ACCOUNTING RELEVANCE IN CHANGING TIMES

An investigation of the change in the value relevance of accounting information as the US economy transitions from a manufacturing economy into a service economy.

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Abstract

Prior literature states the value relevance of accounting information, in particular earnings, has declined over time due to the rise of the new economy. To verify this, Barth et al. (2018) consider multiple accounting amounts and find no decline in the combined value relevance of accounting information from 1962 to 2014. Instead, they found evidence of an economy-wide increase, mainly related to intangible assets, growth opportunities, and alternative performance measures. Consistently, I find no decline in combined value relevance from 1970 to 2017, robust to partitioning the sample by firm type and industry. Secondly, I find a decrease in the value relevance of earnings, partially offset by the book value of equity. Furthermore, I find an increase in the number of value relevant accounting amounts, especially of those related to intangible assets, growth opportunities, and alternative performance measures. However, applying conditional permutation leads to less strong evidence for this. Regarding firms emblematic of the new economy, contrary to Barth et al. (2018), only the relevance trends related to growth opportunities are the most pronounced. Also, the industry analysis shows just the relevance trends related to alternative performance measures really seem to be economy-wide. Lastly, I find evidence for a general increase in the intangible intensity of firms.

Keywords: *Capital Markets; Equity Valuation; Financial Reporting; Value Relevance; New Economy; Classification and Regression Trees*

Disclaimer: *The content of this thesis is the sole responsibility of the author and does not reflect the view of either Erasmus School of Economics or Erasmus University Rotterdam.*

Preface

This master thesis is the crown and capstone of my economic study at the Erasmus University of Rotterdam. Spending more than three months working on it, I hope it is satisfying. At least to me it is! Day after day, I performed the job with great pleasure; even forced at the end to realize the job was done. Most satisfying to me were the statistical activities in R. Writing the correct algorithms needed time and energy, but the outcomes sugarcoated this completely. Fortunately, since I am in a double degree program, ending this thesis does not mean leaving the Erasmus University behind me.

Although this thesis is written by me, it came into being thanks to many others. Firstly, I would like to thank the Erasmus School of Economics for providing excellent education and facilities throughout the study. Secondly, I am thankful to my supervisor Sander Renes for his time, explanations, and hints during the writing process. Thirdly, a special thanks goes to my fellow students Corstiaan Anker, Rutger Both, Peter Mastenbroek, Rik-Jan Veldhuijzen, and Arjan van der Waal for providing me the opportunity to be the first to graduate from college.

Personally, my deep gratitude goes to my family, in particular my parents. I really thank them for their love, caring, support, patience, and many other things. Also to my little sister Loïs for preferring horses over their brothers. Lastly, as an educated man, I am deeply aware numerous human success factors are out of our depth. To that end, I am grateful to the Creator, in Whom we live and move and have our being.

Enjoy reading!

Jacob Gerard Verheul BSc
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List of Abbreviations

Abbreviation	Definition
APM	Accounting performance measure
BVE	Book value of equity
CAPX	Capital expenditures
CART	Classification and regression trees
CCP	Cost-complexity pruning
CMBAR	Capital market-based accounting research
COGS	Cost of goods sold
EPM	Equity performance measure
FASB	Financial Accounting Standards Board
GAAP	Generally accepted accounting principles
IASB	International Accounting Standards Board
IFRS	International Financial Reporting Standards
MSPE	Mean squared prediction error
MVE	Market value of equity
OOB	Out-of-bag
OCF	Operating cash flow
OCI	Other comprehensive income
R&D	Research and development
SG&A	Selling, general, and administrative (expense)
VRR	Value relevance research

Note: In this thesis, the abbreviations are **capitalized** but **not italicized**. Contrary to the variables, they are **capitalized** and **italicized**.

Chapter 1

Introduction

1.1 Social Relevance

The 1980s and 1990s marked the beginning of a new era, heralded by the birth of the personal computer. An era in which information technology promised to increase productivity through the automation of many processes. New companies were founded and market capitalizations reached record levels. For example, the NASDAQ Composite Index, which was composed mainly of new economy firms, increased by more than 70% from July 1999 to February 2000, compared to an 8% decrease of the Dow Jones Industrial Average, which was composed mainly of old economy firms (Palepu, Healy, & Peek, 2017). Since the opportunities appeared to be boundless, market analysts predicted 'pots of gold' and believed this was just the beginning of the Third Industrial Revolution (Greenwood & Jovanovic, 1999).

However, in the spring of 2000, there was a dramatic drop in the valuation of many companies in the internet sector (often referred to as 'dot-com bubble'). The NASDAQ dropped with more than 50% from 5,132.52 at the end of March 2000 to 2,470.52 year-end. Consequently, several of these, once high-flying, internet firms now filed for bankruptcy or were forced to close down their operations. Furthermore, millions of individual investors lost money and decreased their spending level. Naturally, this whole phenomenon raised a lot of questions, which, in essence, all boil down to the single question: "How could this crash happen in such a sophisticated capital market system?" (Palepu et al., 2017).

In a well-functioning capital market system, the incentives of intermediaries, who are needed to reduce the information asymmetry between investors and companies, are fully in line with their responsibilities. In that case, companies will be valued correctly and investors earn a 'normal' rate of return. The integrity of this process is critical since investors need to be willing to invest their money. Regarding the accounting profession, their responsibility in this process is to guarantee the accuracy of financial reporting information. However, during the bubble, the accounting practices of some internet firms posed serious challenges for them. While some observers afterwards blamed the accountants for not doing a good enough job, others questioned whether the current accounting standards had become obsolete for the new economy. For instance, it was argued that current accounting standards did not allow new economy firms to capitalize their major (intangible) investments, while the old economy firms were allowed to capitalize their major (tangible) investments (Palepu et al., 2017). To answer this question, so whether current accounting standards have become less relevant for today's economy, empirical research is necessary.

1.2 Scientific Relevance

Empirical research into the relevance of accounting information is in the accounting literature known as value relevance research (VRR). Francis and Schipper (1999) define value relevance as the ability of financial statement information to capture or summarize information that affects the value of a firm. Overall, the results in VRR indicate a decline in the value relevance of earnings (for instance, see Collins, Maydew, and Weiss (1997), Ely and Waymire (1999), Francis and Schipper (1999), and Lev and Zarowin (1999)). The accounting literature provides two primary explanations for the decline: 1) a transition to a service economy in which earnings depends to a larger extent on investments in intangible assets (Collins et al., 1997; Francis & Schipper, 1999; Srivastava, 2014), and 2) an increase in the frequency of losses (Basu, 1997; Hayn, 1995). Furthermore, Collins et al. (1997) argue there is an inverse relation between the value relevance of earnings and the value relevance of the book value of equity (BVE). However, the evidence for this hypothesis is mixed (Balachandran & Mohanram, 2011; Brown, Lo, & Lys, 1999; Collins et al., 1997; Francis & Schipper, 1999; Goodwin & Ahmed, 2006).

Contrary to prior studies, Core, Guay, and Van Buskirk (2003) also include advertising expenditures, research and development (R&D) expenditures, capital expenditures (CAPX), and sales growth. However, their findings still reveal a decline in the combined value relevance over time. Soon thereafter the literature began to focus on the effect of the adoption of the International Financial Reporting Standards (IFRS) on the value relevance of earnings and BVE. So, less was done to extend the prior literature by examining other accounting amounts.

Recently, Barth, Li, and McClure (2018) started to work on a paper which actually examines the *trend* in the value relevance of *various* accounting amounts, several of which also relate to the new economy. In contrast to prior research, they do not find a decline in the combined value relevance of accounting information. Instead, they state that if they found something, it is evidence of an increase, mainly related to intangible assets, growth opportunities, and alternative accounting performance measures (APM) becoming more relevant. Because they found these trends are evident for the full sample, they conclude that new economy firms are not solely responsible for the relevance increases. So, their conclusion suggests a general increase in the intangible intensity of firms as the explanation for their findings. But, this stands in stark contrast to the study of Srivastava (2014), who contributes the earnings relevance decrease to an increase in the listing of intangible-intensive firms rather than a general increase in the intangible intensity of firms. Therefore, more comprehensive evidence is needed.

1.3 Research Question and Thesis Structure

In short, prior research disagrees on the precise effects of the transition of modern economies from primarily manufacturing activities to service-providing activities on the value relevance of accounting information. This thesis *verifies* the study of Barth et al. (2018) by estimating the relation between the stock price and various accounting amounts for US firms from 1970 to 2017, based on the classification and regression trees (CART) method. In extension of this study, I perform an industry analysis to check whether the relevance trends are really economy-wide, and I recalculate the individual value relevance measures based on conditional permutation to take the *time-dependent* correlation structure between accounting amounts into account. Based on the foregoing, the following research question can be formulated:

How did the value relevance of accounting amounts of firms listed in the United States of America evolve as the new economy developed?

The findings show no decline in the combined value relevance of accounting information, robust to partitioning the sample by firm type and industry. Secondly, they reveal a(n) decrease (increase) in the value relevance of earnings (BVE). Moreover, there is an increase in the number of value relevant accounting amounts, especially of those related to intangible assets, growth opportunities, and alternative APMs. However, the evidence for this is less strong when individual value relevance is calculated based on conditional permutation. Concerning firms emblematic of the new economy, only the relevance trends related to growth opportunities are the most pronounced, which is contrary to Barth et al. (2018). Also, the industry analysis shows just the relevance trends related to alternative APMs really seem to be economy-wide. Lastly, the findings reveal each industry's Q ratio increases over time, implying a general increase in the intangible intensity of firms.

The remainder of this thesis proceeds as follows. In Chapter 2, I review the accounting literature on value relevance, I derive hypotheses for the empirical analysis, and I identify relevant accounting amounts and predict their trends. In Chapter 3, I develop the research design underlying to the empirical analysis and describe the sample. In Chapter 4, I document the outcomes of the empirical analysis. In Chapter 5, I discuss and summarize this thesis and its empirical findings.

Chapter 2

Theoretical Framework

In this chapter, I develop a theoretical framework by reviewing the literature on value relevance. To that end, I first introduce the broader research area on the relation between capital markets and financial statements (Section 2.1). Secondly, I introduce the value relevance literature by looking at its subject, underlying theories, distinctive characteristics, and relevance to society (Section 2.2). Thirdly, I discuss three types of valuation models that are widely used in the literature, together with issues related to the implementation of these models (Section 2.3). Fourthly, I review the empirical evidence into the value relevance of accounting information (Section 2.4). Fifthly, I derive hypotheses (Section 2.5). Sixthly, I identify relevant accounting amounts and predict the trend in their value relevance (Section 2.6). Lastly, I summarize this chapter in Section 2.7.

2.1 Introduction to CMBAR

2.1.1 Genesis of CMBAR

The empirical research on the relation between capital markets and financial statements is a broad area of research and is generally referred to as capital market-based accounting research (CMBAR). Modern CMBAR originated half a century ago with the pioneering studies of Ball and Brown (1968) and Beaver (1968). Until that moment, accounting theory was mainly normative (Kothari, 2001). Theory development depended on the objectives put forward by the researcher, and theory evaluation was based on 'logic reasoning'. Since the theories were logically consistent, the scientific debate was little more than a discussion on the 'true' objectives of accounting. As a result, the general lack of consensus led to skepticism about the ability of historical cost accounting amounts to accurately reflect the financial health of firms.

The non-consensus state of science[1] paved the way for the application of a new

[1] For other (possible) reasons, I refer to the paper of Kothari (2001).

approach called 'positive economics'.[2] So, the ability of historical cost accounting amounts to accurately reflect the financial health of firms became a statement open for empirical examination. To that end, both pioneering studies perform an event study, while Ball and Brown (1968) also performed an association study.[3] With regards to the event studies, both document that accounting earnings are informative to investors. The association study of Ball and Brown (1968), however, demonstrates that a clear majority of the information content in annual earnings is preempted by other information sources (including interim reports). These results, together with others[4], initiated a long stream of empirical studies.

2.1.2 Categorization of CMBAR

The long stream of empirical studies initiated by Ball and Brown (1968) and Beaver (1968) can be categorized into several substreams. According to Kothari (2001), CMBAR can be divided into the following four topics: 1) fundamental analysis and valuation, 2) market efficiency, 3) role of accounting in contracts and in the political process, and 4) standard setting. Another categorization, proposed by Beaver (2002), distinguishes five subfields: 1) market efficiency, 2) Feltham-Ohlson modeling, 3) value relevance, 4) analysts' behavior, and 5) discretionary behavior. Beaver (2002) adds to his categorization that the first two areas should be seen as the basic platforms comprising the role of accounting in capital markets, while the last three should be seen as applications.

Since no research field classification is both perfectly mutually exclusive and collectively exhaustive, the classification choice is a matter of preference. For example, while Beaver (2002) views Feltham-Ohlson modeling as a subfield on its own, Kothari (2001) includes this type of research under fundamental analysis and valuation. Further, Beaver (2002) states in his paper he selected the five research areas which made, according to him, the greatest contribution to existing knowledge, and that he chose to sacrifice depth for breadth. Based on these statements, I prefer the categorization by Kothari (2001) over Beaver (2002).

[2]According to Friedman (1953), the ultimate goal of science is not to develop theories that yield *true* predictions (i.e., normative science), but to develop theories that yield *valid* and *meaningful* predictions about phenomena not yet observed (i.e., positive science).

[3]In an event study, the researcher examines whether an event (e.g., an earnings announcement) conveys new information to the market as reflected in changes in the level or volatility of security prices or trading volume over a short period of time around the event (Kothari, 2001; Kothari & Warner, 2007). In an association study, the researcher tests for positive correlations between accounting performance measures (APM; e.g., earnings or operating cash flow (OCF)) and equity performance measures (EPM; e.g., stock prices or stock returns) over relatively long, coetaneous periods of time (Kothari, 2001).

[4]For instance, Ball and Brown (1968) provided preliminary evidence for a post-earnings announcement drift, but were not able to fully explain this.

2.2 Introduction to VRR

2.2.1 Standard Setting and Value Relevance

In view of the research question, I will look in more detail to the fourth main topic in CMBAR, which is, according to Kothari (2001), standard setting. This field of research examines whether financial reporting objectives are (better) served by the currently issued accounting standards. In view of the rapid globalization of markets, an important question to be answered is whether there should be a uniform set of accounting standards worldwide or whether diversity should be allowed. And if a uniform set of accounting standards is preferable, which generally accepted accounting principles (GAAP) have to be chosen? Or if accounting diversity should be allowed, what are relevant environmental factors in deciding so? So, this research field is, in essence, about the evaluation of accounting standards.

One financial reporting objective is to provide information about the reporting entity that is useful to existing and potential investors (FASB, 2010). For financial information to be useful to investors, there should be a statistical association between accounting amounts and the stock price. In that case, an accounting amount is classified as value relevant in the academic literature (Barth, Beaver, & Landsman, 2001; Beaver, 2002; Holthausen & Watts, 2001). More formally, Francis and Schipper (1999) define value relevance as the ability of financial statement information to capture or summarize information that affects the value of a firm.

2.2.2 Theories Underlying to VRR

Holthausen and Watts (2001) state that VRR is only useful if there are descriptive theories underlying it. In other words, mere associations are not informative. Researchers should therefore clearly specify the objective of standard setting and explain how the results enable standard setters to serve that objective better. In line with this, Barth et al. (2001) mention that relevance and reliability are the two main criteria the Financial Accounting Standards Board (FASB) utilizes in choosing between alternative accounting methods.[5] Hence, they state VRR's whole task is to operationalize these criteria (i.e., not to determine them).

Although many VRR studies base their theoretical reasoning on statements of the FASB, Holthausen and Watts (2001) identify three 'assumptions' that are inconsistent to them. Firstly, VRR would assume *equity* investors are the dominant users of FR. Even if this is true, this argument, however, does not undermine VRR. It only serves as a reminder that financial reporting also has applications beyond

[5]Under Statements of Financial Accounting Concepts No. 5, an accounting amount is relevant if it is capable of making a difference in user decisions, and it is reliable if it is representationally faithful, verifiable, and neutral (FASB, 1984).

equity investment. Secondly, VRR would assume stock prices adequately represent the information equity investors utilize in their valuation of equity securities. Granted, it could perfectly be that the individual demand for information may be more diverse than is reflected in stock prices. This, though, does not imply that, by utilizing the aggregation of individual investors' valuations, VRR is not relevant to standard setters at all.

According to Holthausen and Watts (2001), VRR would also assume the absence of measurement errors. Stated differently, VRR studies would not take into account that FASB's verifiability attribute (see prior paragraph) may not be fully adhered to by managers because of their incentives to misrepresent accounting amounts (Watts & Zimmerman, 1978, 1990).[6] Interestingly, as the authors themselves recognized, various VRR studies make an attempt to operationalize FASB's reliability criterion in order to examine the extent to which such behavior takes place (Barth et al., 2001; Holthausen & Watts, 2001). For a discussion how VRR precisely controls for such behavior, I refer to Section 2.3.2 'Implementation of Valuation Models'. For now, I admit it is true VRR is neither necessary nor sufficient for standard setting, but that is also not what it is intended to be (like all empirical studies). VRR is designed to be informative and helpful to standard setters in their deliberations, and as such it is worth taking the list of 'inconsistent VRR assumptions' of Holthausen and Watts (2001) into account when drawing inferences in VRR (albeit I would not refer to them as 'inconsistent assumptions', but as 'inferential issues').

2.2.3 Distinctive Characteristics of VRR

In comparing VRR to other CMBAR subfields, it can be observed that VRR requires more in-depth knowledge of the institutional context. Precisely this context incorporation enables researchers to come up with powerful predictions and clear improvements for standard setting (Beaver, 2002). In addition to this, the timeliness of information is relatively irrelevant. This is due to the fact VRR examines the relation between the level of stock prices and accounting amounts over relatively long periods of time. So, information does not have to be new to users of financial statements to be value relevant (Barth et al., 2001; Beaver, 2002).[7]

2.2.4 Relevance of VRR

VRR is of potential interest to standard setting agencies such as the FASB or the International Accounting Standards Board (IASB), other regulatory agencies, and

[6]Needless to say, measurement error as a sole econometric problem is not at issue since Miller and Modigliani clearly showed in 1966 that this type of econometric problem can be mitigated by applying instrumental variables estimation (see footnote 29 of Barth et al. (2001)).

[7]Naturally, for decision relevance it does have to be so.

financial statements preparers and users. In fact, VRR studies are often motivated by demand of one of these non-academic parties (Barth et al., 2001; Beaver, 2002). The most obvious is the relevance to standard setting agencies. For example, VRR is relevant because it does not avoid normative questions like "Are new fair value accounting estimates too noisy to disclose?".[8] On the contrary, it actually makes an attempt to answer these questions by testing whether new disclosures provide significant explanatory power for stock prices incremental to current disclosures. By doing so, it enables standard setters to update their beliefs about the extent to which financial reporting objectives are currently served (Barth et al., 2001).

Regarding other regulatory agencies, a similar 'reasoning' could be applied. For instance, VRR tests could show banks are relatively unable to estimate accurately the fair value of loans issued. Such empirical evidence is relevant for agencies designing financial regulations, like the Securities and Exchange Commission. Notice, however, at the same time it is relevant to financial statements preparers and users. Preparers could, based on this empirical evidence, decide to voluntarily disclose more accurate information, while users could search for alternative sources of information. In summary, VRR is not only of interest to academic researchers, but also to non-academic parties like regulatory agencies, firm managers, and investors.

2.3 Empirical Testing in VRR

2.3.1 Choice of Valuation Models

An important issue in VRR is the selection of a *proper*[9] valuation model. After having reviewed the VRR literature, Holthausen and Watts (2001) distinguish three types of models. Many incremental VRR studies[10] utilize a valuation model in which the market value of equity (MVE) equals the market value of assets (MVA) plus the market value of liabilities (MVL) plus the market value of the *balance sheet* component whose incremental association is being examined (MVC; naturally, this item is excluded from MVA or MVL) (referred to as BS model):

$$MVE = MVA + MVL + MVC.$$

This model, however, only holds when competitive markets exist for each asset and liability as well as for the stock. Furthermore, competitive advantage is allowed if

[8]Normally, normative questions are avoided in accounting research because of their complex and judgmental character (Barth et al., 2001).

[9]Holthausen and Watts (2001) state that many studies, considering their research objective, utilize inappropriate valuation models. Hence, a thorough understanding of valuation models is required.

[10]Incremental association studies in VRR examine whether a specific accounting amount has significant explanatory power for EPM *given* other specified accounting amounts (Holthausen & Watts, 2001).

and only if the advantage can be sold separately from the firm, otherwise the market value of equity (MVE) exceeds the market value of net assets. Lastly, the BS model assumes the absence of corporate control frictions, so that managers liquidate the firm if that is the most optimal action (Holthausen & Watts, 2001).

Related to the BS model, various relative VRR studies[11] regress the market value of equity on components of earnings (referred to as EARN model). In that case, the accounting amount whose regression yield the highest R^2 is considered the most value relevant. Further, the EARN model is also utilized in VRR studies on the incremental value relevance of specific revenue or cost components. In general, these studies assume earnings equal 'unconditional' or 'permanent' earnings and stock price equals 'capitalized' earnings. Regarding the former, current earnings and permanent earnings are equal if future earnings are assumed to follow a random walk (Holthausen & Watts, 2001).

