

Dreher, Sandra; Eichfelder, Sebastian; Noth, Felix

Working Paper

Does IFRS information on tax loss carryforwards and negative performance improve predictions of earnings and cash flows?

arqus Discussion Paper, No. 276

Provided in Cooperation with:

arqus - Working Group in Quantitative Tax Research

Suggested Citation: Dreher, Sandra; Eichfelder, Sebastian; Noth, Felix (2022) : Does IFRS information on tax loss carryforwards and negative performance improve predictions of earnings and cash flows?, arqus Discussion Paper, No. 276, Arbeitskreis Quantitative Steuerlehre (arqus), Berlin

This Version is available at:

<https://hdl.handle.net/10419/267908>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



Arbeitskreis Quantitative Steuerlehre
Quantitative Research in Taxation – Discussion Papers

Sandra Dreher, Sebastian Eichfelder, Felix Noth

**Does IFRS information on tax loss carryforwards and
negative performance improve predictions of earnings
and cash flows?**

arqus Discussion Paper No. 276
December 2022

Does IFRS information on tax loss carryforwards and negative performance improve predictions of earnings and cash flows?[∞]

Sandra Dreher^{*}, Sebastian Eichfelder[♦] and Felix Noth[^]

We analyze the usefulness of accounting information on tax loss carryforwards and negative performance to predict earnings and cash flows. We use hand-collected information on tax loss carryforwards and the corresponding deferred taxes from the International Financial Reporting Standards tax footnotes for listed firms from Germany. Our out-of-sample tests show that considering accounting information on tax loss carryforwards does not enhance the accuracy of performance predictions and even worsens predictions. Besides, common forecasting approaches that deal with negative performance are prone to prediction errors. We provide a simple empirical specification to reduce forecast errors. We find evidence that more elaborate machine learning models (least absolute shrinkage and selection operator method) typically do not perform better or even worse than our simple specification in out-of-sample tests.

Keywords: performance forecast, out-of-sample tests, deferred tax assets, tax loss carryforwards,

JEL codes: M40; M41; C53

[∞] We are grateful to Kathleen Andries, Inga Bethmann, Paul Demeré, Stefan Dierkes, Vanessa Flagmeier, Martin Jacob, Urska Kosi, Olaf Korn, Ralf Maiterth, Jens Müller, Maximilian Müller, Andreas Oestreicher, Terry Shevlin, Antonio de Vito, and the participants of the 2016 arqus Conference in Munich, the 2017 Faculty Research Seminar of the University of Göttingen, the Seventh Workshop on Current Research in Taxation in Vienna, and the 81st VHB Annual Meeting 2019 in Rostock for helpful comments and advice. All remaining errors and deficiencies are our own.

^{*} Faculty of Business and Economics, Otto-von-Guericke-Universität Magdeburg, Magdeburg, Germany

[♦] Corresponding author: Faculty of Business and Economics, Otto-von-Guericke-Universität Magdeburg, Universitätsplatz 2, 39106 Magdeburg, Germany; tel. +49-391-67-58811, fax +49-391-67-51142, email sebastian.eichfelder@ovgu.de.

[^] Department of Financial Markets, Halle Institute for Economic Research, Halle, Germany.

1. Introduction

Using hand-collected data from German IFRS accounts, we investigate whether accounting information regarding deferred taxes from tax loss carryforwards and negative firm performance can improve predictions of future firm performance. Research provides evidence of a significant association between financial reporting information on deferred tax assets and future firm performance (Herbohn, Tutticci, and Khor 2010; Flagmeier 2017) that increases the explanatory power of forecasting regressions (Dhaliwal, Kaplan, Laux, and Weisbrod 2013). Evidence also suggests a higher persistence of positive than negative current performance (Hayn 1995; Li 2011).

As outlined by the statistical literature (e.g., Hagerty and Srinivasan 1991; Konishi and Kitagawa 2008; Shmueli 2010) testing in sample (explanation) and out of sample (prediction) are distinct concepts that can require different types of models.^a Since previous research relies exclusively on in-sample testing, we contribute to the literature by analyzing whether information on negative current firm performance and deferred taxes from tax loss carryforwards improves predictions out of sample. While some papers use out-of-sample tests in other areas of accounting research (e.g., Ciconte, Donohoe, Lisowsky, and Mayberry 2016), more research using this method is needed.

Our analysis 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.^b Thus, it is critical for investors, creditors, and other stakeholders to know if specific accounting items can improve predictions. Second, correctly specified predictions of future cash flows and

^a In-sample tests use a given data set to identify relations between variables, including the assumed causes and effects. Out-of-sample tests use subsamples of a data set (training data) to predict variables in other subsamples (testing data). Thus, the intention is not to identify (causal) relations among variables, but to minimize prediction errors. Research provides evidence that models that enhance explanatory power do not necessarily improve out-of-sample predictions (e.g., Sarstedt and Danks, 2022). Out-of-sample tests contribute substantially to understanding the usefulness of accounting items, since they simulate what most investors and analysts do: ‘predict, with no ex-post information (as implicitly assumed by in-sample studies), future earnings and cash flows’ (Lev, Li and Sougiannis 2010, p. 784).

^b The empirical literature also provides evidence that accounting standards affect the information content of stock prices (e.g., Wang and Yu 2015).

earnings are essential for practitioners (e.g., analysts), as well as for many research questions in the accounting and finance literature (e.g., to calculate the cost of capital; see Fama and French 2006; Hou, van Dijk and Zhang 2012). Third, accounting standards' essential target is to provide useful information about a firm's financial position and performance. The complexity of accounting for deferred taxes and respective costs has often been criticized (Weber 2009; Laux 2013). Thus, standard setters and authorities such as the Financial Accounting Standards Board and the International Accounting Standards Board should consider whether such items' information content helps improve predictions.

Corresponding to International Accounting Standard (IAS) 12.34, deferred tax assets from tax loss carryforwards are only recognized to the extent that the tax benefit's realization is likely. This is only the case if the firms generate sufficient future (taxable) profits to offset tax loss carryforwards. It has been argued that firms can use additional deferred tax assets from tax loss carryforwards to signal positive future firm performance (Herbohn et al. 2010; Flagmeier 2017). Considering loss persistence, several studies argue that negative firm performance is typically less persistent (Hayn 1995; Li 2011). Transitory losses are a primary reason for that (Joos and Plesko 2005). Due to business cycles, economic shocks, restructurings, and similar issues, firms might be able to transform their current losses into future profits. Thus, positive performance outcomes are more persistent and have higher predictive validity than adverse ones.

We use a unique hand-collected panel of firms listed on the German stock market that encompasses detailed information on deferred taxes and tax loss carryforwards from the tax footnote under International Financial Reporting Standards (IFRS). Unlike US Generally Accepted Accounting Principles (GAAP), the tax footnote of IFRS accounts contains mandatory details on the amount of unrecognized (i.e., the nonvaluable component of) tax loss carryforwards. Since this information should be based on a firm's *internal* estimate of future taxable earnings, it could be a helpful predictor of future pre-tax earnings, post-tax

earnings, and cash flows. In addition, we analyze the usefulness of voluntarily disclosed accounting information on tax loss carryforwards (i.e., the total amount of tax loss carryforwards, the book value, and changes in valuation allowances for deferred tax assets from tax loss carryforwards that are not mandatory under IFRS) for performance predictions. We confirm previous findings suggesting a negative association between unrecognized (deferred taxes from) tax loss carryforwards and future firm performance in in-sample tests (Herbohn et al. 2010; Flagmeier 2017). However, our out-of-sample tests, including a battery of robustness checks, reveal that such items typically reduce predictive validity.

A theoretical explanation for our finding is model overfitting (Shmueli 2010; Sarstedt and Danks 2022), which means that a model overfits its training data and thus also captures unstable relations. This problem is especially relevant for noisy predictors with potential measurement error. Regarding unrecognized tax loss carryforwards (ULCFs), there are three main reasons for measurement error. First, ULCFs result from the internal estimates of managers that by themselves can be subject to forecasting error. Lev et al. (2010) provide evidence that such estimate-based items are less useful for forecasting. Second, several papers suggest that ULCFs are used for earnings management (e.g., Schrand and Wong 2003; Gordon and Joos 2004), which reduces the accuracy of that information. Third, differences in tax and financial accounting induce additional measurement error if ULCFs are used for the prediction of consolidated earnings and cash flows.^c

We also find robust evidence that common forecasting approaches that treat positive and negative performance similarly (e.g., Barth et al. 2001; Kim and Kross 2005; Dichev and Tang 2009; Lev et al. 2010) overestimate the persistence of current negative firm performance. This holds especially for long-un prediction horizons, increasing the likelihood of loss reversal. Considering differences in the persistence of negative and positive current

^c Deferred tax assets (from tax loss carryforwards) result from the projection of future taxable income at the entity level. In addition, restrictions in the settlement of tax losses with future taxable income could reduce the predictive ability of this item.

performance in regressions significantly increases the explanatory power and predictive validity. In additional out-of-sample tests, we find mixed evidence for standard proxies of persistent and transitory losses (see also Joos and Plesko 2005; Li 2011).

We contribute to the literature in three ways. First, while in-sample tests typically find a significant association between deferred taxes from the tax loss carryforwards with future tax payments (Laux 2013; Flagmeier 2022) and firm performance (Flagmeier 2017, 2022 Herbohn et al. 2010), our out-of-sample tests show that such items typically worsen predictions. This holds even for after-tax cash flow predictions, suggesting the limited usefulness of deferred tax components in predicting cash taxes. Laux (2013) finds only a weak marginal increase in adjusted R^2 values by adding deferred tax items to a prediction model of cash taxes and does not perform out-of-sample tests. Chluddek (2011a) even finds that information on deferred taxes worsens the out-of-sample predictions of cash taxes. Thus, our results should also be relevant to the literature on the information content of deferred taxes for future cash taxes. At a broader level, our findings also contribute to the literature on the informational content and real effects of firms' tax loss carryforwards (e.g., Henry and Sansing 2018; Bührle et al. 2022; Heitzman and Lester 2022; Olbert 2022).

Our outcome fits well with the results of Flagmeier (2022), who finds stock prices to be significantly associated with deferred tax items, but not with deferred tax assets from tax loss carryforwards. The combined results of Flagmeier's and our study suggest that investors do not consider deferred tax assets from tax loss carryforwards in their investment decisions, since these items do not provide a robust signal of future firm performance. As the aim of accounting standards is not primarily to produce the best predictors for future firm performance, this does not mean that such information does not have relevant value. Nevertheless, in a cost–benefit analysis, it might also be interesting for standard setters to know which characteristics are relevant for performance predictions.

Second, we contribute to the literature on the information content of losses and negative cash flows. While the literature suggests a lower information content of losses than of profits (Hayn 1995; Joos and Plesko 2005; Li 2011), the relevance of this insight for performance predictions has not been analyzed yet. We find that considering the asymmetry in the information content of negative and positive performance with an interaction term of a dummy for negative performance and current performance enhances predictions. We find mixed evidence in testing the predictive validity of different proxy variables for persistent negative performance. Variables capturing the sequence of past losses and variables measuring the change in performance compared to the last year often significantly enhance (but also, in one specification, worsen) predictive validity. Other proxy variables (dividend-paying firms, firm-years with first-time negative performance) are inconclusive. While distinguishing between transitory and persistent negative performance is challenging, adding information on performance history can be useful for performance forecasts.

Finally, we contribute to the literature on forecasting and predictions. In line with Hagerty and Srinivasan (1991), Shmueli (2010), or Sarstedt and Danks (2022), we provide evidence that models can perform very differently in in-sample and out-of-sample testing. Thus, even the so-called true (i.e., correctly specified) explanatory model can underperform in predictions, since the minimization of expected prediction errors is statistically not equivalent to the minimization of the bias. As documented by Shmueli (2010), this holds especially in situations with noisy data, small sample sizes, highly correlated prediction errors, and low absolute values of omitted variables. In line with this, we find limited predictive validity of accounting information on tax loss carryforwards that can be biased by a) errors in the prediction of future performance, b) earnings management, and c) mismatches between tax and financial accounting. Our findings suggest that in-sample tests are not an appropriate statistic for identifying predictive validity and can lead to misleading results. Although this insight is not new, it is not always considered in accounting research (Lev et al. 2010;

Chluddek 2011a; Laux 2013). Furthermore, while several papers acknowledge loss reversal tendencies (e.g., Fama and French 2000), only a few explicitly account for firms' differences between negative and positive performance with an indicator variable (Fama and French 2006; Hou et al. 2012). We find that this approach is insufficient to capture the lower persistence of negative performance.

We structure our paper as follows. Section 2 discusses the institutional background and hypotheses. Section 3 describes our methodology and data. Section 4 documents the empirical analysis and results. Section 5 concludes the paper. The Appendix (Table 8) provides the variable definitions. Additional analyses and tests are presented in an Online Appendix.

2. Related literature and hypotheses

2.1. Evidence

As mentioned before, evidence on the information content of deferred taxes from tax loss carryforwards relies on in-sample testing. Using UK GAAP data, Gordon and Joos (2004) find a significant and negative association between the sum of unrecognized deferred tax assets and pre-tax performance indicators. Legoria and Sellers (2005) and Jung and Pulliam (2006) use US GAAP data and find a significant association between future cash flows, respectively, cash flows and earnings, and changes in the valuation allowance on deferred tax assets. Christensen, Paik, and Stice (2008) find that observations with abnormally high valuation allowances in US GAAP annual reports have lower operating performance in future periods. Jackson (2015) finds a significant association between deferred taxes and future pre-tax earnings in US GAAP reports.

Only two papers explicitly consider information in financial reports on tax loss carryforwards. Herbohn et al. (2010) find a negative association between the valuation allowance regarding deferred tax assets from tax loss carryforwards and indicators of future firm performance (earnings, cash flows, and EBITDA) for Australian GAAP data. Flagmeier (2017) finds a negative and significant association between unrecognized tax losses (the same

accounting measure as in our study) in IFRS accounts of German firms and future pre-tax cash flows and earnings. The author also finds a similar association between the US GAAP valuation allowance and future performance indicators. Some studies also find a significant association between accounting information on deferred taxes and future tax payments for US GAAP data (Laux 2013) and IFRS data (Flagmeier 2022).

We are aware of only one paper that tests the predictive validity of deferred tax items by out-of-sample tests. Chludek (2011a) uses the annual accounts of Standard & Poor's 500 firms to test the explanatory power and predictive validity of deferred tax assets and deferred tax liabilities for future cash taxes. She finds that including deferred tax items increases explanatory power in sample but worsens out-of-sample predictions. Chludek's analysis, however, does not allow for a statement of whether more detailed IFRS information on tax loss carryforwards might improve performance predictions, since it uses aggregate information of US GAAP accounts to predict cash taxes (and not firm performance).

Regarding the lower persistence of negative performance compared to positive performance, we are unaware of papers that analyze this heterogeneity's effect on the quality of performance predictions by out-of-sample tests. While prediction models consider current performance as the main predictor, they typically do not account for differences in the persistence of negative and positive performance (e.g., Barth, Cram, and Nelson 2001; Kim and Kross 2005; Hou and Robinson 2006; Dichev and Tang 2009; Lev et al. 2010; Bostwick, Krieger and Lambert 2016). Exceptions are the works of Fama and French (2000) and Hou et al. (2012), who use a simple indicator variable for loss firms that only partially captures firms' heterogeneity with positive and negative performance.

2.2. Theoretical background and hypotheses

IAS 12.34 requires the recognition of deferred tax assets from the carryforward of tax losses and tax credits "to the extent that it is probable that future taxable profit will be available against that unused tax losses and unused tax credits can be utilized." Under similar

preconditions, IAS 12.24 requires the recognition of deferred tax assets from temporary deductible differences. Thus, the recognition is generally limited to the fraction of deferred tax assets expected to reduce future tax payments. By contrast, Accounting Standards Codification (ASC) 740 US GAAP requires a two-step approach. As a first step, deferred tax assets must be recognized for the total amount of unused tax losses, unused tax credits, and temporary deductible differences. In a second step, firms must reduce the amount of deferred tax assets by a valuation allowance (VAL) if the amount is more likely than not to be realized in the future (ASC 740-10-30-5).

While the net recognized amount is conceptually the same under both approaches, there are differences regarding the disclosure of the unusable amount and its composition. Under US GAAP, the VAL is a recognized contra-asset (i.e., non-valuable component) of deferred tax assets from unused tax losses, unused tax credits, and temporary deductible differences. Instead, IAS 12.81(e) requires a footnote disclosure of “the amount (and the expiry date if any) of temporary deductible differences, unused tax losses, and unused tax credits for which no deferred tax asset is recognized (...).” Thus, IAS 12 does not disclose the value of unrecognized tax assets from the sum of these components, but detailed information (the amount and potentially the expiry date) for each element.

There are two theoretical arguments why deferred tax assets in general and especially deferred tax assets from unused tax losses could be informative of future firm performance. First, deferred tax assets reflect future cash tax savings and should be instructive of future tax cash flows (Chludek 2011b; Laux 2013; Flagmeier 2022). If this is the case, they should also be informative of future after-tax cash flows.

Second and more relevant, the recognition in IAS 12 is only allowed to the extent that there are sufficient expected future profits against which the unused tax losses and unused tax credits can be utilized. Hence, IAS 12.34 requires managers to forecast future taxable income that can be offset against the remaining tax loss carryforwards. For example, if managers

expect higher future earnings as well as higher taxable income, they might increase the amount of deferred tax assets from tax loss carryforwards and reduce the amount of ULCFs (Herbohn et al. 2010). Such an *internal* estimate can be a valuable predictor of future firm performance under the following requirements: a) managers have better information than external stakeholders, b) managers use the discretion provided by IAS 12.34 to signal future firm performance by a truthful estimate,^d and c) future taxable income is strongly correlated with accounting measures of future firm performance (cash flows and earnings before and after taxes) and therefore helps to predict those items.

There are several reasons why these requirements might not be met. First, the internal estimates of managers can be subject to errors as well. Lev et al. (2010) provide evidence that estimate-based accounting items are less useful for performance predictions. Second, firms might manage their deferred tax assets from tax loss carryforwards for purposes such as a big bath or meeting analysts' expectations. Several studies provide evidence that deferred tax positions and deferred tax assets from tax loss carryforwards are used for earnings management (e.g., Schrand and Wong 2003; Gordon and Joos 2004; Frank and Rego 2006; Christensen et al. 2008; Herbohn et al. 2010). Third, future taxable profits against which unused tax losses can be utilized might be a relatively poor predictor of future firm performance. Most relevant, taxable income differs in many ways from pre-tax earnings and cash flows (book-tax differences), depends on the jurisdiction, and is typically calculated at the single entity level and not on a consolidated level.^e Furthermore, specific tax provisions can limit the amount of taxable profits against which tax loss carryforwards can be utilized.

^d A reason for standard-conforming accounting is the (reputational) risk of financial restatements and unstable accounting practices, which can be substantial. Lys, Naughton, and Wang (2015) denote standard-conforming accounting practices that unintentionally reveal managers' private information through passive signaling.

^e For example, in the German corporate income tax code, only 5% of dividend income is typically regarded as taxable. In addition, taxable income is calculated for each legally distinct group entity (every single corporate unit) if no group taxation regime is applied, while earnings and cash flows in IFRS accounts will be consolidated at the group level.

While most studies find that the unrecognized component of deferred tax assets from tax loss carryforwards is negatively associated with future firm performance in in-sample tests (e.g., Gordon and Joos 2004; Christensen et al. 2008; Herbohn et al. 2010; Jackson 2015; Flagmeier 2017), this does not necessarily mean that such items will help to improve predictions. Therefore, we empirically test the hypothesis that accounting information on unrecognized loss carryforwards enhances the prediction of future earnings and cash flows.

H1: *Considering accounting information on ULCFs improves the accuracy of performance predictions.*

In line with the literature, we do not use recognized deferred tax assets (from tax loss carryforwards) for our statistical tests but follow Flagmeier (2017), who uses unrecognized tax losses (ULCFs) for her analysis. The main reason for that approach is that deferred tax assets from tax loss carryforwards are positively affected by future taxable income and former tax losses.^f Following Flagmeier (2017) and Herbohn et al. (2010), we expect a negative association between ULCFs and future firm performance for two reasons: a) current losses predict negative future performance and b) *unrecognized* losses result from lower expectations of future (taxable) income as a proxy of future firm performance.

Our data show considerable heterogeneity of the tax footnote and voluntary disclosure behavior concerning tax loss carryforwards (see Section 3.1). For example, 28.9% of our firm-years *voluntarily* disclose the book value of a valuation allowance on deferred tax assets from tax loss carryforwards, and 51.7% the total amount of tax loss carryforwards.^g

^f 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 does not necessarily imply better future firm performance. Other papers also rely on the valuation allowance encompassing the value of unrecognized deferred tax assets (from tax loss carryforwards; see Herbohn et al. 2010; Dhaliwal et al. 2013). In this case, the unrecognized losses are multiplied by the applicable tax rate, which differ among countries. Thus, a benefit of ULCFs as an explanatory variable is that it is not affected by differences in the various tax rates of a multinational group, which could bias unrecognized deferred taxes from tax loss carryforwards as a measure of non-valuable tax losses. For example, a firm with a high average tax rate and a low fraction of valuable tax losses can 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 tax losses.

