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Predicting earnings and cash flows:

The information content of losses and tax loss carryforwards

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Abstract

We analyze the relevance of losses, accounting information on tax loss carryforwards, and deferred taxes for the prediction of earnings and cash flows up to four years ahead. We use a unique hand-collected panel of German listed firms encompassing detailed information on tax loss carryforwards and deferred taxes from the tax footnote. Our out-of-sample predictions show that considering accounting information on tax loss carryforwards and deferred taxes does not enhance the accuracy of performance forecasts and can even worsen performance predictions. We find that common forecasting approaches that treat positive and negative performances equally or that use a dummy variable for negative performance can lead to biased performance forecasts and we provide a simple empirical specification to account for that issue.

Keywords: performance forecast, in-sample prediction, out-of-sample prediction, loss persistence, deferred taxes, tax loss carryforwards

JEL Codes: M40; M41; C53

Conflicts of Interest: None

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1. Introduction

Recent research in financial accounting examines whether accounting items on deferred taxes and losses provide useful information to investors and creditors. For example, Dhaliwal et al. (2013) find evidence that the valuation allowance on deferred tax assets provides incremental information about the persistence of accounting losses. Herbohn et al. (2010) and Flagmeier (2017) show a significant correlation of unrecognized deferred taxes from tax loss carryforwards and unrecognized tax loss carryforwards, respectively, with future firm performance. The findings of Joos and Plesko (2005) and Li (2011) suggest that (transitory) losses are less informative than earnings for future firm performance. Since current papers rely on in-sample tests (e.g., Gordon and Joos, 2004; Flagmeier, 2017; Herbohn et al., 2010), it is still an open question whether the information content of deferred taxes (from tax loss carryforwards) and losses is sufficient to improve out-of-sample predictions.

This research question is of interest for at least three reasons. First, as shown by Ohlson (1995, 2001), future firm performance—earnings and cash flows—is value relevant. Thus, if current accounting information provides valuable insights into future performance, this facilitates firm valuation and provides relevant information to investors, creditors, and other stakeholders. Second, correctly specified predictions of future cash flows and earnings are important for practitioners (e.g., analysts), as well as for a number of research questions in the accounting and finance literature (e.g., to calculate the cost of capital; see Fama and French, 2006; Hou et al., 2012). Third, the target of accounting standards is to provide useful information about a firm's financial position and performance. Since the complexity of the accounting for deferred taxes and respective costs has often been criticized (Laux, 2013; Weber, 2009), the information content of accounting items on deferred taxes and tax loss carryforwards for performance forecasts should also be relevant for standard setters and authorities such as the Financial Accounting Standards Board (FASB) or the International Accounting Standards Board (IASB).

We analyze the information content of the corresponding items for the prediction of future earnings and cash flows, with a focus on two aspects. First, deferred tax assets from tax loss carryforwards are capitalized to account for the value of future tax savings from current unused tax loss carryforwards. In prominent accounting systems—US Generally Accepted Accounting Principles (GAAP) and International Financial Reporting Standards (IFRS)—deferred tax assets from tax loss carryforwards are only recognized if realization of the tax benefit is regarded as likely. Thus, the capitalization of deferred tax assets from tax loss carryforwards requires an internal estimate of future taxable income, which could contain valuable information for future firm performance (e.g., Dhaliwal et al., 2013; Flagmeier, 2017; Gordon and Joos, 2004; Herbohn et al., 2010; Legoria and Sellers, 2005).

Second, considering current losses, the literature documents the lower persistence of negative performance outcomes compared to positive performance outcomes (Hayn, 1995; Li, 2011), implying that losses are less informative than earnings. Transitory losses as defined by Joos and Plesko (2005) have a tendency toward loss reversal, ultimately resulting in positive future firm performance. Thus, if researchers treat negative current performance the same way as positive current performance in prediction models, this could lead to an overestimation of the persistence of losses and an underestimation of the persistence of earnings. This effect holds especially for long-run predictions of performance outcomes.

We analyze the information content of accounting items on (the non-valuable component of) tax loss carryforwards, negative current firm performance, a measure for past (persistent) losses, and deferred taxes for future firm performance. Different from the literature addressing the impact of accounting items on security prices (e.g., Amir et al., 1997; Amir and Sougiannis, 1999; Kumar and Visvanathan, 2003; Lynn et al., 2008), we focus on the question of if and to what extent such items provide incremental information on measures of future firm performance and could help to enhance out-of-sample predictions. In in-sample tests, we analyze the explanatory power of variables and their correlation with future performance in a given sample. However, our main interest is on out-of-sample tests addressing the enhancement of performance forecasts by the inclusion of additional variables. Thus, out-of-sample tests focus on the predictive ability of a model and not only on the explanatory power of a variable in a given sample.

We use a unique hand-collected panel of public firms listed on the German stock market that encompasses detailed information on deferred taxes and tax loss carryforwards from the tax footnote. Most relevant, we consider unrecognized tax loss carryforwards (i.e., the non-valuable component of tax loss carryforwards). We further analyze voluntarily disclosed information on the total amount of tax loss carryforwards, the book value of the valuation allowance on deferred tax assets from tax loss carryforwards, and changes in the corresponding valuation allowance. In addition, we consider deferred tax assets from tax loss carryforwards, deferred taxes from timing differences and tax credits, and deferred tax liabilities.

We confirm empirical findings suggesting a negative correlation of deferred tax assets (from tax loss carryforwards) and a measure of future firm performance (Dhaliwal et al., 2013; Christensen et al., 2008; Gordon and Joos, 2004; Herbohn et al., 2010). However, in-sample tests suggest a relatively weak impact on the explanatory power of prediction models. More relevant, our out-of-sample tests reveal that including such items in forecasting regressions typically reduces the predictive ability of our models and leads to higher forecasting errors.

A theoretical explanation for our finding is the limited accuracy of accounting information on the value of tax loss carryforwards. As suggested by Lev et al. (2010), estimates-based accounting items are less useful for forecasting regressions, which is a consequence of the difficulty of making reliable forecasting estimates and the managerial misuse of estimates (i.e., earnings management; Lev et al., 2010). Deferred tax assets (from tax loss carryforwards) result from a projection of future taxable income and are affected by restrictions in the settlement of tax losses with future taxable income. Frank and Rego (2006), Gordon and Joos (2004), Herbohn et al. (2010), and Schrand and Wong (2003) provide evidence of earnings management via deferred tax assets (from tax loss carryforwards). Thus, accounting information on tax loss carryforwards might not be sufficiently accurate to enhance forecasting regressions.

We further find strong empirical evidence that common forecasting approaches that treat positive and negative performance similarly (e.g., Barth et al., 2001; Dichev and Tang, 2009; Kim and Kross, 2005; Lev et al., 2010) overestimate the persistence of current negative firm performance. This effect holds especially for long-run prediction horizons, which increase the likelihood of a loss reversal. As documented by in-sample and out-of-sample tests, considering differences in the persistence of negative and positive firm performance significantly increases the explanatory power and predictive ability of our forecasting models.

Testing the information content of a variable for past (persistent) losses, we find a negative correlation with future firm performance but no reduction of forecasting errors in out-of-sample predictions of future cash flows. Nevertheless, and in line with findings on loss persistence (Joos and Plesko, 2005; Li, 2011), results suggest that such a variable makes forecasting regressions with earnings before and after taxes (*EBT*, *EAT*) up to three years ahead as the dependent variable more accurate. In additional analyses, we find a positive impact of measures for firm size and (to a small extent) the market-to-book ratio on the accuracy of performance forecasts. We find mixed evidence for research and development (R&D) expenditures and indicator variables for dividend-paying stocks or firms with a first loss as an indicator of a transitory loss in the current period.

We contribute to the literature in several ways. Tax accounting literature suggests that unrecognized deferred taxes (from tax loss carryforwards) provide information on future tax payments (Laux, 2013) and the persistence of losses (Dhaliwal et al., 2013). They are also correlated with measures of future firm performance (Flagmeier, 2017; Gordon and Joos, 2004; Herbohn et al., 2010; Legoria and Sellers, 2005). However, a significant correlation with future performance measures does not necessarily mean an enhancement of performance predictions. As shown by Lev et al. (2010), estimates-based accounting items might not be sufficiently robust to help in prediction models. While our in-sample tests suggest a negative correlation of unrecognized tax loss carryforwards and corresponding deferred taxes with future performance (albeit with a weak impact on R^2), our out-of-sample tests show a negative effect of considering such accounting information in performance forecasts. This holds even for after-tax cash flows, suggesting a limited usefulness of deferred taxes from tax loss carryforwards in the prediction of cash tax payments. Laux (2013) finds only a weak marginal increase in adjusted R^2 by adding deferred tax components to a prediction model of cash taxes and does not perform out-of-sample predictions. Thus, our findings should also be relevant to the literature on the information content of deferred taxes for future cash taxes.

We further contribute to the literature on the information content of losses. Our findings and statistical tests underline the argumentation of papers suggesting a lower information content of losses compared to positive performance outcomes (Hayn, 1995; Joos and Plesko, 2005; Li, 2011). Consideration of this asymmetry clearly improves predictive ability. By contrast, indicators for past (persistent) losses seem to be helpful in predictions of earnings but not necessarily for cash flows and we find mixed evidence for other indicators tested by the literature (e.g., for first-year losses, dividend-paying stocks). Thus, while disentangling the effects of persistent and transitory losses seems to be challenging in predictions of future firm performance, the asymmetry of earnings and losses is central for performance predictions.

Lastly, correctly specified predictions of future cash flows and earnings are important for a wide range of research questions and for practitioners (e.g., analysts). While a number of papers acknowledge loss reversal tendencies (Fama and French, 2000; Hayn, 1995; Li, 2011), only a few explicitly account for the differences of profit and loss firms in their forecasting models with a dummy variable (Fama and French, 2006; Hou et al., 2012). Our findings suggest that this approach is not sufficient to capture the lower persistence of negative earnings and cash flows. We solve that problem by including an interaction term and provide evidence of a significant reduction in forecasting errors. We also add to the scarce literature on forecasts of more than one-year-ahead performance (in our model up to four years) and show that including the logarithm of total assets enhances predictive ability.

We structure our paper as follows. Section 2 discusses the theoretical background and the hypotheses. Section 3 describes our methodology and the data. Section 4 documents the empirical analysis and results. Section 5 concludes. Appendix A and Appendix B contain robustness checks and additional analyses.

2. Theory and hypotheses

Flagmeier (2017), Gordon and Joos (2004), Herbohn et al. (2010), and Legoria and Sellers (2005) provide evidence that unrecognized deferred tax assets (from tax loss carryforwards) are significantly correlated with future performance outcomes. From a theoretical perspective, there are two reasons why accounting information on tax loss carryforwards can provide valuable information on future firm performance. First, deferred tax assets reflect future cash tax savings and therefore affect a firm's after-tax cash flow (Laux, 2013; Legoria and Sellers, 2005). Second, in prominent accounting systems such as IFRS or US GAAP, the capitalization of deferred tax assets from tax loss carryforwards is only allowed if expected tax savings are foreseeable. As exemplified by International Accounting Standards (IAS) 12.34,

> A deferred tax asset shall be recognized for the carryforward of unused tax losses and unused tax credits to the extent that it is probable that future taxable profit will be available against which the unused tax losses and unused tax credits can be utilized.

Thus, accounting for deferred tax assets from tax loss carryforwards requires managers to forecast future taxable income that can be offset against remaining tax loss carryforwards.

While the definition of taxable income is not identical to book income, taxable income correlates with performance measures such as operating cash flow and earnings before taxes (Herbohn et al., 2010). Thus, if managers comply with accounting principles and provide high-quality information, deferred tax assets from tax loss carryforwards contain managers' private information about future firm developments, which would be valuable for forecasts of future earnings and cash flows. A reason for standard-conforming behavior are (reputational) risks of financial restatements and unstable accounting practices, which can be quite substantial.[1] In line with this argumentation, Dhaliwal et al. (2013) show that the valuation allowance on deferred tax assets (instead of deferred taxes from tax loss carryforwards as in our case) provides incremental information about the persistence of accounting losses.

Following the literature, we do not directly use recognized deferred tax assets (from tax loss carryforwards) as an explanatory variable.[2] Some papers rely on the valuation allowance encompassing the value of unrecognized deferred tax assets (from tax loss carryforwards) (Dhaliwal et al., 2013; Herbohn et al., 2010). The impairment approach of SFAS 109.17 in the US GAAP requires, in a first step, the capitalization of the sum of recognized and unrecognized deferred tax assets. In a second step, the approach corrects the non-valuable (unrecognized) component of deferred tax assets by a valuation allowance (SFAS 109.43c, similar also in Australian GAAP and UK GAAP). Instead, the affirmative judgment approach of IFRS does not require the disclosure of a valuation allowance. Instead, IFRS provides detailed information on the amount of tax losses for which no deferred tax asset has been recognized in the notes of the financial statement (IAS 12.81e). Since unrecognized deferred tax assets from tax loss carryforwards (respectively the corresponding valuation allowance) are defined as the aggregate sum of the unrecognized tax loss carryforwards of all subunits of a group multiplied by the relevant tax rates, unrecognized tax loss carryforwards should be well suited as an alternative measure for the non-valuable component of tax loss carryforwards. A benefit of this variable is that it is not affected by differences in the various tax rates of a multinational group, which might bias unrecognized deferred taxes from tax loss carryforwards as a measure for tax

[1] Lys et al. (2015) denote such standard conforming accounting practices that unintentionally reveal managers' private information as passive signaling. Among others, Gleason et al. (2008) provide evidence that financial restatements are punished by capital markets.

[2] The reason is that deferred tax assets from tax loss carryforwards are positively affected not only by future taxable income but also by former tax losses. For example, additional tax losses in the past increase the total amount of tax loss carryforwards, which can result in higher expected future tax savings, but do not necessarily imply better future firm performance.

losses that cannot be offset in future periods. For example, a firm with a high average tax rate and a low fraction of valuable losses may have the same deferred tax asset from tax loss carryforwards as a firm with a low average tax rate and a high fraction of valuable losses.

From a theoretical perspective, unrecognized tax loss carryforwards should be negatively correlated with future firm performance. An increase in unrecognized tax loss carryforwards could be driven by either an impairment of deferred tax assets from tax loss carryforwards (negatively adjusted expectations) or additional unrecognized losses in the current period. Since current losses are a predictor of future losses (Li, 2011), both cases suggest a reduction in future firm performance. A reduction in unrecognized tax loss carryforwards could be due to a) reversal of an impairment loss (positively adjusted expectations), b) a reduction in unrecognized tax loss carryforwards resulting from a settlement with current earnings, or c) the expiration of unrecognized tax loss carryforwards. At least cases a) and b) suggest higher future firm performance. We hypothesize the following.

H1a: *There is a negative correlation between unrecognized tax loss carryforwards and future firm performance.*

H1b: *The consideration of unrecognized tax loss carryforwards improves the accuracy of forecasts of future firm performance.*

In our data, we find great heterogeneity of the tax footnote and voluntary disclosure behavior concerning tax loss carryforwards (see Section 3.1). For example, 28.86% of our firm–year observations voluntarily disclose the book value of the valuation allowance on deferred tax assets from tax loss carryforwards and 51.74% the total amount of tax loss carryforwards.[3] Considering other research (Dhaliwal et al., 2013; Gordon and Joos, 2004; Herbohn et al., 2010) as well as the literature on tax disclosure (Flagmeier and Müller, 2016; Hamrouni et al., 2015;

[3] The total amount of tax loss carryforwards is considered voluntarily disclosed if it is disclosed either directly or indirectly by disclosing the amount of unrecognized and recognized tax loss carryforwards simultaneously.

Jiao, 2011), we expect the provision of more detailed (voluntary) accounting information to improve forecasting models on future firm performance. We hypothesize the following.

H1c: *Considering additional (voluntary) information on tax loss carryforwards and deferred taxes improves the accuracy of forecasts of future firm performance.*

Accounting and finance research provides compelling evidence that negative cash flows and losses are, on average, less persistent than positive cash flows and earnings (Hayn, 1995; Joos and Plesko, 2005; Li, 2011). Nevertheless, widely applied forecasting models of cash flows and earnings treat losses and negative cash flows the same way as profits and positive cash flows (Barth et al., 2001; Bostwick et al., 2016; Dichev and Tang, 2009; Hou and Robinson, 2006; Kim and Kross, 2005; Lev et al., 2010). While some papers acknowledge tendencies of loss reversal (Fama and French, 2000; Hayn, 1995; Li, 2011), only a few explicitly account for the differences of profit and loss firms by adding a dummy variable for loss firms (Fama and French, 2006; Hou et al., 2012). However, even that approach may be insufficient to capture the lower persistence of negative earnings and cash flows, since it does not consider the heterogeneity in the correlation of current and future performance for profit and loss firms. Thus, existing forecasting models should lead to an overestimation of the persistence of losses and an underestimation of the persistence of profits. We hypothesize a weaker correlation of current firm performance with future firm performance for loss firms. Considering that aspect should increase the accuracy for forecasting models.

