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Working Paper, University of Cologne.

Brunke, L., Vater, T., 2022,
The Relation Between Earnings Management and Model-Based Earnings Forecast Accuracy,
Working Paper, University of Cologne.

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Chapter 1

Introduction

Earnings, or profitability, are a central measure of a firm's performance.[1] Obtaining accurate earnings forecasts is of special interest for practitioners and academics alike, as they are an important input for firm valuation, asset allocation, or cost of capital calculation (Tian et al. (2021) and Azevedo et al. (2021)). In recent years, research on cross-sectional model forecasts as an alternative to analysts' earnings forecasts emerged. Studies provide evidence that model-based forecasts beat analysts' forecasts in terms of coverage, forecast bias, and earnings response coefficient, and further result in more reliable expected return proxies (e.g., Hou et al. (2012) or Hess et al. (2019)). Konstantinidi and Pope (2016) and Chang et al. (2021) argue that the risk associated with future earnings is of importance, too. It affects firms' investment and financing policies as well as their legal contracts (Chang et al. (2021)). They suggest the higher moments of the future earnings distribution, i.e., dispersion, skewness, and kurtosis, as measures of risk in future earnings, and show that these measures are related to common risk metrics such as credit risk ratings or corporate bond spreads. Intuitively, risk in future earnings should also be related to a firm's bankruptcy risk. A firm facing higher uncertainty regarding their future earnings has potentially a higher probability of failure. Correia et al. (2018) provide initial evidence on this by testing whether the higher moments of future earnings improve bankruptcy predictions. They find that particularly dispersion is positively associated with future bankruptcies of bond issuers.

In general, incorporating forward-looking measures into bankruptcy prediction models seems useful as bankruptcy prediction is per se a future-oriented process. A model that predicts a firm to become bankrupt in a future period should be more reliable if it includes expectations about firm characteristics in this future period. However, research incorporating forward-looking measures into bankruptcy prediction is very limited (e.g., Correia et al. (2018) or Hess

[1] Throughout this thesis, the terms "earnings" and "profitability" are used interchangeably, as earnings either refer to earnings per share or earnings scaled by total assets.

and Hüttemann (2019)). Therefore, Chapter 2 and Chapter 3 of this thesis further examine the relation between such measures, i.e., earnings forecasts, and bankruptcy risk.

When making use of earnings forecasts, it is crucial that they are accurate. As reported earnings are a key explanatory variable in most earnings forecast models (e.g., Hou et al. (2012) or Li and Mohanram (2014)), their reliability should have a critical impact on the predictive ability of these models. One factor that potentially affects the reliability of reported earnings is the extent of a firm's earnings management (EM). EM is commonly defined as the use of managerial discretion in order to deceive stakeholders about a firm's financial position or to affect contractual obligations that are based on reported financial numbers (e.g., Healy and Wahlen (1999) or Dechow and Skinner (2000)). However, the relation between the extent of a firm's EM and the ability to forecasts its respective earnings has not been examined by prior research yet. Hence, Chapter 4 of this thesis aims to analyze this relation, and further use it to improve the predictive ability of earnings forecast models.

The first essay (Chapter 2) is based on the working paper "Analyzing Expected Accounting Losses in the Context of Bankruptcy Prediction" co-authored by Simon Wolf.

As noted above, we examine the relation between earnings forecasts and bankruptcy risk further. In detail, we analyze the role of expected accounting losses in bankruptcy prediction. We focus on losses, as losses should arguably contain more information about a firm's bankruptcy risk than profits. Our analysis is based on the following hypotheses. First, we hypothesize that an expected loss signal reveals information about a firm's bankruptcy risk. To test this, we add an expected loss dummy to the bankruptcy prediction models by Shumway (2001), Altman (1983), and Ohlson (1980). Second, we hypothesize that the expected profitability distribution reveals further insights into a firm's bankruptcy risk and increases the ability of expected accounting losses to predict future bankruptcies. In contrast to previous literature, we do not estimate the higher moments of future profitability (e.g., Konstantinidi and Pope (2016), Correia et al. (2018), and Chang et al. (2021)). Instead, we use the expected profitability distribution to replace the expected loss dummy with two probability measures: (i) the probability over a one-year horizon that a firm will realize losses and (ii) the probability that these losses will exceed a firm's current cash balance. The second probability measure serves as a proxy for illiquidity.

We find that the empirical results support our hypotheses. While adding the expected loss dummy already increases the predictive ability of the bankruptcy prediction models, adding the probability measures improves performance even further. For instance, for the model by Shumway (2001), using the expected probability to realize losses instead of the expected loss dummy increases the "10th performance decile" criterion introduced by Shumway (2001) by 3.08% instead of 1.38% compared to the initial model. Results are even stronger when changing the probability's threshold from losses in general to losses that exceed current cash balances. The probability of becoming illiquid shows the overall strongest predictive performance increase of 5.80% in the 10th performance decile throughout our analyses. This is unsurprising, as the inability to fulfil financial obligations is intuitively the economic rationale to file for bankruptcy. In total, we find a strong link between our expected loss measures and future bankruptcy filings.

In addition, previous studies provide evidence that losses occur more frequently for smaller firms (e.g., Klein and Marquardt (2006)). Therefore, it becomes more challenging to detect the relevant loss that is causing bankruptcy out of all reported losses. Thus, the ability of our expected loss measures to predict future bankruptcies potentially depends on firm size. To account for this, we conduct a size analysis by interacting our expected loss measures with size classes. We find that the parameter estimates of our measures increase in firm size, indicating that the relevance of expected accounting losses grows in firm size when assessing a firm's bankruptcy risk. Further, ex ante controlling for size in the relation between expected losses and bankruptcy risk significantly improves out-of-sample forecast accuracy. For example, the interacted model using the expected loss dummy (loss probability, illiquidity probability) shows a 10th performance decile value of 71.85% (74.45%, 74.72%). Overall, these findings indicate a size effect in the relation between expected losses and bankruptcy risk.

Our study has implications for everyone facing counterparty risk, especially banks and investors. We provide evidence that expected accounting losses capture bankruptcy risk and thus, are a strong predictor for future bankruptcy filings. Particularly information about the expected profitability distribution substantially improves bankruptcy prediction models. By being able to assess the bankruptcy risk of a counterparty more accurately, market participants can take actions to avoid risk or install mechanism to mitigate the impact of potential risk factors. Also, standard setters for regulatory frameworks of banks and insurance companies should consider the insights expected accounting losses reveal about a firm's liquidity when formulating capital requirements. Additionally, the idea to relate expected profitability distributions to different economic threshold is neither limited to bankruptcy prediction nor to the selected thresholds. Therefore, practitioners and researchers in related disciplines could easily adopt this approach for their specific research. Lastly, while our empirical results are based on a sample of US public firms, our measures rely solely on accounting numbers and do not depend on market data. Therefore, they can be added to bankruptcy prediction models intended for non-listed firms, too. This is crucial as previous research on increasing predictive performance mostly refers to market variables as useful predictors (e.g., Beaver et al. (2005), Campbell et al. (2008), Beaver et al. (2012), among others). However, models that include such variables are not applicable to non-listed firms and therefore, to an enormous share of the cross-section of firms. For instance, in the 27 member states of the European Union (EU) in 2020, small and medium enterprises (SMEs) accounted for more than 99% of all firms, contributed to 53% of total value added and generated 65% of employment (European Commission (2021)).[2] The economic significance of non-listed firms further highlights the usefulness of our measures. However, our results need to be verified using an actual sample of non-listed firms.

The second essay (Chapter 3) based on the working paper "Using the Expected Profitability Distribution to Predict SME Bankruptcy" tackles this task.

Using an approach similar to Chapter 2, I analyze if measures based on the expected profitability distribution also improve SME bankruptcy prediction accuracy. In detail, using a sample of German SMEs, I extend the models by Altman and Sabato (2007), Altman (1983), and Ohlson (1980) by three measures based on the expected profitability distribution, particularly the area covering losses. First, I measure the probability that a firm will realize losses in general. Firms that are expectedly unprofitable should differ from expectedly profitable firms in terms of bankruptcy risk and thus, the probability to realize losses should improve bankruptcy prediction accuracy. Second, I estimate the probability that losses will consume current cash balances, serving as a proxy for illiquidity. Third, I compute the probability that losses exceed book equity, signaling that a firm becomes overindebted. Both illiquidity and overindebtedness are included as reasons for bankruptcy filing in the German insolvency statute. Hence, I expect a positive link between both measures and bankruptcy filing for German SMEs.

I find that, in line with expectations, incorporating the expected loss probability or the expected illiquidity probability significantly improves the accuracy of SME bankruptcy prediction models. For instance, for the model by Altman and Sabato (2007), including the expected illiquidity probability significantly increases the 10th performance decile from 36.80% to 40.21% compared to the initial model. Including the expected loss probability shows an even stronger improvement with a value of 42.18%. This is in line with the findings of the previous chapter and provides evidence for a strong relation between both measures and SME bankruptcy risk. In contrast, the expected overindebtedness probability shows weaker results. While the 10th performance decile still increases to 37.18%, the difference to the initial model

[2] Throughout this thesis, the terms "SME", "non-listed firm", and "private firm" are used interchangeably.

is statistically insignificant, indicating a weaker link to SME bankruptcy risk. A potential explanation is that firms do not immediately file for bankruptcy in case of overindebtedness as the insolvency statute leaves firms some leeway, i.e., if a recovery is expected, bankruptcy filing is not necessary. Overall, findings indicate that the expected loss probability performs best. Further, using a hypothesized competitive SME loan market, I show that banks would economically benefit from incorporating this measure into bankruptcy prediction models.

Moreover, analogous to Chapter 2, I perform a size analysis to test for a size effect in the relation between the probability measures and SME bankruptcy risk, by additionally interacting the three measures with SME size classes. In contrast to Chapter 2, out-of-sample prediction results do not provide evidence for a size effect as the performance is not significantly increased. However, this is in line with the results of Gupta et al. (2015) who show that considering small and medium firms separately when predicting SME bankruptcy is not necessary.

My findings primarily contribute to the literature by showing that incorporating firm-specific forward-looking measures into SME failure prediction models significantly improves forecast accuracy. To my knowledge, no other SME study incorporates such measures. I provide evidence that measures based on the expected profitability distribution, particularly the area covering losses, are a strong predictor for SME bankruptcy filing and improve forecast accuracy. This is crucial, because as Altman and Sabato (2007) show, more accurate predictions lead to lower capital requirements and lower credit costs. Therefore, I suggest that banking institutions incorporate the probability measures, particularly the probability to realize losses, when assessing SME bankruptcy risk in order to sustain SME financing.

A requirement for the valuable findings of Chapter 2 and Chapter 3 is that the utilized earnings forecasts are accurate. As noted above, a factor that potentially affects the predictive ability of earnings forecasts models is EM. Therefore, the third essay (Chapter 4) examines the relation between the extent of a firm's EM and the ability to forecasts its respective earnings. It is based on the working paper "The Relation Between Earnings Management and Model-Based Earnings Forecast Accuracy" co-authored by Luca Brunke.

The analysis is structured as follows. First, we examine the general relation between the extent of a firm's EM and the accuracy of model-based earnings forecasts. That is, we run annual cross-sectional regressions of forecast accuracy on the level of EM. We generate earnings forecasts for up to three years ahead for the residual income (RI) model by Li and Mohanram (2014) and use the price-scaled absolute forecast error (PAFE) to evaluate forecast accuracy. Further, in line with the bigger part of research on EM, we use absolute discretionary accruals as a measure for the extent of a firm's EM (e.g., Frankel et al. (2002), Klein (2002), Bergstresser and Philippon (2006), among others), and we estimate discretionary accruals using the accruals model of Dechow et al. (1995). Second, we aim to use the relation between the extent of a firm's EM and forecast accuracy to improve the predictive ability of earnings forecast models. We rank firms annually into quintiles based on the extent of a firm's EM and create five dummy variables that indicate a firm's respective quintile. We then interact the earnings forecast model with the EM quintile dummy variables, and we again generate earnings forecasts for up to three years ahead. Third, we test whether implied cost of capital (ICC) estimates based on the interacted model are more reliable expected return proxies in comparison to the initial model. For the cross-section of firms, we annually (i) regress realized future returns on the ICCs, and (ii) rank firms into deciles based on the ICCs and implement a long-short-strategy, i.e., we compute the spread between the highest and lowest decile.

