UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Intangible Assets and Analyst Forecast Errors

Master Thesis

Graduate School

GM0360 V17 Master Degree Project in Accounting
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Abstract

We examine whether firms' total underlying intangible assets and the proportion of capitalized intangibles assets are related to analyst forecast errors, using a sample of listed firms using IFRS on the European stock markets. Previous research has shown that firms with high levels of intangible assets are more difficult for analysts to forecast correctly due to the uncertainty and complexity of intangible assets. Furthermore, earlier research also show that capitalization of intangible assets lead to lower analyst forecast errors. This study is conducted on the European market between the years 2005-2015, examining all listed firms in Europe with available forecast data, resulting in a final sample of 20 285 firm-years. Data was collected from the Bloomberg database and the results show patterns similar to the ones found in previous research on the subject. We find that analyst earnings forecast errors are positively associated with firms' levels of intangible assets, and negatively associated with the proportion of capitalized intangible assets over total underlying intangible assets. We also find that the latter association is more negative for firms with high levels of intangible assets compared to firms with no or low levels of intangible assets. Thus, the results suggest that intangible assets complicate the earnings forecasting task for analysts, and we find evidence that strongly suggest that capitalization of intangible assets provides analysts with valuable information that increases the accuracy of their earnings forecasts.

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Introduction

During the last decades, the way firms conduct business has shifted from a productional approach to putting more emphasis on being service providers or delivering products that are technological rather than physical. This has led to that in modern economies a larger part of company value stem from intangible assets, such as brands and knowledge (Hoegh-Krohn & Knivsflå, 2008). Under commonly accepted IFRS accounting principles, large parts of intangible assets are not allowed to be accounted for in the financial statements, leading to insufficient accounting information and potentially making firms' earnings harder to forecast (Chan et al., 2010; Barth 2104). With this problematization in mind, the aim of this study is to illustrate the complexity of assessing and valuing intangibles in strict accounting regulations, where most intangible assets are expensed, and how capitalization of such assets affects the accuracy of investor predictions. This study examines the association between the proportion of capitalized to total underlying intangible assets (capitalized as well as not capitalized or identified intangible assets) and analysts' earnings forecast error. The study is performed on IFRS firms listed on stock markets in Europe through the years 2005-2015.

This study relates to two vast streams of literature. The first stream of research concerns the association between firms' levels of intangible assets and analyst earnings forecasts. As there is scarce amount of research on the subject conducted on European firms using IFRS, conclusions and arguments from studies on the US and Australian markets are used to create an understanding, raise important arguments and focal points within this field of research. Even though there are some evident differences between these two regulations in terms of intangible assets treatment (Høegh-Krohn & Knivsflå, 2000) that will be raised later, the accounting issue of intangibles is similar and comparable between the two regulations. Matolcsy & Wyatt (2006) and Chalmers et al. (2012) examine intangibles effect on analyst earnings forecast and find that high amounts of underlying intangible assets lead to forecasting difficulties for analysts due to uncertainty and lack of information regarding the value of the assets (e.g. Barron et al., 2002; Dehning et al., 2006; Demers, 2002). Barth et al. (2001) argues that this lack of information leads to intangible intensive firms having higher analyst following, since analysts can gain advantages by obtaining private information to predict the value of firms' intangible assets. Further, several studies have found that analysts make larger forecast errors for firms with higher levels of intangibles (Barron et al., 2002; Demers, 2002). However, Gu et al. (2005) found a positive relation between higher levels of intangibles and forecast error only when a firm's intangible intensity deviated from the industry mean, finding no evidence that intangible intensive industries would have higher forecast errors than industries with lower levels of intangible assets.

The second stream of research indicates that disclosed intangibles are connected to firms' future cash flows and earnings, and therefore should bring useful information to analysts and investors, reducing the uncertainty of whether intangible assets will generate future earnings (e.g. Ritter & Wells, 2006; Kohlbeck & Warfield, 2002). This is supported by Matolcsy & Wyatt (2006), Anagnostopoulou (2010) and Jones (2007), who all find a positive relation between intangibles-related disclosures and forecast accuracy. US GAAP regulations, with a few exceptions, impose internally generated intangible assets to be expensed rather than capitalized. Consequently, the underlying economics of the firms are not correctly embodied in the financial statements (Barth et al., 2001; Lev & Zarowin, 1999). As intangible intensive firms are subject to larger information asymmetry between investors and managers (Barth et al., 2001), a regulation allowing a higher degree of capitalization of intangibles should lower the information asymmetry, resulting in more accurate analyst earnings forecasts. This is supported by the results of Matolcsy and Wyatt's (2006) study on the Australian market, conducted prior to the adoption of IFRS in Australia. In the studied period, the Australian GAAP allowed firms to capitalize all identifiable intangible assets. They found evidence that capitalization of intangible assets is associated with lower absolute analyst earnings forecast errors, concluding that analysts benefit from firms having the option to capitalize intangibles. Therefore, Matolcsy and Wyatt (2006) argued that the adoption of IFRS would result in a loss of useful information, as it meant stricter requirements in terms of intangible assets recognition. Contradictory, when Chalmers et al. (2012) used the same model to investigate whether the adoption of IFRS did in fact result in a loss of useful information about intangible assets, they found that the negative association between the accuracy of analyst earnings forecasts and capitalized intangible assets became stronger subsequent to IFRS adoption. However, their result was mainly attributed to reported goodwill rather than other intangible assets, indicating that the impairment based approach to goodwill used in IFRS conveys more useful information than the amortization approach previously used in the Australian GAAP.

This study contributes to the body of research in both streams of literature, filling a conceivable gap in the research on European firms. First, we examine the effect that the amount of underlying intangible assets has on analyst earnings forecast accuracy. Second, we examine whether firms' capitalization of these assets improve analysts' forecast accuracy. Thus, the results of this study can be compared to research from both the US and the Australian settings. Using a significantly larger sample, we complement Matolcsy & Wyatt's (2006) and Chalmers et al.'s (2012) studies and test their model on the European market where, to our knowledge, no similar research has previously been conducted.

The remainder of this paper is organized as follows; Section 2 develops the hypotheses. Section 3 describes the research setting, sample and variables. Section 4 reports the empirical analysis and section 5 concludes the study.

Theoretical framework

Intangible assets

Why should high intangible intensity affect the accuracy of analysts' earnings forecasts? A useful starting point of the discussion is the underlying cause for why value of intangible assets is being difficult to estimate. Previous literature has shown that the complexity lies within the assets' nature, and the characteristics that differentiate them from tangible assets are: intangibility, non-tradability, scarce disclosures, and uncertainty of future inflow of economic benefits associated with such assets (Lev, 2001; Lev, 2005; Jennewein, 2004).

