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Value Relevance of Capitalized Intangibles

Abstract:

This study aims to examine the value relevance of different accounting treatments of intangibles. We investigate the immediate expensing of intangible investments in Research and Development (R&D) and Selling, General, and Administrative (SG&A) and, by using methods that attempt to adjust financial statements, we investigate if capitalizing these investments results in a measure with higher value relevance. We use the Classification and Regression Trees (CART) method and linear regression to examine the value relevance of the two different approaches. We find no support that the capitalization approach is more value relevant than current accounting practices.

Authors: Adam Groundstroem, Martin Svedin

Supervisor: Irina Gazizova

Keywords: Intangible assets; Capitalization; Value relevance; Financial reporting

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1 Introduction

The last several decades have seen an increase in the importance of intangible items, and they have become a key value driver for many firms as the economy has seen an increased focus on services and information technology instead of physical products. Lev (2019) presents data that indicate that investments in intangible items have seen a steady increase during the 40 year period from 1977 to 2016, while investments in tangible items have seen an opposite trend and a steady decrease. According to this data, investments in intangibles overtook investments in tangibles towards the end of the 1990s.

Examples of intangible items are diverse, and include R&D which aims to discover new knowledge and develop this knowledge into useful products; IT systems which work to support or even automate certain business processes; employee knowledge and skills as well as the firm’s culture which allow the firm to differentiate or more efficiently provides its products and services; and the firm’s understanding of and relation with its customers through brands and other channels. In some cases, legal protections ensure that the firm can obtain economic benefits from an intangible item, as is the case with patents, copyrights, and trademarks, but in many cases, such protections are not present.

The accounting treatment of intangible items differs depending on whether the intangibles are generated in-house or acquired externally. Under both US GAAP and IFRS, most internally generated intangibles are expensed immediately rather than being capitalized on the balance sheet (Robinson et al, 2020, p. 344). There are some exceptions, for example, US GAAP requires that certain costs related to software development be capitalized after the project reaches a certain maturity (Robinson et al, 2020, p. 345). There is however some judgment involved as to when a project enters this phase, which gives management some freedom in how to deal with these costs (Robinson et al, 2020, p. 356).

Similarly, under IFRS costs related to research and development, after the project reaches a certain maturity and enters the development phase, can be capitalized. Intangible assets can also be created during an acquisition of a company and the purchase price of a company exceeds the fair value of its identifiable assets and liabilities and the exceeding amount is recognized as an intangible asset in the form of Goodwill.

In this thesis our focus is on in-house generated intangible items and, unless stated otherwise, we use the term intangibles to refer to in-house generated intangibles. Furthermore, we focus on those intangibles that under current accounting standards are expensed as part of the R&D and SG&A expenses. When we talk about an intangible investment we refer to the parts of these expenses that are expected to generate economic benefits in future years, rather than generating benefits the same year as the expense.

In the literature, several problems with the current treatment and immediate expensing of intangible investments have been identified, even if there is no clear consensus regarding the magnitude of the issue and if a solution is needed, and if that is the case, what such a solution might look like. The main argument against the immediate expensing of intangible investments is that this distorts significant portions of both the balance sheet (Srivastava & Rajgopal, 2023) and the income statement (Lev, 2019).

In particular, the balance sheet is distorted since potentially large investments that are expected to generate future economic benefits are missing from the assets. Their absence from the balance sheet in turn causes equity to appear artificially low. Unless adjustments are made, these problems then propagate to financial ratios like return on assets and return on equity and other types of financial analysis.

The expensing of intangible investments also impacts the connection between market-values and book-values, since investors may recognize the value and future economic benefits from the intangibles, while they may not be recognized on the financial statements. Srivastava & Rajgopal (2023) take Apple as an example, which at the end of fiscal year 2021 had a market value of more than $2 trillion yet a recorded book-value of assets of approximately $350 billion, of which roughly $160 billion was cash.

As argued by Lev (2019), the immediate expensing also impacts the income statement, and in particular, the earnings measure which often is a key focus for investors. The immediate expensing of intangible investments distorts the matching between revenues and costs, which has been identified by investors as a key aspect for a useful earnings measure (Dichev et al, 2013).

Lev & Gu (2016, p. 88-90) also identifies that during the period when intangibles have become an increasingly large part of firms' investments, there has been a decline in the ability to predict stock prices based on book-value of equity and earnings, that is, the value relevance of book-value of equity and earnings has decreased. This is interpreted as a decrease in the usefulness of book-value of equity and earnings as a source of information for investors, and potentially a reduced usefulness of accounting information as a whole.

A recent paper by Barth et al (2023) provides an alternative view. They investigate a larger set of 18 accounting items and find an increase in the total value relevance of accounting information. This is attributed to more nuance in the relevance of accounting items, and while the relevance of book-value of equity and earnings may have decreased, there has also been an increase in the relevance of accounting items related to intangibles, growth opportunities and alternative performance measures.

While issues have been identified with the current treatment of intangible investments, their current treatment is not without reason. Several arguments for preferring the immediate expensing of intangibles have been identified and include practical matters, such as the difficulty in even identifying that a cost will generate revenues in future years and how to split the costs into different parts. An example by Appleton (2023) is a short-term sales campaign that as a by-product happens to generate important information about customers, that end up generating economic benefits for several years.

More fundamental matters are also important, such as the difficulty in determining whether an investment into e.g. R&D or a marketing campaign will pay off at all, or the issue that the value of intangibles can evaporate quickly. This later case is exemplified by Srivastava & Rajgopal (2023) with the case of Nokia and Blackberry as examples of firms that were once very successful and relied largely on intangible assets but have since seen a significant decline.

In the literature, there is no clear consensus on how to proceed. Appleton (2023) provides a review of the different arguments and finds that some argue that while the current treatment may have issues, it might still be the best way to treat intangible investments and that investors might still be able to derive an approximation of how much is invested from the expenses in the income statement. Others have argued for recognizing the investment into intangibles as an asset on the balance sheet and then amortizing this asset over its useful life. As a third option, it has been proposed that intangible investments can be expensed as they are today, but that firms give additional disclosures regarding these expenses.

In order to support users of accounting information as well as researchers, several methods have been developed in the literature, with different levels of sophistication, that attempt to adjust the financial statements and separate the expenses from the income statement into an investment part that is related to benefits in future years, and an expense part that is related to benefits in the current year. The investment part of the expense is then capitalized and added to the balance sheet and later amortized over its useful life. The methods we are aware of are the ones by Lev & Sougiannis (1996), Peters and Taylor (2017) and Iqbal et al (2023).

Previous research has investigated if these different measures related to intangibles have value relevance, that is, if they are useful for predicting stock prices and thus if they seem to provide useful information to investors. The work by Barth (1998) and Banker et al (2019) finds that the R&D and SG&A expenses from the income statement are value-relevant and provide information to investors. The work by Lev & Sougiannis (1996) and Banker et al (2019) on the other hand uses the method by Lev & Sougiannis (1996) for adjusting financial statements and capitalizing parts of the R&D and SG&A expenses. They find that resulting measures from capitalizing these expenses provide value-relevant information as well.

This raises the question of which way of presenting information about investments in intangibles is the most useful for investors. In this thesis we investigate this question, we compare the value-relevance of:

- The R&D and SG&A expenses from the financial statements with no adjustments being made, and
- The measures resulting from splitting the R&D and SG&A expenses into an expense part and an investment part, where the investment part is capitalized and then amortized.

We compare the expenses from the unadjusted income statement with two different methods for capitalizing the R&D and SG&A expenses, the methods by Peters and Taylor (2017) and Iqbal et al (2023). We also use two different methods for investigating value-relevance, we use both the recent method by Barth et al (2023) which uses the non-linear CART (Category and Regression Trees), as well the more standard method based on linear regression.

In none of these cases do we find that the process of capitalizing the R&D and SG&A expenses provides more value relevant information than the unadjusted R&D and SG&A expenses from the income statement. We find instead that both ways of treating intangible investments seem to have the same value-relevance to investors.