H2a: *Compared to positive current firm performance, negative current firm performance has a weaker correlation with future firm performance.*

H2b: *Accounting for the heterogeneity of the persistence of positive and negative performance improves the accuracy of forecasts of future firm performance.*

Research on accounting losses documents that some losses are persistent while others are not (Dhaliwal et al., 2013; Hayn, 1995). Joos and Plesko (2005) as well as Li (2011) provide forecasting models to identify firm–years with persistent losses. Evidence suggests that past (persistent) losses provide information about future losses. Thus, we hypothesize:

H3a: *There is a negative correlation between past (persistent) losses and future firm performance.*

H3b: *The consideration of past (persistent) losses improves the accuracy of forecasts of future firm performance.*

3. Data and methodology

3.1 Data

We use hand-collected accounting information from consolidated German business reports. We manually collect consolidated IFRS accounts from 2004 to 2012 for all firms that were been listed in the most relevant German stock indices (DAX 30 and MDAX 50) for at least one year from 2005 until 2012. For example, if a firm was listed in the MDAX in 2005, we consider the IFRS accounts of that firm over the whole period. Our goal is to obtain a comprehensive time series of IFRS accounts. Consolidated IFRS accounts became obligatory for all listed firms on the German stock market in 2005.[4] In addition, we consider IFRS accounts from 2004 if they are available. Altogether, we obtain 866 observations from 106 firms.[5]

Using the Worldscope database (Thomson Reuters, 2012), we complement our hand-collected data with annual accounting information, searching for missing information in Worldscope when possible. We also sent requests by mail to all firms with missing information on a) deferred tax assets from tax loss carryforwards, b) the amount of unused tax loss carryforwards that had not been recognized as deferred tax assets, and c) the aggregate amount of recognized and unrecognized tax loss carryforwards in their annual reports. We change observations with a deviating fiscal year to the calendar year in which the fiscal year ended

[4] Firms listed at non-EU stocks exchanges and using non-EU financial reporting standards were permitted to delay the adoption of IFRS until 2007, https://www.iasplus.com/en/jurisdictions/europe/germany (see also PwC, 2015).
[5] In addition, 30 business annual reports were unavailable due to insolvencies, mergers, or acquisitions, even upon request via mail. These reports were not included in our initial sample.

(e.g., 2012 for the fiscal year from October 2011 to August 2012). In case of financial restatements, we use the corrected accounts to avoid errors. Loss carryforwards in foreign currencies are converted to euro values using the conversion rate on the accounting date. To obtain a consistent data set, we exclude observations with incomplete fiscal years (12 observations), inconsistent statements (three observations), or missing values (16 observations) regarding total assets, operating cash flows, and earnings before taxes at time *t* (TA_t, CFO_t, EBT_t). Since our goal is to predict future firm performance, we also exclude observations with missing information on cash flows and earnings the next year (CFO_{t+1}, EBT_{t+1}). Our final sample contains 835 observations and we provide detailed information in Table 1.

[Table 1 about here]

Our sample documents wide heterogeneity in disclosure behavior regarding deferred taxes and tax loss carryforwards. While there is no mandatory information regarding tax loss carryforwards for some firm–years, additional information is disclosed in a significant number of observations. Table 2 provides detailed documentation of the disclosure behavior in our data. As mandatory information (see IAS 12.81e and IAS 12.81g(i)), we consider recognized deferred tax assets from tax loss carryforwards, *DTA LCF*, as well as the value of unrecognized tax loss carryforwards, *ULCF*. In addition, we report voluntary disclosure for the book value of the valuation allowance regarding deferred tax assets from tax loss carryforwards, *VAL*; the change in the corresponding valuation allowance, ΔVAL; and the total amount of tax loss carryforwards *TLCF* (i.e., the sum of recognized and unrecognized carryforwards).

[Table 2 about here]

It turns out that information on deferred tax assets from tax loss carryforwards is provided in the tax footnote in only 77.84% of the observations and on unrecognized tax loss carryforwards in only 70.18%, despite these disclosures being mandatory according to IAS 12.81. Thus, more than a quarter of our observations do not provide all the required items. In the case of deferred tax assets from tax loss carryforwards, this lack is mainly driven by observations disclosing an aggregate sum of all deferred tax assets (e.g., from tax loss carryforwards and timing differences), of different components of deferred tax assets (from tax loss carryforwards and interests), or the net of deferred tax assets and deferred tax liabilities. It is not possible to identify deferred tax assets from tax loss carryforwards in these cases. Similar issues hold for unrecognized tax loss carryforwards, since some observations provide the aggregate sum of total tax loss carryforwards instead of their unrecognized component. It is possible that some observations do not disclose information, since the value of their tax loss carryforwards is zero. However, if the information in the tax footnote does not allow for the identification of such cases, we treat that information as missing. As mentioned before, we mail a request to all firms with missing information to provide us with that data. Concluding, we treat all observations without detailed information on either deferred tax assets from tax loss carryforwards or unrecognized tax loss carryforwards as non-disclosures if either 1a) the corresponding values are reported in an aggregate sum with other items or 1b) the corresponding items are not reported and 2) our mailed request regarding these items was not answered. While part of the relatively high non-disclosure of mandatory items should be subject to the IFRS introduction period (Table 2), our findings also cast doubt on the quality of IFRS accounting practices.

Information that IAS 12.81 does not require is voluntarily provided in a significant number of observations: 28.86% report the book value of the valuation allowance on deferred tax assets from tax loss carryforwards, 14.49% the change of the corresponding valuation allowance in the current year, and more than half (51.74%) the aggregate amount of total tax loss carryforwards. Mandatory and voluntary disclosures increase over time, which should be due to the introduction period of the IFRS from 2004 to 2007. We expect that firms needed time to fully implement IFRS tax accounting.

The statistics in Table 2 have two important implications for our analysis. First, although we want to address the informational value of mandatory and voluntary IFRS information, not all firms disclose that information. Thus, our empirical specification must account for the fact that not all observations provide the same information in their financial reports. To address this problem, we use dummy variables to account for observations disclosing (D = 1) or not disclosing (D = 0) a certain type of information. Second, poor disclosure could be a red flag for investors. As suggested by Hamrouni et al. (2015) and Jiao (2011), firms with poor future expected performance could choose a lower disclosure level, even if this increased their cost of capital (Healy and Palepu, 2001; Verrecchia, 1983). Therefore, we test if observations with a higher disclosure level differ, on average, from observations with a lower disclosure level and if a higher disclosure level improves performance forecasts (H1c).

We use the general industry classification of Thomson Reuters (2012) to allocate our observations to industries. By far the majority of our observations are industrial firms (617 firm–years). Further relevant industries are public utilities (23 firm–years), transportation (27 firm–years), banks (61 firm–years), insurances (43 firm–years), and financial service providers and other firms (73 firm–years). Due to the limited number of observations, we abstain from a more precise industry classification and the exclusion of financial firms and potential outliers from our main setting (for an analysis excluding financial firms and outliers, see Appendix A).

3.2 Methodology

In our analysis, we refer to three types of empirical tests. First, we test the correlation of our explanatory variables with future performance measures. Generally, indicators for future losses should be negatively correlated with future firm performance (H1a, H2a, H3a). Second, we test whether the inclusion of additional explanatory variables increases the explanatory power of our forecasting regressions. These in-sample tests mainly rely on F-tests, as well as on comparisons of adjusted R^2 values. Third and most relevant, we perform out-of-sample tests if and how the inclusion of additional explanatory variables affects the predictive ability of our forecasting models (H1b, H1c, H2b, H3b). As indicators for our out-of-sample tests, we refer to the mean absolute forecast error (MAFE) and Theil's U (Eng and Vichitsarawong, 2017; Lev et al., 2010). MAFE is the mean of the absolute differences of actual and predicted performance.

Theil's U-statistic is the unweighted average of U-statistics over all predicted years, with U defined as $U = \sqrt{\sum(Actual - Forecast)^2 / \sum(Actual)^2}$. Thus, Theil's U provides a weighted average statistic of forecasting errors, with higher weights on larger errors.

We initially focus on two pre-tax performance measures as the dependent variables: a) (pre-tax) cash flow from operations (*CFO*) and b) earnings before taxes (*EBT*). For cash flows, we adjust the after-tax operating cash flow as provided by Worldscope (Net Cash flow – Operating Activities Field 04860) by current taxes corresponding to IAS 12.15 to approximate the pre-tax operating cash flow. In Section 4.4, we extend the analysis to the post-tax performance measures of cash flow after cash taxes, *CFAT*, and earnings after taxes, *EAT*.

Following the literature on the prediction of future cash flows and earnings (Barth et al., 2001; Dechow et al., 1998; Eng and Vichitsarawong, 2017; Finger, 1994; Lev et al., 2010; Lorek and Willinger, 1996), we rely on two widely applied reference models. First, the findings of Lev et al. (2010) suggest that a simple prediction model with current performance as the only explanatory variable could be well suited to predict future firm performance. Thus, similar to Herbohn et al., (2010), our baseline model regresses a measure of future firm performance (e.g., operating cash flow) ($PERF_{t+x}$) on the same current performance measure ($PERF_t$) and dummy control variables for industry and year fixed effects.[6] Corresponding to Flagmeier (2017), we scale performance measures by total assets:

$$PERF_{it+x} = \alpha + \beta_1 \cdot PERF_{it} + \gamma_1 \cdot INDUSTRY_i + \gamma_2 \cdot YEAR_t + u_{it}. \tag{1}$$

Second, a widely applied model for the prediction of cash flows (Bostwick et al., 2016, with further references) is the approach of Barth et al. (2001, in the following BCN), which regresses future cash flow on current cash flow and six accrual variables. In detail, the BCN model considers the current year's change in accounts receivable (*ΔAR*), change in accounts payable

[6] Since performance is scaled by total assets, it does not seem to be necessary to explicitly control for firm size. We further address this issue in Appendix B.

(ΔAP), change in inventories (ΔINV), depreciation ($DEPR$), amortization ($AMORT$), and other changes in accruals ($OTHER$), where $OTHER$ is the difference in earnings before taxes and operating cash flow adjusted by the five other accrual items of the regression model ($OTHER = EBT - (CFO + \Delta AR - \Delta AP + \Delta INV + DEPR + AMORT)$). We scale all variables by total assets. While this model has been typically used for the prediction of one-year-ahead cash flows, it can also be used for the prediction of other performance measures in the next year or more distinct future periods. A generalized version of the model is

$$\begin{aligned} PERF_{it+x} = {} & \alpha + \beta_1 \cdot PERF_{it} + \beta_2 \cdot \Delta AR_{it} + \beta_3 \cdot \Delta AP_{it} + \beta_4 \cdot \Delta INV_{it} + \beta_5 \cdot DEPR_{it} \\ & + \beta_6 \cdot AMORT_{it} + \beta_7 \cdot OTHER_{it} + \gamma_1 \cdot INDUSTRY_i + \gamma_2 \cdot YEAR_t + u_{it} . \end{aligned} \tag{2}$$

To analyze the relevance of additional accounting items, we test if the inclusion of these items increases the explanatory power (in-sample tests) as well as the predictive ability (out-of-sample tests) of the baseline model and the BCN model. If we refer to the baseline model as a reference point and consider all additional variables, we obtain the following extended model

$$\begin{aligned} PERF_{it+x} = {} & \alpha + \beta_1 \cdot PERF_{it} + \beta_2 \cdot LOSS_{it} + \beta_3 \cdot LOSS_{it} \times PERF_{it} \\ & + \beta_4 \cdot D_{it}^{ULCF} + \beta_5 \cdot D_{it}^{ULCF} \times ULCF_{it} + \beta_6 \cdot D_{it}^{LSEQ} + \beta_7 \cdot D_{it}^{LSEQ} \times LSEQ_{it} \\ & + \beta_8 \cdot VD_{it}^{TLCF} + \beta_9 \cdot VD_{it}^{TLCF} \times TLCF_{it} + \beta_{10} \cdot VD_{it}^{VAL} + \beta_{11} \cdot VD_{it}^{VAL} \times VAL_{it} \\ & + \beta_{12} \cdot VD_{it}^{\Delta VAL} + \beta_{13} \cdot VD_{it}^{\Delta VAL} \times \Delta VAL_{it} \\ & + \beta_{14} \cdot D_{it}^{DTA\,LCF} + \beta_{15} \cdot D_{it}^{DTA\,LCF} \times DTA\,LCF_{it} \\ & + \beta_{16} \cdot D_{it}^{DTAD} \times DTAD_{it} + \beta_{17} \cdot D_{it}^{DTL} \times DTL_{it} + \gamma_1 \cdot INDUSTRY_i + \gamma_2 \cdot YEAR_t + u_{it} , \end{aligned} \tag{3}$$

where $LOSS$ is a dummy variable for firms with negative current performance, $PERF$, and conforms to the forecasting approach of Fama and French (2006) and Hou et al. (2012). The term $LOSS \times PERF$, the interaction term of $LOSS$ and $PERF$, accounts for the fact that we expect lower earnings persistence if $PERF$ is negative. Hypothesis H2a implies that positive outcomes of current firm performance are more positively correlated with future performance, $PERF_{t+x}$, compared to negative performance outcomes. Thus, the inclusion of $LOSS \times PERF$ allows H2a to be tested. We expect a positive and significant coefficient for $PERF$ and a negative and significant coefficient for $LOSS \times PERF$. The aggregate partial effect of negative current firm performance on future performance is the sum of both effects.

To test H1a and H1b, we enrich the model by information on unrecognized tax loss carryforwards scaled by total assets (*ULCF*). The literature typically refers to changes in the amount of unrecognized deferred tax assets (from tax loss carryforwards) (Gordon and Joos, 2004; Herbohn et al., 2010). As mentioned before, the item is not mandatory under IFRS. We use the carrying amount of unrecognized tax loss carryforwards, since the use of annual unrecognized tax-loss-carryforward changes would result in the loss of one observation period. In addition, the carrying amount of unrecognized tax loss carryforwards encompasses information about unrecognized tax-loss-carryforward changes in earlier periods (i.e., t - 1, t - 2), which increases the variation in our data, as well as the explanatory power of our models. To account for the variation in mandatory disclosure in our data, we further include the dummy variable D^{ULCF} , which equals one if unrecognized tax loss carryforwards have been reported. The integration of this variable has two benefits. First, D^{ULCF} controls for differences between observations reporting unrecognized tax loss carryforwards and observations not reporting unrecognized tax loss carryforwards. It therefore allows us to keep observations in our sample that do not disclose unrecognized tax loss carryforwards. These observations could provide valuable information (e.g., voluntary disclosure) and increase our sample size. Second, D^{ULCF} provides us with information if and how a firm's higher mandatory disclosure level is related to future firm performance. While related to mandatory disclosure, this should also be relevant for H1c suggesting a higher predictive ability if more voluntarily disclosed information is considered. We use the interaction of the dummy D^{ULCF} with unrecognized tax loss carryforwards scaled by total assets $D^{ULCF} \times ULCF$ to identify the effect of unrecognized tax loss carryforwards (with a value of zero in the case of non-reporting).

Testing H3a and H3b, we further include D^{LSEQ} and $D^{LSEQ} \times LSEQ$, encompassing information about the persistence of losses in earlier periods. Similar to D^{ULCF}, D^{LSEQ} accounts for whether such information is available. We only consider information from IFRS accounts. Thus, if there was a change in the accounting method in the last three years, we regard the information on loss persistence as missing and set the value of D^{LSEQ} to zero. The term $D^{LSEQ} \times LSEQ$ is the interaction of D^{LSEQ} and a variable *LSEQ* with a value of one for negative firm performance in the last year (earnings or cash flows, depending on the performance measure *PERF*), a value of two for negative performance in the two last years, and a value of three for negative performance in the three last years. In our standard specification, a positive value of LSEQ does not require a loss in the current period.[7] In all other cases, *LSEQ* takes a value of zero.

We include a comprehensive set of dummy variables and interaction terms to test H1c suggesting a positive effect of voluntary disclosed information on predictive ability. In detail, we consider three forms of voluntary disclosure: a) voluntary disclosure of total tax loss carryforwards, with the dummy variable VD^{TLCF} and the interaction term $VD^{TLCF} \times TLCF$, b) voluntary disclosure of the book value of the valuation allowance on deferred tax assets from tax loss carryforwards, with the dummy variable VD^{VAL} and the interaction term $VD^{VAL} \times VAL$, and c) voluntary disclosure of the annual change in the corresponding valuation allowance, with the dummy variable $VD^{\Delta VAL}$ and the interaction term $VD^{\Delta VAL} \times \Delta VAL$.

Similar to the literature (Flagmeier, 2017; Gordon and Joos, 2004; Herbohn et al., 2010), we further consider additional accounting items on deferred taxes including the (mandatory) disclosure of recognized deferred tax assets from loss carryforwards, $D^{DTA\,LCF}$, and a

[7] One might argue that *LSEQ* should only consider persistent losses over at least two periods. Therefore, we also calculate an alternative specification, where *LSEQ* has only positive values if a) there has been a negative performance in the last one, two, or three years and b) current firm performance is negative. While this significantly reduces the number of observations with positive values of *LSEQ*, it does not lead to better predictions. Indeed, this alternative version of LSEQ performs typically worse in out-of-sample tests and therefore leads to higher forecasting errors.

corresponding interaction term $D^{DTA\ LCF} \times DTA\ LCF$. Regarding deferred tax assets from timing differences, *DTAD*, and deferred tax liabilities, *DTL*, we abstain from including additional dummy variables and confine ourselves to the interaction terms $D^{DTAD} \times DTAD$ and $D^{DTL} \times DTL$. D^{DTAD} is almost perfectly collinear with $D^{DTA\ LCF}$ and therefore does not provide additional information. D^{DTL} has a value of one in 98.7% of the observations in our data. There are only 11 observations with $D^{DTL} = 0$, a number that seems too small for meaningful inferences. In untabulated robustness checks, we also test models that include these dummy variables but find no relevant changes in the estimates for our other covariates. Table 3 provides an overview of the definitions of the dependent and explanatory variables.

[Table 3 about here]

A number of observations provide sufficient information for the baseline model but not for the BCN model due to missing information on accrual items such as deprecation or amortization. Therefore, the BCN model reduces our sample size from 835 to 646 observations. Table 4 reports the descriptive statistics of the most relevant variables for the full (baseline) sample (Panel A) and the BCN sample (Panel B). Total assets are presented in millions of euros and reveal wide variations in firm size in our data. All other variables are scaled by total assets. On average, total assets amount to €62.9 billion (median €4.8 billion) in the baseline sample and €20.1 billion (median €3.5 billion) in the BCN sample. Thus, missing information seems to be concentrated in firms with a high value of total assets. Average cash flows from operations, *CFO* (earnings before taxes *EBT*), to total assets are higher in the BCN sample, with values of 11.1% (6.6%), but nevertheless close to the performance outcomes in the baseline sample of 9.1% (5.5%). The mean (median) cash flow is positive and higher than earnings in both samples. Regarding *LOSS CFO* × *CFO* and *LOSS EBT* × *EBT*, we report descriptive information for all firms, as well as for loss firms (observations with negative performance, in italics). For these loss observations, average negative cash flows (earnings) amount to -3.6% to

-4.9% (-6.0% to -6.6%) of total assets. As indicated by *LOSS CFO* and *LOSS EBT*, we find that about 12.1% to 13.1% of the observations report negative earnings, while 9.9% report negative cash flows in the baseline sample and 6.0% report negative cash flows in the BCN sample.