The third valuation model utilized in VRR is the FO model (Feltham & Ohlson, 1995; Ohlson, 1995). It models the market value of equity (MVE) as a linear function of the book value of equity (BVE) and the PV of expected future abnormal earnings, defined as forecasted net income ($\widehat{NI}$) minus forecasted BVE ($\widehat{BVE}$) multiplied by the risk-adjusted rate of return on equity (r):

$$MVE_t = BVE_t + \sum_{k=1}^{\infty} E_t[\widehat{NI}_{t+k} - r \times \widehat{BVE}_{t+k-1}]/(1+r)^k.$$

While it assumes capital markets to be competitive[12], it allows, in contrast to the BS model, the other markets to be non-competitive also. By making additional assumptions regarding the information dynamics of earnings, MVE can be expressed as a linear function of BVE, net income, dividends, and other information. Importantly, the FO model does not assume accounting amounts are unbiased measures of respective market values (BS model) or earnings equal the earnings power of the firm in the long run (EARN model). Thus, since this model does not require the researcher to specify a link between EPM (see footnote 3) and the accounting amounts, it is frequently used in recent studies in VRR (Barth et al., 2001).

Despite its characteristics, Holthausen and Watts (2001) criticize the FO model for excluding positive net PV projects. However, Barth et al. (2001) suggest these expected rents can be incorporated in the model by including the PV of *their* expected future cash flows in BVE. Furthermore, they criticize the model for being

[11] Relative association studies in VRR compare the association between a specific EPM and alternative bottom line accounting amounts in order to determine which one is the most value relevant (Holthausen & Watts, 2001).

[12] Needless to say, assuming capital markets to be competitive is not identical to assuming capital markets to be efficient. In general, VRR only requires the first. Therefore, stock prices have to reflect investors' consensus beliefs, but do not have to be unbiased measures of the unobservable 'true value' of equity (Barth et al., 2001).

linear. Granted, MVE is defined as a linear function of BVE and the PV of expected future abnormal earnings (see prior paragraph). Nonetheless, researchers in VRR could allow coefficients to vary cross-sectionally or across components of BVE and abnormal earnings (Barth et al., 2001; Burgstahler & Dichev, 1997). Furthermore, recent research of Barth et al. (2018) overcomes this issue by utilizing CART estimation. Contrary to prior studies, this flexible method does not impose a particular functional form, which could understate the explanatory power of accounting amounts, and so their value relevance (Hastie, Tibshirani, & Friedman, 2017; Holthausen & Watts, 2001).

2.3.2 Implementation of Valuation Models

In examining the statistical association between equity performance and accounting amounts, the researcher should determine which EPM to use. This depends on the research objective. Logically, if the research objective is to determine what is reflected in firm value over a specific period of time, the researcher should opt for a level-based approach (i.e., utilize stock prices). If, instead, the objective is to determine what is reflected in changes in firm value over time, the researcher should adopt a difference-based approach (i.e., utilize stock returns). So, the latter is about the determination of the timeliness of accounting information. Since a lot of studies in VRR are motivated by non-academic parties (see Section 2.2.4 'Relevance of VRR'), timeliness determination is relatively unimportant, and thus the difference-based approach is being utilized less. Naturally, failure to recognize these differences results in drawing incorrect inferences (Barth et al., 2001).

Unfortunately, the level-based approach is subject to more serious econometric problems than the difference-based approach (Christie, 1987; Kothari & Zimmerman, 1995; Landsman & Magliolo, 1988). Two important issues are biased coefficient estimates and heteroskedastic regression error variances. These issues are, at least partially, the result of cross-sectional differences in firm scale (Barth & Kallapur, 1996). Related to this, Brown et al. (1999) show the presence of a positive relation between the R^2 and scale factor's coefficient of variation. So, this evidence suggests between-sample comparisons based on the R^2 are misleading, *unless* one controls for scale effects.[13] Consequently, they recommend to deflate all variables by lagged stock prices. Gu (2005, 2007), though, states that even in the absence of scale effects and heteroskedasticy, the R^2 is not comparable across samples due to changing sampling properties. This problem is particularly serious for VRR, which examines relatively long periods of time. He instead proposes to utilize the residual dispersion matrix to examine the value relevance of accounting information.

[13] Barth and Clinch (2009) prefer to use the term 'scale effects' to distinguish variation in firm size, as measured by BVE, from variation in firm size that *actually* leads to incorrect inferences.

Although Gu (2005, 2007) states that the R^2 is not comparable across samples due to changing sampling properties, cross-sectional differences in firm scale could still result in biased coefficient estimates and heteroskedastic regression error variances. Thus, it is still necessary to control for scale effects. Barth and Clinch (2009), however, investigate the effectiveness of several specifications to mitigate a variety of scale effects and find deflation by shares generally is more effective than deflation by lagged stock prices. Moreover, deflating by the stock price at the beginning of the year effectively transforms the stock prices in stock returns (which have a different economic interpretation, see prior paragraph) (Barth et al., 2018).

Naturally, the researcher should also specify the independent variables in the estimation equation. Same as before, this depends on the research objective. Remember from Section 2.3.1 'Choice of Valuation Models', the FO model does not require the researcher to design a general equilibrium model in order to specify a link between EPM and the accounting amounts. On the other hand, the inclusion of the correct accounting amounts is critical for the final outcome. As such, it is important in the model implementation process to reason which accounting amounts should be included and which ones should be excluded. Since these reasoning processes are really dependent on the specific context of a study, I will not review the VRR literature in general, but will instead, based on the specific context of this thesis, reason which accounting amounts should be included. This will be done in Section 2.6 'Accounting Amounts and Predictions'.

Finally, according to positive accounting theory, managers have incentives to misrepresent accounting amounts (Watts & Zimmerman, 1978, 1990). Therefore, various VRR studies make an attempt to operationalize FASB's reliability criterion in order to examine the extent to which such behavior takes place (Barth et al., 2001). This is often done in terms of 'measurement error'. Naturally, to define measurement error, a benchmark should be specified. To that end, an often used operationalization is 'economic amounts'. In such cases, measurement error is defined as the differences between accounting amounts and economic amounts. According to Barth et al. (2001), this type of VRR studies additionally have to assume both *capital* and *non-capital* markets are *efficient* (see Section 2.3.1 'Choice of Valuation Models').

Another approach in the literature to operationalize FASB's reliability criterion is to utilize amounts as reflected in stock prices. While this operationalization only assumes *capital* markets are *competitive*, in drawing inferences the researcher still has to assume that capital markets' estimates are *unbiased* (i.e., efficient; see also footnote 12 of Chapter 2 'Literature Review') (Holthausen & Watts, 2001). So, seen from a theoretical perspective, the differences between both approaches are relatively small. Overall, this specific field of VRR is relatively underdeveloped, which makes future research both necessary and valuable.

2.4 Empirical Findings of VRR

2.4.1 Decline in Earnings Relevance: New Economy

A lot of studies have been done into the value relevance of accounting information. Overall, the results indicate a decline in the value relevance of earnings (for example, see Collins et al. (1997), Ely and Waymire (1999), Francis and Schipper (1999), and Lev and Zarowin (1999)). Already in 1996, Amir and Lev found that earnings, but also BVE and OCF, are largely irrelevant for security valuation of independent cellular companies. Consequently, Collins et al. (1997) argue that because current accounting rules only record intangible assets in limited circumstances, financial accounting information may not be very useful in predicting the MVE of companies with a lot of intangible assets. In their paper they find consistent evidence: a steady increase in the percentage of firms operating in intangible-intensive industries, which is significant in explaining the observed shift in value relevance from earnings to BVE.

Research of Francis and Schipper (1999) and Ely and Waymire (1999) leads to similar conclusions with respect to the changes in the value relevance of accounting information: a decline in the relevance of earnings and an increase in the relevance of BVE. However, Francis and Schipper (1999) do not find a significant difference between the levels of, and changes in, the relevance of earnings between high- and low-technology firms. This result is inconsistent with their expectation that any decline would be most apparent in high-technology industries, because of a potentially wider disparity between what is included in the financial statements and what is relevant to investors.

In line with Collins et al. (1997), Lev and Zarowin (1999) document a negative association between the informativeness of earnings and R&D spending. They attribute this finding to the large investments that are generally related to R&D, which are directly expensed while the benefits are recorded later (i.e., problem of timing mismatch). Because of an *increase*[14] in the level of investments in intangible assets, Lev and Zarowin (1999) label in their paper the accounting for intangible assets as a major reason for the decline in the value relevance[15] of earnings.

[14]It is important to note that the authors state: "It is *not* the high *level* of intangible investment, indicated in those papers by a firm's membership in a high-tech industry or by high intensity of R&D, that is expected to cause a decrease in the informativeness of financial information. (...) It is only when the investment rate in intangibles *changes* over time that reported earnings based on immediate expensing *will differ materially* from economic earnings based on capitalization of intangibles." (Lev & Zarowin, 1999; cursivations added).

[15]Collins et al. (1997) state in footnote 3 of their paper that Lev and Zarowin (1999) focus on the information content of earnings (i.e., stock price reaction to earnings announcement) while they focus on the value relevance (i.e., association between stock price and earnings). According to them, this is an important difference, for the information content could decrease over time as

Consistent with the (increasing) problem of timing mismatch, Dichev and Tang (2008) observe an economically substantial negative trend in the contemporaneous correlation between revenue and expense for the 1,000 largest US firms over almost 40 years. They explain in their paper that this decline could happen because of changes in the real economy or changes in accounting standards. However, neither of these was able to fully account for their findings. Additionally, Donelson, Jennings, and McInnis (2011) conclude that the increase in the problem of timing mismatch is attributable primarily to a steady increase in the frequency of special items. They find strong evidence that changes in economic activity are a primary reason for the increase in special items, but are not able to rule out the possible influence of accounting standards at all.

Srivastava (2014) is also not able to completely rule out the accounting standard possibility. Nevertheless, he provides even stronger evidence for appointing changes in the economic activity as the primary reason for the decrease in matching and, related to this, the decrease in the value relevance of earnings. He does so by showing that the majority of the changes in matching and value relevance is due to firms getting listed after 1970 (i.e., “new firms”) and not to firms getting listed before 1970 (i.e., “old firms”). In addition to this, he finds that the later a firm got listed after 1970, the larger the difference between the intangible intensity of this firm and firms that got listed before 1970. Therefore, he contributes the decrease in the value relevance of earnings to an increase in the listing of intangible-intensive firms rather than a general increase in the intangible intensity of firms.

2.4.2 Decline in Earnings Relevance: Bad Economy

There is also some literature which provides another explanation for the decline in the value relevance of earnings over time: an increase in the presence of unprofitable firms. Hayn argued in 1995 that because shareholders have a liquidation option, losses are likely to be considered as temporary. Therefore, they provide less information than profits. She finds consistent results. Her results even show that when only unprofitable firm-years are considered, reported losses are not significantly correlated with price movements at all. Furthermore, she documents an increase in the frequency of losses over time.

non-accounting information becomes more timely, while the value relevance might be constant or even improving. However, they did not notice that Lev and Zarowin (1999) stated, based on their results, that the increase in the availability of non-accounting information could not be the only reason for the decrease in earnings usefulness (see the end of Section 1.1 'Social Relevance'). Consequently, the authors use these two terms interchangeably. Furthermore, both papers look to the association between stock prices and earnings plus BVE, as measured by the R^2. Therefore, I consider the criticism of Collins et al. (1997) as ungrounded.

Related to the study of Hayn (1995) is a paper written by Basu (1997). He argues that negative earnings changes are less persistent than positive earnings changes because of accounting conservatism. His empirical tests support this hypothesis. Moreover, he provides indirect evidence for an increase in the degree of accounting conservatism over time and ascribes this (partly) to the mandatory recognition of previously off-balance sheet liabilities. These two studies together suggest the temporal decline in the value relevance of earnings is due to an increased frequency of unprofitable firms.

2.4.3 VRR into Combined Value Relevance

Collins et al. (1997) state that if the value relevance of earnings has decreased over time, the value relevance of BVE should show up a temporal increase. They argue so because they conjecture that the same factors contributing to a decline in the value relevance of earnings, are contributing to an increase in the value relevance of BVE. This conjecture is rooted in a study of Collins, Pincus, and Xie, which was published later in 1999. Collins et al. (1999) demonstrate that the omission of BVE in regressing the stock price on earnings, will induce a negative bias in the coefficient of earnings for unprofitable firms and a positive bias for profitable firms. Explanations they provide for the role of BVE in the equity valuation of unprofitable firms are: 1) it serves as a proxy for the expected future normal earnings, and 2) it serves as a proxy for the liquidation value. Further, their findings suggest the relative importance of the two explanations depends on the estimated likelihood of liquidation (Collins et al. 1999).

In line with the aforementioned explanations, both Collins et al. (1997) and Francis and Schipper (1999) document a temporal decline in the value relevance of earnings which is offset by an increase in the value relevance of BVE. However, Brown et al. (1999) show that after controlling for differences in the coefficient of variation in the scale factor[16], there has been a decrease over time in the explanatory power of earnings together with BVE. This finding has been confirmed by Goodwin and Ahmed (2006) and Balachandran and Mohanram (2011). Furthermore, even without controlling for scale effects, Lev and Zarowin (1999) conclude that there is a temporal decline in the combined value relevance of earnings and BVE. Therefore, it can be stated that the evidence for a *positive* evolution in the combined value relevance of earnings and BVE is mixed.

[16]Brown et al. (1999) show that the R^2 is an unreliable statistic in the presence of scale. Differences in the R^2 from samples drawn in different time periods or across countries can, in fact, be driven by differences in the coefficient of variation in the scale factor. Therefore, controlling for scale effects is necessary in examining whether the value relevance has changed over time or (only) differs across samples. See also Section 2.3.2 'Implementation of Valuation Models'.

2.4.4 VRR into Multiple Accounting Amounts: Start

At the beginning of this millennium, there appeared to be a widespread belief that the growing importance of the internet heralded a new era in which equity valuation is different from prior periods. Therefore, Core et al. (2003) examine whether there is an unusual reduction in the ability of financial information to explain firm valuation during the period from 1996 to 1999 in comparison to the years 1975-1995. To test whether valuation characteristics have changed for some group of firms but not for others, they also examine subsamples of high-technology firms, young firms, and young firms with losses. Moreover, in contrast to prior studies, Core et al. (2003) include advertising expenditures, R&D expenditures, CAPX, and sales growth. Their findings reveal a decline in the combined value relevance over the period from 1975 to 1999 for the full sample and a significant lower combined value relevance in the years 1996-1999, both in the full sample and in the separate subsamples.

While Kothari and Shanken (2003) published in the same year a paper in which they discuss several econometric issues related to the paper of Core et al. (2003), soon thereafter the literature began to focus on the effect of the voluntary and/or mandatory adoption of IFRS on the value relevance of earnings and BVE. So, studies did not longer search for a *trend* in the value relevance, but were in line with Core et al. (2003) searching for an *unusual shift* from a specific point in time and onwards. Related to this, many studies were performed for various specific contexts[17], but less[18] was done to extend the prior literature by examining *other* accounting amounts than the ones mentioned above. This stands in contrast to the suggestions for future research provided by Holthausen together with Watts and Barth et al. in 2001 (so relatively shortly before the change in focus).

2.4.5 VRR into Multiple Accounting Amounts: Restart

In 2016, Lev and Gu published a book titled "The end of accounting and the path forward for investors and managers". In part I of their book, the authors document a decline in the combined value relevance from 1950 to 2013 by looking at revenues, cost of goods sold (COGS), selling, general, and administrative (SG&A) expenses,

[17]While no literature review papers about VRR and IFRS adoption are written until so far, a recent paper of García, Alejandro, Sáenz, and Sánchez (2017) provides a relatively extensive overview of the specific contexts in which research has been performed.

[18]There are many studies examining the effect of IFRS adoption on accounting amounts other than earnings or BVE in one way or another, but only a few studies actually incorporate extra amounts in the FO model. Examples: Dahmash, Durand, and Watson (2009) and Ji and Lu (2014) examine Australian firms and include goodwill and other identifiable intangible assets; Oliveira, Rodrigues, and Craig (2010) examine Portuguese firms and include goodwill, R&D, intellectual property, and other identifiable intangible assets; Shah, Liang, and Akbar (2013) examine UK firms and include capitalized R&D and expensed R&D.

earnings, total assets, and total liabilities. In response to this book, Barth et al. (2018) started to work on a paper which actually does take *even more* accounting amounts into account in examining the *trend* in combined value relevance. In contrast to prior research, they do not find a decline in the combined value relevance of accounting information. What is more, Barth et al. (2018) state that if they found something, it is evidence of an increase, mainly related to intangible assets, growth opportunities, and alternative APMs becoming more relevant. Because they found these trends are evident for the full sample, they conclude that new economy firms are *not solely* responsible for the relevance increases.

However, Barth et al. (2018) do in their conclusion not reflect on their definition of 'new economy firms' at all. It could perfectly be possible that their definition is too strict such that many intangible-intensive firms are left out. This could explain the trends are also found for firms labeled as old economy. So, their conclusion suggests a general increase in the intangible intensity of firms as the explanation for their findings, but this stands in stark contrast to the recent paper of Srivastava (2014). Therefore, more comprehensive evidence is needed.

2.5 Hypothesis Development

2.5.1 VRR into Trends

Thus, while some studies show that the increase in the value relevance of BVE actually offsets the decrease in the value relevance of earnings over time, others conclude there is a temporal decline in the combined value relevance of earnings and BVE. Contrary to prior studies, Lev and Gu (2016) also take other components of earnings into account and document a decline in the combined value relevance over their relatively long time period. Barth et al. (2018) take even more accounting amounts into account and do not find a decline in the combined value relevance of accounting information. Moreover, they state that if they found something, it is evidence of an increase related to intangible assets, growth opportunities, and alternative APMs becoming more relevant. Because of the mixed evidence, the first hypothesis is:

H1: *There is no temporal trend in the combined value relevance of accounting amounts.*

Barth et al. (2018) decided to include various accounting amounts in their CART estimation, several of which also relate to the new economy. To test for a trend in the number of value relevant accounting amounts, they order the amounts and add them up until they explain a specific percentage of combined value relevance. The authors' findings suggest that earnings are substituted by various other relevant amounts, of which the majority relates to intangible assets, growth opportunities, and alternative APMs. So, Barth et al. (2018) document an increase in the number of value relevant accounting amounts. The second hypothesis (stated in null form) can thus be formulated as follows:

H2: *There is no temporal trend in the number of value relevant accounting amounts.*

2.5.2 Tobin's Q Ratio

In 1969, Tobin introduced the Q ratio, which is defined as the market value of assets divided by its replacement costs. The idea behind this ratio is that if Q exceeds 1, firms are encouraged to invest since the revenues of investing will be greater than its costs (Tobin, 1969, 1978). As Lindenberg and Ross (1981) explain, it is expected that in the absence of entry and exit barriers, Q tends to 1. However, they also state that the possession of production factors not captured in replacement costs biases Q upward. For this reason, several studies utilize the Q ratio as a measure for the intangibility of a firm (for example, see Cockburn and Griliches (1988), Megna and Klock (1993), and Villalonga (2004)).

For modern economies investments in intangible assets has grown strongly in recent decades, both in absolute terms and relative to tangible assets (Corrado, Haskel, Jona-Lasinio, & Iommi, 2016; ECB, 2018). Based on this data, I expect that the growth in investments in intangible assets will lead to more value generation by firms' intangible assets. In other words, the Q ratio of Tobin (1969, 1978) will move further away from 1 over time. Hence, the third hypothesis (also stated in null form) reads as follows:

H3: *There is no temporal trend in Tobin's Q ratio.*

One explanation for the decline in the value relevance of earnings is the increase in the level of investments in intangible assets. To verify this explanation, Collins et al. (1997), Francis and Schipper (1999), and Core et al. (2003) set out criteria to determine whether a firm is emblematic of the new economy or not. On the basis of these studies, Barth et al. (2018) classify a firm as a new economy firm if it has two out of these three characteristics: belongs to the high-technology industry, has negative earnings, and is listed for a maximum of five years. Their findings suggest the observed relevance trends not to be applicable just to new economy firms. Though, this suggests a general increase in the intangible intensity of firms as the explanation for their results. Therefore, following the same logic as for H3, I expect firms of the various industries of the economy to invest more in intangible assets and thereby to generate more value from intangible assets:

H4: *There is no temporal trend in Tobin's Q ratio when the sample is partitioned by industry.*

2.5.3 VRR into Differences in Trends

However, the conclusion of Barth et al. (2018) is contradictory to Srivastava (2014), who contributes the decline in the value relevance of earnings to an *increase in the listing* of intangible-intensive firms rather than a *general increase* in the intangible intensity of firms. Since Barth et al. (2018) do in their conclusion not reflect on their definition of 'new economy firms', it could perfectly be that their definition is too strict such that many intangible-intensive firms are left out. So, more research is needed to clarify and solve these contradictory statements. To that end, I also re-examine H1 and H2 to see whether the various industries, each with their own intangible intensity (as measured by the Q ratio), are going through the same changes in value relevance. As a result:

H5: *There is no temporal trend in the combined value relevance of accounting amounts when the sample is partitioned by firm type or industry.*

H6: *There is no temporal trend in the number of value relevant accounting amounts when the sample is partitioned by firm type or industry.*

2.6 Accounting Amounts and Trend Predictions

2.6.1 Rationale and General Expectations

As stated in Section 2.3.2 'Implementation of Valuation Models', in VRR the inclusion of the correct accounting amounts is critical for the final outcome. Therefore, it is important in the model implementation process to reason which accounting amounts should be included and which ones should be excluded. Naturally, this reasoning should be based on prior research. To that end, in this section I identify relevant accounting amounts and predict the trend in their value relevance.