^g We regard the total amount of tax loss carryforwards as voluntarily disclosed if it is disclosed either directly or if firms report the amount of both unrecognized and recognized tax loss carryforwards.

Considering the evidence (Gordon and Joos 2004; Herbohn et al. 2010; Dhaliwal et al. 2013) as well as the related literature on tax disclosure (e.g., Hamrouni, Miloudi, and Benzakriem 2015; Flagmeier and Müller 2016; Lang 2017), it seems plausible to consider the (voluntary) disclosure of specific accounting information as a firm characteristic that could itself be useful for performance predictions. Hamrouni et al. (2015) and Jiao (2011) argue and provide evidence that firms with poor expected future performance choose a lower disclosure level and hide information from potential investors. Leung and Veenman (2018) find a positive association between the (voluntary) disclosure of non-GAAP earnings and future firm performance for loss firms. By contrast, the findings of Lang (2017) suggest that managers of firms with low expected performance choose a higher disclosure level to reduce analysts' earnings expectations. Thus, future firm performance will be higher if firms voluntarily report non-GAAP earnings. Both mechanisms suggest that voluntary disclosure could be a helpful characteristic for predictions. We hypothesize the following.

H2: *Considering additional voluntarily disclosed accounting information on tax loss carryforwards improves the accuracy of performance predictions.*

Accounting research provides compelling evidence that losses are, on average, less persistent than profits (Hayn 1995; Joos and Plesko 2005; Li 2011). There are two main arguments for the lower persistence of negative firm performance. Hayn (1995) claims that the investors of a firm with negative performance can liquidate the firm (abandonment option). Investors will therefore limit their losses if they believe that losses are becoming persistent. In addition, some firms can turn current losses into future profits (Joos and Plesko 2005). Such transitory losses can be observed for growth-oriented firms (e.g., Amazon in the 2000s, Tesla in the 2010s), firms restructuring their business (e.g., Apple in the 1990s), or firms being hit by economic shocks (e.g., Lufthansa in the COVID-19 crisis). Thus, negative performance will be less persistent than positive performance, which suggests weaker associations for firm-years with negative performance (e.g., Joos and Plesko 2005; Li 2011).

Nevertheless, widely applied forecasting models of cash flows and earnings treat losses and negative cash flows equally with profits and positive cash flows (Barth et al. 2001; Kim and Kross 2005; Hou and Robinson 2006; Dichev and Tang 2009; Lev et al. 2010; Bostwick et al. 2016). Only a few papers explicitly account for the differences between firms with negative and positive current performance by adding a simple indicator variable for firms with losses (Fama and French 2006; Hou et al. 2012). Even that approach, however, will not be sufficient to capture the lower persistence of negative performance, since it does not account for differences in the association between current and future performance for firms with negative and positive current performance.

A simple example can document this. Assume that the average association between current performance and future performance is 1.1 for firms with positive performance (high persistence), 0.5 for firms with negative performance (low persistence), and 0.9 for the average of all firms (profit and loss firms). Thus, a profit of 100 in t would suggest a profit of 110 in $t + 1$, since profits are persistent and tend to grow. By contrast, a loss in t of -100 would indicate a loss of -50 in $t + 1$ as firms transform transitory losses into profits. Considering the average association of 0.9 would result in an underestimated profit for a profitable firm (90 in $t + 1$) and an overestimated loss for a loss firm (-90 in $t + 1$). Since the size of the measurement error depends on the value of current performance, a simple loss dummy will not fully capture the heterogeneity in performance persistence. We hypothesize:

H3: *Considering the lower persistence of negative firm performance improves the accuracy of performance predictions.*

3. Data and methodology

3.1. Data

For our analysis, we use hand-collected accounting information from 2004 to 2012 from consolidated German annual reports from 2005 to 2012. In detail, we hand-collect the following information from the tax footnote: a) ULCFs (mandatory item), b) total tax loss

carryforwards, and c) a potential valuation allowance from tax loss carryforwards (all voluntary items under IFRS). We use this information to predict one- to four-year-ahead earnings and cash flows. We use Worldscope (Thomson Reuters 2012) to collect data on (future) firm performance from 2004 to 2015 and to complement our data with additional characteristics such as total assets.^h

Consolidated IFRS accounts became obligatory for all listed firms on the German stock market in 2005.ⁱ Since 2005 annual reports typically provide information on IFRS accounts from the preceding year, 2004, we consider that information as well. We manually collect consolidated IFRS accounts for all firms listed in the most relevant German stock indices (DAX 30 and MDAX 50) for at least one year, from 2005 until 2012. For example, suppose a firm was listed on the MDAX in 2005. In that case, we consider that firm's data over the whole period to obtain a comprehensive time series of IFRS accounts. A total of 30 annual business reports were unavailable due to insolvencies, mergers, or acquisitions, even upon request via mail.^j For these firms, we consider all available business reports. Altogether, we collected 866 observations from 106 firms.

We adjusted observations with deviating fiscal years to the calendar year in which the fiscal year ended (e.g., 2012 for the fiscal year from October 2011 to August 2012). Loss carryforwards in foreign currencies were converted to euro values using the conversion rate on the accounting date. We excluded observations with incomplete fiscal years (12 observations), inconsistencies in the financial statements (three observations), or missing values (16 observations) regarding total assets, operating cash flows, and earnings before taxes at time t (TA_t , $CFBT_t$, EBT_t) or cash flows and earnings at $t + 1$ ($CFBT_{t+1}$, EBT_{t+1}). Our

^h We only had data access until 2015 when we collected these additional data from Worldscope.

ⁱ Firms listed at non-European Union (non-EU) stock exchanges and using non-EU financial reporting standards were permitted to delay their adoption of IFRS until 2007 (see also PwC 2015).

^j To further complement our data, we also sent requests by mail to all observations 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 tax loss carryforwards and ULCFs in their annual reports.

final sample contains 835 observations of 106 firms. We provide detailed information on the sample composition in Table 1, Panel A.

[Table 1 about here]

Our sample documents wide heterogeneity in disclosure behavior. While mandatory information on tax loss carryforwards is missing for a relevant fraction of firm-years, additional information is disclosed in many cases. Table 1, Panel B, provides detailed documentation of the disclosure behavior. As mandatory information, we consider recognized deferred tax assets from tax loss carryforwards, *DTA LCF*. The variable *ULCF* describes the amount of unused tax losses for which no deferred tax asset has been considered. We also report voluntary disclosures of the book value of valuation allowances regarding deferred tax assets from tax loss carryforwards, *VAL*. If voluntarily reported, we further document changes in the valuation allowance, ΔVAL , and the total amount of tax loss carryforwards *TLCF* (i.e., the sum of recognized tax loss carryforwards and ULCFs). If possible, we calculate ΔVAL from information on *VAL*.

Information on deferred tax assets from tax loss carryforwards is provided in the tax footnote in only 77.8% of the observations and on ULCFs in only 70.2%, despite these disclosures being mandatory according to IAS 12.81. 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 (i.e., from tax loss carryforwards and interests) or the net of deferred tax assets and deferred tax liabilities. Similar issues hold for ULCFs.^k While part of the relatively high non-disclosure of mandatory items could be subject to the IFRS

^k It is possible that some observations do not disclose information, since the value of their tax loss carryforwards is zero. Nevertheless, if the tax footnote information does not allow for identifying such cases, we treat that information as missing. Note that we also sent a mail request to observations with missing information. We treat all observations without detailed information on either deferred tax assets from tax loss carryforwards or ULCFs 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.

introduction period (Table 1, Panel B), our findings also raise doubt regarding the quality of IFRS accounting practices in German firms.¹

We observe a significant number of observations with additional voluntarily disclosed information: 28.9% report the book value of the valuation allowance on deferred tax assets from tax loss carryforwards, 14.5% the change of the corresponding valuation allowance in the current year, and more than half (51.7%) the aggregate amount of total tax loss carryforwards. Mandatory and voluntary disclosures increase moderately over time.

The statistics in Table 1, Panel B, have two important implications. First, although we want to address the predictive validity of mandatorily and voluntarily disclosed IFRS information, not all observations disclose that information. Thus, our empirical specification must account for the fact that not all observations provide the same information in the financial reports. To address this problem, we use indicator (i.e., dummy) variables to account for observations disclosing ($D = 1$) or not disclosing ($D = 0$) a particular type of information.

Second, disclosure behavior could be related to future firm performance. Hamrouni et al. (2015), Jiao (2011), and Leung and Veenman (2018) provide evidence that firms with poor performance will choose a lower disclosure level, and, therefore, voluntary disclosure signals higher future firm performance. By contrast, Lang's (2017) findings suggest that managers of firms with bad news can also increase voluntary disclosure to create lower earnings expectations for analysts and investors. Therefore, from the perspective of an external person who wants to predict future firm performance (e.g., an analyst), the disclosure of certain accounting items could be a relevant firm characteristic for performance prediction. By including disclosure indicator variables, we control for differences in firms' future performance with high and low disclosure levels.

¹ Indeed, the non-disclosure of recognized deferred tax assets from tax loss carryforwards, *DTA LCF*, remains relatively stable over time. In the first two years of our sample, 23.0% of firm-years did not report this item, while 23.7% did not report this item in the last two years. In the case of ULCFs, we observe a fraction of 24.2% not reporting this footnote item in the last two years.

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). Other relevant industries are public utilities (23 firm-years), transportation (27 firm-years), banking (61 firm-years), insurance (43 firm-years), financial services, and others (73 firm-years). Due to the limited number of observations, we abstain from a more precise industry classification. We do not exclude financial firms or potential outliers from our primary setting. In an untabulated robustness test, we also excluded financial firms and outliers. The corresponding results confirm our findings.

3.2. Methodology

Our analysis is primarily based on Lev et al. (2010) who analyze mean absolute forecast errors (MAFEs) in out-of-sample tests (Lev et al. 2010; Eng and Vichitsarawong 2017). In doing so, we first perform a regression using a standard prediction model that we enrich with additional accounting information on deferred tax assets and tax losses. In the second step, we use these regression results to predict performance indicators and calculate the forecast error as the difference between the observable “true” performance (e.g., true cash flow in 2012) and its predicted value (e.g., predicted cash flow prediction in 2012). Since the error can be positive and negative, we take its absolute value and then calculate the mean of the absolute forecasting error for each year. Thus, the MAFE over n observations can be described as

$$MAFE = \frac{\sum |Actual - Forecast|}{n}.$$

We then perform a t -test if the errors of alternative prediction

models differ significantly from each other.

Following Lev et al. (2010), we also calculate Theil’s U as an alternative statistic. Theil’s U is the unweighted average of U -statistics over all predicted years, where $U = \sqrt{\frac{\sum (Actual - Forecast)^2}{\sum (Actual)^2}}$. Theil’s U virtually provides a weighted average statistic of absolute forecast errors, with higher weights on larger errors. Since Theil’s U is an aggregate statistic, we cannot test for statistically significant differences in errors (as in

MAFEs). As complementary test statistics, we also calculate with in-sample tests whether specific variables increase the explanatory power of our models (see Online Appendix B).

We consider two pre-tax performance measures as the dependent variables for our analyses: a) cash flow from operations before taxes (*CFBT*) and b) earnings before taxes (*EBT*). For cash flows, we adjust the after-tax operating cash flow, as provided by our hand-collected data or by Worldscope (Net Cash flow – Operating Activities Field 04860), with current taxes corresponding to IAS 12.15 to approximate the pre-tax operating cash flow. In additional analyses, we consider the after-tax performance indicators c) cash flow from operations after taxes (*CFAT*) and d) earnings after taxes (*EAT*).

Following the literature on predicting future cash flows and earnings (Finger 1994; Lorek and Willinger 1996; Dechow, Kothari, and Watts 1998; Lev et al. 2010), we rely on a simple standard prediction model. Lev et al. (2010) suggest that a parsimonious model with current performance as the only explanatory variable is well suited to predict future firm performance. Similar to Herbohn et al. (2010) and Flagmeier (2017), our baseline model regresses a measure of future firm performance ($PERF_{t+x}$) on the same current performance measure ($PERF_t$) and indicator variables for industry and year fixed effects. As an alternative robustness check, we also use the widely-applied prediction model of Barth et al. (2001; see Table A3, Panels C and D, in Online Appendix C). Corresponding to the work of Flagmeier (2017), we scale performance measures by total assets and do not explicitly control for firm size (for tests including firm size, see Online Appendix D). Thus, our baseline model is

$$PERF_{it+x} = \alpha + \beta_1 \times PERF_{it} + \gamma_1 \times INDUSTRY_i + \gamma_2 \times YEAR_t + u_{it}. \quad (1)$$

To analyze the relevance of additional accounting items, we test whether the inclusion of these items increases the baseline model's predictive validity (out-of-sample tests). If we consider all other variables, we obtain the following extended model:

$$\begin{aligned}
PERF_{it+x} = & \alpha + \beta_1 \times PERF_{it} + \beta_2 \times NPI_{it} + \beta_3 \times NPI_{it} \times PERF_{it} \\
& + \beta_4 \times D_{it}^{ULCF} + \beta_5 \times D_{it}^{ULCF} \times ULCF_{it} \\
& + \beta_6 \times VD_{it}^{TLCF} + \beta_7 \times VD_{it}^{TLCF} \times TLCF_{it} + \beta_8 \times VD_{it}^{VAL} + \beta_9 \times VD_{it}^{VAL} \times VAL_{it} \\
& + \beta_{10} \times VD_{it}^{\Delta VAL} + \beta_{11} \times VD_{it}^{\Delta VAL} \times \Delta VAL_{it} \\
& + \beta_{12} \times D_{it}^{DTALCF} + \beta_{13} \times D_{it}^{DTALCF} \times DTALCF_{it} \\
& + \beta_{14} \times D_{it}^{DTAD} \times DTAD_{it} + \beta_{15} \times D_{it}^{DTL} \times DTL_{it} + \gamma_1 \times INDUSTRY_i + \gamma_2 \times YEAR_t + u_{it}.
\end{aligned} \tag{2}$$

In this model, the negative performance indicator NPI is a dummy variable for firm-years with negative current performance ($PERF$). It conforms to the forecasting approach of Fama and French (2006) and Hou et al. (2012). The interaction term $NPI \times PERF$ accounts for the lower expected performance persistence if $PERF$ is negative. Research (e.g., Hayn 1995) suggests that positive outcomes of current performance are more strongly associated with future performance, $PERF_{t+x}$, than negative performance outcomes. Therefore, we expect a positive and significant coefficient for $PERF$ and a negative and significant coefficient for $NPI \times PERF$. While the $PERF$ coefficient β_1 captures the persistence of positive performance outcomes, the expected lower persistence of negative performance outcomes is captured by the sum of the coefficients β_1 and β_3 .

We enrich the model by ULCFs scaled by total assets ($ULCF$).^m To account for the variation in mandatory disclosure, we include the indicator variable D^{ULCF} , which equals one if ULCFs have been reported. This approach has two advantages. First, D^{ULCF} controls for differences between observations reporting and not reporting that item. Therefore, it allows us to keep observations that do not report $ULCF$, which increases our sample size and reduces concerns of a non-representative sample and external validity. Second, D^{ULCF} enables us to test how a firm's higher mandatory disclosure level is related to future firm performance.

^m While parts of the literature refer to changes in the amount of unrecognized deferred tax assets (from tax loss carryforwards; see Gordon and Joos 2004; Herbohn et al. 2010), this item is not mandatory in IFRS. Thus, in line with Flagmeier (2017), we rely on ULCFs. We consider the carrying amount, since the use of annual changes would result in the loss of one observation period and the carrying amount encompasses information on changes of ULCF in earlier periods, increasing the variation in our data and the explanatory power of our models.

Thus, while D^{ULCF} accounts for the disclosure of ULCF as such, $D^{ULCF} \times ULCF$ identifies the association of current ULCFs with future firm performance. The coefficient for $D^{ULCF} \times ULCF$ captures the effect of the reported value of $ULCF$ on future firm performance.ⁿ

A potential concern regarding our approach is (endogenous) sample selection, which is accounted for by models such as the Heckman model (e.g., Lennox, Francis, and Wang 2012). While such models are used to identify (typically causal) relations between variables, they are neither used in nor appropriate for performance predictions.^o In our analysis, we take the role of an external stakeholder who wants to predict future firm performance. From this perspective, all current observable characteristics are exogenous in a way that will not be affected by future performance outcomes (time lag) and can also not be affected by the external observer. Thus, while the accounting choice can be regarded as endogenous “self-selection” at the level of the firm, it is an exogenous characteristic for an outsider who intends to predict future firm performance.^p

We further include a comprehensive set of indicator variables and interaction terms to test H2, suggesting a positive effect of voluntarily disclosed information on predictive validity. We consider the voluntary disclosure of a) total tax loss carryforwards (an indicator variable

ⁿ There might be concern that the coefficient estimates of $D^{ULCF} \times ULCF$ are biased, since the (endogenous) dummy variable D^{ULCF} effectively uses firms with a reported ULCF value of zero as a reference point for firms that do not report ULCFs. Thus, one might think that excluding those 249 observations could be useful. However, this would generate a serious problem for external validity, since a significant fraction of even the largest listed German firms does not report ULCFs. Hence, prediction models must also provide valid results for firms that do not report all obligatory items. Endogeneity is not a serious problem for our prediction models, since such models do not intend to identify causal relationships but simply to minimize prediction errors. We also show in Online Appendix E that our results remain almost unchanged if we choose another reference point for firms not reporting ULCFs (e.g., the sample mean or the sample median of the value of $ULCF$).

^o The reason is that the targets of prediction models differ from those of explanatory models. While explanatory models intend to identify causal relationships among variables, prediction models intend to reduce prediction errors (Hagerty and Srinivasan 1991; Shmueli 2010; Sarstedt and Danks 2022).

^p From this perspective, the question is rather which functional form of the information at the disclosure level might be considered (Jiao 2011; Hamrouni et al. 2015; Sarstedt and Danks 2022). In our case, we choose a parsimonious specification that accounts for the disclosure of a specific item via indicator variables. Note that our specification tests whether and how the disclosure of $ULCF$ and the disclosed value of $ULCF$ are associated with future performance outcomes. To rule out potential concerns regarding self-selection, we also perform a robustness check that exclusively considers observations that disclose the mandatorily required information (i.e., see Table A3, Panels A and B, in the Online Appendix C).

with a value of one if the information is disclosed, VD^{TLCF} , with an interaction term with the disclosed value, $VD^{TLCF} \times TLCF$); b) the book value of the valuation allowance on deferred tax assets from tax loss carryforwards (with the indicator variable VD^{VAL} and the interaction term $VD^{VAL} \times VAL$); and c) the annual change in the corresponding valuation allowance (with the indicator variable $VD^{\Delta VAL}$ and interaction term $VD^{\Delta VAL} \times \Delta VAL$), with all accounting items scaled by total assets.

As in the related literature (Gordon and Joos 2004; Herbohn et al. 2010), we also consider accounting items on deferred taxes, including the (mandatory) disclosure of recognized deferred tax assets from loss carryforwards, D^{DTALCF} , and the corresponding interaction term $D^{DTALCF} \times DTALCF$. Regarding deferred tax assets from timing differences, $DTAD$, and deferred tax liabilities, DTL , we abstain from including additional indicator variables and confine ourselves to the interaction terms $D^{DTAD} \times DTAD$ and $D^{DTL} \times DTL$. The variable D^{DTAD} is almost entirely collinear with D^{DTALCF} and therefore does not provide additional information. The variable D^{DTL} has a value of one in 98.7% of our observations. There are only 11 observations with $D^{DTL} = 0$, a number that seems too small for meaningful inferences. We also test models that include these indicator variables in untabulated robustness checks but find no relevant changes in results. We provide detailed variable definitions as Appendix in Table 8.

3.3. Descriptive analyses

Table 2 reports the descriptive statistics of the most relevant variables of our sample. We report information on the full sample for firms disclosing information on ULCFs (Panel B) and for firms not disclosing information on ULCFs (Panel C). We present total assets in millions of euros and scale other variables by total assets. An exception is the market-to-book value MTB , which is scaled by the book value of equity. Average (median) total assets

amount to €62.9 billion (€4.8 billion) in the full sample, €77.3 billion (€4.7 billion) in the ULCF sample, and €29.0 billion (€5.2 billion) in the non-ULCF sample. Thus, firms reporting ULCFs are larger. Average cash flow from operations to total assets, *CFBT* (earnings before taxes *EBT*), amounts to 9.1% (5.5%) in the full sample. About 9.9% (13.1%) of the observations report negative cash flows (earnings), as denoted by *NCFBT* (*NEBT*). Comparing Panels B and C reveals that observations disclosing ULCF report higher performance (earnings, cash flows, EBITDA) and smaller losses.