[Table 4 about here]

Regarding the variables on deferred taxes and tax loss carryforwards, our descriptive statistics consider observations with non-missing information. We account for observations with missing information by the use of disclosure dummy variables, as documented in Equation (3) and Table 3. Unrecognized tax loss carryforwards *ULCF* are, on average, 7.3% of total assets in the baseline sample and 7.6% in the BCN sample. These are significant fractions and unrecognized tax loss carryforwards could therefore be a relevant indicator of future firm performance. The number of observations with sufficient information for the calculation of *LSEQ CFO* and *LSEQ EBT* is 698 in the baseline sample and 533 in the BCN sample (equal to the number of observations with IFRS information on past performance in the last three years). In most cases, these variables have a value of zero, indicating no loss the previous year (about 85% in the case of *LSEQ EBT* and more than 90% in the case of *LSEQ CFO*).

Recognized deferred tax assets from tax loss carryforwards comprise, on average, 0.9% of total assets (1.0% for the BCN sample), while deferred tax assets from timing differences, *DTAD*, and deferred tax liabilities, *DTL*, are higher, at 2.9% to 3.5% and 4.3% to 4.9%, respectively. Regarding voluntary disclosure, the most relevant item seems to be the total sum of tax loss carryforwards, with a relatively high number of observations and an average value of 11.2% to 11.8% of total assets. By contrast, there is a significantly smaller number of observations disclosing information on the valuation allowance on deferred tax assets from tax loss carryforwards (especially on changes in the valuation allowance). For these observations, the fraction of the valuation allowance on deferred tax assets from tax loss carryforwards to total assets is small (1.5–1.6% for *VAL* and about 0.2% for *ΔVAL*).

4. Analysis and results

4.1 Multivariate correlation tests

To test H1a, H2a, and H3a, we analyze the signs and significance of the regression coefficients of our explanatory variables in Equation (3). In doing so, we estimate a restricted regression model including exclusively the (likewise) most relevant variables $LOSS, LOSS \times PERF$, D^{ULCF}, and $D^{ULCF} \times ULCF$, as well as an extended model including all the additional explanatory variables of Equation (3). We perform these regressions for a) one- and three-year-ahead performances,[8] b) with earnings before taxes, *EBT*, and (pre-tax) cash flow from operations, *CFO*, as the performance measures, and c) with the baseline and the BCN models as the reference model. Table 5 documents the regression results for the restricted model and Table 6 those for the extended model. For the estimation, we use ordinary least squares (OLS). We use robust standard errors clustered on the firm level to account for heteroscedasticity and autocorrelation. As documented by Petersen (2009), these clustered (Rogers) standard errors produce correct estimates and correctly sized confidence intervals in the presence of time-series correlations of standard errors. Variance inflation factors never exceed 3.22 suggesting that multi-collinearity is not a problem. We report the regular R^2 as well as the adjusted R^2 values.

[Table 5 about here]

Confirming H2a, we observe a positive and highly significant regression coefficient for *PERF* but a negative and typically highly significant coefficient for $LOSS \times PERF$. The coefficient for *LOSS* is typically positive but not significantly different from zero in any specification. For example, model 1 (model 5) in Table 5 suggests that a change in the current *CFO* (*EBT*) of 10 percentage points, ceteris paribus, predicts a corresponding change in *CFO* at $t + 1$ of 7.45 (8.47) percentage points. By contrast, if the current *CFO* (*EBT*) values are negative, a change

[8] We also test (untabulated) regressions with two- and four-year-ahead performances with similar findings and implications. The results are available upon request. In our in- and our out-of-sample tests in the Section 4.2 and 4.3, we generally perform forecasts over one, two, three, and four years for earnings and cash flows.

in performance at time t of 10 percentage points predicts a corresponding change in *CFO* (*EBT*) at $t + 1$ of only 3.09 (4.82) percentage points, which is calculated by the sum of the coefficients for *PERF* and $LOSS \times PERF$ = 0.745 – 0.436 (0.847 – 0.365). This difference in the effect of current firm performance on future outcomes is highly significant, as indicated by the interaction term.

In line with the literature on earnings persistence (e.g., Hayn, 1995), our evidence underlines the higher persistence of positive performance outcomes compared to negative performance outcomes, which has not yet been considered in the literature on performance predictions. This effect holds not only for earnings but also (to a lesser significance level) for cash flows and could lead to biased estimates of future firm performance. Table 5 further reveals that the coefficient of *LOSS* does not differ significantly from zero if the interaction term $LOSS \times PERF$ is included. This has two implications. First, including a dummy variable *LOSS* is not sufficient to account for the heterogeneity in the persistence of profit and loss firms. Second, in a horse race, the interaction term $LOSS \times PERF$ clearly surpasses a simple dummy variable such as *LOSS*.

Confirming H1a and the literature on the information content of unrecognized deferred tax assets (from tax loss carryforwards) (Dhaliwal et al., 2013; Flagmeier, 2017; Gordon and Joos, 2004; Herbohn et al., 2010), we find a negative regression coefficient for the interaction term $D^{ULCF} \times ULCF$, indicating that unrecognized tax loss carryforwards may serve as a red flag for lower future firm performance. This holds for earnings and cash flows, as well as for the baseline and BCN models. However, in the case of three-year-ahead cash flows, the coefficients are only significant at the 10% level for the BCN model and not significant for the baseline model. Regarding the control variables (*PERF* and the accrual items of the BCN model), our regression results are in line with the literature. Thus, we obtain positive regression coefficients for *ΔAR*, *ΔINV*, *DEPR*, and *AMORT* and a negative regression coefficient for *ΔAP* if cash flow is the dependent variable (these variables are typically used for cash flow predictions). The coefficients of *DEPR* and *AMORT* are not significant for one-year-ahead cash flows and coefficients typically become less significant for three-year-ahead cash flows.

[Table 6 about here]

While the extended model in Table 6 clearly confirms our findings of negative current firm performance (negative and significant coefficient of $LOSS \times PERF$), the evidence for unrecognized tax loss carryforwards becomes somewhat weaker with negative but insignificant coefficients for three-year ahead cash flow as the dependent variable (see models 2 and 4). To test H3a (negative effect of past losses), we further include D^{LSEQ} and the interaction term $D^{LSEQ} \times LSEQ$. Note that we focus on $D^{LSEQ} \times LSEQ$ and have no expectations with regard to the dummy variable D^{LSEQ}. Confirming H3a, we observe negative and significant coefficients in models 1 to 4, with cash flow as the dependent variable. However, the coefficient estimates are not significantly different from zero if the dependent variable is one- or three-year-ahead *EBT*. A potential explanation for the relatively weak empirical evidence for $D^{ULCF} \times ULCF$ (for cash flows) and $D^{LSEQ} \times LSEQ$ (for earnings) in Table 6 is that both variables are related to past losses and therefore measure similar aspects (which reduces their explanatory power in models with both variables). We will consider this estimation problem in our in- and out-of-sample tests.

Contrasting empirical evidence suggesting a higher disclosure level for more successful firms (e.g., Hamrouni et al., 2015; Jiao, 2011), we find almost no significant correlation of the various dummy variables considering mandatory (D^{ULCF}, $D^{DTA\ LCF}$) or voluntary (VD^{TLCF}, VD^{VA}, $VD^{\Delta VA}$) disclosure and future firm performance. This also holds for additional (untabulated) regressions including only part of these disclosure dummies and can be considered a first indicator that the consideration of additionally disclosed information on deferred taxes and tax loss carryforwards may not be that helpful for performance predictions.

4.2 In-sample tests on explanatory power

As a second step, we test the impact of our additional covariates on the explanatory power of our prediction models. Our main test statistic is an F-test for nested models. We start with a standard model as reference point (either the baseline or BCN model). We extend that model by including either: (H1b) our unrecognized tax loss carryforward variables D^{ULCF} and $D^{ULCF} \times ULCF$ (ULCF model); (H1c) our additional variables regarding voluntary disclosure on tax loss carryforwards, that is, VD^{TLCF}, $VD^{TLCF} \times TLCF$, VD^{VAL}, $VD^{VAL} \times VAL$, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times \Delta VAL$ (VD model); (H2b) the dummy variable *LOSS* (LOSS model), or both the dummy variable *LOSS* and the interaction term $LOSS \times PERF$ accounting for the different persistence of positive and negative performances (NPERF model); (H3b) the variables for past (persistent) losses, D^{LSEQ} and $D^{LSEQ} \times LSEQ$ (LSEQ model).

Regarding the model VD, we also test alternative versions including only part of the voluntary disclosure information on deferred taxes from tax loss carryforwards (e.g., voluntary disclosure on total tax loss carryforwards *TLCF*). As corresponding tests do not lead to substantially different evidence, we abstain from reporting these results. In all models, we further include industry and year dummy variables, as documented in Equation (3). As we itemize the different explanatory factors, results should not be driven by the interrelations of the different factors, for example, unrecognized tax loss carryforwards and our measure for past losses, $D^{LSEQ} \times LSEQ$.

We test each of these extended models against the nested reference model (either the baseline or BCN model) and calculate the adjusted R^2 values. In the case of the NPERF model, we also perform an F-test against the LOSS model [in square brackets]. This is to make sure that the inclusion of the interaction term $LOSS \times PERF$ increases the explanatory power of our forecasting regressions not only compared to the reference model, but also compared to the LOSS model including a dummy variable for loss firms (similar to Fama and French, 2006;

Hou et al., 2012). We consider earnings before taxes and cash flow from operations up to four years ahead as our dependent variables. Thus, different from Tables 5 and 6, the analysis here is not limited to one- and three-year-ahead performances.

In addition to the itemized models, we test the explanatory power of more comprehensive models encompassing combinations of the different modeling approaches. Tables 5 and 6 provide evidence of a strong and highly significant connection of $LOSS \times PERF$ with future firm performance. Therefore, we add this variable as well as the dummy variable *LOSS* to all the other models (the ULCF, VD, and LSEQ models) and test the combined models (the NPULCF, NPVD, and NPLSEQ models) against the nested NPERF model, which only accounts for *LOSS* and $LOSS \times PERF$ as additional explanatory variables. Furthermore, we test an aggregate JOINT model that encompasses all the explanatory variables as documented in Equation (3) and thus further includes information on recognized deferred tax assets from tax loss carryforwards *DTA LCF*, deferred tax assets from timing differences *DTAD*, and deferred tax liabilities *DTL*. Table 7 documents statistics on our F-test values and adjusted R^2 values. Panel A (B) documents our results with the baseline (BCN) model as reference.

[Table 7 about here]

Regarding H1b and H1c, we find only a relatively moderate increase in the explanatory power of our ULCF and VD prediction models. In case of the ULCF and VD model, only one of the performed F-tests in the Panels A and B is significantly different from zero and the adjusted R^2 value is not much higher (typically smaller) than in the baseline and BCN models. In line with H2b, Table 7 suggests that including $LOSS \times PERF$ significantly increases the explanatory power of our forecasting models. In both panels, all the F-tests of the NPERF model against the reference model are highly significant. In addition, F-tests of the NPERF model against the LOSS model are significant in almost all specifications and the adjusted R^2 values of the NPERF model are higher or at least not smaller than the adjusted R^2 values of the LOSS model and the reference model in all specifications. Regarding LSEQ, we observe a significant increase in the explanatory power of cash flow predictions but not of earnings predictions.

Considering the more comprehensive NPULCF, NVD, NPLSEQ, and JOINT models, we generally find an increase in the explanatory power of the more comprehensive models compared to the NPERF model. Thus, enriching the NPERF model by variables regarding information on unrecognized tax loss carryforwards, deferred taxes, and total tax loss carryforwards or past losses typically increases the explanatory power of our forecasting regressions. Regarding NPULCF (NPLSEQ), this holds especially for earnings (cash flow). Considering adjusted R^2 values, the JOINT model, with the maximum number of variables, also seems to provide the highest explanatory power. In conclusion, Table 7 suggests an especially high explanatory power for the additional variable $LOSS \times PERF$, as well as a generally positive impact of a higher number of explanatory variables regarding tax loss carryforwards, deferred taxes (from tax loss carryforwards), and past losses on performance forecasts.

4.3 Out-of-sample tests on predictive ability

Finally, we turn to out-of-sample tests addressing the predictive ability of our forecasting models. Since H1b, H1c, H2b, and H3b hypothesize an increase in the predictive ability of performance forecasts, the out-of-sample tests are our most relevant empirical tests for these hypotheses. In-sample tests do not account for the fact that information on future firm performance cannot be used for performance forecasts. By contrast, out-of-sample tests simulate the prediction of future periods and treat the actual performance outcomes in these periods as unknown. While the regression models use information from earlier periods in the data, later periods can be used for predictions and comparisons of the predicted and actual performance outcomes.

In our case, we opt for a rolling prediction window, considering the information of all available previous periods for the prediction of a given year t. Note that we enrich our data with information on future firm performance from Worldscope. Thus, while the explanatory variables for our hand-collected data on tax loss carryforwards and deferred taxes are limited to the period from 2004 to 2012, actual performance outcomes are also available for 2013 to 2015. Thus, for the prediction of three-year-ahead cash flows in 2015 (2012), we use data on three-year-ahead cash flows from 2007 to 2014 (2007–2011) and explanatory variables from the three-years-ago period 2004 to 2011 (2004–2008). Therefore, predictions of late periods rely on regressions with higher numbers of observations and periods. We regard this as an advantage, since correlations between variables can vary significantly between two years due to macroeconomic shocks but should revert to the mean in the long run. Therefore, we use a minimum of six years for our forecasting regressions and consider the last three observation years (in the case of the predictions of four-year-ahead earnings and cash flows the last two observation years) for our out-of-sample tests on forecasting errors.

As test statistics, we use two indicators in line with Eng and Vichitsarawong (2017) and Lev et al. (2010). First and most relevant, we consider the MAFE of the prediction, which is the mean of the absolute difference between the performance forecast and the actual performance outcome. To identify statistically significant deviations for the various prediction models, we perform one-sample t-tests on the equality of the MAFEs in a reference model R and an extended model E (e.g., additionally considering information on unrecognized tax loss carryforwards, *ULCF*). The prediction models are the same as in our in-sample tests. Thus, we test the ULCF, VD, LOSS, NPERF, and LSEQ models against the corresponding reference models (either the baseline or BCN model). Second, we test the NPULCF, NPVD, NPLSEQ, and the aggregate JOINT models against the NPERF model.

As already mentioned in Section 3.2, we calculate Theil's U-statistics over the last three years (in the case of the predictions of four-year-ahead earnings and cash flows the last two years) in our sample. Compared to the MAFE, Theil's U gives greater weight to larger errors and ranges from zero to one. Since it is an aggregate measure over all observations, it does not allow for tests of significant deviations.

Table 8 provides statistics on the MAFE and Theil's U (in parentheses). Panel A (B) documents our results with the baseline (BCN) model point of reference. Statistically significant differences between the MAFEs of the respective model (e.g. ULCF) and the reference (either baseline/BCN model or, in the case of more comprehensive models, the NPERF model) are denoted by * (10% level), ** (5% level), and *** (1% level). In case of the NPERF model, we also report significant differences to the LOSS model, denoted by $^{+}$ (10% level), $^{++}$ (5% level) and $^{+++}$ (1% level).

[Table 8 about here]

Contradicting H1b and H1c, we do not find greater predictive ability of the ULCF and VD models compared to the reference case. Thus, the MAFE is typically and often significantly higher, as it is for the baseline and BCN models. We also find higher Theil's U-statistics. Thus, Table 8 suggests that considering information on unrecognized tax loss carryforwards and related deferred taxes worsens performance predictions.

Confirming H2b, we find lower MAFE values for the NPERF model (compared to the baseline, BCN, and LOSS models) that are significantly different from those of the reference model and the LOSS model in most specifications. Table 8 provides robust evidence that the inclusion of the interaction term $LOSS \times PERF$ significantly enhances the predictive ability of our performance forecasts, in addition to a pure loss dummy, *LOSS*. In line with that statement, we also find a reduction of Theil's U for the NPERF model compared to the reference model in almost all specifications (except for the prediction of one-year-ahead cash flows). The empirical evidence for the LSEQ model is mixed. Thus, considering information on past (persistent) losses could improve but could also worsen predictions. In the case of up-to-three-years ahead earnings, LSEQ leads to better predictions.

Comparing our more comprehensive NPULCF, NPVD, NPLSEQ, and JOINT models with the NPERF model leads to similar implications as the analysis of the itemized models. Except for the NPLSEQ model (which is usually worse than but sometimes also better than the NPERF model), the NPERF model clearly outperforms all the other models, especially those with the highest numbers of variables, NPVD and JOINT. Hence, while our in-sample tests suggest a higher explanatory power for models with a high number of explanatory variables, the implications of our out-of-sample predictions are almost the opposite. This finding is consistent with evidence suggesting limited usefulness of a high number of explanatory variables for out-of-sample predictions (Lev et al., 2010; Lorek and Willinger, 1996). Compared to the reference case, there seems to be only one specification (NPERF) that clearly enhances the accuracy of our predictions. This underlines the relevance of the interaction term $LOSS \times PERF$.