In line with our expectations, we find a significantly positive relation between forecast errors and the extent of a firm's EM for all forecast horizons. That is, we provide empirical evidence that a higher degree of EM corresponds to a worse performance in terms of model-based earnings forecast accuracy. In detail, for one-, two-, and three-year ahead earnings forecasts, we find significantly positive average parameter estimates of 0.0204, 0.0189, and 0.0182, respectively. Subsequently, when interacting the earnings forecast model with the EM quintile dummy variables, we find that PAFEs significantly decrease compared to the initial model. For instance, for one-year ahead forecasts, the median (mean) PAFE of the initial model is 3.72% (13.30%), whereas the PAFE of the interacted model is 3.18% (11.76%). Furthermore, we show that ICCs based on the interacted model exhibit higher correlations to realized future returns and that the long-short strategy yields higher returns for holding periods of up to three years. For example, for one-year ahead forecasts, the initial model shows an average parameter estimate of 0.1904 and a buy-and-hold return of 10.63%, while the interacted model shows values of 0.2176 and 12.32%, respectively.

Our findings contribute to the literature by providing first empirical evidence on the significantly negative relation between the extent of a firm's EM and the ability to forecast its respective earnings figure. The negative relation we find indicates that managers' actions lower earnings predictability. This is potentially related to an impaired quality of reported earnings as a consequence of opportunistic managerial discretion. By showing this, we add to the debate on managers' incentives for EM. We support the findings of previous studies indicating that EM is performed for opportunistic reasons, i.e., with the intention of misleading stakeholders to obtain some personal gain (e.g., Perry and Williams (1994), Teoh et al. (2002), or Bergstresser and Philippon (2006)), instead of aiming to increase the information content of reported earnings (Beneish (2001)). Moreover, the results of the interacted model highlight that information about firms' EM should be incorporated into earnings forecast models as it improves the predictive ability and results in more reliable ICCs that yield higher investment strategy returns. This supports previous research (e.g., Hou et al. (2012) or Hess et al. (2019)), and further establishes model-based earnings forecasts as a viable alternative to analysts' earnings forecasts.

In summary, Chapter 2 of this thesis contributes to the literature by providing evidence that expected accounting losses capture bankruptcy risk and thus, are a strong predictor for future bankruptcy filings of listed firms. Particularly information about the expected profitability distribution significantly improves the accuracy of bankruptcy prediction models. Building on these findings, Chapter 3 shows that these measures are also a strong predictor for SME bankruptcy filings and that they improve forecast accuracy. This result is crucial, as banking institutions that incorporate our measures could lower their capital requirements and consequently decrease SME credit costs. Finally, Chapter 4 provides first evidence for a significantly negative relation between the extent of a firm's EM and model-based earnings forecast accuracy. Further, Chapter 4 presents how information about firms' EM can be used to improve the predictive ability of earnings forecast models.

Chapter 2

Analyzing Expected Accounting Losses in the Context of Bankruptcy Prediction

2.1 Introduction

Bankruptcy prediction has been studied intensively in finance and accounting for decades.[3] The ability to forecast bankruptcy probabilities is relevant whenever market participants need to assess counterparty risk. For instance, it enables creditors to allocate loans more profitably, investors to assign capital resources more efficiently, or regulators to formulate capital requirements.

Following the Financial Accounting Standard Board (FASB), a firm fulfills the "going concern" condition if there are, in aggregate, no "… conditions or events that raise substantial doubt about the entity's ability to continue …" (FASB (2014), p. 1). According to FASB, stakeholders expect firms to have higher bankruptcy probabilities in case substantial doubt exists. Moreover, FASB lists adverse financial trends like "recurring operating losses" (FASB (2014), p. 13) as an example for events that raise such substantial doubt. Hence, the risk of being unprofitable is directly linked to a firm's bankruptcy risk. Literature already provides empirical evidence for this. For example, Ohlson (1980) shows that firms that realize negative net income in two consecutive years show significantly higher bankruptcy probabilities than comparable firms with less persistent losses. In addition, Beaver et al. (2012) find similar results when current loss information is incorporated into a bankruptcy prediction model. Both studies are evidence for the predictive power of accounting losses as a simple but strong signal for assessing a firm's bankruptcy risk, confirming the position of FASB.

[3] See for example Beaver et al. (2012) for an overview of bankruptcy prediction literature.

In terms of accounting losses, previous literature mainly examines past profitability.[4] However, a recent body of research tackles the relation of risk measures and expected profitability (e.g., Konstantinidi and Pope (2016), Correia et al. (2018), or Chang et al. (2021)). Modelling forward-looking measures has at least two advantages for bankruptcy prediction. First, “predicting” is a future-oriented process that aims to make statements about a firm’s future condition. A model that predicts a firm to become bankrupt in a future period should intuitively be more reliable if it includes expectations about firm characteristics in this future period. Second, estimating expectations allows to model firm-specific distributions. This is important as information embedded in a single observation (e.g., past profitability) and in a distribution substantially differs. For example, two firms with equal realized profitability could have unequal risk characteristics, and therefore, ex ante probabilities to realize this profitability could be fundamentally different. When forming expectations about future profitability, this can be accounted for and the model can draw on this distributional information. Recent studies provide empirical evidence for this. For example, Konstantinidi and Pope (2016) and Chang et al. (2021) find a strong relation between expected profitability distributions and common risk measures like equity ratings and bond ratings. Moreover, Correia et al. (2018) directly link expected distributions of future profitability to bankruptcies of bond issuers.

Building on that, we explore the role of expected profitability distributions in bankruptcy prediction further. In line with FASB, we focus on accounting losses, as the part of the distribution showing unprofitability should arguably be of higher interest when estimating a firm’s bankruptcy risk.[5] In short, our paper shows that extending bankruptcy prediction models by information about expected accounting losses, specifically information embedded in loss distributions, significantly improves forecast accuracy.[6] We use the Shumway (2001)-model as benchmark throughout the paper as previous literature points out that this model exhibits high predictive accuracy (e.g., Shumway (2001), Chava and Jarrow (2004), and Bauer and Agarwal (2014)). By improving an already well-performing prediction model, we highlight the predictive power of our measures. However, inferences are unchanged when alternative models are tested. In detail, we also show results for the Ohlson (1980)-model and the Altman (1983)-

[4] While some models use market data to implicitly incorporate forward-looking characteristics (e.g., Shumway (2001)), the majority of models does not.

[5] Throughout this paper, the term “unprofitable” refers to realizing “accounting losses”. Further, we will use the terms “accounting losses” and “losses” interchangeably.

[6] We define the area of the profitability distribution that relates to losses as “loss distribution” throughout this paper.

model (see Table A2.2).[7] In contrast to Shumway (2001), these models do not rely on market variables and thus, are applicable to private firms as well.

To show how expected loss information improves forecast accuracy, we follow a stepwise approach. In a first step, we analyze the predictive power of a simple binary loss variable. That is, we add a loss dummy to the Shumway (2001)-model. However, contrary to Ohlson (1980) and Beaver et al. (2012), we use a forward-looking signal, i.e., an expected loss dummy based on median profitability forecasts.[8] In a second step, we expand the idea of expected losses as a predictor of future bankruptcies by using distributional information. Previous literature uses the entire expected profitability distribution to compute the distribution's higher moments (e.g., Konstantinidi and Pope (2016), Correia et al. (2018), and Chang et al. (2021)). We deviate from this approach by using a concept similar to value at risk (VaR) that allows us to solely focus on the part of the distribution covering losses. While a VaR is typically defined as a value not exceeded given a certain probability, we rearrange the concept. That is, we compute firm-specific expected probabilities to exceed certain accounting losses in the future. In detail, following Chang et al. (2021), we estimate out-of-sample conditional distributions of future profitability for each firm-year. We then use these firm-specific distributions to replace the binary loss signal by two probability measures: (i) the probability over a one-year horizon that a firm will realize losses and (ii) the probability that these losses will exceed a firm's current cash balance (i.e., illiquidity proxy).[9] In line with Konstantinidi and Pope (2016), we expect our measures to capture risk in future profitability that translates into firm-specific bankruptcy risk. In a last step, we test for non-linearity in the relation between accounting losses and bankruptcy risk. Previous studies provide evidence that losses occur more frequently for smaller firms (e.g., Klein and Marquardt (2006)). Therefore, the ability of our expected loss measures to predict future bankruptcies potentially depends on firm size. To account for this, we conduct a size analysis by interacting our measures with size classes.

We find that adding our expected accounting loss measures to the Shumway (2001)-model significantly improves performance. While an expected loss dummy already increases forecast accuracy, the probability measures improve performance further. For example, using the expected loss probability instead of a simple dummy increases the "10th performance decile"

[7] Further, untabulated tests show comparable results for the bankruptcy prediction models by Altman (1968) and Zmijewski (1984).

[8] Previous literature (e.g., Evans et al. (2017) or Tian et al. (2021)) provides evidence that earnings forecasts based on quantile regressions, specifically median regressions, outperform forecasts generated by Ordinary-Least-Squares regressions in terms of predictive accuracy.

[9] The probability of losses exceeding current cash balances is only a proxy for becoming illiquid. However, we refer to this as "illiquidity" throughout this paper. Section 2.3.2 further outlines the rationale to use this proxy and briefly discusses potential alternatives.

criterion introduced by Shumway (2001) by 3.08% instead of 1.38%. Results are even stronger when changing the probability's threshold from losses in general to losses that exceed current cash balances. That is, the probability of becoming illiquid shows the overall strongest predictive performance increase (5.80%) in the 10^{th} performance decile throughout our analyses. This is as expected, as the inability to fulfil financial obligations or claims is intuitively the economic rationale to file for bankruptcy. Hence, we find a strong link between expected illiquidity and future bankruptcy filings. Inferences are unchanged when looking at the "Area Under the Receiver Operating Characteristics Curve" (AUC) criterion. Furthermore, a time-series analysis reveals that the superior performance of our models holds for the bulk of years in our sample period. For the size analysis, we find that the relevance of the loss signal is reduced for firms with more frequent losses but increased for firms with infrequent losses. That is, the signal is less important for smaller firms, but more important for larger firms. Consequently, when ex ante controlling for different size classes, i.e., fitting different parameter estimates for different firm sizes, forecast accuracy increases even more. This is evidence for a size effect in the relation between expected losses and bankruptcy risk.

Our paper contributes to the literature as follows. First, we provide evidence that expected accounting losses capture bankruptcy risk and thus, are a strong predictor for future bankruptcy filings. Especially when using information about the expected profitability distribution, we improve the Shumway (2001)-model substantially. Second, we show that losses that might deplete a firm's current cash balance are more relevant than losses in general. Therefore, besides the fact that a firm will realize losses with a certain probability, the severity of these losses is relevant, too. In result, a high probability of expected losses exceeding current cash balances is a strong sign that the firm could suffer from illiquidity and become bankrupt. Third, we add to previous literature on the relation between accounting losses and firm size. We find that for firms with more frequently occurring losses (i.e., smaller firms), expected losses are a weaker signal for future bankruptcies. Fourth, our approach is not limited to extending the Shumway (2001)-model. Instead, our measures can theoretically be added to any bankruptcy prediction model. Further, because our measures do not depend on market data, they can also be added to bankruptcy prediction models intended for non-listed firms. Fifth, the idea to relate the conditional distribution of future profitability to different economic threshold is neither limited to bankruptcy prediction nor to the selected thresholds. Therefore, practitioners and researchers in related disciplines could easily adopt this approach and evaluate the loss probability against different threshold that are reasonable for their specific research. Ultimately, we provide guidance for regulators, rating agencies, banks, practitioners, and academics. They should adopt our measures to capture the underlying risk in a firm's profitability when assessing creditworthiness, bankruptcy risk, and solvency.