Financial statements should reflect the underlying economics of the firm (Barth et al., 2001), and since intangible resources, such as R&D, advertising, and knowledge has become an increasingly important part of modern economies (Hoegh-Krohn & Knivsflå, 2008; Lev, 1997), the issues of accounting for intangible assets has become an important problem for standard setters. There is an evident distinction between the accounting treatment of physical and intangible investments; physical investments are considered assets and reported on firm's balance sheets, while intangible investments are usually expensed in the income statement (Lev, 2001). Since a large part of intangible investments are not allowed to be recognized in the balance sheet, the underlying economics is not correctly embodied by the financial statements (Barth et al., 2001). This difference in accounting treatment between tangibles and intangibles aggravates the analyzing process for investors and analysts, and could mislead those relying upon financial statements as their primary source of information (Hoegh-Krohn & Knivsflå, 2008). The primary reason behind having different accounting treatments is the high uncertainty regarding future outcomes of intangible investments (Lev, 2001). Further, the lack of a liquid market to trade those assets, and the fact that many intangibles cannot be fully controlled by the firm, having an inability to exclude non-owners from enjoying some of the economic benefits, are other arguments for expensing intangibles (Lev, 2001; Hoegh-Krohn & Knivsflå, 2008). Current regulations' conservative approach towards capitalizing intangible assets is largely a result of not wanting to give the assumptions made by management too great impact on company asset value (Barker, 2015). However, Lev (2001) points out that almost all assets recognized in the balance sheet are heavily dependent on management assumptions:

"Despite widely held belief that corporate financial statements convey historical, objective facts, practically every material item on the balance sheet and income statement, with the exception of cash, is based on subjective estimates about future events" (Lev, 2001, p.81).

Lev (2001) mentions a few examples of such subjective estimates; obligations for pensions and postretirement benefits rely on long-term assumptions concerning future wages and the return on pension assets; net value of property, plant and equipment is a result of management's depreciation estimates; and contingent liabilities are based on estimates of future payments to fulfill obligations, often stretching over several years.

The purpose of this paper is to investigate how intangible assets affect analyst earnings forecasts, and whether capitalizing intangibles in the balance sheets provides analysts with valuable information and increases the accuracy of their forecasts. However, it is important to note that deciding whether to use a more strict or permissible regulatory framework regarding intangible assets capitalization is a highly complex matter, where several aspects must be considered. The complexity of intangible assets makes it difficult to objectively value them, and using a regulatory framework that is more permissible in terms of capitalization may result in an increase of earnings management, given that a firm's management itself can make assessments whether an intangible asset will lead to future economic value or not (Healy et al., 2001). The problem that then may arise is that although capitalization of intangible assets provides valuable information to investors, the potential increase in earnings management has a negative effect on substantiality and distorts financial statements (Hoegh-Krohn & Knivsflå, 2008). However, Markarian et al. (2008) argue that this increased risk of earnings management is well compensated by the increase in value relevance that is generated by capitalization of intangible assets.

Accounting for intangible assets

According to IAS 38, an intangible asset, including expenditure on advertising, training, start-up, and R&D activities, should be recognized at its purchase price, including import duties and import taxes, after deducting discounts and directly attributable costs for putting it in the right condition for its supposed usage (IASB, 2016). However, an entity may only recognize an intangible asset if the asset is identifiable, separable, and it is "probable that the future economic benefits that are specifically attributable to the asset will flow to the entity; and the cost of the asset can be measured reliably" (IASB, 2016). While IAS 38 specifically prohibits recognition of internally generated assets such as: goodwill, brands, mastheads, publishing titles, customer lists and items of similar substance, some of the R&D expenditure may be capitalized. Research costs are always expensed, while development costs should be capitalized only after the commercial feasibility of the final product has been established, meaning that the entity must be able to demonstrate how the asset will generate future economic benefits. If an entity cannot distinguish the research phase from the development phase, the entity should treat the expenditure for that project as if it were incurred in the research phase only, and thus expense all costs. In practice, these rather strict rules for recognition results a large part of R&D expenditures being expensed as incurred (Damodaran, 2009).

A significant part of the research on the subject of intangible assets is conducted in a US GAAP setting (Gu et al., 2005; Barth et al., 2001), which has a regulation that is relatively similar to IFRS. However, there are some differences between the regulations that we believe should be emphasized in order for us to be able to compare our results with the results of these studies.

While development costs are capitalized under IFRS if they meet certain recognition criteria, the US GAAP prohibits capitalization of all internally generated intangibles, with very limited exceptions. Another dissimilarity between the two regulations concerns software development costs. Whereas under IFRS no difference is made between internal or external use, US GAAP has different rules depending on whether the software is developed for commercial or internal use. If the software is for sale, US GAAP permits capitalization of the asset, while software for internal use shall be expensed (PWC, 2015). Further, while IFRS permits capitalization of externally purchased research and development assets if it is probable that they will have future economic benefits, the US GAAP permits capitalization only under certain circumstances. Under US GAAP, purchased research and development assets are capitalized only if they have an alternative future use and it is reasonably expected that the entity will achieve economic benefit from such alternative use. Also, there has to be no need for further development in order to use the asset for capitalization to be permitted (PWC, 2015).

Analyst forecasts

Accounting regulations aim to improve the financial information that is disclosed to stakeholders, and thus limit the information asymmetry between managers and external stakeholders (Matolcsy & Wyatt, 2006). However, as these regulations limit the accounting for intangible assets, the true economic value of intangibles is not correctly embodied by the financial statements (Lev & Zarowin, 1999; Barth et al., 2001). According to Barth et al. (2001) intangibles intensive firms are subject to larger information asymmetry between investors and managers compared to firms with less or no intangible assets. The absence of concrete information regarding whether intangibles lead to economic value or not, makes it difficult for the average investor to value companies with a large stock of intangible assets, which creates opportunities for analysts to gain an information advantage towards less experienced investors (Gu et al., 2005). This information gap between management and investors regarding intangible assets is reflected in the analyst forecast error and are referred to as information risk, meaning that investors do not have the same information about the value of a firm's intangible assets as the management do, resulting in a risk that the assets are being valued incorrectly (Healy et al., 1999; Lang et al., 2003). The information risk could be mitigated by disclosures and by the capitalization of intangible assets (Anagnostopulos, 2010; Dehning et al., 2006; Matolcsy & Wyatt, 2006; Wolfe, 2009). Further, this should mean that stricter regulations lead to increased information risk for analysts and investors, since they would not be able access as much information, which in turn means that the connection between intangibles and forecast errors grows stronger in such situations. Matolcsy and Wyatt (2006) argued that this would be the case when Australia was to go through the transition from Australian GAAP to the more strict IFRS regulation, since potentially useful intangibles related information from the financial statements would be lost when the regulation regarding intangible assets would change.

Barth et al. (2001) examines the relation between firms' intangible assets and analyst incentives to cover these firms. They argue that firms with more intangible assets are likely to have less informative share prices that less precisely reflect the firm's fundamental values. This suggests the possibility for more profitable investment recommendations and higher trading commissions for analysts, and since analyst coverage is greater for firms that are perceived as being mispriced, firms with more intangible assets are likely to have higher analyst coverage (Barth et al., 2001). In their study, Barth et al. (2001) find evidence that intangible assets, most of which are not recognized as assets in firms' financial statements, are associated with greater incentives for analysts to cover firms.