2 Literature and Theory

2.1 Value relevance

Value relevance research attempts to understand to what extent accounting items or other information is useful to investors (Barth, 2023). The approach for studying this question is not to directly observe investors, their behavior or what information they consume, but rather to investigate to what extent the information under consideration can be applied in a consistent way to explain the market-values of firms. Instead, an accounting item or other information is value relevant “if it explains variation in share price” (Barth, 2023, p. 2). Thus the approach taken is to fit a mathematical model relating a measure based on the market-value of equity with the accounting items and information in question. If a statistically significant relation between market-values and the information can be established, then it seems this information is useful to investors, even if they might not use this information directly.

The exact measure used to represent the market-value of equity varies between different studies, where the price per share is one option, and the return of the stock is another common measure. Barth et al (2001) suggest that the measure used should be tailored to the research question, where the price per share is suitable when investigating how the market-value can be related to different items. Using returns as the dependent variable might be suitable when changes in market-value might be important, such as questions regarding timeliness (Barth 2001) or how changes in information impact the market-value as in Barth et al (1998) where the change in brand value is related to changes in market-values.

In the literature, we have seen two main ways that value relevance is evaluated. One approach focuses on performing a linear regression and seeing if the coefficients are significantly different from zero, which then indicates a relation between stock price and the information. The other approach also performs a regression but instead looks at the goodness-of-fit of the resulting model, where a higher goodness-of-fit indicates higher value relevance.

The first approach, based on finding a significant coefficient for a variable representing accounting items or other information, is often used when determining if the item or information has value relevance or not. Examples include Barth et al (1998) who establish that brand value is value relevant by regressing price per share on book-value of equity, earnings and the value of the brand.

The second approach, where a goodness-of-fit measure is used to evaluate value relevance, is often used when comparing value relevance between different time periods, accounting items or groups of firms.

Collins et al (1997) investigate how the value relevance of book-value of equity and earnings have developed over the 41 year period between 1953 and 1993. Their method is based on doing cross-sectional regressions for each year, and observing how the R2 for these regressions have developed over time. Besides studying the combined value-relevance of book-value of equity and earnings, they also study how each accounting item contributes by doing regressions with each item separately. They then assign the contribution in value relevance for a particular item as the difference between the R2 of the regression with both items and the R2 of the regression without the item in question, that is, the incremental R2 for the item.

A study by Brown and Sivakumar (2003) compares the value relevance of operating earnings derived from financial statements with non-GAAP operating earnings based on adjustments by analysts and the excluding non-recurring or special items. They perform two regressions for each test, varying the operating earnings measure used in the regression between the GAAP and non-GAAP measures. They compare the value relevance of the measures by comparing the R2 of the two regressions. In one test, they regress price per share on book-value of equity, net earnings, and the operating income measure. In another test, they regress abnormal returns after the announcement date based on the difference between the actual and expected operating earnings.

The recent paper by Barth et al (2023) used CART (Classification and Regression Trees) instead of linear regression to predict price per share based on accounting information. They investigate the evolution in value relevance for a larger set of 18 accounting items over the time period 1962 to 2018. Similar to Collins et al (1997), they investigate both the combined value relevance for these accounting items as a whole, as well as the contribution of individual accounting items. Their methodology is based on cross-sectional estimation of their model for each year and observing the development of the R2 for these models. To investigate the contribution of individual accounting items they look at a measure similar to the incremental R2. Instead of leaving out a particular accounting item and then estimating a new model, they compute a new R2 based on these predictions for the data where the accounting item has been assigned a random value for all data points.

2.2 Capitalization of intangibles

Several previous works have developed methods that attempt to split the R&D or SG&A expenses from a firm's income statement into two parts, an investment part that generates benefits in future years and an expense portion that is related to benefits during the current year. The methods also estimate the useful life for the investment part. Having divided the expenses into these two parts, the methods then capitalize the investment part as an asset on the balance sheet and then amortize this asset over its useful life.

An early work in this area is Lev & Sougiannis (1996) who in their work mainly investigated the capitalization of the R&D expense. Their method works by doing a linear regression with an adjusted operating income as the dependent variable and previous years' R&D expenses from the income statement as the independent variables. This regression is done on an industry-year basis. The coefficients in the linear regression are then used to determine the size of the investment part of the expense. They try different linear regressions and vary the number of years of past R&D expenses to decide on the useful life of the capitalized asset.

Banker et al (2019) then apply the method by Lev & Sougiannis (1996) to the SG&A expense rather than the R&D expense. Both Lev & Sougiannis (1996) and Banker et al (2019) find that the capitalized asset from the respective expense is value relevant, by doing a linear regression with market-value of equity as the dependent variable and with independent variables that include book-value of equity, earnings, the capitalized asset. They find the coefficient for the capitalized asset to be significant, and thus conclude that the capitalized asset is relevant to investors.

Another method was developed by Peters and Taylor (2017) with the purpose of developing a better version of Tobin's Q which they refer to as Total Q. Their method is straightforward and just assumes that a constant fraction of the R&D and SG&A expenses constitute the investment portion. They set the investment portion for SG&A to be 30% of the expense, and the investment portion of R&D to be 100% of the expense. The capitalized asset from SG&A expenses is amortized over 5 years while the asset from R&D expenses is amortized over 7 years. They find that this method is sufficient for their purpose and see a significant improvement in R2 when regressing future investments on their Total Q. We are not aware of any study that investigates the value relevance of the capitalized asset using the method by Peters and Taylor (2017).

Lastly, we have the method by Iqbal et al (2023). Similar to Lev & Sougiannis (1996), Iqbal et al (2023) estimate the investment portion of an expense as well as the useful life for each industry-year. Iqbal et al apply their method to both R&D and SG&A expenses and use the Fama and French 48 industry classification to group firms into industries. Their method is based on doing a linear regression with the current expense from the income statement as the dependent variable, and future revenues as the independent variables. By appealing to matching, they treat each term in the regression as the portion of the expense that matched with revenues that year. They include the intercept in the investment portion since this can be considered an industry-wide investment needed to stay competitive. To find the useful life, they perform several linear regressions, varying the number of future years of revenues, and select the model with the highest adjusted R2.

Iqbal et al test their method by updating Tobin's Q in a similar way to Peters and Taylor (2017), and notice that their method yields a better R2 than the method by Peters and Taylor (2017). They also show that, after updating the book-value of equity, their method results in superior returns when following a value-investing strategy. The strategy is to take a long position in firms with a high book-to-market ratio and a short position in firms with a low book-to-market ratio. If firms with a low book-to-market ratio are overvalued on average, while firms with a high book-to-market ratio are undervalued on average, then the strategy will generate positive returns as this over- and under-valuation is corrected.

Banker et al (2019) also show that an investment strategy involving a long position in a high SG&A portfolio and a short position in a low SG&A portfolio generates an annualized excess return of 7.27. They conclude that this return can either be compensation for additional risk or be due to mispricing by investors. They make additional tests and find that those tests are not consistent with a risk-compensation explanation, and conclude that investors may not fully recognize the long-term value of the intangible items expensed as part of SG&A expenses.

2.3 Is financial statement analysis becoming irrelevant?

Previous studies have found that parts of the R&D and SG&A expenses are in fact investments, in the sense that they create value in future periods (Balachandran & Mohanram, 2011; Banker et al., 2011; Lev & Gu, 2016; Lev & Zarowin, 1999). One example is the advertising expenses, which are included in the SG&A expense, that have been found to have a positive correlation with brand value (Barth et al., 1998).

The growing importance of internally generated intangibles such as R&D and SG&A is highlighted by Iqbal et al. (2023). Iqbal argues that the exclusion of these accounting items under U.S. GAAP is diminishing the usefulness of financial statements. The treatment of R&D and SG&A expenses is a critical part of the decline in value relevance of financial statements and it fails to capture a true picture of how the modern economy is generating value. Additionally, in the modern economy where firms' internal knowledge and brand have become more important these expenditures in SG&A have become an increasingly important part of many firm’s intangible investments (Barth et al., 2023; Peters & Taylor, 2017). In the same spirit, Banker et al. (2019) question the traditional approach that treats SG&A as solely a periodic cost and argues that the expenses in SG&A create long-term value and challenge the traditional view of these expenditures.

