Research and Development, Uncertainty, and Analysts' Forecasts: The Case of IAS 38

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Abstract

This study analyzes the consequences of the capitalization of development expenditures under IAS 38 on analysts' earnings forecasts. We use unique hand-collected data in a sample of highly research and development (R&D)-intensive German-listed firms over the period 2000–2007. We find that the capitalization of development costs is significantly associated with both higher individual analysts' forecast errors and forecast dispersion. This suggests that the increasing complexity surrounding the capitalization of development costs negatively impacts forecast accuracy. However, for firms with high underlying environmental uncertainty, forecast errors are negatively associated with capitalized development expenditures. This indicates that the negative impact of increased complexity on forecast accuracy can be outweighed by the information contained in the signals from capitalized development costs when the underlying environmental uncertainty is high. The findings contribute to the ongoing controversial debate

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on the accounting for self-generated intangible assets. Our results provide useful insights on the link between capitalization of development costs, environmental uncertainty, and analysts' forecasts for accounting academics and practitioners alike.

1. Introduction

This study analyzes the consequences of capitalizing development expenditures under IAS 38 for analysts' forecast accuracy and forecast dispersion. The standard requires capitalizing development costs under specific, restrictive conditions.[1] As a consequence, not all research and development (R&D) is capitalized but only an *a priori* unknown fraction. Analysts need to forecast not only future amounts of R&D, but also capitalization rates, amortization rates on previously capitalized amounts, and potential write-offs. Consequently, the forecasting complexity increases with the capitalization of development expenditures. Analysts' forecast accuracy has been found to decrease with increasing forecast complexity (see Ramnath et al., 2008 for a review). Accordingly, Aboody and Lev (1998) find that the complexities involved in the capitalization process lead to higher analysts' forecast errors for firms who capitalize parts of their software development costs. This is consistent with other studies showing that R&D is highly uncertain and complex, making it hard to obtain accurate analysts' forecasts (Amir et al., 2003; Chambers et al., 2003; Gu and Wang, 2005).

In other settings, however, the evidence points to the contrary. Some studies find evidence for higher forecast accuracy (Anagnostopoulou, 2010) associated with capitalized development costs. Similarly, research has found higher value relevance associated with R&D capitalization (Lev and Sougiannis, 1996) and lower information asymmetries for capitalized software development (Mohd, 2005). Matolcsy and Wyatt (2006) find that capitalization of intangible assets is associated with lower earnings forecast dispersion and lower absolute earnings forecast error. These benefits from capitalization derive from the discretion involved in the capitalization decision, which allows managers to signal their private information on the prospects of the investment to the market (Matolcsy and Wyatt, 2006; Ahmed and Falk, 2009). The evidence in Wyatt (2005) suggests that management is capitalizing when their firm has more certain intangible investments, that is, investments with less uncertain future benefits and, therefore, more predictable earnings (Matolcsy and Wyatt, 2006).

Given these conflicting findings, it is unclear whether the benefits of capitalization prevail or whether the additional complexities in the forecasting process resulting from capitalizing development expenditures thwart the informativeness of the capitalization signal for financial analysts. In this study, we provide evidence for this trade-off for the case of capitalizing development costs under IAS 38, which, to our best knowledge, has not been analyzed before.

Also, we aim to provide an explanation for these conflicting findings by analyzing the influence of the underlying environmental uncertainty. Environmental uncertainty refers to the unpredictability related to the actions of a firm's customers, suppliers, competitors, and regulators and other factors affecting its operations (Ghosh and Olsen, 2009). With regard to R&D, environmental uncertainty affects the outcome of its R&D ventures and the benefits accruing to the firm from these. Ghosh and Olsen (2009) find that managers make more use of discretionary accruals in the presence of high environmental uncertainty because of the timing and matching problems of cash flows being more severe under such conditions. Managers respond to the uncertainty of the external environment by signaling "their private information about the firm's performance and/or in an attempt to reduce perceptions of risk" (Ghosh and Olsen, 2009, p. 189). They conclude that the related benefits for earnings informativeness (Subramanyam, 1996; Louis and Robinson, 2005; Tucker and Zarowin, 2006) are likely to *only* occur to firms with high uncertainty environment (Ghosh and Olsen, 2009, p. 203). They call for more research into this matter. Based on this notion that in an environment of high operating uncertainty, managers use discretionary accruals for signaling and income smoothing, Tan and Sidhu (2012) show that analysts recognize and incorporate this information in their forecasts, particularly for firms with a high level of income smoothing related to high levels of uncertainty. Our study aims to provide further empirical evidence for this notion.

Environmental uncertainty affects the underlying economics of a firm that shape management's choice to recognize intangible assets (Wyatt, 2005). We conjecture that higher environmental uncertainty increases the need for additional information and, *ceteris paribus*, makes capitalization signals more valuable to analysts. Given that information asymmetries increase with higher environmental uncertainty and signaling becomes more costly, and hence more credible with increasing uncertainty (Verrecchia, 2001), we expect that the signals from capitalizing development expenditures become more informative for high uncertainty environments. Based on Ghosh and Olsen (2009), the benefits from such discretionary accrual accounting[2] should only materialize for firms with high environmental uncertainty.

In summary, R&D capitalization poses additional challenges for analysts to make accurate forecasts due to the high complexity involved in the process of forecasting the benefits of R&D projects, capitalization rates, subsequent amortization, and impairments. At the same time, the informativeness of the capitalization signal increases with greater environmental uncertainty, potentially exceeding the additional challenges that result from the complexity. Hence, we test whether under conditions of high uncertainty the capitalization signal is more informative than under more stable conditions. We find evidence consistent with these expectations.

We analyze a sample of the 150 largest German-listed companies during the period from 2000 until 2007.[3] We analyze a sample of large German firms that are highly R&D intensive and report under IFRS. In Germany, the importance of intangible assets is high due to the lack of natural resources. Indeed, Germany spent about 2.5 per cent of its GDP on R&D during the last decade, which is similar to the United States and substantially higher than the average of all other European Union countries as well as of all OECD countries (OECD, 2009).

We find that on average, the capitalization of development expenditures is associated with both higher analysts' earnings forecast errors and higher dispersion of forecasts. In line with Aboody and Lev (1998) for SFAS 86 (now ASC 350–40), this is likely to be due to the forecasting complexities associated with capitalized development costs. However, running the regressions separately for different sextiles of both share volatility and sales volatility, we further show that at least for forecast accuracy, this is not generalizable for the whole sample. Our results suggest that for high levels of uncertainty, the capitalization of development costs is significantly associated with lower forecast errors and, hence, contains valuable information for analysts.

We contribute to the accounting literature in a number of ways. Firstly, our study provides new evidence on the usefulness of capitalizing internally generated intangible assets. Our study extends prior U.S. evidence by Aboody and Lev (1998) for SFAS 86 (ASC 350–40) on software development for the IFRS setting. The capitalization of development expenditures under IAS 38 is an exception to the general rule of expensing investments in intangibles prevalent in most GAAP and provides a natural experiment to investigate the consequences. Pownall and Schipper (1999) point out that little evidence exists about the economic consequences of accounting standards and request additional evidence on differences in the adoption and interpretation of accounting standards. Our study sheds light on how information under a specific accounting standard, that is, IAS 38, is processed by market participants, in particular, by analysts. IAS 38 was introduced to increase decision usefulness and to improve market efficiency by providing relevant information through the capitalization of development expenditures. Our results suggest that capitalization of development costs on average impedes the forecasting process and results in lower forecast accuracy and higher dispersion. However, our findings establish that the signal from capitalization is informative under conditions of high environmental uncertainty, consistent with Ghosh and Olsen (2009).

Secondly, our study contributes to the literature on analysts' forecasts, particularly the effects of information complexity (e.g., Duru and Reeb, 2002; Plumlee, 2003; Hirst et al., 2004; Hope, 2004; Kang et al., 2014). Consistent with this literature, our findings suggest that the increasing complexity surrounding capitalized development costs negatively impacts forecast accuracy and forecast dispersion. However, we show that the negative impact of increased complexity can be outweighed by the signaling benefits from capitalized development expenditures when the underlying environmental uncertainty is high. The findings imply that signals from discretionary accruals become more informative with increased environmental uncertainty and directly speak to Ghosh and Olsen's (2009) call for future research on the impact of uncertainty on managerial discretion.