The remainder of this paper is structured as follows. Section 2.2 provides a brief overview of related literature. Section 2.3 outlines our research hypotheses, the methodology, and the underlying data for our empirical analysis. Section 2.4 presents the empirical results. Section 2.5 concludes and gives an outlook for future research.

2.2 Related Literature

The objective of our paper is to analyze the role of expected losses, particularly loss distributions, for bankruptcy prediction. Therefore, we use this section to provide a brief overview of literature on bankruptcy prediction and on model-based earnings forecasts.[10] Additionally, we review recent studies that explicitly link forecasted profitability to accounting-based risk measures, a concept that we adopt for bankruptcy prediction.

Altman (1968) was first to introduce a multivariate bankruptcy prediction model based on financial ratios. Using a matched sample, he implements multiple discriminant analysis (MDA) to detect systematic differences in characteristics of bankrupt and non-bankrupt firms. In result, Altman (1968) combines leverage, profitability, liquidity, solvency, and activity to define the Z-Score bankruptcy prediction model.[11]

In the following decade, MDA is used extensively for bankruptcy prediction. Yet, critics outline that two restrictive assumptions of MDA, namely the multinormality and common dispersion matrices assumptions, are frequently violated (e.g., Joy and Tollefson (1975) or Eisenbeis (1977)). Besides these problematic assumptions, MDA has practical problems, too. For example, it is not possible to measure the relative importance of one explanatory variable based on MDA's standardized coefficients (e.g., Altman et al. (1977), Joy and Tollefson (1975), or Eisenbeis (1977)). In response to these drawbacks, Ohlson (1980) suggests a logit model to forecast bankruptcies. Even when forecast accuracy does not substantially increase compared to MDA, logit models show statistical advantages compared to MDA and are better suited for predicting a binary outcome.[12] After Ohlson (1980), bankruptcy prediction using logit models gains popularity and applicants continue to set up static logit models to forecast bankruptcies.

[10] We use earnings scaled by total assets (i.e., profitability) for our analysis. The terms "earnings" and "profitability" are used interchangeably throughout this paper.

[11] In addition, Altman (1983) modifies his Z-Score model for private firms (Z'-Score model) by calculating financial leverage based on book values instead of market values. Moreover, Altman (1983) argues that industry effects potentially affect asset turnover and thus, excludes asset turnover from the model (Z''-Score model).

[12] For example, the approach needs no assumptions about prior bankruptcy probabilities or the distributions of explanatory variables (Ohlson (1980)).

However, Shumway (2001) points out potential inconsistencies when applying static logit models. Those models use exactly one observation per firm throughout the entire sample period to estimate parameters. He argues that this ignores the dynamics in firm characteristics and bankruptcy probabilities prior to the infrequent event of filing for bankruptcy. Hence, as each firm contributes to the fit with exactly one static set of explanatory variables, there is a large loss in information. In consequence, the research design induces a selection bias. To solve this, Shumway (2001) suggests a discrete hazard model, i.e., a multi-period logit model that accounts for the dynamics in firm characteristics to fit the model. Such models use all available firm-year observations and allow bankruptcy probabilities to change in accordance to changing firm characteristics (i.e., a dynamic set of predictors). Until today, discrete hazard models are commonly used to predict bankruptcy probabilities.

More recently, Beaver et al. (2012) analyze how characteristics of financial statement quality influence the information accounting measures provide for assessing a firm's bankruptcy risk. Using a fully interacted model to account for losses, they find that the occurrence of a loss significantly increases a firm's bankruptcy probability. Therefore, the authors provide evidence for the relevance of accounting losses when assessing a firm's bankruptcy risk. Moreover, the authors show that accounting measures and market variables are complemental, such that bankruptcy prediction models should include measures of both.

In terms of model-based earnings forecasts, recent studies focus on cross-sectional models because of the extensive growth in archival data over the past decades. Hou et al. (2012) are the first to provide empirical evidence for the applicability of cross-sectional earnings forecast models for a broad set of firms. As the authors outline, these models minimize data requirements and hence, in contrast to time-series models, do not induce survivorship bias. To generate firm-specific forecasts, only the most recent firm fundamentals are required. Hou et al. (2012) test how these model-based forecasts perform compared to analysts' forecasts. They find that model-based forecasts show larger earnings response coefficients (e.g., Ball and Brown (1968), Brown et al. (1987), among others) and lead to more accurate expected return proxies.

In a subsequent study, Li and Mohanram (2014) argue that the approach of Hou et al. (2012) can be improved by: (i) allowing the model to differentiate between the earnings persistence of profit and loss firms, (ii) adjusting the earnings metric for special items, and (iii) estimating standardized earnings (i.e., earnings per share). In their empirical test, the authors find that their adjusted model outperforms the Hou et al. (2012)-model.

While Hou et al. (2012) and Li and Mohanram (2014) provide evidence for the validity of cross-sectional earnings forecasts in general, Konstantinidi and Pope (2016) analyze how these forecasts relate to a firm's risk. The authors apply a cross-sectional model to estimate certain percentiles of firm-specific future earnings distributions using quantile regressions. Next, they convert these percentile estimates into measures of expected level, dispersion, asymmetry, and tail risk (i.e., higher moments). They find that these measures correlate with various risk proxies, such as credit risk ratings and corporate bond spreads. These findings raise the question whether distributional properties of future earnings might also help to estimate firm-specific bankruptcy risk.

Taking on this question, Correia et al. (2018) test whether the higher moments of future earnings improve out-of-sample bankruptcy predictions. They find that particularly the dispersion measure is positively associated with future bankruptcies of bond issuers, and that this finding is robust to controlling for further risk measures. With this, Correia et al. (2018) are the first to shed light on the value of future earnings' distributional properties for bankruptcy prediction.

Chang et al. (2021) pick up the approach of Konstantinidi and Pope (2016) to estimate the distribution of future earnings and derive the higher moments using quantile regressions. However, the authors raise concerns about the consistency of the higher moment estimates by Konstantinidi and Pope (2016). They argue that (i) using ad hoc formulas based on seven percentiles instead of adequate descriptions of the higher moments and (ii) the fact that estimated quantiles might cross, can lead to inconsistencies. To resolve this, Chang et al. (2021) approximate the entire distribution by estimating 150 percentiles and adjust this distribution for quantile crossing using a rearrangement method introduced by Chernozhukov et al. (2010). Afterwards, the authors use standard formulas to calculate the higher moments. They find that these consistent earnings-based risk measures are reflected in equity prices and credit spreads, providing further empirical evidence for the relevance of accounting-based risk measures.

Given this recent development in literature, extending bankruptcy prediction models with information about expected loss distributions is a straightforward task to tackle.

2.3 Hypotheses, Methodology, and Data

This section outlines our research hypotheses and the methodology we use to test them. Further, we provide a detailed description of the data sample used for our empirical analysis.

2.3.1 Research Hypotheses

First, we hypothesize that expected accounting losses have predictive power for future bankruptcies in general. Firms that are expectedly unprofitable differ from expectedly profitable firms in terms of bankruptcy risk. To test this, we follow Ohlson (1980) and Beaver et al. (2012) and use a dummy variable to capture the information expected losses provide. That is, we use a simple binary variable that indicates whether a firm is expected to be profitable or not in the upcoming fiscal period.[13] Therefore, we hypothesize that:

H1: *Expected accounting losses increase a firm's bankruptcy risk. Including an expected loss dummy in bankruptcy prediction models improves forecast accuracy.*

Second, we hypothesize that information about the distribution of expected accounting losses better predicts future bankruptcy filings than a dummy signal. To test this, we use a VaR measure that captures a firm's expected probability to realize accounting losses in the upcoming fiscal period. Thereby, we deviate from previous literature that uses standardized distributional moments based on the entire distribution to capture risk (e.g., Chang et al. (2021)). We argue that the area of the distribution dealing with accounting losses should be of higher interest for bankruptcy prediction.[14] This idea is in line with FASB's position that losses are relevant when assessing bankruptcy risk (FASB (2014)). Therefore, we hypothesize that:

H2: *The expected profitability distribution provides additional insights into a firm's bankruptcy risk. Replacing the expected loss dummy with the probability to realize future losses further improves forecast accuracy.*

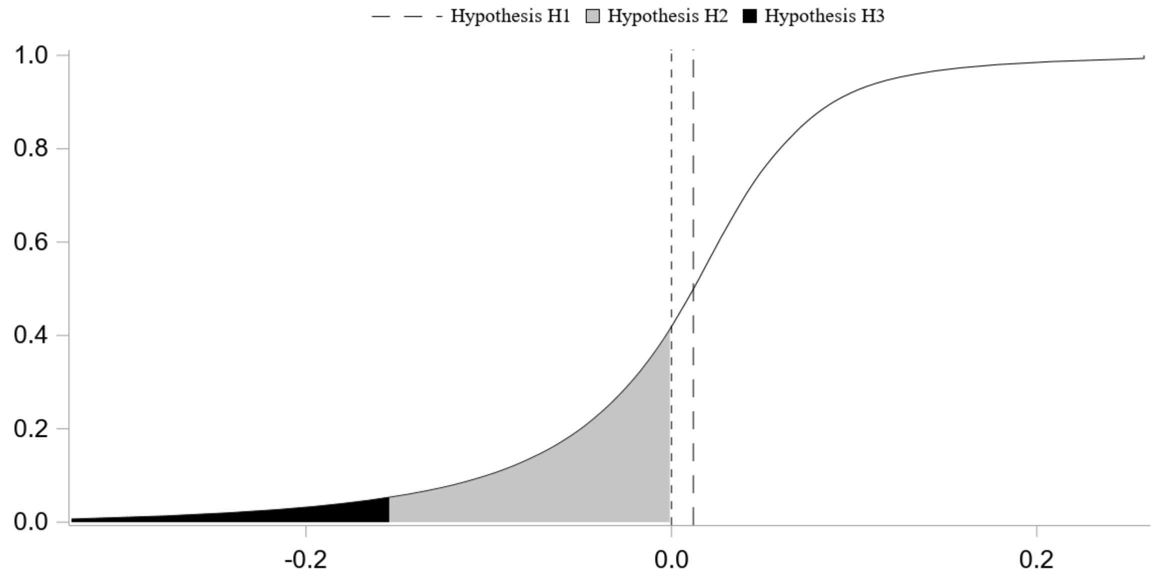
Third, we hypothesize that the area of the distribution dealing with severe losses better predicts future bankruptcy filings than the area of the distribution covering losses in general. In more detail, a firm's profitability distribution can intuitively be tested against economic thresholds besides zero. In the context of bankruptcy prediction, alternative thresholds originate from the regulatory bankruptcy filing requirements. Specifically, a firm's inability to pay its obligations when due (i.e., illiquidity) requires filing for bankruptcy. This illiquidity could be affected by accounting losses. That is, a firm could realize severe losses that potentially translate into a depletion of the current cash balance and leave the firm illiquid. We hypothesize that:

[13] For robustness, we also test a current loss dummy following Beaver et al. (2012). Untabulated tests reveal that results are comparable. However, our hypotheses H2 and H3 relate to the distribution of future accounting losses. Obtaining a distribution from a single observed profitability is not possible. Therefore, we estimate firm-specific conditional distributions of expected profitability. Thus, to be consistent with hypothesis H2 and H3, we use an expected loss dummy for hypothesis H1.

[14] For robustness, we also test the higher moments of the distribution. Untabulated tests show that these measures are not consistently related to future bankruptcies and do not improve out-of-sample performance substantially.

Figure 2.1: Visualization of the Research Hypotheses

This figure visualizes our research hypotheses using an exemplary cumulative profitability distribution. The dotted line separates negative and positive profitability, and the dashed line represents the median profitability forecast (H1). The gray plus the black area refer to the probability of expected losses (H2), while the black area only refers to the illiquidity probability (H3).