On average, the firms in our sample distribute 2.1% of their total asset values as dividends, which is a high value and about 38.3% of their pre-tax earnings. Non-ULCF firms distribute slightly less (1.9%) than ULCF firms (2.2%). Average sales amount to 92.3% of total assets and do not vary significantly between the different subsamples. Research and development (R&D) expenses, *RD* (2.8% of total assets in the full sample), are slightly higher in the ULCF sample (2.9% versus 2.7%). In comparison, EBITDA (10.4% of total assets in the full sample) and market-to-book values (227.8% of the book value of equity in the full sample) are more minor in the ULCF sample (9.7% versus 11.8% and 216.9% versus 251.8%, respectively).

Considering information on deferred tax assets, ULCFs are, on average, 7.3% of total assets. This is a relevant fraction. Recognized deferred tax assets from tax loss carryforwards comprise, on average, 0.9% of total assets. Deferred tax assets from timing differences, *DTAD*, and deferred tax liabilities, *DTL*, are both more relevant, at 2.9% and 3.5% of total assets, respectively. These values are very similar in the ULCF and non-ULCF samples.

Regarding voluntary disclosure, the most relevant item is the total sum of tax loss carryforwards, with a relatively high number of observations and an average value of 11.2% of total assets. By contrast, the fraction of (changes of) the corresponding valuation allowance to total assets is relatively small (1.5 for *VAL* and only 0.2% for ΔVAL). Comparing the ULCF and non-ULCF samples reveals that observations not disclosing ULCFs have higher total tax

loss carryforwards $TLCF$, a higher median (but not mean) of the valuation allowance VAL , and more remarkable changes in the valuation allowance ΔVAL .

[Table 2 about here]

To conclude our comparison of firms that disclose and do not disclose ULCFs in their financial reports, we find several interesting differences. First, non-disclosing firms are smaller, on average. This fits well with the finding of the literature that the compliance costs of taxes and bookkeeping have large economies of scale (see the review of Eichfelder and Vaillancourt 2014). Therefore, smaller firms have a stronger incentive to reduce compliance costs by simplifying financial reporting. Second, firms that disclose ULCFs report lower earnings and cash flows and have a higher probability of losses. This is consistent with the consideration that firms tend to disclose ULCFs if these become more relevant. Third, the differences in other observed indicators (sales, R&D expenses, dividend payments, and market-to-book ratios) among these groups are relatively small. Overall, our findings do not suggest that firms that do not disclose ULCFs have the intention to hide information, and non-disclosure does not seem to be a red flag for low-quality firms.

We also compare our descriptive information with two studies using hand-collected information on deferred taxes from tax loss carry forwards. In a recent study on the impact of tax loss carryforwards on cash holdings, Heitzman and Lester (2022) rely on 6,884 observations of listed US firms from 2010 to 2015. Benefits from loss carry forwards in their data amount to 3.1% of total assets (TA) and are therefore considerably higher than deferred tax assets from loss carryforwards in our sample (0.9%). At least in part, this is due to a difference in accounting systems. While net operating loss benefits in US GAAP are recognized *before deducting* the valuation allowance, the $DTA LCF$ value in our data has already been corrected by ULCFs. If we weight ULCFs with a tax rate of 35%, we would obtain a slightly higher value for gross (i.e., uncorrected) benefits from loss carryforwards (3.5%), which is similar to the result of Heitzman and Lester (2022). The firms of Heitzman

and Lester (2022) are significantly smaller (with an average TA value of \$8.3 billion), have a slightly lower EBITDA (9.3% of TA) and market-to-book ratio (198.9%), and pay out fewer dividends (only 55.2% of observations pay dividends, compared to 80.1% in our sample) but have significantly higher R&D expenses (4.3%) than the firms in our sample.

In a study on the association between information on tax loss carryforwards and future firm performance, Flagmeier (2017) uses a hand-collected sample of 664 observations of German firms from 2010 to 2012. The author reports similar deferred taxes from tax loss carryforwards (0.9%, compared to 0.9% in our sample) and smaller ULCFs (6.1%, compared to 7.3% in our sample), average earnings (4.3%, compared to 5.5% in our sample), and cash flows (6.8%, compared to 9.1% in our sample).

4. Analysis and results

4.1. Multivariate associations of variables

We initially analyze the signs and significance levels of our explanatory variables' regression coefficients in Equation (2). In doing so, we estimate a restricted regression model including exclusively the most relevant variables NPI , $NPI \times PERF$, D^{ULCF} , and $D^{ULCF} \times ULCF$, as well as the full model including all the additional explanatory variables of Equation (2). In Online Appendix A, we also provide information on the bivariate correlations of the variables. We perform ordinary least squares (OLS) regressions in Table 3 for a) one-year-ahead and three-year-ahead performances,⁹ with b) earnings before taxes, EBT , and (pre-tax) cash flow from operations, $CFBT$, as the performance measures. We use robust standard errors clustered at the firm level to account for heteroscedasticity and autocorrelation (Petersen 2009). The variance inflation factors never exceed 3.04, and their average values range from 1.69 to 1.83.

⁹ 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 out-of-sample tests in Sections 4.2 and 4.3, we generally perform forecasts over one, two, three, and four years for earnings and cash flows.

Thus, multicollinearity is not a problem. We report the regular R^2 as well as the adjusted R^2 values.

[Table 3 about here]

As expected, we observe a positive and significant coefficient for $PERF$, but a negative and significant coefficient for $NPI \times PERF$. Model 1 (5) in Table 3 suggests that a current $CFBT$ (EBT) value of 10 percentage points of total assets, ceteris paribus, predicts a future $CFBT$ (EBT) value at $t+1$ of 7.45 (8.47) percentage points of total assets. This suggests a persistence of positive performance of 74.5–84.7%. If the current $CFBT$ (EBT) values are negative, the aggregate effect on future performance can be calculated by the sum of the coefficients on $PERF$ and $NPI \times PERF$. Thus, a negative performance at time t of 10 percentage points predicts a negative performance at $t+1$ of $CFBT$ of only 3.09 percentage points of total assets ($= 0.745 - 0.436$) and of EBT of 4.82 percentage points ($= 0.847 - 0.365$). In line with the literature (e.g., Joos and Plesko 2005; Li 2011), we find a higher persistence of positive performance outcomes and a lower persistence of adverse performance outcomes.

By contrast, the coefficient of NPI does not differ significantly from zero. This finding has two implications. First, including the dummy NPI is insufficient to account for the heterogeneity in the persistence of firms with negative and positive performance. Second, in a horse race, the interaction term $NPI \times PERF$ outperforms the simple indicator variable NPI . Thus, adding $NPI \times PERF$ might also be helpful for predictions.

Confirming the evidence (Herbohn et al. 2010; Flagmeier 2017), we find a negative and significant coefficient for the interaction term $D^{ULCF} \times ULCF$ that measures the effect of the reported value of ULCFs. This indicates that firms with more unrecognized tax loss carryforwards (a higher non-valuable component of tax loss carryforwards) have lower expected performance in the future. Nevertheless, this does not mean that this information improves predictions. The extended models confirm our findings on the negative and significant coefficients of $NPI \times PERF$ and $D^{ULCF} \times ULCF$ (Models 3, 4, 7, and 8).

In these models, we find almost no significant association between the different indicator variables considering mandatory (D^{ULCF} , $D^{DTA LCF}$) or voluntary (VD^{TLCF} , VD^{VAL} , $VD^{\Delta VAL}$) disclosure and future firm performance. This also holds for additional (untabulated) regressions, including only part of these disclosure dummies. For three-year-ahead cash flows and earnings, we obtain a positive and significant association with changes in the valuation allowance captured by $VD^{\Delta VAL} \times \Delta VAL$. This association should be treated with caution, since we find no significant associations with one-year-ahead performances. The coefficient in Model 4 is significant only at the 10% level.

4.2. *Out-of-sample tests on predictive validity*

We next turn to our out-of-sample tests addressing the predictive validity of our forecasting models. Since H1 to H3 hypothesize an increase in performance forecasts' predictive validity, the out-of-sample tests are our primary test statistic. To use as much information in our database as possible, we follow Lev et al. (2010) and use a rolling prediction window that considers the information of all available previous periods for predicting a given year t . Note that we enrich our data with information on future firm performance from Worldscope. Hence, while the explanatory variables for our hand-collected data on tax loss carryforwards and deferred taxes are limited to 2004 to 2012, performance outcomes are also available for 2013 to 2015.

We explain our statistical tests with the following example.

1. For the prediction of one-year-ahead cash flows in the year 2012 (2013 cash flows), we perform a regression of cash flows in 2012 and earlier years on once-lagged explanatory variables in 2011 and earlier years. Thus, we do not only consider data from the preceding year, since we want to rely on statistically robust relations that do not mainly depend on year cycles. We account for year cycles by the use of year dummies.
2. We use the information from the forecasting regression to predict cash flows in 2013 by using data from 2012.

3. Comparing the predicted cash flow in 2013 with the actual cash flow in 2013, we calculate the MAFEs and Theil's U-statistics for the reference model and the more specific models that include additional variables.
4. We compare the reference and alternative models' MAFEs and Theil's U-statistics. In doing so, we perform t-tests to determine whether additional explanatory variables significantly reduce the MAFEs.

In the case of one-year-ahead (two-year-ahead) performance, we carry out this exercise for earnings and cash flows from 2010 to 2013 (2011 to 2014; see Figure 1). As documented in Figure 1, we generally use all earlier years' information for our estimation sample. Predictions in earlier years rely on a smaller number of observations than predictions in later years.[†] We regard more extended estimation periods and samples as beneficial, since correlations between variables can vary significantly between two years, due to macroeconomic shocks and they should revert to the mean in the long run. Thus, we use a minimum of six years for the regression sample, limiting the prediction sample to the years 2010 to 2013. We follow the same procedure for predictions of two-, three-, and four-year-ahead performance, but rely on explanatory variables lagged by more than one period.

[Figure 1 about here]

We include industry and year indicator variables and industry and year fixed effects in all the models and perform two series of out-of-sample tests. In a *first series*, we test extended prediction models against the baseline model. The extended models generally add one category of additional variables to our baseline model from Equation (1) (see also Table 4, Panel A). To test H1, Model ULCF adds the indicator variable D^{ULCF} , denoting disclosure on *ULCF*, and the reported value of *ULCF* for firms reporting this information ($D^{ULCF} \times ULCF$).

[†] For example, we can use data from 2004 to 2012 (with current year performance as the dependent variable and once-lagged explanatory variables) to predict the performance in 2013. By contrast, we only have the sample from 2004 to 2009 to predict the performance in 2010.

To test H2, Model VD considers all the variables on the voluntary disclosure of total tax loss carryforwards $TLCF$ and the valuation allowance VAL (specifically, VD^{TLCF} , $VD^{TLCF} \times TLCF$, VD^{VAL} , $VD^{VAL} \times VAL$, $VD^{\Delta VAL}$, and $VD^{\Delta VAL} \times \Delta VAL$). Regarding Model VD, we also tested alternative versions, including only part of the voluntary disclosure information on deferred taxes from tax loss carryforwards (e.g., only voluntary disclosure on total tax loss carryforwards $TLCF$). Since corresponding tests do not lead to substantially different evidence, we abstain from reporting these results, which can be provided upon request.

To test H3, we consider two alternative models. Model NPI exclusively includes an indicator variable with a value of one in the case of negative current performance (NPI). Model NPERF further adds an interaction term of this variable and the (negative) performance of the firm ($NPI \times NPERF$). Thus, unlike Model NPI, Model NPERF considers differences in earnings persistence between observations with positive and negative performance (see Table 3). We document these models in detail in Table 4, Panel A.

In a *second series*, we test whether adding information on deferred tax assets enhances predictions if the variables on performance persistence are already included. In these tests, we use Model NPERF (including NPI and $NPI \times NPERF$) as a reference model and further add information on ULCFs (Model NPULCF) and the voluntary disclosure of information on deferred taxes from tax loss carryforwards (Model NPVD). Finally, we add a model including all variables from Equation (2) and test that model against the Model NPERF. Thus, Model JOINT tests whether a combination of all variables might perform better than Model NPERF. We describe these models in detail in Table 4, Panel B.

[Table 4 about here]

Initially, we provide graphical documentation of the MAFE statistics and the Theil's U-statistics. Figure 2 documents the MAFEs of all the analyzed models in percentages (see Table 4) compared to the baseline model (100%). We report evidence on pre-tax performance in Panel A and on after-tax performance in Panel B. We see that forecasting errors of Model

NPERF are, in almost all cases, lower than the baseline errors ($< 100\%$), the NPI model errors, or the errors of any other models. By contrast, we find higher average errors for models that include information on tax loss carryforwards. Especially high errors can be observed for the JOINT, VD, NPVD, and ULCF models. An interesting observation is that the relative errors of the more comprehensive models (JOINT, NPULCF, NPVD, NPERF) decrease in the length of the prediction period (one to four years ahead) for cash flows but increase with the length of the prediction period for earnings.

[Figure 2 about here]

Figure 3 documents the Theil U-statistics of all the analyzed models compared to the baseline model (100%). We can see that Model NPERF Theil's U-statistics are, in almost all cases, lower than the baseline Theil's U and that of Model NPI or of any other models. Exceptions are predictions of one-year-ahead cash flows (with a higher Theil's U for Model NPERF) or four-year-ahead cash flows (with lower errors for Models NPULCF, NPVD, and JOINT). Instead, we observe higher Theil's U-statistics for models including information on tax loss carryforwards. Exceptionally high Theil's U-statistics can be observed for Model JOINT as well as for Models ULCF, VD, NPULCF, and NPVD. Similar to MAFEs, the relative Theil's U-statistics of the more comprehensive models (Models JOINT, NPULCF, NPVD, and NPERF) decrease in the length of the prediction period (one to four years ahead) for cash flows but increase with the length of the prediction period for earnings.

[Figure 3 about here]

We document the results of our out-of-sample tests in Table 5. Panel A documents the results of the out-of-sample test against the baseline model, while Panel B provides the test results against the NPERF Model. In both cases, we initially report the reference models'

(baseline or NPERF) *absolute values* of the MAFEs and of the Theil's U-statistics (in parentheses). We multiply all values by 100 for readability.⁵

For models tested against the reference model, we only report the *differences* between the MAFEs and the Theil's U-statistics (again multiplied by 100 for readability) to simplify interpretation. Thus, we subtract the absolute value of the reference model from the tested model. For example, the value of the ULCF difference of 0.15 for the prediction of one-year-ahead cash flows ($CFBT_{t+1}$) in Table 5, Panel A suggests that the MAFE increases by 0.15 (5.1% of the error of the baseline model of 2.93) if the additional variables of Model ULCF are added to the baseline model. In similar terms, the value of the NPERF difference for the prediction of two-year-ahead earnings (EBT_{t+2}) suggests that the MAFE decreases by 0.17 (4.5% of the error of the baseline model of 3.82) if the additional variables of Model NPERF are added to the baseline model.

Note that the absolute values of the MAFEs and Theil's U-statistics can be calculated by adding the reported differences to the reference model's absolute values (the baseline model in Panel A and Model NPERF in Panel B). Thus, the absolute MAFE of Model ULCF in Panel A for predicting $CFBT_{t+1}$ is 3.08 (= 2.93 + 0.15), while the absolute value of Theil's U is 18.65 (= 16.32 + 2.33). In similar terms, the absolute MAFE of Model JOINT in Panel B for predicting EBT_{t+3} is 4.20 (= 3.87 + 0.33), while the absolute value of Theil's U is 49.21 (= 41.62 + 7.59).

To identify statistically significant deviations, we perform one-sample t-tests on the equality of the MAFEs between the tested model and the reference model (either the baseline model or Model NPERF). For Model NPERF, we further investigate whether the MAFE is statistically significantly different from the MAFE of Model NPI. Therefore, we test whether

⁵ For example, to predict one-year-ahead cash flows (earnings), the MAFE of the baseline model in Table 5, Panel A multiplied by 100 is 2.93 (2.58), which amounts to 32% (47%) of the average cash flows (earnings) as documented in Table 2, Panel A. By contrast, the corresponding prediction errors of Model NPERF, as reported in Table 5, Panel B, would be 2.95 (2.43) for cash flows (earnings).

adding information on the interaction term $NPI \times PERF$ significantly increases or reduces errors. We denote significant differences in the errors of Model NPERF against the baseline (Model NPI) by *, **, and *** (by +, ++, and +++).

[Table 5 about here]

Panel A of Table 5 documents that neither Model ULCF nor Model VD significantly reduce prediction errors in any specification. By contrast, we find that using both models significantly *increases* errors (documented in the *positive and significant differences* of MAFEs). For both models, we never see a negative and significant error difference. By contrast, we find increases (positive changes) in errors for Model ULCF in all specifications (for Model VD in seven of eight specifications). For the Model ULCF (Model VD), five (six) error changes differ significantly from zero. In addition, Theil's U values indicate that Models ULCF and VD effectively increase errors.

On the other hand, Models NPI and NPERF typically reduce MAFEs and Theil's U. We find a statistically significant reduction of errors for the prediction of three- and four-year-ahead cash flows, as well as for one- to three-year-ahead earnings. These error reductions range from 2.2% to 5.4% (0.8% to 3.5%) of the baseline model's error for Model NPERF (Model NPI). Comparing the results of Models NPI and NPERF suggests that the latter outperforms the former.[†] Overall, Table 5, Panel A, documents that Model NPERF outperforms the other models, while Models ULCF and VD increase prediction errors.

In Table 5, Panel B, we extend Model NPERF with additional information (e.g., on unrecognized loss carryforwards, *ULCF*) and test these augmented models against Model NPERF as a point of reference. Again, Model NPERF outperforms the other models. By

[†] We find that the error changes of Model NPERF are typically more negative than those of Model NPI, implying lower MAFEs for Model NPERF. In addition, this negative error difference of Model NPERF to Model NPI is statistically significant for predicting two- and three-year-ahead cash flows and for predicting one- to three-year-ahead earnings. We also find that Theil's U differences are more negative for Model NPERF than for Model NPI. The only relevant exception is the prediction of one-year-ahead cash flows ($CFBT_{t+1}$), where we find increases in the MAFEs and Theil's U for Model NPERF and reductions for Model NPI. In this case, the differences in the MAFEs of Model NPERF compared to the baseline model are not statistically significant.

contrast, Model ULCF significantly increases errors in five of eight specifications compared to Model NPERF. For Model NPVD, we find significant increases in the MAFEs in six of eight specifications, while Theil's U increases in seven of eight specifications. We obtain almost identical results for the comprehensive Model JOINT, including all Equation (2) variables. In addition, in relation to Model NPERF, Model JOINT significantly increases prediction errors for one- and two-year-ahead cash flows and all earnings specifications. These increases in errors are also relevant from a quantitative perspective. Compared to the absolute MAFE of Model NPERF, errors increase by 5.7% (EBT_{t+2}) to 15.0% (EBT_{t+4}). By contrast, for Model JOINT, we find no significant reduction in the MAFEs and increases in Theil's U in seven of eight specifications.

The results of Table 5, Panel B, underline that adding information on tax loss carryforwards and corresponding deferred taxes to Model NPERF significantly reduces predictive validity. This finding is also interesting from a methodological perspective. As documented by in-sample tests in Table A.2 in Online Appendix B, models with a high number of variables (e.g., Model JOINT) typically increase explanatory power. Thus, the unexplained variation of the dependent variable *decreases*. However, this mechanism of reducing errors by adding more variables does not work for out-of-sample tests. The main reason for that is likely model overfitting, which results in unstable relations among variables that depend on the relevant test data set. Adding variables only enhances the predictive validity if the statistical relation between both variables is sufficiently valid (Lev et al. 2010).

4.3. *Out-of-sample tests on after-tax performance*

In the following, we present out-of-sample tests on the after-tax performance measures of cash flow from operations after taxes (*CFAT*) and earnings after taxes (*EAT*). A theoretical argument for the more substantial explanatory power of information on deferred taxes in this context is that deferred tax items can provide information on future cash taxes (Laux 2013;

Flagmeier 2022). Thus, one could expect information on ULCFs (Model ULCF) or deferred tax assets (Models VD and JOINT) to become more relevant for after-tax cash flows.

Apart from using after-tax performance measures, our specifications conform to those of Table 5. We report the results in Table 6, which confirm our previous findings. Similar to the pre-tax variables, we find that Model NPERF outperforms all the other prediction models. Including variables that account for negative performance (*NPI*) as well as for the degree of negative performance and the differences in the performance persistence of firms with negative and positive performance ($NPI \times PERF$) reduces the MAFEs compared to those in the baseline model (Panel A). By contrast, enriching Model NPERF by additional variables on tax loss carryforwards and deferred taxes increases the MAFEs (Panel B). Again, including all variables of Equation (2) (Model JOINT) leads to significantly higher MAFEs in six of eight specifications.

[Table 6 about here]

4.4. *Least absolute shrinkage and selection operator analyses*

While our analysis is based on parsimonious prediction models similar to Lev et al. (2010), the literature has also developed models that optimize predictions in sample by selecting explanatory parameters. A common approach is the least absolute shrinkage and selection operator (LASSO) method. Freyberger, Neuhierl, and Weber (2020) use this method to select characteristics that explain share prices and find that LASSO methods can reduce prediction errors. However, this is not necessarily the case, since LASSO estimators do not optimize out-of-sample predictions but are—similar to OLS—focused on optimizing in-sample tests and in-sample predictions. This is primarily a concern in our case. Our sample is relatively small, and thus ULCFs might be subject to considerable measurement error and earnings management, and their relevance for explanatory power is limited (Shmueli 2010).