Lev & Gu (2016) have noted the increasing presence of intangible assets and the shift in the relation between investments in tangible versus intangible assets where there is a significant increase in intangible investments. They go on to highlight that intangible assets have overtaken tangible assets in being the leading source of value creation (Lev & Gu, 2016). In light of this, previous literature argues that the current accounting standards do not fully capture the true value of these intangible assets and argue that they are not faithfully presented in the financial statements (Barth et al., 2023; Lev & Gu, 2016). Since newly listed firms have a strong intensity of intangible investments, scholars argue that this has caused a decline in the value relevance of financial statements (Dichev & Tang, 2008; Lev & Gu, 2016; Lev & Zarowin, 1999; Srivastava, 2014).

Lev & Sougiannis (1996) offered a unique perspective with an industry-specific approach that highlights that some industries at the time like wireless communication were largely irrelevant to the valuation of firms. Lev also points to the increasing necessity of including nonfinancial data to more accurately capture firms that are heavily reliant on intangible assets.

Contrary to previous literature Appleton et al's (2023) research suggests no decline in value relevance of all accounting items combined and their study acknowledges the increasing value relevance of items connected to intangible assets. Additionally, their study observes an increase of the number of relevant items. Balachandran et al (2010) study how conservative accounting principles such as expensing R&D and SG&A affect the relevance of accounting information. Their study suggests that there is no decline in value relevance for firms with greater conservatism and in fact, the greatest decline in value relevance was noted in firms with decreasing conservatism. It suggests that financial markets are efficiently pricing these intangible assets even during current accounting principles.

In summary, there is a growing consensus about the need to rethink the treatment of intangible assets and how they are reported in financial statements. The critique indicates that there may be a need for a more adaptive approach to the valuation of firms that are heavily reliant on intangibles and the ongoing debate highlights the complexity of financial reporting in the modern economy.

2.4 Hypothesis development

As described above, previous research has shown that the resulting items from adjusting financial statements to capitalize parts of the R&D and SG&A expenses are value relevant. Many common equity valuation models, such as the discounted dividend model, discounted cash flow model and residual income valuation model, are focusing on future economic benefits. Thus, it seems that splitting the R&D and SG&A expenses into two parts, one that is related to benefits in the current period and one that is related to benefits in future periods, should be a more useful measure for the valuation of a firm's equity if investors use methods based on future benefits.

Lev and Gu (2016) argue that investors and managers should be having significantly more information about intangible assets since they are difficult to manage and their future economic benefit and value are very hard to predict.

Another reason that capitalization of R&D and SG&A expenses might be more useful to investors is that it lessens the potential issues caused by the different accounting treatment of intangibles depending on whether they are internally generated or acquired externally. In light of this, we have developed the following hypothesis:

H1: The capitalization of intangible assets from the R&D and SG&A expenses has higher value relevance than the R&D and SG&A expenses from the unadjusted financial statements.

3 Method

3.1 Research design

We investigate our hypothesis by capitalizing the R&D and SG&A expenses using the method by Iqbal et al (2023) (*see Appendix B for our implementation of Iqbal*) as well as the method by Peters and Taylor (2017). To investigate the value relevance of the resulting items, we do several regressions with price per share as the dependent variable and vary which measure is used to represent intangibles among the independent variables. To compare the value relevance of the different measures we compare the R2 of the regressions using the corresponding measures.

We use price per share as our dependent variable since we are not investigating timing issues or how a change in the independent variables affects the firm value, but rather the relevance of the different measures for representing intangibles. Similarly, since we wish to compare the value relevance of the different measures, R2 seems like the natural choice, and we follow Collins (1997) and Barth (2023) and use the incremental R2 for comparing the different measures for representing intangibles.

We perform two sets of tests, one where we follow Barth et al (2023) and use CART (Classification and Regression Trees) with a set of 15 accounting items as independent variables, not counting the variables representing intangibles, and 10 industry indicator variables. We also do a second set of tests where we use linear regression, which is more standard in the literature, but in this case, we use a more limited set of variables.

3.1.1 Variables

In our tests we use the price per share P as the dependent variable. This price is from 3 months after the end of the fiscal year since at this point the financial statements for the year should be publicly available. Similar to the dependent variable, all our independent variables are on a per share basis. As independent variables we use the intangible measures, which we describe below, as well as a subset of the accounting items in the following list: $EARN$ is the earnings before extraordinary items, BVE is the book-value of equity, $INTAN$ is the intangible assets recognised on the firm's balance sheet, $CASH$ is cash and cash equivalents, CF is operating cash flow, REV is revenue, SPI is special items from the income statement, OCI is other comprehensive income, DIV is dividends, $CAPX$ is capital expenditure, $COGS$ is cost of goods sold, TAX is income tax, $EARNGR$ is the absolute growth in earnings, $ASSETS$ is the book-value of total assets. We denote the tuple consisting of all of these variables by VAR. We use a set of 10 indicator variables IND that represent the firm's industry according to Fama & French 10-industry classification.

One set of intangible measures we use are the items from the unadjusted financial statements, where the variable RD denotes the R&D expense from the income statement and SGA denotes the SG&A expense from the income statement.

Another set of intangible measures we use are the values we get when running the methods by Peters and Taylor (2017) and Iqbal et al (2023). We get as output from these methods the end-of-year asset that is present on the balance sheet due to capitalized investments, we get the investment part of the expense as well as the amortization that year on previously capitalized investments. We use the following variables to denote these items: $AssetRD$ is the the asset at the end-of-year due to capitalization of R&D expenses, $AssetSGA$ is the asset at the end-of-year due to capitalization of SG&A expenses, $IncomeRD$ is the correction to the income statement from adding back the investment part of the R&D expense and subtracting the amortization on previously capitalized R&D expenses and $IncomeSGA$ is the correction to the income statement from adding back the investment part of the SG&A expense and subtracting the amortization on previously capitalized SG&A expenses.

We largely follow Barth et al (2023) in our choice of variables, with the difference that we omit a variable for the advertising expense, since this overlaps with the SG&A expense and we do not have separate capitalized measures for the advertising expense. We also construct the SG&A expense differently and use the method by Peters and Taylor (2017). We describe the construction of the variables from Compustat columns in more detail in Appendix A.

With the exception of the industry indicator variables, we winsorize all variables at the 1% and 99% level. Since all our regression uses cross-sectional data for a single year, this is how we winorize them as well.

3.1.2 CART

Our main set of tests use CART (Classification and Regression Trees) where we largely follow the methodology by Barth et al (2023). We employ bootstrap aggregation, also known as bagging, and each model consists of 500 trees. To make a prediction we take the output from all 500 trees and aggregate these outputs to form a single prediction from the model. We describe this in more detail below.

For each year we estimate three separate cross-sectional models:

$$P_i = CART(VAR_i, IND_i)$$

$$P_i = CART(VAR_i, RD_i, SGA_i, IND_i)$$

$$P_i = CART(VAR_i, AssetRD_i, AssetSGA_i, IncomeRD_i, IncomeSGA_i, IND_i)$$

The first model is our baseline which does not include any variables directly related to intangibles. In the second model, we use the same variables as in the baseline but also provide the R&D and SG&A expenses from the firm's income statement. In the third model, we also use the same variables as in the baseline but for this model, we instead provide the variables related to the capitalization of the R&D and SG&A expenses.

We employ CART in a similar way to Barth et al (2023). As mentioned, we employ bootstrap aggregation, also called bagging, and for each year we fit 500 trees using the CART methodology. We now describe this in more detail, assuming we have a set D with cross-sectional data for a particular year. For each $k = 1, ..., 500$ we take a bootstrap sample D_k from D, that is, we form the set D_k with the same size as D by sampling uniformly from the elements of D with replacement. We then fit the regression tree T_k on the bootstrap sample D_k.