Lev & Sougiannis (1996) show that, despite an absence of mandatory disclosures for R&D, investors use information regarding the value and productivity of R&D investments when valuing firms. The information complexity and lack of details about intangible assets in financial statements provides opportunities for experienced analysts to find misvalued stock (Lev, 2001). However, it also complicates analysts' task of estimating future earnings, which has led to several studies in the subject of intangible assets having used analyst forecast errors as an indicator of the quality of the earnings forecasts, regarding it as an important determinant of the usefulness of analysts' research. Plumlee (2003) finds evidence that analysts' forecast errors are positively related to the complexity of the forecasting task. Further, intangible assets are identified as a source of information complexity that distorts the analyst forecasts.

In the US setting, where US GAAP requires most intangible assets to be expensed, studies have shown that analyst earnings forecast errors are larger for firms with higher underlying intangibles (Barron et al., 2001; Demers, 2002). Barron et al.'s (2001) study on the US market shows that the consensus of analyst forecasts is lower for firms with high intangibles intensity; analyst forecast errors increase for firms with large intangibles, and that analysts who use private information to value such firms are more successful in their analysis. Gu et al. (2005) examine the relation between analyst earnings forecasts and technology-based, brand names and recognized intangible assets. They find similar evidence of a positive association between analyst forecast errors and firms with an intangible intensity that deviates from the industry mean. However, no evidence suggesting that industries characterized by a high intensity of intangibles is subject to larger forecast errors is found.
Contradictory to the results of Barth et al., (2001), Matolcsy & Wyatt (2006) find that in the Australian setting, firms with higher underlying intangibles have lower analyst following. They use a sample of Australian companies during 1990 - 1997, which was a period where the Australian GAAP allowed capitalization of identifiable intangible assets if the associated costs were expected to be recoverable. They argue that firms with more certain intangible assets would signal this by capitalizing them, and thus attracting higher analyst following, and in the absence of this capitalization signal, firms have lower analyst coverage and higher analyst forecast errors. Further, the study finds that firms capitalizing a larger proportion of their underlying intangible assets have higher analyst following, lower dispersion of analysts' earnings forecasts, and more accurate earnings forecast. The article was written prior to Australia's adoption of IFRS in 2005, and based on the results from the study, the authors challenge what they consider to be an implicit assumption in IAS 38; that capitalized intangible assets are generally not useful information. Therefore, Matolcsy & Wyatt (2006) argued that rather than improving the quality of financial

reporting, the implementation of IAS 38 removes a useful source of public information and would reduce the quality and usefulness of the financial reports.
Chalmers et al.'s (2012) study is built upon the Matolcsy & Wyatt (2006) and uses the same model to test whether the adoption of IFRS in Australia has affected the association between intangible asset recognition and the accuracy and dispersion of analysts' earnings forecasts. Like the previous study, they argue that removing potentially relevant information about intangible assets from financial reports would increase information risk faced by analysts and investors, and therefore lead to a reduction in the strength of association between disclosed intangible assets and analyst earnings forecast accuracy and dispersion. Surprisingly, the results showed that the negative association between reported intangibles and forecast error becomes more strongly negative after the adoption of IFRS by Australian firms. However, when dividing the intangible assets into goodwill and other intangible assets, they find that the results are mainly attributable to reported goodwill, rather than other intangible assets. This indicates the impairment approach to goodwill valuation conveys more useful information compared to the previously used straight-line amortization.

The above mentioned studies suggest that analysts in the US context find firms' underlying intangible assets difficult to evaluate and thereby reducing the consensus and accuracy of the earnings forecasts (Barth et al., 2001; Barron et al., 2001; Plumlee, 2003). Therefore, firms with higher underlying intangible assets should have future earnings that are more difficult for analysts to predict. Based on this previous literature, in examining what effect intangible assets have on analyst forecast accuracy, we hypothesize as follows:

H1: A firm's total underlying intangible assets are positively related to analyst forecast errors.

Evidence from the Australian context shows that recognizing intangible assets is associated with lower forecast errors and dispersion (Matolcsy & Wyatt, 2006) and using impairment based approach to goodwill valuation further strengthens the association (Chalmers et al., 2012). Therefore, we predict that forecast error will be lower for firms with a larger proportion of their total underlying intangible assets recognized in the balance sheet. Earlier studies have shown a more evident and stronger association between the proportion of capitalized intangible assets and forecast error, for firms with high level of intangibles compared to firms with low levels of intangibles (Matolcsy & Wyatt, 2006; Chalmers et. al., 2012). This is reasonable, since the intangibles for firms with very low amounts of underlying intangible assets should not have a heavy impact on future cash flows, and thus the potential information benefit from the capitalization of these assets is low. However, if a firm has large amounts of intangible assets, the information from capitalization would be much more important and useful for analysts in their forecasting task. Thus, our second hypothesis is:

H2: Capitalization of intangible assets relative to total underlying intangible assets is negatively related to analyst forecast errors.

Methodology

Intangible Assets Proxy

Since the vast majority of firms' intangible assets are not recognized in the balance sheets (Lev, 2001), a proxy for total underlying intangible assets has to be used in order to test our hypotheses. Previous literature has used several different proxies for intangible assets; Gu et al. (2005) uses R&D expenses, advertising expenses and acquired intangibles, while Barth et al. (2001) further adds depreciation expenses. However, in our study emphasis lies in the capitalization of intangible assets, and we want our results to be comparable to Matolcsy & Wyatt (2006) and Chalmers et al. (2012), which is why we choose to use their proxy for underlying intangible assets; market capitalization of equity less book value of equity, plus capitalized intangible assets. Further, Chung & Charoenwong (1991), Smith & Watts (1992) and Cohen et al. (2003) are other studies using the same measure, providing additional support for the use of this proxy for total underlying intangible assets.

The main weakness of this study relates to the validity issue of using this proxy for intangible assets; the difference between market value and book value of equity is not exclusively related to intangible assets. While the proxy captures differences in book and market values suggesting that the stock market estimates firm value or assets that may not be recognized in the balance sheet, there are a variety of factors unrelated to off-balance sheet intangibles that may cause the market value to differ from the book value. For example, stock prices are affected by speculation regarding the market as well as speculations about the future of a firm and single stock prices. Further, differences between book value and market value could simply devolve upon a firm's tangible assets having market value that is higher than the book value. Consequently, there are certain types of firms where this proxy is a poor measure of intangible assets. For example, oil companies have high uncertainty and speculation about whether new oil deposits will be found, and the real estate industry is characterized by buildings with extremely high market values relative to book values. Therefore, robustness tests will be made where industries that are unsuitable for our proxy for intangible will be removed from the sample.

