg. 1316
Sougiannis	1994	TAR	U.S.	1975–1985	66	Table 2, Mean model, pg. 57
Tutticci, Krishnan, and Percy	2007	JIAR	Australia	1992–2002	386	Table 3, pg. 96
Weiss, Falk, and Zion	2013	AF	U.S.	1990–2005	528	Table 4, model 2, pg. 852
Zhao	2002	JIFMA	Intl. (includes U.S.)	1990–1999	13029	Table 4 Panel B, pg. 170

This table provides the list of papers included in the meta-analyses. For each paper, the table presents the sample period, sample size, and indicates the table, model, and page number from where we collected the necessary data for meta-analyses.

Table 3. Meta-analyses results

Dependent variable	Independent variable	k	Combined Effect Size (CES)	Z-stat	Sig	I^2 (%)	Prediction Interval		Rosenthal's FSN	Is Rosenthal's FSN < Critical FSN?	Fisher's FSN
							Lower Bound	Upper Bound			
Disclosure score	Size	5	0.067	4.80	***	5.09%	0.0213	0.1126	33	Yes	25
Analyst earnings forecast error	R&D Expense	6	−0.018	−0.53	n.s.	89.40%	−0.1521	0.1155			5
Future profitability	R&D expense	5	0.014	1.63	*	79.24%	−0.0160	0.0444	17	Yes	14
Volatility of future profitability	R&D expense	5	0.071	5.74	***	94.28%	0.0043	0.1386	52	No	36
Share Price	R&D expense	11	0.057	0.73	n.s	97.01%	−0.1929	0.3060			52
Stock Return	R&D expense	14	0.044	3.66	***	95.72%	−0.0103	0.0993	126	No	54

This table presents the results of meta-analyses for which there are five or more primary studies observed that examine the relation between two variables. The input to each of the meta-analyses is the partial correlational data extracted from the multivariate regression models reported in the primary studies (i.e., partial effect sizes). The meta-analyses are based on a random effects model which assumes heterogeneity in the population of studies and automatically reverts to the fixed effects model when there is no heterogeneity between the observed studies (i.e., $\tau^2 = 0$). Column *k* refers to the number of independent studies included in each meta-analysis. The combined effect size (*CES*) is the inverse-weighted average of the partial effect sizes from the studies included in the meta-analysis under the assumption of heterogeneity in the population of studies (i.e., random effects model). The *Z-stat* is the z-statistic of the *CES*, computed as *CES* divided by its standard error, and assumed to follow the normal distribution. The column *Sig* indicates the significance level for the hypothesis that *CES* = 0 by comparing its *Z-stat* to the cumulative normal distribution function. Statistical significance is indicated as follows: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; n.s. denotes p-value not significant at conventional levels. The I^2 shows the percentage of total variability that is due to uncertainty and variability in the "true" effect sizes rather than the within-study variability or sampling error. The *Prediction Interval* is a measure of heterogeneity of the observed studies and gives the approximate range within which the effect size of about 95% of studies will probably be located. The *Prediction Interval* is the t-statistic at a 0.05 confidence level with $k - 2$ degrees of freedom times the standard deviation of the within-study and between-study variability (i.e., $t_{0.05;k-2} \times \sqrt{Variance\ of\ CES + \tau^2}$) around *CES*. Two measures of fail-safe N are shown in the columns *Rosenthal's FSN* and *Fisher's FSN* to assess the sensitivity of meta-analysis results to publication bias. They indicate the number of studies with null results that would be necessary to overturn the significance of the CES (in the case of *Rosenthal's FSN*) and the number of studies with null results that would be necessary to overturn the significance of Fisher's (1932) test statistic of combined significance levels (in the case of *Fisher's FSN*). The column *Is Rosenthal's FSN < Critical FSN?* indicates with "Yes" the cases when *Rosenthal's FSN* is smaller than the critical FSN of 5 × k + 10 studies (i.e., results are likely sensitive to publication bias) and with "No" the cases when Rosenthal's FSN is larger than the critical FSN (i.e., results are likely not sensitive to publication bias). There is no statistical significance testing for *Fisher's FSN*.