For prediction, we use the out-of-bag predictor which for input values x form the prediction $\widehat{P}^{OOB}$ by taking the average prediction of those T_k where x was not an element of D_k, that is,

$$\widehat{P}_i^{OOB} = \frac{1}{n} \sum_{x \notin D_k} T_k(x_i)$$

where $n = |\{k : x \notin D_k\}|$. The out-of-bag predictor is well known in the literature, and Hastie et al (2009, p. 593) notes that the out-of-bag error approaches the n-fold cross-validation error as the number of bootstrap samples approaches infinity.

To compute the out-of-bag R2 we use the method by Liaw and Weiner (2002) based on the out-of-bag predictor. If we let $\overline{P}$ denote the mean of the observed prices per share in D, then the out-of-bag R2 is given by:

$$1 - \frac{\sum_{i \in D} (P_i - \widehat{P}_i^{OOB})^2}{\sum_{i \in D} (P_i - \overline{P})^2}$$

3.1.3 Linear regression

We also do a second set of tests with the more standard methodology based on linear regression. In these tests we estimate three separate cross-sectional linear regressions for each year:

$$P_i = EARN_i + BVE_i$$

$$P_i = EARN_i + BVE_i + RD_i + SGA_i$$

$$P_i = EARN_i + BVE_i + AssetRD_i + AssetSGA_i + IncomeRD_i + IncomeSGA_i$$

As in the case with CART, the idea is that the first regression is a baseline model with only earnings and book-value of equity. The other two regressions then add the variables from one of the two different intangible measures we are comparing. When comparing the goodness-of-fit between the different regressions we use the adjusted R2 computed in-sample.

3.1.4 Statistical Significance

We compare the goodness-of-fit for our different models by bootstrapping confidence intervals for their R2 values. We use the percentile method, that is, we take different bootstrap samples D_i from the dataset D for $i = 1, \ldots, n$. We then for each D_i we get a R^2 value R_i^2. To get a two-sided confidence interval with confidence level α we take the end points as the $\frac{1-\alpha}{2}$ quantile and the $\frac{1+\alpha}{2}$ quantile of the R_i^2 values.

In the case of linear regression, we form the R_i^2 by estimating a linear regression on the bootstrap sample D_i and then taking R_i^2 as the in-sample adjusted R^2. For CART we use a different methodology, since CART uses bootstrap internally it does not seem to make much sense to reestimate the CART trees for each bootstrap sample, this is also computationally expensive. Instead, we estimate the CART trees once on D, and then we compute the out-of-bag R^2 on D_i to get our R_i^2. It should be noted that we are not aware of this method being justified in the literature, but at least it gives some indication of the variability of the R^2. Furthermore, it seems unlikely that this would underestimate the variability in R^2, since we estimate the model only once which might reduce the variability.

3.2 Sample selection

We use the Compustat North America Fundamentals Annual and Quarterly databases for our empirical investigation. All variables are from Compustat Annual except the price per share which we take from Compustat Quarterly, see appendix A for more details. We discard rows where columns *gvkey*, *curcd* or *fyear* are missing, since this is basic information that is needed to determine what firm the row refers to, what currency is being used, or what financial year the row refers to, respectively.

We use those rows from Compustat where the industry format is “Industrial” (column *indfmt* is “INDL”), where data format is “Standardized” (column *datafmt* is “STD”), population source is “Domestic” (column *popsrc* is “D”) and the consolidation level is “Consolidated” (column *consol* is “C”).

We use the Fama-French 48 industry classification and only keep those firms in industries 1-43, since these are the industries used by Iqbal et al (2023) for their method. That is, we exclude the banking, insurance, real estate trading and “almost nothing” industries. We discard rows where the column *sic* is missing since in this case we cannot assign an industry to the firm.

3.2.1 Value relevance tests

For our value relevance tests we use data from fiscal years ranging from 1980 to 2022.

For the tests comparing value relevance, we follow Barth et al (2023) and in order to focus on firms with high economic significance, we only use firms listed on the New York Stock Exchange, Nasdaq Stock Market, and NYSE American (previously known as American Stock Exchange). This corresponds to the Compustat column *exchg* being equal to 11, 12 or 14.

We drop those rows with missing values for number of shares outstanding (column *csho*), earnings before extraordinary items (column *ib*), book-value of equity (column *ceq*), total assets (column *at*), beginning of year total assets (column *at* for previous financial year) and revenue (column *revt*). We drop rows where shares outstanding (column *csho*) is non-positive.

The sample used for our value-relevance tests consists of 135 975 firm-years and 11 300 distinct firms.

3.2.2 Method by Iqbal et al (2023)

The method by Iqbal et al (2023) estimates, based on accounting information, for each industry-year what fraction of the expenses are considered an investment, as well as the useful life of the resulting asset. We compute these estimates using the same data as used by Iqbal et al (2023), that is we do not restrict ourselves to the stock exchanges listed above but rather use all firms in Compustat North America Fundamentals Annual.

When using this larger dataset with the method by Iqbal et al (2023), firms have rows in Compustat in both USD and CAD. In order to avoid duplicates, if a firm has any rows in Compustat that use USD as the currency, we only take rows for that firm where USD is the currency. If there are only rows for the firm in CAD, we use those rows. After this process, we still end up with 10 firm-years with duplicate entries that we resolve manually, it turns out that only one row has non-missing values for the variables we need.

4 Findings and analysis

This section aims to present the results of our variables from the descriptive statistics in 4.1 as well as presenting our results from the statistical tests in 4.2 as described in section 3.1.

4.1 Descriptive statistics

4.1.1 Iqbal et al (2023)

The summary statistics including mean and standard deviation of our variables are reported in Table 1 where R&D and SG&A are the reported non-adjusted values from the income statement. AssetR&D, IncomeR&D, AsseSG&A and IncomeSG&A are the values from our implementation of Iqbal et al (2023) representing capitalized assets for R&D and SG&A and adjusted earnings for R&D and SG&A.

In Table 1 we can see the significant effect of capitalizing intangible investments and we can observe a significant increase in the mean of the capitalized values compared to the reported ones. We can also see that the standard deviation increases which is not very surprising since the industry specific approach of Iqbal et al's method will result in some industries capitalizing a larger proportion than others leading to a greater spread between industries.

Table 1: Summary statistics, Iqbal

	Mean	Standard deviation
R&D	0.45	0.88
SG&A	3.95	5.87
AssetR&D	1.54	3.22
IncomeR&D	0.17	0.45
AssetSG&A	9.95	16.98
IncomeSG&A	0.97	2.53

Table 2 and 3 presents the Pearson correlation matrix for R&D and SG&A respectively. The strong correlations between the non-adjusted values and their capitalized counterpart eg. between R&D and AssetR&D at 0.90, as well as the correlation between SG&A and AssetSG&A at 0.93 suggest a strong positive relationship which indicates that as one variable increases the other variable increases as well. This strong correlation highlights that larger traditional expenses are closely correlated with larger expenses in the respective capitalized asset and income values. We can observe overall higher correlations for R&D values compared to SG&A and higher correlation for the variables representing the capitalized total assets than the capitalized income statement.

Table 2: Pearson correlation for R&D, Iqbal

	R&D	AssetR&D	IncomeR&D
R&D	-	0.91	0.81
AssetR&D	0.91	-	0.63
IncomeR&D	0.81	0.63	-

Table 3: Pearson correlation for SG&A, Iqbal

	SGA	AssetSGA	IncomeSGA
SGA	-	0.86	0.57
AssetSGA	0.86	-	0.52
IncomeSGA	0.57	0.52	-

4.1.2 Peters & Taylor (2017)

The same variables as in the previous section are shown for the Peters & Taylor method of capitalizing R&D and SG&A in Table 4, 5 and 6. As in Iqbal et al's tables, we can see a clear increase in the mean for the capitalized values compared to their reported counterparts in table 4. Compared to Iqbal the capitalized means of R&D is slightly higher but quite similar to Peters & Taylor's values however, the capitalized values of SG&A is significantly lower for Peters & Taylor's method suggesting a smaller proportion of SG&A being capitalized.