Our results are useful for standard setters and practitioners alike. While it is acknowledged that internally generated intangibles are assets, they are not capitalized under most accounting regulations on the grounds that the future benefits of such investments are too uncertain. Our results imply that capitalization may be particularly informative, especially when uncertainty is high. On the other hand, when uncertainty is low, the complexities of the rules for capitalization thwart the informativeness of the capitalization signal. Under such circumstances, less complex mandatory accounting rules may be more informative. These results are of interest particularly for standard setters with regard to the ongoing debate about the accounting for self-generated intangible assets.

The study is organized as follows: Section 2 provides the literature review and development of hypotheses; Section 3 shows our research design and describes the sample; and Section 4 presents our empirical results and Section 5 concludes.

2. Related Literature and Hypotheses Development

2.1. Capitalizing Intangibles and Analyst Forecasts

There is an intensive debate about the capital market consequences of capitalizing intangibles. In this research, we focus on analysts as skilled users of accounting information. Prior research finds that analysts have strong incentives to provide investors with additional information, such as accurate earnings forecasts, for highly intangible-intensive firms (e.g., Barron et al., 2002; Amir et al., 2003; Gu and Wang, 2005). An accounting regime that allows capitalizing internally generated intangible assets, such as R&D, may aid analysts in making their forecasts and in providing both more relevant and accurate information on future earnings. Matolcsy and Wyatt (2006) find that Australian financial analysts expect firms to capitalize expenditures related to more certain intangibles. For the Dutch setting, Peek (2005) also provides evidence that a change from expensing to capitalization improves forecast accuracy. Anagnostopoulou (2010) finds similar results for the United Kingdom.

On the other hand, research in other settings has found evidence for the contrary. Gu and Wang (2005) find that the high information complexity of intangibles increases analysts' forecast error of intangible-intensive firms. Under US-GAAP, investments in intangibles, such as R&D expenditures, are generally expensed as incurred. The only exception is provided by SFAS 86 (ASC 350–40), which allows partially capitalizing software development costs. In this setting, Aboody and Lev (1998) find that management's discretion in capitalizing software development expenditures introduces noise into analysts' earnings forecasts.[4] This is particularly interesting because at the same time, they find an increase in value relevance, that is, the reported software asset is positively associated with stock prices indicating the informativeness of capitalized software costs.[5] Along these lines, Mohd (2005) shows that SFAS 86 (ASC 350–40) reduces information asymmetries measured by bid-ask spreads for software development. Mohd cautions researchers to generalize his findings to all R&D because of the differences in uncertainty of the future benefits (Mohd, 2005, p. 1229).

Hence, even though the recognition criteria under IAS 38 are almost identical to SFAS 86 (ASC 350–40), it is unclear whether the results for SFAS 86 (ASC 350–40) translate to the capitalization of development costs under IAS 38. Dinh and Schultze (2010) find that capitalization of development costs under IAS 38 is not value relevant and does not decrease information asymmetries in a German setting. Cazavan-Jeny et al.'s (2011) results for French GAAP are similar.

Given these conflicting results, both the information complexities and the uncertainties related to the future benefits of intangible investment seem to influence the question of whether capitalization impedes or aids in the forecasting process.

2.2. Information Complexity and Forecasting

Gu and Wang (2005) find that intangibles involve, by nature, more complex information than other assets. Consequently, the high information complexity of intangibles increases the difficulty of processing the information and making forecasts. While capitalization of intangibles may help in this process, literature finds that the capitalization of development expenditures imposes additional complexities on the analyst when making forecasts. Independent of the R&D accounting, analysts need to forecast the outcome of current R&D projects as well as future R&D expenditures and their subsequent consequences for investments in PPE, working capital as well as revenue and costs. Under IAS 38, analysts additionally need to differentiate between capitalized development costs and expensed R&D costs in order to forecast book values and earnings. Due to the partial recognition rule, analysts need to forecast not only the amount of R&D expenditures but also capitalization and subsequent amortization rates. They further need to predict the success of projects with previously capitalized development costs to forecast possible impairment charges. Based on an example from the automobile industry, Wrigley (2008) illustrates this increasing complexity of forecasting. He shows that forecasting earnings has become considerably more complex after the adoption of IAS 38 because of the changing rates of capitalization. Capitalized development expenditures introduce additional noise into analysts' earnings forecasts due to uncertain earnings components like the capitalization rate in next year's financial report (Aboody and Lev, 1998).

The literature on earnings forecasts has found that complexity reduces analysts' use of the related information and decreases forecast accuracy (e.g., Plumlee, 2003; Hirst et al., 2004; Hope, 2004). For example, Duru and Reeb (2002) find that international diversification presents unique challenges for forecasting and is associated with less accurate and more optimistic forecasts. Kang et al. (2014) test analysts' information processing inefficiency, captured by the serial correlation of earnings, as an explanation for the price-earnings-announcement drift, based on the idea that analysts do not adequately process information contained in prior earnings. They find the effect to be stronger for international firms because of the additional complexities contained in evaluating international firms, consistent with Duru and Reeb (2002).

In summary, prior results indicate that the complexities of information on R&D-intensive firms and the additional complexities involved in forecasting the earnings of firms capitalizing portions of their development costs present additional challenges for making accurate earnings forecasts.

2.3. Uncertainty of Future Benefits of R&D Investments

Standard setters restrict the capitalization of investments in intangibles because of the uncertainty associated with the future benefits from these assets (Wyatt, 2005). Wyatt (2005) identifies technological and property rights conditions within the firm's business environment that determine the predictability of future benefits and the probability that the firm will appropriate these benefits. Uncertainties related to these elements of the business environment directly relate to the uncertainties of the future benefits. Accordingly, we consider two related but different levels of uncertainty: The uncertainty of the environment the firm is operating in and the uncertainty of the future benefits resulting from the firm's R&D activities. Regarding the first, the uncertainty of a firm's business environment, a firm's operations are faced with uncertainty because the actions of their customers, suppliers but also competitors and regulators are not predictable (Govindarajan, 1984; Ghosh and Olsen, 2009). These factors external to the entity may affect the firm's output as captured in a higher variability of net sales and, consequently, higher variability of operating performance as captured by cash flows and earnings before discretionary accruals (Cheng and Kesner, 1997; Ghosh and Olsen, 2009; Tan and Sidhu, 2012). Similarly, share volatility constitutes an external factor that captures the degree of environmental uncertainty a firm is operating in.

Technological and property rights conditions within the business environment affect the appropriation of future benefits from the R&D investment (Wyatt, 2005). By nature, future economic benefits related to intangible assets such as R&D are far more uncertain than those related to tangible assets, particularly in R&D-intensive industries (Kothari et al., 2002; Amir et al., 2007). Although R&D expenditures have the character of an investment, that is, are undertaken with the prospect to generate higher future benefits (Fisher, 1930), they differ from capital investments in several ways. R&D investments generate innovations while capital expenditures are necessary to produce products that embody these innovations. On a time line, R&D outlays precede fixed capital investments required to produce the goods ready to be sold to customers (Wyatt, 2008). The longer the technology life cycle and the lower the strength of the particular technology, the more uncertain the future benefits of the investment outlays are (Wyatt, 2005). Accordingly, R&D investments are not directly associated with a stream of revenues from the sale of goods, but suffer from complex lead–lag relations between investment and future expected benefits. Due to its heterogeneity and non-standardized nature, R&D success is highly uncertain and its benefits are more difficult to control and to predict compared to the output from capital investments (Webster, 1999).

A further source of uncertainty related to the future benefits may result from the inability to assign property rights over extended periods to an R&D project separately (Skinner, 2008). In the event of project failure, there are typically few alternative uses for R&D investments and the liquidation value is usually not substantial (Kothari et al., 2002). So R&D investments are significantly associated with higher subsequent earnings variability than investments in PPE (e.g., Kothari et al., 2002; Amir et al., 2007; Ahmed and Falk, 2009). Amir et al. (2007) demonstrate that the greater future earnings variability is mainly driven by firms of R&D-intensive industries and does not generally extend to all industries. This high uncertainty of the benefits of R&D activities explains considerably higher information asymmetries for R&D-intensive firms (Mohd, 2005). Earnings volatility has been shown to be associated with lower earnings predictability and lower forecast accuracy (Graham et al., 2005; Dichev and Tang, 2009; Tan and Sidhu, 2012). Accordingly, different types of intangibles differ in terms of the uncertainty of future benefits (Wyatt, 2008). In this research, we focus on R&D investments for which the future benefits are less certain than for, for example, software development costs (as analyzed in Aboody and Lev, 1998) but more certain compared to other intangible assets such as brands, publishing titles, and customer lists (as analyzed, e.g., in Matolcsy and Wyatt, 2006). Depending on the particular kind of R&D within the particular operating environment, the uncertainties of future benefits of different R&D investments differ widely (Wyatt, 2008).