Remember from Section 2.4.3 'VRR into Combined Value Relevance', evidence for a positive evolution in the combined value relevance of earnings and BVE is mixed. This thesis, though, utilizes CART estimation, as introduced by Barth et al. (2018) for this field of research. In addition to utilizing this flexible, non-parametric estimation method, I also consider a lot more accounting amounts; several of them are also related to the new economy. Based on this, I expect the combined value relevance to show a positive trend over time. A potential threat to this expectation is that several papers are questioning whether accounting amounts *related* to the new economy are also *relevant* to the new economy (see Section 2.4.1 'Decline in

Earnings Relevance: New Economy'). More specifically, my expectation may not be met because current accounting standards do not disclose the value of intangible assets, do not make an attempt to reflect growth opportunities, and are primarily earnings focused (Barth et al., 2018).

2.6.2 Earnings, BVE, and Dividends

As could be seen in the studies discussed above, earnings and BVE are the two most widely used accounting amounts in VRR. The theoretical support for these amounts is provided by the FO model. Needless to say, the FO model defines MVE as a linear function of BVE and the PV of all expected future abnormal earnings (see Section 2.3.1 'Choice of Valuation Models'). By making additional assumptions regarding earnings' information dynamics, MVE can be expressed as a linear function of BVE, net income, dividends, and other information. Thus, I will particularly include earnings, BVE, and dividends.

With reference to the studies discussed in Section 2.4.3 'VRR into Combined Value Relevance', I expect a negative trend in the value relevance of earnings and a positive trend in the value relevance of BVE. With regards to dividends, research of Floyd, Li, and Skinner (2015) documents that percentage of US industrial firms paying dividends decreased from 60% in 1980 to 15% in 2002, whereafter it slightly increases to 28% in 2012. One could reason that this decline in dividends propensity leads to a decrease in the relevance of dividends to equity investors. However, it could also be that the relevance for firms that actually pay dividends increases. Since the decline in dividends propensity is relatively large, I expect, together with Barth et al. (2018), the former effect to be stronger than the latter.

2.6.3 Intangible Assets

The FO model also allows for other accounting information. As discussed in Section 2.4.1 'Decline in Earnings Relevance: New Economy', several papers argue that because current accounting rules only record intangible assets in limited circumstances, financial accounting information may not be very useful in predicting the market values of companies with a lot of intangible assets. Even so, the (early) evidence for this hypothesis is mixed. Research of Collins et al. (1997) and Francis and Schipper (1999) shows a shift in value relevance from earnings to BVE. However, while the former study shows an increase in the percentage of firms operating in intangible-intensive industries is significant in explaining this shift, the latter documents insignificant results.

Later research on the hypothesis of an intangibility-related decrease in the value relevance of accounting information is more consistent. Lev and Zarowin (1999) document a negative association between the informativeness of earnings and R&D

spending, and attribute this finding to the large, directly expensed investments that are generally related to R&D. Core et al. (2003) include, inter alia, advertising expenditures and R&D expenditures, and find a decline in the combined value relevance over the period from 1975 to 1999 for their full sample and a significant lower combined value relevance in the years 1996-1999, both in their full sample and in separate subsamples of high-technology firms, young firms, and young firms with losses. Additionally, Srivastava (2014) find that the majority of the decrease in earnings relevance is due to firms getting listed after 1970, and that the later a firm got listed after 1970, the larger the difference between its intangible intensity and firms that got listed before 1970. Lastly, although Barth et al. (2018) do not find a decline in the combined value relevance of accounting information, they do find evidence for an increase related to intangible assets.

To capture expected growth in future earnings associated with investments in intangible assets, I include advertising expenses and R&D expenses. Moreover, in line with Barth et al. (2018), I also consider recognized intangible assets, including capitalized software, goodwill, and other purchased intangible assets. Since the US economy is more and more transitioning from a manufacturing economy into a service economy, I expect these three accounting amounts to become more relevant for firm value over time. In this case, a potential threat could be that the expenses are not designed to reflect intangible asset values. For instance, advertising expenses are not designed to reflect a firm's brand value (Barth et al., 2018).

2.6.4 Growth Opportunities

Current accounting rules do not only record intangible assets in limited circumstances, they also do not make an attempt to reflect growth opportunities (see Section 2.6.1 'Rationale and General Expectations'). That having said, growth opportunities are becoming increasingly relevant to investors with the rise of the new economy (Barth et al., 2018). To that end, I consider cash and revenue growth. Utilizing cash is relevant since Opler, Pinkowitz, Stulz, and Williamson (1999) show that firms with strong growth opportunities hold more cash than other firms. Regarding revenue growth, Core et al. (2003) and Barth et al. (2018) utilize revenue growth as a(nother) proxy for expected earnings growth. Finally, similar as to intangible assets (see Section 2.6.3 'Intangible Assets'), I predict a positive trend in their value relevance, although they are not likely to capture the underlying construct completely, since they are not designed for that purpose.

2.6.5 Alternative APMs

As stated in Section 2.6.1 'Rationale and General Expectations', current accounting standards are primarily earnings focused. Further, the studies discussed in Section

2.4.1 'Decline in Earnings Relevance: New Economy' and 2.4.2 'Decline in Earnings Relevance: Bad Economy' provide evidence for a decline in earnings relevance which is (partially) offset by an increase in BVE relevance. To examine this offsetting effect in more detail, I will also include several alternative APMs.

Firstly, I consider OCF because Barth, Beaver, Hand, and Landsman (1999) show that the OCF provides explanatory power for MVE incremental to BVE and abnormal earnings (i.e., the FO model). Secondly, I consider revenues since empirical research of Callen, Robb, and Segal (2008) suggests that market participants tend to value unprofitable firms on the basis of the level and growth in revenues[19], rather than net income or OCF. Lastly, I consider special items and other comprehensive income (OCI) based on a paper of Jones and Smith (2011), who document that both special items and OCI are value relevant.

Regarding the trends in the value relevance of the APMs, I expect them to be positive since it is likely that the earnings relevance decrease is offset by alternative APMs. However, it could be the case that the APMs I utilize are different from the ones investors utilize in firm valuation. Stated differently, where Callen et al. (2008) state that market participants tend to value unprofitable firms on the basis of the level and growth in revenues, rather than net income or OCF, it could perfectly be that for other firm types the APMs are different again.

2.6.6 Other Accounting Amounts

In addition to the accounting amounts discussed above, I also consider, like Barth et al. (2018), CAPX, COGS, SG&A expenses, and total assets.[20] These are included because Lev and Gu (2016) state that six key financial indicators are revenues, COGS, SG&A expenses, earnings, total assets, and total liabilities. Revenues and earnings are already incorporated in the model, and total liabilities is left out since including total assets effectively means including total liabilities also[21]. With regards to CAPX, this accounting amount is included to test whether the new economy's focus is on intangible assets only. In that case, one would expect CAPX to become less relevant since it reflects investments in tangible assets. Concerning the other accounting amounts, I do not have clear predictions for the trend in their value relevance.

[19]Remember, I do already consider revenue growth, as explained in Section 2.6.4 'Growth Opportunities'.

[20]Barth et al. (2018) state that including total assets in CART estimation effectively means including asset-based ratios, such as, for example, the sales-to asset ratio. However, this should not be a problem since research of Ou and Penman (1989) shows these are relevant in explaining stock returns.

[21]Notice, total liabilities is the difference between total assets and total equity. So, given that BVE is already incorporated in the model, including total assets effectively means including total liabilities also.

2.7 Conclusion

In this chapter, I developed a theoretical framework by reviewing the literature on value relevance. VRR examines the ability of financial statement information to capture information that affects firm value. It is of interest to standard setting agencies such as the FASB or the IASB, other regulatory agencies, and financial statements preparers and users. Overall, the results in VRR indicate a decline in the value relevance of earnings. The literature states this can be due to either an increase of investments in intangible assets or an increase in the frequency of losses. Furthermore, it is argued that the same factors contributing to a decline in the value relevance of earnings, are contributing to an increase in the value relevance of BVE. However, the evidence for this hypothesis is mixed. At the beginning of this millennium, two studies started to perform VRR into multiple accounting amounts. Even so, soon thereafter the literature began to focus on IFRS adoption.

Recently, Barth et al. (2018) started to work on a paper which actually examines the *trend* in the value relevance of *various* accounting amounts, several of which also relate to the new economy. They state that if they found evidence for an increase in combined value relevance, it is related to intangible assets, growth opportunities, and alternative APMs becoming more relevant. Because they found these trends are evident for the full sample, they conclude that new economy firms are not solely responsible for the relevance increases. However, this suggests a general increase in the intangible intensity of firms, which stands in stark contrast to Srivastava (2014). Therefore, more comprehensive evidence is needed.

Firstly, by utilizing the same flexible, non-parametric estimation method as Barth et al. (2018), I test for a temporal trend in the combined value relevance of accounting amounts and in the number of value relevant accounting amounts. The latter is performed since Barth et al. (2018) document that earnings are substituted by various other relevant amounts, of which the majority relates to intangible assets, growth opportunities, and alternative APMs. Secondly, several studies utilize the Q ratio as a measure for the intangibility of a firm. Since for modern economies investments in intangible assets has grown strongly in recent decades, I hypothesize that there is no temporal trend in Tobin's Q ratio. To verify the existence of a general increase in the intangible intensity of firms, I also hypothesize that there is no temporal trend in Tobin's Q ratio for the various industries of the economy. Lastly, I re-examine H1 and H2 while partitioning the sample by firm type and industry. This is done to investigate how the value relevance of accounting information evolved as the new economy developed and to check whether the observed changes are economy-wide. The accounting amounts taken into account are: earnings, BVE, dividends, advertising expenses, R&D expenses, recognized intangible assets, cash, revenue growth, OCF, revenues, special items, OCI, CAPX, COGS, SG&A expenses, and total assets.

Chapter 3

Research Design

In this chapter, I develop the research design underlying to the empirical analysis and describe the sample. Firstly, I elaborate on the CART method needed to estimate the relation between the stock price and the accounting amounts (Section 3.1). Secondly, I introduce the tests that will be used to examine the hypotheses derived in Chapter 3 'Hypothesis Development' (Section 3.2). Thirdly, I present the data collection process and describe the sample (Section 3.3). Lastly, I summarize this chapter in Section 3.4.

3.1 Value Relevance Measurement

3.1.1 CART Relation

To test for a trend in the value relevance of accounting information, I utilize CART estimation, as introduced by Barth et al. (2018) for VRR. Thus, I estimate *for each year* the relation between the stock price and various accounting amounts:

$$SP_i = CART(VAR_i, IND10_i), \tag{1}$$

where SP_i is defined as the stock price of firm i measured three months after fiscal year-end; *VAR* is a vector of the following accounting amounts: net income before extraordinary items (NI), book value of equity (BVE), dividends declared to common shareholders (DIV), advertising expenses ($ADVX$), R&D expenses (RDX), recognized intangible assets, including capitalized software, goodwill, and other purchased intangible assets ($INTAN$), cash, including cash equivalents and short-term investments ($CASH$), one-year growth in revenues ($REVGR$), operating cash flow (OCF), revenues (REV), special items (SI), other comprehensive income (OCI), capital expenditures ($CAPX$), cost of goods sold ($COGS$), SG&A expenses ($SGAX$), and total assets (TA); *IND10* is a set of indicator variables based on the industry classification of Fama and French (2019) into ten groups (see Appendix A 'Variable

Definitions'). The stock price is measured three months after fiscal year-end to ensure the respective financial statements are available to the public. Furthermore, in line with prior studies (for example, see Collins et al. (1997), Brown et al. (1999), Lev and Zarowin (1999), Balachandran and Mohanram (2011), Barth et al. (2018)), all accounting amounts are deflated by the number of common shares outstanding.[1]

3.1.2 CART Theory

CART estimation is a method commonly used in machine learning and data mining. It was introduced by Breiman, Friedman, Olshen, and Stone in 1984, and is part of a family of decision tree-based estimation methods. In general, a decision tree is a model that predicts the value of a target variable (represented in the leaves) based on several input variables (represented in the branches). So, it partitions the feature space into regions, and then fit a simple model in each one (Hastie et al., 2017). Further, decision trees in which the target variable is continuous are called *regression trees*, while decision trees in which the target variable is categorical are called *classification trees* (Rokach & Maimon, 2015).[2] Finally, since decision trees are flexible models, they do not require the researcher to specify the functional form of the relation under examination. This is important since unmodeled interactions and nonlinearities in linear estimation methods can lead to an understatement of the explanatory power of accounting amounts, and so their value relevance (Barth et al., 2018; Hastie et al., 2017; Holthausen & Watts, 2001).

CART is characterized by recursive binary partitioning, which means that the feature space is partitioned, based on the best split, into *two* regions, whereafter the splitting process is repeated continuously on the resulting regions (Hastie et al., 2017). Moreover, in regression trees the prediction for each leaf is simply the *average value*. Logically, two important issues in decision tree learning are partitioning determination ('best split') and partitioning termination ('repeated continuously'). In CART regression, partitioning determination is performed by means of minimization of the sum of squared residuals. However, the squared-error splitting criterion is not suitable for classification trees, instead the splits are selected using the Twoing criterion. This measure is an adjustment to the Gini index, which may encounter problems when the set of values the target variable can take is relatively wide (Rokach & Maimon, 2015). By grouping the multi-class target into two 'superclasses', it can be shown that the best split at a node is determined by maximizing

$$\frac{P_L P_R}{4}[\sum_j |p_{j,L} - p_{j,R}|]^2,$$

[1]For a discussion of alternative deflating variables, I refer to Section 2.3.2 'Implementation of Valuation Models'.

[2]Importantly, although the name may suggest otherwise, CART is *only one method* for decision tree estimation. For its characteristics, I refer to the following paragraphs.

where P_L (P_R) is the proportion of the population at the node sent left (right), and $P_{j,L}$ ($P_{j,R}$) is the proportion of class j at the node sent left (right) (Breiman, 1996). Finally, notice that when the target variable is binary, the Gini index and the Twoing criterion lead to equivalent outcomes (Rokach & Maimon, 2015).

Another issue in CART estimation is partitioning termination. An easy strategy would be to stop splitting if the best splitting criterion is not greater than a predetermined threshold. However, this strategy leads to underfitted decision trees, since it does not take into account that a 'useless' split can be followed by a 'useful' split. CART, therefore, only stops the splitting process when the minimum node size is reached, and subsequently prunes the decision tree based on cost-complexity pruning (CCP) to avoid overfitting (Rokach & Maimon, 2015). In CCP, the total cost of tree T ($C_\alpha(T)$) is defined as

$$C_\alpha(T) = R(T) + \alpha\tilde{T},$$

where $R(T)$ is the sum of squared residuals (for regression trees) or the Twoing measure (for classification trees), and $\alpha\tilde{T}$ is a penalty for the complexity of the tree represented by the number of terminal nodes ($\tilde{T}$) (Hastie et al., 2017). Naturally, with $\alpha = 0$ the total cost is minimized for the full tree (T_0). Starting from T_0, CCP calculates for each node the value of α at which the total cost of the tree before and after the (hypothetical) pruning are equal. Then it prunes in all nodes for which α achieves the minimum and repeats this procedure until it reaches the root node. As a result, for each α the subtree that minimizes $C_\alpha(T)$ is identified. Finally, it estimates the generalization error (i.e., the out-of-sample error) for each of the optimal subtrees by applying cross-validation, and then selects the one with the lowest error (Hastie et al., 2017; Rokach & Maimon, 2015).

Another way to improve generalization performance (i.e., reduce overfitting) is to estimate a set of decision trees (i.e., a decision forest) instead of only a single tree (Rokach & Maimon, 2015). To see the rationale behind this, notice that the mean variance of n independent observations, each with variance σ^2, is given by $\frac{\sigma^2}{n}$. Since it is impracticable to take many samples from the population, a commonly used technique is bagging (i.e., bootstrap aggregating).[3] Applied to CART, bagging will grow a specified number of *unpruned*[4] trees, each based on a sample which is randomly drawn from the original sample with replacement (Breiman, 2001; Hastie et al., 2017; Rokach & Maimon, 2015). Since bagging generates samples with replacement, a bootstrapped sample contains, on average, 63.2% (more precisely, $1 - \frac{1}{e}$) of unique observations; the remaining observations are called out-

[3]Notice, since each tree grown by means of bagging is identically distributed, bagging does *not* remove bias, contrary to another machine learning method called 'boosting'. For more information on this ensemble method, I refer to Rokach and Maimon (2015) and Hastie et al. (2017).

[4]Bagging trees do not have to be pruned because overfitting is already dealt with by averaging. Moreover, trees that are sufficiently deep grown have relatively low bias (Hastie et al., 2017).

of-bag (OOB). Consequently, by *averaging* these OOB predictions *per observation*, standard out-of-sample performance measures can be used to evaluate the model (e.g., the out-of-sample R^2 or the mean squared prediction error (MSPE)) (Hastie et al., 2017; Rokach & Maimon, 2015).

Related to CART estimation with bootstrapped samples is the random forest ensemble method. It differs from the former method in that it only allows a *random selection* of input variables to be considered at each split (i.e., feature bagging) (Breiman, 2001; Hastie et al., 2017; Rokach & Maimon, 2015). As default values, for classification trees it is recommended to set the number of input variables considered at each split close to $\sqrt{p}$, and for regression trees close to $\frac{p}{3}$, where p is defined as the total number of input variables. Under feature bagging, each decision tree separately is likely to be less accurate. Nonetheless, the growth of an ensemble of trees (i.e., a forest) can improve generalization performance, especially if there is variation in the importance of the input variables (Hastie et al., 2017; Rokach & Maimon, 2015). In that case, the estimated prediction functions are *not* independent. But, if observations are not independent, the mean variance is calculated differently:

$$\rho\sigma^2 + \frac{1-\rho}{n}\sigma^2,$$

where ρ is the pairwise correlation (assuming it is positive). As n increases, the first term remains, which implies an undermining of the idea of forest estimation. Random forest estimation attempts to solve this issue by growing *decorrelated* trees, with the aim of making the average of the resulting trees more reliable (Breiman, 2001; Hastie et al., 2017; Rokach & Maimon, 2015).

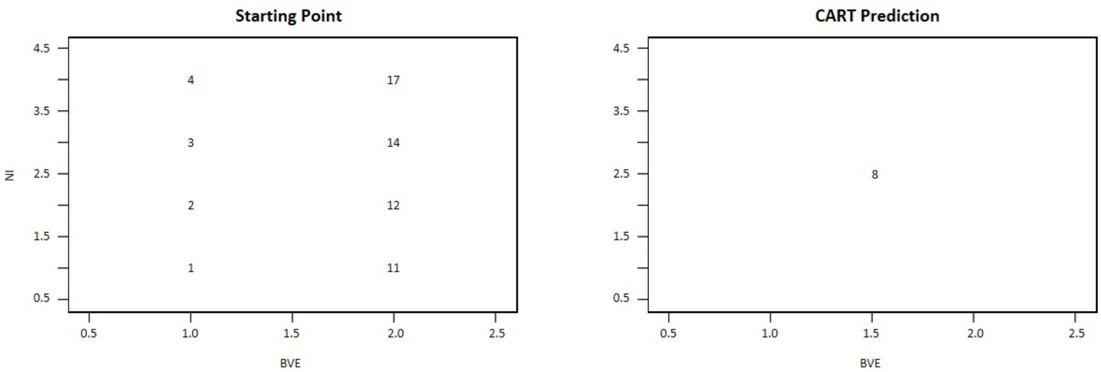
Although tree-based models perform relatively well in case of *feature* correlation, the correlated input variables themselves tend to receive *undeserved* importance (Strobl, Boulesteix, Kneib, Augustin, & Zeileis, 2008). Breiman (2001) measures the importance of an input variable as the (forest) average of the differences in prediction performance before and after randomly permuting the variable in the OOB sample. However, while Breiman (2001) suggests to increase the number of input variables considered at each split to alleviate the problem, Nicodemus, Malley, Strobl, and Ziegler (2010) show that the tendency to overestimate the importance of correlated input variables continues to exist. To remedy this, Strobl et al. (2008) propose to permute the input variable randomly *within partitions*, based on the splitting criteria of the correlated input variables in the fitted tree. By doing so, it measures the association between the specific input variable and the target variable, *given* its *time-dependent* correlation structure with the other input variables.