H3: *The area of the expected profitability distribution covering severe losses provides additional insights into a firm's bankruptcy risk. Replacing the probability to realize future losses in general with the probability to realize severe future losses that potentially translate into illiquidity further improves forecast accuracy.*

However, we acknowledge that illiquidity is mainly driven by the net cash outflow over a fiscal period and that using accounting losses only serves as a proxy.[15] We further elaborate on this in Section 2.3.2.

To summarize, Figure 2.1 visualizes our research hypotheses using an exemplary cumulative distribution function. The dotted line separates positive and negative profitability and serves as reference point for our analysis. Hypothesis H1 tests whether the firm is expected to be profitable or not, i.e., whether the median expected profitability (dashed line) is left or right from the reference point. Hypothesis H2 assesses the probability of a firm to be unprofitable in the subsequent fiscal year (gray plus black area). In addition, hypothesis H3 accounts for the severity of the expected loss by moving the reference point from "loss" to "depleting current cash balance" (black area).

[15] However, literature provides evidence for a strong relation between earnings and cash flow (e.g., Bowen et al. (1986) or Dechow et al. (1998)).

2.3.2 *Methodology*

Predicting Future Profitability Distributions

We use quantile regressions to forecast firm-specific quantile functions of one-year ahead profitability out-of-sample. In line with Koenker and Bassett (1978), Angrist and Pischke (2009), and Konstantinidi and Pope (2016), we fit the following regression model to obtain individual percentile estimates:

$$
\begin{aligned}
Q_\tau\left(\mathrm{Prof}_{i,t+1} \middle| X_{i,t}\right) &= \arg_{\beta_\tau} \min E\left[\rho_\tau\left(\mathrm{Prof}_{i,t+1} - X'_{i,t}\beta_\tau\right)\right] \\
&= \arg_{\beta_\tau} \min E\left[\rho_\tau\left(u_{i,t+1}\right)\right] \\
&= \arg_{\beta_\tau} \min E\left[\tau \cdot \left|u_{i,t+1}\right|_{u_{i,t+1}>0} + (1-\tau) \cdot \left|u_{i,t+1}\right|_{u_{i,t+1}\leq 0}\right] \qquad (2.1)
\end{aligned}
$$

where Q_τ is the τ^{th} percentile of one-year ahead expected profitability ($\mathrm{Prof}_{i,t+1}$) conditional on the set of explanatory variables $X_{i,t}$ for firm i in the t^{th} period. It is derived by minimizing the check function $\rho_\tau(u_{i,t+1})$ that weighs the forecast errors $u_{i,t+1}$ asymmetrically.[16] Afterwards, we obtain the firm-specific cumulative distribution function by inverting the forecasted quantile function.

Analogously to recent literature on earnings forecasts, we perform rolling window cross-sectional regressions to fit the model (e.g., Hou et al. (2012), Li and Mohanram (2014), and Konstantinidi and Pope (2016)).[17] We follow Chang et al. (2021) and estimate 150 percentiles evenly spread between 0 and 1 to predict the shape of the distribution. According to Koenker and Bassett (1978), a substantial problem that may occur with this approach that leaves the estimated distribution inconsistent is “quantile crossing”. Quantile crossing means that the estimated percentiles are not monotonously increasing, e.g., that lower percentiles exceed higher percentiles at some point in the distribution. Quantile crossing typically occurs because of estimation errors. As estimation errors are potentially higher for extreme percentiles, the risk of quantile crossing increases the more percentiles are estimated. However, Chernozhukov et al. (2010) introduce a rearrangement method to resolve quantile crossing and to obtain consistent distributions. In line with Chang et al. (2021), we implement this method and obtain consistent estimates of future profitability distributions.[18]

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[16] See Konstantinidi and Pope (2016) for a more detailed description of the approach.

[17] To lower data requirements, we start with a five-year window at the beginning of our sample period and expand it to ten years successively.

[18] See Chernozhukov et al. (2010) or the online appendix of Chang et al. (2021) for a detailed description of this approach.

We deviate from Chang et al. (2021) in terms of the specific cross-sectional forecast model we use. To estimate the conditional distribution of future profitability, we employ the model by Konstantinidi and Pope (2016):

$$\begin{aligned}\mathrm{Prof}_{i,t+1} = \quad & \beta_{+,0} + \beta_{+,1} \cdot \mathrm{OCF}_{i,t} + \beta_{+,2} \cdot \mathrm{ACC}_{i,t} + \beta_{+,3} \cdot \mathrm{SPI}_{i,t} \\ & + \beta_{-,0} + \beta_{-,1} \cdot \mathrm{OCF}_{i,t} + \beta_{-,2} \cdot \mathrm{ACC}_{i,t} + \beta_{-,3} \cdot \mathrm{SPI}_{i,t} + \varepsilon_{t+1}\end{aligned} \tag{2.2}$$

where $\mathrm{Prof}_{i,t+1}$ is profitability (asset-scaled earnings), $\mathrm{OCF}_{i,t}$ is operating cash flow, $\mathrm{ACC}_{i,t}$ is accruals, and $\mathrm{SPI}_{i,t}$ is special items. Furthermore, (+) is an indicator for profit firms and (-) indicates a loss firm. All explanatory variables are deflated by total assets.[19] We select the Konstantinidi and Pope (2016)-model as previous research shows that there is a substantial difference in earnings persistence between profit and loss firms (e.g., Li (2011), Li and Mohanram (2014), among others). As we are particularly interested in the role of losses within our analysis, we argue that a fully interacted model that fits different parameters for profitable and unprofitable firms produces more reliable distribution estimates for our task.[20]

We obtain out-of-sample firm-specific estimates for each percentile and by that, for the conditional distribution, by combining each percentiles' parameter estimates for profit and loss firms with current firm fundamentals ($\mathrm{OCF}_{i,t}$, $\mathrm{ACC}_{i,t}$, and $\mathrm{SPI}_{i,t}$). As firm fundamentals vary across firms and over time, the conditional distribution estimates are firm-specific and time-varying.

Predicting Future Bankruptcy Filings

We predict firm-specific one-year ahead bankruptcy probabilities with a discrete hazard model, i.e., a logistic regression model that uses multiple observations per firm (e.g., Shumway (2001), Chava and Jarrow (2004), or Correia et al. (2018)):

$$P_{i,t}\left(y_{i,t+1} = 1 \middle| X_{i,t}\right) = \frac{1}{1 + \exp\left(-X_{i,t}'\beta\right)} \tag{2.3}$$

[19] We describe all variables used in this paper in more detail in Section 2.3.3 and Table A2.1.

[20] Untabulated tests show that the tenor of results is unchanged when we use alternative earnings forecast models, e.g., the model by Hou et al. (2012), the RI model and EP model by Li and Mohanram (2014), or the model by Chang et al. (2021).

where $y_{i,t+1}$ is a dummy variable that indicates whether a firm files for bankruptcy within the subsequent twelve months, $X'_{i,t}$ is the set of explanatory variables, and β is the vector of parameters.

To predict bankruptcy probabilities out-of-sample, we use the Shumway (2001)-model as Shumway (2001), Chava and Jarrow (2004), and Bauer and Agarwal (2014) provide evidence that it shows a high accuracy and outperforms other prediction models (e.g., the Altman (1968)-model or Zmijewski (1984)-model). The Shumway (2001)-model is defined by the following equation:

$$\begin{aligned} X'_{i,t}\beta = {} & \beta_0 + \beta_1 \cdot \mathrm{RoA}_{i,t} + \beta_2 \cdot \mathrm{Debt\ Ratio}_{i,t} + \beta_3 \cdot \mathrm{Rel.\,Size}_{i,t} \\ & + \beta_4 \cdot \mathrm{Ex.\,Return}_{i,t} + \beta_5 \cdot \mathrm{Sigma}_{i,t} \end{aligned} \tag{2.4}$$

with return on assets ($\mathrm{RoA}_{i,t}$) and excess returns ($\mathrm{Ex.\,Return}_{i,t}$) as profitability measures that capture book and market return, and $\mathrm{Debt\ Ratio}_{i,t}$, $\mathrm{Rel.\,Size}_{i,t}$, and $\mathrm{Sigma}_{i,t}$ (idiosyncratic risk) as risk measures.

To test our research hypotheses, we use univariate extensions of the Shumway (2001)-model with three measures based on the predicted profitability distribution. First, we extend the model by an expected loss dummy based on the median profitability forecast. Second and third, we add two probability measures, namely the probability to realize future accounting losses in general and the probability that these losses deplete a firm's current cash balance. For simplicity, we describe the univariate model extensions by adding the explanatory variable $Z_{i,t}$, representative for each of the three additional variables:

$$\begin{aligned} X'_{i,t}\beta = {} & \beta_0 + \beta_1 \cdot \mathrm{RoA}_{i,t} + \beta_2 \cdot \mathrm{Debt\ Ratio}_{i,t} + \beta_3 \cdot \mathrm{Rel.\,Size}_{i,t} \\ & + \beta_4 \cdot \mathrm{Ex.\,Return}_{i,t} + \beta_5 \cdot \mathrm{Sigma}_{i,t} + \beta_6 \cdot Z_{i,t} \end{aligned} \tag{2.5}$$

Our three expected accounting loss measures are defined as follows:

(i) $\mathrm{E}[\mathrm{LossDummy}_{t+1}] = \begin{cases} 1, & \mathrm{E}\left[\mathrm{Prof}_{t+1,P50}\right] < 0 \\ 0, & \mathrm{E}\left[\mathrm{Prof}_{t+1,P50}\right] \geq 0 \end{cases}$

(ii) $\mathrm{P}(\mathrm{E}[\mathrm{Prof}_{t+1}] < 0)$

(iii) $\mathrm{P}(\mathrm{E}[\mathrm{Prof}_{t+1}] < -\mathrm{Cash\ Balance}_t)$

For the remainder of our paper, we will refer to (i) as "Loss Dummy", (ii) as "Loss Probability", and (iii) as "Illiquidity Probability". Loss Dummy equals 1 if the median profitability forecast is negative, and 0 otherwise. Loss Probability equals the largest percentile of the profitability distribution with negative profitability. Therefore, it is the value of the VaR's inverse function when using future accounting losses as threshold. Analogously, Illiquidity Probability is the value of the VaR's inverse function when defining future accounting losses depleting current cash balances as threshold.[21]

As stated before, we acknowledge that illiquidity is mainly driven by the net cash outflow over a fiscal period. That is, if net cash outflow ($\Delta(\text{Cash Balance})_{t+1}$) depletes the cash balance, a firm is unable to pay further obligations:

$$0 = \frac{\text{Cash Balance}_t}{\text{Total Assets}_t} + \frac{\text{E}[\Delta(\text{Cash Balance})_{t+1}]}{\text{Total Assets}_t} \tag{2.6}$$

In terms of financial reporting, net cash outflow is limited to the current cash balance.[22] Therefore, we cannot observe the contractual claims that would exceed a firm's cash balance. Thus, a reliable estimation of future illiquidity is difficult. To address this issue, we use profitability (Prof_{t+1}) to approximate this risk of becoming unable to pay:[23]

$$0 > \frac{\text{Cash Balance}_t}{\text{Total Assets}_t} + \text{E}[\text{Prof}_{t+1}] \tag{2.7}$$

Further, to perform the size analysis in Section 2.4.3, we annually form size terciles based on total assets to class observations into "small", "medium", and "large" firms. Next, we interact our loss measures with dummy variables ($d_{j,t}$) for each size group. Additionally, we include group-specific intercepts. The size analysis is described by the following equation:

---

[21] Our probability measures are based on a concept introduced by Hüttemann (2019). Assuming a standard normal distribution, he uses the mean and standard deviation of an individual firm's conditional earnings estimate to compute the probability that a firm's future losses exceed currently available book equity. We deviate from this approach by directly estimating the underlying distribution of future earnings and by using losses and current cash balances instead of book equity as threshold values.