In summary, the economic characteristics of R&D investments involve various uncertainties directly related to the uncertainties of the firm's business environment, making forecasts for future benefits from R&D investments more difficult and less reliable than forecasts from capital investments. Particularly, the high uncertainties involved in the future benefits of R&D present additional challenges for analysts (Gu and Wang, 2005).

2.4. Environmental Uncertainty and Signaling

Prior literature finds that capitalizing intangible investments allows managers to signal private information on the future benefits to the market (Matolcsy and Wyatt, 2006; Ahmed and Falk, 2009). The evidence in Wyatt (2005) suggests that management is capitalizing when their firm has more certain intangible investments, that is, investments with less uncertain future benefits and, therefore, more predictable earnings. Accordingly, Matolcsy and Wyatt (2006) find that capitalization of intangible assets is associated with lower earnings forecast dispersion and lower absolute earnings forecast error. These benefits from capitalization derive from the discretion involved in the capitalization decision, which allows managers to signal their private information on the prospects of the investment (Matolcsy and Wyatt, 2006; Ahmed and Falk, 2009).

Signaling theory (Riley, 1975, 2001) suggests that for a signal to be informative, there need to be costs associated with signaling (Verrecchia, 1983; Dye, 2001), otherwise all firms could equally benefit from signaling. Firm's trade-off costs and benefits when making decisions about disclosing or withholding information. Firms can benefit from disclosing information by reductions in information asymmetry (Verrecchia, 2001), which suggests that a key element for linking the firm's disclosure decision to efficiency and incentives is information asymmetry. The latter increases with increasing uncertainty; hence, the benefits from disclosing information increase with higher uncertainty.

Basic disclosure models in agency and signaling theory imply full disclosure for firms to avoid high costs of capital. Proprietary cost theory suggests that there are direct and indirect costs arising from the preparation, dissemination, and the auditing of information including possibly harmful competitive reactions (Verrecchia, 1983, 2001) or actions of regulatory authorities (Lambert et al., 2007). These costs explain why firms withhold some of the information (Verrecchia, 1983). Uncertainty offers an alternative rationale similar to disclosure cost because it creates doubt in the minds of the uninformed, supporting the withholding of information (Verrecchia, 2001). In the presence of uncertainty, withholding information may prevent the manager from a potential loss in credibility in the future period, once more information is released at a later date (Teoh and Hwang, 1991).

Consequently, in cases of high uncertainty, firms could withhold information without fear of negative consequences. Hence, firms that disclose information by capitalizing development expenditures in the presence of high environmental uncertainty would only do so if they do not fear negative consequences. Hence, higher uncertainty makes the disclosed information more credible. Consequently, we expect the capitalization signal to be informative in highly uncertain environments.

2.5. Capitalization of Development Expenditures and Analyst Forecasts

The capitalization of development costs under IAS 38 may help in reducing information asymmetries, as has been shown by Mohd (2005) for software development costs under SFAS 86 (ASC 350–40). However, software development costs are a type of investment for which future economic benefits are more certain relatively to R&D and, as such, the results may not directly translate to the R&D setting. They may differ for various levels of external environmental uncertainty. The difference in uncertainty is reflected in the accounting for R&D under IAS 38, which prescribes the capitalization of development costs if specific recognition criteria are met while prohibiting the capitalization of other intangible assets such as brands and customer lists. Hence, the future benefits related to capitalized development costs are more certain than for the expensed portion.

If capitalized development costs are more certain than expensed R&D, consistent with Wyatt (2005), then the capitalization signal should be informative to investors (Matolcsy and Wyatt, 2006). Only if the signals from capitalization are considered credible by market participants and outweigh the additional complexities associated with it, we can expect capitalization to improve forecasting, resulting in a decrease in forecast errors and dispersion.

To the best of our knowledge, no study, so far, has analyzed the relationship between capitalized development expenditures under IFRS and forecast accuracy. Given the different levels of uncertainty of R&D compared to software development and other intangibles, and given that the findings from prior research on the association of capitalized development costs and forecast accuracy are mixed, we state our H1a in the null:

> **H1a:** Capitalized development expenditures under IAS 38 are not associated with individual analysts' forecast errors.

Consistent with Aboody and Lev (1998), we also examine the influence of capitalized development costs on the dispersion of analysts' forecasts. Dispersion of analysts' forecasts can be interpreted as an alternative measure of information asymmetry in the capital market (Mohd, 2005). Based on the arguments presented above, we also argue that the association of capitalized development costs under IAS and dispersion of analysts' forecasts may be both positive and negative and state H1b in the null as follows:

> **H1b:** Capitalized development expenditures under IAS 38 are not associated with dispersion of analysts' forecasts.

While the non-directional hypotheses H1a and H1b refer to the entire sample, in a next step, we analyze whether conditions exist under which the capitalization of development expenditures may be more or less favorable for analysts' forecasts of earnings. In this study, we are interested in the combined effect of the accounting for a firm's highly uncertain R&D investment when the entity is operating in an environment of high uncertainty. We argue that both high environmental uncertainty and investments for which future economic benefits are highly uncertain will result in a situation where information asymmetry is particularly high. This is based on evidence that information asymmetry is positively related to both R&D investment (Aboody and Lev, 2000) and uncertainty (Akerlof, 1970; Umanath et al., 1996; Ghosh and Olsen, 2009).

The literature on disclosure suggests that a firm discloses information if the benefits of disclosing the information outweigh the costs related to it (Verrecchia, 2001). In our context, the benefits of disclosing capitalized development expenditures may materialize by signaling external users' private information about the prospects of future economic benefits related to an R&D project. If analysts are able to interpret the information correctly, forecast errors would decrease. This needs to be weighed against the costs of preparing the information. Once more information suggests that the estimate about the positive prospects did not prove right, companies may face a potential loss in credibility (Teoh and Hwang, 1991).

Wyatt (2005) shows that management's choice to record intangible assets is shaped by a firm's underlying economics and the related uncertainty. Ghosh and Olsen (2009) find that managers make more use of discretionary accruals in the presence of high environmental uncertainty because of the timing and matching problems of cash flows being more severe under such conditions. Managers respond to the uncertainty of the external environment by signaling (Ghosh and Olsen, 2009). They find that firms with high environmental uncertainty show significantly higher discretionary accruals to signal information on the companies' performance by smoothing earnings. While such discretion may be exercised opportunistically, prior evidence shows that discretionary accruals are used for increasing earnings informativeness (Subramanyam, 1996; Louis and Robinson, 2005; Tucker and Zarowin, 2006). Ghosh and Olsen (2009) conclude that the related benefits are likely to *only* occur to firms with high uncertainty environment (Ghosh and Olsen, 2009, p. 203). Dichev and Tang (2009) find that considering earnings volatility substantially improves earnings predictability and allows identifying systematic errors in analyst's forecasts. Based on the notion that in an environment of high uncertainty, managers use discretionary accruals for signaling and income smoothing, Tan and Sidhu (2012) show that analysts recognize and incorporate this information in their forecasts, particularly for firms with a high level of income smoothing related to high levels of uncertainty.

Weiss et al. (2013) illustrate that equal investments in different R&D ventures are associated with differential variability of future earnings in the US-GAAP setting where R&D capitalization is not allowed. Their findings suggest that additional information is needed to incorporate the information contained in earnings variability in forecasts. Weiss et al. (2013) evidence indicates that high-risk R&D investments are accompanied by a significantly larger frequency of press releases to meet the needs for additional information when uncertainty is high. Instead of press releases, R&D capitalization may provide such additional information by signaling the prospects of the project to the market. Hence, we expect that capitalized development costs are informative, that is, are associated with lower forecast errors for firms with high underlying environmental uncertainty.

Capitalizing development expenditures can be used to signal private information on the future benefits related to the investment. Hence, we can expect that most notably firms with high environmental uncertainty will benefit from the signaling effects when capitalizing development expenditures. While we do not have an ex-ante prediction about the direction of the association of capitalized development expenditures with forecast accuracy, we expect a significant and positive association for firms with high underlying environmental uncertainty, that is, significantly lower forecast errors.