Unlike OLS, LASSO methods not only minimize the sum of squared residuals with a given set of variables and a specific functional form, but also select a set of variables and functional

forms that optimize the prediction of a dependent variable in sample. We use two alternative specifications: a) the adaptive LASSO (Freyberger et al. 2020) and b) a non-parametric square-root LASSO (Belloni, Chernozhukov, and Wang 2014). As Freyberger et al. (2020), we use the Bayesian information criterion for variable selection. We start with all variables from Equation (2), including year and industry dummies.

First, we test with the whole data set, which variables are selected by the applied LASSO models. For pre-tax performance, the models choose *PERF* in all specifications and the interaction term *NPI*×*PERF* in 15 of 16 specifications (four estimates with cash flows and four estimates with earnings for each LASSO-type model). By contrast, the interaction term $D^{ULCF} \times ULCF$ is only selected in eight of 16 specifications, and other indicators of Equation (2) in only a few specifications.^u These analyses confirm that Model NPERF is the most preferred.

Second, we perform out-of-sample tests of whether the applied LASSO estimation models enhance our predictions. Similar to Panel B of Table 5, we use Model NPERF as the reference. We report the absolute MAFEs and Theil's U-statistics (both multiplied by 100) for this model, as well as the differences in the MAFEs and Theil's U-statistics (multiplied by 100) of the adaptive LASSO and the square-root LASSO compared to Model NPERF. We perform out-of-sample tests in the same way as in Table 5 for pre-tax performance and report the results in Table 7. We find that LASSO methods are not necessarily sufficient to enhance predictive validity in out-of-sample testing. Especially for cash flows, we find significantly larger MAFEs compared to Model NPERF as a reference. For pre-tax earnings, the evidence is mixed, with lower errors for two-year-ahead earnings and higher errors for four-year-ahead earnings, as well as higher errors for one-year-ahead earnings for the square-root LASSO.

^u The adaptive LASSO model selects $D^{ULCF} \times ULCF$ in five of eight specifications and the square-root LASSO in only three of eight specifications. Other selected parameters are $VD^{TLCF} \times TLCF$ (three of 16 specifications), $D^{DTL} \times TDL$ (two of 16 specifications), and $D^{DTAD} \times DTAD$ (one of 16 specifications). We do not report which industry and year dummies have been selected.

The reason for the limited performance of the LASSO models is that in-sample and out-of-sample testing are conceptually different (Shmueli 2010).^v Thus, in line with the literature (e.g., Konishi and Kitagawa 2008; Shmueli 2010), our findings suggest that the optimization of predictive validity requires out-of-sample testing to realize an optimal outcome (e.g., Sarstedt and Danks 2022).

[Table 7 about here]

4.5. Robustness checks

We perform several robustness checks that are documented in detail in Online Appendix C. As mentioned earlier, there might be a concern that self-selection regarding the (mandatory) disclosure of information on ULCFs could affect our results. Therefore, we show in a robustness check that the results of out-of-sample tests do not change significantly if we reduce our sample to observations that report ULCFs (Online Appendix C, Table A3, Panels A and B). Again, we find that Models ULCF and VD increase the MAFEs and Theil's U if compared to the baseline model, while Model NPI and especially Model NPERF reduce the MAFEs. Thus, the best choice for predictions is Model NPERF.

In a second test, we consider the widely applied model of Barth et al. (2001, BCN hereafter) as an alternative reference model (see also Bostwick et al. 2016, with further references). This model regresses future cash flow on current cash flow and six accruals: the current year's change in accounts receivable (ΔAR), the change in accounts payable (ΔAP), the 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 ($OTHER = EBT - CFO + \Delta AR -$

^v In-sample tests address the question of which estimator fits in the best way a specific data set and therefore explains that data. This also holds for the LASSO method, which minimizes the sum of squared residuals (similar to OLS) but also accounts for a penalty parameter to reduce the number of explanatory variables (Freyberger et al. 2020).

$\Delta AP + \Delta INV + DEPR + AMORT$). The results are documented in Online Appendix C, Table A3, Panels C and D, and confirm our main findings.^w

In a third test (not tabulated), we exclude observations from the year 2004, since IFRS financial reporting was introduced in 2005, which can limit the validity of the information from 2004. While we generally find a lower number of significant differences in the MAFEs (lower robustness of a smaller data set), our findings remain qualitatively unchanged. In a fourth test (not tabulated), we adjust our data. We exclude financial firms' observations (banks, insurance companies, and other financial firms) and outliers from our sample. The remaining sample comprises 614 observations of 85 firms, and the results remain broadly unchanged. In a fifth test (not tabulated), we use EBIT and EBITDA (both scaled by total assets) as alternative dependent variables with consistent results. In a sixth set of tests (not tabulated), we consider alternative empirical specifications of our regression models. Most relevantly, we analyze itemized prediction models, where we test the predictive validity of the itemized explanatory factors of Model JOINT (e.g., *DTAD*).

4.6. Additional analyses

We further test whether complementing Model NPERF with other explanatory variables improves predictions (Online Appendix D). Joos and Plesko (2005) and Li (2011) develop models to identify persistent negative performance and transitory negative performance. Testing critical indicators of their models, we find that considering the sequence of past losses and negative cash flows typically enhances predictive validity. Only in one specification do we see weak evidence at the 10% level that including such a variable results in higher forecast errors. We obtain similar results for including a variable considering a relative change in performance (weaker performance compared to the last year). By contrast, we find no

^w Unlike the previous analysis, using BCN as a reference reduces the number of significant changes in MAFEs. Hence, since BCN add controls, it seems less relevant when other variables are included. Nevertheless, we still find that Models ULCF and VD will not enhance performance predictions (and, in some specifications, significantly worsen predictions), while Model NPI and especially Model NPERF significantly reduce MAFEs if compared to the BCN model as the reference.

conclusive evidence for an indicator variable for dividend-paying firms and an indicator variable for firm-years with first-time negative performance in the current year. Our evidence suggests that such variables do not improve out-of-sample predictions.

We further test whether including information on R&D activities enhances predictive validity, since high-R&D firms' negative performance can be transitory (Kothari, Laguerre, and Leone 2002; Darrough and Ye 2007; Ciftci and Darrough 2015). In contrast to our expectations, considering R&D information decreases predictive validity. Finally, we find that the market-to-book ratio has only minor relevance for predictive validity and typically worsens Theil's U-statistics. By contrast, including firm size typically enhances predictive validity. We also test models that include interaction terms of explanatory variables and industry dummy variables or industry trends (Online Appendix E). Our evidence suggests that the interaction terms of explanatory variables (e.g., current performance) and industry dummy variables can be useful for the prediction of earnings but not for the prediction of cash flows. Interaction terms of explanatory variables and industry-specific trends clearly worsen predictions.

5. Conclusion

We analyze whether accounting information on tax loss carryforwards and negative performance helps to predict future firm performance, using a hand-collected panel of German-listed firms. While we find a negative association of unrecognized tax loss carryforwards (ULCF) with future firm performance, out-of-sample tests show that considering such information typically even worsens predictions. By contrast, accounting for the different informational values of negative and positive performance enhances performance predictions.

In additional analyses, we do not see that machine-learning approaches that optimize predictions in sample (i.e., the LASSO method) help improve out-of-sample predictions. Thus, the main takeaway of our analysis is that indicators that help explain variation within samples are not necessarily valuable for enhancing predictions. Predictions differ

methodologically from explanatory models, which should be considered in future research. The main reason is model overfitting (Shmueli 2010; Sarstedt and Danks 2022).

An important limitation of our paper is the external validity of our findings. We rely on a relatively small sample of annual IFRS accounts of the largest public German firms. The results are not representative of small firms or firms using different accounting standards. There are relevant differences between IFRS and other prominent standards, such as US GAAP, regarding deferred tax assets from tax loss carryforwards. Thus, more research is needed that relies on alternative data sets and accounting systems to determine whether our results hold in a more general context.

Disclosure statement

No potential conflict of interest.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon request.

References

- Barth ME, Cram DP, Nelson KK (2001) Accruals and the prediction of future cash flows. *The Accounting Review* 76:27–58. DOI: 10.2139/ssrn.194931.
- Belloni A, Chernozhukov V, Wang L (2014) Pivotal estimation via square-root lasso in nonparametric regression. *The Annals of Statistics* 42:757–788. DOI: 10.1214/14-AOS1204.
- Bostwick ED, Krieger K, Lambert SL (2016) Relevance of goodwill impairments to cash flow prediction and forecasting. *Journal of Accounting, Auditing & Finance* 31:339–364. DOI: 10.1177/0148558X15596201.
- Bührle AT, Casi E, Stage B, Voget J (2022) The value of a loss: The economic impact of restricting tax loss transfers. Retrieved from (20.12.2022) <https://nathanseegert.com/utaxi2022material/Stage.pdf>.
- Chludek AK (2011a) On the relation of deferred taxes and tax cash flow. Retrieved from (20.12.2022) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1778265.
- Chludek AK (2011b) Perceived versus actual cash flow implications of deferred taxes – An analysis of value relevance and reversal under IFRS. *Journal of International Accounting Research* 10:1–25. DOI: 10.2308/jiar.2011.10.1.1.
- Christensen TE, Paik GH, Stice EK (2008) Creating a bigger bath using the deferred tax valuation allowance. *Journal of Business Finance & Accounting* 35:601–625. DOI: 10.1111/j.1468-5957.2008.02092.x.
- Ciconte WA, Donohoe MP, Lisowsky P, Mayberry MA (2016) Predictable uncertainty: The relationship between unrecognized tax benefits and future income tax cash outflows. Retrieved from (20.12.2022) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2390150.
- 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, © © DOI: 10.1111/jbfa.12108.
- Darrough M, Ye J (2007) Valuation of loss firms in a knowledge-based economy. *Review of Accounting Studies* 12:61–93. DOI: 10.1007/s11142-006-9022-z.
- Dechow PM, Kothari SP, Watts RL (1998) The relation between earnings and cash flows. *Journal of Accounting and Economics* 25:133–168. DOI: 10.1016/S0165-4101(98)00020-2.
- Dhaliwal DS, Kaplan SE, Laux RC, Weisbrod E (2013) The information content of tax expense for firms reporting losses. *Journal of Accounting Research* 51:135–164. DOI: 10.1111/j.1475-679X.2012.00466.x.
- Dichev ID, Tang VW (2009) Earnings volatility and earnings predictability. *Journal of Accounting and Economics* 47:160–181. DOI: 10.1016/j.jacceco.2008.09.005.
- Eichfelder S, Vaillancourt F (2014) Tax compliance costs: A review of cost burdens and cost structures. *Hacienda Pública Española/Review of Public Economics* 210, S111–148. DOI: 10.7866/HPE-RPE.14.3.5.
- Eng LL, Vichitsarawong T (2017) Usefulness of accounting estimates: A tale of two countries (China and India). *Journal of Accounting, Auditing & Finance* 32:123–135. DOI: 10.1177/0148558X16657756.
- Fama EF, French KR (2000) Forecasting profitability and earnings. *Journal of Business* 73:161–175. DOI: 10.1086/209638.
- Fama EF, French KR (2006) Profitability, investment, and average returns. *Journal of Financial Economics* 82:491–518, 10.1016/j.jfineco.2005.09.009.
- Finger CA (1994) The ability of earnings to predict future earnings and cash flow. *Journal of Accounting Research* 32:210–223, 10.1111/j.1475-679X.2005.00189.x.

- Flagmeier V (2017) The information content of tax loss carryforwards - IAS 12 vs. valuation allowance (arqus-working paper no. 216). University of Paderborn.
- Flagmeier V (2022) The information content of deferred taxes under IFRS. *European Accounting Review* 31:495–518. DOI: 10.1080/09638180.2020.1826338.
- Flagmeier V, Müller J (2016) Tax loss carryforward disclosure and uncertainty (arqus-working paper no. 208). University of Paderborn.
- Frank MM, Rego SO (2006) Do managers use the valuation allowance account to manage earnings around certain earnings targets? *Journal of the American Taxation Association* 28:43–65. DOI: 10.2139/ssrn.427300.
- Freyberger J, Neuhiel A, Weber M (2020) Dissecting characteristics nonparametrically. *The Review of Financial Studies* 33:2326–2377. DOI: 10.1093/rfs/hhz123.
- Gordon E, Joos P (2004) Unrecognized deferred taxes: Evidence from the UK *The Accounting Review* 79:97–124. DOI: 10.2308/accr.2004.79.1.97.
- Hagerty MR, Srinivasan S (1991) Comparing the predictive powers of alternative multiple regression models. *Psychometrika* 56:77–85. DOI: 10.1007/BF02294587.
- Hamrouni A, Miloudi A, Benzkrriem R (2015) Signaling firm performance through corporate voluntary disclosure. *Journal of Applied Business Research* 31:609–620. DOI: 10.19030/jabr.v31i2.9157.
- Hayn C (1995) The information content of losses. *Journal of Accounting and Economics* 20:125–153. DOI: 10.1016/0165-4101(95)00397-2.
- Heitzman S, Lester R (2022) Net operating loss carryforwards and corporate savings policies. *The Accounting Review* 97:267–289. DOI: 10.2308/TAR-2019-0085.
- Henry E, Sansing R (2018) Corporate tax avoidance: Data truncation and loss firms. *Review of Accounting Studies* 23:1042–1070. DOI: 10.1007/s11142-018-9448-0.
- 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. DOI: 10.1111/j.1468-5957.2010.02207.x.
- Hou K, Robinson DT (2006) Industry concentration and average stock returns. *The Journal of Finance* 61:1927–1956. DOI: 10.1111/j.1540-6261.2006.00893.x.
- Hou K, van Dijk MA, Zhang Y (2012) The implied cost of capital: A new approach. *Journal of Accounting and Economics* 53:504–526. DOI: 10.1016/j.jacceco.2011.12.001.
- Jackson M (2015) Book-tax differences and future earnings changes. *Journal of the American Taxation Association* 37:49–73. DOI: 10.2308/atax-51164.
- Jiao Y (2011) Corporate disclosure, market valuation, and firm performance. *Financial Management* 40:647–676. DOI: 10.1111/j.1755-053X.2011.01156.x.
- Joos P, Plesko GA (2005) Valuing loss firms. *The Accounting Review* 80:1847–1870. DOI: 10.2139/ssrn.562043.
- Jung D-J, Pulliam D (2006) Predictive ability of the valuation allowance for deferred tax assets. *Academy of Accounting and Financial Studies Journal* 10:49–70.
- 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. DOI: 10.1111/j.1475-679X.2005.00189.x.
- Konishi S, Kitagawa G (2008) *Information criteria and statistical modelling*. Springer.
- Kothari SP, Laguerre TE, Leone AJ (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. DOI: 10.1023/A:1020764227390.

- Lang K (2017) Voluntary disclosure and analyst forecast. *European Accounting Review* 27:23–36. DOI: 10.1080/09638180.2016.1217783.
- Laux RC (2013) The association between deferred tax assets and liabilities and future tax payments. *The Accounting Review* 88:1357–1383. DOI: 10.2139/ssrn.1859633.
- Legoria J, Sellers KF (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. DOI: 10.1016/S1052-0457(05)18007-2.
- Lennox CS, Francis JF, Wang Z (2012) Selection models in accounting research. *The Accounting Review* 87:589–616. DOI: 10.2139/ssrn.1120796.
- Leung E, Veenman D (2018) Non-GAAP earnings disclosure in loss firms. *Journal of Accounting Research* 56:1083–1137. DOI: 10.1111/1475-679X.12216.
- 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 DOI: 10.1007/s11142-009-9107-6.
- Li KK (2011) How well do investors understand loss persistence? *Review of Accounting Studies* 16:630–667. DOI: 10.1007/s11142-011-9157-4.
- Lorek KS, Willinger GL (1996) A multivariate time-series prediction model for cash-flow data. *The Accounting Review* 71:81–101.
- Lys T, Naughton JP, Wang C (2015) Signaling through corporate accounting reporting. *Journal of Accounting and Economics* 60:56–72. DOI: 10.1016/j.jacceco.2015.03.001.
- Ohlson JP (1995) Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Research* 11:661–687. DOI: 10.1111/j.1911-3846.1995.tb00461.x.
- Ohlson JP (2001) Earnings, book values, and dividends in equity valuation: An empirical perspective. *Contemporary Accounting Research* 18:117–120. DOI: 10.1506/7TPJ-RXQN-TQC7-FFAE.
- Olbert M (2022) The impact of tax shields on bankruptcy risk and resource allocation. Retrieved from (20.12.2022) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3467669. DOI: 10.2139/ssrn.3467669.
- Petersen MA (2009) Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies* 22:435–480: DOI: 10.1093/rfs/hhn053.
- PwC (2015) IFRS adoption by country. Retrieved from (20.12.2022) <https://www.pwc.com/gr/en/publications/pwc-ifs-by-country-2015.pdf>.
- Sarstedt M, Danks NP (2022) Prediction in HRM research – A gap between rhetoric and reality. *Human Resource Management* 32:485–513. DOI: Prediction in HRM research – A gap between rhetoric and reality. DOI: 10.1111/1748-8583.12400.
- Schrand CM, Wong MHF (2003) Earnings management using the valuation allowance for deferred tax assets under SFAS No. 109. *Contemporary Accounting Research* 20:579–611.
- Shmueli G (2010) To explain or to predict. *Statistical Science* 25:289–310. DOI: 10.1506/480D-098U-607R-5D9W.
- Thomson Reuters (2012) *Worldscope database: Data definitions guide*. Retrieved from (20.12.2022) <https://documents.pub/document/worldscope-database-datatype-definitions-guide.html?page=1>.
- Wang YW, Yu WW (2015) The information content of stock prices, legal environments, and accounting standards: International evidence. *European Accounting Review* 24:471–493. DOI: 10.1080/09638180.2014.977802.
- Weber C (2009) Do analysts and investors fully appreciate the implications of book-tax differences for future earnings. *Contemporary Accounting Research* 26:1175–1206. DOI: 10.1506/car.26.4.7.

Table 1. Sample information

Panel A: 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
Inconsistent 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
Panel B: Disclosure of information on losses and tax loss carryforwards											
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
Δ VAL	No	11	16	12	9	17	16	15	13	12	121

The term *DTA LCF* denotes recognized deferred tax assets from tax loss carryforwards, *VAL* is the (voluntarily disclosed) book value of a valuation allowance on deferred tax assets from tax loss carryforwards, Δ *VAL* is the (voluntarily disclosed) change in a valuation allowance on deferred tax assets from tax loss carryforwards in year *t*, *ULCF* is the (mandatorily disclosed) unrecognized (i.e., the nonvaluable component of) tax loss carryforwards and *TLCF* is the (voluntarily disclosed) total tax loss carryforward.