[22] That means that reporting a negative cash balance in the balance sheet occurs very rarely. In case a firm overdraws its cash balance, it is typically recognized as a liability position.

[23] We acknowledge that this approximation introduces measurement errors that might affect our findings. To account for this, we test other approximations as well. First, we use direct estimates of change in cash balance predicted by an autoregressive model. Second, we test cash flow forecasts estimated using specific cash flow forecast models (e.g., Barth et al. (2001)). Finally, we approximate future cash flow from future earnings using different definitions of the cash conversion rate. However, all alternative proxies lead to noisier estimates, resulting in worse out-of-sample performance than the approximation based on profitability.

$$X'_{i,t}\beta = \sum_{j=1}^{3} \beta_{0,j} \cdot d_{j,t} + \beta_1 \cdot \mathrm{RoA}_{i,t} + \beta_2 \cdot \mathrm{Debt\ Ratio}_{i,t} + \beta_3 \cdot \mathrm{Rel.Size}_{i,t} + \beta_4 \cdot \mathrm{Ex.Return}_{i,t} + \beta_5 \cdot \mathrm{Sigma}_{i,t} + \sum_{j=1}^{3} \beta_{6,j} \cdot d_{j,t} \cdot Z_{i,t} \tag{2.8}$$

Assessing Bankruptcy Predictions

We strictly separate in-sample and out-of-sample performance when assessing our prediction models. In-sample, we provide empirical evidence that our expected accounting loss measures in fact capture bankruptcy risk as they help explaining future bankruptcy filings. Out-of-sample, we draw inferences on how well our variables improve bankruptcy detection in real forecast scenarios.

To evaluate the in-sample fit of our logistic regression models, we employ the Akaike (1974) Information Criterion (AIC). In general, the AIC statistic compares different models applied to the same task on the same data set while controlling for overfitting by accounting for the complexity of the competing models. Therefore, we can directly compare the Shumway (2001)-model and our extended models. Mathematically, AIC is defined as:

$$\mathrm{AIC} = -2 \cdot \mathrm{Log\ L} + 2 \cdot p \tag{2.9}$$

where Log L equals the log likelihood estimate and p equals the number of explanatory variables including the intercept. The lower the AIC of a model, the better it is at data fitting.

To assess out-of-sample performance, we employ two test statistics commonly used in literature. The first measure, i.e., AUC, is a general approach to assess binary classifications. The “Receiver Operating Characteristics” (ROC) curve plots the classification’s true positive rates against its false positive rates for all possible classification cutoff points. For any threshold value between 0 and 1, the observations are reclassified into either case (i.e., bankrupt) or control (i.e., non-bankrupt) based on the predicted probabilities. The area under this curve (AUC) measures how well the model distinguishes between both classes. While a value of 0.5 implies a random allocation (i.e., no predictive ability), a value of 1.0 represents perfect discrimination.

Second, we use the Shumway (2001) performance decile criterion. At any estimation date, firms are sorted into deciles based on their predicted bankruptcy probabilities. After actual bankruptcies become observable, we calculate the share of bankruptcies in each decile. The higher the shares of bankrupt firms in deciles with the highest predicted bankruptcy probabilities, the better the predictive performance of a model. This is rather a practitioner's approach to assess bankruptcy prediction models as this measure outlines the relative number of defaults a bank avoids if it does not grant credits to a certain share (e.g., 10%) of firms with the highest expected bankruptcy probabilities.

2.3.3 Data and Variables

Our sample consists of the intersection of the annual COMPUSTAT North American database and the monthly CRSP stock return file. The total sample period spans from 1967 to 2019 and contains US American firms reporting in US Dollar. Following our two-step prediction methodology, the earnings prediction sample period spans from 1967 to 2019, leading to first out-of-sample predictions of conditional profitability distributions in 1972. Analogously, the bankruptcy prediction sample ranges from 1972 to 2019, with out-of-sample forecasts starting in 1977. We assume a three-month reporting lag for firm fundamentals to become publicly available (e.g., Konstantinidi and Pope (2016)). In addition, we obtain bankruptcy information from Sudheer Chava's database. It is used in Chava and Jarrow (2004), Chava et al. (2011), Chava (2014), and the latest update is available in Alanis et al. (2018).[24] We define bankruptcy as filing for Chapter 7 (liquidation) or Chapter 11 (reorganization). Following Correia et al. (2018), we delete observations of bankrupt firms after the bankruptcy filing date. In case of multiple bankruptcy entries for one firm, we keep the first filing. In line with previous literature (e.g., Shumway (2001), Chava and Jarrow (2004), or Konstantinidi and Pope (2016)), we exclude financial service companies (SIC codes 6,000 to 6,999) from our analysis as we expect their fundamentals to be different because of the regulatory framework. Table 2.1 presents the sample distribution of bankrupt and non-bankrupt firms by year. In total, our sample consists of 161,237 non-bankrupt and 1,492 bankrupt firm-years, with a mean annual bankruptcy rate of 0.93% and peaks during the crises in 2001 (3.07%) and 2009 (1.68%).

The explanatory variables for the Konstantinidi and Pope (2016)-model to predict future profitability are defined as follows. The central variable, profitability (Prof), is earnings (IBC) deflated by total asset (AT). In case of missing IBC, we replace it by IB. Prior to the FASB No. 95 in 1988, IBC is systematically missing as filing a cash flow statement was not mandatory. That is, prior to 1988, we systematically replace IBC by IB, while the replacement is unsystematic after 1988. Operating cash flow (OCF) is defined as OANCF minus XIDOC. Accruals (ACC) is defined as earnings minus operating cash flow. We calculate OCF as well as

[24] We thank Sudheer Chava for providing us with his bankruptcy data updated until 2020.

Table 2.1: Number of Bankrupt and Non-Bankrupt Firms per Year

This table contains the number of firm-years separated into bankrupt and non-bankrupt firms and the corresponding bankruptcy rates in the sample period from 1967 to 2019.

Year	Non-Bankrupt Firm-Years	Bankrupt Firm-Years	Bankruptcy Rate (%)	Year	Non-Bankrupt Firm-Years	Bankrupt Firm-Years	Bankruptcy Rate (%)
1967	903	-	-	1994	3,831	20	0.52
1968	1,106	-	-	1995	4,145	24	0.58
1969	1,204	-	-	1996	4,344	36	0.82
1970	1,354	-	-	1997	4,542	39	0.85
1971	1,611	-	-	1998	4,823	60	1.23
1972	1,684	5	0.30	1999	4,685	62	1.31
1973	1,765	6	0.34	2000	4,341	62	1.41
1974	2,403	12	0.50	2001	4,076	129	3.07
1975	2,938	10	0.34	2002	3,964	86	2.12
1976	2,955	10	0.34	2003	3,699	62	1.65
1977	2,734	10	0.36	2004	3,427	24	0.70
1978	2,799	12	0.43	2005	3,288	24	0.72
1979	2,936	9	0.31	2006	3,248	16	0.49
1980	3,074	18	0.58	2007	3,147	26	0.82
1981	2,937	21	0.71	2008	3,032	42	1.37
1982	2,955	27	0.91	2009	2,990	51	1.68
1983	3,140	25	0.79	2010	2,880	11	0.38
1984	3,214	31	0.96	2011	2,735	16	0.58
1985	3,355	42	1.24	2012	2,626	17	0.64
1986	3,582	43	1.19	2013	2,558	14	0.54
1987	3,526	27	0.76	2014	2,498	20	0.79
1988	3,601	39	1.07	2015	2,512	28	1.10
1989	3,701	29	0.78	2016	2,569	23	0.89
1990	3,620	47	1.28	2017	2,519	19	0.75
1991	3,569	45	1.25	2018	2,458	20	0.81
1992	3,579	37	1.02	2019	2,454	23	0.93
1993	3,601	33	0.91	Total	161,237	1,492	0.93

ACC using the balance sheet approach when they are missing.[25] Following Li and Mohanram (2014), we define special items (SPI) as SPI and set accruals and special items to zero when missing. To match the left-hand side variable, we deflate all explanatory variables by total assets.

The explanatory variables for the Shumway (2001)-model to predict future bankruptcies are defined as follows. Return on assets (RoA) is net income (NI) divided by total assets. Debt Ratio is long-term liabilities (LT) relative to total assets (AT), while Relative Size is a firm's market capitalization (|PRC| multiplied by VOL) divided by the total market capitalization (USDVAL). We calculate Excess Return as the sum of differences between monthly returns (RET) and monthly value-weighted market returns (VWRETD) over a

[25] The balance sheet approach calculates operating cash flow as the difference between earnings and accruals. Following Hou et al. (2012), we define balance sheet accruals as the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense. See Table A2.1 for a detailed description of the calculations.

Table 2.2: Descriptive Statistics

This table contains descriptive statistics for the pooled cross-section. Panel A displays summary statistics for the winsorized explanatory variables of the Shumway (2001)-model as well as for the expected accounting loss measures. Panel B reflects their respective cross-correlations following Pearson (Spearman) below (above) the diagonal. All correlations are statistically significance at the 1% significance level.

Panel A: Summary Statistics

Variable	N	Mean	STD	Min	1%	25%	Median	75%	99%	Max
Debt Ratio	156,551	0.50	0.25	0.04	0.06	0.32	0.50	0.65	1.28	2.05
RoA	156,551	-0.04	0.29	-4.23	-1.37	-0.03	0.04	0.08	0.23	0.33
Relative Size	156,551	-10.75	2.08	-15.93	-15.06	-12.24	-10.83	-9.36	-5.81	-4.80
Excess Return	156,551	0.02	0.64	-1.15	-0.94	-0.34	-0.07	0.22	2.46	7.06
Sigma	156,551	0.12	0.08	0.02	0.03	0.07	0.10	0.15	0.44	0.74
Loss Dummy	156,551	0.27	0.45	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Loss Prob.	156,551	0.31	0.31	0.00	0.00	0.07	0.16	0.57	0.96	0.97
Illiquidity Prob.	156,551	0.16	0.24	0.00	0.00	0.01	0.05	0.18	0.91	0.95

Panel B: Correlation Analysis

Variable	Debt Ratio	RoA	Relative Size	Excess Return	Sigma	Loss Dummy	Loss Prob.	Illiquidity Prob.
Debt Ratio	-	-0.21	0.06	-0.05	-0.03	0.03	0.15	0.39
RoA	-0.17	-	0.43	0.36	-0.38	-0.71	-0.86	-0.66
Relative Size	0.02	0.35	-	0.31	-0.52	-0.43	-0.47	-0.35
Excess Return	-0.06	0.19	0.19	-	-0.09	-0.30	-0.34	-0.31
Sigma	0.03	-0.40	-0.46	0.16	-	0.43	0.41	0.25
Loss Dummy	0.07	-0.57	-0.42	-0.18	0.42	-	0.77	0.56
Loss Prob.	0.10	-0.65	-0.48	-0.20	0.46	0.92	-	0.74
Illiquidity Prob.	0.31	-0.62	-0.42	-0.23	0.37	0.68	0.73	-

12-month period. To calculate idiosyncratic risk (Sigma), we follow a two-step approach. First, we run firm-specific time-series regressions of monthly return on value-weighted market return over the past 12 months. Afterwards, we calculate Sigma as the standard deviation of the regression residuals. Following Shumway (2001), we drop observations with less than 12 months of return data to calculate Sigma. To extend the Shumway (2001)-model, we use a firm's expected profitability distribution to define Loss Dummy and Loss Probability, and additionally a firm's current cash balance (CHE) to assess whether a firm potentially becomes illiquid (Illiquidity Probability).

For our analysis, we require that all relevant variables are non-missing.[26] To mitigate the impact of outliers, we winsorize all variables annually at the top and bottom percentiles.