The Model

Our research design largely follows that of Matolcsy & Wyatt (2006) and Chalmers et al. (2012) to increase the comparability between our studies. The following OLS regression model will be used for our main analysis:

$$\ln(ABSFE/TA) = B_0 + B_1 MVAD/MV + B_2 INTANG/MVAD + B_3 \ln(MV) + B_4 LEVERAGE + B_5 LOSS + B_6 \ln(EARNSD) + B_7 OPER\_CASH/DEBT + B_8 FOLLOWING + B_9 PRICECHANGE + \sum_{2005}^{2015} YEAR + \sum_{1}^{40} COUNTRY + \sum_{1}^{10} INDUSTRY \tag{1}$$

Where ABSFE/TA is the absolute forecast error, measured as the absolute value of earnings minus the mean of analysts' one year ahead earnings forecasts, scaled by total assets to increase comparability between firms of different sizes. Further, the dependent variable is logged to induce normality and reduce the influence of outlier observations in the tails of the distribution (Alford & Berger, 1999). MVAD is a proxy for the market value of a firm's total underlying intangible assets, measured as market capitalization of equity less (book value of equity less capitalized intangible assets). MVAD/MV is total underlying intangible assets divided by total market capitalization and is thus a proxy for intangibles intensity. Barron et al. (2002) find that US firms with higher levels of intangible assets have larger analyst forecast errors, which is also confirmed by Matolcsy & Wyatt (2006) and Chalmers et al. (2012) in an Australian setting. These studies suggest a positive relationship between MVAD/MV and analyst forecast error, which is in line with our first hypothesis. INTANG/MVAD is capitalized intangible assets divided by MVAD. This variable captures the proportion of the firms' total intangible assets that are capitalized in the balance sheet, and is the variable of interest for our second hypothesis. Including both MVAD/MV and INTANG/MVAD in the same model ensures that the total level of underlying intangibles, and the accounting option to capitalize them, are separately entered into the model (Matolcsy & Wyatt, 2006), which is necessary to test both our hypotheses.

Further, we include control variables to capture other factors that may affect analysts' ability to predict earnings forecasts. The control variables used are derived from the wider analyst forecast literature (Barth et al., 2001; Barron et al., 2001; Gu et al., 2005; Chalmers et al., 2012). Uncertainty and volatile performance has also been shown to influence analyst forecast errors (Lang & Lundholm, 1996) and control variables capturing this is therefore added to the model. First, we use the natural logarithm of EARNSD, which is the standard deviation of actual earnings over the full sample period, which reflects the increasing difficulty in forecasting firms with high volatility in earnings. Further, we use LOSS as a dummy variable for negative earnings, PRICECHANGE is the percentual change in price per share from the beginning to the end of the fiscal year, OPER_CASH/DEBT is operating cash flows to debt. A proxy for firm size, the natural logarithm of the market value of equity: ln(MARKETCAP), is used given large firms have higher analyst following (Lang & Lundholm, 1996) and generally less risky earnings (Matolcsy & Wyatt, 2006).

Table 1: Variable overview

Variable	Description
ln (ABSFE/TA)	The natural logarithm of the absolute average analyst earnings forecast errors, measured as the difference between estimated and actual earnings, over total book value of assets
MVAD/MV	Total underlying intangible assets, measured as market value of equity less book value of equity plus capitalized intangible assets, over market capitalization
INTANG/MVAD	Capitalized intangible assets over total underlying intangible assets
OPER CASH DEBT	Operating cash flow over total liabilities
PRICE CHANGE	Percentual change in price per share from the beginning to the end of the fiscal year
ln (EARNSD)	Natural logarithm of the standard deviation of actual earnings during the full sample period
LEVERAGE	Book value of total liabilities over book value of equity
ln (MV)	Natural logarithm of market value of equity
LOSS	Dummy variable for negative earnings
FOLLOWING	Total number of analyst forecasts made for a given year
ln (BESTSD/TA)	Natural logarithm of the standard deviation of analyst earnings forecasts over total assets

LEVERAGE is total book value of liabilities to book value of equity, to capture financial risk of the firm. Further, total number of analyst forecasts is added as a control variable to capture variation in the forecast errors that is a result of the number of forecasts made (Chalmers et al., 2012). Lastly, dummy variables for year, industry and country are also added to the model to control for effects on forecast error that are specific to differences between years and firm characteristics. Predicted in our second hypothesis is that the influence that capitalization of intangible assets has on analyst earnings forecast errors will differ for firms with respectively high and low levels of intangibles. Therefore, we divide our sample into two subgroups; one with observations with an above median level of intangibles (MVAD/MV > median) and one with observations with a level of intangibles that is below median (MVAD/MV < median), on which we also run our regressions.

As shown in previous studies, analysts demand information about firms' underlying intangible assets because they prefer to follow firms expected to perform well in the future (Barron et al., 2002). This creates incentives for firms to report intangible assets in order to attract analyst following by signaling certain future economic benefits (Barth et al., 2001). Matolcsy & Wyatt (2006) argue that this codetermination of the variables causes a causality loop which violates the OLS independence assumption with risk for biased standard errors and t-statistics. Therefore, they test their hypotheses using both OLS and two stage least squares (2SLS) regressions to evaluate the impact of this endogeneity. IFRS does not permit as subjective judgements about the capitalization of intangibles as the regulations did in Australia during Matolcsy & Wyatt's (2006) study, and thus this endogeneity problem might not be as severe for our sample. However, to improve comparability between our studies, and the robustness of our tests, we choose to also perform two stage least squares regressions.

$$\begin{aligned}\mathrm{fitted(INTANG/MVAD)}\\ &= B_0 + B_1 MVAD/MV + B_2 INTANG/TA + B_3 \ln(MV) + B_4 LEVERAGE + B_5 LOSS \\ &+ B_6 \ln(EARNSD) + B_7 OPER\_CASH/DEBT + B_8 FOLLOW + B_9 PRICECHANGE \\ &+ \ln(\mathrm{BESTSD}/TA) + \sum_{2005}^{2015} YEAR + \sum_{1}^{40} COUNTRY + \sum_{1}^{10} INDUSTRY\end{aligned} \tag{2}$$

$$\begin{aligned}\ln(ABSFE/TA) &= B_0 + B_1 MVAD/MV + B_2 fitted(INTANG/MVAD) + B_3 \ln(MV) + B_4 LEVERAGE \\ &+ B_5 LOSS + B_6 \ln(EARNSD) + B_7 OPER\_CASH/DEBT \\ &+ B_8 PRICECHANGE \qquad + \sum_{2005}^{2015} YEAR + \sum_{1}^{40} COUNTRY + \sum_{1}^{10} INDUSTRY\end{aligned} \tag{3}$$

To perform a 2SLS regression, a set of instrument variables that are correlated with the explanatory variables and uncorrelated with the disturbances should be used (Greene, 2000). Model 2 shows the first step of our 2SLS regression, where we estimate fitted values of INTANG/MVAD using instrumental variables. Matolcsy and Wyatt (2006) argue that it is expected that the supply of capitalized intangible asset and analysts' demand for this information are jointly determined by industry- and firm attributes, and instrument variables that are correlated with these attributes are needed. Like Matolcsy and Wyatt (2006), we use INTANG/TA (intangible assets over total assets, which is a measure of the firm's asset structure), FOLLOW (number of analysts following the firm) and ln BESTSD/TA (the logarithm of analyst earnings forecast dispersion scaled by total assets) as instrument variables in the first step of the regression where we estimate the fitted values of INTANG/MVAD.

Model 3 shows the second step of our 2SLS, where we run the regression replacing the original values with the fitted values of INTANG/MVAD, which we got from the first step. This way, we mitigate the endogeneity between the analyst earnings forecast errors and the option and incentives to capitalize intangible assets (Matolcsy & Wyatt, 2006).