Table 2. Descriptive statistics

Panel A: Baseline sample						
Variable	Observations	Mean	Median	S.D.	Min	Max
Total assets (millions €)	835	62,896	4,7845	206,817	132	2,202,423
CFBT	835	0.091	0.081	0.093	-0.332	0.635
EBT	835	0.055	0.044	0.090	-0.695	0.553
NCFBT	835	0.099	0.000	0.299	0.000	1.000
NEBT	835	0.132	0.000	0.338	0.000	1.000
NCFBT×CFBT	835	-0.004	0.000	0.019	-0.332	0.000
NEBT×EBT	835	-0.008	0.000	0.041	-0.695	0.000
DIV	835	0.021	0.010	0.101	0.000	2.744
EBITDA	821	0.104	0.099	0.093	-0.575	0.585
SALES	816	0.923	0.848	0.650	0.020	5.307
MTB	784	2.278	1.717	3.305	-7.425	76.512
RD	495	0.028	0.024	0.027	0.000	0.208
ULCF	586	0.073	0.018	0.177	0.000	2.050
DTA LCF	650	0.009	0.003	0.013	0.000	0.086
DTAD	648	0.029	0.024	0.024	0.000	0.139
DTL	824	0.043	0.037	0.033	0.000	0.384
TLCF	432	0.112	0.044	0.235	0.000	2.140
VAL	241	0.015	0.004	0.034	0.000	0.234
ΔVAL	121	0.002	0.000	0.004	-0.003	0.033
Panel B: Sample reporting information on ULCFs (ULCF sample)						
Total assets (millions €)	586	77,304	4,680	243,230	142	2,202,423
CFBT	586	0.087	0.077	0.093	-0.332	0.635
EBT	586	0.049	0.041	0.088	-0.695	0.499
NCFBT	586	0.108	0.000	0.310	0.000	1.000
NEBT	586	0.142	0.000	0.349	0.000	1.000
NCFBT×CFBT	586	-0.004	0.000	0.021	-0.332	0.000
NEBT×EBT	586	-0.009	0.000	0.046	-0.695	0.000
DIV	586	0.022	0.010	0.117	0.000	2.744
EBITDA	573	0.097	0.096	0.092	-0.575	0.529
SALES	567	0.910	0.844	0.668	0.025	5.307
MTB	541	2.169	1.647	2.075	-7.425	27.136
RD	312	0.029	0.022	0.030	0.000	0.208
ULCF	586	0.073	0.018	0.177	0.000	2.050
DTA LCF	500	0.009	0.003	0.013	0.000	0.086
DTAD	499	0.0289	0.023	0.023	0.000	0.125
DTL	580	0.0414	0.035	0.032	0.000	0.384
TLCF	315	0.0957	0.040	0.210	0.000	2.050
VAL	154	0.0168	0.003	0.040	0.000	0.234
ΔVAL	97	0.0013	0.000	0.004	-0.002	0.033
Panel C: Sample not reporting information on ULCFs (non-ULCF sample)						
Total assets (millions €)	249	28,988	5,275	51,425	147	228,630
CFBT	249	0.101	0.090	0.092	-0.120	0.582
EBT	249	0.069	0.052	0.094	-0.393	0.553
NCFBT	249	0.080	0.000	0.272	0.000	1.000
NEBT	249	0.108	0.000	0.312	0.000	1.000
NCFBT×CFBT	249	-0.002	0.000	0.011	-0.120	0.000
NEBT×EBT	249	-0.005	0.000	0.292	-0.393	0.000
DIV	249	0.019	0.011	0.041	0.000	0.430
EBITDA	248	0.118	0.111	0.097	-0.312	0.585
SALES	249	0.952	0.860	0.607	0.020	3.049
MTB	243	2.518	1.817	5.066	0.210	76.512
RD	183	0.027	0.027	0.0199	0.000	0.107
DTA LCF	150	0.009	0.004	0.013	0.000	0.074
DTAD	149	0.031	0.028	0.027	0.000	0.139
DTL	244	0.048	0.041	0.036	0.000	0.201
TLCF	117	0.156	0.059	0.288	0.003	2.140
VAL	87	0.013	0.005	0.018	0.000	0.095
ΔVAL	24	0.002	0.001	0.004	-0.003	0.013

Descriptive statistics of the full sample and the restricted ULCF sample reporting information on ULCFs. The variable definitions are provided in Table 8 in the Appendix.

Table 3. Regression results

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Dependent variable	CFBT _{t+1}	CFBT _{t+3}	CFBT _{t+1}	CFBT _{t+3}	EBT _{t+1}	EBT _{t+3}	EBT _{t+1}	EBT _{t+3}
PERF	0.745*** (0.057)	0.564*** (0.071)	0.732*** (0.057)	0.570*** (0.071)	0.847*** (0.063)	0.592*** (0.145)	0.832*** (0.066)	0.577*** (0.144)
NPI	0.013 (0.010)	0.010 (0.019)	0.013 (0.010)	0.009 (0.020)	0.010 (0.010)	-0.006 (0.016)	0.010 (0.010)	-0.008 (0.017)
NPI×PERF	-0.436*** (0.166)	-0.422* (0.228)	-0.442*** (0.164)	-0.448* (0.252)	-0.365*** (0.109)	-0.625*** (0.173)	-0.378*** (0.124)	-0.659*** (0.182)
D ^{ULCF}	-0.002 (0.004)	-0.001 (0.006)	-0.006 (0.004)	0.000 (0.007)	0.007 (0.005)	0.009 (0.008)	0.004 (0.005)	0.004 (0.009)
D ^{ULCF} ×ULCF	-0.067*** (0.022)	-0.034 (0.021)	-0.062** (0.028)	-0.059** (0.027)	-0.051** (0.023)	-0.107*** (0.039)	-0.042** (0.021)	-0.095** (0.045)
VD ^{TLCF}			0.003 (0.004)	-0.000 (0.007)			-0.005 (0.005)	-0.000 (0.008)
VD ^{TLCF} ×TLCF			-0.011 (0.016)	0.021 (0.026)			-0.023 (0.016)	-0.037 (0.035)
VD ^{VAL}			-0.007 (0.005)	-0.006 (0.008)			0.003 (0.005)	-0.002 (0.009)
VD ^{VAL} ×VAL			0.041 (0.142)	0.104 (0.125)			0.001 (0.079)	0.046 (0.209)
VD ^{ΔVAL}			-0.003 (0.005)	-0.004 (0.009)			-0.010 (0.006)	-0.009 (0.009)
VD ^{VAL} ×ΔVAL			0.230 (0.562)	1.437* (0.834)			0.726 (1.235)	1.189** (0.552)
D ^{DTA LCF}			0.005 (0.006)	0.005 (0.009)			0.004 (0.007)	0.005 (0.011)
D ^{DTA LCF} ×DTA LCF			-0.107 (0.219)	0.244 (0.307)			0.093 (0.182)	0.344 (0.411)
D ^{DTAD} ×DTAD			0.106 (0.122)	-0.110 (0.167)			0.090 (0.098)	-0.033 (0.183)
D ^{DTL} ×DTL			-0.079 (0.076)	0.029 (0.117)			-0.084 (0.059)	-0.114 (0.115)
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	835	792	835	792	835	792	835	792
R ²	0.644	0.504	0.647	0.508	0.617	0.352	0.623	0.359
Adjusted R ²	0.636	0.492	0.635	0.490	0.608	0.337	0.610	0.336

The dependent variables are the operating cash flow before taxes *CFBT* at time $t + 1$, *CFBT* at time $t + 3$, earnings before taxes *EBT* at time $t + 1$, or *EBT* at time $t + 3$ (in each case scaled by total assets). The estimates are calculated by OLS. 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 8 in the Appendix provides detailed variable definitions.

Table 4. Models for out-of-sample tests

Model	Definition
Panel A: Baseline model as the reference model	
Baseline	The model corresponds to Equation (1), including current performance <i>PERF</i> and industry and year fixed effects. The model is used as a reference model for Models ULCF, VD, NPI, and NPERF.
ULCF	Baseline model enriched by all variables on ULCFs: D^{ULCF} and $D^{ULCF \times ULCF}$.
VD	Baseline model enriched by all additional variables on voluntary disclosure regarding deferred taxes from tax loss carryforwards: VD^{TLCF} , $VD^{TLCF \times TLCF}$, VD^{VA} , $VD^{VAL \times VAL}$, $VD^{\Delta VAL}$, and $VD^{\Delta VAL \times \Delta VAL}$.
NPI	Baseline model enriched by <i>NPI</i> .
NPERF	Baseline model enriched by <i>NPI</i> and by the interaction term $NPI \times PERF$.
Panel B: Model NPERF as the reference model	
NPERF	Baseline model enriched by <i>NPI</i> and by the interaction term $NPI \times PERF$. The model is used as a reference model for Models NPULCF, NPVD, and JOINT.
NPULCF	Model NPERF enriched by all variables on ULCFs: D^{ULCF} and $D^{ULCF \times ULCF}$.
NPVD	Model NPERF enriched by all additional variables on voluntary disclosure regarding deferred taxes from tax loss carryforwards: VD^{TLCF} , $VD^{TLCF \times TLCF}$, VD^{VA} , $VD^{VAL \times VAL}$, $VD^{\Delta VAL}$, and $VD^{\Delta VAL \times \Delta VAL}$.
JOINT	Model NPERF enriched by all additional explanatory variables in Equation (2): D^{ULCF} and $D^{ULCF \times ULCF}$, VD^{TLCF} , $VD^{TLCF \times TLCF}$, VD^{VA} , $VD^{VAL \times VAL}$, $VD^{\Delta VAL}$, and $VD^{\Delta VAL \times \Delta VAL}$, $D^{DTA LCF}$, $D^{DTA LCF \times DTA LCF}$, $VD^{DTAD \times DTAD}$, and $D^{DTL \times DTL}$.
Panel C: LASSO models	
Adaptive LASSO	Starting with the JOINT model, we apply the adaptive LASSO method to obtain an optimal prediction model.
Square-root LASSO	Starting with the JOINT model, we apply the square-root LASSO method to obtain an optimal prediction model.
This table presents the documentation of the prediction models. We provide detailed variable definitions in Table 8 in the Appendix.	

Table 5. Out-of-sample tests: Pre-tax performance

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations before taxes				Earnings before taxes			
Prediction years	1 year	2 years	3 years	4 years	1 year	2 years	3 years	4 years
	(CFBT _{t+1})	(CFBT _{t+2})	(CFBT _{t+3})	(CFBT _{t+4})	(EBT _{t+1})	(EBT _{t+2})	(EBT _{t+3})	(EBT _{t+4})
Panel A: Baseline model as the reference model								
Baseline absolute	2.93 (16.32)	3.45 (20.31)	4.58 (42.07)	4.76 (53.49)	2.58 (23.08)	3.82 (40.17)	4.00 (43.26)	4.06 (51.61)
ULCF difference	0.15** (2.33)	0.08* (1.17)	0.08 (2.19)	0.05 (1.59)	0.08*** (0.54)	0.13** (0.86)	0.21** (2.87)	0.10 (3.35)
VD difference	0.18*** (1.84)	0.10** (1.02)	0.00 (0.90)	-0.03 (-0.66)	0.21*** (1.53)	0.13* (1.60)	0.28*** (4.00)	0.29** (4.50)
NPI difference	-0.04 (-0.32)	0.02 (-0.50)	-0.07** (-0.62)	-0.06** (-1.05)	-0.09*** (-0.17)	-0.07*** (-0.38)	-0.03*** (-0.18)	0.00 (-0.03)
NPERF difference	0.02 (0.10)	-0.04 ⁺⁺⁺ (-0.87)	-0.10 ^{***/+} (-0.84)	-0.18** (-3.71)	-0.14 ^{***/+} (-1.57)	-0.17 ^{***/+} (-1.75)	-0.13 ^{***/+} (-1.64)	0.01 (-0.93)
Panel B: NPERF model as the reference model								
NPERF absolute	2.95 (17.35)	3.42 (19.40)	4.48 ⁺ (41.23)	4.58 (49.79)	2.43 (21.51)	3.64 (38.42)	3.87 (41.62)	4.06 (50.67)
NPULCF difference	0.11* (1.26)	0.15** (0.96)	0.11** (1.65)	0.06 (0.03)	0.05 (0.03)	0.13** (0.62)	0.18* (3.31)	0.15 (4.99)
NPVD difference	0.17*** (1.52)	0.15** (1.23)	0.04 (1.04)	0.01 (-0.28)	0.22*** (1.33)	0.18** (1.57)	0.34*** (4.28)	0.39*** (5.36)
JOINT difference	0.23*** (2.71)	0.28*** (2.32)	0.07 (1.77)	-0.03 (-1.76)	0.33*** (2.29)	0.22** (2.63)	0.33** (7.59)	0.61*** (11.16)
Observations	285	271	255	167	285	271	255	167

Panel A shows the absolute MAFEs of the baseline model multiplied by 100, with the corresponding Theil's U-statistics multiplied by 100 in parentheses, as well as the differences of the MAFEs, with the corresponding differences of Theil's U-statistics in parentheses (both multiplied by 100), for Models ULCF, VD, NPI, and NPERF compared to the baseline model. Panel B shows the absolute MAFEs, with Theil's U-statistics in parentheses (both multiplied by 100), of the NPERF model and the differences of the MAFEs, with the differences of the Theil's U-statistics in parentheses (both multiplied by 100), for the Models NPULCF, NPVD, and JOINT compared to the NPERF model. The superscripts ***, **, and * (⁺⁺⁺, ⁺⁺, and ⁺) indicate statistically significant differences in MAFEs compared to the reference model (Model NPI) at the 1%, 5%, and 10% levels, respectively. Table 4 provides detailed documentation of the prediction models. We provide the variable definitions in Table 8 in the Appendix.

Table 6. Out-of-sample tests: After-tax performance

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations after taxes				Earnings after taxes			
Prediction years	1 year	2 years	3 years	4 years	1 year	2 years	3 years	4 years
	(CFAT _{t+1})	(CFAT _{t+2})	(CFAT _{t+3})	(CFAT _{t+4})	(EAT _{t+1})	(EAT _{t+2})	(EAT _{t+3})	(EAT _{t+4})
Panel A: Baseline model as the reference model								
Baseline absolute	2.80 (22.05)	3.22 (25.01)	4.35 (52.03)	4.57 (65.08)	2.33 (30.62)	3.47 (55.48)	3.64 (59.96)	3.59 (66.38)
ULCF difference	0.16** (3.18)	0.010** (1.61)	0.09* (3.06)	0.05 (1.97)	0.10*** (0.88)	0.15*** (1.50)	0.25*** (4.04)	0.13 (4.58)
VD difference	0.16*** (2.30)	0.09** (1.13)	0.02 (1.10)	-0.04 (-0.97)	0.23*** (2.77)	0.17** (2.54)	0.32*** (5.62)	0.32*** (6.32)
NPI difference	-0.02 (-0.32)	0.01 (-0.65)	-0.04 (-0.46)	-0.03 (-0.98)	-0.06*** (0.08)	-0.02** (-0.15)	0.00 (0.01)	0.00 (0.11)
NPERF difference	0.02 (1.15)	-0.05 ⁺⁺⁺ (-1.26)	-0.08 ^{**/+} (-0.92)	-0.19 ^{**/+} (-4.77)	-0.12 ^{***/+} (-1.19)	-0.15 ^{***/+} (-1.95)	-0.09 ^{***/+} (-2.09)	-0.01 (-1.27)
Panel B: NPERF model as the reference model								
NPERF absolute	2.82 (23.20)	3.17 (23.75)	4.26 (51.11)	4.38 (60.31)	2.21 (29.43)	3.32 (53.53)	3.55 (57.87)	3.58 (65.12)
NPULCF difference	0.14** (2.13)	0.16** (1.42)	0.11** (2.51)	0.06 (1.04)	0.08** (2.00)	0.16** (0.89)	0.20* (3.46)	0.18 (5.25)
NPVD difference	0.15** (2.16)	0.13** (1.33)	0.05* (1.35)	0.01 (-0.40)	0.23*** (2.52)	0.18** (2.08)	0.33*** (5.19)	0.35*** (6.41)
JOINT difference	0.26*** (3.89)	0.27*** (2.71)	0.09 (2.59)	0.01 (-1.58)	0.31*** (3.38)	0.26*** (3.28)	0.38*** (8.45)	0.58*** (1.18)
Observations	279	265	249	167	279	265	249	167

Panel A shows the absolute MAFEs of the baseline model multiplied by 100, with the corresponding Theil's U-statistics multiplied by 100 in parentheses, as well as the differences of the MAFEs, with the corresponding differences of Theil's U-statistics in parentheses (both multiplied by 100), for Models ULCF, VD, NPI, and NPERF compared to the baseline model. Panel B shows the absolute MAFEs, with Theil's U-statistics in parentheses (both multiplied by 100), of the NPERF model and the differences of the MAFEs, with the differences of the Theil's U-statistics in parentheses (both multiplied by 100), for the Models NPULCF, NPVD, and JOINT compared to the NPERF model. The superscripts ***, **, and * (⁺⁺⁺, ⁺⁺, and ⁺) indicate statistically significant differences in MAFEs compared to the reference model (Model NPI) at the 1%, 5%, and 10% levels, respectively. Table 4 provides detailed documentation of the prediction models. We provide the variable definitions in Table 8 in the Appendix.

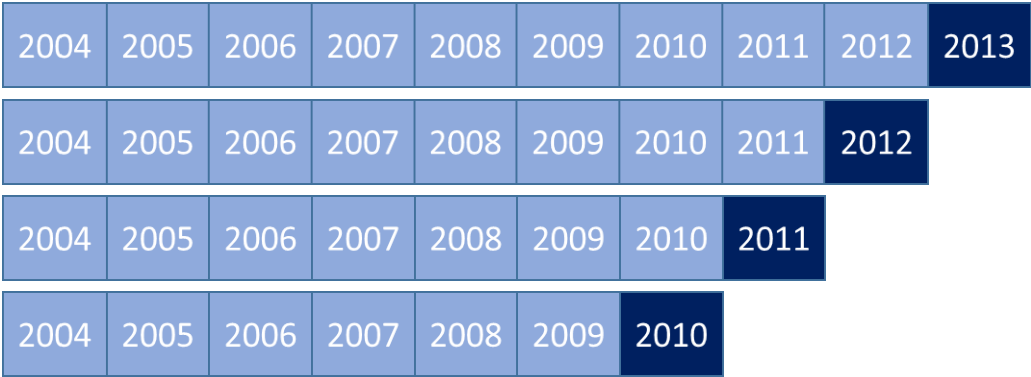
Table 7. LASSO method analyses

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations				Earnings before taxes			
Prediction years	1 year (CFBT _{t+1})	2 years (CFBT _{t+2})	3 years (CFBT _{t+3})	4 years (CFBT _{t+4})	1 year (EBT _{t+1})	2 years (EBT _{t+2})	3 years (EBT _{t+3})	4 years (EBT _{t+4})
LASSO method analyses								
NPERF absolute	2.95 (17.35)	3.42 (19.44)	4.48 ⁺ (41.23)	4.58 (49.79)	2.43 (21.51)	3.64 (38.42)	3.87 (41.62)	4.06 (50.67)
Adaptive LASSO	0.10**	0.09	0.15*	0.35***	0.07	-0.24**	-0.04	0.27**
Difference	(0.84)	(1.13)	(2.42)	(6.50)	(-0.23)	(-1.81)	(2.94)	(4.67)
Square-root LASSO	0.12**	0.05	0.14**	0.37***	0.21***	-0.21*	-0.09	0.22*
Difference	(0.45)	(1.37)	(1.22)	(6.20)	(1.41)	(-0.90)	(2.92)	(3.94)
Observations	285	271	255	167	285	271	255	167

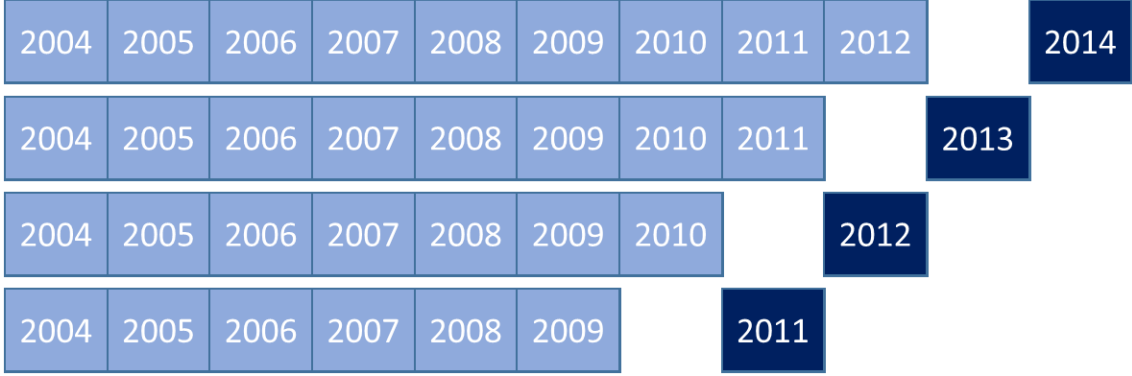
This table shows the absolute MAFEs multiplied by 100 of the NPERF model, with the corresponding Theil's U-statistics multiplied by 100 in parentheses, as well as the differences of the MAFEs, with the corresponding differences of Theil's U-statistics in parentheses (both multiplied by 100) of the adaptive LASSO and square-root LASSO models compared to the NPERF model. The superscripts ***, **, and * indicate statistically significant differences in MAFEs compared to the Model NPERF at the 1%, 5%, and 10% levels, respectively. We provide the variable definitions in Table 8 in the Appendix.