Table 2.2 contains descriptive statistics (Panel A) and correlation analyses (Panel B) of the Shumway (2001) variables as well as of our expected loss measures. Sample characteristics of the Shumway (2001) variables are comparable to those reported in the initial study. Moreover, Panel A reveals that even when the median firm is expected to be profitable (i.e., Loss Dummy

[26] For the analysis of the Ohlson (1980)-model and the Altman (1983)-model (see Table A2.2), we require these variables to be non-missing, too.

equals zero), it has in fact a positive probability to realize losses (i.e., Loss Probability equals 16%). This demonstrates the different information content of a binary and a probability-based loss signal. Panel B outlines that our variables show moderate correlations to accounting-based risk measures (Debt Ratio), indicating that we offer complementary variables instead of substitutes. Moreover, because correlations to market-based measures (Sigma) are more pronounced, our measures seem to rather mimic the effect of market-driven variables.[27]

2.4 Empirical Results

In this section, we present our empirical results. First, we provide evidence that expected losses explain future bankruptcies (in-sample). Second, we confirm that expected losses predict future bankruptcies in out-of-sample applications and show how the ability to predict bankruptcy filings develops over time. Third, we analyze whether there is a size effect in the relation between expected losses and bankruptcy risk.

2.4.1 In-Sample Analysis

Table 2.3 analyzes differences between bankrupt and non-bankrupt firms with respect to our expected loss measures. Panel A shows how the measures develop over time for firms approaching bankruptcy. In detail, we analyze how the measures behave up to five years prior to bankruptcy filing and report values for non-bankrupt firms as benchmark.[28] To ensure that we analyze the same bankrupt firms over time, we include only firms with firm histories of at least five years. Panel B presents results of mean equality tests to analyze whether the levels of our measures systematically differ between bankrupt and non-bankrupt firms.

Various findings are worth highlighting. First, all measures increase monotonously while a firm approaches bankruptcy. For example, the fraction of firms expecting losses among bankrupt firms (i.e., Loss Dummy) more than doubles from 37% five years prior to bankruptcy filing to 81% in the year of filing for bankruptcy. Analogous to that, the average Loss Probability (Illiquidity Probability) increases from 40% (22%) five years before bankruptcy to 69% (55%) in the bankruptcy filing year. Second, tests for equality of means (Panel B) reveal that non-bankrupt firms and bankrupt firms show statistically significant differences with respect to our expected loss measures. For instance, the average share of firms expecting losses among non-bankrupt firms (26%) is significantly lower compared to bankrupt firms (77%). In

[27] This is consistent as both our measures and market variables reflect forward-looking information.

[28] Year 1 indicates the financial statement information released at maximum twelve month before filing for bankruptcy.

Table 2.3: Analysis of the Expected Loss Measures

This table contains an analysis of our expected loss measures and mean differences between bankrupt and non-bankrupt firms. Panel A shows the development of the measures' means for bankrupt firms up to five years prior to bankruptcy filing and for non-bankrupt firms. We only include bankrupt firms with a history of at least five years before bankruptcy to ensure that we investigate the same firms over time. Panel B displays the results of a mean equality test between bankrupt and non-bankrupt firms. We test whether the values in annual means of the expected loss measures are significantly different for both groups. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: Development of Expected Loss Measures Prior to Bankruptcy

Variable	Years Prior to Bankruptcy Filing					Non-Bankrupt
	5	4	3	2	1	Firms
Loss Dummy	0.37	0.42	0.51	0.64	0.81	0.26
Loss Prob.	0.40	0.43	0.49	0.59	0.69	0.30
Illiquidity Prob.	0.22	0.25	0.30	0.40	0.55	0.14
N	692	692	692	692	692	138,574

Panel B: Mean Equality Test of Expected Loss Measures

Variable	Bankrupt Firms	Non-Bankrupt Firms	Difference	t-Statistic	Significance
Loss Dummy	0.77	0.26	0.51	16.60	***
Loss Prob.	0.67	0.30	0.37	14.35	***
Illiquidity Prob.	0.50	0.14	0.36	16.67	***

line with this, the respective probabilities of future losses are significantly lower, too. Moreover, as the difference between non-bankrupt and bankrupt firms is at minimum (maximum) 1.23 (2.52) times the level of non-bankrupt firms, results are also economically significant. In consequence, Table 2.3 provides first evidence in support of our hypotheses H1, H2, and H3, as our measures develop in line with expectations.

Table 2.4 shows time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and AIC values of the annual logistic regressions. Results for the Shumway (2001)-model are comparable to the initial study.[29] Therefore, we focus on the effects of our expected loss measures on the discriminative power of the model.

All parameter estimates are in line with expectations. They are positive and statistically significant and therefore, increase a firm’s one-year ahead bankruptcy probability. When looking at the risk measures that are initially considered in the Shumway (2001)-model, we find that our measures are complementary to accounting-based risk measures (i.e., Debt Ratio) and substitutive to market-based risk measures (i.e., Sigma). This follows from a relatively small decrease in magnitude for the Debt Ratio parameter estimate (3.9665 to 3.5349 at maximum) and a more pronounced drop for the Sigma parameter estimate (2.9111 to 1.8146 at maximum). This is consistent with the correlation analysis in Table 2.2. The correlations of our measures

[29] In contrast to Shumway (2001), we find that RoA is significant at an alpha of 10% in the initial model. Moreover, once we add our loss measures, the variable gains significance in one out of three model specifications and flips its sign. This could be driven by the high correlations between current profitability (RoA) and expected profitability, as Table 2.2 reveals.

Table 2.4: Parameter Estimates of Rolling Logistic Regressions

This table contains the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and AIC values of the annual logistic regressions of the Shumway (2001)-model and the extended models. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Variable	Shumway (2001)	Shumway (2001) Loss Dummy	Shumway (2001) Loss Prob.	Shumway (2001) Illiquidity Prob.
Intercept	-10.3833 ***	-10.0402 ***	-10.2546 ***	-9.5430 ***
	(-21.03)	*(-18.97)*	*(-19.39)*	*(-18.42)*
Debt Ratio	3.9665 ***	3.8033 ***	3.7151 ***	3.5349 ***
	(11.87)	*(11.49)*	*(12.81)*	*(11.36)*
RoA	-0.9663 *	-0.3783	0.3745 ***	0.1030
	(-1.89)	*(-1.10)*	*(3.15)*	*(0.39)*
Relative Size	-0.2035 ***	-0.1406 ***	-0.1248 ***	-0.1092 ***
	(-7.53)	*(-4.35)*	*(-3.99)*	*(-3.53)*
Excess Return	-1.4625 ***	-1.2175 ***	-1.1680 ***	-1.2228 ***
	(-10.46)	*(-9.57)*	*(-8.29)*	*(-9.21)*
Sigma	2.9111 ***	2.1167 ***	1.8146 ***	2.1463 ***
	(13.90)	*(8.88)*	*(6.34)*	*(8.54)*
Loss Dummy		1.3336 ***		
		(35.39)		
Loss Prob.			2.7700 ***	
			(12.65)	
Illiquidity Prob.				2.7108 ***
				(15.58)
AIC	2,507.26	2,443.28	2,439.26	2,427.07

with Debt Ratio are rather moderate, while the correlations with the market-based risk proxy are stronger. A possible explanation for this is the link between returns and expected earnings. Following the residual income valuation (e.g., Feltham and Ohlson (1995)), the value of a stock equals its appropriately discounted earnings expectations. Therefore, returns are just a transformation of expected earnings, and because of this, our measures partly mimic characteristics that are also captured by Sigma. This adds empirical evidence to the debate whether accounting-based measures offer explanatory power in addition to market variables (e.g., Hillegeist et al. (2004), Beaver et al. (2005), Agarwal and Taffler (2008), Campbell et al. (2008), and Beaver et al. (2012)).

Further, all extended models show larger goodness-of-fit than the initial Shumway (2001)-model and therefore, are better at data fitting. In detail, AIC decreases from 2,507.26 to 2,443.28, 2,439.26, and 2,427.07 once the model is extended by Loss Dummy, Loss Probability, and Illiquidity Probability, respectively. Comparing our extended models to each other reveals that information about the distribution of expected losses (H2 and H3) increases the in-sample accuracy stronger than binary loss information (H1). Especially the probability of running into illiquidity substantially outperforms the improvement of Loss Dummy. To conclude, Table 2.4 provides empirical evidence in support of our hypotheses H1, H2, and H3.

2.4.2 Out-of-Sample Analysis

To assess how well our loss measures improve bankruptcy detection in real forecast scenarios, we perform strict out-of-sample tests. Table 2.5 presents time-series averages of the models' AUC (Panel A) and performance decile (Panel B) values. Moreover, Panel C displays time-series averages of differences in AUC and 10th decile values across models and the corresponding Newey-West (1987) t-statistics.

Mean AUC values in Panel A and differences in Panel C support the hypothesis that information about expected losses improves bankruptcy prediction. Including the Loss Dummy (H1) significantly increases the forecast accuracy of the Shumway (2001)-model, leading to an AUC of 89.46 compared to 88.78. That means, the probability that a randomly picked bankrupt firm has a higher estimated bankruptcy probability than a randomly picked non-bankrupt firm increases by 0.68 percentage points. When using our probability measures (H2 and H3), the performance increase is even more pronounced. The extended model that includes Loss Probability (Illiquidity Probability) significantly outperforms the model including Loss Dummy and further increases AUC by 0.31 (0.41) percentage points to 89.77 (89.87). Therefore, the assumption that information about loss distributions is substantially more useful than binary loss information for assessing a firm's bankruptcy risk is confirmed.

For the performance deciles, specifically the 10th decile, Panel B reveals a similar pattern. Adding Loss Dummy to the prediction model increases the number of actual bankruptcies in the decile with the ex ante highest bankruptcy probabilities from 69.51% to 70.47% compared to the initial Shumway (2001)-model. That means, a bank can avoid additional 0.96 percentage points of credit defaults if it does not grant credits to these firms. Again, the performance increase is even stronger when using distributional information. While there is already a substantial improvement by Loss Probability (71.65%), the performance peaks using Illiquidity Probability with a 10th decile value of 73.54%.[30] Panel C confirms that performance increases compared to the Shumway (2001)-model are statistically significant, except for the difference in 10th decile for the model extended by Loss Dummy. Moreover, performance differences between the models extended by our probability measures and the model using binary loss information are statistically significant. This again confirms the assumption of different values embedded in binary and distributional loss information for predicting future bankruptcies.

As additional analysis, we track the performance of our expected loss measures throughout the sample period. To keep the analysis manageable, we only show results for the Shumway

[30] Untabulated results show that a combined model, i.e., including both probability measures simultaneously, further increases performance (AUC: 90.00%, 10th performance decile: 73.82%). However, differences to the model only including Illiquidity Probability are insignificant. Therefore, for reasons of parsimoniousness, we do not report the results.