Sample and Variables

As the aim of this study is to investigate how the relation between intangibles and analysts forecast errors appears on the European markets, we have chosen to examine this by using data from all listed firms on the European market with available forecast data in the Bloomberg database, which is used to collect all the financial accounting- as well as the forecast estimates data. Data availability limited the period of this study to the years 2005-2015, as almost no analyst forecast data could be collected for years earlier than 2005 using the Bloomberg database. We limit the scope of this study to examine the general relation between forecast error and intangible assets on the European market, and include all industries in our sample, using the SIC level 1 industry dummies as control variables in our model.

Regarding the decision on what type of income data to use when computing the variable for forecast error, we found three measures that would fit into our model; estimates of EBIT, EPS and net income. It could be argued that EBIT forecasts might be a better measure of earnings for this study as intangible assets have a large effect on future cash flows, but hardly on interest expenses and taxes. However, the Bloomberg database had significantly smaller amounts of data available for EBIT estimates compared to the other two measures. Further, previous research has mainly used net income or earnings per share (e.g. Gu et al., 2005; Matolcsy & Wyatt, 2006; Chalmers et al., 2012), and therefore we chose to use the estimates of net income in our study.

Examining the data in our sample, we found that some firms were applying other accounting standards than IFRS for some of the years in the study period. These observations were excluded, leaving the final sample consisting of 20 285 annual observations between the years 2005-2015, with a yearly range from 980 to 2401 observations, distributed over 40 countries. Descriptive statistics of the sample, showing number of observations per year, industry, and country, as well as the Bloomberg name of all the data variables needed to do the regressions are available in the appendix.

Table 2 shows descriptive statistics for all the variables in used in the regressions. The proxy that we use for underlying intangible assets, MVAD, is the market value of equity at the balance date, less book value of equity plus book value of intangibles. There are several studies that provide support for the use of this measure of underlying intangible assets (Chung & Charoenwong, 1991; Smith & Watts, 1992; Cohen et al., 2003; Matolcsy & Wyatt, 2006; Chalmers et al., 2012). As can be seen in the table, some of the values of our proxy for underlying intangible assets, MVAD, are negative, which has also been the case in previous studies using the same proxy (e.g. Matolcsy & Wyatt, 2006; Chalmers et al., 2012). While negative values on the amount of intangible assets for a firm is not theoretically plausible, Matolcsy & Wyatt (2006) explain that these negative values are most likely a result of falling market value that has preceded the write-down of intangible assets for the firm observations. As we mentioned earlier, it is for firms with higher levels of underlying intangibles that analysts stand to benefit most from the potentially important information attributable to capitalization of such assets. This is incorporated in our research design by conducting our regression analyses in two sub-groups of our sample, partitioned by the median MVAD/MV.

Table 2: Descriptive statistics (n = 20 285)

	Mean	Median	Minimum	Maximum	Standard Dev.
MARKET CAP	3 492,67	440,42	6,10	66 122,32	9 630,86
MVAD	2 210,22	194,48	-3 286,61	39 970,66	6 318,12
ln (ABSFE/TA)	-4,10	-4,03	-8,65	0,47	1,68
MVAD/MV	0,56	0,70	-2,55	2,32	0,68
INTANG/MVAD	0,32	0,22	-4,20	5,10	0,89
ln (MV)	6,32	6,24	1,81	11,10	2,04
LEVERAGE	2,68	1,34	-3,26	27,77	4,53
ln (EARNSD)	3,65	3,55	-0,50	8,58	1,96
OPER CASH/DEBT	0,12	0,12	-3,23	1,51	0,47
PRICE CHANGE	0,12	0,08	-0,81	2,09	0,50
FOLLOWING	9,35	6,00	1,00	58,00	9,27
LOSS	0,18	0,00	0,00	1,00	0,38
INTANG/TA	0,20	0,13	0,00	0,77	0,20
ln (BESTSD/TA)	-9,72	-9,69	-15,41	-4,05	2,28

Results

Table 3 reports both the parametric and non-parametric correlations for the variables used. The correlations between the dependent variable, ABSFE/TA and the variables of interest for our hypotheses, MVAD/MV and INTANG/MVAD, are all significant at a one percent level and have the signs predicted in our hypotheses, with the MVAD/MV correlation being positive and the INTANG/MVAD correlation being negative. Further, the instrument variable INTANG/TA which is used in our 2SLS regression is significantly and highly correlated with INTANG/MVAD, which must be the case in order to get a proper fitting of variables using 2SLS (Matolcsy & Wyatt, 2006). Further, the Spearman's and Pearson's correlations between MVAD/MV and INTANG/MVAD are 27,9 and 40,4 percent respectively. This difference between the parametric and non-parametric correlations suggests a non-linearity between the two variables and provides further support for performing the regression analyses in two groups, one with observations where MVAD/MV values are above median and one with MVAD/MV below median, representing intangibles intensive firms and non-intangibles intensive firms, respectively (Matolcsy & Wyatt, 2006).

Further, the table shows strong and significant correlations between three of the independent variables. The Spearman's and Pearson's correlations between FOLLOW and ln (MV) are 80,0 and 82,9 percent respectively, indicating that larger firms have higher analyst following. The correlations between ln (MV) and ln (EARNSD) also indicate that firm size is strongly positively associated with the dispersion of a firm's yearly earnings, which is also reasonable since larger firms usually have higher earnings than smaller ones. However, these strong correlations between independent variables also indicate that there is a potential multicollinearity problem that could bias the predictor coefficients in our regressions. Therefore, this issue will be handled in the next section where we conduct robustness tests of our model.

Table 4 provides a summary of the results from the regressions of both our regression models for the full sample as well as grouped by high and low intangibles intensity. Our first hypothesis was that a firm's total underlying assets would have a positive association to analyst forecast errors. The results show that MVAD/MV has positive coefficients, significant at a one percent level, for the full sample in both the OLS (0,215) and 2SLS (0,804) regressions, and thus confirms our hypothesis; firms with higher amounts of intangible assets are associated with higher analyst earnings forecast errors. This is consistent with results from previous studies showing that earnings for firms with a higher level of intangible assets are more difficult for analysts to estimate (Barron et al., 2002; Gu et al., 2005). This result is robust through all regressions, except in the OLS for the subset of firms with high intangibles intensity, where the coefficient for MVAD/MV is not statistically significant (t-statistics of -1,62) and have a negative sign.