H1c: For firms with high underlying environmental uncertainty, capitalized development expenditures under IAS 38 are negatively associated with analysts' forecast errors.

Similarly, we expect that the benefits of capitalizing development expenditures related to forecast dispersion will materialize more strongly for firms operating in a high uncertainty environment only. Our H1d is stated as follows:

H1d: For firms with high underlying environmental uncertainty, capitalized development expenditures under IAS 38 are negatively associated with analysts' forecast dispersion.

3. Research Design and Sample

3.1. Research Design

3.1.1. Main empirical models. The main variable of interest is *DCAP*, which represents the annual capitalized development costs. Our main models for testing our hypotheses are as follows (all variables are defined as in the Appendix A):

$$
\begin{aligned}
BFE_{it} = {} & \beta_0 + \beta_1 DCAP_{it} + \beta_2 BETA_{it} + \beta_3 FOL_{it} + \beta_4 IFRS_{it} + \beta_5 LEV_{it} \\
& + \beta_6 LOSS_{it} + \beta_7 RDG_{it} + \beta_8 SCH_{it} + \beta_9 BIG_{it} + IND + YEAR \\
& + \varepsilon_{it} \qquad (1a)
\end{aligned}
$$

$$
\begin{aligned}
SDF_{it} = {} & \beta_0 + \beta_1 DCAP_{it} + \beta_2 BETA_{it} + \beta_3 FOL_{it} + \beta_4 IFRS_{it} + \beta_5 LEV_{it} \\
& + \beta_6 LOSS_{it} + \beta_7 RDG_{it} + \beta_8 SCH_{it} + \beta_9 BIG_{it} + IND + YEAR \\
& + \varepsilon_{it} \qquad (1b)
\end{aligned}
$$

A positive coefficient β_1 of *DCAP* would suggest that the capitalization of development expenditures impedes the forecasting process by increasing analysts' forecast errors (*BFE*) (H1a) and increasing analysts' forecast dispersion (*SDF*) (H1b). A negative coefficient would suggest an improvement in forecast accuracy and forecast dispersion related to the capitalization of development costs. As we use individual broker estimates from 2000 until 2007 to calculate forecast errors, our sample size is significantly larger in equation (1a) compared to equation (1b). For (1b), we use panel least square regressions, because forecast dispersion is measured by the standard deviation of individual analysts' forecast and, hence, is only available at the panel level.

Apart from our variable of interest *DCAP*, we include several variables to control for an additional potential impact on forecast errors consistent with previous research (e.g., Aboody and Lev, 1998; Alford and Berger, 1999; Ashbaugh and Pincus, 2001; Gu and Wang, 2005; Matolcsy and Wyatt, 2006; Hodgdon et al., 2008; Glaum et al., 2013). Detailed definitions for the control variables are outlined in the Appendix A.

BETA is a risk measure for the uncertainty of future performance (e.g., Alford and Berger, 1999). The higher the systematic risk of a firm, the higher the forecast error is expected to be. Analyst following serves as a proxy for disclosure quality (Botosan, 1997; Orens et al., 2009; Boujelbene and Affes, 2013). High analyst following suggests high quality of a firm's information environment as well as large dissemination of financial information. The number of analysts following a firm (*FOL*) should improve forecast accuracy because higher information density of analysts' information facilitates the forecasting process (e.g., Aboody and Lev, 1998; Gu and Wang, 2005).[6] The count variable *IFRS* reflects that after the adoption of IFRS, the forecast error is expected to decrease because of a larger set of disclosures (e.g., Ashbaugh and Pincus, 2001; Hodgdon et al., 2008; Glaum et al., 2013). *LEV* controls for the leverage effect of firms because higher leveraged firms reveal higher risk leading to higher forecast errors (Matolcsy and Wyatt, 2006).

LOSS accounts for the higher forecast bias for firms generating losses (Hwang et al., 1996; Matolcsy and Wyatt, 2006). Consistent with Danielson and Press (2005), we expect higher R&D growth (*RDG*) of a firm to be associated with higher forecast error. Growth firms are often younger firms with a lower level of information available to financial analysts. Danielson and Press (2005) also show that the differences between a firm's growth rate and return on net assets are the main drivers for estimates of the future firm's performance. As the change in sales (*SCH*) is a primary driver for future performance of a firm, it may influence forecasting accuracy (Penman, 2007). We conjecture that higher changes in sales reflect a more volatile business leading to higher forecast errors. Audit quality is proxied for by a dummy variable *BIG* which is 1 if a firm belongs to one of the BIG 5 accounting firms at the time and 0 otherwise. Consistent with prior literature, we expect higher audit quality to reduce forecast errors and forecast dispersion (Behn et al., 2008). Our models include both industry (*IND*) and year (*YEAR*) fixed effects.

In our hypotheses H1c and H1d, we investigate the influence of uncertainty on the association of capitalized development costs and forecast accuracy and forecast dispersion, respectively. While we do not have an *a priori* expectation about the association for the whole sample (H1a and H1b), we expect the capitalization to be informative in situations where additional information may be useful to overcome existing information asymmetries, that is, under conditions of high environmental uncertainty.

We therefore include share volatility (and alternatively sales volatility) in our regression to proxy for environmental uncertainty (Ghosh and Olsen, 2009). We adapt (1a) and (1b) and include *ShareVola* (and alternatively *SalesVola*) as well as the binary variable *dummy_CAP* and the interaction with the two variables in our regressions. This allows us to distinguish the impact of uncertainty on forecast accuracy and forecast dispersion for capitalizers and expensers:

$$
\begin{aligned}
BFE_{it} = \beta_0 &+ \beta_1 ShareVola_{it} + \beta_2 dummy\_CAP_{it} \\
&+ \beta_3 ShareVolaxdummy\_CAP_{it} + \beta_4 BETA_{it} + \beta_5 FOL_{it} \\
&+ \beta_6 IFRS_{it} + \beta_7 LEV_{it} + \beta_8 LOSS_{it} + \beta_9 RDG_{it} + \beta_{10} SCH_{it} \\
&+ \beta_{11} BIG_{it} + IND + YEAR + \varepsilon_{it}
\end{aligned}
\tag{2a}
$$

$$
\begin{aligned}
SDF_{it} = \beta_0 &+ \beta_1 ShareVola_{it} + \beta_2 dummy\_CAP_{it} \\
&+ \beta_3 ShareVolaxdummy\_CAP_{it} + \beta_4 BETA_{it} + \beta_5 FOL_{it} \\
&+ \beta_6 IFRS_{it} + \beta_7 LEV_{it} + \beta_8 LOSS_{it} + \beta_9 RDG_{it} + \beta_{10} SCH_{it} \\
&+ \beta_{11} BIG_{it} + IND + YEAR + \varepsilon_{it}
\end{aligned}
\tag{2b}
$$

Consistent with H1c and H1d, we predict a significant and negative coefficient for β_3 in both regressions, expecting the capitalization of development expenditures to reduce analysts' forecast errors. In addition, we rerun (1a) for different levels of uncertainty and analyze the impact of uncertainty on forecast accuracy for each sextile of share volatility and sales volatility separately.[7] We expect forecast errors and capitalization of development expenditures to show a negative association in higher sextiles of volatility only (H1c).[8]

3.1.2. Endogeneity. Previous empirical results indicate that the decision to capitalize is not only driven by accounting rules like IAS 38, but also by different characteristics of companies (e.g., Aboody and Lev, 1998; Cazavan-Jeny and Jeanjean, 2006; Oswald, 2008). As a consequence, the capitalization of development costs may be endogenously determined by other firm properties rather than by the capitalization rule of IAS 38. Due to that endogeneity problem, our inferences on forecast accuracy may be biased. Hence, we adopt a 2SLS approach, consistent with previous studies (e.g., Barth et al., 2001; Matolcsy and Wyatt, 2006).

In the first stage, we consider different fundamental characteristics that previously have been shown to affect firms' reporting behavior (e.g., Gu and Wang, 2005). Besides fundamental properties, we further include potential opportunistic factors likely influencing managers' decisions to capitalize development expenditures under IAS 38.