3.1.3 CART Implementation

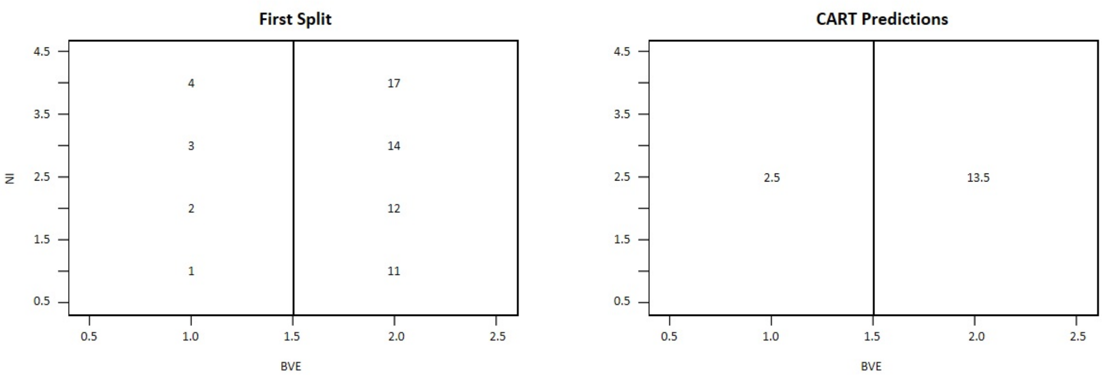
To illustrate CART estimation and how it is able to manifest value relevance more fully, suppose the following dataset:

Observation	NI	BVE	SP
1	1	1	1
2	2	1	2
3	3	1	3
4	4	1	4
5	1	2	11
6	2	2	12
7	3	2	14
8	4	2	17

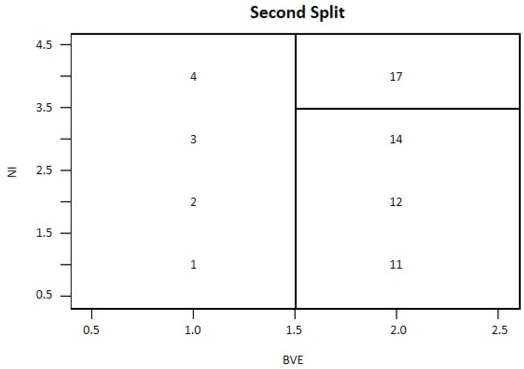
In this dataset there is a positive relation between P and BVE. Moreover, the relation between P and NI is linear when BVE equals 1, while it is nonlinear when BVE equals 2. Naturally, the starting point of CART estimation is one region which contains all observations:

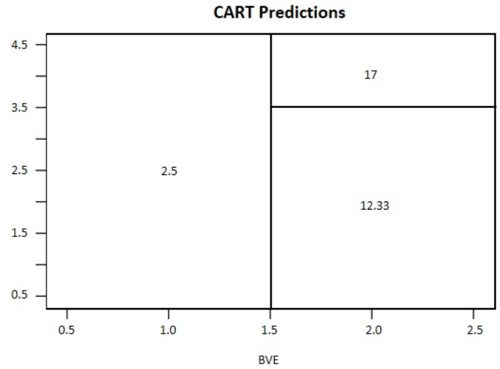


At this point, the sum of squared residuals equals 268. CART then splits the initial region into two sub-regions based on a value of one of the two input variables. For each sub-region, the predicted stock price is the average price of the observations included. The split that leads to the largest reduction in the sum of squared residuals is selected:

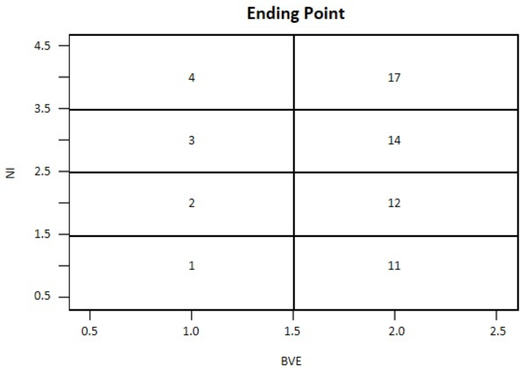


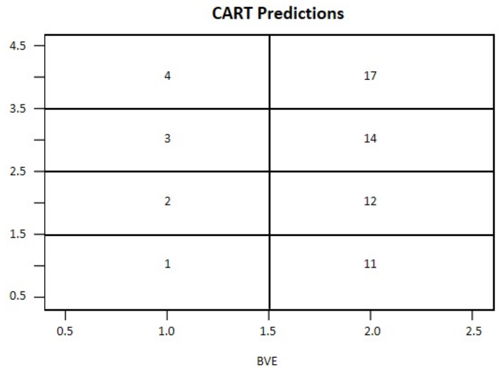
So, CART decided to split the initial region into two sub-regions based on BVE. Consequently, the predicted price for BVE equal to 1 is 2.5, and for BVE equal to 2 is 13.5. Furthermore, the sum of squared residuals is equal to 26. Thus, at this stage the largest reduction in the sum of squared residuals is 242. As could be expected given the dataset, CART next splits on *NI*:



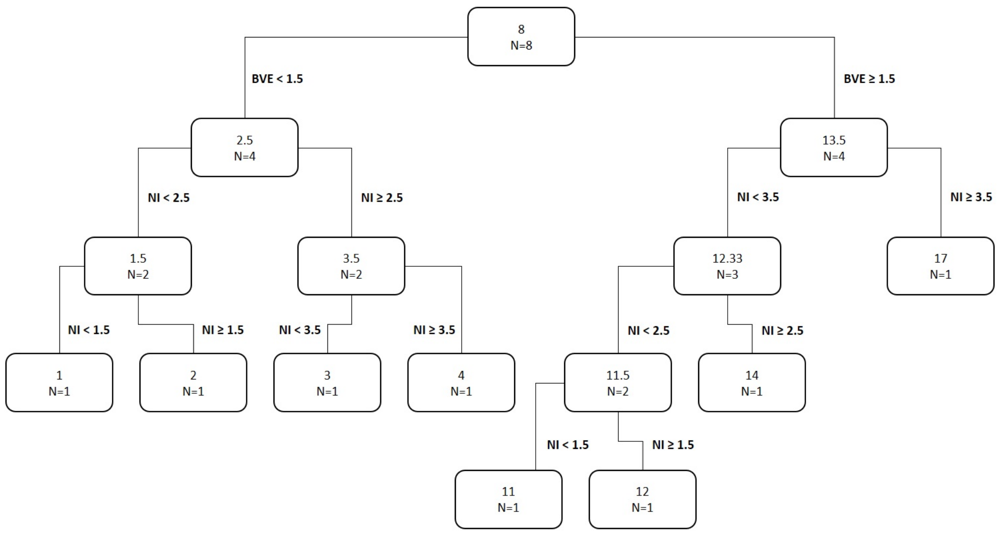


In this case, CART decided to split the sub-region with *BVE* equal to 2. As a result, when *NI* is smaller than 3.5 the predicted stock price is 12.33, otherwise it is equal to 17. Moreover, the total sum of squared residuals amounts 9.67, which means this split has reduced the sum of squared residuals with 16.33. In absence of further specifications, CART repeats the splitting procedure until there is one region for each observation:





Or, presented as a decision tree:



Notice, CART incorporates the *interaction* between BVE and *NI*, because when BVE equals 1 the predicted stock price is linear in *NI*, while it is *nonlinear* when BVE equals 2. Further, although it cannot be derived from the example, input variables can be re-used to identify subsequent splits (Barth et al., 2018). Finally, for a real example of one decision tree, I refer to Appendix C 'CART Example'.

In estimating the CART relation, I follow Hastie et al. (2017) and Barth et al. (2018). Firstly, I set the minimum size of the terminal nodes to five. Secondly, I utilize bootstrapped samples with the same sample size as the original sample, meaning each bootstrapped sample contains, on average, 63.2% of unique observations. Thirdly, I set the number of input variables considered at each split equal to the total number of input variables, because optimization of this hyperparameter should be performed for each year separately. However, this limits inter-year comparison. Moreover, the bias of variable importance measures due to feature correlation will be less (Breiman, 2001; Nicodemus et al., 2010).

Fourthly, as combined value relevance metric, contrary to many VRR studies, I utilize the out-of-sample R^2:

$$OOSRSQ = 1 - \frac{\sum_{n=1}^{N}(SP_n - \widehat{SP}_n)^2}{\sum_{n=1}^{N}(SP_n - \overline{SP})^2},$$

where SP is defined as the stock price, $\overline{SP}$ as the average value of the stock prices, and $\widehat{SP}$ as the average value of the OOB predictions per observation. The in-sample R^2 is susceptible to overstatement when many explanatory variables are included (Barth et al., 2018; Hastie et al., 2017). Fifthly, to measure individual value relevance, I apply both the unconditional and the conditional permutation importance method. Regarding the conditional method, OOB permuting is conditioned on partitions of input variables having an absolute Spearman correlation coefficient greater than 0.2, up to a maximum number of 2^K partitions. To ensure at least two observations per partition, K is set equal to $log_2(N * 0.368 * 0.5) - 1$ (Ellis, Smith, & Pitcher, 2012; Strobl et al., 2010). Lastly, for the pseudocode of the algorithms, I refer to Appendix B 'Pseudocode of Algorithms'.

3.2 Hypothesis Testing

3.2.1 H1 & H2: VRR into Trends

To test for a temporal trend in the combined value relevance of accounting information, I regress the out-of-sample R^2 on time:

$$OOSRSQ_t = \beta_0 + \beta_1 YEAR_t + \epsilon_t, \tag{2}$$

where $OOSRSQ_t$ is the out-of-sample R^2 estimated from equation 1 for year t, and $YEAR$ is the fiscal year, running from 1970 up to and including 2017. This test fails to reject H1 if B_1 does not significantly differ from 0.

In order to examine H2, I first estimate whether the value relevance of various accounting amounts has increased or decreased over time:

$$VR_{kt} = \beta_0 + \beta_1 YEAR_t + \epsilon_t, \tag{3}$$

where VR_k is the value relevance of accounting amount k, defined as the increase in the MSPE of the OOB observations, averaged over all bootstrapped samples, when CART randomly permutes the accounting amount, relative to the sum of increases of all accounting amounts. An accounting amount becomes more (less) relevant over time if B_1 is significantly greater (smaller) than 0. Subsequently, I test for a temporal trend in the number of value relevant accounting amounts:

$$NUMVR_t = \beta_0 + \beta_1 YEAR_t + \epsilon_t, \tag{4}$$

where *NUMVR* is defined as the number of accounting amounts required to explain a specifiable percentage of the combined value relevance of accounting information. Particularly, I order the accounting amounts by *VR* from high to low, and add, according to the order, amounts until the sum of *VR* is equal to or larger than 50%, 75%, 90%, and 95%. In this case, a positive (negative) β_1 implies a more (less) nuanced relation between accounting amounts and the stock price over time.

3.2.2 H3 & H4: Tobin's Q Ratio

To test for an increase in the value generation by firms' intangible assets in recent years, I also regress the Q ratio on time:

$$TOBINQ_t = \beta_0 + \beta_1 YEAR_t + \epsilon_t, \tag{5}$$

where *TOBINQ* is the Q ratio of Tobin (1969, 1978), defined as the ratio between total assets plus number of common shares outstanding multiplied by stock price minus book value of equity and total assets (Kaplan & Zingales, 1997). H3 and/or H4 is rejected if β_1 is significantly different from 0, meaning that the intangibility of firms has not stayed constant throughout time.

3.2.3 H5 & H6: VRR into Differences in Trends

H5 and H6 are examined in the same way as H1 and H2, respectively, except for the sample. In contrast to Barth et al. (2018), this will not only be divided into new economy firms, profitable old economy firms, and unprofitable old economy firms, but also into industries based on the industry classification of Fama and French (2019) into five groups. In view of the possibility of an increase in the presence of unprofitable firms to be responsible for the changes in value relevance, I also investigate the development of the population over time.

3.3 Data Description

3.3.1 Sample Description

The full sample, comprising 143,419 firm-year observations from 1970 up to and including 2017[5], is obtained from the Compustat and CRSP databases. I begin this sample in 1970 in order to obtain a sufficient sample size for each year-group, and because of the fact the disproportionate growth of the service sector becomes apparent in the 1970s (Barth et al., 2018; Buera & Kaboski, 2012). I end this sample in 2017 to ensure all financial information is available. Naturally, during the sample period economic conditions changed extensively and continuously (e.g., the dot-com bubble and the financial crisis of 2007-2008), which impacts the value relevance of accounting information (see Section 1.1 'Social Relevance').[6]

To facilitate comparison with Barth et al. (2018), I restrict the sample to include non-financial firms listed on AMEX, NYSE, or NASDAQ. Furthermore, I require each observation to have non-missing *SP*, *NI*, *BVE*, *REV*, *TA*, and number of common shares outstanding. If *OCF* is not available, it is calculated as net income before extraordinary items minus accruals, where accruals are defined as change in current assets minus change in cash minus change in current liabilities plus change in short-term debt plus change in income taxes payable (Barth et al., 2018; Sloan, 1996). The remaining accounting amounts are set to zero. To reduce the effect of possibly spurious outliers, all non-indicator variables are winsorized at the top and bottom 1 percent of their distributions.

Regarding the operationalization of *NEWECO*, high-technology firms are those in three-digit industries with SIC code 283, 357, 360-368, 481, 737, and 873 (Barth et al., 2018; Core et al., 2003; Francis and Schipper, 2003). Broadly, these include pharmaceuticals, electronic equipment, computer hardware and software, and telecommunications. Furthermore, in line with Srivastava (2014), the listing year is defined as the first year in which a firm's data is available. Thus, a firm-year observation satisfies the condition of being listed for a maximum of five years until four years after the year in which firm's data is available for the first time.

3.3.2 Descriptive Statistics

Table 1 presents the distributional statistics for the accounting amounts, the stock price, and the Q ratio. Panel A shows the mean of *SP* is 21.553, while its standard deviation equals 21.329. Furthermore, the means (standard deviations) of *NI* and

[5]Notice, a firm-year observation corresponds to calendar year X if firm's fiscal year ends between June of year X and May of year $X + 1$.

[6]The sample partitioned by firm type begins in 1980 to ensure a sufficient sample size for new economy firms also. Otherwise, the regression trees cannot be grown sufficiently deep, which disables variable importance calculations.

TABLE 1: Distributional Statistics

	SP	NI	BVE	DIV	ADVX	RDX	INTAN	CASH	REVGR	OCF	REV	SI	OCI	CAPX	COGS	SGAX	TA	TOBINQ
Panel A: Composition of full sample (1970-2017)																		
N	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419	143,419
Mean	21.553	0.983	10.726	0.369	0.254	0.397	2.549	2.366	2.376	1.726	29.588	-0.166	-0.160	1.793	21.406	4.662	26.793	1.969
Std. dev.	21.329	1.986	10.660	0.644	0.703	0.755	5.778	3.180	6.437	2.804	39.070	0.656	0.986	2.696	31.983	6.131	29.305	1.690
Min.	0.437	-5.609	-3.552	0.000	0.000	0.000	0.000	0.000	-16.750	-4.559	0.034	-4.221	-5.359	0.000	0.043	0.000	0.305	0.603
Max.	117.220	8.316	56.010	3.182	4.359	4.268	34.647	18.925	34.880	13.836	232.104	1.266	3.698	15.430	193.854	34.654	156.036	11.312
Panel B: Composition of subsamples by firm type (1980-2017)																		
New economy																		
N	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985	27,985
Mean	12.560	-0.580	4.100	0.056	0.094	0.561	1.417	2.012	0.630	0.180	7.789	-0.278	0.016	0.635	5.184	2.148	9.909	2.914
Std. dev.	16.181	1.438	5.699	0.300	0.350	0.773	4.278	2.606	3.245	1.675	16.259	0.773	0.761	1.554	12.788	3.274	16.593	2.596
Old economy: Profit																		
N	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926	83,926
Mean	26.620	1.649	12.268	0.456	0.286	0.373	3.302	2.560	2.753	2.491	33.349	-0.075	-0.216	1.996	23.870	5.085	30.387	1.868
Std. dev.	22.883	1.635	10.696	0.706	0.755	0.767	6.576	3.414	6.498	2.923	40.080	0.444	1.050	2.739	33.085	6.387	30.165	1.297
Old economy: Loss																		
N	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796	12,796
Mean	10.717	-1.316	6.971	0.140	0.213	0.243	2.536	1.829	-0.622	0.845	24.054	-0.729	-0.128	1.396	18.704	3.927	24.285	1.581
Std. dev.	13.589	1.593	8.882	0.396	0.639	0.598	5.745	2.989	6.058	2.510	35.086	1.281	1.167	2.500	29.614	5.465	29.457	1.481
Panel C: Composition of subsamples by industry (1970-2017)																		
Industry 1: Consumer goods and services																		
N	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872	30,872
Mean	22.023	1.271	11.744	0.390	0.629	0.165	2.853	2.139	3.931	1.787	49.723	-0.158	-0.210	1.660	37.082	8.446	28.608	1.687
Std. dev.	20.497	1.845	10.342	0.604	1.057	0.550	5.954	2.993	8.338	2.800	52.495	0.630	1.022	2.109	43.633	8.314	27.278	1.253
Industry 2: Manufacturing, energy, and utilities																		
N	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903	40,903
Mean	24.281	1.529	14.588	0.643	0.165	0.368	2.193	2.196	2.527	2.482	35.497	-0.165	-0.223	2.783	26.251	4.242	38.116	1.495
Std. dev.	21.045	2.149	11.702	0.775	0.609	0.727	5.157	3.068	7.140	3.094	37.030	0.694	1.106	3.183	30.490	5.435	32.584	0.998
Industry 3: Business equipment, telephone and television transmission																		
N	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534	34,534
Mean	19.712	0.475	7.495	0.166	0.132	0.694	2.703	2.594	1.322	1.168	13.997	-0.175	-0.106	1.010	8.368	3.504	16.566	2.367
Std. dev.	21.581	1.744	8.537	0.464	0.413	0.874	6.226	3.138	3.722	2.289	19.827	0.638	0.844	1.929	14.114	4.283	21.712	2.011
Industry 4: Healthcare, medical equipment, and drugs																		
N	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500	16,500
Mean	18.461	0.182	5.844	0.137	0.114	0.718	2.229	2.220	1.054	0.606	10.028	-0.169	-0.056	0.591	6.063	2.764	12.047	3.134
Std. dev.	22.007	1.691	7.623	0.416	0.459	0.932	5.607	2.840	3.031	2.045	16.869	0.612	0.779	1.219	12.377	4.241	17.670	2.483
Industry 5: Other (mines, construction, building materials, transport, business services, hotels, and entertainment)																		
N	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610	20,610
Mean	20.997	0.963	10.855	0.318	0.188	0.045	2.797	2.779	2.575	1.967	29.482	-0.163	-0.136	2.299	22.437	3.289	30.544	1.730
Std. dev.	21.462	2.035	11.069	0.616	0.557	0.230	5.982	3.860	6.750	3.020	38.689	0.677	1.031	3.459	32.804	5.047	33.044	1.365

Notes: This table presents distributional statistics for the 143,419 firm-year observations for 10,694 firms from 1970 up to and including 2017. Panel A presents the statistics for the full sample, Panel B presents the statistics for the sample partitioned by firm type, and Panel C presents the statistics for the sample partitioned by industry. For variable definitions, I refer to Appendix A 'Variable Definitions'. All variables are winsorized at the top and bottom 1 percent of their distributions.

TABLE 2: Correlational Statistics

	SP	NI	BVE	DIV	ADVX	RDX	INTAN	CASH	REVGR	OCF	REV	SI	OCI	CAPX	COGS	SGAX	TA	TOBINQ
SP		0.670	0.666	0.508	0.062	0.090	0.253	0.426	0.352	0.599	0.518	-0.007	-0.108	0.526	0.442	0.324	0.626	0.315
NI	0.582		0.667	0.593	0.062	-0.059	0.124	0.275	0.449	0.611	0.614	0.236	-0.161	0.538	0.543	0.310	0.611	-0.025
BVE	0.589	0.625		0.591	0.034	-0.022	0.193	0.402	0.330	0.564	0.729	0.044	-0.123	0.671	0.683	0.398	0.853	-0.375
DIV	0.463	0.533	0.574		0.021	-0.073	0.063	0.170	0.188	0.471	0.531	0.073	-0.127	0.505	0.497	0.204	0.587	-0.154
ADVX	0.179	0.173	0.205	0.141		0.056	0.101	0.093	0.075	0.025	0.126	-0.024	-0.005	0.022	0.076	0.329	0.037	0.019
RDX	0.275	0.082	0.194	0.088	0.073		0.052	0.242	-0.055	-0.098	-0.108	-0.094	0.018	-0.145	-0.148	0.216	-0.110	0.188
INTAN	0.369	0.171	0.293	0.121	0.110	0.091		0.123	0.090	0.259	0.235	-0.221	-0.032	0.082	0.197	0.269	0.278	0.003
CASH	0.432	0.293	0.445	0.189	0.141	0.298	0.178		0.118	0.286	0.273	-0.039	-0.032	0.201	0.230	0.269	0.356	0.000
REVGR	0.218	0.364	0.290	0.133	0.137	0.037	0.105	0.130		0.176	0.432	0.101	-0.014	0.348	0.404	0.268	0.340	-0.002
OCF	0.574	0.566	0.559	0.462	0.143	0.095	0.343	0.375	0.126		0.519	-0.031	-0.149	0.530	0.452	0.219	0.608	-0.046
REV	0.365	0.460	0.634	0.380	0.298	0.124	0.222	0.337	0.490	0.421		0.009	-0.162	0.672	0.974	0.629	0.841	-0.379
SI	-0.042	0.341	-0.032	-0.010	-0.035	-0.109	-0.192	-0.064	0.059	-0.058	-0.079		0.000	0.050	0.022	-0.060	-0.021	-0.015
OCI	-0.109	-0.153	-0.086	-0.061	-0.053	-0.050	-0.064	-0.059	0.018	-0.158	-0.122	0.028		-0.143	-0.148	-0.075	-0.167	0.056
CAPX	0.359	0.416	0.601	0.447	0.131	0.058	0.076	0.226	0.262	0.492	0.478	-0.027	-0.094		0.638	0.292	0.766	-0.285
COGS	0.299	0.397	0.582	0.339	0.231	0.083	0.183	0.307	0.481	0.367	0.984	-0.073	-0.104	0.442		0.532	0.798	-0.416
SGAX	0.324	0.316	0.450	0.218	0.512	0.269	0.228	0.268	0.301	0.264	0.686	-0.087	-0.107	0.246	0.581		0.417	-0.151
TA	0.519	0.514	0.819	0.565	0.208	0.152	0.391	0.443	0.319	0.600	0.711	-0.122	-0.137	0.694	0.668	0.439		-0.414
TOBINQ	0.207	-0.088	-0.288	-0.129	-0.063	0.055	-0.094	-0.047	-0.071	-0.116	-0.251	0.060	0.027	-0.215	-0.245	-0.170	-0.296	

Notes: This table presents correlational statistics, with Pearson (Spearman) correlations above (below) the diagonal. For variable definitions, I refer to Appendix A 'Variable Definitions'. All variables are winsorized at the top and bottom 1 percent of their distributions.