Additionally, as mentioned earlier the industry-specific approach of Iqbal et al. is likely to increase the standard deviation and we can see in Peters & Taylors' more generalized method that the standard deviation has not been as affected as for Iqbal et al.

Table 4: Summary statistics, Peters & Taylor

	Mean	Standard deviation
R&D	0.45	0.88
SG&A	3.95	5.87
AssetR&D	1.92	3.87
IncomeR&D	0.20	0.48
AssetSG&A	4.48	6.88
IncomeSG&A	0.37	0.66

We can similarly to Iqbal et al. (2023) state that the correlation matrices in table 5 and 6 shows a strong positive correlation between the non-adjusted values and their capitalized counterpart.

Table 5: Pearson correlation for R&D, Peters & Taylor

	R&D	AssetR&D	IncomeR&D
R&D	-	0.92	0.88
AssetR&D	0.92	-	0.65
IncomeR&D	0.88	0.65	-

Table 6: Pearson correlation for SG&A, Peters & Taylor

	SG&A	AssetSG&A	IncomeSG&A
SG&A	-	0.96	0.79
AssetSG&A	0.96	-	0.61
IncomeSG&A	0.79	0.61	-

4.2 CART

An overview of how the out-of-bag R2 for our three models has evolved over the period from 1980 to 2022 is shown in Figure 1. Our results are similar to those reported by e.g. Balachandran and Mohanram (2011). We see an increasing trend in value relevance during the early 1980s, this is followed by a sharp decline in the late 1990s during the dot-com bubble. However, the value relevance of accounting information recovers fairly quickly after the burst of the bubble. From 2005 until 2020, the value relevance of accounting information has been fairly stable, with dips in 2008 and 2020. The former can perhaps be explained by the 2007-2008 financial crisis. The period from 2020 until 2022, that is, the period during the COVID-19 pandemic, sees another significant decrease in the value relevance of accounting information.

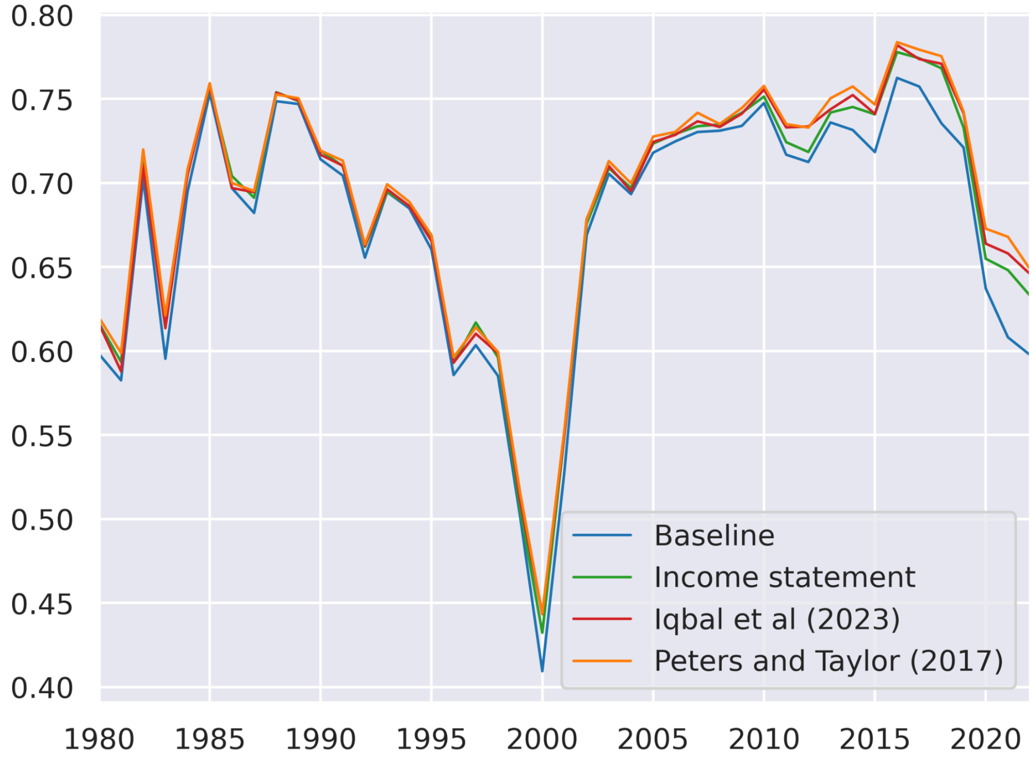

Figure 1: *Out-of-bag R2 for different years. These same models are used for the entire analysis. Baseline refers to the model:* $P = CART(VAR, IND)$. *Income statement:* $P = CART(VAR, RD, SGA, IND)$ *Iqbal (2023) and Peters Taylor (2017)* $P = CART(VAR, AssetRD, AssetSGA, IncomeRD, IncomeSGA, IND)$ *where* $AssetRD, AssetSGA, IncomeRD, IncomeSGA$ *are from the method by Iqbal et al (2023) and Peters and*

Taylor (2017), respectively.

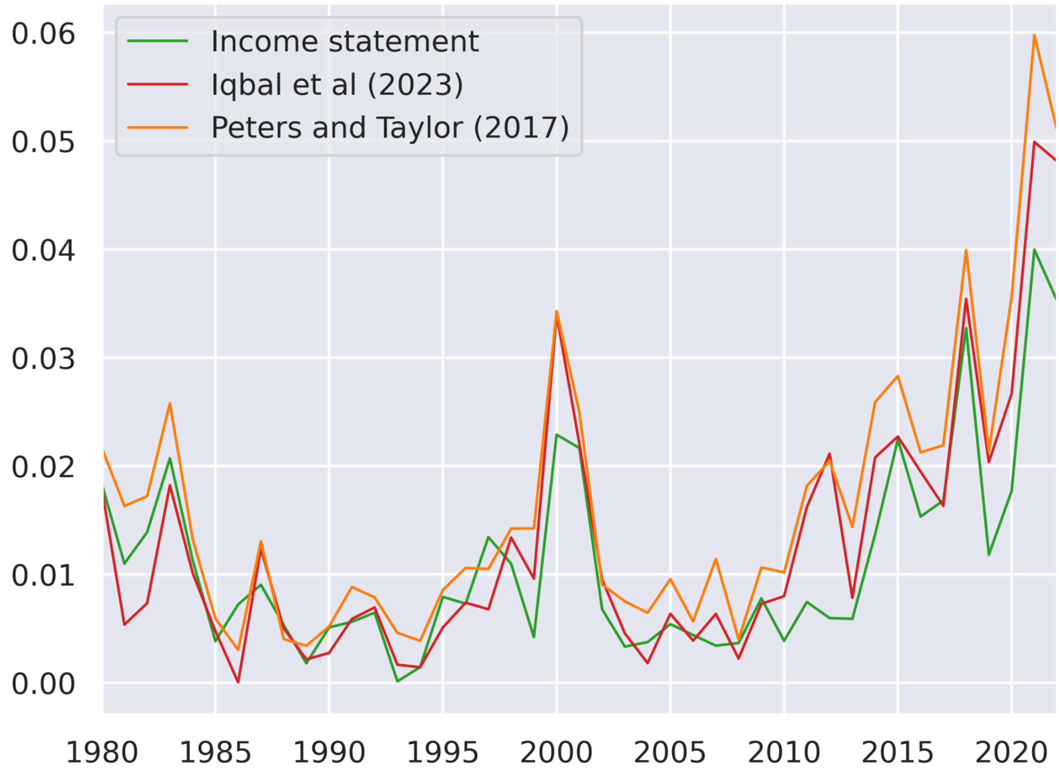

Figure 2: *Incremental out-of-bag R2 from baseline model. See figure 1 for definition of the models.*

While the difference in R2 between the different models can be seen in figure 1, we present the difference between our baseline model and the models using various intangible measures in figure 2. Our results regarding the evolution of the value relevance of intangibles seem to agree with those from Barth (2023). We observe a decrease in the value relevance of intangibles during the early 1980s which is then followed by a fairly stable period until the dot-com bubble when their value relevance sees a sharp increase. However, this increase is quickly reversed and a few years after the bubble the value relevance of intangibles is back at the levels before the bubble. From the middle of the 2000s, we do however see a steady trend of increasing value relevance of intangibles.