Our dependent variable *DCAP* in the first stage is limited to a range not below zero (censored), and we have many observations equal to zero due to full R&D expensers. Hence, ordinary least squares estimates would be biased (Kennedy, 2008), and we run our test based on the following Tobit model (all variables are defined as in the Appendix A):

$$DCAP_{it} = \beta_0 + \beta_1 BETA_{it} + \beta_2 FOL_{it} + \beta_3 IFRS_{it} + \beta_4 LEV_{it} + \beta_5 LOSS_{it} + \beta_6 MB_{it} + \beta_7 RDINT_{it} + \beta_8 DCAPlag_{it} + IND + YEAR + \varepsilon_{it} \tag{3}$$

In the second stage of the 2SLS approach, the original variable of *DCAP* is replaced by the instrumented value from the first-stage estimation. By including all right-hand variables of equation (3) as instruments in equation (4), we satisfy the condition for identification and rank. We further include the variable *SCH* capturing the absolute value of change in sales and *RDG* as a measure for R&D growth as independent variables in the first stage. These variables will represent control variables when estimating forecast accuracy/dispersion in the second stage.

$$DCAP_{it} = Equation(3) + \beta_9 RDG_{it} + \beta_{10} SCH_{it} + \varepsilon_{it} \tag{4}$$

The determinants used in the first stage that significantly impact the amount of capitalized development expenditures are consistent with previous research (e.g., Aboody and Lev, 1998; Alford and Berger, 1999; Barth et al., 2001; Wyatt, 2005; Oswald and Zarowin, 2007; Markarian et al., 2008; Cazavan-Jeny et al., 2011). Based on the estimated *DCAP*, we run the second-stage estimation as stated in equation (5a) and (5b), respectively.

$$BFE_{it} = \beta_0 + \beta_1 Instrumented(DCAP)_{it} + CONTROLS + \varepsilon_{it} \tag{5a}$$

$$SDF_{it} = \beta_0 + \beta_1 Instrumented(DCAP)_{it} + CONTROLS + \varepsilon_{it} \tag{5b}$$

CONTROLS in (5a) and (5b) are consistent with the control variables used in (1a) and (1b).

3.2. *Sample Characteristics and Summary Statistics*

The initial sample of our study comprises observations based on the 150 largest firms listed on the German Stock Exchange during the period of 2000–2007. Our observation period ends in 2007 to avoid confounding effects with the global financial crisis starting in 2008 (e.g., Kang et al., 2014). Our original sample represents the entire DAX and MDAX indices, parts of the SDAX and the TecDAX indices, and firms from the so-called General Standard, due to changes in the composition of the indexes over time. The majority of firms in the initial sample (90 per cent) are part of the Prime Standard of the German Stock Exchange, which requires international transparency rules of the listed firms.[9] As a consequence, more than 90 per cent of our sample belongs to the Prime Standard. The rest of the original sample is part of the General Standard which requires lower disclosure and publication, for example, no mandatory analyst conference.[10]

Our final sample is restricted to firms having adopted IFRS. We have two different samples to perform our analyses: Panel sample A′ comprises 520 IFRS firm years belonging to different industries excluding the financial sector given the industry's specific business and reporting structures and the pooled sample A encompasses 9,654 individual analyst years under IFRS also from industries other than the financial sector. Due to the lack of reported information on R&D activities and on capitalization by some firms, missing data for forecasts of earnings per share, and missing data for different control variables such as analyst following or beta, our panel sample and pooled sample decrease to 248 and 4,284 observations, respectively (see Table 1 Panel A).

Panel B of Table 1 provides summary statistics for the main firm characteristics in our sample. Our sample consists of moderate growth firms with market equity twice their book equity. The debt-to-equity ratio indicates substantial funding by debt, which is common for German firms. The divergence between median and mean of *LEV* (1.731 versus 2.459) shows that some firms are exposed to very high debt-to-equity ratios. On average, about 17 financial analysts follow a firm and IFRS standards are applied for around 4 years. R&D intensity is relatively large in the sample, with 4.2 per cent of sales, compared to the average R&D intensity in Germany of 2.5 per cent, which is about identical to the United States (OECD, 2009).

Table 1. *Sample Description (2000–2007)*

	Panel sample A′ (firm years)	Pooled sample A (individual analyst years)
Panel A: Sample composition		
150 largest German HDAX firms	1,200	15,201
IFRS sample excluding financial sector	520	9,654
Less: missing data concerning R&D capitalization	(53)	(1,039)
Less: missing data concerning R&D expenditures	(48)	(1,717)
Less: missing data concerning forecasts of EPS	(45)	(228)
Less: analyst following < 3		(23)
Less: missing data concerning control variables and instruments	(126)	(2,363)
Final sample	= 248	= 4,284

	Mean	Median	Standard deviation
Panel B: Summary statistics			
BFE	0.052	0.018	0.138
SDF	0.019	0.007	0.011
DCAP	0.008	0	0.020
SIZE	7.58e + 09	2.58e + 09	1.19e + 10
MB	2.321	1.936	1.553
LEV	2.459	1.731	3.010
ANAFOL	17	18	9.034
RDINT	0.042	0.024	0.053
BETA	0.973	0.960	0.450
IFRS	4.036	3.500	2.264
LOSS	0.097	0.000	0.296
RDG	0.367	0.141	1.001

Table 1 *(Continued)*

	Mean	Median	Standard deviation
SCH	0.278	0.108	0.586
BIG	0.907	1	0.291

	SDF	*BFE*	*DCAP*	*SIZE*	*MB*	*LEV*	*ANAFOL*	*RDINT*	*BETA*	*IFRS*	*LOSS*	*RDG*	*SCH*	*BIG*
Panel C: Pearson's Correlation														
SDF	1													
BFE	**0.350**	1												
DCAP	**0.219**	**0.040**	1											
SIZE	−0.020	**−0.142**	**0.159**	1										
MB	**−0.645**	**−0.287**	**−0.284**	**0.093**	1									
LEV	**0.241**	**0.104**	**0.185**	**0.193**	**−0.109**	1								
ANAFOL	**0.126**	**−0.109**	**0.366**	**0.811**	**−0.034**	**0.175**	1							
RDINT	0.021	−0.017	**0.186**	**−0.051**	0.019	**−0.220**	**0.146**	1						
BETA	**0.279**	**0.115**	**0.080**	**−0.038**	**−0.187**	**0.100**	0.009	**−0.100**	1					
IFRS	**−0.206**	**−0.152**	**−0.115**	**0.259**	**0.160**	0.027	**0.073**	**−0.058**	**−0.039**	1				
LOSS	**0.205**	**0.377**	−0.004	**−0.222**	**−0.128**	0.021	**−0.150**	**0.155**	**0.242**	**−0.092**	1			
RDG	**0.056**	−0.021	**−0.052**	**−0.038**	0.010	0.019	**−0.060**	**−0.131**	**0.056**	0.021	**−0.033**	1		
SCH	**0.225**	**0.159**	**0.069**	**−0.225**	**−0.224**	**0.101**	**−0.157**	**−0.094**	**0.107**	**−0.348**	**0.076**	**−0.040**	1	
BIG	**0.042**	−0.015	**0.098**	**0.131**	−0.002	**0.106**	**0.158**	−0.020	**−0.081**	**0.235**	**−0.117**	−0.016	**−0.039**	1

This table provides information on our sample. Panel A shows the sample composition for both the panel sample A′ (firm years) and the pooled sample A (individual analyst years). Panel B displays the summary statistics for the main firm characteristics. Note that for descriptive purposes, we display the non-logged values in Panel B for *BFE*, *SDF*, and *SIZE*. The number of observations in Panel B is 248, except for *BFE* with 4,284 observations. Panel C provides the Pearson's correlation matrix for our variables with coefficients displayed in bold figures if p-value < .05.

The number of capitalizers in our sample augments from 30 to 60 per cent of all IFRS reporting firms, while the portion of capitalized development costs relative to the total amount of R&D expenditures increases from about 5 to 20 per cent on average (not tabulated). Thus, the portion of capitalized development costs has increased more strongly than the portion of firms adopting IFRS. On average, a third of the firms capitalize about 20 per cent of their R&D costs. The increasing number of capitalizers indicates a learning effect among the sample firms.

Panel C of Table 1 presents the Bravais–Pearson correlation matrix. For both dependent variables (i) analyst forecast errors (*BFE*) and (ii) analyst forecast dispersion (*SDF*), the correlation coefficient with capitalized development expenditures (*DCAP*) is significantly positive (.219 and .040, p-value $<$ .01). This is consistent with the notion that capitalization of development costs adds complexity to the forecasting process resulting in a loss in forecast accuracy. Further, the correlation coefficient for *SIZE* and *ANAFOL* is very high (.811, p-value $<$ .01). We therefore only include *ANAFOL* in our multiple regressions capturing size as well as analyst following effects. The variance inflation factors are all lower than the critical value of 5, and we can rule out multicollinearity problems in our sample.