Table 2.5: Performance Evaluation of One-Year Ahead Bankruptcy Forecasts

This table shows the out-of-sample performance of one-year ahead bankruptcy forecasts. Panel A contains the time-series averages of AUC for the Shumway (2001)-model and the extended models. Panel B shows time-series averages of the performance deciles. Panel C shows the difference (y-axis minus x-axis) in out-of-sample performances of one-year ahead bankruptcy forecasts. It contains the time-series averages of the differences in AUC (above the diagonal) and 10th performance decile (below the diagonal), and the corresponding Newey-West (1987) t-statistics. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: AUC

Variable	Shumway (2001)	Shumway (2001) Loss Dummy	Shumway (2001) Loss Prob.	Shumway (2001) Illiquidity Prob.
AUC	88.78	89.46	89.77	89.87

Panel B: Performance Deciles

Decile	Shumway (2001)	Shumway (2001) Loss Dummy	Shumway (2001) Loss Prob.	Shumway (2001) Illiquidity Prob.
1	1.02	0.92	1.03	1.20
2	0.48	0.28	0.39	0.35
3	0.81	1.45	1.08	0.97
4	1.45	1.12	0.91	0.69
5	1.43	1.23	0.85	1.31
6	2.47	1.88	2.21	1.56
7	3.54	2.21	2.48	2.88
8	5.06	5.94	5.21	4.68
9	14.22	14.49	14.19	12.82
10	69.51	70.47	71.65	73.54

Panel C: Differences in AUC (Above the Diagonal) and 10th Decile (Below the Diagonal)

Variable	Shumway (2001)	Shumway (2001) Loss Dummy	Shumway (2001) Loss Prob.	Shumway (2001) Illiquidity Prob.
Shumway (2001)	-	-0.6760 *** *(-3.84)*	-0.9870 *** *(-5.09)*	-1.0910 *** *(-6.28)*
Shumway (2001) Loss Dummy	0.9640 *(1.14)*	-	-0.3110 ** *(-2.58)*	-0.4140 ** *(-2.51)*
Shumway (2001) Loss Prob.	2.1370 ** *(2.13)*	1.1730 ** *(2.04)*	-	-0.1040 *(-0.68)*
Shumway (2001) Illiquidity Prob.	4.0343 *** *(4.21)*	3.0703 *** *(4.12)*	1.8973 ** *(2.42)*	-

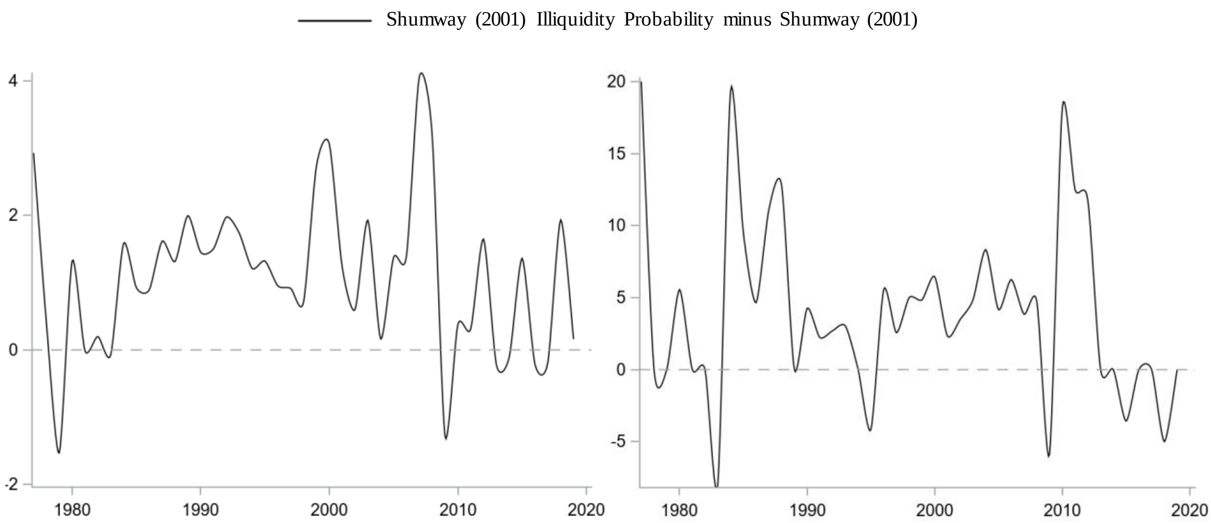
(2001)-model and our best performing model (Illiquidity Probability). Therefore, results in Figure 2.2 only provide evidence for hypothesis H3. However, untabulated tests reveal that the other models (H1 and H2) show comparable performance improvements. Panel A (Panel B) presents the time-series of differences in AUC (10^{th} decile) for the Shumway (2001)-model and the model extended by Illiquidity Probability. Differences in AUC (10^{th} decile) reveal that the Illiquidity Probability model performs better or equal in 81.40% (88.37%) of the sample period.

Further, Panel C (Panel D) plots levels of AUC (10^{th} decile) for both models over time. Results show that both models have similar performance patterns. That is, once the performance of the Shumway (2001)-model increases or decreases from one year to another, the performance of the model extended by Illiquidity Probability moves accordingly. However, as indicated by

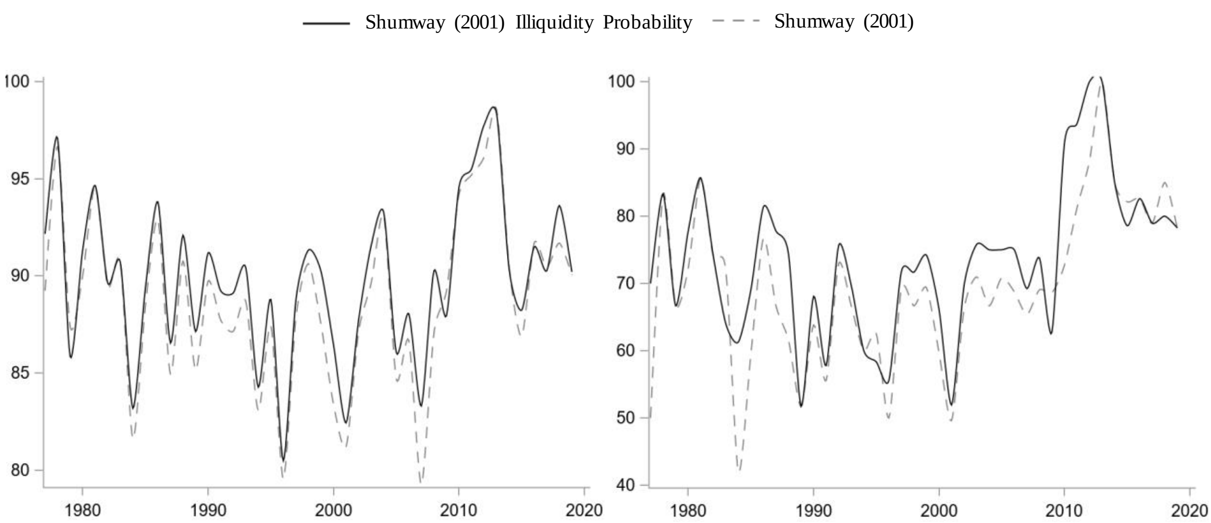
Figure 2.2: Differences and Levels of Out-of-Sample Performance Over Time

This figure contains the percentage point differences (Panel A and Panel B) in out-of-sample performance (AUC and 10th performance decile) of the Shumway (2001)-model and the model extended by Illiquidity Probability. Further, it shows their absolute levels (Panel C and Panel D) throughout the sample period.

Panel A: Difference in AUC	Panel B: Difference in 10th Decile



Panel C: AUC	Panel D: 10th Decile



Panel A and Panel B, the absolute level of accuracy for the extended model is higher in over 80% of the sample period. Further, untabulated tests reveal that the performance of the extended model is slightly less volatile (e.g., AUC standard deviation of 3.99 compared to 4.39), implying that this model performs more consistently over time.

In aggregate, Table 2.5 together with Figure 2.2 support our three research hypotheses. First, expected accounting losses (H1) improve bankruptcy prediction in general. Second, looking at the expected profitability distribution to obtain loss probabilities (H2 and H3) increases performance even further. Therefore, prediction models make more use of distributional information than of binary loss information.

2.4.3 Size Analysis

The information expected accounting losses provide about a firm's bankruptcy risk could differ in firm size. For example, Klein and Marquardt (2006) find that small firms report accounting losses at a higher frequency than larger firms. The authors argue that this is because small firms tend to be less diversified and show a higher idiosyncratic risk, among other characteristics. Therefore, as losses occur more frequently the smaller the firm is, we expect that it becomes more challenging to detect the "relevant loss" that is causing bankruptcy out of "all losses" reported. When differently sized firms (i.e., small, medium, and large) disproportionally report accounting losses compared to filing for bankruptcy, the prediction model will be adversely affected from pooling firms together. This negatively affects the overall fit and potentially leads to less accurate predictions.

Panel A of Table 2.6 provides evidence for this disproportionality. On average, for firm-years with reported losses, 56.98% of the firms are small, while 28.44% (14.58%) of firms are medium (large). Analogously, firm-years with expected losses contain 62.35%, 26.36%, and 11.29% of small, medium, and large firms, respectively. However, small firms account for 41.23% of all bankruptcies, while 38.33% and 20.44% of the bankrupt firms are medium and large. That means, small firms report accounting losses more than twice as frequent as medium firms, but file for bankruptcy only slightly more often. Also, small firms report losses roughly four times as frequent as large firms, but only file for bankruptcy twice as often. We observe an even more pronounced pattern when looking at expected losses instead of reported losses. This disproportionality between losses and bankruptcies indicates why the relevance of an expected loss signal should differ for small firms and larger firms when assessing bankruptcy risk.

To account for this disproportionality, we interact our measures with size classes and rerun the bankruptcy prediction. We form size classes by grouping firms into size terciles based on total assets. Further, we group firms annually to avoid recency bias, i.e., to avoid having early (later) firm-years in our sample mainly allocated to the small (large) size class due to increasing average total assets over time.

Panel B of Table 2.6 shows regression results for the interacted models. All interaction parameters are statistically significant and monotonously increasing in size classes. For example, the parameter estimate of Illiquidity Probability equals 1.8919, 3.3727, and 4.1190

Table 2.6: Relation Between Expected Accounting Losses and Size Classes

This table analyzes the relation between expected accounting losses and size classes. We annually rank firms into terciles based on total assets. Panel A shows the disproportionality in size of realized losses, expected losses, and filing for bankruptcy. Values are time-series averages for the sample period. Panel B presents regression results. It contains the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and AIC values for the annual logistic regressions of the size interacted models. Panel C shows the out-of-sample results for AUC and 10th performance decile. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: (Expected) Accounting Losses across Size Classes

Size Class	Small	Medium	Large
% Realized Losses	56.98	28.44	14.58
% Expected Losses	62.35	26.36	11.29
% Bankruptcies	41.23	38.33	20.44

Panel B: Logistic Regression Results for Size-Interactions

Variable	Shumway (2001) Interacted Loss Dummy	Shumway (2001) Interacted Loss Prob.	Shumway (2001) Interacted Illiquidity Prob.
Debt Ratio	3.3129 ***	3.1593 ***	3.0261 ***
	(10.09)	*(10.72)*	*(9.86)*
RoA	-0.9287 **	-0.2941 *	-0.5538 **
	(-2.58)	*(-1.97)*	*(-2.03)*
Relative Size	-0.3861 ***	-0.3769 ***	-0.3454 ***
	(-9.39)	*(-8.89)*	*(-9.05)*
Excess Return	-0.9705 ***	-0.8549 ***	-0.9334 ***
	(-9.44)	*(-7.82)*	*(-8.58)*
Sigma	2.0539 ***	1.6068 ***	2.0205 ***
	(10.54)	*(7.07)*	*(8.95)*
Interaction Terms			
Loss Dummy | Small	1.0137 ***		
	(16.60)		
Loss Dummy | Medium	1.3520 ***		
	(37.54)		
Loss Dummy | Large	2.0940 ***		
	(6.96)		
Loss Prob. | Small		2.2225 ***	
		(10.47)	
Loss Prob. | Medium		3.2842 ***	
		(16.38)	
Loss Prob. | Large		4.6550 ***	
		(7.35)	
Illiquidity Prob. | Small			1.8918 ***
			(8.60)
Illiquidity Prob. | Medium			3.3727 ***
			(24.43)
Illiquidity Prob. | Large			4.1190 ***
			(9.68)
Size-Specific Intercept	Yes	Yes	Yes
AIC	2,370.69	2,345.43	2,337.24

Panel C: Performance Evaluation for Size-Interactions

Measure	Shumway (2001) Interacted Loss Dummy	Shumway (2001) Interacted Loss Prob.	Shumway (2001) Interacted Illiquidity Prob.
AUC	90.25	90.82	90.88
10th Decile	71.85	74.45	74.72

for small, medium, and large firms, respectively. That is, in contrast to the non-interacted model with a parameter estimate of 2.7108, the interacted model lowers the relevance of a loss signal for small firms, whereas the relevance increases for larger firms. We find this exact same pattern for parameter estimates of Loss Dummy and Loss Probability, too. This confirms that frequency and relevance of the signal are directly linked when assessing bankruptcy risk. In line with that, the model fit improves once we interact our measures with size. For all models, AIC increases compared to the non-interacted counterparts. Moreover, the worst performing interacted model shows a more accurate in-sample fit (AIC of 2,370.69) than the best performing non-interacted model (AIC of 2,427.07). Analogous to the results of the previous section, explanatory power peaks when using Illiquidity Probability (AIC of 2,337.24).