Figure 1. Data used for performance predictions

Panel A: Data used for one-year-ahead performance



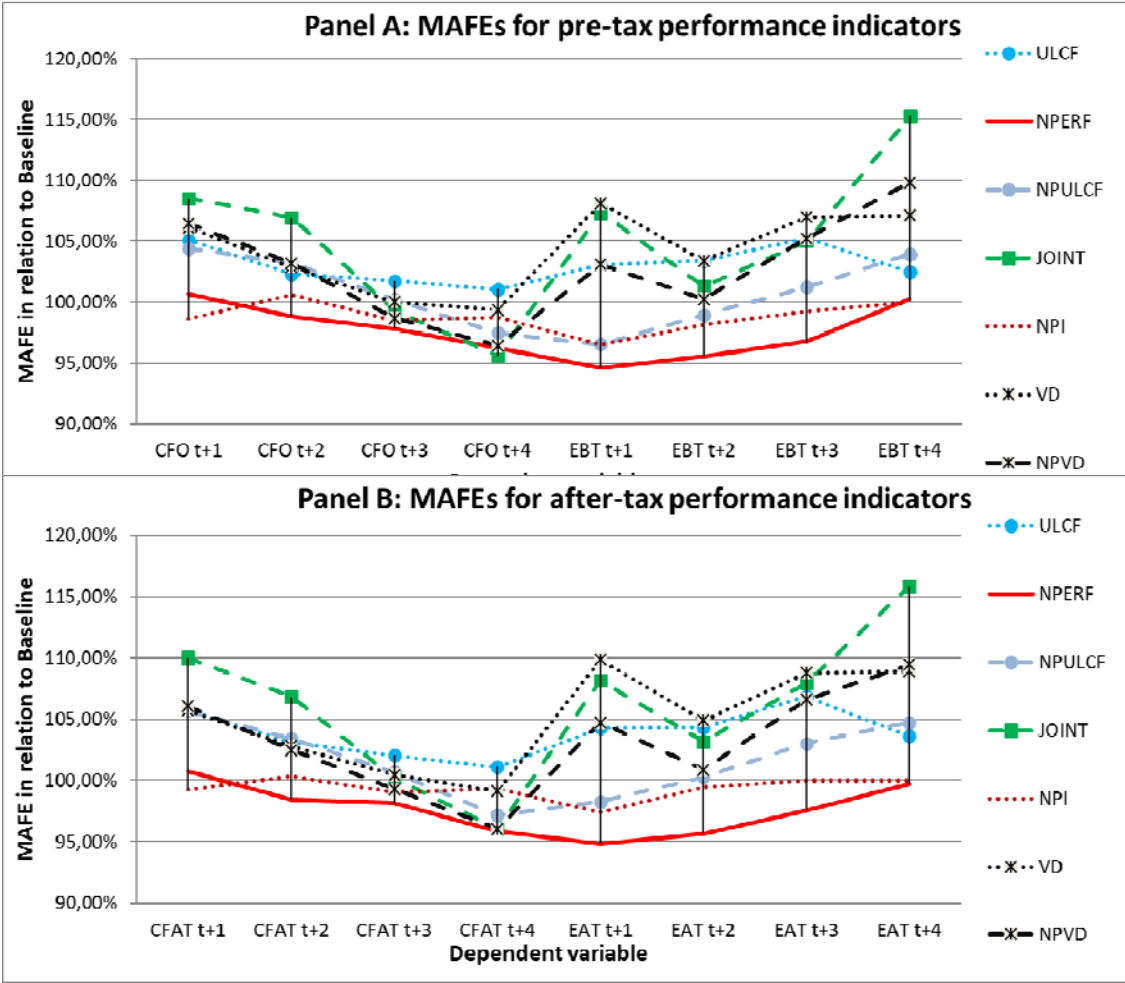
Panel B: Data used for two-year-ahead performance



f Year f of analysed forecasting error (out-of-sample tests)

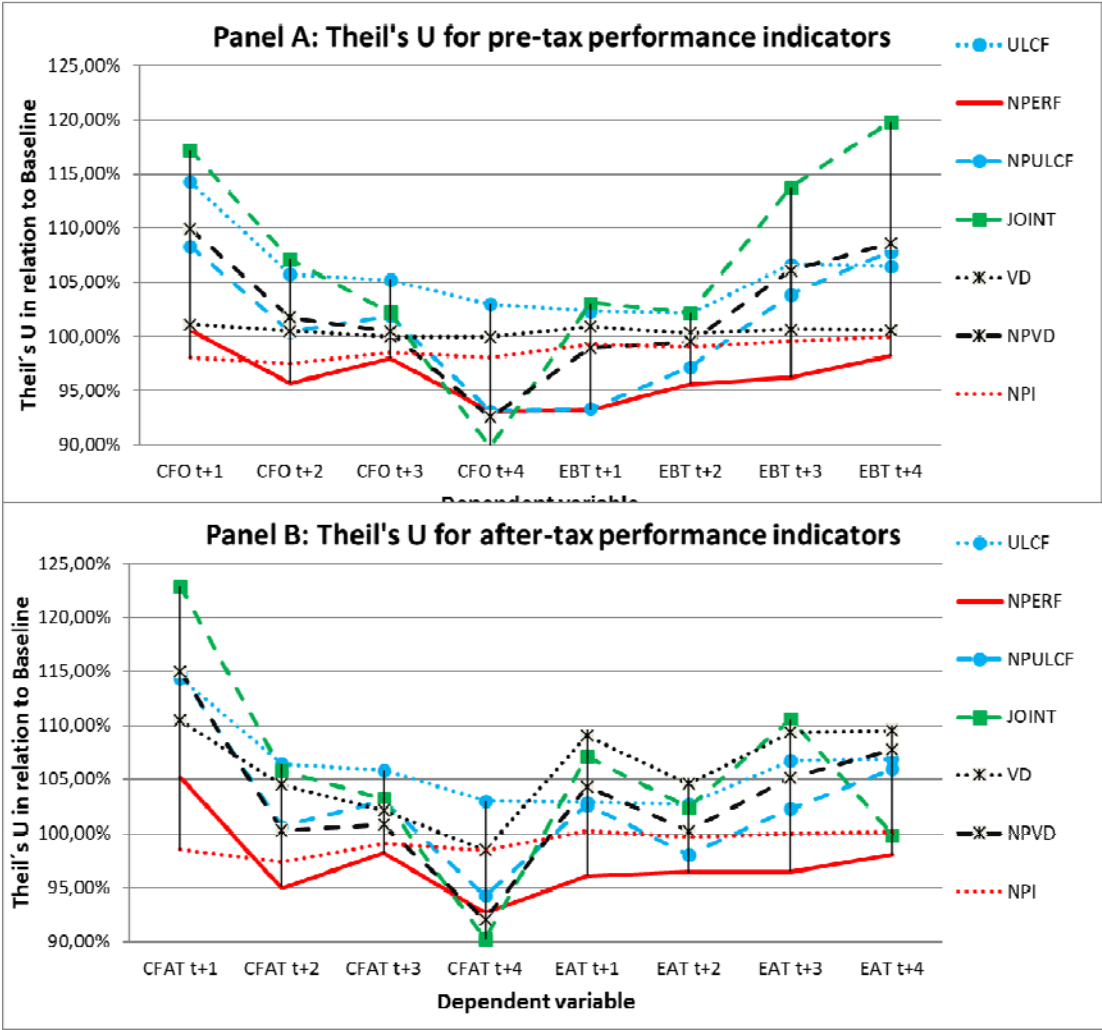
f - k Estimation sample for out-of-sample tests in year f

Figure 2. MAFEs as a percentage of the error of the baseline model



Notes: This figure documents the MAFEs of the extended models (Models NPI, NPERF; ULCF, NPULCF, VD, NPVD, and JOINT) compared to the MAFEs of the simple baseline model (100%) in percentages for the pre-tax performance indicators (Panel A) and post-tax performance indicators (Panel B).

Figure 3. Theil's U-statistics compared to Theil's U of the Baseline model



Notes: This figure illustrates the Theil's U-statistics of the extended models (Models NPI, NPERF; ULCF, NPULCF, VD, NPVD, JOINT) compared to the Theil's U of the simple baseline model (100%) in percentages for the pre-tax performance indicators (Panel A) and post-tax performance indicators (Panel B).

Appendix

Table 8. Variable definitions

Variable	Definition
Dependent variables	
CFAT _{t+x}	Cash from operations after taxes scaled by total assets at time $t + x$.
CFBT _{t+x}	Cash from operations before taxes scaled by total assets at time $t + x$.
EAT _{t+x}	Earnings after taxes scaled by total assets at time $t + x$.
EBT _{t+x}	Earnings before taxes scaled by total assets at time $t + x$.
PERF _{t+x}	Firm performance (measured either by cash flows or by earnings) scaled by total assets at time $t + x$.
Explanatory variables for current firm performance	
CFAT _t	Cash from operations after taxes scaled by total assets at time t .
CFBT _t	Cash from operations before taxes scaled by total assets at time t .
EAT _t	Earnings after taxes scaled by total assets at time t .
EBT _t	Earnings before taxes scaled by total assets at time t .
PERF _t	Firm performance (measured either by cash flows or by earnings) scaled by total assets at time t .
NCFAT	Indicator variable for observations with negative after-tax cash flows.
NCFBT	Indicator variable for observations with negative pre-tax cash flows.
NEAT	Indicator variable for observations with negative after-tax earnings.
NEBT	Indicator variable for observations with negative pre-tax earnings.
NPI	Indicator variable for negative firm performance (measured either by cash flows or by earnings).
NPI×PERF	This interaction term of NPI and PERF accounts for differences in association of future performance to current performance for firm-years with negative performance compared to firm-years with positive performance. Potential versions include NCFAT×CFAT, NCFBT×CFBT, NEAT×EAT, and NEBT×EBT.
Explanatory variables for ULCFs	
D ^{ULCF}	Indicator variable with a value of one if the information on ULCF is disclosed.
D ^{ULCF} ×ULCF	Interaction term of D ^{ULCF} and ULCFs scaled by total assets.
Explanatory variables for voluntary disclosure	
VD ^{TLCF}	Indicator variable for the disclosure of total tax loss carryforwards, TLCF.
VD ^{TLCF} ×TLCF	Interaction term of VD ^{TLCF} and total tax loss carryforwards scaled by total assets.
VD ^{VAL}	Indicator variable for disclosing the book value of a valuation allowance on deferred tax assets from tax loss carryforwards, VAL.
VD ^{VAL} ×VAL	Interaction term of VD ^{VAL} and the book value of a valuation allowance on deferred tax assets from tax loss carryforwards scaled by total assets.
VD ^{ΔVAL}	Indicator variable for disclosing the change in a valuation allowance on deferred tax assets from tax loss carryforwards, ΔVAL.
VD ^{ΔVAL} ×ΔVAL	Interaction term of VD ^{ΔVAL} and the change in a 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}	Indicator variable for the disclosure of deferred tax assets from tax loss carryforwards, DTA LCF.
D ^{DTA LCF} ×DTA LCF	Interaction term of D ^{DTA LCF} and DTA LCF scaled by total assets.
D ^{DTAD} ×DTAD	Interaction term of an indicator variable for disclosing deferred tax assets from timing differences and tax credits (DTAD) and DTAD scaled by total assets.
D ^{DTL} ×DTL	Interaction term of an indicator variable for the disclosure of deferred tax liabilities (DTL) and DTL scaled by total assets.
Additional firm information (relevant for descriptive statistics)	
DIV	Dividend payment scaled by total assets.
EBITDA	Earnings before interests, taxes, depreciation and amortization scaled by total assets.
SALES	Total sales scaled by total assets.
MTB	Market to book ratio (market capitalization scaled by the book value of equity).
RD	Expenses for research and development scaled by total assets.

Online Appendix

Online Appendix A: Univariate Correlations

Table A1 documents univariate correlations. We consider all variables included in Equation (2) and total assets. We denote statistically significant correlations by ***(1% level), ** (5% level), and * (10% level). As should be expected, we find a strong correlation between our alternative performance indicators, $CFBT$ and EBT . The same holds for the interaction terms in case of negative performance $NCFBT \times CFBT$ and $NEBT \times EBT$. In line with our theoretical expectations, we also find a negative correlation between unrecognized tax loss carryforwards ($D^{ULCF} \times ULCF$) and the performance indicators $CFBT$ and EBT . Simultaneously, $ULCF$ tends to be larger in case of negative performance ($NCFBT$ and $NEBT$). The same holds for total loss carryforwards $TLCF$ ($D^{TLCF} \times TLCF$) that are also strongly correlated with $ULCF$ ($D^{ULCF} \times ULCF$). These associations suggest that firms with higher unrecognized tax loss carryforwards tend to have lower performance and higher total loss carryforwards and vice versa.

[Table A1 about here]

We typically do not find strong associations for the indicator variables regarding the (voluntary) disclosure of information on deferred taxes from tax loss carryforwards. Observations disclosing information on recognized deferred tax assets from loss carryforwards (D^{DTALCF}) have a higher tendency to disclose information on unrecognized tax loss carryforwards (D^{ULCF}), and the amount of recognized deferred tax assets from loss carryforwards ($D^{DTALCF} \times DTALCF$) is positively correlated with unrecognized loss carryforwards ($D^{ULCF} \times ULCF$). Observations with high deferred tax assets from timing differences ($D^{DTAD} \times DTAD$) have a higher tendency to disclose information on deferred taxes from loss carryforwards (D^{DTALCF}) and to voluntarily disclose a corresponding valuation allowance (VD^{VAL}). Deferred tax liabilities ($D^{DTAD} \times DTAD$) are weakly positively correlated to the voluntary disclosure of total loss carryforwards (VD^{TLCF}) and the valuation allowance (VD^{VAL}).

Table A1. Univariate correlations

Variables	CFBT	EBT	NCFBT	NEBT	NCFBT × CFBT	NEBT × EBT	D ^{ULCF}	D ^{ULCF} × ULCF	VD ^{TLCF}	VD ^{TLCF} × TLCF	VD ^{VAL}	VD ^{VAL} × VAL	VD ^{ΔVAL}	VD ^{VAL} × ΔVAL	D ^{DTALCF}	D ^{DTALCF} × DTALCF	D ^{DTAD} × DTAD	D ^{DTL} × DTL	Total assets
CFBT	1.00																		
EBT	0.72**	1.00																	
NCFBT	-0.46**	-0.32**	1.00																
NEBT	-0.22**	-0.50**	0.32**	1.00															
NCFBT × CFBT	0.40**	0.39**	-0.57**	-0.26**	1.00														
NEBT × EBT	0.23**	0.59**	-0.31**	-0.49**	0.62**	1.00													
D ^{ULCF}	-0.07*	-0.10**	0.04	0.05	-0.04	-0.05	1.00												
D ^{ULCF} × ULCF	-0.28**	-0.37**	0.26**	0.25**	-0.57**	-0.56**	0.22**	1.00											
VD ^{TLCF}	0.17**	0.06+	-0.10**	-0.01	-0.01	-0.04	0.06+	-0.02	1.00										
VD ^{TLCF} × TLCF	-0.19**	-0.35**	0.22**	0.29**	-0.50**	-0.54**	-0.06	0.57**	0.32**	1.00									
VD ^{VAL}	0.08*	0.05	-0.09*	-0.05	0.06	-0.00	-0.09*	-0.08*	0.18**	-0.03	1.00								
VD ^{VAL} × VAL	-0.05	-0.07+	-0.01	0.02	-0.01	-0.09*	0.00	0.22**	-0.07*	-0.01	0.36**	1.00							
VD ^{ΔVAL}	-0.03	-0.07+	0.06	0.03	0.02	-0.02	0.09**	-0.03	0.04	-0.03	0.11**	0.03	1.00						
VD ^{VAL} × ΔVAL	-0.03	-0.07*	0.04	0.10**	0.00	-0.10**	0.00	0.08*	-0.01	0.04	0.00	0.02	0.31**	1.00					
D ^{DTALCF}	0.05	0.07*	0.09**	0.00	-0.05	-0.05	0.28**	0.09**	-0.07+	-0.01	0.10**	0.01	0.09*	0.03	1.00				
D ^{DTALCF} × DTA LCF	-0.12**	-0.13**	0.08*	0.16**	-0.04	-0.07+	0.07*	0.19**	-0.04	0.15**	0.12**	0.28**	-0.05	0.00	0.31**	1.00			
D ^{DTAD} × DTAD	0.11**	0.05	-0.03	-0.00	0.05	-0.01	0.12**	0.01	0.04	-0.03	0.30**	0.16**	0.06+	0.06+	0.50**	0.32**	1.00		
D ^{DTL} × DTL	-0.00	-0.09**	-0.08*	0.04	0.03	-0.00	-0.08*	0.03	0.12**	0.07+	0.11**	-0.02	-0.08*	-0.04	-0.16**	0.12**	0.36**	1.00	
Total assets	-0.21**	-0.14**	0.07*	0.02	0.03	0.05	0.11**	-0.08*	-0.09*	-0.08*	-0.03	-0.06	0.15**	-0.04	0.05	-0.12**	-0.12**	-0.16**	1.00

Univariate correlations between regression variables as well as total assets. We denote statistically significant correlations by ** (1% level), * (5% level) and + (10% level). We provide variable definitions in Table A1.

Online Appendix B: In-sample tests

Our primary test statistic in these tests is an F-test for nested models. We use the same prediction models, as documented in Table 4, Panels A and B (see also Tables 5 and 6). Our analysis aims to determine whether specific models increase the explanatory power of our in-sample regressions. The nested F-test compares the explanatory power of the augmented model, including additional explanatory variables, with the reference model (either Baseline or NPERF). Therefore, it tests which of the models provides more explanatory power. As an alternative statistic, we document in brackets the absolute values of the adjusted R^2 for each model. For the NPERF Model, we also perform an F-test against the NPI Model [in square brackets]. This is to ensure that the interaction term's inclusion increases explanatory power compared to the reference and NPI models. We report the results in Table A2. Like in Table 5, we test the models in Panel A against the Baseline Model and Panel B against the NPERF Model.

Table A2. In-sample tests

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations before taxes				Earnings before taxes			
Prediction years	1 year (CFBT _{t+1})	2 years (CFBT _{t+2})	3 years (CFBT _{t+3})	4 years (CFBT _{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 as the reference model								
Baseline	(0.625)	(0.537)	(0.487)	(0.446)	(0.593)	(0.381)	(0.302)	(0.231)
ULCF	4.16** (0.628)	0.54 (0.537)	0.13 (0.486)	0.26 (0.445)	0.57 (0.592)	0.64 (0.380)	1.86 (0.303)	1.10 (0.232)
VD	0.60 (0.624)	0.86 (0.537)	0.50 (0.485)	0.79 (0.445)	1.05 (0.593)	0.66 (0.379)	0.72 (0.300)	0.97 (0.231)
NPI	8.22*** (0.628)	16.49*** (0.546)	5.27** (0.490)	3.82* (0.448)	7.50*** (0.596)	2.56 (0.382)	0.83 (0.302)	0.29 (0.231)
NPERF	4.50** [0.77] (0.628)	11.18*** [5.78**] (0.549)	4.23** [3.18*] (0.491)	6.19*** [8.52***] (0.455)	12.68*** [17.71***] (0.604)	13.44*** [24.25***] (0.399)	10.15*** [19.44***] (0.318)	6.63*** [12.96***] (0.244)
Panel B: NPERF Model as the reference model								
NPERF	(0.628)	(0.549)	(0.491)	(0.455)	(0.604)	(0.399)	(0.318)	(0.244)
NPULCF	9.87*** (0.636)	4.32** (0.552)	1.92 (0.492)	1.80 (0.456)	5.37*** (0.608)	8.60*** (0.410)	11.94*** (0.337)	7.97*** (0.259)
NPVD	1.28 (0.629)	1.11 (0.549)	0.27 (0.488)	0.36 (0.451)	2.39** (0.608)	2.48** (0.406)	2.81** (0.327)	3.10*** (0.258)
JOINT	2.20** (0.635)	1.33 (0.551)	0.86 (0.490)	0.94 (0.454)	2.00** (0.610)	2.35*** (0.411)	2.76*** (0.336)	2.52*** (0.264)
Observations	835	815	792	691	835	815	792	691

Panel A shows the adjusted R^2 (in parentheses) of the Baseline Model and the results of nested F-tests (adjusted R^2 in parentheses) of the ULCF, VD, NPI, and NPERF Model against the Baseline Model. Panel B shows the adjusted R^2 (in parentheses) of the NPERF Model, as well as the results of nested F-tests (adjusted R^2 in parentheses) of the NPULCF, NPVD, and JOINT Models against the NPERF Model. The superscripts ***, **, and * indicate statistically significant nested F-tests compared to the reference model (to the NPI Model in squared brackets) at the 1%, 5%, and 10% levels. Table 4 provides detailed documentation of the prediction models. We provide variable definitions in Table 8 in the Appendix.

We find no apparent increase in the ULCF and VD prediction models' explanatory power compared to the Baseline Model. Only in one specification ($CFBT_{t+1}$). We find that the explanatory power of ULCF significantly exceeds the power of the Baseline Model. Related to H3, Table A2 suggests that including $NPI \times PERF$ significantly increases explanatory power. The NPERF Model's F-tests against the Baseline are positive and significant. Besides, F-tests of the NPERF Model against the NPI Model are positive and significant in 7 of 8 specifications. Considering the more comprehensive NPULCF, NPVD, and JOINT Models, we find a significant increase in the explanatory power in most specifications compared to the NPERF Model. Thus, enriching the NPERF Model by providing information on unrecognized tax loss carryforwards, deferred taxes, and related items increases explanatory power. This holds especially for earnings as dependent variables. Considering adjusted R^2 , the more comprehensive models with more variables (especially NPULCF and JOINT) provide the highest explanatory power.

Online Appendix C: Robustness tests

Table A3 provides robustness tests. As mentioned earlier in the paper, there might be a concern that self-selection regarding the (mandatory) disclosure of information on unrecognized tax loss carryforwards (*ULCF*) could affect our results. Therefore, we perform a first robustness check considering the sample disclosing information on *ULCF*. As documented in Table 2, the descriptive statistics of the *ULCF* Sample do not differ vastly from our full sample. As the indicator variable D^{ULCF} takes a value of one for all observations in this sample, it will drop out the regressions in this robustness check. Apart from that and the fewer observations, our approach is the same as in the out-of-sample tests in Table 5. The results are documented in Table A3, Panels A, and B, and confirm our previous findings. Again we find that the Models *ULCF* and *VD* increase mean forecast errors and Theil's U if compared to the Baseline Model, while *NPI* and especially *NPERF* reduce forecast errors. Furthermore, augmenting *NPERF* by additional variables leads to significantly larger errors in most specifications (Table A3, Panel B). Thus, the best choice for predictions is *NPERF*.