Our data source for analysts' forecasts is the *Institutional Brokers Estimate System* (IBES). Absolute forecast errors (*BFE*) are computed at the individual level. The forecast error is calculated as the difference between actual earnings per share and the one-year predicted earnings per share, scaled by end of year share price. Furthermore, we calculate analysts' forecast dispersion (*SDF*) using individual analysts' forecasts and the mean forecast for the panel sample. Both dependent variables are logged to induce normality.

4. Empirical Results

4.1. Main Findings

As discussed, the decision to capitalize is likely to be endogenous, so that we first need to analyze the factors influencing the capitalization of development costs. Table 2 displays the empirical results for the determinants of capitalizing development expenditures (equation 3).

The results of Table 2 show the relevance of different instrumental variables (panel sample A′). In particular, we identify lagged capitaliza-

Table 2. *Tobit Regression Results for the Determinants of R&D Capitalization (Equation 3)*

Dependent variable		*Panel sample A′ DCAP*
BETA	−	0.001 (0.55)
FOL	+/−	0.000 (1.16)
IFRS	+/−	−0.001** (−2.05)
LEV	+	0.001** (2.62)
LOSS	+	−0.003 (−0.90)
MB	+/−	−0.002** (−2.18)
RDINT	+/−	0.038 (0.77)
DCAPlag	+	0.828*** (14.38)
(Intercept)		−0.000 (−0.00)
Industry fixed effects		Included***
Year fixed effects		Included
Log likelihood		327.849
LR χ^2 (21)		377.43***
Total observations		299
Left censored observations		177

This table displays Tobit regression results on the determinants of capitalizing development costs (equation 3) using Huber/White adjusted standard errors for Tobit regression (*z*-statistics in parentheses). All variables are defined as outlined in the appendix.
Two-tailed significance: *p < .10, **p < .05, ***p < .01.

tion of development costs as appropriate instrumental variable. However, we do not find significant regression coefficients for all independent variables. Only the variables *IFRS*, *MB*, *LEV*, and *DCAPlag* have a significant influence on a firm's amount of capitalized development costs. Our results indicate that a firm capitalizes more development expenditures not only when it has already capitalized some amounts in previous periods, but also when it has higher leverage, is in a mature state, and has not adopted IFRS for a long time.[11]

After considering determinants of capitalizing development expenditures in the first-stage regression, we can analyze the association of capitalized development costs with forecast errors and forecast dispersion in the second stage. The analysis on forecast errors is performed at the individual analyst level (pooled sample A) permitting a thorough breakdown of the forecasting result and the forecasting complexity for each analyst. The impact on forecast dispersion is examined at the panel level (panel sample A′) as the dispersion cannot be calculated at the individual analyst level. The results for hypotheses 1a and 1b based on 2SLS regressions controlling for endogeneity are presented in Table 3.

Overall, all regressions are significant with a high goodness of fit. We constrain our pooled sample of individual analyst forecasts to

Table 3. *2SLS Regression Results for Capitalization of Development Costs and Forecast Accuracy (Equation 5a) and Forecast Dispersion (Equation 5b)*

Dependent variable		*Pooled sample A: BFE*	*Panel sample A′: SDF*
DCAP (instrumented)	+	15.041*** (8.22)	12.593*** (3.19)
BETA	+	0.221*** (3.23)	0.128 (0.96)
FOL	−	−0.030*** (−7.40)	−0.004 (−0.46)
IFRS	−	−0.050*** (−2.66)	0.003 (0.07)
LEV	+	0.009 (1.19)	−0.025 (−1.17)
LOSS	+	2.168*** (34.51)	0.393* (1.85)
RDG	+	0.045 (1.31)	−0.060* (−1.85)
SCH	+	0.102*** (5.15)	0.231*** (2.97)
BIG	−	0.154 (1.58)	0.160 (0.68)
(Intercept)		−3.144*** (−13.72)	−4.469*** (−9.36)
Industry fixed effects		Included	Included
Year fixed effects		Included	Included
Adjusted R^2		0.30	0.45
F-statistic		150.44***	16.05***
Total observations		4,284	248

This table shows empirical results related to hypotheses 1a and 1b. The results from Table 2 are used here to estimate the instrumented value of *DCAP*. This table presents the 2SLS results for forecast accuracy (first column) and forecast dispersion (second column) separately using Huber/White sandwich estimators to estimate robust standard errors. Pooled sample A is used in the regression with individual analysts' forecast errors *BFE* as the dependent variable. Panel sample A′ is used in the regression with forecast dispersion *SDF* as the dependent variable, calculated on the basis of individual analysts' forecast errors.
Two-tailed significance: *p < .10, **p < .05, ***p < .01.

firms followed by at least three analysts. All standard errors are estimated using the Huber/White sandwich estimators. The results in the first column of Table 3 are consistent with the notion that capitalization of development costs is significantly positively associated with forecast errors (*DCAP* 15.041, p-value < .01).

The results for forecast dispersion (second column of Table 3) are quite similar to the ones for forecast errors. Consistent with the notion on increased forecast complexity, *DCAP* is again positive and significant at the .01 level (12.593) confirming that capitalized development expenditures are positively associated with the dispersion of analysts' forecasts. Most of our control variables are significant with the expected sign but to a lesser degree in the panel regression (for *SDF*) compared to the pooled regression (for *BFE*).

In a next step, we analyze the impact of environmental uncertainty on the association between capitalized development costs and forecast accuracy (H1c) and forecast dispersion (H1d). We use stock return volatility on a daily trade basis (*ShareVola*) lagged by 1 year and also

Table 4. *The Role of Underlying Environmental Uncertainty for Capitalization of Development Costs and Analysts' Forecasts*

Dependent variable		*Pooled sample A: BFE*	*Pooled sample A: BFE*	*Panel sample A′: SDF*	*Panel sample A′: SDF*
Panel A: 2SLS regression results for equations (2a) and (2b) with instrumented DCAP					
DCAP (instrumented)	+	15.489*** (8.12)		11.519*** (2.95)	
ShareVola	+	0.014** (2.38)	0.120*** (7.32)	0.150*** (4.53)	0.114*** (3.62)
dummy_CAP	+		0.894*** (9.38)		0.329 (1.35)
ShareVola x dummy_CAP	−		−0.104*** (−6.49)		−0.079** (−2.49)
BETA	+	0.238*** (3.31)	0.153** (2.20)	0.100 (0.75)	0.036 (0.27)
FOL	−	−0.029*** (−7.01)	−0.023*** (−5.53)	0.002 (0.15)	0.008 (0.80)
IFRS	−	−0.092*** (−4.93)	−0.045** (−2.43)	−0.003 (−0.08)	−0.011 (−0.30)
LEV	+	0.007 (0.94)	0.004 (0.48)	−0.034* (−1.72)	−0.009 (−0.39)
LOSS	+	2.132*** (31.69)	2.118*** (32.28)	0.084 (0.37)	0.287 (1.41)
RDG	+	0.032 (0.96)	0.029 (0.93)	−0.101*** (−3.02)	−0.081** (−2.34)
SCH	+	0.079*** (3.79)	0.078*** (3.76)	0.156** (2.20)	0.124* (1.66)
BIG	−	0.295*** (2.98)	0.352*** (3.64)	0.236 (1.04)	0.332 (1.43)
(Intercept)		−3.412*** (−14.58)	−3.520*** (−14.76)	−4.765*** (−9.81)	−5.361*** (−10.04)
Industry fixed effects		Included	Included	Included	Included
Year fixed effects		Included	Included	Included	Included
Adjusted R^2		0.30	0.31	0.49	0.48
F-statistic		137.46***	141.96***	17.61***	15.64***
Total observations		4,152	4,181	242	255

ShareVola	*Mean BFE*	*Median BFE*	*Mean DCAP*	*Capitalizers in %*	*Number of observations*	*Coefficient DCAP (instrumented)*[2]
Panel B: Capitalization of development costs and forecast accuracy for different sextiles of share volatility						
1. Sextile (lowest)	0.033	0.023	0.004	53	790	99.457***
2. Sextile	0.046	0.006	0.011	35	744	140.044***
3. Sextile	0.026	0.018	0.008	52	712	26.730
4. Sextile	0.044	0.021	0.027	72	788	20.638***