Table 3: Pearson's and Spearman's correlations

Pearson's correlations												
	ln (ABSFE/ TA)	INTANG/ MVAD	MVAD/ MV	FOLLOW	OPCASH/ DEBT	CHANGE IN PRICE	ln (EARNSD)	LEVERAGE	ln (MV)	LOSS	INTANG / TA	ln (BESTSD / TA)
ln (ABSFE/ TA)		,026**	,024**	-,222**	-,137**	-,095**	-,134**	-,307**	-,338**	,438**	,079**	,368**
INTANG/ MVAD	-,044**		,279**	-,036**	-,004	-,034**	-,061**	-,071**	-,081**	,015*	,310**	,013
MVAD/ MV	,042**	,404**		,071**	,031**	,172**	-,067**	-,078**	,113**	-,091**	,550**	,029**
FOLLOW	-,226**	,019**	,079**		,098**	-,041**	,676**	,233**	,800**	-,143**	,001	-,532**
OPCASH/ DEBT	,003	-,036**	,115**	,087**		,106**	,040**	-,061**	,167**	-,392**	,009	-,081**
CHANGE IN PRICE	-,150**	-,058**	,164**	-,001	,172**		-,035**	-,041**	,114**	-,173**	-,004	,011
ln (EARNSD)	-,128**	-,029**	-,057**	,683**	-,064**	-,017*		,279**	,752**	-,014*	-,107**	-,531**
LEVERAGE	-,311**	,090**	,067**	,268**	-,382**	-,030**	,292**		,243**	-,016*	-,204**	-,395**
ln (MV)	-,327**	-,040**	,092**	,829**	,117**	,161**	,753**	,277**		-,284**	-,065**	-,634**
LOSS	,455**	-,013	-,048**	-,179**	-,368**	-,219**	-,025**	-,068**	-,285**		,021**	,195**
INTANG/ TA	,073**	,662**	,682**	,003	,150**	,007	-,110**	-,123**	-,055**	,001		-,008
ln (BESTSD / TA)	,339**	-,062**	-,014	-,520**	,097**	-,016*	-,530**	-,389**	-,627**	,181**	0,013	
Spearman's correlation												

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

MVAD is market value less book value of equity plus book value of intangibles; MV is market value of equity at balance date; MVAD/MV is MVAD divided by MV; LEVERAGE is total liabilities divided by book value of equity; EARNSD is the standard deviation of reported earnings for a firm over the entire sample period (2005-2015); OPER_CASH/DEPT is operating cash divided by total liabilities; FOLLOWING is the average amount of analysts making predictions for a firm, measured over a twelve month period; PRICE CHANGE is the annual change in share price between the two balance dates divided by the beginning share price; INTANG/TA is recognized intangible assets divided by total assets; ABSFE/TA is the absolute forecast error for an observation divided by total assets; LOSS is a dummy variable for observations with negative earnings. All variables are winsorized at the 1st and 99th percentile to clean the data from erroneous data values and reduce the influence of outliers. Reported are coefficients (t-statistics) and the adjusted R2. Unreported year, industry and country dummies are included in the estimation. OLS is ordinary least squares, 2SLS is two-stage least squares.

Table 4: Regression results on analyst forecast errors

Variable	Sign	OLS Full Sample (n = 20 285)	OLS >median MVAD (n = 10 142)	OLS <median MVAD (n = 10 143)	2SLS Full sample (n = 20 285)	2SLS > median MVAD (n = 10 142)	2SLS < median MVAD (n = 10 143)
INTANG/MVAD	-	-0,121**	-0,663**	-0,054**	-1,473**	-1,136**	-0,353**
		(-10,74)	(-17,98)	(-4,72)	(-16,45)	(-13,91)	(-5,71)
MVAD/MV	+/-	0,215**	-0,122	0,278**	0,804**	0,128*	0,448**
		(-12,63)	(-1,62)	(11,12)	(17,94)	(2,00)	(10,82)
OPER CASH DEBT	+	0,102**	0,094**	0,162**	0,148**	0,130**	0,207**
		(-4,50)	(-3,05)	(4,87)	(4,27)	(3,65)	(5,12)
PRICE CHANGE	-	-0,045*	-0,133**	-0,128**	-0,211**	-0,217**	-0,148**
		(-1,97)	(-4,23)	(-3,83)	(-6,22)	(-6,17)	(-3,96)
ln EARNSD	+	0,177	0,207**	0,235**	0,228**	0,237**	0,223**
		(-21,47)	(-17,51)	(19,58)	(18,33)	(17,66)	(16,16)
LEVERAGE	-	-0,085	-0,049**	-0,110**	-0,090**	-0,052**	-0,107**
		(-33,32)	(-13,16)	(-31,50)	(-25,79)	(-13,09)	(-29,10)
ln MV	-	-0,263	-0,340**	-0,306**	-0,373**	-0,341**	-0,333**
		(-23,73)	(-20,27)	(-19,82)	(-26,26)	(-23,14)	(-21,93)
LOSS	+	1,474	1,599**	1,391**	1,473**	1,670**	1,438**
		(-49,69)	(-35,16)	(36,24)	(34,80)	(33,59)	(33,52)
FOLLOWING	+/-	-0,001	0,011**	-0,004			
		(-0,31)	(-3,56)	(-1,52)			
Adjusted R2		0,37	0,35	0,43	0,26	0,33	0,43

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

MVAD is market value less book value of equity plus book value of intangibles; MV is market value of equity at balance date; MVAD/MV is MVAD divided by MV; LEVERAGE is total liabilities divided by book value of equity; EARNSD is the standard deviation of reported earnings for a firm over the entire sample period (2005-2015); OPER_CASH/DEPT is operating cash divided by total liabilities; FOLLOWING is the average amount of analysts making predictions for a firm, measured over a twelve month period; PRICE CHANGE is the annual change in share price between the two balance dates divided by the beginning share price; INTANG/TA is recognized intangible assets divided by total assets; ABSFE/TA is the absolute forecast error for an observation divided by total assets; LOSS is a dummy variable for observations with negative earnings. All variables are winsorized at the 1st and 99th percentile to clean the data from erroneous data values and reduce the influence of outliers. Reported are coefficients (t-statistics) and the adjusted R2. Unreported year, industry and country dummies are included in the estimation. OLS is ordinary least squares, 2SLS is two-stage least squares.

Our second hypothesis was that the capitalization of intangible assets relative to total underlying assets would have a negative association to analyst earnings forecast errors. Consistent with our hypothesis, INTANG/MVAD is negative and significant at a one percent level, and this result is robust through all regressions. The OLS regression output show that INTANG/MVAD has a negative coefficient (t-statistic) of -0,121 (-10,74) for the full sample, indicating that firms capitalizing a larger proportion of their intangible assets are associated with lower absolute analyst earnings forecast errors. When we run the regression in our subset of firms with low underlying intangible assets, we find that the association is a lot weaker, with a coefficient (t-statistic) of -0,054 (-4,72). However, the subset of firms with high underlying intangible assets have a much stronger relationship with a coefficient (t-statistic) of -0,663 (-17,98). This suggests that for firms that do have a considerable stock of intangible asset, recognition of these assets is strongly associated with a reduction of earnings forecast errors, while this effect is small or almost negligible for firms with low intangible assets. The 2SLS regression yields similar results, although here also the below median group shows a stronger negative association compared to the OLS, with the groups showing coefficients (t-statistics) of -1,136 (-13,91) and -0,353 (-5,71) respectively. Hence, our findings strongly suggest that capitalizing intangible assets provides analysts with valuable information that increases the accuracy of their earnings forecasts.

The direction of our control variables is consistent with prior studies. Our proxy for firm size, the natural logarithm of market capitalization, has a negative coefficient across all regressions. This evidence is consistent with smaller companies having less developed information environment and higher uncertainty regarding future prospects (Agarwal & Audretsch, 2001). Larger companies, on the other hand, are usually associated with better information flows, and their earnings are easier for analysts to accurately forecast. Other robust results from our regressions are that higher forecasting errors are associated with high volatility in earnings and loss-making firm years, while leverage and price change are associated with a decrease in forecast errors. These results are consistent with the results of Matolcsy & Wyatt (2006) as well as Chalmers et al. (2012).