Based on figure 2 we also see that, at least from a practical perspective, it does not seem to matter much which measure is used to represent the intangibles. Whether we use the R&D and SG&A expenses from the income statement, or if we use the method by Iqbal et al (2023) or Peters and Taylor (2017) to capitalize these expenses, the increase in value relevance from the baseline model seems to be almost identical.

In figure 3 below we again show the difference between the baseline model and the models with the different intangible measures, but with the additional information that we have added confidence intervals created using Bootstrap and the percentile method.

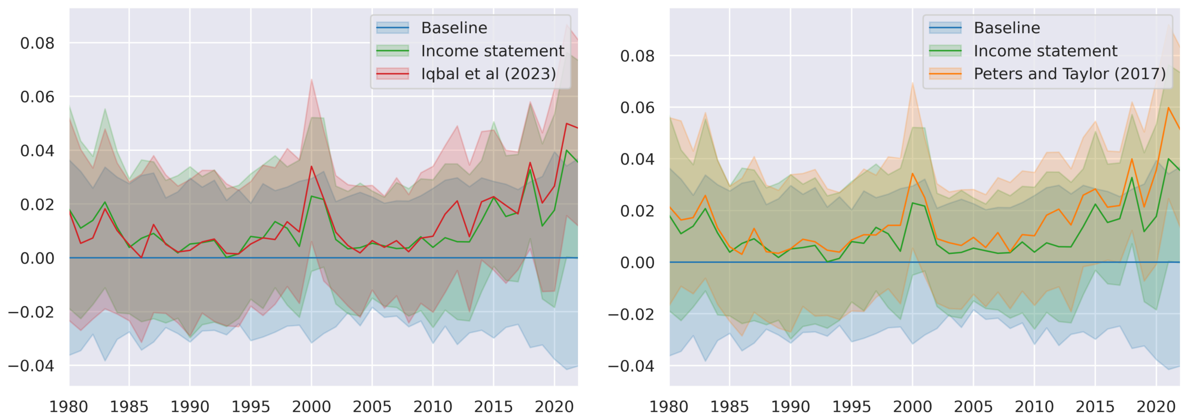

Figure 3*: Incremental out-of-bag R2 from baseline model with plotted 95% confidence intervals based on 1000 bootstrap samples. See figure 1 for definition of the models.*

From these graphs, we see that the confidence interval for the models with capitalized intangibles and for the models based on the income statement overlap to a large extent, and thus the difference between the two models is not statistically significant. We even observe that, with the exception of years during the dot-com bubble and from the mid-2010s and forward, the confidence intervals between the baseline model and the models using intangibles overlap. This would suggest that the value relevance of intangibles may not be as strong as would appear at first sight.

4.3 Linear regression

To validate and strengthen our findings, we also performed the same analysis but using linear regression instead of CART. In this case, we use a more restricted set of variables, the baseline model using earnings and book-value of equity. We then compare this baseline with three other models. In one model we add variables for the R&D and SG&A expenses from the income statement. The other two models add variables by capitalizing the R&D and SG&A using the methods by Peters and Taylor (2017) and Iqbal et al (2023), respectively.

Our results when using linear regression are consistent with the results obtained using CART. Figure 1 and 2 shows the evolution of in-sample adjusted R2 and the incremental R2 when adding the different intangible measures are shown in figure 4. We note that, in relative terms, the increase in value relevance of intangibles since 2010 is larger in the results from linear regression than in those obtained with CART. That is, the peak around 2020 is almost 50% larger than the peak during the dotcom bubble in the linear regression results, while when using CART these peaks have roughly the same size. Presumably, this is due to CART using a larger set of variables, some of which may overlap in explanatory power with the intangible measures.

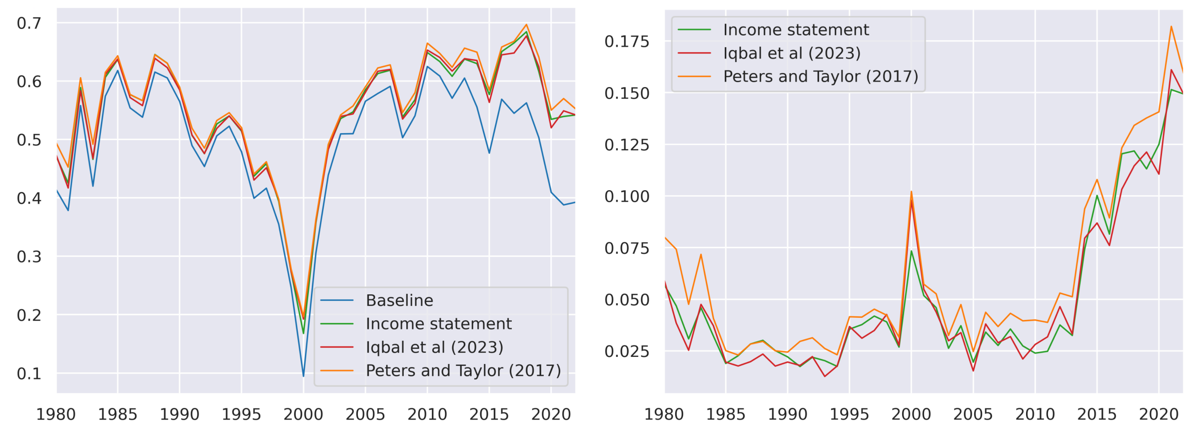

Figure 4: *Left graph shows the adjusted R2 for different years. Right side is incremental adjusted R2 from the baseline model. Baseline:* $P = EARN + BVE$. *Income statement:* $P = EARN + BVE + RD + SGA$ *Iqbal (2023) and Peters Taylor (2017)* $P = EARN + BVE + AssetRD + AssetSGA + IncomeRD + IncomeSGA$ *where* $AssetRD$, $AssetSGA$, $IncomeRD$, $IncomeSGA$ *are from the method by Iqbal et al (2023) and Peters and Taylor (2017), respectively.*

Figure 4 shows the result from running linear regression on the difference in R2 between the model with expenses from the income statement and the model with capitalized investments. Like in the case with CART, we do not find any support that the difference between these models is significant.

Finally, figure 5 shows the incremental R2 when adding measures related to intangibles to the baseline model, but with the addition of bootstrapped confidence intervals the percentile method.

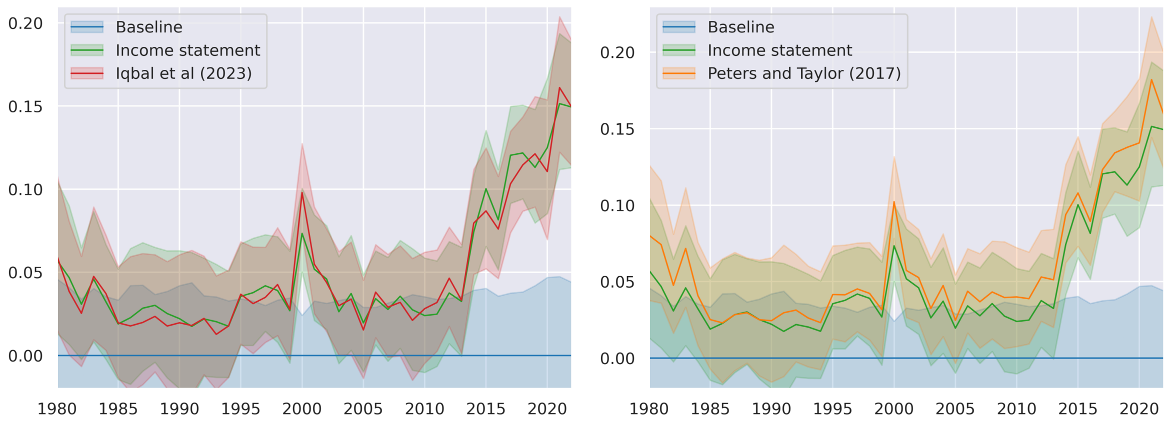

Figure 5: *Incremental adjusted R2 from baseline model with plotted 95% confidence intervals based on 10000 bootstrap samples. See figure 4 for definition of the models.*

Again, our results are similar to those obtained when using CART. The difference in R2 between the model with expenses from the income statement and the models with capitalized expenses is negligible compared to the size of the confidence intervals. Thus this test does not indicate a statistically significant difference between these measures.