Table 4 *(Continued)*

ShareVola	*Mean BFE*	*Median BFE*	*Mean DCAP*	*Capitalizers in %*	*Number of observations*	*Coefficient DCAP (instrumented)*^{2}
5. Sextile	0.048	0.023	0.006	48	674	58.935***
6. Sextile (highest)	0.119	0.059	0.009	40	444	−13.135**
Panel C: Capitalization of development costs and forecast accuracy for different sextiles of sales volatility						
1. Sextile (lowest)	0.054	0	0.010	66	467	72.040***
2. Sextile	0.060	0.023	0.006	78	655	39.136**
3. Sextile	0.038	0.019	0.007	48	796	81.164*
4. Sextile	0.039	0.017	0.019	49	733	19.297
5. Sextile	0.063	0.043	0.025	38	760	−26.680**
6. Sextile (highest)	0.042	0.019	0.003	35	686	−21.848

This table shows analyses related to capitalization of development costs and forecast accuracy/forecast dispersion and the impact of environmental uncertainty proxied by share volatility. Panel A shows regression results for equation (2a) and (2b) with instrumented *DCAP* focusing on how the relationship between capitalization of development costs and forecast accuracy/forecast dispersion may be different for firms of varying degrees of underlying environmental uncertainty. Panel B displays regression results for equation (5a) on forecast accuracy for different quintiles of share volatility. Robust standard errors are estimated using the Huber/White sandwich estimators. In the sextile regressions, control variables from equation (5a) are included.

Two-tailed significance: *$p < .10$, **$p < .05$, ***$p < .01$.

sales volatility as the standard deviation of sales over the sample period normalized by a firm industry's sales volatility as a proxy for environmental uncertainty. Due to some more missing values for *ShareVola*, our sample sizes are slightly reduced.[12]

Consistent with our expectations, we find evidence that both forecast errors and forecast dispersion (*SDF*) significantly increase with higher stock volatility (see first and third column of Panel A of Table 4). The regression coefficient for *ShareVola* is significantly positive at the .01 level and .05 level, respectively, suggesting higher forecast errors and forecast dispersion in the presence of high environmental uncertainty.[13] The results in the second and fourth column of Table 4 show that *ShareVola* is significantly positively associated with forecast errors and forecast dispersion as predicted (p-level < .01). The interaction term *ShareVolaxdummy_CAP* with forecast errors as the dependent variable amounts to −.104 and is also significant at the .01 level. For the panel sample with forecast dispersion, the interaction term *ShareVolaxdummy_CAP* is also significantly negative at the .05 level (−.079).

This indicates that for the group of capitalizers, the negative effect of share volatility on forecast accuracy and forecast dispersion is reduced when uncertainty is high. We calculate and analyze the joint impact of *dummy_CAP* and *ShareVola* on both forecast error and forecast dispersion. In the case of forecast error, for *dummy_CAP* = 0, *BFE* can be expressed by the following: *BFE* = −3.520 + 0.120x*ShareVola*. When *ShareVola* increases by one unit, *BFE* increases by 0.120. For *dummy_CAP* = 1, *BFE* can be expressed as follows: *BFE* = −2.626 + 0.016x*ShareVola*. When *ShareVola* increases by one unit, *BFE* for the group of capitalizers augments by 0.016 only. However, the increase is still significant at the 0.01 level. We observe the same associations in our regression with forecast dispersion (*SDF*) as our dependent variable.

Although forecast errors are generally higher for capitalizers, the increase in forecast error in uncertainty is moderated by capitalization. Hence, there is very little additional error from increased uncertainty in the forecasts for capitalizers. This suggests that capitalization as such introduces a general problem into the forecasting process but also helps in the resolution of uncertainty. Yet, this moderation does not fully compensate for the additional forecasting problems associated with capitalization. Forecast errors and forecast dispersion for capitalizers still remain higher than for expensers. The results confirm H1c and H1d on uncertainty and forecast errors and forecast dispersion. When using sales volatility instead of share volatility, the results remain qualitatively unchanged.

Further, we test equation (5a) for each sextile of *ShareVola* based on 2 SLS. The results are presented in Panel B of Table 4. The last column shows the regression coefficient for the instrumented variable *DCAP* of regression (5a) per sextile. We find that the regression coefficient of the instrumented variable *DCAP* is significantly different for the six sextiles. While the regression coefficient is positive for the sextile of low uncertainty (99.457, p-value $< .01$), we find the opposite for the sextile of high uncertainty. The significantly negative coefficient for the instrumented variable *DCAP* (-13.135, p-value $< .05$) indicates that if uncertainty runs high, capitalization of development expenditures reduces forecast errors. This is consistent with our hypothesis 1c and the notion that the value of the capitalization signal increases in the presence of high uncertainty and compensates for additional forecasting problems resulting from capitalization.

Further, the results presented in the first two columns of Panel B of Table 4 suggest that forecast errors increase when uncertainty increases. The columns display the descriptive mean and median values for the absolute amount of individual forecast error (non-logged value of *BFE*) per sextile. We find that with higher sextiles of *ShareVola,* the mean as well as the median of forecast errors is significantly increasing (for mean values of non-logged *BFE* from .033 to .119; for median values of non-logged *BFE* from .023 to .059). At the same time, capitalizing development expenditures seems to speak to the increasing complexity when uncertainty is high. This is evidenced by the significantly negative regression coefficient of *DCAP* in sextile 6 suggesting lower forecast errors when firms in a highly uncertain environment capitalize part of their R&D.

The results remain consistent when using sales volatility instead of share volatility as a proxy for uncertainty (see Panel C of Table 4). We observe a significant and positive association of capitalized development costs with analysts' forecast errors when uncertainty is low (positive regression coefficient of instrumented *DCAP* for sextiles 1–4). On the other hand, the sign of the regression coefficient turns negative if uncertainty is high (-26.680 and -21.848 for sextiles 5–6). Hence, for uncertain environments, the capitalization of development expenditures does not increase but rather seems to reduce forecast errors.

Further, while the descriptive mean value of capitalized development expenditures scaled by market value of equity as displayed in the third column is higher for the upper sextiles of sales volatility (e.g., 0.019 and 0.025 for sextiles 4 and 5), the number of capitalizers is higher for the lower sextiles (e.g., 66 and 78 per cent for sextiles 1 and 2). This indicates that high uncertainty imposes increasing difficulty for firms to meet the recognition criteria. Consequently, less firms tend to capitalize. However, for those firms that do capitalize under such uncertain circumstances, the signal related to the capitalization appears informative and the benefits seem to prevail. Note that we do not run the analysis based on different levels of uncertainty for H1d related to forecast dispersion given the small sample size in the Panel Sample A′.

4.2. *Robustness Checks*

We apply several sensitivity checks. First, we include net capital expenditures in property, plant, and equipment as an additional control variable in our analyses because it is likely to be an additional forecasting component. Our main results remain unchanged.

Second, we use book value of equity instead of market value as a deflator for our independent variables because the latter could be biased by market imperfections and higher volatility. The significance of the regression coefficient of *DCAP* decreases, but the results remain qualitatively unchanged.

Third, the non-reported DW statistic indicates a positive autocorrelation in the regression of equation (5b) for the panel sample A′. We rerun (5b) for the panel sample integrating a first-order autoregressive component to mitigate the autocorrelation in the residuals. The results for *DCAP* are similar with a positive sign (p-value = .06). The results also remain robust when using Panel corrected standard errors.

Finally, because *DCAP* is defined as an absolute amount only being deflated, we alternatively use the ratio of capitalized development expenditures to all R&D investments of a firm in order to detect a potential sensitivity of *DCAP*. Our inferences remain unaffected.

5. Conclusion

This study provides new empirical evidence on whether capitalizing development costs under IFRS improves forecast accuracy and reduces forecast dispersion, or whether additional complexities in the forecasting process thwart the informativeness of the signal from capitalizing. Our findings suggest that, on average, the partial recognition rule under IAS 38 introduces a random element into earnings, which negatively affects forecast accuracy and increases forecast dispersion. This finding is consistent with previous U.S. evidence by Aboody and Lev (1998) for the capitalization of software development costs under SFAS 86 (ASC 350–40). The result is not surprising given the high complexity analysts are faced with when making earnings forecasts for companies that capitalize part of their R&D. The portion being capitalized is an *a priori* unknown fraction of the total amount of R&D. Hence, to forecast future earnings accurately, analysts need to estimate not only these capitalization rates but also amortization rates on previously capitalized amounts plus potential impairments.