Second, one might challenge our straightforward Baseline Model that exclusively considers past performance, year dummies, and industry dummies for predictions (Equation 1). Therefore, we also consider the widely applied model of Barth et al. (2001, in the following *BCN*) as an alternative reference model for our analysis (see also Bostwick et al. 2016, with further references). This model regresses future cash flow on current cash flow and six accruals: the current year's change in accounts receivable (ΔAR), the change in accounts payable (ΔAP), the 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 ($OTHER = EBT - (CFO + \Delta AR - \Delta AP + \Delta INV + DEPR + AMORT)$). We scale all variables by total assets. While this model has been typically used to predict one-year-ahead cash flows, it can also be used to predict other performance measures. A generalized version of the model is

$$PERF_{it+x} = \alpha + \beta_1 \cdot PERF_{it} + \gamma_1 \cdot \Delta AR_{it} + \gamma_2 \cdot \Delta AP_{it} + \gamma_3 \cdot \Delta INV_{it} + \gamma_4 \cdot DEPR_{it} + \gamma_5 \cdot AMORT_{it} + \gamma_6 \cdot OTHER_{it} + \gamma_7 \cdot INDUSTRY_i + \gamma_8 \cdot YEAR_t + u_{it}. \quad (3)$$

Table A3. Out-of-sample tests: Robustness checks

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations before taxes				Earnings before taxes			
Prediction years	1 year	2 years	3 years	4 years	1 year	2 years	3 years	4 years
	(CFBT _{t+1})	(CFBT _{t+2})	(CFBT _{t+3})	(CFBT _{t+4})	(EBT _{t+1})	(EBT _{t+2})	(EBT _{t+3})	(EBT _{t+4})
Panel A: ULCF Sample and Baseline Model as the reference model								
Baseline absolute	2.98 (13.81)	3.56 (16.77)	4.68 (34.62)	4.64 (38.81)	2.66 (13.53)	3.86 (33.87)	3.96 (35.54)	4.44 (45.92)
ULCF difference	0.22** (2.41)	0.09* (1.09)	0.09 (2.38)	0.08* (2.15)	0.09** (0.67)	0.17** (1.31)	0.27** (3.91)	0.16 (3.35)
VD difference	0.26** (2.98)	0.12* (1.62)	0.06 (2.57)	0.05 (1.13)	0.23*** (2.20)	0.32** (4.13)	0.44*** (6.30)	0.32** (4.67)
NPI difference	-0.02 (-0.10)	-0.01 (-0.39)	-0.07** (-0.23)	-0.02 (-0.29)	-0.11*** (-0.67)	-0.09*** (-0.47)	-0.01 (-0.08)	-0.01 (-0.37)
NPERF difference	0.04 (0.94)	-0.08 (-0.77)	-0.12** (-0.76)	-0.17 (-2.34)	-0.16**/++ (-1.12)	-0.25**/+++ (-2.37)	-0.25**/+ (-2.82)	-0.12 (-2.49)
Observations	216	204	190	124	216	204	190	124
Panel B: ULCF Sample and NPERF Model as the reference model								
NPERF absolute	3.06 (14.75)	3.48 (16.01)	4.56 (33.86)	4.47 (36.48)	2.50 (12.40)	3.61 (31.50)	3.72 (32.72)	4.33 (43.43)
NPULCF difference	0.18*** (1.55)	0.19*** (0.86)	0.20** (1.87)	0.10* (0.88)	0.06 (0.13)	0.12 (0.77)	0.30* (4.38)	0.39** (5.55)
NPVD difference	0.25*** (2.26)	0.22*** (1.75)	0.15** (2.32)	0.08 (1.23)	0.31*** (2.35)	0.39*** (5.95)	0.58*** (9.12)	0.66*** (9.06)
JOINT difference	0.32*** (3.01)	0.30*** (1.96)	0.24** (2.68)	0.16* (1.59)	0.38*** (2.49)	0.35** (5.76)	0.51** (10.07)	0.73*** (10.17)
Observations	216	204	190	124	216	204	190	124
Panel C: BCN Model as the reference model								
BCN absolute	3.28 (14.65)	3.88 (19.27)	5.37 (46.24)	5.25 (53.88)	2.87 (21.41)	3.85 (36.27)	3.89 (36.48)	3.84 (41.94)
ULCF difference	0.12* (1.74)	0.00 (0.31)	0.03 (0.95)	0.04 (1.03)	0.04* (0.57)	0.05 (1.03)	0.06 (2.26)	0.07 (2.50)
VD difference	0.04 (0.68)	0.04 (0.53)	-0.04 (-0.36)	-0.09 (-1.62)	0.20*** (1.35)	0.06 (1.53)	0.10 (1.76)	0.24** (3.23)
NPI difference	-0.11 (-0.23)	-0.15 (-1.95)	-0.12 (-2.95)	-0.11 (-2.42)	-0.02** (-0.6)	0.00 (-0.02)	-0.02 (-0.03)	0.00 (-0.04)
NPERF difference	0.02 (2.23)	-0.06 (-0.67)	-0.11** (-0.88)	-0.18* (-3.71)	-0.12**/++ (-1.13)	-0.17**/+++ (-1.19)	-0.12**/+ (-1.15)	-0.02 (-1.33)
Observations	220	215	209	140	220	215	209	140
Panel D: BCN NPERF Model as reference model								
BCN NPERF absolute	3.30 (16.88)	3.83 (18.60)	5.26 (45.36)	5.07 (50.17)	2.75 (20.29)	3.67 (35.09)	3.77 (35.33)	3.86 (40.61)
NPULCF difference	0.07 (0.12)	0.07 (0.14)	0.03 (-0.26)	-0.02 (-1.06)	0.07 (0.61)	0.33** (3.39)	0.19 (5.30)	0.27 (4.65)
NPVD difference	0.05 (0.39)	0.08 (0.81)	-0.06 (-0.59)	-0.10* (-1.75)	0.21*** (1.55)	0.26** (2.57)	0.20* (2.81)	0.26* (3.58)
JOINT difference	0.10 (0.70)	0.24* (1.83)	-0.08 (-1.61)	-0.28** (-5.04)	0.42*** (4.72)	0.50* (10.10)	0.29 (12.23)	0.71** (12.89)
Observations	220	215	209	140	220	215	209	140

Panel A and B report results for the ULCF Sample, while Panel C and D report results for the full sample and the BCN Model. Panel A (C) shows the absolute mean forecasting errors (MAFEs) of the Baseline Model (BCN Model) and corresponding Theil's U statistics in parentheses, as well as the differences of MAFEs (differences of Theil's U statistics in parentheses) of the ULCF, VD, NPI, and NPERF Models compared to the Baseline Model (BCN Model). Panel B (D) shows the absolute MAFEs (Theil's U statistics in parentheses) of the NPERF Model (BCN NPERF Model) and the differences of MAFEs (differences of Theil's U statistics in parentheses) of the NPULCF, NPVD, and JOINT Models compared to the NPERF Model (BCN NPERF Model). The superscripts ***, **, and * (+++, ++, and +) indicate statistically significant differences in MAFEs compared to the reference model (to the NPI Model) at the 1%, 5%, and 10% levels. Table 4 provides detailed documentation of the prediction models. We provide variable definitions in Table 8 in the Appendix.

Due to missing information, using the BCN Model as an alternative reference point reduces observations. The results are documented in Table A3, Panels C, and D and widely confirm our previous findings. Unlike previous analyses, using BCN as a reference point reduces the

number of significant changes in MAFEs. Hence, as BCN adds controls, it seems less relevant when other variables are included. Nevertheless, we still find that ULCF and VD will not enhance performance predictions (and, in several specifications, significantly worsen predictions), while NPI and especially NPERF significantly reduce MAFEs if compared to the BCN Model as a point of reference. In the case of NPERF, we observe significant reductions of errors in 5 of 8 specifications. An interesting further observation is that absolute average errors using the BCN Model seem higher than in the simpler Baseline Model. For example, the absolute BCN error (multiplied as usual by 100) for one-year-ahead cash flow in Panel C is 3.28. The absolute Baseline error (multiplied by 100) for one-year-ahead cash flow in Panel A is 2.98. This finding fits well with Lev et al. (2010) and supports the view that variables based on estimates and subject to discretion may increase forecast errors. Nevertheless, as the samples of Panel A and Panel C differ, the outcome should be interpreted cautiously.

In Panel D, we compare the BCN Model enriched by *NPI* and $NPI \times NPERF$ (BCN NPERF) with augmented models using additional information from Equation (2). While we find significantly larger forecasting errors for earnings, some results suggest a significant reduction of forecasting errors for four-year-ahead cash flows. While the results are mixed and are not very robust, we may still conclude that we do not find evidence that NPULCF, NPVD, or JOINT significantly reduce prediction errors.

Online Appendix D: Model extensions

We further extend our analyses by several additional variables. We intend to test whether these variables increase predictive validity (out-of-sample tests). Joos and Plesko (2005) and Li (2011) develop models to predict loss reversals. These models predict the probability that firm–years with (persistent) negative performance in previous years retain positive earnings or cash flows in the current period. As a measure of persistent negative performance, both models rely on count variables for a sequence of persistent negative performance and find a positive impact on the probability of future negative performance. Two other important variables for identifying persistent negative performance in these models are an indicator variable for the firm–years with a first negative performance year and a variable for firms paying out a dividend in the current year. The authors find that firm–years with a sequence of adverse performance outcomes have a lower probability of loss reversal in past years. In comparison, first-year negative performance and dividend payment are indicators of a higher likelihood of loss reversal. Forecasting models also consider indicator variables for dividend payments for expected earnings in the tradition of Fama and French (2000; see, e.g., Fama and French 2006; Hou et al. 2012).

To account for sequences of years with negative performance, we enrich the model by D^{NSEQ} and $D^{NSEQ} \times NSEQ$. D^{NSEQ} accounts for whether information on past negative performance is available. We only consider information from IFRS accounts. We regard the information on loss persistence as missing and set the value of D^{NSEQ} to zero in case of a change in accounting methods. The term $D^{NSEQ} \times NSEQ$ is the interaction of D^{NSEQ} and a variable $NSEQ$ 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 all other cases, $NSEQ$ takes a value of zero. In our standard specification, a positive value of $NSEQ$ does not require a loss in the current period. In unreported tests (available upon request), we test an alternative specification of $NSEQ$ ($NSEQA$), where only firm–years with negative performance in the current period and a sequence of negative performance in previous periods are considered (past and present negative performance). $NSEQA$ 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 $NSEQ$. Thus, we abstain from reporting results. As for indicators for transitory negative performance, we also test an indicator variable for the

firm–years with a first-time negative performance ($FNPI$) (that means no negative performance in the preceding period) and a variable DIV defined as the ratio of the cash dividend (Worldscope item 04551) and total assets.¹ Like our standard procedure, we enrich the Model NPERF by indicator variables with zero value if the corresponding information is unavailable (D^{FNPI} , D^{DIV}) and interaction terms ($D^{FNPI} \times FNPI$, $D^{DIV} \times DIV$).

Following a suggestion of one of our reviewers, we also test a parameter on relative negative performance (i.e., a reduction in the performance parameter (earnings or cash flows) compared to the preceding period) as an additional measure for transitory losses. The indicator variable $RNPI$ takes a value of one if the current performance is smaller than the performance in the previous year. Again, we enrich the Model NPERF by an indicator variable with zero value if the corresponding information is unavailable (D^{RNPI}) and a related interaction term ($D^{RNPI} \times RNPI$).

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 value relevance (Kothari et al. 2002). Since R&D is a business investment (Ciftci and Darrough 2015; Darrough and Ye 2007), one might expect higher future earnings and cash flows for high R&D firm–years. Besides, high R&D levels could be an indicator of future loss reversal. Adding information on R&D to the prediction model could enhance predictive validity. We enrich the model with an indicator 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 indicator variable for loss firms to control for different R&D effects for the firm–years with negative performance and firm–years with positive performance ($NPI \times D^{RD} \times RD$).

Furthermore, we test whether considering the market-to-book ratio (MTB) or firm size ($SIZE$) improves predictive validity. We measure MTB as the ratio of the market value of the firm at year-end (Worldscope item 07210) to the book value of equity (Worldscope item 07220) and consider an indicator 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 our sample observations provide this information, we do not consider a disclosure dummy or an interaction term in this case.

¹ Similar to Joos and Plesko (2005), we also test an indicator variable for dividend-paying firms, $DIVDUM$. However, since this variable generated statistically insignificant regression results (in part with the wrong sign of the coefficient), we only report results for the specification considering the cash value of the dividend in relation to total assets.

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 *FNPI*, *DIV*, *RD*, and *MTB* are positively associated with future firm performance, while *NSEQ* is negatively related to future performance. Since our interest is in these variables' predictive validity, we concentrate on our out-of-sample tests compared to our best-practice model, NPERF. We also calculated (unreported) tests against the Baseline Model with consistent results. The specifications of these tests are the same as in the previous subsamples. We test the following models in addition to our NPERF Model: The NPNSEQ, NPFNPI, NPRNPI, NPDIV, NPRD, and NPMTB, NPSIZE Models. We document the models' detailed definitions and the variables' definitions in Table A4.

Table A4. Additional variables and models for out-of-sample tests

Panel A: Variables	
Variable	Definition
D^{NSEQ}	Indicator variable with a value of one if the information on NSEQ is available (information on $PERF_{t-1}$, $PERF_{t-2}$, and $PERF_{t-3}$ available).
$D^{NSEQ} \times NSEQ$	Interaction term of D^{NSEQ} and NSEQ, where NSEQ documents the sequence of perpetual years with negative firm performance (either earnings or cash flows as a performance measure) in the last three years. 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 $t - 3$).
D^{FNPI}	Indicator variable with a value of one if the information on FNPI is available.
$D^{FNPI} \times FNPI$	Interaction term of D^{FNPI} and FNPI, where the indicator variable FNPI has a value of one if the firm has a first-time negative performance (i.e., negative earnings or cash flows) in the current period, with non-negative earnings or cash flows in the previous period.
D^{RNPI}	Indicator variable with a value of one if the information on RNPI is available.
$D^{RNPI} \times RNPI$	Interaction term of D^{RNPI} and RNPI, where the indicator variable RNPI has a value of one if the firm has a relative negative performance (i.e., lower earnings or cash flows) compared to the performance in the last period
D^{DIV}	Indicator variable with a value of one if the information on cash dividends is available.
$D^{DIV} \times DIV$	Interaction term of D^{DIV} and cash dividends scaled by total assets.
D^{RD}	Indicator variable with a value of one if the information on research & development expenses is available.
$D^{RD} \times RD$	Interaction term of D^{RD} and research & development expenses scaled by total assets.
$D^{RD} \times RD \times NPI$	Interaction term of D^{RD} , research & development expenses scaled by total assets, and NPI.
D^{MTB}	Indicator variable with a value of one if the 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.
Panel B: Models	
Model	Definition
NPNSEQ	NPERF Model enriched by variables on a sequence of negative performance: D^{NSEQ} and $D^{NSEQ} \times NSEQ$.
NPFNPI	NPERF Model enriched by variables on first-time negative performance: D^{FNPI} and $D^{FNPI} \times FNPI$.
NPRNPI	NPERF Model enriched by variables on relative negative performance (compared to the previous year): D^{RNPI} and $D^{RNPI} \times RNPI$.
NPDIV	NPERF Model enriched by variables on dividend payments: D^{DIV} and $D^{DIV} \times DIV$.
NPRD	NPERF Model enriched by variables on research and development expenses: D^{RD} , $D^{RD} \times RD$, and $D^{RD} \times RD \times NPI$.
NPMTB	NPERF Model enriched by variables on the market-to-book ratio: D^{MTB} and $D^{MTB} \times MTB$.
NPSIZE	NPERF Model enriched by firm size: SIZE.
Documentation of models for additional out-of-sample tests. Detailed variable definitions are also provided in Table 8 in the Appendix.	

Table A5 documents the estimates of our out-of-sample tests. Similar to Tables 6 and 7, additional variables do not necessarily enhance predictive validity. For the NPRD model, we even find significantly higher forecasting errors in most specifications. Thus, adding information on R&D expenditures reduces the predictive validity of our models. Regarding NPFNPI and NPDIV, we obtain inconclusive results. Thus, including variables on first-time negative performance or dividends could either reduce or increase forecasting errors. Including information on the market-to-book ratio (NPMTB) typically has a positive but not statistically significant effect on predictive validity. Only in one of the 8 model specifications we find a reduction of the forecasting error being statistically significant at the 10% level. The only models that typically enhance predictive validity if compared to the NPERF Model are NPSIZE and (with less clear evidence) NPNSEQ and NPRNPI. For NPNSEQ and NPRNPI, we find one specification (in both cases with four-years-ahead earnings as the dependent variable) with a significant increase in MAFE. For NPSIZE, we find a significant reduction in forecasting errors in half of the specifications and never a significant increase.

Concluding, adding information on firm size (measured by the logarithm of total assets), as well as adding information on the sequence of past years with negative performance (*NSEQ*) or relative changes in performance (*RNPI*) rather enhances predictive validity. In unreported tests, we also analyze variables for extraordinary items (Li 2011) and alternative specifications for dividend-paying firms and firm-years with a sequence of past losses or negative cash flows with virtually unchanged results.

Table A5. 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 (CFBT _{t+1})	2 years (CFBT _{t+2})	3 years (CFBT _{t+3})	4 years (CFBT _{t+4})	1 year (EBT _{t+1})	2 years (EBT _{t+2})	3 years (EBT _{t+3})	4 years (EBT _{t+4})
NPERF absolute	2.95 (17.35)	3.42 (19.44)	4.48*** (41.23)	4.58** (49.79)	2.43*** (21.51)	3.64*** (38.42)	3.87*** (41.62)	4.06 (50.67)
NPNSEQ difference	0.00 (-0.04)	0.04 (0.05)	0.04 (-0.09)	-0.10** (-1.63)	-0.01 (-0.13)	-0.23*** (-1.72)	-0.25*** (-1.28)	0.10* (1.11)
NPFNPI difference	0.01 (0.33)	0.43*** (3.02)	0.29 (0.20)	-0.21 (-4.99)	0.13*** (1.85)	-0.46*** (-2.75)	-0.38*** (-1.00)	0.89*** (9.64)
NPRNPI difference	0.04 (-0.65)	-0.02 (-0.10)	-0.09** (-1.84)	-0.09 (-2.35)	-0.00 (-0.09)	-0.01*** (-0.09)	-0.14*** (-0.86)	0.03** (0.34)
NPDIV difference	-0.02 (-0.16)	0.00 (-0.03)	0.02 (0.28)	0.08** (1.13)	0.01* (0.01)	-0.00 (-0.01)	0.00 (-0.01)	0.00 (0.30)
NPRD difference	0.02 (0.14)	0.03 (0.51)	0.05 (0.64)	0.08 (1.27)	0.03 (0.03)	0.10** (0.65)	0.11** (1.91)	-0.02 (1.74)
NPMTB difference	0.09 (2.86)	0.19 (9.92)	0.13 (2.87)	-0.02 (2.00)	0.07 (8.89)	0.09 (19.94)	-0.20* (0.18)	0.02 (-0.20)
NPSIZE difference	-0.01 (-0.04)	-0.03** (-0.07)	-0.08** (-0.74)	-0.05 (-0.86)	-0.01 (-0.03)	-0.02*** (-0.13)	-0.02*** (-0.07)	0.00 (-0.02)
Observations	285	271	255	167	285	271	255	167

This table shows the absolute MAFEs (Theil's U statistics in parentheses) of the NPERF Model and the differences of MAFEs (differences of Theil's U statistics in parentheses) of the NPNSEQ, NPFNPI, NPRNPI, NPDIV, NPRD, NPMTB, and NPSIZE Models compared to the NPERF Model. The superscripts ***, **, and * indicate statistically significant differences in MAFEs compared to the NPERF Model at the 1%, 5%, and 10% levels. Panel B of Tables 5 and A4 provides detailed documentation of the prediction models. We provide variable definitions in Table 8 and in Table A3, Panel A.

Online Appendix E: Industry interaction terms and trends

Economic trends and developments can differ between industries. Therefore, an interesting question is whether considering industry-specific relationships among variables might help improve predictions. As documented by previous analyses, the best performing model is NPERF. Thus, we use this model as a starting point. We interact all main explanatory variables of this model ($PERF_{it}$, NPI_{it} , and $PERF_{it} \times NPI_{it}$) with either a) dummy variables for industries or b) linear industry trends. As trend indicators, we use the survey years (i.e., 2,004 for 2004).² Thus, in the industry-adjusted model NPERF INDUSTRY, we have an industry-specific version of $PERF_{it}$, NPI_{it} , and $PERF_{it} \times NPI_{it}$, for all industries, and in the NPERF INDTREND model, interactions terms of all variables with industry-specific trends. Table A6 provides an overview of our industry-specific models.