5 Discussion

In this section we aim to analyze the results in section 5.1 and the robustness of the tests are presented in section 5.2.

5.1 Analysis of results

Our study aimed to study if the capitalization of these items using the models by Iqbal et al (2023) and Peters & Taylor (2017) would enhance the value relevance of R&D and SG&A as previous literature suggest that the current treatment of these investments is reducing the usefulness of financial statements.

Another potential benefit from capitalization is that common equity valuation models focus on future benefits, and thus splitting the expenses into an investment part and expense part might provide useful information. Capitalizing would also reduce the differences between internally generated intangibles and externally acquired intangibles.

When testing our hypothesis with the two different capitalization methods by Peters and Taylor (2017) and Iqbal et al (2023), as well as two different regression methods, we did not find any support for an increase in value relevance from capitalizing the R&D and SG&A expenses. Instead we found that the capitalized expenses seem to perform equally well as using the unadjusted values from the financial statements. In line with previous research, both of these measures seem to be value relevant.

These results are perhaps not very surprising, given the strong correlation found between the R&D and SG&A expenses, and the resulting assets after capitalization (see section 4.1). The strength of the correlation, in combination with our results, suggests that the information content of the different measures is roughly the same. This is reinforced by the use of CART, which is a non-linear method. If there had been non-linear relationships in the data, which linear correlation might not take into account, one would imagine that CART would have been able to exploit such relationships.

This raises the question of how these results should be interpreted. One line of reasoning might be that since we do not see any increase in value relevance when capitalizing intangible investments, it follows that investors would not see a large benefit from capitalization of intangible investments or additional disclosure regarding them.

However, an alternative explanation might be that it is difficult to undo the expensing of intangible investments based on public information. And that as a result, the methods that attempt to do this give a value for the asset that has high correlation with the original expense. If this is the case, it would point towards additional disclosure being needed, since the information in financial statements based on current accounting standards is not sufficient for understanding what parts of the expense is related to benefits in future years versus the current period.

As an additional complication, it is not clear to us whether this correlation between the capitalized asset and the original expense is unrealistic or not. It does not seem implausible that if a firm has fairly stable investments over a long period of time, one would end up with a correlation between the capitalized asset and the expense. Since our study is based on the large, well established stock exchanges in the United States, this might be a limitation in our study.

We leave it to future research to resolve what the answer to this question is, and we note that we find no support for capitalization of intangible investments having higher value relevance and being a more useful measure for investors.

5.2 Robustness of results

5.2.1 Validation of CART

The method developed by Barth et al. (2023) uses the Classification and Regression Trees (CART) method since it offers a nonlinear and flexible approach to the study of value relevance. This choice is crucial for our methodology as it fully captures the value relevance of the accounting items and is not constrained by predetermined conditions. The use of the out-of-bag predictor when using the CART method decreases the risk of overfitting which is a common problem when using within-sample R2 and can lead to incorrect analysis of value relevance.

Validating the CART method, Barth et al. (2023) demonstrated the method's ability to capture the dynamic economic landscape, especially in relation to intangible assets. Their method estimates yearly trends in out-of-sample R2 and they reinforced their hypothesis that the relevance of financial statements has not declined by presenting no significant negative trend in the value relevance of accounting items. The approach of randomly assigning each item to measure its impact on the out-of-sample R2 is a unique approach to understanding the relative importance of each individual item for the combined value relevance which truly demonstrates the efficiency of CART's ability to distinguish the different impacts of different items.

Alongside the CART method and to enhance the validity of our results we have also used a linear regression model as a comparison tool to the CART method. The purpose of this approach is to determine and observe if there are any significant differences in the results of the two different approaches. In our method, we found the results to be interesting as they showed that despite the CART method's great ability to handle non-linear data, our linear regression model provided us with similar results. These results suggest that non-linearities are not critical for modeling the relationship between R&D and SG&A with stock prices and that a linear relationship is sufficient.

5.2.2 Capitalization Methods

In the same spirit as for the statistical tests to ensure the validity of our results we have used two different methods for capitalizing intangible assets. The different methods developed by Iqbal et al. (2023) and Peters & Taylor (2017) complement each other in a strengthening manner for our analysis. Iqbal et al's industry-specific approach to the capitalization of intangible assets offers a detailed study that acknowledges the different attributes of each industry. This offers an adaptable and nuanced analysis of how the internally generated assets create economic value for different industries.

We also use Peters & Taylor (2017) which on the other hand offers a more generalized approach by assuming constant proportions of investments in R&D and SG&A to be capitalized. This method complements Iqbal et (2023) by offering a simpler perspective which makes it very useful for analyzing comparisons across industries.

Together, the methods by Iqbal et al. (2023) and Peters & Taylor (2017) provide a comprehensive approach to analyze the value relevance of intangible assets. This dual approach increases the robustness and credibility of our research and ensures that the capitalization of intangible assets is both comprehensive and adaptable to various industries.

6 Conclusion

Our study contributes to the understanding of the value relevance of internally generated assets in financial reporting. Consistent with previous research, we observed a positive trend during the 2000s and onwards for the value relevance of R&D and SG&A for both the non-adjusted and capitalized values. This supports the growing importance of these items in financial reporting regardless of the accounting treatment.

Additionally, our research provides necessary insights into the applicability and utility of the capitalization models proposed by Iqbal (2023) and Peters & Taylor (2017) in financial reporting relevance.

The findings of our study primarily highlights the challenge to capitalize intangible investments based on public information in an accurate manner. We observed a strong positive correlation between capitalized intangibles and their original expense which indicates that the current methods might not distinguish between the proportion of the expense that yield future benefit and those relevant to the current period. This suggests that current financial reporting might not provide enough information to investors for understanding the economic benefits of intangible investments. These insights open up for further discussion and exploration of the financial treatment of intangible assets.

This study also has certain limitations that we want to acknowledge. First and foremost, our study does not use and test the model developed by Lev & Sougiannis (1996) that proposes a method to capitalizing and amortizing intangible investments based on criterias such as being identifiable, legal control and ability to create future benefits. Also, due to certain details missing from the methodology by Iqbal (2023), there is a possibility that our implementation of the capitalization method is not entirely accurate and this could potentially affect the validity of our results. Finally, this research has focused on firms listed on major stock markets like NYSE and Nasdaq which suggest that the firms included in our study are dominated by larger mature firms. This raises concerns about the validity of our conclusion and that the results might differ if smaller, less established firms were considered.

Our study investigates one approach for improving financial reporting in the modern economy. Since we could not establish an increase in value relevance for the capitalization of intangible assets we suggest that future research investigate alternative approaches such as enhanced disclosure and how that could improve the quality of financial reporting. Additionally, since value relevance of intangible investments might vary across industries as mentioned by Lev & Sougiannis (1996), future studies could focus on a more industry-specific analysis which would help to understand how the current accounting treatment alters between different sectors.