By nature, R&D investments are more uncertain than other assets (Kothari et al., 2002; Wyatt, 2005). As such, information asymmetries are particularly large if such uncertain investments exist in an environment that is highly uncertain itself. High uncertainty also increases the credibility of the capitalization signal (Verrecchia, 2001). Under such conditions, we therefore expect that the benefits of signaling may outweigh the additional complexities of capitalizing development. We find evidence consistent with this notion, that is, for levels of high environmental uncertainty (proxied by both share and sales volatility), the association between capitalized development costs and forecast errors turns negative, indicating an improvement in forecast accuracy.

Our study contributes to the regulatory debate on the usefulness of capitalizing R&D expenditures. While IAS 38 claims to increase decision usefulness and to improve market efficiency, our results suggest that capitalizing development costs generates additional challenges for the forecasting process and impedes forecast accuracy due to the complexities involved. These results are in line with prior work by Aboody and Lev (1998) for SFAS 86 (ASC 350–40). Based on the notion that the future benefits of intangible investments are too uncertain, these investments are not capitalized under most accounting standards and IAS 38 is one big exception to this. Our results inform this debate by showing that discretionary capitalization may be particularly useful, *especially* when the future benefits are highly uncertain.

Secondly, our study contributes to the literature on analysts' forecasts, particularly the effects of information complexity (e.g., Duru and Reeb, 2002; Plumlee, 2003; Hirst et al., 2004; Hope, 2004). Consistent with this literature, our findings suggest that the increasing complexity surrounding capitalization of development expenditures negatively impacts forecast accuracy resulting in higher individual forecast errors and forecast dispersion. In addition, we show that the negative impact of increased complexity can be outweighed by the information contained in the signals from capitalization of development costs when the underlying environmental uncertainty is high. The interpretation of the information contained in capitalized development costs seems to vary across different levels of underlying economic uncertainty. Our findings contribute to the discussion of the role of analysts as financial intermediaries in the capital market and may help in understanding their use of information and process of dissemination more closely (Ramnath et al., 2008).

We acknowledge a number of caveats in our study. The German setting allows us to hold country-specific changes constant. However, we are aware that the findings might differ in environments where analysts are historically more familiar with interpreting the information contained in capitalized development expenditures (e.g., United Kingdom, France, and Australia). A cross-cultural analysis might provide useful insights into that matter.

We do not—apart from the count variable of years of IFRS—explicitly account for behavioral aspects concerning how analysts process information, for example, a possible learning effect from a change in accounting rules or herding behavior. We encourage future research to consider such behavioral aspects and to analyze our research question using an experimental research design. This allows drawing further conclusions on how capitalization of development costs under IAS 38 affects the forecasting process of market participants, in particular of analysts.

Notes

1. IAS 38 requires firms to capitalize development costs from the point in time when the criteria in IAS 38.57 are cumulatively met. Research costs as well as development costs incurred before the criteria are met are expensed.
2. Even though IAS 38 requires firms to capitalize development costs, the application of the criteria in IAS 38.57 involves significant discretion (e.g., Leibfried and Pfanzelt, 2004; Meyer and Naumann, 2009).
3. Our observation period ends in 2007 to avoid confounding with the recent financial crisis (e.g., Kang et al., 2014). Our expectations are based on the conjecture that firms react to higher levels of business risk by a greater use of discretionary accruals and that at the same time, the resulting signals are more informative. Hence, we are interested in the effects of economic risk affecting management's choice to recognize intangible assets. As the financial crisis was an exogenous shock to the entire financial system and caused large distortions in the global economy, it is not the type of uncertainty we are investigating. Rather, the resulting distortions conceal the underlying economic risks of

a firm's regular operations and would likely bias our analyses. It is unlikely that R&D capitalizations would resolve the uncertainties caused by the financial crisis. To the contrary, Francis et al. (2013) find conservative accounting practices, such as expensing R&D, to be an important governance mechanism ensuing less declines in stock prices during the financial crisis. Therefore, we exclude the time period of the financial crisis from our analysis.

4. This is consistent with Hope (2004) who reveals that forecast accuracy also deteriorates if the forecasting process is complicated by extensive accounting choices.

5. However, recent work by Ciftci (2010) also suggests that the capitalization of software development under SFAS 86 (ASC 350–40) reduces earnings quality.

6. As *SIZE* and *FOL* have been found to be of concern for multicollinearity (Botosan, 1997), we only use one control variable of the two at a time. In our sample, *SIZE* and *FOL* show a correlation of 75 per cent with firm size measured by the natural logarithm of market value of equity. The reported results include *FOL,* but our results remain unaffected when using *SIZE* instead (negative regression coefficient with p-value < .01). Similarly to *FOL*, *SIZE* also proxies for disclosure quality (Bailey et al., 2003).

7. Our results remain qualitatively unchanged when running the regressions for each quintile of volatility instead of sextile.

8. In our analyses on forecast dispersion, the sample size is fairly small due to the calculation of standard deviation of forecast errors. Hence, we focus the analysis using sextiles of uncertainty on forecast errors only (H1c).

9. To avoid survivorship bias, all acquired or failed companies during the observation period remain in the sample even when data are not available for subsequent periods.

10. We also run our main regression models without firms belonging to the General Standard and the results remain unchanged.

11. The negative sign for *IFRS* implies that companies that just recently moved to IFRS are more likely to capitalize more development costs than companies that have been using IFRS for some time already. Under German GAAP (HGB), the capitalization of development expenditures was strictly prohibited. Anecdotal evidence suggests that the possibility to capitalize development costs was one of the main drivers for a number of German companies to voluntarily adopt IFRS pre-2005.

12. Note that the last column in Panel A of Table 4 shows 255 observations at the panel level (instead of 248) because for some firm years, we have information on the decision to capitalize (*dummy_CAP*) but not on the amount of capitalized development expenditures (*DCAP*).

13. Note that *BIG* is significant and positive in the pooled sample, which is not consistent with our expectations. This may be due to the large dominance of firms in our sample that are audited by a big auditor (about 90 per cent).

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Appendix A

Dependent variables

BFE_{it} = natural logarithm of absolute individual analyst forecast error (= difference between actual earnings per share and forecasted earnings per share by a financial analyst, scaled by end of year share price).
SDF_{it} = natural logarithm of standard deviation of analysts' forecast, scaled by end of year share price.

Independent variables related to R&D

$dummy\_CAP_{it}$ = binary variable equal to 1 if a firm capitalizes development expenditures on the balance sheet, 0 otherwise.
$DCAP_{it}$ = annual capitalized development expenditures deflated by market value at the end of a year.
$DCAPlag_{it}$ = annual capitalized development expenses in period t-1 deflated by market value of equity at the end of year.
RDG_{it} = absolute change in total R&D expenditures relative to the prior period as a growth measure.
$RDINT_{it}$ = R&D intensity for firm i in year t computed as R&D expenditures divided by total sales.

Control variables

$ANAFOL_{it}$ = number of analysts following a firm.
$BETA_{it}$ = systematic risk proxied by beta on a 1-year basis.
BIG_{it} = binary variable equal to 1 if a firm is audited by one of the BIG 5 auditors at the time, 0 otherwise.

$dummy\_CAP_{it}$ = binary variable equal to 1 if a firm capitalizes development expenditures on the balance sheet, 0 otherwise.
FOL_{it} = natural logarithm of the number of analysts following a firm.
$IFRS_{it}$ = count variable of years of IFRS application.
LEV_{it} = leverage measured by total liabilities divided by book value of equity at the end of a year, adjusted by capitalized development expenditures.
$LOSS_{it}$ = binary variable which equals 1 if earnings are negative, 0 otherwise.
MB_{it} = market-to-book equity ratio, adjusted by capitalized development expenditures.
SCH_{it} = absolute change in sales, scaled by market value of equity at the end of a year.
$ShareVola_{it-1}$ = lagged share price volatility measured by share price deviation on a daily basis during one period.
$SalesVola_{it}$ = sales volatility measured by standard deviation of sales calculated over the sample period normalized by the firm industry's sales volatility.
$SIZE_{it}$ = firm size measured by the natural logarithm of market value of equity at the end of a year.