BVE are 0.983 (1.986) and 10.726 (10.660), respectively. In comparison to the sample of Barth et al. (2018), the means of all three variables are higher. Concerning the other accounting amounts, *DIV* is considerably smaller than in Barth et al. (2018) and *INTAN* and *CASH* are considerably greater. Finally, the average value of the Q ratio is 1.969 and its standard deviation is 1.690.

Table 1, Panel B presents distributional statistics for the sample partitioned by firm type. It shows the mean of *SP* is relatively higher for profitable firms emblematic of the old economy (26.620 versus 12.560 and 10.717). The same applies to the mean of *BVE*: 12.268 versus 4.100 and 6.971. Interestingly, from the three proxies for intangible assets (see Section 2.6.3 'Intangible Assets'), only for *RDX* the mean is higher for new economy firms. This seems to be due to the fact new economy firms are smaller: mean *REV* and *TA* for new economy firms equal 7.789 and 9.909, while for both old economy firm types the means are higher than 20. Nevertheless, the average value of *TOBINQ* is greater for new economy firms, suggesting they generate more value from intangible assets.

Table 1, Panel C presents distributional statistics for the sample partitioned by industry. It reveals the means of *SP*, *NI*, *BVE*, and *DIV* are the highest for the manufacturing, energy, and utilities industry and the lowest for the healthcare, medical equipment, and drugs industry. Regarding the three intangible asset proxies, the mean of *ADVX* is much higher for the consumer goods and services industry, while the mean of *RDX* is much higher for the business equipment, telephone and television transmission industry and the healthcare, medical equipment, and drugs industry. Further, the means of *REVGR*, *REV*, *SI*, *COGS*, and *SGAX* are the highest for the consumer goods and services industry, while the means of *CAPX* and *TA* are the highest for the manufacturing, energy, and utilities industry and the other industry, containing, inter alia, mines, construction, and building materials. Finally, mean *TOBINQ* is the lowest for the (conservative) manufacturing, energy, and utilities industry and the highest for the (progressive) healthcare, medical equipment, and drugs industry. Remarkably, while the majority of the SIC codes considered to be high-technology firms (see Section 3.3.1 'Sample Description') are included in the business equipment, telephone and television transmission industry, its mean *TOBINQ* is somewhat lower.

Table 2 presents correlational statistics for the accounting amounts, the stock price, and the Q ratio. Notice, CART is a non-parametric estimation method, meaning it does not require the population to fulfill certain assumptions. Thus, although the absence of skewness in variable distributions is required for Pearson's correlation coefficient, it is not required for CART estimation. Logically, the most relevant correlations in the table are those with *SP*. Like the sample of Barth et al. (2018), *BVE*'s and *NI*'s correlation with *SP* are the greatest, closely followed by *OCF*'s and *TA*'s correlation. However, when comparing the samples by looking at

Spearman's correlation coefficient, the correlations of *DIV* and *REV* are stronger, while the correlations of the three intangible assets proxies are weaker. Regarding Pearson's correlation coefficient, the correlations of the tree intangible assets proxies are stronger, but the correlations of *CASH*, *REVGR*, *CAPX*, and *COGS* are weaker. Lastly, *TOBINQ* is positively related to both *SP* and *RDX*.

3.4 Conclusion

In this chapter, I developed the research design underlying to the empirical analysis and described the sample. To test for a trend in the value relevance of accounting information, I estimate by means of CART for each year the relation between the stock price and various accounting amounts. In general, decision trees predict the value of a target variable (represented in the leaves) based on several input variables (represented in the branches). The advantage of decision trees is that they do not require the researcher to specify the functional form of the relation under examination. CART is characterized by only allowing binary splits and making regression tree predictions based on the average value.

In CART estimation, partitioning determination is performed by minimizing the sum of squared residuals or maximizing the Twoing criterion. Moreover, CART only stops the splitting process when the minimum node size is reached. Subsequently, it prunes the decision tree based on CCP to avoid overfitting. Another way to reduce overfitting is bagging. Since bagging generates samples with replacement, it is possible to utilize standard out-of-sample performance measures. Regarding the implementation of CART, the minimum size of terminal nodes is set to five observations, and the bootstrapped samples are of the same size as the original sample. Moreover, I do not apply feature bagging since hyperparameter optimization limits inter-year comparison, and variable importance measures will be less biased. Finally, to measure value relevance, I utilize the out-of-sample R^2 and the unconditional and conditional permutation importance methods.

Concerning hypothesis testing, I first regress the out-of-sample R^2 on time. Secondly, I examine the value relevance of the separate accounting amounts by looking at the average increase in the MSPE of the OOB observations after the random permutation of an input variable. Thirdly, I regress the Q ratio on time, both for the full sample and for the sample partitioned by industry. Fourthly, I re-run the test procedure of H1 and H2 while partitioning the sample based on firm type and industry. The full sample only includes non-financial firms listed on AMEX, NYSE, and NASDAQ, and comprises 143,419 firm-year observations from 1970 up to and including 2017.

Chapter 4

Empirical Results

In this chapter, I document the outcomes of the empirical analysis. Firstly, I present the outcomes of the empirical analysis for the full sample (Section 4.1). Secondly, I repeat the analysis for the sample divided into new economy firms, profitable old economy firms, and unprofitable old economy firms (Section 4.2). Thirdly, I perform the analysis for the sample partitioned by industry (Section 4.3). Fourthly, to control for the time-dependent correlation structure of the accounting amounts, I recalculate the individual value relevance outcomes based on conditional permutation (Section 4.4). Lastly, I summarize this chapter in Section 4.5.

4.1 Analysis of Full Sample

4.1.1 Combined Value Relevance

Table 3, Panel A presents the combined value relevance of accounting information for the full sample. It reveals that the mean *OOSRSQ* for the period 1970-2017 equals 68.124%. This number is quite similar to Barth et al. (2018), who document a mean of 69.3% over their period running from 1962 to 2014. More importantly, *OOSRSQ* shows an increasing trend of 0.150 percentage points per year, significant at a 10% level. Barth et al. (2018) document for their sample period a slightly higher trend coefficient: 0.218, significant at a 1% level. This seems to be due to their inclusion of the 1960s (mean *OOSRSQ* in 1960s equals 57.6%).

The fact *OOSRSQ* does not show a highly significant trend implies the combined value relevance fluctuates across decades. In particular, in the 1970s its mean amounts 63.522%, which increases to an average of 73.179% in the 1980s. Then, it decreases to a minimum of 41.990% in 1999, leading to a decade average of 63.334%. A clear explanation for this phenomenon is the dot-com bubble, characterized by an increase in the percentage of unprofessional security traders and leading to increased noise in stock prices (Barth et al., 2018; Core et al., 2003). At the beginning of this millennium, *OOSRSQ* reverts to its ‘old level’, leading to a mean of 68.196% for the

TABLE 3: Value Relevance of Accounting Amounts: Full Sample

	All	1970s	1980s	1990s	2000s	2010s	Trend
Panel A: Combined value relevance							
OOSRSQ	68.124	63.522	73.179	63.334	68.196	73.454	0.150*
Panel B: Individual value relevance							
NI	46.100	57.255	53.993	41.742	41.086	34.009	-0.615***
BVE	12.695	5.339	15.074	12.383	20.892	9.057	0.158*
RDX	2.917	3.270	2.401	2.760	2.422	3.938	0.009
INTAN	0.948	0.084	0.721	1.001	1.188	1.943	0.042***
ADVX	0.516	0.319	1.304	0.437	0.239	0.223	-0.012**
CASH	2.677	0.998	1.225	4.206	1.952	5.585	0.101***
REVGR	2.632	0.806	1.090	5.598	2.162	3.722	0.082***
OCF	6.244	0.435	0.793	3.892	6.948	22.379	0.476***
REV	3.342	2.901	3.323	3.850	3.873	2.622	0.007
SI	1.014	0.048	0.388	2.401	1.541	0.614	0.025**
OCI	0.451	0.498	0.454	0.450	0.336	0.533	0.000
DIV	3.487	5.331	5.025	3.323	1.840	1.525	-0.108***
CAPX	2.150	1.856	2.289	2.460	2.352	1.704	0.000
COGS	5.468	9.620	4.023	5.466	4.060	3.848	-0.110***
SGAX	1.697	0.982	2.497	1.397	1.216	2.569	0.017
TA	6.933	9.671	4.387	7.652	7.264	5.380	-0.066*
IND10	0.727	0.588	1.015	0.981	0.627	0.348	-0.008
Intans	4.381	3.673	4.425	4.199	3.849	6.104	0.040*
Growth	5.309	1.804	2.315	9.804	4.115	9.307	0.183***
AltPerf	11.052	3.882	4.958	10.592	12.699	26.148	0.507***
NUMVR - 50%	1.750	1.300	1.300	2.100	2.000	2.125	0.025***
NUMVR - 75%	4.104	3.100	3.300	5.200	4.100	5.000	0.048***
NUMVR - 90%	8.021	6.100	7.600	9.400	8.200	9.000	0.064***
NUMVR - 95%	10.292	8.000	10.100	11.700	10.600	11.250	0.072***
Panel C: Other							
TOBINQ	1.967	1.272	1.669	2.241	2.061	2.253	0.023***

Notes: This table presents results for the value relevance of accounting information over the period 1970-2017 for the full sample. Panel A presents the means of and trends in combined value relevance (*OOSRSQ*), Panel B presents the means of and trends in individual value relevance (VR_k; based on **unconditional permutation**) and the number of accounting amounts required to explain a specific percentage of combined value relevance (*NUMVR*; idem), and Panel C presents the means of and and trends in Tobin's Q ratio (*TOBINQ*). *Intans* refers to the sum of value relevance of *RDX*, *INTAN*, and *ADVX*, *Growth* refers to the sum of value relevance of *CASH* and *REVGR*, and *AltPerf* refers to the sum of value relevance of *OCF*, *REV*, *SI*, and *OCI*. *, **, and *** indicate two-tailed significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

2000s and of 73.454% for the 2010s. Finally, since the positive temporal trend in combined value relevance is not significant at a 5% level, H1 cannot be rejected. Nevertheless, the result is inconsistent to a decline in the combined value relevance of accounting information, as suggested by prior literature.

4.1.2 Individual Value Relevance

Figure 1 shows the evolution in the value relevance of each accounting amount (VR_k). Firstly, the figure reveals a decline in the value relevance of *NI*, which is partially offset by *BVE*. Secondly, the figure reveals an increase in the number of value relevant accounting amounts, especially of those related to intangible assets, growth opportunities, and alternative APMs (compare the left y-axis with the right y-axis). Thirdly, the figure reveals a sharp decrease in the value relevance of *NI* and *BVE* in the late 1990s and the early 2000s. This decrease is almost fully offset by both growth opportunities proxies. As with *OOSRSQ*, this finding can be explained by the dot-com bubble (see Section 4.1.1 'Combined Value Relevance'). Furthermore, also in this case the decrease is only of a temporary nature, and so is the offsetting effect. Finally, although the similarities with the figure of Barth et al. (2018) are many, *IND10* is more relevant in their study. Comparison of the figures also shows the negative growth of *BVE*, which started a few years before their sample end, continued in the last years of this updated sample, such that *BVE* reaches sample start relevance.

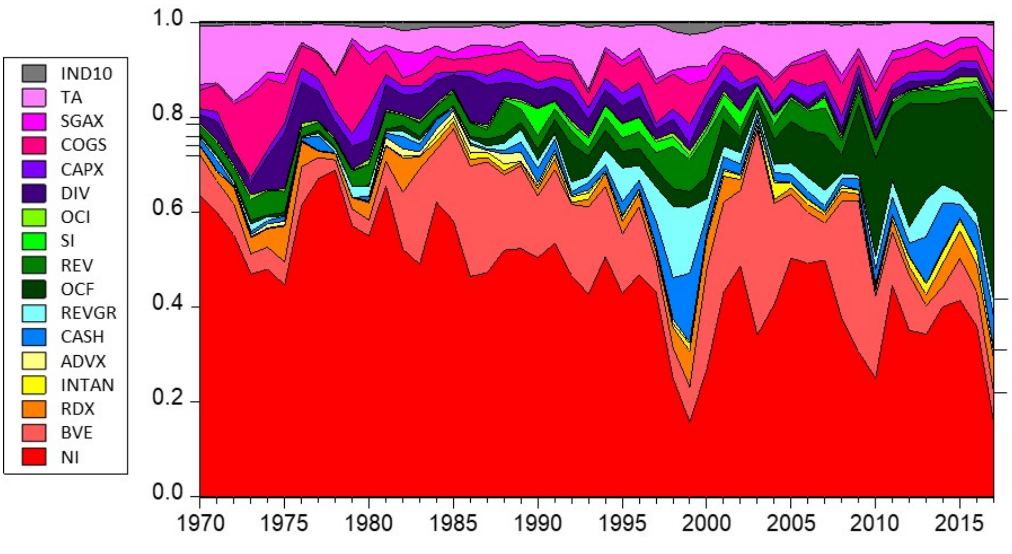


FIGURE 1: Individual Value Relevance for Full Sample

Notes: This figure presents the value relevance of each accounting amount (VR_k; based on **unconditional permutation**) over the period 1970-2017 for the full sample.

Table 3, Panel B presents the statistics underlying to Figure 1. It reveals the most relevant accounting amount is *NI*. Starting with a mean of 57.255% in the 1970s, it ends with a mean of 34.009% in the 2010s. Consequently, it shows a decreasing trend in value relevance of 0.615 percentage points per year, significant at a 1% level. The second most relevant accounting amount is *BVE*, with a mean *VR* of 12.695% across all sample years. Although its value relevance increases considerably from the 1970s to the 2000s (from 5.339% to 20.892%), it decreases afterwards (in the 2010s a mean of 9.057%). This leads to an increasing trend of 0.158 percentage points per year, which is only weakly significant. Further, *OCF* is the accounting amount showing the largest increase in value relevance over time. From a mean *VR* of 0.435% in the 1970s, it increases to a mean of 22.379% in the 2010s, thereby replacing *BVE* as the second most relevant accounting amount at sample end. Its trend coefficient equals 0.476 percentage points per year, being significant at a 1% level.

Regarding other accounting amounts, at a 5% significance level, *INTAN*, *CASH*, *REVGR*, and *SI* all show a significant temporal increase in value relevance. Similarly, *ADVX*, *DIV*, and *COGS* show a decrease, of which the first is contrary to expectation (see Section 2.6.3 'Intangible Assets'). Consistent with these individual relevance trends, grouping the accounting amounts related to intangible assets (*Intans*), growth opportunities (*Growth*), and alternative APMs (*AltPerf*) leads to highly positive and significant trend coefficients for *Growth* and *AltPerf* (0.183 and 0.507, both significant at a 1% level), but a weakly positive and significant trend coefficient for *Intans* (0.040, significant at a 10% level). The latter result stands in contrast to Barth et al. (2018), who also find for this group a positive coefficient at a 1% significance level.

Table 3, Panel B also presents the means of and trends in the number of (decreasingly ordered) accounting amounts required to explain a specific threshold percentage of combined value relevance (*NUMVR*). In the 1970s, explaining 75% of combined value relevance requires, on average, the 3.100 most relevant accounting amounts, while in the 2010s it requires the 5.000 most relevant accounting amounts. Similarly, explaining 95% of combined value relevance requires, on average, the 8.000 most relevant accounting amounts in the 1970s, while it requires the 11.250 most relevant accounting amounts in the 2010s. In line with Barth et al. (2018), for all four threshold percentages, the temporal trends in *NUMVR* are positive and significant at a 1% level. Based on these highly significant trends, H2 can be rejected.

4.1.3 Tobin's Q Ratio

Table 3, Panel C presents the means of and trends in Tobin's Q ratio. Considering the entire sample period, firms, on average, have a Q ratio of 1.967. This implies they significantly generate value from intangible assets. In the 1970s, mean *TOBINQ* amounts 1.272, which increases to 2.241 in the 1990s. Thereafter, it slightly decreases to 2.061 in the 2000s, and then reverts in the 2010s (2.253). Consistently, the trend coefficient equals 0.023, which is significant at a 1% level. Thus, H3 can be rejected.

4.2 Analysis of Subsamples by Firm Type

4.2.1 Combined Value Relevance

Table 4, Panel A presents the combined value relevance of accounting information for the sample partitioned by firm type. Notice, to ensure a sufficient sample size for each firm type, the sample starts in 1980. Across all sample years, mean *OOSRSQ* is the highest for profitable old economy firms: 67.298%, compared to 50.076% (new economy firms) and 50.404% (unprofitable old economy firms). Further, in the 1980s mean *OOSRSQ* for new economy firms amounts 58.620%, while it amounts 50.803% in the 2010s. Similar numbers are found for unprofitable old economy firms: 59.741% in the 1980s and 50.643% in the 2010s. However, both do not show a negative trend at a 5% significance level. Profitable old economy firms have a mean *OOSRSQ* of 70.903% in the 1980s and of 70.925% in the 2010s. Moreover, its trend coefficient equals -0.014, which is not even significant at 10% level. Since no significant trend can be detected, H5 cannot be rejected for the firm type part.

4.2.2 Individual Value Relevance

Figure 2 shows the evolution in the value relevance of each accounting amount (VR_k) for the following three firm groups: new economy firms (Figure 2A), profitable old economy firms (Figure 2B), and unprofitable old economy firms (Figure 2C). Concerning new economy firms, it shows a steep decline in the value relevance of *NI* and large increases in the value relevance of accounting amounts related to growth opportunities and alternative APMs. Comparing Figure 2A with Barth et al. (2018) leads to the conclusion there are many similarities. However, *IND10* is still much less relevant, and the steep relevance increase they observe for *Intans* in the last years of their sample, does not apply to and continue in this updated sample.

Regarding profitable old economy firms, the figure reveals *NI*'s relevance declines over time. However, as expected, this trend is less pronounced than for new economy firms. Furthermore, the relevance of accounting amounts related to growth opportunities and alternative APMs increases also, but is stronger for this firm type for the latter. With regards to unprofitable old economy firms, over the years the value relevance of *NI* is almost zero. In this case, the most relevant accounting amount is *BVE*. Throughout the sample period, *BVE* becomes less dominant, primarily explained by an increase in the number of value relevant accounting amounts, of which the majority relates to intangible assets, growth opportunities, and alternative APMs. So, only for this firm type an increase in the value relevance of *Intans* can be observed. Despite this, *IND10* is also relatively irrelevant for old economy firms. Finally, Figure 2 shows the offsetting effect of *CASH* and *REVGR* during the dot-com bubble most strongly applies to new economy firms.