4.4 Tests on after-tax performance

We also present in- and out-of-sample tests on the after-tax performance measures of cash flow from operations after taxes (*CFAT*) and earnings after taxes (*EAT*). Thus, we analyze if our results also hold for the prediction of after-tax performance measures. A theoretical argument for the stronger explanatory power of information on deferred taxes in this context is that deferred tax items provide information on future cash taxes and cash tax savings (Laux, 2013). Thus, one could expect information on unrecognized tax loss carryforwards (ULCF model) or deferred tax assets (VD and JOINT models) to become more relevant in this case.

We abstain from reporting simple multivariate correlation tests, which confirm our previous findings in Tables 5 and 6, and focus on our in- and out-of-sample tests. Apart from using after-tax performance measures, our specification conforms to Tables 7 and 8. We report the results in Tables 9 and 10. Our results are broadly in line with our previous findings. Similar to the pre-tax variables, we find that including $LOSS \times PERF$ largely increases the explanatory power of our models and reduces forecast errors. By contrast, considering accounting information on unrecognized tax loss carryforwards (ULCF and NPULCF models) and deferred taxes in general (VD, NPVD, and JOINT models) does not add much explanatory power in our in-sample tests and again leads to a deterioration of our out-of-sample forecasting models with higher MAFEs. Information on the sequence of past losses (LSEQ and NPLSEQ models) typically increases explanatory power (especially for cash flows) and reduces forecast errors (especially for earnings). Thus, the evidence for our measure of past losses *LSEQ* is stronger for post-tax performance than for pre-tax performance. Finally, including a high number of variables (JOINT model) improves explanatory power in our in-sample tests but is counterproductive for forecasting because it never significantly reduces but often significantly increases forecasting errors.

[Table 9 about here]

[Table 10 about here]

Our findings for after-tax cash flows are especially interesting, since deferred tax assets (and deferred tax liabilities) should contain valuable information about future tax savings and tax liabilities. We conclude that accounting information on deferred taxes (from tax loss carryforwards) does not seem to provide significant value for the prediction of future firm performance. In part, this could be driven by the fact that not all firms provide comprehensive mandatory accounting information on deferred tax assets from tax loss carryforwards.

4.5 Robustness tests and additional analyses

We conduct a battery of tests and additional analyses to control for the robustness of our findings. In a first set of robustness tests, we adjust our data and exclude observations of financial firms (banks, insurance companies, other financial firms) and outliers from our sample. We define outliers as observations with very high performance, very low performance, or abnormally high standard errors in forecasting regressions. We provide a detailed description of the definition of outliers in Appendix A. The remaining sample consists of 614 observations and the results remain broadly unchanged (see Appendix A). In a second (unreported) set of robustness tests, we consider alternative definitions of dependent and explanatory variables. We test an alternative specification of *LSEQ (LSEQA)*, where only firm–years with losses in the current period and a sequence of losses in previous periods are considered (past and current losses). *LSEQA* has a value of one to three if performance is negative in the current year and one to three preceding years. This alternative specification typically leads to higher forecasting errors than our standard specification of *LSEQ*. In addition, while *LSEQA* increases the explanatory power of our models (similar to *LSEQ*), in does not consistently improve predictive ability. Thus, overall results remain virtually unchanged. We also use EBITDA as alternative dependent variable with consistent empirical findings. In a third set of tests, we consider alternative empirical specifications of our regression models. Most relevant, we analyze itemized prediction models, where we test the additional explanatory power (predictive ability) for itemized explanatory factors of the JOINT model (e.g., deferred tax assets from timing differences and tax credits, *DTAD*). We also test alternative variable specifications (e.g., regarding regression controls).

In additional analyses, we test if the inclusion of further control variables improves predictions (see Appendix B). Considering the findings in the literature (Darrough and Ye, 2007; Joos and Plesko, 2005; Kothari et al., 2002; Li, 2011), we test the following variables and factors: a dummy variable for dividend-paying firms and a dummy variable for firms with a first-time loss (as an indicator of transitory losses), the market-to-book ratio, R&D expenditures scaled by total assets, and firm size (measured by the logarithm of total assets). While these additional variables increase the explanatory power of our in-sample tests (especially the market-to-book ratio, R&D expenditures, and a dummy for first-year losses), only firm size clearly enhances the predictive ability of out-of-sample tests. In addition, we find a (weak) reduction in forecasting errors for the market-to-book ratio and mixed results for the other variables.

5. Conclusion

We analyze the information content of accounting items on tax loss carryforwards, deferred taxes, and losses to predict future firm performance. For our analysis, we use a hand-collected panel of German listed firms (listings in the DAX 30 or MDAX 50 index). While we find a negative and significant correlation of unrecognized tax loss carryforwards and future firm performance, out-of-sample predictions show that considering accounting information on tax loss carryforwards and deferred taxes does not improve and can even worsen the accuracy of performance forecasts. We also find that common forecasting approaches treating positive and negative performances equally or with a dummy variable can lead to biased performance forecasts and provide a simple empirical specification accounting for that problem. In addition, adding variables on firm size seems to increase the predictive ability of our models.

An important aspect is the external validity of our findings. We rely on a sample of annual IFRS accounts of the largest public German firms. Thus, results are not representative of small firms or firms using different accounting standards. Regarding deferred tax assets from tax loss carryforwards, there are relevant differences between IFRS and other prominent standards like US GAAP. While the impairment approach of US GAAP requires the capitalization of all deferred tax assets and a valuation allowance VA (but not of the VA component on deferred tax assets from tax loss carryforwards), the affirmative judgment approach of the IFRS requires the capitalization of the recognized deferred tax assets and a disclosure of unrecognized tax loss carryforwards in the tax footnote. Hence, the IFRS provide mandatory information on the valuable component of tax loss carryforwards, which should be theoretically the most powerful predictor of future firm performance. Nevertheless, we do not find empirical evidence on a usefulness of such itemized accounting information for cash flow and earnings predictions. It seems unlikely that accounting systems without such detailed information on the valuable component of tax loss carryforwards should lead to significantly better forecasts, since main problems (estimation of future taxable income, earnings management) are similar and mandatory accounting information provides less detail on valuable tax loss carryforwards.

Regarding heterogeneity in the correlation of negative and positive performance outcomes with future firm performance, evidence for cash flow and EBITDA (in robustness checks) suggests that our findings are relevant not only for a specific accounting system (Germany GAAP). Nevertheless, more research on these issues considering other accounting systems would be most welcome.

Appendix A: Restricted sample

Due to the relatively limited size of our hand-collected sample, we abstain from excluding observations of financial firms (banks, insurances, other financial firms) and do not account for potential outliers in our baseline specification. Since corresponding observations could drive our results (even if we control for industry dummy variables), we perform a robustness check excluding these observations. First, we exclude all banks, insurance companies, and other financial firms, reducing our sample size by 168 observations. Second, we identify potential outliers, which we exclude from our restricted sample. As a first step, we identify 1% of the observations with the highest positive pre-tax performance and 1% of the observations with the lowest negative pre-tax performance. Thus, observations with either the highest 1% of pre-tax earnings, the highest 1% of pre-tax cash flows, the lowest 1% of pre-tax earnings, and the lowest 1% of pre-tax cash flows are interpreted as outliers. As a second step, we exclude observations where the residual of a simple forecasting regression on one-year-ahead earnings or cash flows exceeds three times the standard deviation of this regression (see Equation 1). Overall, we identify 53 observations as outliers. The remaining restricted sample consists of 614 observations.

As first statistical tests, we perform untabulated regressions as in Tables 5 and 6. While the signs and sizes of the coefficient estimates are close to those for our unrestricted sample, the significance level of our results is somewhat smaller. We report the results for in-sample tests in Table 11 and those for out-of-sample tests in Table 12. The specifications of these tests are the same as in the previous sections.

[Table 11 about here]

[Table 12 about here]

We find evidence that considering additional variables and especially $LOSS \times PERF$ increases the explanatory power of the model (Table 11). Table 12 reveals very similar findings as Table 8. Thus, while the inclusion of $LOSS \times PERF$ significantly improves predictions in a relevant number specifications and never leads to significantly higher MAFEs compared to the reference model, the evidence is much more negative for the other explanatory variables. This holds especially for unrecognized tax loss carryforwards, since the ULCF and NPULCF models typically lead to higher forecasting errors as the reference model (baseline or BCN model) or the NPERF model. Regarding loss persistence, we find that including information on *LSEQ* can help to predict earnings but typically worsens cash flow predictions. Overall, Tables 11 and 12 confirm the findings of Tables 7 and 8.

Appendix B: Additional analyses

We further extend our forecasting models by a number of additional variables. We intend to test if these variables increase explanatory power (in-sample tests) and predictive ability (out-of-sample tests). Joos and Plesko (2005) and Li (2011) develop models for the prediction of loss reversals. These models predict the probability that firms with (persistent) losses in previous years retain positive earnings or cash flows in the current period. Two important and statistically significant variables in these models are a dummy variable for firms with a first loss in the current year and no losses in previous periods and a variable for firms paying out a dividend. The authors find that firms without losses in previous years and dividend-paying firms have a higher probability of loss reversal. Dummy variables for dividend payments are also considered by forecasting models for expected earnings in the tradition of Fama and French (2000; see, e.g., Fama and French, 2006; Hou et al., 2012). Therefore, we test a dummy variable for firms with a first-time loss (*FLOSS*) (that means no loss in the preceding period) and a variable *DIV* defined as the ratio of the cash dividend (Worldscope item 04551) and total assets.[9] In both cases, we enrich the model by dummy variables with a value of zero if the corresponding information is not available (D^{FLOSS}, D^{DIV}) and interaction terms ($D^{FLOSS} \times FLOSS$, $D^{DIV} \times DIV$).

Another relevant issue is the information content of R&D for profit and, especially, loss firms. Theory and empirical evidence suggest that R&D expenditures are related to (uncertain) future earnings and therefore value relevant (Kothari et al., 2002). Since R&D is a form of business investment (Ciftci and Darrough, 2015; Darrough and Ye, 2007), one might expect higher future earnings and cash flows for high R&D firms. In addition, high R&D levels could be an indicator of future loss reversal. Adding information on R&D to the prediction model could

[9] Similar to Joos and Plesko (2005), we also test a dummy variable for dividend-paying firms, *DIVDUM*. However, since this variable generated statistically insignificant regression results (in part with the wrong sign), we include a revised version accounting for the cash value of the dividend in relation to total assets.

therefore enhance predictive ability. We enrich the model by a dummy variable for firm information on R&D expenditures (D^{RD}), an interaction term of R&D expenditures scaled by total assets ($D^{RD} \times RD$), and an additional interaction term with our dummy variable for loss firms to control for different R&D effects for loss firms ($LOSS \times D^{RD} \times RD$).

Furthermore, we test if the consideration of the market-to-book ratio (*MTB*) or firm size (*SIZE*) improves predictive ability. We measure *MTB* as the ratio of the market value of the firm at year-end (Worldscope item 07210) to the common book value of equity (Worldscope item 07220) and consider a dummy variable for a firm's information on *MTB* (D^{MTB}) and an interaction term ($D^{MTB} \times MTB$). We define *SIZE* as the logarithm of total assets. Since all the firms in our standard sample provide this information, we do not consider a disclosure dummy or an interaction term in this case.

Untabulated regression results confirm our expectations and the findings of the literature (Darrough and Ye, 2007; Joos and Plesko, 2005; Kothari et al., 2002; Li, 2011) that *FLOSS*, *DIV*, *RD*, and *MTB* are positively correlated with future firm performance. For *SIZE* we typically find negative regression coefficients, which are (weakly) significant for cash flows as dependent variable. Since our interest is on the explanatory power and predictive ability of these variables, we concentrate on our in- and out-of-sample tests. The specifications of these tests are the same as in the previous subsamples. In addition to our reference model (either the baseline or BCN model), we test the following models. As in Sections 5.2 and 5.3, the NPERF model adds the variables *LOSS* and $LOSS \times PERF$. The NPFLOSS, NPDIV, NPRD, and NPMTB models further enrich that model by D^{FLOSS} and $D^{FLOSS} \times FLOSS$; D^{DIV} and $D^{DIV} \times DIV$; D^{RD}, $D^{RD} \times RD$, and $LOSS \times D^{RD} \times RD$; and D^{MTB} and $D^{MTB} \times MTB$, respectively, while the NPSIZE model enriches the NPERF model by the variable *SIZE*. We report the definitions of these additional explanatory variables in Table 13.

[Table 13 about here]

Table 14 provides the results of our in-sample tests. Overall, we find that additional variables (in most specifications, significantly) increase the explanatory power of our regression models compared to the NPERF model. This holds especially for the NPMTB model as well as for the NPFLOSS and NPRD models. Thus, Table 14 suggests that additional information on the market-to-book ratio, R&D expenditures, and observations with a first loss increases the explanatory power for our regressions as measured by nested F-tests and adjusted R^2 values.

[Table 14 about here]

Table 15 documents the estimates of our out-of-sample tests. These findings differ in a number of aspects from our in-sample tests. Most relevant, additional variables do not necessarily enhance the predictive ability of our forecasting models. For the NPRD model, we even find significantly higher forecasting errors. Thus, adding information on R&D expenditures reduces the predictive ability of our models. Regarding NPFLOSS and NPDIV, we obtain inconclusive results. Thus, including variables on first-time losses or dividends could either reduce or increase forecasting errors. Including information on the market-to-book ratio (NPMTB) can slightly reduce forecasting errors and thus increases predictive ability. However, the difference is not significant in most specifications (just in one of 16 specifications at the 10% level). The only model that clearly enhances predictive ability if compared to the NPERF model is NPSIZE. In this model, we typically find a significant reduction in forecasting errors and never a significant increase. In conclusion, additional information on firm size (measured by the logarithm of total assets) significantly enhances the predictive ability of our models. Apart from the variables in Tables 14 and 15, we also test variables for extraordinary items (Li, 2011) and alternative specifications for dividend-paying firms and firms with persistent losses in earlier periods. These alternative specifications lead to either inconsistent results or results similar to those in previous specifications. Thus, we abstain from reporting these results.

[Table 15 about here]

References

Amir, E., Kirschenheiter, M., Willard, K., 1997. The valuation of deferred taxes. Contemporary Accounting Research 14, 597–622.

Amir, E., Sougiannis, T., 1999. Analysts' interpretation and investors' valuation of tax carryforwards. Contemporary Accounting Research 16, 1–33.

Barth, M.E., Cram, D.P., Nelson, K.K., 2001. Accruals and the prediction of future cash flows. The Accounting Review 76, 27–58.

Bostwick, E.D., Krieger, K., Lambert, S.L., 2016. Relevance of goodwill impairments to cash flow prediction and forecasting. Journal of Accounting, Auditing & Finance 31, 339–364.

Ciftci, M., Darrough, M., 2015. What explains the valuation difference between intangible-intensive profit and loss firms? Journal of Business Finance & Accounting 42, 138–166.

Christensen, T.E., Paik, G.H., Stice, E.K., 2008. Creating a bigger bath using the deferred tax valuation allowance. Journal of Business Finance & Accounting 35, 601–625.

Darrough, M., Ye, J., 2007. Valuation of loss firms in a knowledge-based economy. Review of Accounting Studies 12, 61–93.

Dechow, P.M., Kothari, S.P., Watts, R.L., 1998. The relation between earnings and cash flows. Journal of Accounting and Economics 25, 133–168.

Dhaliwal, D.S., Kaplan, S.E., Laux, R.C., Weisbrod, E., 2013. The information content of tax expense for firms reporting losses. Journal of Accounting Research 51, 135–164.

Dichev, I.D., Tang, V.W., 2009. Earnings volatility and earnings predictability. Journal of Accounting and Economics 47, 160–181.

Eng, L.L., Vichitsarawong, T., 2017. Usefulness of accounting estimates: A tale of two countries (China and India). Journal of Accounting, Auditing & Finance 32, 123–135.

Fama, E.F., French, K.R., 2000. Forecasting profitability and earnings. Journal of Business 73, 161–175.

Fama, E.F., French, K.R., 2006. Profitability, investment, and average returns. Journal of Financial Economics 82, 491–518.

Finger, C.A., 1994. The ability of earnings to predict future earnings and cash flow. Journal of Accounting Research 32, 210–223.

Flagmeier, V., 2017. The information content of tax loss carryforwards - IAS 12 vs. valuation allowance. arqus working paper 216.

Flagmeier, V., Müller, J., 2016. Tax loss carryforward disclosure and uncertainty. Arqus working paper 208.

Frank, M.M., Rego, S.O., 2006. Do managers use the valuation allowance account to manage earnings around certain earnings targets? Journal of the American Taxation Association 28, 43–65.

Gleason, C., Jenkins, N., Johnson, W., 2008. The contagion effects of accounting restatements. The Accounting Review 83, 83–110.

Gordon, E., Joos, P., 2004. Unrecognized deferred taxes: Evidence from the U.K. The Accounting Review 79, 97–124.

Hamrouni, A., Miloudi, A., Benzkriem, R., 2015. Signaling firm performance through corporate voluntary disclosure. Journal of Applied Business Research 31, 609–620.

Hayn, C., 1995. The information content of losses. Journal of Accounting and Economics 20, 125–153.

Healy, P.M., Palepu, K.G., 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics 31, 405–440.

Herbohn, K., Tutticci, I., Khor, P., 2010. Changes in unrecognised deferred tax accruals from carry-forward losses: Earnings management or signaling? Journal of Business Finance & Accounting 37, 763–791.

Hou, K., Robinson, D.T., 2006. Industry concentration and average stock returns. The Journal of Finance 61, 1927–1956.

Hou, K., van Dijk, M.A., Zhang, Y., 2012. The implied cost of capital: A new approach. Journal of Accounting and Economics 53, 504–526.

Jiao, Y., 2011. Corporate disclosure, market valuation, and firm performance. Financial Management 40, 647–676.

Joos, P., Plesko, G.A., 2005. Valuing loss firms. The Accounting Review 80, 1847–1870.

Kim, M., Kross, W., 2005. The ability of earnings to predict future operating cash flows has been increasing—not decreasing. Journal of Accounting Research 43, 753–780.