Table A6. Models with industry interaction terms

Model	Definition
NPERF INDUSTRY	NPERF Model enriched by interaction terms with industry dummy variables.
NPERF INDTREND	NPERF Model enriched by interaction terms with industry trends.
NPULCF INDUSTRY	NPULCF Model enriched by interaction terms with industry dummy variables.
NPULCF INDTREND	NPULCF Model enriched by interaction terms with industry trends.
LASSO INDUSTRY	Starting with the JOINT model enriched by interaction terms with industry dummies, we apply the adaptive LASSO method to obtain an optimal prediction model.
LASSO INDTREND	Starting with the JOINT model enriched by interaction terms with industry trends, we apply the adaptive LASSO method to obtain an optimal prediction model.

Documentation of the prediction models. We provide detailed variable definitions in Table 8 in the Appendix.

As our focus is also on the analysis of unrecognized loss carryforwards (ULCF), we further consider industry-adjusted versions of the NPULCF Model that enriches NPERF by the variables D_{it}^{ULCF} and $ULCF_{it} \times ULCF_{it}$ (NPULCF INDUSTRY and NPULCF INDTREND). In principle, we could also interact all Equation (2) variables with industry indicators or trends, resulting in an industry-specific version of the model JOINT. However, a problem with such a specification is that it results in many explanatory variables. As already documented by the model JOINT, a very high number of predictors may increase prediction errors if associations between variables are unstable (model overfitting). Therefore, we use an industry-adjusted version of JOINT as a starting point and then apply the adaptive LASSO method to reduce the number of explanatory variables. In doing so, we either use a) industry dummy variables or b)

² An alternative would have been to subtract 2003 from the survey year to get a linear trend from 1 to 9. However, this would suggest an extreme and unrealistic assumption for the dynamics regarding the associations of current performance and future performance. A trend from 1 to 9 suggests that this association will change largely over a period of 9 years. Explorative analysis suggest that our trend specification resulted in more robust and realistic regression estimates regarding the association between current and future firm performance.

industry trends to calculate interactions. We test all these models against NPERF as the baseline model and present out-of-sample results in Table A7.

Results document that interactions with industry trends are not useful to reduce forecasting errors. We find almost no specification that reduces Theil's U or MAFEs in such models (only for the LASSO INDTREND model, which probably does not select trend variables). In addition, we also find high increases in Theil's U statistics in some models that point to considerable noise in measurement errors. Indeed, Theil's U can increase by more than 10,000% in earnings forecasts (see NPERF INDTREND and NPULCF INDTREND). The main problem should be that trends often change over time. However, this is hard to foresee in a prediction model. While we assume a linear trend, the underlying functional form of trends is uncertain and might also change over time.

Regarding interactions with industry dummies, the evidence is less clear. While LASSO INDUSTRY and NPULCF INDUSTRY, in most specifications, suggest a reduction of predictive validity, we do not find any statistically significant increase of MAFEs for the NPERF INDUSTRY model. For four-years-ahead earnings, we also state a significant reduction of MAFEs of NPERF INDUSTRY compared to NPERF. Theil's U statistics of this model suggest that industry interactions may enhance predictive validity for earnings (lower Theil's U in models 5 to 8) but reduce predictive validity for cash flows (higher Theil's U in models 1 to 4). Overall, our evidence suggests that industry interaction terms can be useful for the prediction of earnings but not for cash flows. Industry trends worsen predictions.

Table A7. Industry interaction terms

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow from operations				Earnings before taxes			
Prediction years	1 year (CFBT _{t+1})	2 years (CFBT _{t+2})	3 years (CFBT _{t+3})	4 years (CFBT _{t+4})	1 year (EBT _{t+1})	2 years (EBT _{t+2})	3 years (EBT _{t+3})	4 years (EBT _{t+4})
NPERF absolute	2.95 (17.35)	3.42 (19.44)	4.48+ (41.23)	4.58 (49.79)	2.43 (21.51)	3.64 (38.42)	3.87 (41.62)	4.06 (50.67)
NPERF INDUSTRY difference	0.09 (4.00)	-0.01 (1.05)	0.07 (2.81)	0.01 (1.50)	0.00 (-0.12)	-0.00 (-0.24)	0.03 (-0.76)	-0.20* (-4.63)
NPERF INDTREND difference	0.79*** (6.50)	0.18** (2.45)	-0.17 (-1.71)	0.37*** (6.30)	1.03 (22,027.84)	1.93 (46,545.98)	3.07 (133,267.11)	2.15 (66,514.65)
NPULCF INDUSTRY Difference	0.26** (4.68)	0.18* (2.59)	0.20** (4.43)	0.14 (3.02)	0.13* (0.94)	0.29** (4.36)	0.27 (5.76)	-0.15 (0.39)
NPULCF INDTREND difference	0.72*** (6.36)	0.31*** (3.66)	-0.12 (-0.45)	0.41** (6.82)	1.29 (42,529.84)	1.91 (41,454.72)	3.18 (138,354.63)	2.35 (78,313.34)
LASSO INDUSTRY difference	0.28*** (1.55)	0.15* (1.55)	0.19** (2.41)	0.39*** (6.82)	0.09 (0.24)	-0.34*** (-1.94)	-0.22 (3.80)	0.09 (2.27)
LASSO INDTREND difference	0.08 (1.00)	0.04 (0.94)	0.20*** (2.41)	0.37*** (6.26)	0.13* (1.78)	-0.24* (-0.47)	-0.23 (2.49)	-0.07 (-0.03)
Observations	285	271	255	167	285	271	255	167

The table shows the absolute MAFEs and Theil's U statistics in parentheses (both multiplied by 100) of the NPERF Model and the differences of MAFEs as well as differences of Theil's U statistics in parentheses (both multiplied by 100) of the NPERF INDUSTRY, NPERF INDTREND, NPULCF INDUSTRY, NPULCF INDTREND, LASSO INDUSTRY, and LASSO INDTREND Models compared to the NPERF Model. The superscripts ***, **, and * (+++, ++, and +) indicate statistically significant differences in MAFEs compared to the reference model (to the NPI Model) at the 1%, 5%, and 10% levels. Table A6 provides detailed documentation of the prediction models. We provide variable definitions in Table 8 in the Appendix.

Online Appendix F: Coefficients of dummy variables and interaction terms

To account for the missing information in our data (that also arises in real prediction cases, as information might not be disclosed), we divide our measure for ULCF (similar to other accounting items) into two variables. The following Online Appendix discusses how the corresponding coefficient might be interpreted. D^{ULCF} measures the difference between disclosing and non-disclosing firms CONDITIONAL on disclosing firms having $ULCF = 0$. This is because we subdivide the effect of ULCF reporting into two effects considered by two distinct variables:

- The first variable (D^{ULCF}) captures the effect of reporting versus not reporting ULCF (regardless of the reported value). We find that the association of this disclosure effect with future firm performance is not statistically significant (see Table 3).
- The second effect (denoted by $D^{ULCF} \times ULCF$) captures the impact of the reported value of ULCF.

As the reported value must of ULCF be positive (also suggesting a positive mean value of ULCF), the aggregate effect of a firm reporting ULCF compared to a firm not reporting ULCF results from the sum of both a) the disclosure effect (denoted by D^{ULCF}) and the significantly negative impact of the reported value (indicated by $D^{ULCF} \times ULCF$).

D^{ULCF} can be regarded as an endogenous variable. However, this is not a problem for our analysis. First, as already mentioned, this endogeneity concern holds for most financial account variables.³ Second and more relevant, as predictions are conceptually different from explanatory models (Hagerty and Srinivasan 1991; Shumeli 2010; Sarstedt and Danks 2022), they do not require exogenous parameters. Indeed, a prediction does not intend to identify a causal relationship or even the coefficient of a specific parameter. Instead, a prediction intends to identify modeling choices or parameter choices that minimize prediction errors. This is also the intention of our model, and the analysis of the MAFEs is a sufficient statistic to analyze if the models meet our targets or not. From this perspective, even the question of how specific coefficients should be interpreted is not the central issue of the paper.

In the following, we provide evidence that the separation of the ULCF effect in the two variables D^{ULCF} and $D^{ULCF} \times ULCF$ does not induce a relevant bias into our model. Indeed, we

³ Indeed, as firms must be consistent in their reporting behavior (continuity in financial accounts), we expect D^{ULCF} to be less endogenous than $D^{ULCF} \times ULCF$ as the second indicator can be affected by “manipulated” by earnings management in each period in a way to either reduce or increase earnings. For example, if firms expect higher/lower future earnings, they might consider that in their accounting choices in $D^{ULCF} \times ULCF$.

show that the primary results do not change for difference specifications of both variables. First of all, we present our baseline regression in Table A8 for our standard specification but also for the BCN model from Online Appendix C.

Table A8: Baseline model

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Reference model	Baseline		BCN		Baseline		BCN	
Dependent variable	CFBT _{t+1}	CFBT _{t+3}	CFBT _{t+1}	CFBT _{t+3}	EBT _{t+1}	EBT _{t+3}	EBT _{t+1}	EBT _{t+3}
PERF	0.732*** (0.057)	0.570*** (0.071)	0.844*** (0.054)	0.670*** (0.056)	0.832*** (0.066)	0.577*** (0.144)	0.880*** (0.061)	0.718*** (0.078)
NPI	0.013 (0.010)	0.009 (0.020)	0.011 (0.021)	0.000 (0.036)	0.010 (0.010)	-0.008 (0.017)	-0.001 (0.014)	-0.010 (0.021)
NPI × PERF	-0.442*** (0.164)	-0.448* (0.252)	-0.619*** (0.199)	-0.797** (0.360)	-0.378*** (0.124)	-0.659*** (0.182)	-0.427*** (0.095)	-0.729*** (0.190)
D ^{ULCF}	-0.006 (0.004)	0.000 (0.007)	0.001 (0.005)	0.004 (0.007)	0.004 (0.005)	0.004 (0.009)	0.001 (0.005)	-0.001 (0.008)
D ^{ULCF} × ULCF	-0.062** (0.028)	-0.059** (0.027)	-0.073** (0.030)	-0.095*** (0.033)	-0.042** (0.021)	-0.095** (0.045)	-0.050*** (0.017)	-0.126*** (0.036)
DTA and VD variables	YES	YES	YES	YES	YES	YES	YES	YES
BCN controls	NO	NO	YES	YES	NO	NO	YES	YES
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	0.647	0.508	0.653	0.512	0.623	0.359	0.647	0.452
Adjusted R ²	0.635	0.490	0.635	0.486	0.610	0.336	0.629	0.422

The dependent variable is operating cash flow before taxes CFBT at time $t + 1$, CFBT at time $t + 3$, earnings before taxes EBT at time $t + 1$, or EBT at time $t + 3$ (in each case scaled by total assets). Estimates are calculated by OLS. 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 8 in the Appendix provides detailed variable definitions.

Table A9: Exclusively ULCF dummy variable

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Reference model	Baseline		BCN		Baseline		BCN	
Dependent variable	CFBT _{t+1}	CFBT _{t+3}	CFBT _{t+1}	CFBT _{t+3}	EBT _{t+1}	EBT _{t+3}	EBT _{t+1}	EBT _{t+3}
PERF	0.733*** (0.057)	0.571*** (0.070)	0.850*** (0.053)	0.680*** (0.054)	0.830*** (0.066)	0.575*** (0.144)	0.881*** (0.061)	0.723*** (0.078)
NPI	0.016* (0.009)	0.010 (0.020)	0.015 (0.021)	0.000 (0.039)	0.011 (0.010)	-0.006 (0.017)	-0.000 (0.015)	-0.007 (0.023)
NPI × PERF	-0.254** (0.117)	-0.299 (0.242)	-0.308*** (0.116)	-0.480 (0.405)	-0.331*** (0.117)	-0.543*** (0.169)	-0.339*** (0.123)	-0.482** (0.230)
D ^{ULCF}	-0.011** (0.004)	-0.004 (0.007)	-0.005 (0.005)	-0.002 (0.007)	0.001 (0.006)	-0.003 (0.009)	-0.003 (0.005)	-0.009 (0.008)
DTA and VD variables	YES	YES	YES	YES	YES	YES	YES	YES
BCN controls	NO	NO	YES	YES	NO	NO	YES	YES
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	0.643	0.504	0.648	0.505	0.621	0.350	0.645	0.442
Adjusted R ²	0.631	0.487	0.630	0.479	0.608	0.327	0.627	0.412

The dependent variable is operating cash flow before taxes CFBT at time $t + 1$, CFBT at time $t + 3$, earnings before taxes EBT at time $t + 1$, or EBT at time $t + 3$ (in each case scaled by total assets). Estimates are calculated by OLS. 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 8 in the Appendix provides detailed variable definitions.

In Table A9 we show results for an alternative specification with only the dummy variable D^{ULCF} but excluding the interaction term $D^{ULCF} \times ULCF$. Our results show that we typically do also not find a significant difference between firms reporting and not reporting ULCF (captured by D^{ULCF}) if the interaction term $D^{ULCF} \times ULCF$ is not included. The only exception is the Baseline Model with one-year-ahead cashflows, where we find a significantly lower performance of firms not reporting ULCF if we do not include the interaction term $D^{ULCF} \times ULCF$. Thus, we do not find much evidence that reporting (or not reporting) ULCF is indicative of future firm performance.

Table A9 does not mean that the coefficient of the interaction term $D^{ULCF} \times ULCF$ remains unaffected by the exact specification of the dummy variable D^{ULCF} that captures in our baseline specification the difference between firms not disclosing ULCF compared to firms disclosing ULCF of zero. Therefore, we perform an additional test that uses a means-adjusted version of $D^{ULCF} \times ULCF$. In this specification, we define *ULCF Mean* as the difference between its baseline value (unrecognized tax loss carryforwards divided by total assets) and the sample mean for observations reporting ULCF. Hence, the average value of *ULCF Mean* is zero, and firms with abnormally high (abnormally low) ULCF values have a positive (negative) value of *ULCF Mean*. In this specification, D^{ULCF} captures the difference in the future firm performance of firms not reporting ULCF and firms reporting the average value of ULCF for firms disclosing ULCF. We report corresponding results in Table A10.

Table A10: Mean-adjusted ULCF interaction term

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Reference model	Baseline		BCN		Baseline		BCN	
Dependent variable	CFBT _{t+1}	CFBT _{t+3}	CFBT _{t+1}	CFBT _{t+3}	EBT _{t+1}	EBT _{t+3}	EBT _{t+1}	EBT _{t+3}
PERF	0.732*** (0.057)	0.570*** (0.071)	0.844*** (0.054)	0.670*** (0.056)	0.832*** (0.066)	0.577*** (0.144)	0.880*** (0.061)	0.718*** (0.078)
NPI	0.013 (0.010)	0.009 (0.020)	0.011 (0.021)	0.000 (0.036)	-0.378*** (0.124)	-0.659*** (0.182)	-0.427*** (0.095)	-0.729*** (0.190)
NPI × PERF	-0.442*** (0.164)	-0.448* (0.252)	-0.619*** (0.199)	-0.797** (0.360)	0.010 (0.010)	-0.008 (0.017)	-0.001 (0.014)	-0.010 (0.021)
D ^{ULCF}	-0.010** (0.004)	-0.004 (0.007)	-0.005 (0.005)	-0.003 (0.007)	0.001 (0.006)	-0.003 (0.009)	-0.002 (0.005)	-0.010 (0.008)
D ^{ULCF} × ULCF Mean	-0.062** (0.028)	-0.059** (0.027)	-0.073** (0.030)	-0.095*** (0.033)	-0.042** (0.021)	-0.095** (0.045)	-0.050*** (0.017)	-0.126*** (0.036)
DTA and VD variables	YES	YES	YES	YES	YES	YES	YES	YES
BCN controls	NO	NO	YES	YES	NO	NO	YES	YES
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	0.647	0.508	0.653	0.512	0.623	0.359	0.647	0.452
Adjusted R ²	0.635	0.490	0.635	0.486	0.610	0.336	0.629	0.422

The dependent variable is operating cash flow before taxes CFBT at time $t + 1$, CFBT at time $t + 3$, earnings before taxes EBT at time $t + 1$, or EBT at time $t + 3$ (in each case scaled by total assets). Estimates are calculated by OLS. 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 A1 provides detailed variable definitions. ULCF Mean is the difference of the reported ULCF scaled by total assets and its sample mean.

As documented by Table A8 to Table A10, the alternative specification of the interaction term ($D^{ULCF} \times ULCF$, respectively $D^{ULCF} \times ULCF \text{ Mean}$) does not significantly affect its coefficient. Indeed, the coefficients of the means-adjusted interaction term in Table A10 are identical to the coefficients of the unadjusted interaction term in the baseline specification in Table A8. This underlines that that the coefficient of the interaction term captures the effect of the reported value of ULCF and not of the disclosure decision, which is captured by D^{ULCF} . In addition, the results of Table A8 with regard to D^{ULCF} are widely the same as for the tables A8 and A9. Again, we do not find much evidence that the disclosure of ULCF as such provides a useful indicator of future performance. The same holds for a median-adjusted version of the interaction term reported in Table A11. Here, we subtract the median of ULCF (for observations reporting this information) from the baseline value. Thus, D^{ULCF} captures the difference between firms not reporting ULCF and firms reporting the median value of ULCF. Again, this does not have a relevant influence on our results.

Table A11: Median-adjusted ULCF interaction term

Model	1	2	3	4	5	6	7	8
Performance measure	Cash flow				Earnings before taxes			
Reference model	Baseline		BCN		Baseline		BCN	
Dependent variable	CFBT _{t+1}	CFBT _{t+3}	CFBT _{t+1}	CFBT _{t+3}	EBT _{t+1}	EBT _{t+3}	EBT _{t+1}	EBT _{t+3}
PERF	0.732*** (0.057)	0.570*** (0.071)	0.844*** (0.054)	0.670*** (0.056)	0.832*** (0.066)	0.577*** (0.144)	0.880*** (0.061)	0.718*** (0.078)
NPI	0.013 (0.010)	0.009 (0.020)	0.011 (0.021)	0.000 (0.036)	-0.378*** (0.124)	-0.659*** (0.182)	-0.427*** (0.095)	-0.729*** (0.190)
NPI × PERF	-0.442*** (0.164)	-0.448* (0.252)	-0.619*** (0.199)	-0.797** (0.360)	0.010 (0.010)	-0.008 (0.017)	-0.001 (0.014)	-0.010 (0.021)
D ^{ULCF}	-0.007 (0.004)	-0.001 (0.007)	-0.001 (0.005)	0.003 (0.007)	0.004 (0.005)	0.003 (0.009)	0.000 (0.005)	-0.003 (0.008)
D ^{ULCF} × ULCF Median	-0.062** (0.028)	-0.059** (0.027)	-0.073** (0.030)	-0.095*** (0.033)	-0.042** (0.021)	-0.095** (0.045)	-0.050*** (0.017)	-0.126*** (0.036)
DTA and VD variables	YES	YES	YES	YES	YES	YES	YES	YES
BCN controls	NO	NO	YES	YES	NO	NO	YES	YES
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	0.647	0.508	0.653	0.512	0.623	0.359	0.647	0.452
Adjusted R ²	0.635	0.490	0.635	0.486	0.610	0.336	0.629	0.422

The dependent variable is operating cash flow before taxes CFBT at time $t + 1$, CFBT at time $t + 3$, earnings before taxes EBT at time $t + 1$, or EBT at time $t + 3$ (in each case scaled by total assets). Estimates are calculated by OLS. 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. The Appendix provides detailed variable definitions. ULCF Median is the difference of the reported ULCF scaled by total assets and its median value.

Our additional tests suggest the following. First, we do not find evidence for a significant difference in the future firm performance of firms disclosing and not disclosing ULCF. Second, we also do not find that the dummy variable D^{ULCF} (capturing the disclosure effect) has any relevant impact on the coefficient of the interaction term. Thus, we may conclude that the interaction term captures the effect of the disclosed value of ULCF for future firm performance while the dummy variable D^{ULCF} captures the disclosure effect as such.

Impressum:

Arbeitskreis Quantitative Steuerlehre, arqus, e.V.

Vorstand: Prof. Dr. Ralf Maiterth (Vorsitzender),
Prof. Dr. Kay Blaufus, Prof. Dr. Dr. Andreas Löffler
Sitz des Vereins: Berlin

Herausgeber: Kay Blaufus, Jochen Hundsdoerfer,
Martin Jacob, Dirk Kieseewetter, Rolf J. König,
Lutz Kruschwitz, Andreas Löffler, Ralf Maiterth,
Heiko Müller, Jens Müller, Rainer Niemann,
Deborah Schanz, Sebastian Schanz, Caren Sureth-
Sloane, Corinna Treisch

Kontaktadresse:

Prof. Dr. Dr. h.c. Dr. h.c. Caren Sureth-Sloane,
Universität Paderborn, Fakultät für
Wirtschaftswissenschaften,
Warburger Str. 100, 33098 Paderborn,
www.arqus.info, Email: info@arqus.info

ISSN 1861-8944