TABLE 4: Value Relevance of Accounting Amounts: Subsamples by Firm Type

	New economy				*Old economy: Profit*				*Old economy: Loss*			
	All	**1980s**	**2010s**	**Trend**	**All**	**1980s**	**2010s**	**Trend**	**All**	**1980s**	**2010s**	**Trend**
Panel A: Combined value relevance												
OOSRSQ	50.076	58.620	50.803	-0.120	67.298	70.903	70.925	-0.014	50.404	59.741	50.643	-0.349*
Panel B: Individual value relevance												
NI	21.633	39.533	3.689	-1.186***	49.053	55.695	41.384	-0.475***	0.568	0.219	0.404	0.009
BVE	13.600	18.560	6.194	-0.262	12.339	12.720	9.940	-0.035	39.899	55.378	23.513	-0.795***
RDX	3.459	4.406	4.391	-0.022	3.497	2.741	4.244	0.039	3.519	1.504	6.177	0.159**
INTAN	1.364	0.610	2.029	0.040*	1.380	0.910	2.202	0.044***	2.003	0.766	3.362	0.068*
ADVX	0.212	0.293	0.099	-0.008	0.722	1.525	0.354	-0.039***	0.266	0.403	0.282	-0.002
CASH	13.104	6.146	25.787	0.518***	1.721	0.930	2.383	0.050**	5.033	1.678	9.174	0.262***
REVGR	9.366	3.361	12.982	0.236**	1.713	0.823	2.409	0.044***	1.654	0.808	2.353	0.049*
OCF	6.214	0.873	9.052	0.352***	6.882	0.846	19.285	0.571***	6.191	1.077	13.666	0.417***
REV	5.005	4.229	4.730	0.015	2.815	2.857	2.082	-0.014	2.022	1.050	2.082	0.058**
SI	0.683	0.185	0.584	0.021*	1.370	0.192	1.001	0.022	1.313	0.755	1.765	0.022
OCI	0.819	0.882	0.548	-0.008	0.412	0.428	0.625	0.004	0.557	0.488	0.149	-0.012
DIV	0.978	2.413	0.122	-0.064**	3.322	5.387	1.740	-0.133***	8.298	13.171	2.892	-0.413***
CAPX	3.265	5.520	2.317	-0.090	2.216	1.876	1.558	-0.003	7.723	10.952	5.500	-0.214
COGS	7.885	5.310	13.170	0.177*	3.639	3.687	2.377	-0.044	2.279	1.408	2.742	0.050*
SGAX	2.074	1.073	4.193	0.087***	2.375	3.583	2.793	-0.025	1.264	0.843	3.246	0.078**
TA	9.768	6.065	9.647	0.198**	5.506	4.530	5.124	0.018	16.975	8.681	22.409	0.283
IND10	0.569	0.541	0.466	-0.005	1.037	1.270	0.500	-0.024*	0.435	0.819	0.284	-0.019*
Intans	5.035	5.309	6.518	0.011	5.599	5.176	6.800	0.044	5.789	2.673	9.821	0.225***
Growth	22.470	9.507	38.769	0.753***	3.434	1.753	4.791	0.094***	6.688	2.485	11.528	0.311***
AltPerf	12.721	6.170	14.914	0.381***	11.480	4.323	22.993	0.583***	10.083	3.370	17.662	0.486***
NUMVR - 50%	2.553	1.800	3.000	0.036***	1.500	1.200	1.875	0.020**	1.789	1.200	2.500	0.036***
NUMVR - 75%	5.263	3.700	6.125	0.070***	4.184	3.300	4.500	0.039**	3.763	2.500	5.000	0.084***
NUMVR - 90%	7.974	6.800	8.375	0.040**	8.447	7.300	8.875	0.047***	6.237	4.800	7.625	0.101***
NUMVR - 95%	9.816	8.700	9.875	0.035*	10.921	9.800	11.625	0.052***	8.158	6.600	9.625	0.105***
Panel C: Other												
TOBINQ	2.914	2.411	3.170	0.014***	1.868	1.547	2.027	0.016***	1.581	1.232	1.654	0.012***
Proportion	21.813	16.658	23.811	0.270***	68.058	75.889	63.542	-0.471***	10.129	7.453	12.647	0.202***

Notes: This table presents results for the value relevance of accounting information over the period 1980-2017 for the sample partitioned by firm type. Panel A presents the means of and trends in combined value relevance (*OOSRSQ*), Panel B presents the means of and trends in individual value relevance (VR_k; based on **unconditional permutation**) and the number of accounting amounts required to explain a specific percentage of combined value relevance (*NUMVR*; idem), and Panel C presents the means of and trends in Tobin's Q ratio (*TOBINQ*). *Intans* refers to the sum of value relevance of *RDX*, *INTAN*, and *ADVX*, *Growth* refers to the sum of value relevance of *CASH* and *REVGR*, and *AltPerf* refers to the sum of value relevance of *OCF*, *REV*, *SI*, and *OCI*. *Proportion* refers to the percentage of the population the firm type covers. *, **, and *** indicate two-tailed significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

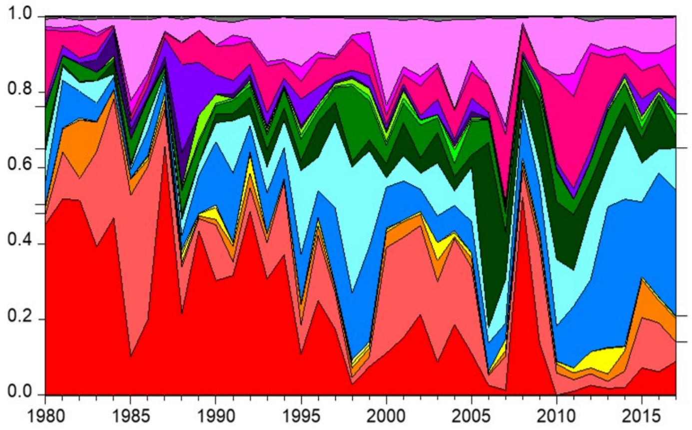


FIGURE 2A: Individual Value Relevance for New Economy Firms

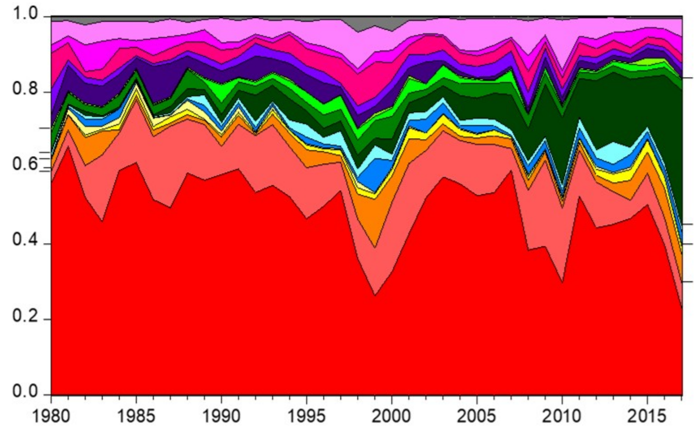


FIGURE 2B: Individual Value Relevance for Profitable Old Economy Firms

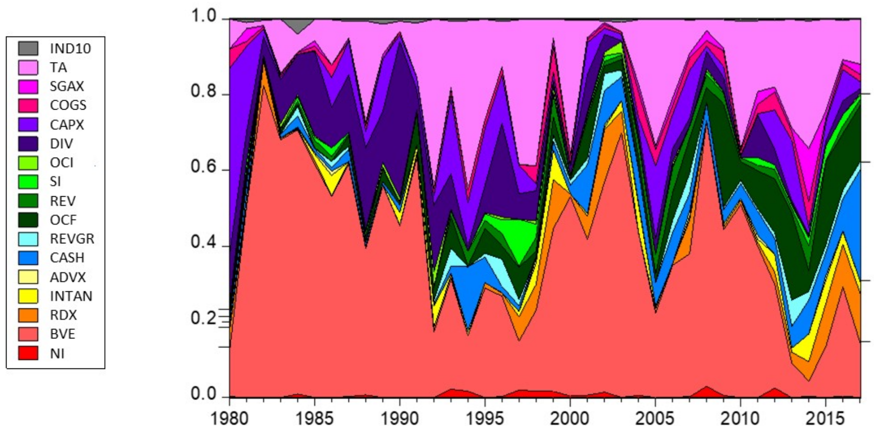


FIGURE 2C: Individual Value Relevance for Unprofitable Old Economy Firms

Notes: These figures present the value relevance of each accounting amount (VR_k; based on **unconditional permutation**) over the period 1980-2017 for the sample partitioned by firm type.

Table 4, Panel B presents the statistics underlying to Figure 2. It reveals the most relevant accounting amount for new economy firms and profitable old economy firms is *NI*. Nevertheless, for new economy firms mean *VR* amounts 39.533% in the 1980s and 3.689% in the 2010s. For profitable old economy firms, mean value relevance equals 55.695% in the 1980s and 41.384% in the 2010s. Thus, their trend coefficients are -1.186 and -0.475 percentage points per year, respectively. *NI* has little relevance for unprofitable old economy firms: in the 1980s, mean value relevance equals 0.219%, and in the 2010s, it equals 0.404%. Logically, the trend coefficient is not statistically significant at any level. For this firm type, however, the most value relevant accounting amounts is *BVE*, with a sample mean of 39.899%. Even so, it shows a decline over time: -0.795 percentage points per year, significant at a 1% level. Finally, notice the proportion of new economy firms and unprofitable old economy firms increases over time. For the full sample, this fosters the process of *NI* becoming less relevant and limits the process of *BVE* becoming more relevant.

Table 4, Panel B also reveals the accounting amounts related to intangible assets are not more relevant for new economy firms. This finding applies to all years, the 1980s, and the 2010s, and is contrary to what I expected beforehand and to the study of Barth et al. (2018). Having said that, accounting amounts related to growth opportunities are more relevant for new economy firms. For these firms, *CASH* shows a mean value relevance of 6.146% in the 1980s and of 25.787% in the 2010s, while profitable and unprofitable old economy firms show a mean of 0.930% and 1.678% in the 1980s, and of 2.383% and 9.174% in the 2010s. The same applies to *REVGR*: the sample mean value relevance amounts 9.366%, compared to 1.713% and 1.654%, respectively. Regarding the accounting amounts related to alternative APMs, in line with Barth et al. (2018), only *REV*'s relevance is considerably higher for new economy firms across all sample years: 5.005%, compared to 2.815% (profitable old economy firms) and 2.022% (unprofitable old economy firms).

Concerning the trends of accounting amounts related to intangible assets, none of the trend coefficients for new economy firms does significantly differ from 0 (at a 5% significance level). Despite this, profitable old economy firms show a highly significant trend coefficient of 0.044 for *INTAN* and of -0.039 for *ADVX*. Furthermore, unprofitable old economy firms' relevance of *RDX* increases with 0.159 percentage points per year. Regarding the trend of accounting amounts related to growth opportunities, for both *CASH* and *REVGR* the trends are highly significant and positive, and substantially higher than those of old economy firms. From the accounting amounts related to alternative APMs, only *OCF* shows a significant positive trend, but this is lower than for both old economy firm types. Grouping the accounting amounts shows the relevance of *Intans* only increases for unprofitable old economy firms (trend coefficient equals 0.225, significant at a 1% level). Further, it shows highly significant positive relevance trends in *Growth* and *AltPerf* for all firm types, but the trend is only the strongest for new economy firms for the former.

Regarding the other accounting amounts, mean *VR* of *DIV* is the lowest and the least decreasing for new economy firms. Across the entire sample, *CAPX* is the most relevant for unprofitable old economy firms, and *COGS* the most relevant for new economy firms. Further, the relevance of *SGAX* does not differ substantially between firm types, and does significantly increase for new economy firms and unprofitable old economy firms only. Finally, *TA* is the most relevant for unprofitable old economy firms and shows a significant increase just for new economy firms.

Table 4, Panel B also presents the means of and trends in the number of accounting amounts needed to explain a specific percentage of combined value relevance (*NUMVR*) for the sample partitioned by firm type. Regardless of the threshold percentage, with one exception, it reveals an increase in the number of relevant accounting amounts for all three firm types. For instance, explaining 75% of combined value relevance in the 1970s needs for new economy firms, profitable old economy firms, and unprofitable old economy firms, on average, the 3.700, 3.300, and 2.500 most relevant accounting amounts, while in the 2010s it needs the 6.125, 4.500, and 5.000 most relevant accounting amounts. Overall, the highly positive trend coefficients imply a more nuanced relation between accounting amounts and the stock price over time. Therefore, H6 can be rejected for the firm type part.

4.2.3 Tobin's Q Ratio

Table 4, Panel C presents the means of and trends in Tobin's Q ratio for the firm type subsamples. As expected, mean *TOBINQ* is notably higher for new economy firms: 2.914, compared to 1.868 (profitable old economy firms) and 1.581 (unprofitable old economy firms). That said, for all three firm types the Q ratio shows a temporal increase, significant at a 1% level. By suggesting a general increase in the intangible intensity of firms, this provides preliminary evidence against H4.

4.3 Analysis of Subsamples by Industry

4.3.1 Combined Value Relevance

Table 5, Panel A presents the combined value relevance of accounting information for the sample partitioned by industry. Across all sample years, mean combined value relevance is the highest for the healthcare, medical equipment, and drugs industry (hereafter 'healthcare industry'), closely followed by the manufacturing, energy, and utilities industry (hereafter 'manufacturing industry'). Both are slightly higher than mean *OOSRSQ* for the full sample. Moreover, the manufacturing industry shows a positive trend in value relevance over time: 0.175 percentage points per year, significant at a 5% level. While the means of *OOSRSQ* for the other three indus-

TABLE 5: Value Relevance of Accounting Amounts: Subsamples by Industry

	Industry 1				*Industry 2*				*Industry 3*				*Industry 4*				*Industry 5*			
	All	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**
Panel A: Combined value relevance																				
OOSRSQ	63.01	58.55	72.47	0.205**	69.08	61.20	72.66	0.175**	63.31	56.63	69.53	0.217*	70.18	65.30	73.81	0.107	62.11	53.78	69.26	0.302***
Panel B: Individual value relevance																				
NI	64.25	65.05	62.32	-0.153	49.69	61.20	44.73	-0.365***	44.53	67.95	23.12	-1.132***	49.22	72.94	19.80	-1.367***	53.76	57.16	50.47	-0.271**
BVE	7.47	4.70	4.21	0.024	13.85	5.66	8.11	0.045	11.57	9.14	9.54	-0.014	14.82	1.19	32.21	0.659***	16.40	10.24	9.05	0.034
RDX	0.56	0.40	0.83	0.007	3.74	1.70	3.43	0.032	2.41	5.67	2.82	-0.070**	5.62	3.55	4.64	0.037	0.54	1.45	0.52	-0.022
INTAN	0.59	0.09	0.99	0.030***	0.75	0.04	2.02	0.050***	0.91	0.18	1.90	0.040***	0.72	0.75	1.83	0.028***	1.38	0.54	2.61	0.048***
ADVX	0.42	0.13	0.69	0.007	0.28	0.36	0.14	-0.002	0.26	0.34	0.23	-0.004	0.43	0.91	0.056	-0.025***	0.22	0.19	0.11	0.002
CASH	1.26	0.61	1.58	0.030**	0.93	1.07	0.95	0.003	3.39	1.58	6.69	0.131***	3.63	1.99	5.36	0.093**	2.34	1.90	2.93	0.028
REVGR	2.05	0.65	3.58	0.075***	0.74	0.81	0.35	-0.002	4.98	1.03	7.10	0.171***	2.10	0.42	4.14	0.101***	1.40	0.95	1.55	0.022
OCF	4.34	0.30	13.62	0.310***	6.48	0.71	18.76	0.426***	10.60	0.79	28.80	0.677***	6.59	2.15	11.34	0.293***	6.18	0.64	18.91	0.381***
REV	1.93	2.54	1.09	-0.032***	2.27	3.29	1.80	-0.019	3.98	0.99	2.55	0.087*	1.98	1.00	2.68	0.066***	1.79	0.97	2.21	0.041***
SI	0.71	0.02	0.31	0.021*	0.48	0.07	0.68	0.018***	0.60	0.02	0.22	0.016	0.29	0.00	0.28	0.011**	0.42	0.08	0.53	0.013***
OCI	0.39	0.48	0.58	0.002	0.54	0.98	0.37	-0.015**	0.55	0.64	0.34	-0.004	0.36	0.53	0.37	-0.002	0.57	0.30	0.51	0.006
DIV	6.02	11.73	1.79	-0.249***	6.58	5.09	4.05	-0.048	1.09	2.29	0.34	-0.046***	4.62	11.68	0.23	-0.299***	6.82	18.40	3.55	-0.349***
CAPX	1.85	1.05	1.93	0.022*	2.63	2.39	2.40	0.017	2.67	1.49	1.38	-0.001	1.78	0.24	1.57	0.036*	1.88	1.91	1.21	-0.013
COGS	2.44	4.24	1.25	-0.062***	2.87	6.45	1.46	-0.097***	4.44	3.43	5.76	0.042	2.50	1.37	2.84	0.053**	1.59	1.12	2.15	0.039***
SGAX	1.04	1.06	0.76	-0.010	2.54	1.55	3.59	0.008	1.47	0.93	3.34	0.041***	1.26	0.70	2.78	0.064***	0.58	0.14	1.18	0.036***
TA	4.68	6.95	4.47	-0.023	5.65	8.63	7.17	-0.051	6.55	3.53	5.87	0.065	4.09	0.58	9.88	0.250***	4.12	3.99	2.51	0.005
Intans	1.56	0.63	2.51	0.044***	4.77	2.10	5.59	0.081**	3.59	6.19	4.95	-0.034	6.77	5.22	6.53	0.040	2.14	2.18	3.25	0.028
Growth	3.31	1.27	5.16	0.106***	1.67	1.88	1.30	0.001	8.38	2.61	13.79	0.302***	5.73	2.40	9.50	0.194***	3.74	2.85	4.48	0.050
AltPerf	7.38	3.34	15.61	0.301***	9.76	5.05	21.60	0.409***	15.73	2.44	31.91	0.777***	9.21	3.67	14.67	0.368***	8.97	1.99	22.16	0.441***
NUMVR - 50%	1.08	1.10	1.13	0.003	1.52	1.00	1.63	0.015**	1.81	1.20	2.25	0.030***	1.58	1.10	2.13	0.029***	1.35	1.20	1.50	0.011*
NUMVR - 75%	2.44	2.00	2.38	0.018*	3.40	2.90	3.75	0.023**	3.94	1.90	5.50	0.093***	3.21	1.50	4.88	0.097***	2.69	2.40	3.00	0.024***
NUMVR - 90%	5.63	4.70	5.75	0.036**	6.63	6.40	6.88	0.019**	6.54	5.00	7.75	0.078***	5.94	3.90	7.63	0.111***	5.33	4.40	6.50	0.070***
NUMVR - 95%	7.88	6.00	8.50	0.065***	8.58	7.80	9.25	0.047***	8.48	6.70	9.38	0.076***	7.77	5.50	9.50	0.116***	7.54	6.40	8.88	0.079***
Panel C: Other																				
TOBINQ	1.69	1.20	2.06	0.020***	1.50	1.20	1.70	0.013***	2.37	1.48	2.43	0.014***	3.13	2.00	3.50	0.024***	1.73	1.28	1.76	0.009***
Proportion	22.53	30.61	18.26	-0.309***	30.33	42.50	23.04	-0.535***	22.43	10.65	26.76	0.448***	10.56	3.90	15.53	0.308***	14.15	12.34	16.41	0.089***

Notes: This table presents results for the value relevance of accounting information over the period 1970-2017 for the sample partitioned by industry. Panel A presents the means of and trends in combined value relevance (*OOSRSQ*), Panel B presents the means of and trends in individual value relevance (VR_k; based on **unconditional permutation**) and the number of accounting amounts required to explain a specific percentage of combined value relevance (*NUMVR*; idem), and Panel C presents the means of and trends in Tobin's Q ratio (*TOBINQ*). Industries: 1) consumer goods and services, 2) manufacturing, energy, and utilities, 3) business equipment, telephone and television transmission, 4) healthcare, medical equipment, and drugs, and 5) other (mines, construction, building materials, transport, business services, hotels, and entertainment). *Intans* refers to the sum of value relevance of *RDX*, *INTAN*, and *ADVX*, *Growth* refers to the sum of value relevance of *CASH* and *REVGR*, and *AltPerf* refers to the sum of value relevance of *OCF*, *REV*, *SI*, and *OCI*. *Proportion* refers to the percentage of the population the industry covers. *, **, and *** indicate two-tailed significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

tries are close to 63%, both the consumer goods and services industry (hereafter 'consumer industry') and the other industry show a significant temporal increase in *OOSRSQ*: 0.205 and 0.302 percentage points per year. The trend in *OOSRSQ* for the business equipment, telephone and television transmission industry (hereafter 'high-tech industry') is positive, but only weakly significant (trend coefficient equals 0.217). Since for three out of five industries a positive trend in the combined value relevance can be detected, H5 can be rejected for the industry part.

4.3.2 Individual Value Relevance

Figure 3 shows the evolution in the value relevance of each accounting amount (VR_k) for the five industry groups based on the classification of Fama and French (2019). Naturally, *IND10* is excluded from the CART regressions for these subsamples. The figure reveals *NI* has the highest mean value relevance for the consumer industry, and, in line with the partial offsetting effect observed earlier, *BVE* the lowest mean value relevance. Moreover, for this industry *NI* and *BVE* do not exhibit a temporal trend in value relevance. While the latter is also found for the other four industries, except the healthcare industry, this does not apply to the former. Finally, all five industries show a steep increase in the relevance of *OCF*.

Importantly, the figure shows an increase in the number of value relevant accounting amounts for each of the industry subsamples. This corroborates the earlier evidence of this increase being economy-wide. For the consumer industry, accounting amounts related to intangible assets, growth opportunities, and alternative APMs all become more relevant over time, and so can explain the increase. For the manufacturing industry, the increase can mainly be contributed to accounting amounts related to intangible assets and alternative APMs. For the high-tech industry, the increase is primarily due to accounting amounts related to growth opportunities and alternative APMs becoming more relevant. The same applies to the healthcare industry and the other industry.