Additional analyses

As mentioned earlier, there are several weaknesses in the model. First, the problem of measuring unrecognized intangible assets requires a proxy to be used, which in our model is the MVAD variable, measured as market value of equity less book value of equity plus book value of intangible assets. An apparent weakness of this proxy is that firms with a lot of tangible assets that are recognized well below market value will appear to have a lot of intangibles, while this is not actually the case. Further, industries like oil & gas are characterized by a lot of speculation, which also affects the market value of equity. Therefore, to test the robustness of our model, we re-estimated all the regressions after removing industries like oil & gas, real estate and metals & mining from our sample, as our proxy for intangible assets was deemed unsuitable for these industries. All the regressions give the same results as reported in Table 4, although the 2SLS shows slightly weaker coefficients on INTANG/MVAD.

Further, the correlation table showed a potential problem of multicollinearity, which could have a biasing effect on our estimated coefficients. Therefore, we also re-estimated the OLS regressions after removing FOLLOW and ln (EARNSD) from the model. Also here, the results are the same as in Table 4, having coefficients with the same signs and similar t-statistics of the variables. However, the coefficient for ln (MV) is less negative in this further testing for all three groups of firms, and the group of below median intangibles had a smaller coefficient of MVAD/MV compared to our original tests (0,146 down from 0,278).

We also ran all the regressions using a model where we replaced the absolute values analyst forecast errors with the dispersion of the earnings forecasts (ln (BESTSD/TA), measured as the standard deviation of all the available forecasts for a given firm and year, logged and scaled by total assets. The results from these regressions are shown in table 5. Consistent with our first hypothesis that the amount of intangible assets decreases the accuracy of analyst earnings forecasts, results show that this is also true for the dispersion of analyst forecasts. For the full sample regressions, MVAD/MV has highly significant coefficients of 0,336 and 1,213 for the OLS and 2SLS, respectively. As in our main analysis, this result holds also for the group of below median intangible firms. However, the group of intangible intensive firms has negative coefficients in both the OLS and 2SLS, where the former one is also statistically significant, with t-statistics of -4,61. This result is surprising, as it indicates that for intangible intensive firms, an increase in underlying intangible assets is associated with a decrease in the dispersion of the analyst earnings forecasts. However, for INTANG/MVAD the results show that, consistent with our second hypothesis, the coefficient is negative and statistically significant for all subsets of firms, which shows that the consensus among analysts increases with the proportion of intangible assets that are capitalized in the balance sheet. Further, other robust results from the regressions show that firm size, leverage and the amount of analysts following the firm are associated with a lower dispersion of earnings forecasts, while firm years with negative earnings increases the dispersion.

Table 5: Regression results on analyst forecast dispersion

Variable	Sign	OLS Full Sample (n = 20 285)	OLS > median MVAD (n = 10 142)	OLS < median MVAD (n = 10 143)	2SLS Full sample (n = 20 285)	2SLS > median MVAD (n = 10 142)	2SLS < median MVAD (n = 10 143)
INTANG/MVAD	-	-0,186**	-1,195**	-0,071**	-2,217**	-1,610**	-0,929**
		(-15,27)	(-31,71)	(-5,63)	(-17,38)	(-18,51)	(-11,86)
MVAD/MV	+/-	0,336**	-0,231**	0,579**	1,213**	-0,028	1,012**
		(17,78)	(-4,61)	(20,07)	(19,63)	(-0,45)	(19,36)
OPER CASH DEBT	+	0,000	0,004	0,022	0,004	0,008	0,048
		(-0,01)	(0,13)	(0,54)	(0,09)	(0,24)	(0,94)
PRICE CHANGE	+/-	0,157**	0,024	-0,049	-0,052	-0,013	-0,062
		(6,17)	(0,75)	(-1,29)	(-1,21)	(-0,40)	(-1,32)
ln EARNSD	+/-	-0,051**	-0,008	0,093**	0,036*	0,012	0,102**
		(-5,58)	(-0,71)	(6,62)	(2,28)	(0,98)	(5,93)
LEVERAGE	-	-0,09**	-0,058**	-0,113**	-0,106**	-0,062**	-0,120**
		(-33,61)	(-16,12)	(-29,98)	(-24,26)	(-16,73)	(-25,94)
ln MV	-	-0,606**	-0,710**	-0,730**	-0,843**	-0,781**	-0,851**
		(-47,77)	(-40,91)	(-39,98)	(-45,74)	(-55,12)	(-44,65)
LOSS	+	0,33**	0,514**	0,231**	0,234**	0,505**	0,184**
		(10,06)	(11,16)	(5,34)	(4,43)	(10,91)	(3,43)
FOLLOWING	-	-0,018**	-0,009**	-0,017**			
		(-8,30)	(-2,98)	(-5,95)			
Adjusted R2		0,65	0,66	0,70	0,42	0,64	0,61

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

MVAD is market value less book value of equity plus book value of intangibles; MV is market value of equity at balance date; MVAD/MV is MVAD divided by MV; LEVERAGE is total liabilities divided by book value of equity; EARNSD is the standard deviation of reported earnings for a firm over the entire sample period (2005-2015); OPER_CASH/DEPT is operating cash divided by total liabilities; FOLLOWING is the average amount of analysts making predictions for a firm, measured over a twelve month period; PRICE CHANGE is the annual change in share price between the two balance dates divided by the beginning share price; INTANG/TA is recognized intangible assets divided by total assets; ABSFE/TA is the absolute forecast error for an observation divided by total assets; LOSS is a dummy variable for observations with negative earnings. All variables are winsorized at the 1st and 99th percentile to clean the data from erroneous data values and reduce the influence of outliers. Reported are coefficients (t-statistics) and the adjusted R2. Unreported year, industry and country dummies are included in the estimation. OLS is ordinary least squares, 2SLS is two-stage least squares.

Conclusion

We hypothesize and find that analyst earnings forecast errors are positively associated with firms' level of intangible assets, and negatively associated with the proportion of capitalized intangible assets over total underlying intangible assets. Because most intangible assets are not recognized in firms' financial statements, although having a significant effect on future cash flows, the reporting of firms with a higher level of intangible assets is likely to be less informative for analysts and other stakeholders. For this reason, we expect more inaccurate analyst earnings forecasts for firms with high levels of intangible assets. Further, we also expect the capitalization of such assets to provide analysts with important information that improve the accuracy of their earnings forecast, and thus we predict lower earnings forecasts for firms that capitalize a large proportion of their underlying intangible assets. We base our tests on proxies, used in similar studies, that reflect all underlying intangible assets that are not shown in firms' balance sheets, as well as how large the proportion of such assets that is being capitalized is. The model used is based on Matolcsy & Wyatt's (2006) study on intangible assets effect on analyst following, earnings forecast error and dispersion on the Australian market.