Kothari, S.P., Laguerre, T.E., Leone, A.J., 2002. Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. Review of Accounting Studies 7, 355–382.

Kumar, K., Visvanathan, G., 2003. The information content of the deferred tax valuation allowance. The Accounting Review 78, 471–490.

Laux, R.C., 2013. The association between deferred tax assets and liabilities and future tax payments. The Accounting Review 88, 1357–1383.

Legoria, J., Sellers, K.F., 2005. The analysis of SFAS No. 109's usefulness in predicting future cash flows from a conceptual framework perspective. Research in Accounting Regulation 18, 143–161.

Lev, B., Li, S., Sougiannis, T., 2010. The usefulness of accounting estimates for predicting cash flows and earnings. Review of Accounting Studies 15, 779–807.

Li, K.K., 2011. How well do investors understand loss persistence? Review of Accounting Studies 16, 630–1667.

Lorek, K.S., Willinger, G.L., 1996. A multivariate time-series prediction model for cash-flow data. The Accounting Review 71, 81–101.

Lynn, S., Seethamraju, C., Seetharaman, A., 2008. Incremental value relevance of unrecognized deferred taxes: Evidence from the United Kingdom. Journal of the American Taxation Association 30, 107–130.

Lys, T., Naugthon, J.P., Wang, C., 2015. Signaling through corporate accounting reporting. Journal of Accounting and Economics 60, 56–72.

Ohlson, J.P., 1995. Earnings, book values, and dividends in equity valuation. Contemporary Accounting Research 11, 661–687.

Ohlson, J.P., 2001. Earnings, book values, and dividends in equity valuation: An empirical perspective. Contemporary Accounting Research 18, 117–120.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. The Review of Financial Studies 22, 435–480.

PwC, 2015. IFRS adoption by country, http://www.pwc.com/us/en/cfodirect/assets/pdf/pwc-ifrs-by-country-2015.pdf.

Schrand, C.M., Wong, M.H.F., 2003. Earnings management using the valuation allowance for deferred tax assets under SFAS No. 109. Contemporary Accounting Research 20, 579–611.

Thomson Reuters, 2012. Worldscope database: Data definitions guide, http://datastream.jp/wp/wp-content/uploads/2012/08/guide_Worldscope-Data-Definitions-Guide-Issue-12.pdf.

Verrecchia, R.E., 1983. Discretionary disclosure. Journal of Accounting and Economics 5, 179–194.

Weber, C., 2009. Do analysts and investors fully appreciate the implications of book-tax differences for future earnings. Contemporary Accounting Research 26, 1175–1206.

Table 1: Sample composition

	2004	2005	2006	2007	2008	2009	2010	2011	2012	Sum
Gross observations	73	92	97	103	104	100	100	99	98	866
Reduced by										
Incomplete fiscal year	1	4	2	1	1	1	0	1	1	12
Untrue statements	1	0	1	0	0	0	0	0	1	3
Missing values	2	0	1	1	3	0	1	0	8	16
Net observations (sample)	69	88	93	101	100	99	99	98	88	835

Table 2: Information on deferred taxes

Information	Mandatory	2004	2005	2006	2007	2008	2009	2010	2011	2012	Sum
Observations		69	88	93	101	100	99	99	98	88	835
Disclosure on											
DTA LCF	Yes	52	69	72	82	77	77	77	75	67	650
ULCF	Yes	35	51	65	71	74	75	75	75	66	586
TLCF	No	24	39	47	53	55	56	56	54	48	432
VAL	No	10	20	22	31	32	33	33	32	28	241
ΔVAL	No	11	16	12	9	17	16	15	13	12	121

The term DTA LCF denotes recognized deferred tax assets from tax loss carryforwards (after valuation allowance), VAL is the book value of the valuation allowance on deferred tax assets from tax loss carryforwards, ΔVAL is the change in the valuation allowance on deferred tax assets from tax loss carryforwards in year *t*, ULCF is unrecognized tax loss carryforwards, and TLCF is total tax loss carryforwards.

Table 3: Variable definitions

Variable	Definition
Dependent variables	
$PERF_{t+x}$	We measure future firm performance at time $t + x$ either by earnings before taxes scaled by total assets EBT_{t+x} or by pre-tax cash flow from operations scaled by total assets CFO_{t+x}.
Explanatory variables for current firm performance	
PERF	In line with the dependent variable, we measure current firm performance at time *t* either by earnings before taxes scaled by total assets, EBT, or by pre-tax cash flow from operations scaled by total assets, CFO.
LOSS	This dummy variable has a value of one for observations with negative current performance (either cash flow or earnings) and a value of zero for observations with a positive value of the applied measure.
LOSS × PERF	This interaction term of LOSS and PERF accounts for the different persistence of firm–years with negative and positive performance.
Explanatory variables for unrecognized tax loss carryforwards ULCF	
D^{ULCF}	Dummy variable with a value of one if information on ULCF is disclosed.
$D^{ULCF} \times$ ULCF	Interaction term of D^{ULCF} and unrecognized tax loss carryforwards scaled by total assets.
Explanatory variables for the persistence of previous negative firm performance	
D^{LSEQ}	Dummy variable with a value of one if information on LSEQ is available (information on $PERF_{t-1}$, $PERF_{t-2}$, and $PERF_{t-3}$ available).
$D^{LSEQ} \times$ LSEQ	Interaction term of D^{LSEQ} and LSEQ, where LSEQ documents the sequence of perpetual years with negative firm performance (either earnings or cash flows as a performance measure) in the last three years. Thus, it can have values of one (negative performance NPERF in year t - 1), two (NPERF in years t - 1 and t - 2), and three (NPERF in years t - 1, t - 2, and t - 3).
Explanatory variables for voluntary disclosure	
VD^{TLCF}	Dummy variable for the disclosure of total tax loss carryforwards, TLCF.
$VD^{TLCF} \times$ TLCF	Interaction term of VD^{TLCF} and total tax loss carryforwards scaled by total assets.
VD^{VAL}	Dummy variable for the disclosure of the book value of the valuation allowance on deferred tax assets from tax loss carryforwards, VAL.
$VD^{VAL} \times$ VAL	Interaction term of VD^{VAL} and the book value of the valuation allowance on deferred tax assets from tax loss carryforwards scaled by total assets.
$VD^{\Delta VAL}$	Dummy variable for the disclosure of the change in the valuation allowance on deferred tax assets from tax loss carryforwards, ΔVAL.
$VD^{\Delta VAL} \times \Delta$VAL	Interaction term of $VD^{\Delta VAL}$ and the change in the valuation allowance on deferred tax assets from tax loss carryforwards in the current year scaled by total assets.
Additional variables for deferred taxes (from tax loss carryforwards)	
$D^{DTA\ LCF}$	Dummy variable for the disclosure of deferred tax assets from tax loss carryforwards, DTA LCF.
$D^{DTA\ LCF} \times$ DTA LCF	Interaction term of $D^{DTA\ LCF}$ and DTA LCF scaled by total assets.
$D^{DTAD} \times$ DTAD	Interaction term of a dummy variable for the disclosure of deferred tax assets from timing differences and tax credits (DTAD) and DTAD scaled by total assets.
$D^{DTL} \times$ DTL	Interaction term of a dummy variable for the disclosure of deferred tax liabilities (DTL) and DTL scaled by total assets.
Additional control variables of the BNC model	
ΔAR	Change in accounts receivable in the current year scaled by total assets.
ΔAP	Change in accounts payable in the current year scaled by total assets.
ΔINV	Change in inventories in the current year scaled by total assets.
DEPR	Depreciation and depletion in the current year scaled by total assets.
AMORT	Amortization in the current year scaled by total assets.
OTHER	Earnings before taxes, EBT, minus cash flow from operations, CFO, plus ΔAR + ΔINV – ΔAP + DEPR + AMORT.

Table 4: Descriptive statistics

Variable	Observations	Mean	Median	S.D.	Min	Max
Panel A: Baseline sample (baseline model)						
Total assets (millions €)	835	62,895.9	4,784.9	206,817.0	132.1	2,202,423.0
CFO	835	0.0914	0.0805	0.0926	-0.3321	0.6345
EBT	835	0.0546	0.0441	0.0898	-0.6946	0.5534
LOSS CFO	835	0.0994	0.0000	0.2994	0.0000	1.0000
LOSS EBT	835	0.1317	0.0000	0.3384	0.0000	1.0000
LOSS CFO × CFO	835	-0.0036	0.0000	0.0187	-0.3321	0.0000
LOSS EBT × EBT	835	-0.0079	0.0000	0.0414	0.6946	0.0000
LOSS CFO × CFO < 0	*83*	*-0.0358*	*-0.0168*	*0.0489*	*-0.3321*	*-0.0001*
LOSS EBT × EBT < 0	*110*	*-0.0602*	*-0.0262*	*0.0996*	*-0.6946*	*-0.0004*
ULCF	586	0.0733	0.0175	0.1765	0.0000	2.0497
LSEQ CFO	698	0.1662	0.0000	0.5627	0.0000	3.0000
LSEQ EBT	698	0.2564	0.0000	0.6830	0.0000	3.0000
LSEQ CFO ≥ 1	*70*	*1.6571*	*1.0000*	*0.8321*	*1.0000*	*3.0000*
LSEQ EBT ≥ 1	*106*	*1.6887*	*1.0000*	*0.8090*	*1.0000*	*3.0000*
DTA LCF	650	0.0089	0.0034	0.0128	0.0000	0.0862
DTAD	648	0.0293	0.0237	0.0240	0.0000	0.1394
DTL	824	0.0433	0.0373	0.0334	0.0000	0.3841
TLCF	432	0.1120	0.0436	0.2352	0.0000	2.1395
VAL	241	0.0152	0.0037	0.0338	0.0000	0.2343
Δ VAL	121	0.0015	0.0002	0.0043	-0.0027	0.0330
Panel b: Restricted sample (BCN model)						
Total assets (millions €)	646	20,129.2	3,482.4	40,647.1	132.1	309,644.0
CFO	646	0.1106	0.0972	0.0909	-0.3321	0.6345
EBT	646	0.0662	0.0561	0.0921	-0.6946	0.5534
LOSS CFO	646	0.0604	0.0000	0.2384	0.0000	1.0000
LOSS EBT	646	0.1207	0.0000	0.3261	0.0000	1.0000
LOSS CFO × CFO	646	-0.0030	0.0000	0.0190	-0.3321	0.0000
LOSS EBT × EBT	646	-0.0079	0.0000	0.0418	-0.6946	0.0000
LOSS CFO × CFO < 0	*39*	*-0.0496*	*-0.0273*	*0.0613*	*-0.3321*	*-0.0020*
LOSS EBT × EBT < 0	*78*	*-0.0657*	*-0.0314*	*0.1038*	*-0.6946*	*-0.0006*
ULCF	439	0.0758	0.0196	0.1889	0.0000	2.0497
LSEQ CFO	533	0.0938	0.0000	0.4533	0.0000	3.0000
LSEQ EBT	533	0.2458	0.0000	0.6839	0.0000	3.0000
LSEQ CFO ≥ 1	*28*	1.7857	1.0000	0.9567	1.0000	3.0000
LSEQ EBT ≥ 1	*76*	1.7237	1.0000	0.8579	1.0000	3.0000
DTA LCF	484	0.0099	0.0044	0.0136	0.0000	0.0862
DTAD	484	0.0351	0.0306	0.0241	0.0006	0.1394
DTL	637	0.0488	0.0417	0.0315	0.0001	0.2010
TLCF	371	0.1176	0.0476	0.2494	0.0000	2.1395
VAL	211	0.0164	0.0052	0.0354	0.0000	0.2343
ΔVAL	84	0.0021	0.0006	0.0050	-0.0027	0.0330

In this table, CFO (EBT) is cash flow from operations (earnings before taxes); LOSS CFO (LOSS EBT) is a dummy variable with a value of one for observations with a negative CFO (EBT); LOSS CFO × CFO (LOSS EBT × EBT) are the interaction terms of LOSS CFO (LOSS EBT) and CFO (EBT); LOSS CFO × CFO < 0 (LOSS EBT × EBT < 0) (in italics) provide information for the subgroup of loss firms; ULCF is unrecognized tax loss carryforwards; LSEQ CFO (LSEQ EBT) takes values from one to three for perpetual negative performance in the previous one to three years and is zero in all other cases, with LSEQ CFO ≥ 1 (LSEQ EBT ≥ 1) (in italics) providing information for firms with past (persistent) losses; DTA LCF is (recognized) deferred tax assets from tax loss carryforwards; DTAD is deferred tax assets from timing differences and tax credits; DTL is deferred tax liabilities; TLCF is the total sum of tax loss carryforwards; VAL (ΔVAL) is the book value (change) of the valuation allowance on deferred tax assets from tax loss carryforwards. Apart from total assets, LSEQ CFO, and LSEQ EBT, all variables are scaled by total assets. The terms Δ VAL, VAL, and TLCF are voluntarily disclosed according to IFRS. Table 3 provides detailed variable definitions.

Table 5: Restricted regression models

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Reference model	Baseline		BCN		Baseline		BCN	
Dependent variable	CFO_{t+1}	CFO_{t+3}	CFO_{t+1}	CFO_{t+3}	EBT_{t+1}	EBT_{t+3}	EBT_{t+1}	EBT_{t+3}
PERF	0.745***	0.564***	0.845***	0.645***	0.847***	0.592***	0.889***	0.738***
	(0.057)	(0.071)	(0.051)	(0.061)	(0.063)	(0.145)	(0.057)	(0.079)
LOSS	0.013	0.010	0.015	0.005	0.010	-0.006	0.001	-0.007
	(0.010)	(0.019)	(0.021)	(0.037)	(0.010)	(0.016)	(0.014)	(0.020)
LOSS × PERF	-0.436***	-0.422*	-0.520**	-0.596	-0.365***	-0.625***	-0.393***	-0.664***
	(0.166)	(0.228)	(0.223)	(0.377)	(0.109)	(0.173)	(0.092)	(0.204)
D^{ULCF}	-0.002	-0.001	0.001	0.001	0.007	0.009	0.005	0.002
	(0.004)	(0.006)	(0.004)	(0.006)	(0.005)	(0.008)	(0.005)	(0.007)
D^{ULCF} × ULCF	-0.067***	-0.034	-0.057**	-0.051*	-0.051**	-0.107***	-0.051**	-0.107***
	(0.022)	(0.021)	(0.026)	(0.030)	(0.023)	(0.039)	(0.020)	(0.039)
ΔAR			0.383***	0.203*			-0.196*	-0.228*
			(0.096)	(0.102)			(0.105)	(0.119)
ΔAP			-0.386***	-0.088			0.147	0.243*
			(0.105)	(0.095)			(0.122)	(0.134)
ΔINV			0.360***	0.195**			-0.143	-0.317**
			(0.096)	(0.090)			(0.112)	(0.147)
DEPR			0.147	0.209			0.169*	0.219
			(0.134)	(0.226)			(0.090)	(0.226)
AMORT			0.047	0.554			-0.140	-0.033
			(0.145)	(0.469)			(0.087)	(0.363)
OTHER			0.233**	0.172**			-0.164**	-0.194*
			(0.107)	(0.084)			(0.065)	(0.113)
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	835	792	646	624	835	792	646	624
R^2	0.644	0.504	0.648	0.501	0.617	0.352	0.640	0.442
Adjusted R^2	0.636	0.492	0.636	0.483	0.608	0.337	0.627	0.422

The dependent variable is either operating cash flow CFO at time *t* + 1, CFO at time *t* + 3, earnings before taxes EBT at time *t* + 1, or EBT at time *t* + 3; estimates are calculated by OLS (in each case scaled by total assets). Heteroscedasticity-robust standard errors are clustered at the firm level and documented in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The term PERF is the current value of the dependent variable. Table 3 provides detailed variable definitions.