With regards to the dot-com bubble, the sharp decreases in the relevance of *NI* and *BVE* are offset differently. For the high-tech industry, which overlap to a great deal with the new economy firm type, the relevance decrease is offset by *CASH* and *REVGR*. A similar offsetting effect can be observed for the consumer industry and the other industry. The healthcare industry displays, in addition to this effect, a large increase in the relevance of *RDX* during the bubble. Finally, for the healthcare industry no offsetting effect related to growth opportunities can be detected at all. Instead, the industry shows an offsetting effect related to alternative APMs and other accounting amounts (mainly *DIV* and *TA*).

Table 5, Panel B presents the statistics underlying to Figure 3. It reveals *NI* has the highest mean *VR* for the consumer industry: 64.25%, compared to 49.69% (manufacturing industry), 44.53% (high-tech industry), 49.22% (healthcare indus-

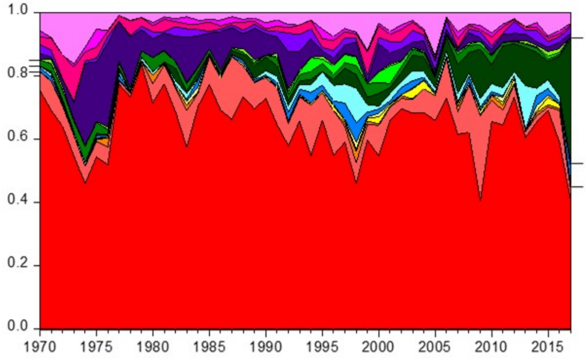


FIGURE 3A: Individual Value Relevance for Industry 1

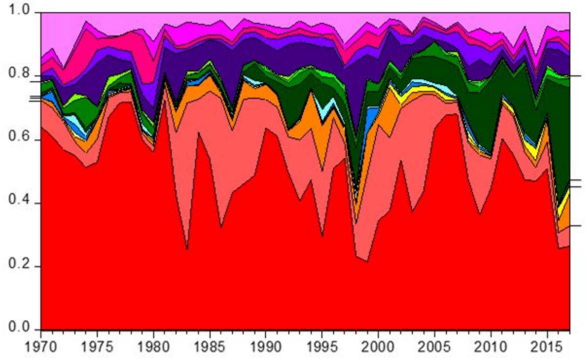


FIGURE 3B: Individual Value Relevance for Industry 2

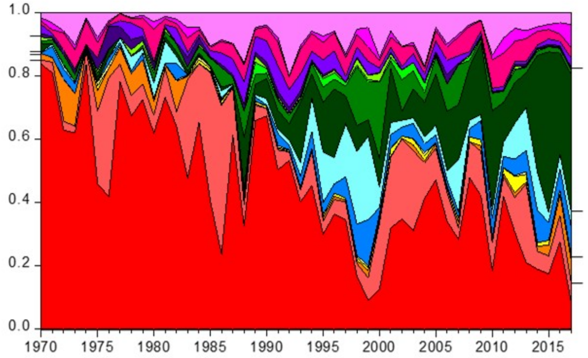
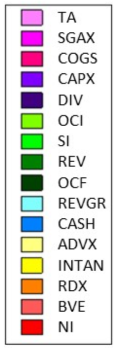


FIGURE 3C: Individual Value Relevance for Industry 3



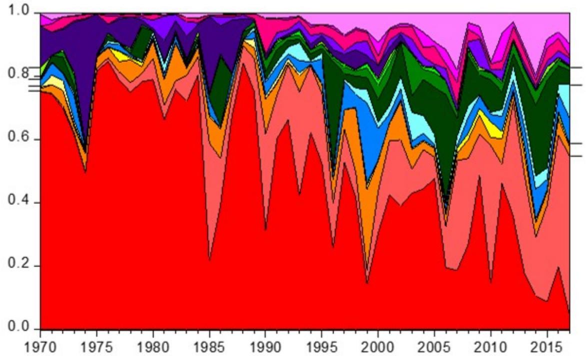


FIGURE 3D: Individual Value Relevance for Industry 4

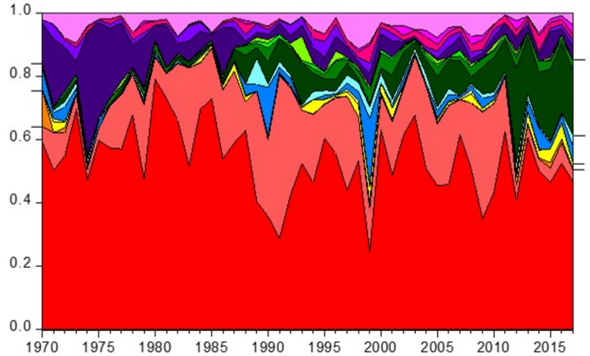


FIGURE 3E: Individual Value Relevance for Industry 5

Notes: These figures present the value relevance of each accounting amount (VR_k; based on **unconditional permutation**) over the period 1970-2017 for the sample partitioned by industry. Industries: 1) consumer goods and services, 2) manufacturing, energy, and utilities, 3) business equipment, telephone and television transmission, 4) healthcare, medical equipment, and drugs, and 5) other (mines, construction, building materials, transport, business services, hotels, and entertainment).

try), and 53.76% (other industry). Moreover, the consumer industry is the only industry for which *NI* does not show a significant decrease in value relevance throughout the sample period. The trend coefficient of *NI* is the most negative for the healthcare industry, followed by the high-tech industry: -1.367 and -1.132 percentage points per year, both significant at a 1% level. Regarding the relevance of *BVE*, across the sample years, mean *VR* is the greatest for the other industry and the smallest for the consumer industry (16.40% and 7.47%, respectively). In addition to this, just for the healthcare industry the relevance of *BVE* increases over time.

Regarding the accounting amounts related to intangible assets, mean *VR* of *RDX* is the highest for the healthcare industry (5.62%), followed by the manufacturing industry (3.74%) and the high-tech industry (2.41%). Furthermore, the relevance of *RDX* is decreasing for the high-tech industry. *INTAN* has the highest mean value relevance for the other industry and increases highly significantly over time for all industry groups. Remember, the relevance of *INTAN* increases over time for the full sample, but for the sample partitioned by firm type, it only increases for unprofitable old economy firms. Finally, the value relevance of *ADVX* is small for all industries. Nevertheless, it shows a significant relevance decrease for the healthcare industry.

Concerning the accounting amounts related to growth opportunities, in the 1970s *CASH* is the most relevant for the healthcare industry (1.99%), closely followed by the other industry (1.90%). In the 2010s, *CASH* is the most relevant for the high-tech industry (6.69%) and the second most relevant for the healthcare industry (5.36%). Significant trends in value relevance can be observed for the consumer industry, the high-tech industry, and the healthcare industry. The same applies to the relevance trends of the other growth opportunity proxy: *REVGR*. However, for this accounting amount the highest mean value relevance can be found for the high-tech industry, both in the 1970s and in the 2010s.

From the accounting amounts related to alternative APMs, the most relevant one concerns *OCF*. On its turn, *OCF* shows the highest mean relevance and trend coefficient for the high-tech industry. The relevance of *OCF* for this industry increases from a mean of 0.79% in the 1970s to a mean of 28.80% in the 2010s. Nonetheless, the other industries also exhibit highly significant and positive trend coefficients. The outcomes for the other accounting amounts related to alternative APMs are less uniform. *REV* is significantly decreasing for the consumer industry and significantly increasing for the healthcare industry and the other industry. Further, *SI* displays significant positive trends in value relevance for the manufacturing industry, the healthcare industry, and the other industry. Finally, *OCI* only shows a negative relevance trend for the manufacturing industry.

Consistent with these individual relevance trends, grouping the accounting amounts reveals a positive trend in *Intans* for the consumer industry and the manufacturing industry, with the trend of the latter being twice as steep. Additionally, it reveals the increase in the relevance of accounting amounts related to growth opportunities is not really economy-wide, since such a positive relevance trend cannot be detected for the manufacturing industry and the other industry. That having said, Table 5, Panel B documents a positive trend in the value relevance of *AltPerf* for all five industry groups. This suggests the relevance increase of accounting amounts related to alternative APMs applies to the economy in its entirety.

When it comes to the other accounting amounts, across the sample years *DIV* is the most relevant for the five industries, except the high-tech industry. For this industry, the most relevant accounting amount is *TA*. The relevance of *DIV* shows a steep temporal decline for all industries, except the manufacturing industry. *TA*'s relevance only increases significantly for the healthcare industry. Regarding the remaining amounts, the relevance of *CAPX* does not change over time for any of the industries. *COGS*'s relevance exhibits a decrease over time for the consumer industry and the manufacturing industry, and an increase for the healthcare industry and the other industry. *SGAX* displays a significant trend coefficient for the high-tech industry, the healthcare industry, and the other industry, all being positive and significant at a 1% level.

Table 5, Panel B also presents the means of and trends in the number of value relevant accounting amounts required to explain a specific percentage of combined value relevance (*NUMVR*) for the industry subsamples. With a few exceptions for the lower threshold percentages, due to the high value relevance of *NI*, the table reveals the increase in the number of value relevant accounting amounts to be applicable to all five industry groups. For example, explaining 75% of combined value relevance in the 1970s requires, on average, the following number of most relevant accounting amounts: 4.70 (consumer industry), 6.40 (manufacturing industry), 5.00 (high-tech industry), 3.90 (healthcare industry), and 4.40 (other industry). In the 2010s, this increases to 5.75, 6.88, 7.75, 7.63, and 6.50 amounts, respectively. Because of the increasingly nuanced relation between accounting amounts and the stock price over time, H6 can also be rejected for the industry part.

4.3.3 Tobin's Q Ratio

Table 5, Panel C presents the means of and trends in the Q ratio of Tobin (1969, 1978) for the sample partitioned by industry. Logically, mean *TOBINQ* is substantially higher for the high-tech industry and the healthcare industry, which includes the medical equipment and drugs industries also (see Section 4.3.1 'Combined Value Relevance'). While the trend coefficient is the highest for the healthcare industry (0.024 points per year), it is followed by the consumer industry (0.020 points per year), and not the high-tech industry (0.014 points per year). Notwithstanding this, all coefficients differ from 0 at a 1% significance level. Because of this clear evidence of each industry's Q ratio to increase over time, H4 can be rejected.

4.4 Analysis Based on Conditional Permutation

4.4.1 Full Sample

Table 7 presents the recalculation of Table 3, Panel B based on conditional permutation. It reveals the relevance of *NI* is less high in the 1970s and less small in the 2010s, resulting in a lower trend coefficient: -0.379, compared to -0.615. Despite this, the coefficient stays significant at a 1% level. For *BVE*'s relevance, while the trend coefficient is lower, it becomes significant at a 5% level.

Regarding the accounting amounts related to intangible assets, *RDX* still does not show a relevance trend over time. *INTAN* and *ADVX* both exhibit their positive and negative temporal trend in value relevance, although the trends are more pronounced. With regards to the accounting amounts related to growth opportunities, both *CASH* and *REVGR* keep to be highly significant, but right now the trend in the latter is stronger. Concerning the accounting amounts related to alternative APMs, also in this case *OCF* is the most relevant across the sample years. However, it merely increases from 1.250% in the 1970s to 14.274% in the 2010s, compared to 0.435% in the 1970s and 22.379% in the 2010s for unconditional permutation, leading to a lower trend coefficient (0.300 percentage points per year, significant at a 1% level). Further, the relevance trend in *REV* becomes negative and weakly significant, and the trend in *SI* becomes more pronounced and significant. Finally, the relevance of *OCI* does not increase over time for this case also.

Grouping the accounting amounts reveals positive and significant trends in value relevance for *Intans*, *Growth*, and *AltPerf* at a 5% level. For the other accounting amounts, compared to the outcomes under unconditional permutation, the relevance trends in *CAPX* and *TA* become negative and highly significant. Additionally, Table 7 presents the recalculations of the means and trends in *NUMVR*. For all four threshold percentages, the temporal trends in *NUMVR* are positive and significant. Thus, H2 can also be rejected when utilizing the conditional permutation method to measure individual value relevance.

4.4.2 Subsamples by Firm Type

Table 8 presents the recalculation of Table 4, Panel B based on conditional permutation. It reveals *NI* stays to be the most relevant accounting amount for new economy firms and profitable old economy firms, while the same applies to *BVE* for unprofitable old economy firms. However, new economy firms only show a significant relevance trend in *NI*, profitable old economy firms in none of the two, and unprofitable old economy firms in *BVE*.

Under the conditional permutation method, the accounting amounts related to intangible assets also do not show a substantially higher mean value relevance for new economy firms. Further, *RDX* only exhibits a significant relevance trend for unprofitable old economy firms, and *INTAN* and *ADVX* for profitable old economy firms. Nonetheless, accounting amounts related to growth opportunities are actually more value relevant for new economy firms. From the two proxies, *CASH*'s relevance only does not increase for profitable old economy firms. Regarding the accounting amounts related to alternative APMs, for all three firm types the most relevant accounting amount concerns *OCF*, which exhibits highly significant and positive trends in value relevance over time.

By grouping the accounting amounts, no clear differences can be observed when looking to the significance levels of the trend coefficients. Further, in general, the value relevance trends in *Intans* and *Growth* become stronger, and in *AltPerf* become weaker. Finally, *NUMVR* shows for each combination of firm type and threshold percentage an increase in the mean from the 1980s to the 2010s. However, when looking to *NUMVR*, less significant results can be observed for new economy firms and profitable old economy firms. So, under this alternative method, there is too less evidence to reject H6 for the firm type part.

4.4.3 Subsamples by Industry

Table 9 presents the recalculation of Table 5, Panel B based on conditional permutation. It reveals *NI* has the highest mean *VR* for the consumer industry. Moreover, the consumer industry and the manufacturing industry are the only industries for which *NI*'s relevance does not significantly decrease over time. Concerning the value relevance of *BVE*, it is the greatest for the other industry and increases the most for the healthcare industry.

Regarding the accounting amounts related to intangible assets, conditional permutation results in less significant results in the relevance trend of *INTAN* for the high-tech industry and the healthcare industry. That having said, it leads to more significant results in the relevance trend of *CASH* and *REVGR* for the other industry. From the accounting amounts related to alternative APMs, OCF keeps to be the most relevant for any industry. Furthermore, under conditional permutation no positive trend can be detected in the relevance of *REV* for the healthcare industry, instead a negative trend can be observed for the manufacturing industry. And, the negative trends in *SI*'s relevance can no longer be found for the healthcare industry and the other industry.

Grouping the accounting amounts related to intangible assets does no longer show a significant relevance decrease for the consumer industry, but does show a significant decrease for the high-tech industry. For *Growth*, the trend coefficient becomes negative for the manufacturing industry and significantly different from 0 for the other industry. For *AltPerf*, no substantial changes can be observed after applying conditional permutation. Lastly, each industry displays, for at least three threshold percentages, the mean of the number of value relevant accounting amounts increases from the 1970s to the 2010s. Despite this, the recalculations of the statistics related to *NUMVR* reveal substantial consequences for the significance of the relevance trends for the manufacturing industry. Based on this, under conditional permutation H6 cannot be rejected for the industry part.

4.5 Conclusion

In this chapter, I documented the outcomes of the empirical analysis. The first analysis is based on the full sample. It does not show a decline in the combined value relevance of accounting information. Barth et al. (2018) document a more positive trend coefficient, which can be explained by including the 1960s in their sample. When looking to the individual value relevance of accounting amounts, I find a decrease in the value relevance of *NI* and an increase in the value relevance of *BVE*. Moreover, I find an increase in the number of value relevant accounting amounts, especially of those related to intangible assets, growth opportunities, and alternative APMs. Concerning the amounts related to intangible assets, in contrast to Barth et al. (2018), I observe a negative trend in the value relevance of *ADVX*. Finally, I find an increase in Tobin's Q ratio for the economy as a whole.

The second analysis is based on the sample partitioned by firm type. For both new economy firms and old economy firms, I find combined value relevance does not significantly decrease over time. Further, I observe *NI* is the most relevant accounting amount for new economy firms and profitable old economy firms, and *BVE* for unprofitable old economy firms. For each firm type, the most relevant accounting amount shows a highly significant and negative temporal trend in value relevance. Lastly, I find overwhelming evidence for an increase in the number of value relevant accounting amounts, both for the new and old economy. However, for firms emblematic of the new economy, only the relevance trends related to growth opportunities are the most pronounced.

The third analysis is based on the sample partitioned by industry. Mean combined value relevance is the highest for the healthcare industry, closely followed by the manufacturing industry. Moreover, none of the industry groups shows a decline in combined value relevance over time. Further, *NI* only does not show a negative temporal trend in value relevance for the consumer industry, while *BVE* only does show a positive temporal trend for the healthcare industry. Also for this analysis, I find an increase in the number of value relevant accounting amounts. However, just the relevance trends related to alternative APMs really seem to be economy-wide. Then, I find clear evidence of each industry's Q ratio to increase over time, suggesting a general increase in the intangible intensity of firms. Finally, applying conditional permutation leads to less significant results.

Chapter 5

Discussion and Conclusion

In this thesis, I investigated how the value relevance of accounting information evolved as the US economy transitions from being primarily a manufacturing economy into a more service oriented economy. Prior literature states the value relevance of accounting information, in particular earnings, has declined over time and attributes this to the rise of the new economy. More specifically, it suggests current accounting standards have become obsolete for the new economy, since they do not disclose the value of intangible assets, do not make an attempt to reflect growth opportunities, and are primarily earnings focused.

To examine the new economy irrelevancy claim, Barth et al. (2018) consider a larger set of accounting amounts, including especially these amounts that could be of importance in the new economy. They find no decline in the combined value relevance of accounting information from 1962 to 2014. Instead, they state that if they found something, it is evidence of an increase, mainly related to intangible assets, growth opportunities, and alternative APMs becoming more relevant. Because they found these trends are evident for the full sample, they conclude that new economy firms are not solely responsible for the relevance increases. However, this suggests a general increase in the intangible intensity of firms, which stands in stark contrast to Srivastava (2014).

I provide more clear evidence on this issue by examining US listed firms from 1970 up to and including 2017. I do so by utilizing the CART method to estimate the relation between the stock price and various accounting amounts, identical to the ones of Barth et al. (2018). CART does not impose a particular functional form, which could understate the explanatory power of accounting amounts, and so their value relevance. Moreover, enabled by bagging, I measure value relevance utilizing out-of-sample explanatory power.

In line with Barth et al. (2018), I find no decline in the combined value relevance of accounting information. This finding is robust to partitioning the sample by firm type and industry. Regarding the value relevance of individual accounting amounts, I find a decrease in the value relevance of earnings and an increase in the value relevance of BVE. Moreover, I find an increase in the number of value relevant accounting amounts, especially of those related to intangible assets, growth opportunities, and alternative APMs. However, the evidence for this is less strong when applying conditional permutation to measure individual value relevance. With regards to firms emblematic of the new economy, only the relevance trends related to growth opportunities are the most pronounced, which is contrary to Barth et al. (2018). Also, the industry analysis shows just the relevance trends related to alternative APMs really seem to be economy-wide. Finally, I find clear evidence of each industry's Q ratio to increase over time, suggesting a general increase in the intangible intensity of firms.

To answer the research question, although the US economy in its entirety is becoming more service oriented, there is no clear evidence accounting information has become less relevant. Instead, the findings reveal a relevance shift from earnings and BVE to accounting amounts reflecting the rise of the new economy. So, the relation between the share price and accounting information is becoming *more nuanced*, but is *not declining*.

Notice, the increasing relevance of accounting amounts related to intangible assets, growth opportunities, and alternative APMs does not imply these amounts are in the most optimal way reflected in accounting. It only implies that the relevance of accounting information could be improved by enhancing their reflection. Consequently, further research into this issue is necessary in order to be able to provide useful advice to standard setters. Additionally, remember that accounting information is not just utilized by equity investors. As such, it is should be taken into account when making a specific policy recommendation.

Finally, as explained above, this thesis does not confirm all findings of Barth et al. (2018). Though, more research should be done into different companies, countries, accounting amounts, and value relevance measures to provide systematic evidence against the hypotheses examined in this thesis. For example, due to data availability, I was forced to start the sample partitioned by firm type in 1980. Consequently, I could not examine the evolvements in value relevance for firms emblematic of the new economy at their very beginning. Furthermore, the industry analysis is based on the classification of Fama and French (2019) into five groups. This analysis could be performed more profoundly in case the dataset can be extended. In short, this thesis should not be seen as an ending point, but rather as a starting point.

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Appendix A

Variable Definitions

TABLE 6: Variable Definitions

Variable	Definition
ADX	Advertising expenses deflated by number of common shares outstanding
BVE	Book value of equity deflated by number of common shares outstanding
CAPX	Capital expenditures deflated by number of common shares outstanding
CASH	Cash, including cash equivalents and short-term investments, deflated by number of common shares outstanding
COGS	Cost of goods sold deflated by number of common shares outstanding
DIV	Dividends declared to common shareholders deflated by number of common shares outstanding
IND10	Set of indicator variables based on the industry classification of Fama and French (2019) into ten groups
INTAN	Recognized intangible assets, including capitalized software, goodwill, and other purchased intangible assets, deflated by number of common shares outstanding
NEWECO	Indicator variable which equals 1 if a firm has two out of these three characteristics: belongs to the high-technology industry, has negative earnings, and listed for five years or less; it equals 0 otherwise.
NI	Net income before extraordinary items deflated by number of common shares outstanding
NUMVR	Number of accounting amounts required to explain a specifiable percentage of the combined value relevance of accounting information
OCF	Operating cash flow deflated by number of common shares outstanding. If not available in cash flow statement, it is calculated as net income before extraordinary items minus accruals, where accruals are defined as change in current assets minus change in cash minus change in current liabilities plus change in short-term debt plus change in income taxes payable (Sloan, 1996).