Table 4. Less than five studies examining the relation between two variables

Panel A: List of papers when there are less than five studies in a meta-analysis

Authors	Year	Journal	Country	Sample period	Sample size	Source of information
Aboody and Lev	1998	JAR	U.S.	1987–1995	778	Table 4 Panel A, pg.176
Amir, Guan, and Livne	2007	JBFA	U.S.	1972–2002	37263	Table 5, Equation 1 full sample, pg. 238
Bah and Dumontier	2001	JBFA	Continental Europe	1996–1996	204	Table 6, model 1, pg.687
			Japan	1996–1996	353	Table 6, model 3, pg.687
			U.S.	1996–1996	1069	Table 6, model 4, pg.687
			UK	1996–1996	233	Table 6, model 2, pg.687
Barron, Byard, Kile, and Riedl	2002	JAR	U.S.	1986–1998	1103	Table 4 pg. 306
Barth, Clement, Foster, and Kasznik	1998	RAST	U.S.	1991–1996	595	Table 4, Pooled fixed year effects model, pg. 55
Barth, Kasznik, and McNichols	2001	JAR	U.S.	1983–1994	10631	Table 4, Fixed Effects model, pg. 18
Bialek-Jaworska	2016	AMIS	Poland	2003–2013	10786	Table 4, Page 700
Bublitz and Ettredge	1989	TAR	U.S.	1974–1983	2832	Table 4, model 1, pg. 118
Cazavan-Jeny and Jeanjean	2006	EAR	France	1993–2002	770	Table 5, model 4, pg. 52
Ciftci and Cready	2011	JAE	U.S.	1975–2003	122636	Table 3 Panel A, model 2 All firms, pg. 72
Ciftci, Lev, and Radhakrishnan	2011	JAAF	U.S.	1979–1997	7591	Table 3 Panel B, model 2, pg. 96
Ely and Waymire	1999	JAR	U.S.	1927–1927	146	Table 3, model 1, pg. 32
García-meca, Parra, Larrán, and Martínez	2005	EAR	Spain	2000–2001	257	Table 10, model 1, pg. 84
Gelb	2002	JBFA	U.S.	1981–1993	710	Table 4, model 2, pg. 470
Gu and Li	2010	JAAF	U.S.	1995–2004	4966	Table 5 Panel A, pg. 105
Gu and Wang	2005	JBFA	U.S.	1981–1998	6167	Table 3, model 5, pg. 1690
Guo, Lev, and Zhou	2004	JAR	U.S.	1995–1997	265	Table 8, model 1, pg. 346
Han and Manry	2004	TIJA	South Korea	1988–1998	3191	Table 4 Panel A, pg. 167
Hirschey and Weygandt	1985	JAR	U.S.	1977–1977	390	Table 1, model 3, pg. 330
Hirschey, Richardson, and Scholz	2001	RQFA	U.S.	1989–1995	1290	Table 2, OLS model, pg. 231
Jones	2007	CAR	U.S.	1997–1997	119	Table 3, model 3, pg. 506
Kallapur and Kwan	2004	TAR	UK	1984–1998	232	Table 3 Panel B, pg.161
Kamardin, Abu Bakar, and Ishak	2015	ARA	Malaysia	2006–2006	64	Table VI, model 1, pg. 288
Kang and Gray	2011	TIJA	Intl.	2002–2002	181	Table 5, pg. 418
Maaloul, Ben Amar, and Zeghal	2016	JAAR	U.S.	2009–2009	125	Table V, model 1, pg. 434
Matolcsy and Wyatt	2006	AF	U.S.	1990–1997	421	Table 5, model OLS Full, pg. 474
Merkley	2014	TAR	U.S.	1996–2007	22482	Table 8, model 3, pg. 750
Muller	1999	JAE	UK	1988–1996	66	Table 2 pg. 189
Rajgopal, Venkatachalam, and Kotha	2003	JAR	U.S.	1999–2000	434	Table 7, model 1, pg. 159
Ritter and Wells	2006	AF	Australia	1979–1997	1078	Table 5 Panel A, pg. 859
Shah, Stark, and Akbar	2009	TIJA	UK	1990–1998	9752	Table 3, model 1, pg. 199
Tutticci, Krishnan, and Percy	2007	JIAR	Australia	1992–2002	386	Table 3, pg. 96
Weiss, Falk, and Zion	2013	AF	U.S.	1990–2005	528	Table 4, model 2, pg. 852
Yu, Wang, and Chang	2015	RQFA	Taiwan	2003–2006	751	Table 4, model 2, pg. 295
Zhao	2002	JIFMA	Intl. (includes U.S.)	1990–1999	13029	Table 4 Panel B, pg. 170