Consistent with prior research, we find that on average, there is a positive association between a firm's level of intangible assets and analyst earnings forecast errors. Through further analysis, we find that this association is stronger for firms with a below median level of intangibles, while we do not find a significant association between the level of intangibles and earnings forecast errors for the group with above median level of intangibles. Conversely, we find that the proportion of capitalized intangible assets is more strongly negatively associated with earnings forecast errors for firms with high levels of intangible assets, compared to firms with no or low levels of intangible assets. Thus, our results suggest that the complexity that lies within the nature of intangible assets complicates the earnings forecasting task for analysts, but the capitalization of such assets can provide analysts with valuable information that increases the accuracy of their earnings forecasts. We also provide evidence that the usefulness of this information increases with the level of intangible assets that a firm has, as intangible assets' impact on future cash flows is not significant for firms with no or low level of intangibles.

In addition to our primary results we also find that firm size is associated with more accurate earnings forecasts, reflecting maturity, more stable growth, and more developed information environment. Further, smaller companies are usually associated with higher uncertainty regarding future prospects, which complicates the forecasting task. We also find that high volatility in earnings and negative earnings increase analyst forecast errors, while a positive and stable growth makes analysts' tasks easier and increases the accuracy of the earnings forecasts.

Overall, our evidence highlights the importance of intangible assets and demonstrates the potential useful information that capitalization of intangible assets could bring to analysts and investors in their forecasts and decision making. As current strict regulations regarding intangible assets results in most intangible assets staying off balance sheets, our results support Lev's (2001) arguing that a firm's underlying economics is not correctly embodied by the financial statements. Matolcsy & Wyatt (2006) and Chalmers et al. (2012) find that in the Australian setting, capitalization of intangible assets is associated with lower absolute analyst earnings forecast errors. Our study contributes to this literature, using the European setting to provide further evidence that capitalized intangible assets are useful to analysts and investors, and that the restrictive rules in IFRS regarding intangibles potentially reduce the usefulness of financial reports.

The limitations of this study that has been brought up and should be taken into consideration are mainly attributed to the difficulty in measuring intangible assets. Since most intangibles are not recognized in firms' balance sheets, a proxy for a firm's total intangible assets had to be used to perform the analyses. While there are a few different types of proxies used in previous research, each one has its limitations. The proxy chosen in this study is based on the difference between the book value and market value of equity, thus it does not well reflect intangible assets of firms that are subject to a lot of speculation or has a lot of tangible assets with market values way above the book values. To address this weakness and test the robustness of our model, additional regressions were run where we tried to exclude such firms from our sample, generating results no different from the ones in our main analyses.

While we find evidence suggesting that accounting regulations could benefit from allowing more capitalization of intangible assets, it is also important to keep in mind that our model does not capture the increased risks of earnings management, which would have a negative effect on the reliability of the accounting. Further, as forecast accuracy increases with the proportion of intangible assets that are capitalized, indicating less measurement uncertainty, one might also argue that firms tend to capitalize their intangible assets when there is less uncertainty regarding future economic benefits of the assets and it is easier to know when they should capitalize or not. Hence, the causality could go both ways as capitalization per se might not reduce measurement uncertainty, but could rather be a signal of an already existing lower uncertainty.

However, the literature could benefit from future research incorporating other measures of intangible assets in order to examine how different categories of intangible assets affect analyst earnings forecasts. Further, our study does not discuss industry specific tendencies regarding the association between intangible assets and analyst forecast errors. As there are certain industries that stand to benefit more than others from allowing capitalization, future research could examine this closer and provide important findings that assist standard setters in developing accounting regulations. The special US GAAP regulations regarding capitalization of development expenses for software companies is a great example of how the frameworks could be developed into having more industry specific accounting principles that better reflects the underlying economics of the firms.

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Appendix

Table A1: Sample by fiscal year

Fiscal year	Frequency	Percent	Cumulative Percent
2005	980	4,8	4,8
2006	1344	6,6	11,5
2007	1584	7,8	19,3
2008	1784	8,8	28,1
2009	1888	9,3	37,4
2010	1906	9,4	46,8
2011	2001	9,9	56,6
2012	2071	10,2	66,8
2013	2111	10,4	77,2
2014	2215	10,9	88,2
2015	2401	11,8	100
Total	20285	100	

Table A2: Sample by industry

Industry	Frequency	Percent	Cumulative Percent
Communications	1308	6,4	6,4
Consumer Discretionary	3582	17,7	24,1
Consumer Staples	1405	6,9	31
Energy	1015	5	36
Financials	2972	14,7	50,7
Health Care	1604	7,9	58,6
Industrials	3648	18	76,6
Materials	1751	8,6	85,2
Technology	2232	11	96,2
Utilities	768	3,8	100
Total	20285	100	

Table A3: Sample by country

Country	Frequency	Percent	Cumulative Percent	Country	Frequency	Percent	Cumulative Percent
AUSTRIA	349	1,7	1,7	**ITALY**	1220	6	70,9
BELGIUM	586	2,9	4,6	**JERSEY**	56	0,3	71,2
BRITAIN	5121	25,2	29,9	**LATVIA**	16	0,1	71,2
CROATIA	65	0,3	30,2	**LIECHTENSTEIN**	19	0,1	71,3
CYPRUS	38	0,2	30,4	**LITHUANIA**	19	0,1	71,4
CZECH	68	0,3	30,7	**LUXEMBOURG**	54	0,3	71,7
DENMARK	432	2,1	32,8	**MACEDONIA**	1	0	71,7
ESTONIA	92	0,5	33,3	**MALTA**	4	0	71,7
FAROE ISLANDS	14	0,1	33,3	**NETHERLANDS**	456	2,2	74
FINLAND	780	3,8	37,2	**NORWAY**	788	3,9	77,8
FRANCE	2458	12,1	49,3	**POLAND**	785	3,9	81,7
GEORGIA	3	0	49,3	**PORTUGAL**	198	1	82,7
GERMANY	2401	11,8	61,2	**ROMANIA**	47	0,2	82,9
GIBRALTAR	23	0,1	61,3	**RUSSIA**	394	1,9	84,9
GREECE	306	1,5	62,8	**SLOVENIA**	59	0,3	85,2
GUERNSEY	38	0,2	63	**SPAIN**	723	3,6	88,7
HUNGARY	47	0,2	63,2	**SWEDEN**	1143	5,6	94,4
ICELAND	10	0	63,3	**SWITZERLAND**	990	4,9	99,2
IRELAND	268	1,3	64,6	**TURKEY**	111	0,5	99,8
ISLE OF MAN	59	0,3	64,9	**UKRAINE**	44	0,2	100
				Total	20285	100	

Table A4: Bloomberg variables

Variable	Bloomberg variable name
Analysts 1 year ahead earnings forecast Mean	BEST_NET_INCOME
Analyst following	TOT_ANALYST_REC
Market cap	HISTORICAL_MARKET_CAP
Earnings (net income)	NET_INCOME
Capitalized intangible assets	BS_DISCLOSED_INTANGIBLES
Book value of equity	TOTAL_EQUITY
Total assets	BS_TOT_ASSET
Accounting regulation used	ACCOUNTING_STANDARD
Goodwill	BS_GOODWILL
Country	COUNTRY_FULL_NAME
Industry	BICS_LEVEL_1_SECTOR_NAME
Operating cash	CF_CASH_FROM_OPER
Operating expenses	IS_OPERATING_EXPN
Total liabilities	BS_TOT_LIAB2
EBIT	EBIT
EPS	IS_EPS
Share prices (yearly)	LAST_PRICE