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Appendix A: Variable Definitions

Variable	Definition
P	Price per share three months after fiscal year-end, described below
EARN	Income before extraordinary items scaled by number of shares (ib/csho)
BVE	Book-value of equity per share at fiscal year-end (ceq/csho)
RD	R&D expense per share (xrd/csho)
INTAN	Recognized intangible assets per share (intan/csho)
CASH	Cash and short-term investments per share (che/csho)
REVGR	Growth in revenue per share ((change in revt)/csho)
CF	Operating cash flow per share (oancf/csho). When missing, we set this to is (EARN - Accruals)/csho. Accruals = (changein current assets (act) - change in cash (che)) - (change in current liabilities (lct) - change in short term debt (dlc) - change in income taxes payable (txp))
REV	Revenue per share (revt/csho)
SPI	Special items per share (spi/csho)
OCI	Other comprehensive income per share. OCI is (retained earnings (re) - lagged retained earnings + divi-dends (dvc) - earnings (ib))/csho
DIV	Dividends per share (dvc/csho)
CAPX	Capital expenditure per share (capx/csho)
COGS	Cost of goods sold per share (cogs/csho)
SGA	SG&A expense per share, described below
TAX	Income tax expense per share (txt/csho)
EARNGR	Growth in earnings per share ((change in ib)/csho)
ASSETS	Assets per share (at/csho)
IND	Indicator variable for membership in Fama–French 10 industries

Price per share: For fiscal year t, we take the price per share from the *prrc_q* column in Compustat North America Fundamentals Quarterly for fiscal year t+1 (column *fyearq*) and the first financial quarter (column *fqtr*).

SG&A: If *xsga* is missing but *at* is not, then we set SGA to zero. We describe the case when *xsga* and *at* are both missing below. Next we check if *xrd* is less than *xsga* or if *xrd* is greater than *cogs*, then we set SGA to (*xsga - xrd - rdip)/csho*. For the purposes of the previous sentence, we set *xrd* and *rdip* to zero if they are missing. In the remaining cases we set SGA to *xsga/csho*. This method is due to Peters and Taylor (2017).

Appendix B: Our implementation of Iqbal et al. (2023)

In this section we describe our understanding of the method developed by Iqbal et al (2023). At times the paper by Iqbal et al (2023) leaves out certain details, and we explain here how we have dealt with these cases in our implementation.

The method by Iqbal et al (2023) aims to estimate how much of an expense from the income statement could in fact be capitalized when only considering the impact of the expense on future revenues. They do this by regressing the expense on future revenues. The regressions are performed on an industry-year basis, with data from a window of previous years.

1. **Preparation of the data**

The method relies on having a dataset with accounting data for a set of firms over a certain time period. We will allow for some data to be missing and explain how we deal with those cases in this section. In the following description we will refer to the following variables:

- $AverageAssetsBalanceSheet$: Average of beginning and end of year total assets for the firm as recorded on the balance sheet.
- $AssetsIntangible$: Estimate produced by the method for the size of the asset that should be added to the balance sheet at the end of the year, if we took into account previous expenses and how they match with future revenues.
- $Assets$: Average of beginning and end of year total assets combining the assets from the balance sheet with estimated *AssetsIntangible* from previous iterations of the method.
- $Revenues$: Revenues for the firm from the income statement
- $Expense$: The expense we are interested in capitalizing. The method allow for multiple expenses, and we will be working with Research and Development expenses (R&D) and Sales, General and Administrative expenses.

We also assume that each firm belongs to a particular industry, even if there is nothing that prevents all the firms from belonging to a single industry.
As a first step we explain how to deal with missing values for the expense variable. We are not clear on how Iqbal et al (2023) deal with this case, and instead we follow Peters and

Taylor (2017). We set the R&D and SG&A expenses to zero when they are missing, with one exception. If the end-of-year total assets are missing as well.

From the data we have, we form for each expense a set $D_{Expense}$ consisting of tuples

$$(Expense_{it}, AverageAssetsBalanceSheet_{it}, Revenues_{it}, ..., Revenues_{i(t+k)})$$

where k is a constant. To include a tuple in $D_{Expense}$, we require that none of the variables are missing and furthermore we require that both $Expense_{it}$ and $AverageAssetsBalanceSheet_{it}$ are positive. Following Iqbal et al (2023), we set k = 7 for R&D expense, and k = 5 for SG&A expense.

The next step is to update our value for total assets if we have done a previous iteration of the method. We set

$$Assets_{it} = AverageAssetsBalanceSheet_{it} + \frac{AssetIntangible_{i(t-1)} + AssetsIntangible_{it}}{2}$$

The method will always produce a value of $AssetsIntangible_{it}$ that is non-negative and it will not be missing for any year. Based on the updated value for $Assets_{it}$ and the tuples in $D_{Expense}$, we form set $R_{Expense}$ with tuples

$$\left(\frac{Expense_{it}}{Assets_{it}}, \frac{Revenues_{it}}{Assets_{it}}, ..., \frac{Revenues_{i(t+k)}}{Assets_{it}}\right)$$

2. **Estimating industry investment percentage**

Now we are ready to estimate the industry investment percentage. For each industry we take those tuples from $R_{Expense}$ that belong to that industry. We winsorize each component of the tuples at the 1% level (i.e. for each industry we winsorize the set consisting of the values $\frac{Expense_{it}}{Assets_{it}}$ etc). $R_{Expense,Ind}$ denote the set of these winsorized tuples belonging to the particular industry.

Next, for each industry-year we take a window of size w from $R_{Expense,Ind}$. That is, we pick those observations of $R_{Expense,Ind}$ with a year t' where $t - w < t' \leq t$. Following Iqbal et al, we use w = 7 for the R&D expense and w = 5 for the SG&A expense. We require there to be at least 10 firm-year observations within the window, otherwise we skip this industry-year.

If there are at least 10 observations in the window, we perform $k + 1$ different linear regressions of the form

$$\frac{Expense_{it}}{Assets_{it}} = \alpha + \beta_0 \frac{Revenues_{it}}{Assets_{it}} + \dots + \beta_{k'} \frac{Revenues_{i(t+k')}}{Assets_{it}}$$

where we vary k' from 0 to k.

We compare these $k + 1$ different linear regressions, and keep the one with the highest goodness-of-fit measure as the best model. In the case of Iqbal et al (2023) they use adjusted R^2 as the goodness-of-fit measure to select the best model.

Next we compute an intermediate investment percentage for each firm, which will be used to form the estimate of the industry investment percentage. For each tuple we compute

$$\widehat{Investment}_{it} = \alpha + \beta_1 \frac{Revenues_{i(t+1)}}{Assets_{it}} + \dots + \beta_{k'} \frac{Revenues_{i(t+k')}}{Assets_{it}}$$

That is, we omit the $\beta_0 \frac{Revenues_{it}}{Assets_{it}}$ term. Iqbal et al (2023) and Enache & Srivatava (2018) interpret this term as the amount of the expense that is matched with revenues in year t, and is thus not an investment and should rather be expensed.

To get a percentage, we then divide $\widehat{Investment}_{it}$ with $\frac{Expense_{it}}{Assets_{it}}$, and then clamp this value to be between 0 and 1. Finally, we average these values for all the tuples in the industry-year window and let this arithmetic average be the investment percentage for that industry-year. We also let $k' + 1$ be the estimate for the useful life for that year's investment in the industry.

3. Estimation of firm investments

At this point we have an estimate of the investment percentage and the useful life for each industry year, having replaced any missing values with linear interpolation. We apply these industry estimates to each firm in the industry in order to get an estimate of the size of the investment for a particular firm-year. That is, we let

$$Investment_{it} = InvestmentPercentage_{Ind,t} \cdot Expense_{it}$$

Since we have an investment percentage for each industry-year and the expense is available for each firm-year, we now have an estimate for the investment for each firm-year.

4. Estimation of asset size

We now tie together the investments from each firm-year to form an estimate of the asset on the firm's balance sheet. Following Iqbal et al (2023) and Peters and Taylor (2017) we do this using the perpetual inventory method. If we let $\delta_{Ind,t}$ be the useful life for investment in the industry of firm i, then the perpetual inventory method states that the end-of-year asset is given by

$$AssetIntangible_{it} = (1 - \frac{1}{\delta_{Ind,t}})AssetIntangible_{i(t-1)} + Investment_{it}$$

5. Dealing with multiple expenses

In the description above we have dealt with just a single expense. However, in our empirical tests we consider both R&D expenses as well as SG&A expenses. Thus we perform the process described above for each expense separately. Then having estimated the intangible assets and investment for each expense, we simply add together these values to get the combined intangible asset and investment derived from any of the expenses.