Table 6: Extended regression models

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Reference model	Baseline		BCN		Baseline		BCN	
Dependent variable	CFO_{t+1}	CFO_{t+3}	CFO_{t+1}	CFO_{t+3}	EBT_{t+1}	EBT_{t+3}	EBT_{t+1}	EBT_{t+3}
PERF	0.726***	0.558***	0.842***	0.667***	0.830***	0.576***	0.877***	0.715***
	(0.058)	(0.072)	(0.055)	(0.059)	(0.067)	(0.144)	(0.064)	(0.080)
LOSS	0.016*	0.012	0.016	0.008	0.011	-0.008	0.000	-0.011
	(0.008)	(0.015)	(0.017)	(0.022)	(0.010)	(0.016)	(0.014)	(0.021)
LOSS × PERF	-0.453***	-0.459*	-0.605***	-0.763**	-0.383***	-0.664***	-0.432***	-0.735***
	(0.164)	(0.233)	(0.190)	(0.296)	(0.124)	(0.181)	(0.099)	(0.180)
D^{ULCF}	-0.005	0.000	0.001	0.004	0.005	0.005	0.001	-0.000
	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)	(0.009)	(0.005)	(0.008)
D^{ULCF} × ULCF	-0.053**	-0.035	-0.049*	-0.036	-0.039*	-0.093*	-0.045**	-0.133***
	(0.026)	(0.025)	(0.029)	(0.040)	(0.020)	(0.048)	(0.017)	(0.036)
D^{LSEQ}	-0.005	-0.009	-0.001	-0.005	-0.010*	-0.023*	-0.010*	-0.018
	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)	(0.012)	(0.006)	(0.011)
D^{LSEQ} × LSEQ	-0.012***	-0.023**	-0.023**	-0.043**	-0.003	0.003	-0.005	0.008
	(0.004)	(0.011)	(0.009)	(0.020)	(0.004)	(0.005)	(0.005)	(0.006)
VD^{TLCF}	0.002	-0.001	0.002	-0.004	-0.005	-0.001	-0.006	-0.007
	(0.004)	(0.007)	(0.004)	(0.008)	(0.005)	(0.008)	(0.005)	(0.009)
VD^{TLCF} × TLCF	-0.005	0.027	0.017	0.030	-0.023	-0.045	-0.020	-0.020
	(0.017)	(0.027)	(0.022)	(0.029)	(0.016)	(0.037)	(0.021)	(0.032)
VD^{VAL}	-0.007	-0.006	-0.012**	-0.012	0.003	-0.001	0.002	-0.004
	(0.006)	(0.009)	(0.006)	(0.009)	(0.005)	(0.009)	(0.005)	(0.010)
VD^{VAL} × VAL	0.010	0.023	0.107	0.098	-0.029	0.002	-0.028	0.174
	(0.141)	(0.131)	(0.109)	(0.139)	(0.077)	(0.220)	(0.094)	(0.207)
$VD^{\Delta VAL}$	-0.002	-0.002	0.004	0.003	-0.009	-0.007	-0.012	-0.009
	(0.005)	(0.009)	(0.007)	(0.011)	(0.006)	(0.009)	(0.008)	(0.011)
VD^{VAL} × ΔVAL	0.021	1.051	0.412	1.837*	0.904	1.226**	1.289	1.257*
	(0.550)	(0.789)	(0.842)	(1.028)	(1.225)	(0.511)	(1.077)	(0.745)
$D^{DTA\ LCF}$	0.007	0.007	-0.004	-0.006	0.004	0.005	0.007	0.007
	(0.006)	(0.008)	(0.008)	(0.008)	(0.007)	(0.011)	(0.008)	(0.012)
$D^{DTA\ LCF}$ × DTA LCF	-0.104	0.264	-0.005	0.353	0.150	0.342	0.392*	0.111
	(0.221)	(0.303)	(0.229)	(0.281)	(0.203)	(0.423)	(0.211)	(0.410)
D^{DTAD} × DTAD	0.099	-0.141	0.180	0.009	0.087	-0.008	-0.015	-0.037
	(0.123)	(0.165)	(0.138)	(0.152)	(0.102)	(0.189)	(0.112)	(0.202)
D^{DTL} × DTL	-0.081	0.030	-0.083	-0.003	-0.081	-0.131	-0.056	-0.168
	(0.075)	(0.113)	(0.088)	(0.111)	(0.056)	(0.116)	(0.072)	(0.149)
ΔAR			0.398***	0.233**			-0.197**	-0.224*
			(0.094)	(0.100)			(0.098)	(0.116)
ΔAP			-0.400***	-0.114			0.161	0.250*
			(0.107)	(0.093)			(0.121)	(0.128)
ΔINV			0.379***	0.222**			-0.132	-0.297**
			(0.098)	(0.088)			(0.103)	(0.140)
DEPR			0.161	0.111			0.233**	0.213
			(0.128)	(0.158)			(0.110)	(0.222)
AMORT			0.141	0.720**			-0.019	0.081
			(0.157)	(0.343)			(0.140)	(0.341)
OTHER			0.244**	0.195**			-0.172***	-0.192*
			(0.106)	(0.076)			(0.057)	(0.109)
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	835	792	646	624	835	792	646	624
R^2	0.651	0.522	0.659	0.535	0.625	0.366	0.649	0.457
Adjusted R^2	0.638	0.503	0.640	0.508	0.611	0.341	0.630	0.425

The dependent variable is either operating cash flow CFO at time $t + 1$, CFO at time $t + 3$, earnings before taxes EBT at time $t + 1$, or EBT at time $t + 3$; estimates are calculated by OLS (in each case scaled by total assets). Heteroscedasticity-robust standard errors are clustered at the firm level and documented in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The term PERF is the current value of the dependent variable. Table 3 provides detailed variable definitions.

Table 7: In-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations				Earnings before taxes			
Prediction years	1 year (CFO_{t+1})	2 years (CFO_{t+2})	3 years (CFO_{t+3})	4 years (CFO_{t+4})	1 year (EBT_{t+1})	2 years (EBT_{t+2})	3 years (EBT_{t+3})	4 years (EBT_{t+4})
Panel A: Baseline model	(0.625)	(0.537)	(0.487)	(0.446)	(0.593)	(0.381)	(0.302)	(0.231)
ULCF	4.16**	0.54	0.13	0.26	0.57	0.64	1.86	1.10
	(0.628)	(0.537)	(0.486)	(0.445)	(0.592)	(0.380)	(0.303)	(0.232)
VD	0.60	0.86	0.50	0.79	1.05	0.66	0.72	0.97
	(0.624)	(0.537)	(0.485)	(0.445)	(0.593)	(0.379)	(0.300)	(0.231)
LOSS	8.22***	16.49***	5.27**	3.82*	7.50***	2.56	0.83	0.29
	(0.628)	(0.546)	(0.490)	(0.448)	(0.596)	(0.382)	(0.302)	(0.231)
NPERF	4.50**	11.18***	4.23**	6.19***	12.68***	13.44***	10.15***	6.63***
	[0.77]	[5.78**]	[3.18*]	[8.52***]	[17.71***]	[24.25***]	[19.44***]	[12.96***]
	(0.628)	(0.549)	(0.491)	(0.455)	(0.604)	(0.399)	(0.318)	(0.244)
LSEQ	4.18**	5.51***	7.98***	3.29**	1.20	1.80	2.64*	1.68
	(0.628)	(0.542)	(0.496)	(0.450)	(0.593)	(0.382)	(0.305)	(0.233)
NPULCF	9.87***	4.32**	1.92	1.80	5.37***	8.60***	11.94***	7.97***
	(0.636)	(0.552)	(0.492)	(0.456)	(0.608)	(0.410)	(0.337)	(0.259)
NPVD	1.28	1.11	0.27	0.36	2.39**	2.48**	2.81**	3.10***
	(0.629)	(0.549)	(0.488)	(0.451)	(0.608)	(0.406)	(0.327)	(0.258)
NPLSEQ	7.97***	12.38***	12.49***	6.48***	2.89*	2.98*	3.06**	2.51*
	(0.634)	(0.561)	(0.506)	(0.463)	(0.606)	(0.402)	(0.322)	(0.247)
JOINT	2.57***	2.51***	2.36***	1.61*	2.04**	2.41***	2.97***	2.39***
	(0.638)	(0.560)	(0.503)	(0.461)	(0.611)	(0.414)	(0.341)	(0.265)
Observations	835	815	792	691	835	815	792	691
Panel B: BCN model	(0.629)	(0.514)	(0.477)	(0.424)	(0.618)	(0.443)	(0.401)	(0.339)
ULCF	0.37	0.65	0.04	0.48	0.04	0.10	0.29	0.43
	(0.628)	(0.514)	(0.476)	(0.423)	(0.617)	(0.441)	(0.399)	(0.338)
VD	0.68	1.97*	0.98	1.19	1.11	0.72	0.63	0.71
	(0.628)	(0.519)	(0.477)	(0.425)	(0.619)	(0.441)	(0.398)	(0.337)
LOSS	6.09**	10.12***	2.35	2.64	0.94	0.29	0.31	0.19
	(0.632)	(0.521)	(0.479)	(0.426)	(0.618)	(0.442)	(0.400)	(0.338)
NPERF	3.97**	7.35***	2.94*	5.90***	6.62***	7.69***	5.98***	6.26***
	[1.84]	[4.52**]	[3.56*]	[9.12***]	[12.27***]	[15.08***]	[11.65***]	[12.33***]
	(0.632)	(0.524)	(0.481)	(0.434)	(0.625)	(0.455)	(0.410)	(0.352)
LSEQ	3.45**	4.82***	10.02***	5.39***	0.83	1.26	1.93	0.22
	(0.632)	(0.520)	(0.493)	(0.433)	(0.618)	(0.443)	(0.402)	(0.337)
NPULCF	4.09**	2.01	2.31	2.13	3.03**	6.54***	6.94***	7.67***
	(0.636)	(0.526)	(0.483)	(0.437)	(0.627)	(0.464)	(0.422)	(0.368)
NPVD	0.60	1.49	0.83	0.84	1.44	1.36	1.21	1.91*
	(0.631)	(0.526)	(0.480)	(0.433)	(0.626)	(0.457)	(0.412)	(0.359)
NPLSEQ	8.34***	12.97***	17.67***	12.85***	1.42	1.23	1.61	0.49
	(0.641)	(0.542)	(0.508)	(0.459)	(0.625)	(0.455)	(0.411)	(0.351)
JOINT	1.94**	2.90***	3.35***	2.63***	1.61*	2.17***	2.14**	2.36***
	(0.640)	(0.544)	(0.508)	(0.458)	(0.630)	(0.469)	(0.425)	(0.375)
Observations	646	636	624	546	646	636	624	546

This table shows the results of testing deviations of the explanatory power of the ULCF, VD, LOSS, NPERF, and LSEQ models from the reference model (either baseline or BCN) via an F-test for nested models, with adjusted R^2 values in parentheses. We also test the NPERF model against the LOSS model [in square brackets]. The NPULCF, NPVD, NPLSEQ, and JOINT models are tested against the NPERF model. The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects, apart from which the baseline model considers only past firm performance PERF. The BCN model builds on the approach of Barth et al. (2001) and further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The ULCF model adds to these reference models (either the baseline or BCN model) the variables D^{ULCF} and $D^{ULCF} \times$ ULCF. The VD model adds VD^{TLCF}, $VD^{TLCF} \times$ TLCF, VD^{VAL}, $VD^{VAL} \times$ VAL, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times$ ΔVAL, the LOSS model the dummy variable LOSS, the NPERF model LOSS and the interaction term LOSS × PERF, and the LSEQ model D^{LSEQ} and $D^{LSEQ} \times$ LSEQ. The NPULCF model considers the variables of the ULCF model plus LOSS and LOSS × PERF. The same holds for the NPVD and NPLSEQ models with regard to the VD and LSEQ models. The JOINT model considers the additional variables of all models and further $D^{DTA\ LCF}$, $D^{DTA\ LCF} \times$ DTA LCF, $D^{DTAD} \times$ DTAD, and $D^{DTL} \times$ DTL. Table 3 provides detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 8: Out-of-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations				Earnings before taxes			
Prediction years	1 year (CFO_{t+1})	2 years (CFO_{t+2})	3 years (CFO_{t+3})	4 years (CFO_{t+4})	1 year (EBT_{t+1})	2 years (EBT_{t+2})	3 years (EBT_{t+3})	4 years (EBT_{t+4})
Panel A:	0.0293	0.0346	0.0457	0.0476	0.0258	0.0382	0.0400	0.0406
Baseline model	(0.163)	(0.205)	(0.423)	(0.535)	(0.231)	(0.402)	(0.433)	(0.516)
ULCF	0.0308**	0.0354*	0.0464	0.0481	0.0265***	0.0395**	0.0421**	0.0416
	(0.187)	(0.217)	(0.445)	(0.551)	(0.236)	(0.410)	(0.461)	(0.549)
VD	0.0311***	0.0355**	0.0456	0.0474	0.0279***	0.0394**	0.0427***	0.0435**
	(0.182)	(0.215)	(0.431)	(0.529)	(0.246)	(0.418)	(0.473)	(0.561)
LOSS	0.0289	0.0348	0.0451**	0.0471**	0.0249***	0.0374***	0.0396***	0.0406
	(0.160)	(0.120)	(0.418)	(0.526)	(0.229)	(0.398)	(0.431)	(0.516)
NPERF	0.0295	0.0343^{+++}	0.0448***$^{/+}$	0.0461**	0.0243***$^{/+}$	0.0364***$^{/+}$	0.0387***$^{/++}$	0.0406
	(0.174)	(0.196)	(0.416)	(0.503)	(0.215)	(0.384)	(0.416)	(0.507)
LSEQ	0.0300**	0.0351	0.0457	0.0467**	0.0253*	0.0358***	0.0370***	0.0416**
	(0.168)	(0.212)	(0.424)	(0.526)	(0.229)	(0.385)	(0.420)	(0.528)
NPULCF	0.0306*	0.0358**	0.0459**	0.0467	0.0248	0.0377**	0.0405*	0.0421
	(0.186)	(0.206)	(0.432)	(0.506)	(0.215)	(0.391)	(0.449)	(0.557)
NPVD	0.0312***	0.0357**	0.0452	0.0462	0.0265***	0.0382**	0.0421***	0.0446***
	(0.189)	(0.208)	(0.426)	(0.500)	(0.228)	(0.400)	(0.459)	(0.560)
NPLSEQ	0.0295	0.0345	0.0450	0.0452**	0.0242	0.0342***	0.0362***	0.0416*
	(0.173)	(0.195)	(0.413)	(0.487)	(0.214)	(0.367)	(0.403)	(0.518)
JOINT	0.0316**	0.0364**	0.0452	0.0448*	0.0283***	0.0366	0.0406	0.0485***
	(0.198)	(0.214)	(0.421)	(0.471)	(0.241)	(0.400)	(0.503)	(0.651)
Observations	285	274	258	167	276	263	249	167
Panel B:	0.0328	0.0388	0.0537	0.0525	0.0287	0.0385	0.0389	0.0384
BCN model	(0.147)	(0.193)	(0.462)	(0.539)	(0.214)	(0.363)	(0.365)	(0.419)
ULCF	0.0340*	0.0388	0.0540	0.0529	0.0291*	0.0390	0.0395	0.0390
	(0.164)	(0.196)	(0.472)	(0.549)	(0.220)	(0.373)	(0.387)	(0.444)
VD	0.0333	0.0393	0.0533	0.0516	0.0306***	0.0391	0.0399	0.0407**
	(0.153)	(0.198)	(0.459)	(0.523)	(0.228)	(0.378)	(0.382)	(0.452)
LOSS	0.0317	0.0373	0.0501***	0.0513	0.0284**	0.0384	0.0388	0.0384
	(0.156)	(0.120)	(0.418)	(0.526)	(0.215)	(0.363)	(0.365)	(0.419)
NPERF	0.0323	0.0382	0.0526**$^{/++}$	0.0507*	0.0275***$^{/++}$	0.0367***$^{/+++}$	0.0377**$^{/+}$	0.0386
	(0.169)	(0.186)	(0.454)	(0.502)	(0.203)	(0.351)	(0.353)	(0.406)
LSEQ	0.0336*	0.0389	0.0532	0.0533	0.0285	0.0367***	0.0374**	0.0384
	(0.154)	(0.194)	(0.457)	(0.562)	(0.212)	(0.353)	(0.366)	(0.421)
NPULCF	0.0337	0.0389	0.0529	0.0505	0.0281	0.0400**	0.0396	0.0408
	(0.170)	(0.187)	(0.451)	(0.491)	(0.209)	(0.385)	(0.406)	(0.453)
NPVD	0.0335	0.0390	0.0521	0.0497*	0.0295***	0.0393**	0.0397*	0.0411*
	(0.173)	(0.194)	(0.448)	(0.484)	(0.218)	(0.377)	(0.381)	(0.442)
NPLSEQ	0.0335	0.0382	0.0529	0.0526	0.0272	0.0352***	0.0367*	0.0385
	(0.162)	(0.179)	(0.447)	(0.516)	(0.200)	(0.341)	(0.354)	(0.406)
JOINT	0.0338	0.0392	0.0520	0.0505	0.0328***	0.0415*	0.0411	0.0464**
	(0.168)	(0.188)	(0.433)	(0.486)	(0.256)	(0.454)	(0.495)	(0.542)
Observations	220	215	209	140	220	215	209	140