Panel B: Combined effect size based on less than five studies per meta-analysis

Dependent variable	Independent variable	k	Combined Effect Size (CES)	Z-stat	Sig	I^2 (%)	Rosenthal's FSN	Is FSN < Critical FSN?	Fisher FSN
Analyst earnings forecast dispersion	Disclosure score	3	−0.014	−2.11	**	0.00%	2	Yes	2
	Intangible assets	2	−0.064	−2.36	***	8.14%	3	Yes	3
	R&D expense	3	0.084	1.47	*	93.78%	0	Yes	0
Analyst earnings forecast error	Advertising expense	3	0.012	0.49	n.s	41.26%			0
	Disclosure score	3	−0.142	−1.47	*	88.63%	0	Yes	0
	Intangible assets	3	−0.017	−0.48	n.s	84.30%			0
Analysts following	Intangible assets	2	0.013	0.17	n.s	89.50%			0
Bid-ask Spread	Disclosure score	2	−0.047	−1.15	n.s	54.96%			0
Disclosure score	Analysts following	2	0.009	1.46	*	0.00%	0	Yes	0
	BTM	2	−0.067	−0.52	n.s	87.37%			0
	Cross-listing	2	0.091	8.15	***	0.00%	1	Yes	1
	Disclosure policy	2	−0.005	−1.25	n.s	0.00%			0
	Equity issuance	2	−0.015	−0.26	n.s	48.55%			0
	Firm age	2	−0.002	−0.24	n.s	0.00%			0
	Leverage	4	0.044	0.42	n.s	84.45%			2
	MTB	3	0.136	1.73	**	65.29%	1	Yes	1
	Number of patents	2	0.020	0.91	n.s	0.00%			0
	Profitability	3	0.019	0.34	n.s	61.10%			0
	R&D expense	2	0.128	14.25	***	0.00%	6	Yes	9
	Stock return volat.	2	0.010	2.35	***	0.00%	0	Yes	0
Future profitability	Advertising expense	3	0.355	1.14	n.s	99.99%			0
	Intangible assets	3	0.002	0.08	n.s	69.10%			0
Future profitability volatility	Advertising expense	3	0.012	0.64	n.s	96.88%			0
	R&D capitalized	2	0.077	115.03	***	0.00%	104	Yes	2058
Indicator Variable for Capitalizers	Equity issuance	2	0.023	2.59	***	0.00%	3	Yes	3
	Leverage	3	0.044	2.17	**	15.74%	4	Yes	3
	Profitability	2	−0.002	−0.04	n.s	53.81%			0
	Size	3	0.043	1.95	**	19.10%	0	Yes	1
Indicator Variable for R&D-intensive	Cash	4	0.632	5.57	***	96.41%	127	No	121
	Dividends	4	0.003	0.03	n.s	95.95%			0
	Leverage	4	0.348	1.67	**	99.43%	0	Yes	0
MTB	R&D expense	3	0.292	1.43	*	97.41%	2	Yes	4
Share Price	Advertising expense	2	0.187	1.20	n.s	97.81%			0
	Brand value	2	0.220	42.15	***	0.00%	29	No	44
	Intangible assets	3	0.139	2.72	***	83.56%	3	Yes	3
	R&D capitalized	2	−0.021	−0.39	n.s	88.39%			0
Stock Return	Advertising expense	3	−0.091	−1.10	n.s	98.81%			0
	Brand value	2	0.218	31.46	***	0.00%	28	No	43
	Disclosure score	2	−0.029	−0.50	n.s	73.95%			0
	R&D capitalized	4	0.157	4.39	***	72.58%	32	No	29

This table presents the results of meta-analyses for which there are less than five primary studies observed that examine the relation between two variables. We present this table for orientation purposes only since the number of studies input to each meta-analysis is very small. The computations and columns are the same as described in Table 3, but cannot be interpreted reliably due to the small sample of studies.