(The table is continued on the next page.)

TABLE 6 (Continued)

Variable	**Definition**
OCI	Other comprehensive income deflated by number of common shares outstanding, where other comprehensive income is defined as change in retained earnings plus dividends minus net income before extraordinary items (Dhaliwal et al., 1999).
OOSRSQ	Out-of-sample R^2
RDX	R&D expenses deflated by number of common shares outstanding
REV	Revenues deflated by number of common shares outstanding
REVGR	One-year growth in revenues deflated by number of common shares outstanding
SGAX	SG&A expenses deflated by number of common shares outstanding
SI	Special items deflated by number of common shares outstanding
SP	Stock price measured three months after fiscal year-end
TA	Total assets deflated by number of common shares outstanding
TOBINQ	Q ratio of Tobin (1969, 1978), defined as the ratio between total assets plus number of common shares outstanding multiplied by stock price minus book value of equity and total assets (Kaplan & Zingales, 1997).
VR	Value relevance of an individual accounting amount, defined as the increase in the MSPE of the OOB observations, averaged over all bootstrapped samples, when CART randomly assigns the accounting amount, relative to the sum of increases of all accounting amounts.
YEAR	Fiscal year, running from 1970 up to and including 2017

Note: In this thesis, the variables are **capitalized** and **italicized**. Contrary to the abbreviations, they are **capitalized** but **not italicized**.

Appendix B

Pseudocode of Algorithms

Algorithm 1: Implementing CART

1. For $b = 1$ to B:
   a) Draw a bootstrapped sample Θ_b from the total number of observations N of the original sample Θ.
   b) Fit a single regression tree $t(\Theta_b)$ by recursively repeating the following steps for each node until the minimum size of five observations is reached:
      i) Determine the input variable $X^* \in \{X_1, ..., X_m\}$ and a splitting point s^* that best splits the data according to the sum of squared residuals.
      ii) Conduct a binary split into two child nodes.
2. Output the regression forest $\{t(\Theta_b) : b \leq B\}$.

Algorithm 2: Calculating the out-of-sample R^2

1. For $n = 1$ to N, calculate the average of the OOB predictions:

   $\overline{\hat{Y}_n^{OOB}} := \frac{1}{O_n} \sum_{o_n=1}^{O_n} \hat{Y}_n^{OOB}(\Theta_b)$,

   where $\hat{Y}_n^{OOB}(\Theta_b)$ is the prediction of the target variable Y, based upon the mean in the terminal leaf where n falls into and performed for all $t(\Theta_b)$ in which n is in the OOB sample O.
2. Calculate the out-of-sample R^2:

   $$R^2_{OOB} := 1 - \frac{\sum_{n=1}^{N}(Y_n - \overline{\hat{Y}_n^{OOB}})^2}{\sum_{n=1}^{N}(Y_n - \overline{Y})^2}.$$

Algorithm 3: Calculating unconditional permutation importance for a single input variable

1. For $b = 1$ to B:
   a) Calculate the MSPE of the OOB observations n^{OOB} for $t(\Theta_b)$:

      $MSPE_b^{OOB} := \frac{1}{N^{OOB}} \sum_{n^{OOB}=1}^{N^{OOB}} (Y_{n^{OOB}} - \hat{Y}_{n^{OOB}}(\Theta_b))^2$.
   b) Permute randomly the observations of input variable X_m in the OOB sample O_b.
   c) Recalculate the MSPE of the OOB observations for $t(\Theta_b)$ using the permuted input.
   d) Calculate the increase in MSPE I_{bm}^{UPI}.
2. Calculate the (forest) average increase in MSPE:

   $I_m^{UPI} := \frac{1}{B} \sum_{b=1}^{B} I_{bm}^{UPI}$.

Algorithm 4: Calculating conditional permutation importance for a single input variable

1. For $b = 1$ to B:
   a) Calculate the MSPE of the OOB observations n^{OOB} for $t(\Theta_b)$:
   $MSPE_b^{OOB} := \frac{1}{N^{OOB}} \sum_{n^{OOB}=1}^{N^{OOB}} (Y_{n^{OOB}} - \hat{Y}_{n^{OOB}}(\Theta_b))^2$.
   b) Select the input variables $X_{l \neq m}$ with $|\rho| > 0.2$, extract for X_l all split points in $t(\Theta_b)$, and construct a grid by bisecting the feature space in each split point. The maximum number of partitions allowed is 2^K, where K is set equal to $log_2(N * 0.368 * 0.5) - 1$.
   c) Within each partition, permute randomly the observations of input variable X_m in the OOB sample O_b.
   d) Recalculate the MSPE of the OOB observations for $t(\Theta_b)$ using the permuted input.
   e) Calculate the increase in MSPE I_{bm}^{CPI}.
2. Calculate the (forest) average increase in MSPE:
   $I_m^{CPI} := \frac{1}{B} \sum_{b=1}^{B} I_{bm}^{CPI}$.

Appendix C

CART Example

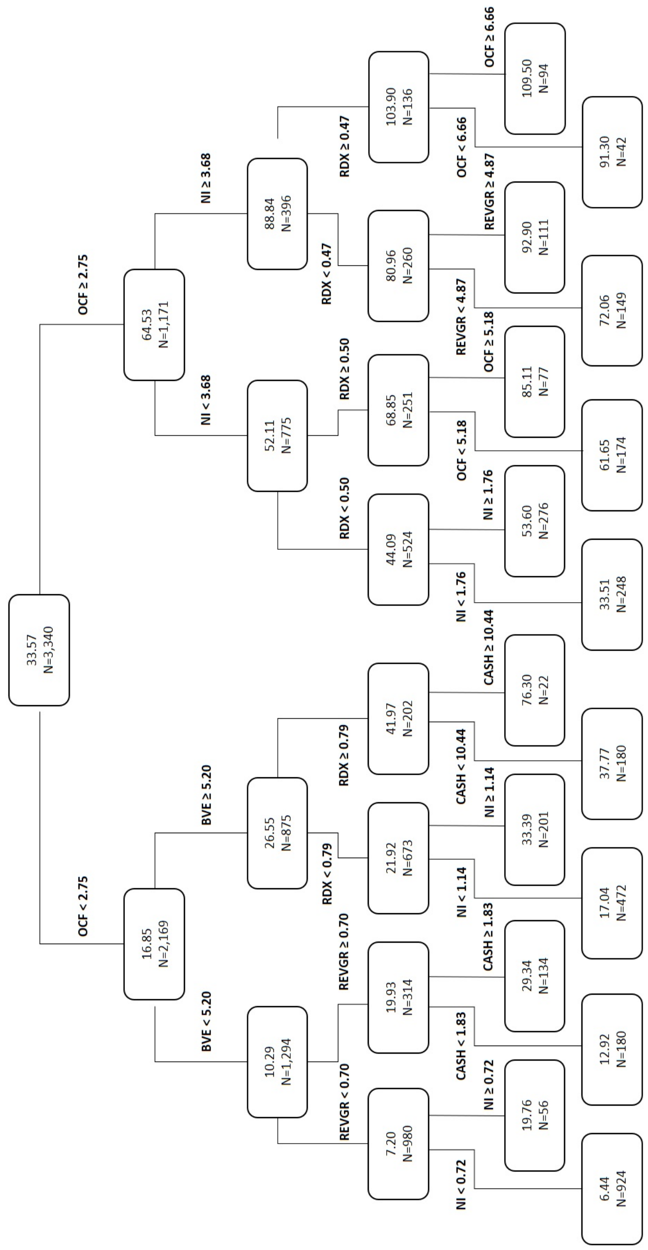

FIGURE 4: Example of CART with 2017 Data

Notes: This figure presents an example of one CART regression tree estimated for 2017. Each node reports the predicted stock price (i.e., the average value) and the number of observations included. Each line shows the splitting criterion. The final stock price prediction for each observation can be found in the terminal nodes. In this example, the maximum number of splits is set to four, the minimum size of the terminal nodes is set to five, and at each split all input variables are considered (i.e., no feature bagging).

Appendix D

Recalculated Tables

TABLE 7: Recalculation of Table 3 Based on Conditional Permutation

	All	**1970s**	**1980s**	**1990s**	**2000s**	**2010s**	**Trend**
NI	47.313	54.302	51.202	44.046	46.220	39.166	-0.379***
BVE	9.499	3.002	12.444	9.441	14.476	7.791	0.130**
RDX	4.280	4.652	2.937	3.903	4.116	6.166	0.039
INTAN	1.404	0.110	1.327	1.138	1.863	2.875	0.060***
ADVX	0.764	0.706	1.659	0.747	0.338	0.268	-0.020**
CASH	3.003	1.139	1.638	5.141	3.040	4.320	0.091***
REVGR	3.954	0.978	2.024	6.764	3.781	6.793	0.141***
OCF	4.637	1.250	0.923	2.572	6.095	14.274	0.300***
REV	3.029	3.294	3.116	3.673	2.710	2.181	-0.024*
SI	1.502	0.102	0.494	2.558	2.759	1.623	0.059***
OCI	0.780	1.080	0.626	0.846	0.546	0.806	-0.007
DIV	3.592	6.549	4.151	3.342	1.969	1.536	-0.121***
CAPX	2.182	3.489	1.931	2.034	1.895	1.406	-0.040***
COGS	5.886	11.180	4.553	5.425	3.829	4.081	-0.151***
SGAX	3.089	1.852	5.312	2.368	2.290	3.754	0.009
TA	3.940	5.321	3.978	4.625	3.080	2.381	-0.073***
IND10	1.148	0.994	1.685	1.376	0.993	0.579	-0.014*
Intans	6.447	5.468	5.924	5.788	6.317	9.309	0.078**
Growth	6.957	2.117	3.662	11.905	6.821	11.113	0.232***
AltPerf	9.948	5.726	5.159	9.650	12.109	18.883	0.328***
NUMVR - 50%	1.688	1.300	1.400	1.900	1.800	2.125	0.023***
NUMVR - 75%	5.083	3.800	4.400	5.900	5.500	6.000	0.058***
NUMVR - 90%	9.000	7.500	8.500	10.000	9.600	9.500	0.056***
NUMVR - 95%	11.479	9.900	11.100	12.500	12.000	12.000	0.053***

Notes: This table presents the means of and trends in individual value relevance (VR_k; based on **conditional permutation**) and the number of accounting amounts required to explain a specific percentage of combined value relevance (NUMVR; idem) over the period 1970-2017 for the full sample. *Intans* refers to the sum of value relevance of *RDX*, *INTAN*, and *ADVX*, *Growth* refers to the sum of value relevance of *CASH* and *REVGR*, and *AltPerf* refers to the sum of value relevance of *OCF*, *REV*, *SI*, and *OCI*. *, **, and *** indicate two-tailed significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

TABLE 8: Recalculation of Table 4 Based on Conditional Permutation

	New economy				*Old economy: Profit*				*Old economy: Loss*			
	All	**1980s**	**2010s**	**Trend**	**All**	**1980s**	**2010s**	**Trend**	**All**	**1980s**	**2010s**	**Trend**
NI	24.180	40.490	4.596	-1.065***	49.873	52.150	47.327	-0.202	0.770	0.555	0.698	0.010
BVE	11.988	16.655	6.256	-0.230*	9.080	9.859	6.926	-0.057	38.440	52.508	20.804	-0.739**
RDX	5.477	5.789	7.423	0.049	4.001	2.822	4.807	0.067	4.687	1.580	9.493	0.252***
INTAN	1.353	1.179	1.626	0.000	2.116	1.813	2.855	0.040**	3.102	1.363	4.700	0.072
ADVX	0.468	0.246	0.560	0.008	0.924	1.913	0.262	-0.052***	0.387	0.323	0.666	0.012
CASH	14.511	7.236	24.455	0.472***	1.934	1.603	1.757	0.017	5.013	1.010	8.185	0.270***
REVGR	12.715	3.513	18.501	0.395***	2.840	1.646	4.145	0.073***	3.145	1.261	5.226	0.123**
OCF	6.165	1.028	9.492	0.323***	5.522	1.060	13.730	0.425***	6.888	1.659	16.010	0.435***
REV	2.904	3.250	2.822	-0.033	2.825	3.420	1.916	-0.051**	1.434	1.011	1.477	0.017
SI	0.546	0.195	0.301	0.007	2.397	0.395	1.686	0.035	1.481	0.490	0.849	0.003
OCI	1.319	1.328	0.810	-0.010	0.717	0.822	0.888	-0.003	0.719	0.747	0.136	-0.024
DIV	1.162	2.461	0.063	-0.064**	3.211	4.243	1.917	-0.080***	9.539	15.043	5.139	-0.390***
CAPX	3.089	4.826	2.121	-0.070	1.884	1.636	1.649	0.003	7.790	11.285	7.536	-0.192
COGS	5.510	4.210	9.622	0.081	3.934	4.273	3.198	-0.040	1.602	0.603	1.759	0.038
SGAX	2.248	1.121	5.103	0.114***	4.100	6.770	3.957	-0.077*	1.778	0.945	3.804	0.085**
TA	5.591	5.471	5.674	0.040	3.142	3.617	2.202	-0.061***	12.563	8.367	13.190	0.054
IND10	0.775	1.003	0.576	-0.018*	1.501	1.957	0.778	-0.038**	0.662	1.248	0.326	-0.027*
Intans	7.298	7.214	9.609	0.057	7.041	6.549	7.923	0.055	8.176	3.266	14.860	0.337***
Growth	27.226	10.748	42.956	0.867***	4.774	3.249	5.903	0.091***	8.159	2.272	13.411	0.394***
AltPerf	10.934	5.801	13.425	0.288***	11.460	5.697	18.221	0.406***	10.522	3.907	18.471	0.431***
NUMVR - 50%	2.526	1.900	3.000	0.033***	1.526	1.300	1.625	0.014	1.974	1.400	2.625	0.030***
NUMVR - 75%	5.342	4.000	6.000	0.058***	5.026	4.400	5.000	0.021	4.105	2.400	5.500	0.094***
NUMVR - 90%	8.184	7.200	8.375	0.030	9.447	8.500	9.375	0.031*	6.605	5.300	8.000	0.090***
NUMVR - 95%	10.342	9.200	10.125	0.029	11.947	11.200	12.000	0.023	8.632	6.900	10.000	0.099***

Notes: This table presents the means of and trends in individual value relevance (VR_k; based on **conditional permutation**) and the number of accounting amounts required to explain a specific percentage of combined value relevance (NUMVR; idem) over the period 1980-2017 for the sample partitioned by firm type. *Intans* refers to the sum of value relevance of *RDX*, *INTAN*, and *ADVX*, *Growth* refers to the sum of value relevance of *CASH* and *REVGR*, and *AltPerf* refers to the sum of value relevance of *OCF*, *REV*, *SI*, and *OCI*. *Proportion* refers to the percentage of the population the firm type covers. *, **, and *** indicate two-tailed significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

TABLE 9: Recalculation of Table 5 Based on Conditional Permutation

	Industry 1				*Industry 2*				*Industry 3*				*Industry 4*				*Industry 5*			
	All	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**	**All**	**'70s**	**'10s**	**Trend**
NI	65.47	63.01	64.47	-0.034	50.29	58.78	50.53	-0.131	45.56	67.41	25.19	-1.016***	50.37	70.10	26.78	-1.110***	54.56	59.10	51.30	-0.329***
BVE	5.22	2.69	3.21	0.027	11.68	3.77	7.27	0.048	9.86	6.49	7.02	0.002	11.41	1.64	24.01	0.461***	13.36	6.73	8.24	0.060
RDX	1.12	0.84	1.62	0.008	4.60	2.56	4.38	0.033	3.90	9.41	3.96	-0.109**	9.16	5.29	9.38	0.131*	1.09	3.16	0.97	-0.051
INTAN	0.58	0.11	1.11	0.024***	1.03	0.04	2.42	0.065***	1.10	0.54	1.58	0.018	0.64	1.32	1.10	0.002	2.29	1.05	4.06	0.063**
ADVX	0.88	1.23	0.97	-0.015	0.44	0.66	0.19	-0.003	0.56	0.60	0.50	-0.006	0.54	1.17	0.11	-0.027**	0.37	0.21	0.11	0.006
CASH	1.07	0.41	1.08	0.027**	1.25	1.72	1.00	-0.014	4.30	2.38	6.09	0.113***	4.54	2.34	8.79	0.156***	2.36	0.76	3.28	0.073**
REVGR	2.84	0.75	4.87	0.107***	1.21	1.04	0.95	0.000	7.72	1.50	12.85	0.312***	3.04	0.58	5.72	0.139***	1.94	0.74	2.78	0.055***
OCF	4.07	0.40	12.29	0.291***	5.33	1.70	11.99	0.267***	8.68	0.63	22.53	0.551***	5.74	2.51	9.50	0.204***	5.30	0.54	14.07	0.321***
REV	1.94	2.49	0.96	-0.034***	2.23	3.11	1.43	-0.034**	3.01	0.82	1.77	0.027	1.30	1.17	1.20	0.014	1.84	0.71	1.84	0.043***
SI	0.81	0.08	0.57	0.026*	0.74	0.14	1.24	0.030***	0.54	0.03	0.19	0.015*	0.68	0.01	0.25	0.024*	0.58	0.17	0.57	0.015*
OCI	0.65	1.04	0.93	-0.004	0.92	1.69	0.67	-0.028***	0.83	1.04	0.39	-0.009	0.46	0.54	0.67	0.006	1.00	0.55	1.06	0.010
DIV	6.87	16.41	2.31	-0.317***	7.63	6.83	5.36	-0.056	0.72	0.61	0.28	-0.003	4.22	9.75	0.16	-0.251***	8.15	22.12	5.28	-0.383***
CAPX	1.83	1.66	1.19	-0.005	2.75	3.75	2.47	-0.011	2.92	2.58	2.51	-0.015	1.34	0.44	1.00	0.002	1.85	1.78	1.12	-0.015
COGS	2.47	4.00	1.51	-0.060***	2.72	6.52	1.28	-0.111***	4.16	3.53	7.18	0.057**	2.00	1.82	0.81	-0.002	1.69	1.44	1.91	0.028*
SGAX	1.18	0.77	0.53	-0.014	3.43	1.88	4.89	-0.002	2.16	1.25	4.88	0.047**	1.21	0.63	2.38	0.057***	0.90	0.01	1.49	0.057***
TA	3.00	4.11	2.37	-0.028*	3.74	5.80	3.93	-0.055*	3.99	1.18	3.08	0.015	3.37	0.69	8.13	0.195***	2.74	0.92	1.93	0.047**
Intans	2.58	2.19	3.70	0.017	6.07	3.26	6.99	0.095**	5.56	10.56	6.04	-0.097**	10.33	7.79	10.58	0.106	3.75	4.41	5.13	0.018
Growth	3.91	1.15	5.95	0.134***	2.46	2.76	1.94	-0.013	12.02	3.87	18.94	0.426***	7.58	2.91	14.52	0.294***	4.29	1.50	6.06	0.128***
AltPerf	7.47	4.01	14.76	0.279***	9.23	6.65	15.32	0.236***	13.05	2.52	24.89	0.584***	8.18	4.23	11.63	0.247***	8.72	1.98	17.53	0.390***
NUMVR - 50%	1.10	1.20	1.13	0.001	1.50	1.20	1.38	0.005	1.79	1.00	2.63	0.039***	1.60	1.00	2.25	0.032***	1.33	1.10	1.50	0.013**
NUMVR - 75%	2.33	2.10	2.13	0.009	3.77	3.40	4.13	0.014	3.85	2.00	5.25	0.073***	3.33	2.00	4.88	0.085***	2.92	2.10	3.38	0.048***
NUMVR - 90%	6.08	5.00	6.25	0.037**	7.08	7.30	7.13	-0.001	6.94	4.80	7.88	0.072***	6.04	4.30	6.88	0.080***	5.79	3.50	7.00	0.106***
NUMVR - 95%	8.33	7.20	8.50	0.045***	9.46	9.30	9.88	0.019**	8.94	6.80	9.88	0.067***	7.77	6.20	8.25	0.076***	7.73	4.90	9.38	0.130***

Notes: This table presents the means of and trends in individual value relevance (VR_k; based on **conditional permutation**) and the number of accounting amounts required to explain a specific percentage of combined value relevance (NUMVR; idem) over the period 1970-2017 for the sample partitioned by industry. Industries: 1) consumer goods and services, 2) manufacturing, energy, and utilities, 3) business equipment, telephone and television transmission, 4) healthcare, medical equipment, and drugs, and 5) other (mines, construction, building materials, transport, business services, hotels, and entertainment). *Intans* refers to the sum of value relevance of *RDX*, *INTAN*, and *ADVX*, *Growth* refers to the sum of value relevance of *CASH* and *REVGR*, and *AltPerf* refers to the sum of value relevance of *OCF*, *REV*, *SI*, and *OCI*. *Proportion* refers to the percentage of the population the industry covers. *, **, and *** indicate two-tailed significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.