This table shows the results of testing the deviations of the MAFEs of the ULCF, VD, LOSS, NPERF, and LSEQ models via a t-test against the MAFEs of a reference model (either the baseline or BCN model), with Theil's U-statistics in parentheses. The MAFEs of the NPULCF, NPVD, NPLSEQ, and JOINT models are tested via a t-test for significant deviations from the MAFEs of the NPERF model. The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects, apart from which the baseline model considers only past firm performance PERF. The BCN model builds on the approach of Barth et al. (2001) and further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The ULCF model adds to these reference models (either the baseline or BCN model) the variables D^{ULCF} and $D^{ULCF} \times$ ULCF. The VD model adds VD^{TLCF}, $VD^{TLCF} \times$ TLCF, VD^{VAL}, $VD^{VAL} \times$ VAL, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times$ ΔVAL, the LOSS model the dummy variable LOSS, the NPERF model LOSS and the interaction term LOSS × PERF, and the LSEQ model D^{LSEQ} and $D^{LSEQ} \times$ LSEQ. The NPULCF model considers the variables of the ULCF model plus LOSS and LOSS × PERF. The same holds for the NPVD and NPLSEQ models with regard to the VD and LSEQ models. The JOINT model considers the additional variables of all models and further $D^{DTA\ LCF}$, $D^{DTA\ LCF} \times$ DTA LCF, $D^{DTAD} \times$ DTAD, and $D^{DTL} \times$ DTL. Table 3 provides detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 9: After-tax performance, in-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations after taxes				Earnings after taxes			
Prediction years	1 year ($CFAT_{t+1}$)	2 years ($CFAT_{t+2}$)	3 years ($CFAT_{t+3}$)	4 years ($CFAT_{t+4}$)	1 year (EAT_{t+1})	2 years (EAT_{t+2})	3 years (EAT_{t+3})	4 years (EAT_{t+4})
Panel A: Baseline model	(0.546)	(0.452)	(0.413)	(0.382)	(0.519)	(0.283)	(0.216)	(0.153)
ULCF	3.86**	0.31	0.14	0.16	1.25	1.62	2.78*	1.76
	(0.549)	(0.451)	(0.412)	(0.381)	(0.519)	(0.284)	(0.220)	(0.155)
VD	0.93	1.03	0.58	0.82	1.36	1.02	1.04	1.28
	(0.546)	(0.452)	(0.411)	(0.381)	(0.520)	(0.283)	(0.216)	(0.155)
LOSS	7.72***	16.42***	6.19**	3.38*	5.38**	0.89	0.06	0.05
	(0.550)	(0.463)	(0.417)	(0.384)	(0.521)	(0.283)	(0.215)	(0.151)
NPERF	4.88***	12.01***	4.92***	7.31***	8.04***	9.42***	6.56***	3.58**
	[2.03]	[7.45***]	[3.64*]	[11.19***]	[10.64***]	[17.93***]	[13.05***]	[7.10***]
	(0.550)	(0.467)	(0.419)	(0.393)	(0.527)	(0.298)	(0.227)	(0.159)
LSEQ	3.88**	5.48***	7.79***	2.48**	1.30	2.76*	2.80*	2.17
	(0.549)	(0.458)	(0.423)	(0.385)	(0.519)	(0.286)	(0.220)	(0.156)
NPULCF	10.20***	4.38**	2.33*	1.91	4.80***	9.00***	10.82***	7.01***
	(0.560)	(0.471)	(0.421)	(0.395)	(0.531)	(0.312)	(0.247)	(0.174)
NPVD	1.57	1.36	0.36	0.33	2.40**	2.79**	2.58**	2.70**
	(0.552)	(0.468)	(0.416)	(0.390)	(0.532)	(0.307)	(0.237)	(0.172)
NPLSEQ	6.95***	11.39***	11.89***	5.12***	2.68*	4.22**	3.36**	2.58*
	(0.557)	(0.481)	(0.435)	(0.401)	(0.529)	(0.304)	(0.232)	(0.163)
JOINT	2.52***	2.49***	2.31***	1.38	1.96**	2.54***	2.56***	2.20***
	(0.562)	(0.481)	(0.433)	(0.398)	(0.534)	(0.317)	(0.249)	(0.180)
Observations	829	809	786	685	829	809	786	685
Panel B: BCN model	(0.551)	(0.438)	(0.408)	(0.365)	(0.552)	(0.352)	(0.321)	(0.257)
ULCF	0.34	0.57	0.03	0.42	0.11	0.07	0.11	0.20
	(0.550)	(0.438)	(0.406)	(0.363)	(0.550)	(0.350)	(0.319)	(0.255)
VD	1.11	2.01*	0.97	1.14	1.21	0.76	0.73	0.62
	(0.551)	(0.444)	(0.408)	(0.366)	(0.553)	(0.351)	(0.319)	(0.254)
LOSS	7.36***	10.89***	3.40*	1.95	0.60	0.16	0.09	0.00
	(0.555)	(0.447)	(0.410)	(0.366)	(0.551)	(0.352)	(0.320)	(0.256)
NPERF	5.93***	9.95***	4.17**	6.76***	5.14***	7.06***	4.69***	5.23***
	[4.46**]	[8.87***]	[4.92**]	[11.52***]	[9.67***]	[13.95***]	[9.28***]	[10.45***]
	(0.558)	(0.454)	(0.414)	(0.378)	(0.557)	(0.365)	(0.329)	(0.269)
LSEQ	2.90*	4.95***	10.48***	5.45***	0.88	1.38	1.72	0.52
	(0.554)	(0.446)	(0.426)	(0.375)	(0.551)	(0.353)	(0.323)	(0.256)
NPULCF	4.95***	2.03	2.71*	2.03	2.75*	6.42***	4.63**	5.56***
	(0.563)	(0.456)	(0.417)	(0.381)	(0.560)	(0.376)	(0.337)	(0.282)
NPVD	0.94	1.52	0.76	0.68	1.37	1.28	0.87	1.38
	(0.558)	(0.457)	(0.412)	(0.376)	(0.559)	(0.367)	(0.328)	(0.272)
NPLSEQ	6.92***	12.44***	17.73***	11.94***	1.40	1.78	1.69	0.76
	(0.566)	(0.474)	(0.445)	(0.403)	(0.558)	(0.367)	(0.331)	(0.268)
JOINT	2.03**	2.91***	3.38***	2.39***	1.37*	2.01**	1.58*	2.03**
	(0.568)	(0.477)	(0.445)	(0.401)	(0.561)	(0.379)	(0.338)	(0.289)
Observations	645	635	623	545	645	635	623	545

This table shows the results of testing deviations of the explanatory power of the ULCF, VD, LOSS, NPERF, and LSEQ models from the reference model (either baseline or BCN) via an F-test for nested models, with adjusted R^2 values in parentheses. We also test the NPERF model against the LOSS model [in square brackets]. The NPULCF, NPVD, NPLSEQ, and JOINT models are tested against the NPERF models. The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects, apart from which the baseline model considers only past firm performance PERF. The BCN model builds on the approach of Barth et al. (2001) and further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The ULCF model adds to these reference models (either the baseline or BCN model) the variables D^{ULCF} and $D^{ULCF} \times$ ULCF. The VD model adds VD^{TLCF}, $VD^{TLCF} \times$ TLCF, VD^{VAL}, $VD^{VAL} \times$ VAL, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times \Delta$ VAL, the LOSS model the dummy variable LOSS, the NPERF model LOSS and the interaction term LOSS × PERF, and the LSEQ model D^{LSEQ} and $D^{LSEQ} \times$ LSEQ. The NPULCF model considers the variables of the ULCF model plus LOSS and LOSS × PERF. The same holds for the NPVD and NPLSEQ models with regard to the VD and LSEQ models. The JOINT model considers the additional variables of all models and further $D^{DTA\ LCF}$, $D^{DTA\ LCF} \times$ DTA LCF, $D^{DTAD} \times$ DTAD, and $D^{DTL} \times$ DTL. Table 3 provides detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 10: After-tax performance, out-of-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations after taxes				Earnings after taxes			
Prediction years	1 year ($CFAT_{t+1}$)	2 years ($CFAT_{t+2}$)	3 years ($CFAT_{t+3}$)	4 years ($CFAT_{t+4}$)	1 year (EAT_{t+1})	2 years (EAT_{t+2})	3 years (EAT_{t+3})	4 years (EAT_{t+4})
Panel A:	0.0280	0.0322	0.0435	0.0457	0.0233	0.0347	0.0364	0.0359
Baseline model	(0.220)	(0.250)	(0.520)	(0.651)	(0.306)	(0.555)	(0.600)	(0.664)
ULCF	0.0296**	0.0332**	0.0443*	0.0462	0.0243***	0.0362***	0.0389***	0.0372
	(0.252)	(0.266)	(0.551)	(0.671)	(0.315)	(0.570)	(0.640)	(0.710)
VD	0.0296***	0.0331**	0.0437	0.0453	0.0256***	0.0363**	0.0397***	0.0391***
	(0.243)	(0.261)	(0.531)	(0.641)	(0.334)	(0.580)	(0.656)	(0.727)
LOSS	0.0278	0.0323	0.0430	0.0454	0.0227***	0.0345**	0.0364	0.0359
	(0.217)	(0.244)	(0.516)	(0.641)	(0.307)	(0.553)	(0.600)	(0.665)
NPERF	0.0283	0.0317^{+++}	0.0426**$^{/+}$	0.0438**$^{/+}$	0.0221***$^{/+++}$	0.0332***$^{/+++}$	0.0355***$^{/+++}$	0.0358
	(0.232)	(0.237)	(0.511)	(0.603)	(0.294)	(0.535)	(0.579)	(0.651)
LSEQ	0.0289**	0.0330	0.0434	0.0449**	0.0231	0.0326***	0.0342***	0.0363
	(0.228)	(0.261)	(0.519)	(0.638)	(0.304)	(0.535)	(0.581)	(0.671)
NPULCF	0.0297**	0.0333**	0.0437**	0.0444	0.0229**	0.0348**	0.0375*	0.0376
	(0.253)	(0.252)	(0.536)	(0.604)	(0.296)	(0.544)	(0.613)	(0.704)
NPVD	0.0298**	0.0329**	0.0432*	0.0438	0.0244***	0.0350**	0.0388***	0.0393***
	(0.254)	(0.251)	(0.525)	(0.599)	(0.320)	(0.556)	(0.631)	(0.715)
NPLSEQ	0.0288	0.0324	0.0425	0.0430**	0.0219	0.0314***	0.0334***	0.0360
	(0.236)	(0.242)	(0.507)	(0.580)	(0.291)	(0.512)	(0.558)	(0.657)
JOINT	0.0310***	0.0345***	0.0429	0.0429	0.0255***	0.0338	0.0376	0.0428***
	(0.272)	(0.263)	(0.521)	(0.578)	(0.329)	(0.554)	(0.668)	(0.799)
Observations	279	265	249	167	279	265	249	167
Panel B:	0.0302	0.0348	0.0491	0.0505	0.0262	0.0359	0.0363	0.0352
BCN model	(0.199)	(0.231)	(0.558)	(0.658)	(0.291)	(0.521)	(0.538)	(0.577)
ULCF	0.0317**	0.0350	0.0494	0.0508	0.0267**	0.0365	0.0368	0.0358
	(0.228)	(0.237)	(0.573)	(0.674)	(0.302)	(0.539)	(0.565)	(0.608)
VD	0.0310	0.0358	0.0491	0.0499	0.0279***	0.0363	0.0369	0.0371**
	(0.207)	(0.237)	(0.558)	(0.646)	(0.313)	(0.539)	(0.557)	(0.611)
LOSS	0.0301	0.0342	0.0469**	0.0496	0.0260	0.0360	0.0363	0.0353
	(0.217)	(0.244)	(0.516)	(0.641)	(0.292)	(0.521)	(0.538)	(0.577)
NPERF	0.0310	0.0341	0.0479*	0.0486*	0.0253***$^{/+}$	0.0342***$^{/+++}$	0.0351***$^{/+++}$	0.0350
	(0.239)	(0.219)	(0.548)	(0.612)	(0.280)	(0.506)	(0.522)	(0.557)
LSEQ	0.0309	0.0350	0.0483	0.0507	0.0259	0.0344***	0.0349**	0.0350
	(0.210)	(0.234)	(0.545)	(0.678)	(0.286)	(0.507)	(0.538)	(0.576)
NPULCF	0.0324*	0.0350	0.0486	0.0483	0.0260	0.0367*	0.0363	0.0365
	(0.245)	(0.224)	(0.549)	(0.599)	(0.291)	(0.551)	(0.570)	(0.607)
NPVD	0.0317	0.0350	0.0478	0.0480	0.0270**	0.0359*	0.0364	0.0366
	(0.243)	(0.228)	(0.545)	(0.600)	(0.305)	(0.535)	(0.549)	(0.594)
NPLSEQ	0.0317	0.0347	0.0479	0.0493	0.0249**	0.0328***	0.0341**	0.0348
	(0.235)	(0.214)	(0.535)	(0.615)	(0.274)	(0.490)	(0.522)	(0.554)
JOINT	0.0331*	0.0360	0.0478	0.0491	0.0289***	0.0381	0.0380	0.0416***
	(0.244)	(0.225)	(0.528)	(0.604)	(0.344)	(0.640)	(0.664)	(0.707)
Observations	219	214	208	140	219	214	208	140

This table shows the results of testing the deviations of the MAFEs of the ULCF, VD, LOSS, NPERF, and LSEQ models via a t-test against the MAFEs of a reference model (either the baseline or BCN model), with Theil's U-statistics in parentheses. The MAFEs of the NPULCF, NPVD, NPLSEQ, and JOINT models are tested via a t-test for significant deviations from the MAFEs of the NPERF model. The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects, apart from which the baseline model considers only past firm performance PERF. The BCN model builds on the approach of Barth et al. (2001) and further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The ULCF model adds to these reference models (either the baseline or BCN model) the variables D^{ULCF} and $D^{ULCF} \times$ ULCF. The VD model adds VD^{TLCF}, $VD^{TLCF} \times$ TLCF, VD^{VAL}, $VD^{VAL} \times$ VAL, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times$ ΔVAL, the LOSS model the dummy variable LOSS, the NPERF model LOSS and the interaction term LOSS × PERF, and the LSEQ model D^{LSEQ} and $D^{LSEQ} \times$ LSEQ. The NPULCF model considers the variables of the ULCF model plus LOSS and LOSS × PERF. The same holds for the NPVD and NPLSEQ models with regard to the VD and LSEQ models. The JOINT model considers the additional variables of all models and further $D^{DTA\ LCF}$, $D^{DTA\ LCF} \times$ DTA LCF, $D^{DTAD} \times$ DTAD, and $D^{DTL} \times$ DTL. Table 3 provides detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 11: Restricted sample, in-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations				Earnings before taxes			
Prediction years	1 year (CFO_{t+1})	2 years (CFO_{t+2})	3 years (CFO_{t+3})	4 years (CFO_{t+4})	1 year (EBT_{t+1})	2 years (EBT_{t+2})	3 years (EBT_{t+3})	4 years (EBT_{t+4})
Panel A: Baseline model	(0.650)	(0.444)	(0.428)	(0.377)	(0.678)	(0.332)	(0.278)	(0.235)
ULCF	1.38	0.68	0.47	0.60	0.12	2.48*	5.99***	10.92***
	(0.651)	(0.444)	(0.427)	(0.376)	(0.677)	(0.335)	(0.290)	(0.264)
VD	1.41	1.88*	1.18	0.80	1.52	0.72	1.31	2.85***
	(0.652)	(0.449)	(0.429)	(0.375)	(0.679)	(0.330)	(0.280)	(0.252)
LOSS	4.97**	16.79***	7.33***	2.86*	23.63***	5.57**	2.07	2.44
	(0.652)	(0.459)	(0.434)	(0.379)	(0.689)	(0.337)	(0.279)	(0.237)
NPERF	2.97**	10.77***	3.66**	5.10***	37.02***	9.46***	2.96*	2.74*
	[0.96]	[4.64**]	[0.00]	[7.30***]	[48.54***]	[13.24***]	[3.84**]	[3.02*]
	(0.652)	(0.462)	(0.433)	(0.387)	(0.712)	(0.350)	(0.283)	(0.240)
LSEQ	0.29	0.87	7.35***	4.32**	0.23	0.39	1.91	0.17
	(0.649)	(0.444)	(0.440)	(0.385)	(0.677)	(0.330)	(0.280)	(0.233)
NPULCF	2.98**	0.92	1.55	1.23	3.54**	8.99***	12.44***	13.31***
	(0.655)	(0.462)	(0.434)	(0.387)	(0.715)	(0.367)	(0.310)	(0.276)
NPVD	1.33	1.74	1.05	0.72	2.36**	1.75	1.87*	3.22***
	(0.654)	(0.466)	(0.433)	(0.385)	(0.716)	(0.355)	(0.289)	(0.260)
NPLSEQ	0.77	4.47**	11.41***	5.95***	0.58	0.54	1.64	0.41
	(0.652)	(0.468)	(0.453)	(0.399)	(0.712)	(0.349)	(0.284)	(0.239)
JOINT	1.71*	1.62*	2.81***	1.90**	1.92**	2.51***	2.98***	3.86***
	(0.658)	(0.470)	(0.457)	(0.402)	(0.718)	(0.372)	(0.315)	(0.296)
Observations	614	605	593	519	614	605	593	519
Panel B: BCN model	(0.679)	(0.471)	(0.443)	(0.386)	(0.721)	(0.383)	(0.349)	(0.305)
ULCF	1.19	0.48	1.60	0.94	1.38	0.77	2.81*	6.80***
	(0.679)	(0.470)	(0.444)	(0.385)	(0.722)	(0.382)	(0.353)	(0.322)
VD	2.04*	2.76**	1.47	0.86	1.30	0.27	0.75	2.57**
	(0.682)	(0.481)	(0.446)	(0.384)	(0.722)	(0.378)	(0.347)	(0.319)
LOSS	2.08	6.51**	2.44	1.51	10.76***	0.97	0.07	0.07
	(0.680)	(0.476)	(0.444)	(0.386)	(0.726)	(0.382)	(0.348)	(0.304)
NPERF	2.32*	4.88***	1.34	3.98**	21.77***	4.90***	0.27	0.08
	[2.56]	[3.22**]	[0.24]	[6.44**]	[32.18***]	[8.81***]	[0.47]	[0.09]
	(0.680)	(0.478)	(0.444)	(0.393)	(0.740)	(0.391)	(0.347)	(0.303)
LSEQ	1.97	2.24	13.05***	10.10***	1.12	0.77	3.07**	0.05
	(0.680)	(0.473)	(0.466)	(0.408)	(0.721)	(0.382)	(0.354)	(0.303)
NPULCF	2.60*	0.54	2.38*	1.51	0.10	3.42**	4.33**	7.28***
	(0.682)	(0.477)	(0.446)	(0.394)	(0.739)	(0.396)	(0.355)	(0.320)
NPVD	1.95*	2.50**	1.36	0.83	0.63	0.57	0.83	2.66**
	(0.684)	(0.486)	(0.446)	(0.392)	(0.739)	(0.388)	(0.346)	(0.317)
NPLSEQ	3.65**	5.27***	15.57***	12.76***	0.37	0.68	3.19**	0.06
	(0.683)	(0.486)	(0.472)	(0.422)	(0.740)	(0.390)	(0.352)	(0.300)
JOINT	2.28***	2.12***	3.59***	2.62***	0.94	1.59*	1.70**	2.65***
	(0.690)	(0.492)	(0.478)	(0.420)	(0.740)	(0.400)	(0.359)	(0.335)
Observations	586	579	569	497	586	579	569	497

This table shows the results of testing deviations of the explanatory power of the ULCF, VD, LOSS, NPERF, and LSEQ models from the reference model (either baseline or BCN) via an F-test for nested models, with adjusted R^2 values in parentheses. We also test the NPERF model against the LOSS model [in square brackets]. The NPULCF, NPVD, NPLSEQ, and JOINT models are tested against the NPERF models. The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects, apart from which the baseline model considers only past firm performance PERF. The BCN model builds on the approach of Barth et al. (2001) and further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The ULCF model adds to these reference models (either the baseline or BCN model) the variables D^{ULCF} and $D^{ULCF} \times$ ULCF. The VD model adds VD^{TLCF}, $VD^{TLCF} \times$ TLCF, VD^{VAL}, $VD^{VAL} \times$ VAL, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times \Delta$VAL, the LOSS model the dummy variable LOSS, the NPERF model LOSS and the interaction term LOSS × PERF, and the LSEQ model D^{LSEQ} and $D^{LSEQ} \times$ LSEQ. The NPULCF model considers the variables of the ULCF model plus LOSS and LOSS × PERF. The same holds for the NPVD and NPLSEQ models with regard to the VD and LSEQ models. The JOINT model considers the additional variables of all models and further $D^{DTA\ LCF}$, $D^{DTA\ LCF} \times$ DTA LCF, $D^{DTAD} \times$ DTAD, and $D^{DTL} \times$ DTL. Table 3 provides detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 12: Restricted sample, out-of-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations				Earnings before taxes			
Prediction years	1 year (CFO_{t+1})	2 years (CFO_{t+2})	3 years (CFO_{t+3})	4 years (CFO_{t+4})	1 year (EBT_{t+1})	2 years (EBT_{t+2})	3 years (EBT_{t+3})	4 years (EBT_{t+4})
Panel A:	0.0275	0.0346	0.0498	0.0520	0.0236	0.0368	0.0384	0.0384
Baseline model	(0.103)	(0.177)	(0.383)	(0.511)	(0.137)	(0.407)	(0.439)	(0.481)
ULCF	0.0280**	0.0352	0.0524**	0.0528*	0.0237	0.0389	0.0424*	0.0401
	(0.107)	(0.183)	(0.419)	(0.521)	(0.138)	(0.451)	(0.561)	(0.496)
VD	0.0280	0.0354	0.0501	0.0513	0.0248**	0.0397***	0.0421**	0.0419**
	(0.104)	(0.182)	(0.384)	(0.505)	(0.150)	(0.438)	(0.496)	(0.518)
LOSS	0.0272	0.0346	0.0486***	0.0514*	0.0225**	0.0356***	0.0379**	0.0383
	(0.102)	(0.170)	(0.372)	(0.502)	(0.130)	(0.407)	(0.437)	(0.477)
NPERF	0.0274	0.0340^{++}	0.0486***	0.0506**	0.0224	0.0357	0.0373***$^{/+}$	0.0382
	(0.106)	(0.166)	(0.373)	(0.488)	(0.123)	(0.405)	(0.434)	(0.475)
LSEQ	0.0275	0.0348	0.0508*	0.0526	0.0234***	0.0357***	0.0354***	0.0386
	(0.104)	(0.182)	(0.390)	(0.513)	(0.137)	(0.400)	(0.424)	(0.483)
NPULCF	0.0276	0.0351	0.0514**	0.0512	0.0223	0.0367	0.0404	0.0402*
	(0.108)	(0.174)	(0.412)	(0.493)	(0.120)	(0.421)	(0.525)	(0.491)
NPVD	0.0281*	0.0350*	0.0491	0.0498	0.0229	0.0375*	0.0408***	0.0417**
	(0.109)	(0.173)	(0.376)	(0.483)	(0.129)	(0.419)	(0.484)	(0.513)
NPLSEQ	0.0274	0.0344	0.0501*	0.0516**	0.0223	0.0348***	0.0349***	0.0385
	(0.106)	(0.168)	(0.386)	(0.492)	(0.122)	(0.398)	(0.421)	(0.477)
JOINT	0.0288*	0.0366**	0.0519	0.0499	0.0236*	0.0392	0.0422	0.0451***
	(0.117)	(0.192)	(0.457)	(0.466)	(0.133)	(0.526)	(0.795)	(0.553)
Observations	216	211	204	138	216	211	204	138
Panel B:	0.0264	0.0352	0.0508	0.0525	0.0243	0.0370	0.0377	0.0370
BCN model	(0.094)	(0.174)	(0.408)	(0.518)	(0.126)	(0.401)	(0.414)	(0.449)
ULCF	0.0272***	0.0357	0.0537**	0.0534*	0.0243	0.0385	0.0405	0.0391**
	(0.099)	(0.182)	(0.437)	(0.529)	(0.126)	(0.438)	(0.518)	(0.463)
VD	0.0265	0.0358	0.0506	0.0514*	0.0247	0.0381	0.0384	0.0379
	(0.093)	(0.182)	(0.401)	(0.504)	(0.130)	(0.424)	(0.445)	(0.467)
LOSS	0.0269	0.0341	0.0485***	0.0511*	0.0236**	0.0367**	0.0378*	0.0370
	(0.102)	(0.170)	(0.372)	(0.502)	(0.122)	(0.400)	(0.415)	(0.449)
NPERF	0.0267	0.0346*	0.0505^{+++}	0.0515**	0.0223***$^{/++}$	0.0352***$^{/+++}$	0.0378	0.0369^{+}
	(0.096)	(0.167)	(0.404)	(0.498)	(0.110)	(0.388)	(0.416)	(0.449)
LSEQ	0.0272***	0.0357	0.0525*	0.0551***	0.0242	0.0360***	0.0356***	0.0369
	(0.099)	(0.180)	(0.419)	(0.550)	(0.125)	(0.395)	(0.409)	(0.450)
NPULCF	0.0270	0.0357	0.0531*	0.0521	0.0226	0.0366	0.0400	0.0390*
	(0.098)	(0.177)	(0.432)	(0.503)	(0.113)	(0.410)	(0.517)	(0.463)
NPVD	0.0269	0.0355	0.0504	0.0503*	0.0226	0.0367**	0.0385	0.0379
	(0.096)	(0.178)	(0.397)	(0.484)	(0.117)	(0.405)	(0.451)	(0.465)
NPLSEQ	0.0270	0.0349	0.0520	0.0544***	0.0225	0.0345**	0.0357***	0.0368
	(0.098)	(0.171)	(0.414)	(0.526)	(0.110)	(0.383)	(0.411)	(0.449)
JOINT	0.0277	0.0367	0.0523	0.0519	0.0235*	0.0383	0.0400	0.0418**
	(0.102)	(0.196)	(0.446)	(0.494)	(0.124)	(0.506)	(0.738)	(0.503)
Observations	206	202	197	134	206	202	197	134

This table shows the results of testing the deviations of the MAFEs of the ULCF, VD, LOSS, NPERF, and LSEQ models via a t-test against the MAFEs of a reference model (either the baseline or BCN model), with Theil's U-statistics in parentheses. The MAFEs of the NPULCF, NPVD, NPLSEQ, and JOINT models are tested via a t-test for significant deviations from the MAFEs of the NPERF model. The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects, apart from which the baseline model considers only past firm performance PERF. The BCN model builds on the approach of Barth et al. (2001) and further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The ULCF model adds to these reference models (either the baseline or BCN model) the variables D^{ULCF} and $D^{ULCF} \times$ ULCF. The VD model adds VD^{TLCF}, $VD^{TLCF} \times$ TLCF, VD^{VAL}, $VD^{VAL} \times$ VAL, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times \Delta$VAL, the LOSS model the dummy variable LOSS, the NPERF model LOSS and the interaction term LOSS × PERF, and the LSEQ model D^{LSEQ} and $D^{LSEQ} \times$ LSEQ. The NPULCF model considers the variables of the ULCF model plus LOSS and LOSS × PERF. The same holds for the NPVD and NPLSEQ models with regard to the VD and LSEQ models. The JOINT model considers the additional variables of all models and further $D^{DTA\ LCF}$, $D^{DTA\ LCF} \times$ DTA LCF, $D^{DTAD} \times$ DTAD, and $D^{DTL} \times$ DTL. Table 3 provides detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 13: Definitions of additional variables

Variable	Definition
D^{FLOSS}	Dummy variable with a value of one if information on FLOSS is available.
$D^{FLOSS} \times$ FLOSS	Interaction term of D^{FLOSS} and FLOSS, where the dummy variable FLOSS has a value of one if the firm has a first-time loss (i.e., negative earnings or cash flows) in the current period, with non-negative earnings or cash flows in the previous period.
D^{DIV}	Dummy variable with a value of one if information on cash dividends is available.
$D^{DIV} \times$ DIV	Interaction term of D^{DIV} and cash dividends scaled by total assets.
D^{RD}	Dummy variable with a value of one if information on research & development expenses is available.
$D^{RD} \times$ RD	Interaction term of D^{RD} and research & development expenses scaled by total assets.
$D^{RD} \times$ RD $\times$ LOSS	Interaction term of D^{RD}, research & development expenses scaled by total assets, and LOSS.
D^{MTB}	Dummy variable with a value of one if information on MTB is available.
$D^{MTB} \times$ MTB	Interaction term of D^{MTB} and the ratio of the market capitalization at the end of the year to the book value of equity.
SIZE	Logarithm of total assets.

Table 14: Additional analyses, in-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Operating cash flow				Earnings before taxes			
Prediction years	1 year (CFO_{t+1})	2 years (CFO_{t+2})	3 years (CFO_{t+3})	4 years (CFO_{t+4})	1 year (EBT_{t+1})	2 years (EBT_{t+2})	3 years (EBT_{t+3})	4 years (EBT_{t+4})
Panel A: Baseline model	(0.625)	(0.537)	(0.487)	(0.446)	(0.593)	(0.381)	(0.302)	(0.231)
NPERF	4.50**	11.18***	4.23**	6.19***	12.68***	13.44***	10.15***	6.63***
	(0.628)	(0.549)	(0.491)	(0.455)	(0.604)	(0.399)	(0.318)	(0.244)
NPFLOSS	8.72***	4.43**	2.64*	3.09**	3.36**	2.22	0.66	0.35
	(0.635)	(0.553)	(0.493)	(0.458)	(0.606)	(0.401)	(0.317)	(0.243)
NPDIV	3.11**	2.10	2.24	1.85	0.14	0.02	0.75	0.60
	(0.630)	(0.550)	(0.493)	(0.456)	(0.603)	(0.398)	(0.317)	(0.243)
NPRD	3.01**	6.61***	5.44***	3.55**	1.41	2.85**	2.16*	2.69**
	(0.631)	(0.558)	(0.500)	(0.461)	(0.605)	(0.403)	(0.321)	(0.250)
NPMTB	4.37**	1.42	9.55***	14.13***	2.85**	0.85	18.39***	24.20***
	(0.631)	(0.549)	(0.502)	(0.475)	(0.606)	(0.399)	(0.347)	(0.293)
NPSIZE	1.34	1.49	4.63**	5.00**	0.08	0.15	0.07	0.00
	(0.628)	(0.549)	(0.494)	(0.458)	(0.604)	(0.399)	(0.317)	(0.243)
Observations	835	815	792	691	835	815	792	691
Panel B: BCN model	(0.629)	(0.514)	(0.477)	(0.424)	(0.618)	(0.443)	(0.401)	(0.339)
NPERF	3.97**	7.35***	2.94**	5.90***	6.62***	7.69***	5.98***	6.26***
	(0.632)	(0.524)	(0.481	(0.434	(0.625	(0.455	(0.410	(0.352
NPFLOSS	0.06	1.17	0.83	0.21	2.11	0.76	0.12	0.90
	(0.631)	(0.524)	(0.481)	(0.433)	(0.626)	(0.454)	(0.409)	(0.352)
NPDIV	2.64*	1.38	2.25	1.34	0.35	0.39	1.45	1.83
	(0.634)	(0.525)	(0.483)	(0.435)	(0.624)	(0.454)	(0.411)	(0.354)
NPRD	1.27	7.14***	6.18***	3.61**	1.27	2.99**	1.49	2.17*
	(0.633)	(0.538)	(0.494)	(0.443)	(0.625)	(0.460)	(0.412)	(0.356)
NPMTB	4.26**	3.60**	8.65***	14.12***	5.05***	2.29	12.55***	12.56***
	(0.636)	(0.528)	(0.494)	(0.461)	(0.630)	(0.457)	(0.432)	(0.379)
NPSIZE	0.45	1.48	4.30**	6.01**	0.42	0.45	0.28	0.00
	(0.632)	(0.525)	(0.484)	(0.440)	(0.625)	(0.454)	(0.410)	(0.351)
Observations	646	636	624	546	646	636	624	546

This table shows the results of testing the explanatory power of extended models compared to a reference model via an F-test for nested models, with adjusted R^2 values in parentheses. We test he NPFLOSS, NPDIV, NPRD, NPMTB, and NPSIZE models against the NPERF model (with either baseline or BCN as underlying model). The superscripts ***, **, and * indicate a statistically significant increase in explanatory power at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects. The NPERF baseline model (Panel A) accounts for current performance PERF, LOSS and the interaction term LOSS × PERF. The NPERF BCN model (Panel B) further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The NPFLOSS model adds to these reference models (either NPERF baseline or NPERF BCN) the variables D^{FLOSS} and $D^{FLOSS} \times$ FLOSS. The NPDIV model adds D^{DIV} and $D^{DIV} \times$ DIV, the NPRD model D^{RD}, $D^{RD} \times$ RD, and $D^{RD} \times$ RD × LOSS, the NPMTB model D^{MTB} and $D^{MTB} \times$ MTB, and the SIZE model SIZE. Table 3 and Table 13 provide detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

Table 15: Additional analyses, out-of-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Operating cash flow				Earnings before taxes			
Prediction years	1 year (CFO_{t+1})	2 years (CFO_{t+2})	3 years (CFO_{t+3})	4 years (CFO_{t+4})	1 year (EBT_{t+1})	2 years (EBT_{t+2})	3 years (EBT_{t+3})	4 years (EBT_{t+4})
Panel A: Baseline model	0.0293	0.0346	0.0457	0.0476	0.0258	0.0382	0.0400	0.0406
	(0.163)	(0.205)	(0.423)	(0.535)	(0.231)	(0.402)	(0.433)	(0.516)
NPERF	0.0295	0.0343	0.0448***	0.0461**	0.0243***	0.0364***	0.0387***	0.0406
	(0.174)	(0.196)	(0.416)	(0.503)	(0.215)	(0.384)	(0.416)	(0.507)
NPFLOSS	0.0295	0.0351	0.0441*	0.0458	0.0249*	0.0357**	0.0377***	0.0412***
	(0.175)	(0.200)	(0.402)	(0.487)	(0.229)	(0.379)	(0.411)	(0.514)
NPDIV	0.0293	0.0344	0.0450	0.0468**	0.0244*	0.0364	0.0387	0.0407
	(0.172)	(0.196)	(0.418)	(0.513)	(0.215)	(0.384)	(0.416)	(0.510)
NPRD	0.0297	0.0347	0.0454	0.0468	0.0246	0.0375**	0.0398**	0.0405
	(0.175)	(0.202)	(0.422)	(0.515)	(0.215)	(0.391)	(0.435)	(0.524)
NPMTB	0.0304	0.0362	0.0461	0.0462	0.0250	0.0374	0.0367*	0.0409
	(0.202)	(0.275)	(0.445)	(0.525)	(0.304)	(0.584)	(0.418)	(0.505)
NPSIZE	0.0294	0.0341**	0.0441**	0.0456	0.0242	0.0362***	0.0385***	0.0406
	(0.173)	(0.196)	(0.409)	(0.495)	(0.215)	(0.383)	(0.415)	(0.507)
Observations	835	815	792	691	835	815	792	691
Panel B: BCN model	0.0328	0.0388	0.0537	0.0525	0.0287	0.0385	0.0389	0.0384
	(0.146)	(0.193)	(0.462)	(0.539)	(0.214)	(0.363)	(0.365)	(0.419)
NPERF	0.0330	0.0383	0.0526**	0.0507*	0.0275***	0.0367***	0.0377**	0.0386
	(0.169)	(0.186)	(0.454)	(0.502)	(0.203)	(0.351)	(0.353)	(0.406)
NPFLOSS	0.0334	0.0378	0.0522	0.0516	0.0284**	0.0365	0.0373***	0.0391
	(0.164)	(0.181)	(0.437)	(0.510)	(0.220)	(0.349)	(0.351)	(0.407)
NPDIV	0.0330	0.0382	0.0526	0.0508	0.0274	0.0367***	0.0377	0.0385
	(0.169)	(0.185)	(0.454)	(0.505)	(0.203)	(0.350)	(0.352)	(0.405)
NPRD	0.0332	0.0388	0.0540***	0.0520**	0.0281***	0.0382***	0.0384**	0.0387
	(0.169)	(0.184)	(0.459)	(0.526)	(0.204)	(0.356)	(0363)	(0.417)
NPMTB	0.0331	0.0401	0.0521	0.0483	0.0287	0.0393	0.0365	0.0386
	(0.183)	(0.285)	(0.455)	(0.477)	(0.295)	(0.609)	(0.361)	(0.419)
NPSIZE	0.0327***	0.0378**	0.0512***	0.0492*	0.0277	0.0363**	0.0371**	0.0386
	(0.169)	(0.185)	(0.442)	(0.481)	(0.204)	(0.350)	(0.353)	(0.407)
Observations	646	636	624	546	646	636	624	546

This table shows the results of testing the deviations of the MAFEs of extended models via a t-test against the MAFEs of a reference model, with Theil's U-statistics in parentheses. We test the NPFLOSS, NPDIV, NPRD, NPMTB, and NPSIZE models against the NPERF (with either baseline or BCN as underlying model) model. The superscripts ***, **, and * indicate statistically significant differences in MAFEs at the 1%, 5%, and 10% levels, respectively. All models include industry and year fixed effects. The NPERF baseline model (Panel A) accounts for current performance PERF, LOSS and the interaction term LOSS × PERF. The NPERF BCN model (Panel B) further includes the variables ΔAR, ΔAP, ΔINV, DEPR, AMORT, and OTHER. The NPFLOSS model adds to these reference models (either NPERF baseline or NPERF BCN) the variables D^{FLOSS} and D^{FLOSS} × FLOSS. The NPDIV model adds D^{DIV} and D^{DIV} × DIV, the NPRD model D^{RD}, D^{RD} × RD, and D^{RD} × RD × LOSS, the NPMTB model D^{MTB} and D^{MTB} × MTB, and the SIZE model SIZE. Table 3 and Table 13 provide detailed variable definitions. The number of observations does not differ between the models and depends on the number of prediction years and the reference model (with fewer observations for BCN models).

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