Panel C presents out-of-sample results. In general, three findings are worth highlighting. First, controlling for size in the relation between expected losses and bankruptcy risk significantly improves prediction accuracy. For example, for AUC, the worst performing interacted model (Loss Dummy, 90.25%) shows a higher accuracy than the best performing non-interacted model (Illiquidity Probability, 89.87%). Second, distributional information is still valuable. For the interacted models, when replacing Loss Dummy with Loss Probability, both AUC and 10th decile values significantly increase. While AUC increases by 0.57 percentage points to 90.82%, the 10th decile increases by 2.60 percentage points to 74.45%. Also, this outperforms the best performing non-interacted model (Illiquidity Probability) with a 10th performance decile value of 73.54%. Third, the exact VaR threshold, i.e., loss or illiquidity, becomes less relevant once we control for size. Performance improves only marginally when changing the threshold from realizing future losses to realizing severe future losses that deplete current cash balances. In detail, AUC increases from 90.82% to 90.88%, and 10th performance decile improves from 74.45% to 74.72%. That suggests that measuring the severity of losses with cash balances in the non-interacted model is already a proxy for the size effect between expected losses and bankruptcy risk. Therefore, it is less relevant once we explicitly model the size effect between losses and bankruptcies but is highly relevant when we do not run interacted models.

To summarize, results suggests that there is a size effect in the relation between expected losses and bankruptcy risk. Moreover, modelling this size effect when using expected losses as input for bankruptcy prediction models improves forecast accuracy. Nevertheless, replacing a binary signal with a probability measure still significantly improves performance. Thus, results still support our hypotheses, shedding further light on the relevance of expected accounting losses for assessing firm-specific bankruptcy risk.

2.5 Conclusion

This paper analyzes the role of expected accounting losses in bankruptcy prediction by testing three hypotheses. First, we hypothesize that an expected loss dummy (H1) is a signal that reveals information about a firm's bankruptcy risk. We use median profitability forecasts as expected values. Second, we hypothesize that the underlying profitability distribution reveals further insights into a firm's risk and increases the ability of expected accounting losses to predict future bankruptcies. We calculate firm-specific estimates of expected profitability distributions using cross-sectional earnings forecast models and predict the probability over a one-year horizon that a firm will realize accounting losses. We hypothesize that this information extends the predictive ability of expected losses, such that the bankruptcy prediction accuracy increases (H2). Third, related to the regulatory bankruptcy framework, we hypothesize that the probability that a firm is not able to meet its contractual claims in the future due to illiquidity exhibits further predictive power (H3). This measure adds information about the severity of expected losses and thus, should contain more insights into a firm's bankruptcy risk. Moreover, previous literature shows a link between accounting losses and firm size. For example, Klein and Marquardt (2006) find that small firms report accounting losses more frequently than larger firms. Therefore, it becomes more challenging to detect the relevant loss that is causing bankruptcy out of all losses reported. To account for this, i.e., to test if there is a size effect in the relation between expected losses and bankruptcy risk, we conduct a size analysis. That is, we interact our expected loss measures with size classes.

To test our hypotheses, we use univariate extensions of the Shumway (2001) bankruptcy prediction model. Additionally, we test the Ohlson (1980)-model and the Altman (1983)-model. In contrast to Shumway (2001), these models do not rely on market data and thus, are also applicable to private firms. We find that empirical results support all of our hypotheses. Both, in-sample and out-of-sample, our expected accounting loss measures contribute to explaining and predicting future bankruptcies.

Starting with the in-sample analysis, results reveal that our measures monotonously increase while a firm is approaching its bankruptcy date. For example, the average Illiquidity Probability five years prior to bankruptcy filing equals 21.69% and more than doubles in the year of bankruptcy filing to 54.59%. We observe similar patterns for Loss Dummy and Loss Probability. As expected, parameter estimates of our measures are statistically significant and positive. Moreover, correlation analyses reveal that our expected loss measures capture incremental accounting-based risk compared to accounting variables already controlled for, and mimic market-based risk measures. This results from relatively low correlations of our measures with Debt Ratio, but relatively strong correlations with Sigma. In consequence, including our measures has moderate effects on the parameter estimates of Debt Ratio, but stronger effects on Sigma's parameter estimates.

In terms of real forecasting ability (i.e., out-of-sample), results show substantial improvements, too. To assess forecast accuracy, we use AUC and the Shumway (2001) performance deciles. Both measures show a monotonous increase in predictive performance from hypothesis H1 to H3. For instance, while Loss Dummy increases AUC by 0.68 percentage points, accuracy can be improved even further when looking at the expected loss distribution. Replacing the binary signal by Loss Probability improves performance by additional 0.31 percentage points. When also accounting for the severity of the loss, i.e., when considering the probability that losses will deplete the current cash balance (Illiquidity Probability), forecast accuracy increases the strongest (additional 0.10 percentage points). A similar pattern can be observed for the performance deciles. For example, the 10th decile values equal 69.51%, 70.47%, 71.65%, and 73.54% for the Shumway (2001)-model, the H1-, the H2-, and the H3-extension, respectively. Additional tests reveal that our results are robust over time and when using alternative bankruptcy prediction models (e.g., Ohlson (1980) and Altman (1983)).

Concerning the size effect, we find that the parameter estimates of our measures increase in firm size, indicating that the relevance of expected accounting losses grows in firm size when assessing a firm's bankruptcy risk. We find that this is driven by the disproportionality between loss occurrence and bankruptcy filing for smaller firms. Ex ante controlling for size in the relation between expected losses and bankruptcy risk significantly improves out-of-sample forecast accuracy. For example, the interacted model using Loss Dummy increases AUC to 90.25% and the 10th decile value to 71.85%. However, performance still peaks with the interacted Illiquidity Probability model at an AUC of 90.88% and a 10th decile value of 74.72%. Hence, distributional information about expected accounting losses is still more valuable for predicting future bankruptcies than binary loss information. Overall, results of the size analysis support our hypotheses as well.

Our paper is not without limitations. To calculate our measures, we rely on profitability estimates. Therefore, these measures are affected by estimation error, possibly negatively impacting our results. Moreover, our illiquidity measure is an approximation. That is, we approximate the change in cash balance using accounting earnings. Therefore, the resulting measure is affected by measurement error, too. To address this issue, we check alternative measures that are more closely related to the change in cash balance. However, we find that our simple proxy outperforms alternative measures.

Our study has implications for everyone facing counterparty risk, especially banks and investors. By being able to assess the bankruptcy risk of a counterparty more accurately, market participants can take actions to avoid risk a priori or install mechanism to mitigate the impact the risk could have on their stake. Also, standard setters working on regulatory frameworks for banks and insurance companies should consider the insights expected accounting losses reveal about a firm's liquidity when formulating capital requirements. As empirical results reveal the strongest performance increase when taking into account the severity of a loss, we recommend incorporating loss information by using Illiquidity Probability, while accounting for size in case of heterogeneous firm sizes. In addition, our approach is neither limited to bankruptcy prediction tasks nor to one-year ahead predictions. We provide general guidance on how to quantify and assess accounting-based risk, specifically profitability risk. Therefore, the insights we provide should also be useful in applications outside of bankruptcy prediction, if the application relates to profitability, illiquidity, solvency, etc. Also, multi-period loss probabilities could be applied for multi-period bankruptcy predictions. We leave this for future research. Finally, as our method focuses solely on accounting numbers, private firms are not systematically uncovered by our measures. To elaborate, previous research on increasing predictive performance mostly refers to market variables as useful predictors (e.g., Beaver et al. (2005), Campbell et al. (2008), Beaver et al. (2012), among others). However, such models are not applicable to private firms and therefore, to an enormous share of the cross-section of firms. In contrast, any prediction model designed for private firms can be extended by our measures.

2.6 Appendices

Table A2.1: Variable Descriptions

This table contains the variable descriptions used throughout Chapter 2. All variables refer to the current period, if not noted otherwise. Panel A contains the variable descriptions for the explanatory variables used for predicting future profitability. Panel B contains the definitions of our expected accounting loss measures. Panels C to E describe the explanatory variables used in the bankruptcy prediction models by Shumway (2001), Ohlson (1980), and Altman (1983), respectively.

Variable	Description	COMPUSTAT/CRSP Variable
	Panel A: Konstantinidi and Pope (2016)-Model	
Profitability	Cash earnings, if missing, accounting earnings, scaled by total assets.	IBC / AT IB / AT
OCF	Operating cash flow minus extraordinary items and discontinued operations, scaled by total assets.	(OANCF - XIDOC) / AT
$OCF_{B/S}$	Profitability minus balance-sheet-method accruals.	Profitability - $ACC_{B/S}$
ACC	Profitability minus operating cash flow minus extraordinary items and discontinued operations, scaled by total assets.	Profitability - OCF
$ACC_{B/S}$	Change in non-cash current assets less current liabilities change without change in short-term debt and change in taxes payable minus depreciation and amortization.	(Δ(ACT - CHE) - Δ(LCT - DLC - TXP) - DP) / AT
SPI	Special items deflated by total assets.	SPI / AT
	Panel B: Accounting Loss Measures	
Loss Dummy	Variable that indicates whether the firm expects losses in the subsequent period.	$f(E[Prof]) = \begin{cases} 1, & E[Prof] < 0 \\ 0, & E[Prof] \geq 0 \end{cases}$
Loss Prob.	Probability that a firm will realize losses in the subsequent period.	$P(E[Prof] < 0)$
Illiquidity Prob.	Probability that a firm will realize losses that exceed the current cash balance in the subsequent period.	$P(E[Prof] < -CHE)$
	Panel C: Shumway (2001)-Model	
RoA	Net income deflated by total assets.	NI / AT
Debt Ratio	Long-term liabilities relative to total assets.	LT / AT
Excess Return	Past year's firm return minus value-weighted index return. Measured via monthly returns over the past 12 months.	$\sum_{t=1}^{12} Return_t - Market\ Return_t$
Sigma	Standard deviation of residuals of firm-specific time-series regressions of excess returns on market returns over the past 12 months.	$\sigma(\varepsilon_{t,CAPM})$
Relative Size	A firm's market capitalization relative to the overall market capitalization.	log(ABS(PRC) · VOL / USDVAL)

(continued)

Table A2.1: Variable Descriptions (continued)

Panel D: Ohlson (1980)-Model		
RoA	Net income deflated by total assets.	NI / AT
Debt Ratio	Long-term liabilities relative to total assets.	LT / AT
Working Capital	Working capital relative to total assets.	WCAP / AT
Current Ratio	Current liabilities relative to current assets.	LCT / ACT
Size	A firm's size.	log(AT)
Overindebted-ness	Dummy that indicates whether total liabilities exceed total assets.	$\mathrm{f(LT - AT)} = \begin{cases} 0, & \mathrm{LT - AT} \leq 0 \\ 1, & \mathrm{LT - AT} > 0 \end{cases}$
Financial Performance	Funds provided by operations relative to total liabilities.	PI / LT
Persistent Loss	Dummy that indicates whether a firm realized losses in two consecutive fiscal years.	$\mathrm{f(NI_{t,t-1})} = \begin{cases} 1, & \mathrm{NI_t, NI_{t-1}} < 0 \\ 0, & \mathrm{NI_t, NI_{t-1}} \geq 0 \end{cases}$
Net Income Change	Scaled change in net income between two consecutive fiscal years.	$\frac{\mathrm{NI_t - NI_{t-1}}}{\lvert\mathrm{NI_t}\rvert + \lvert\mathrm{NI_{t-1}}\rvert}$
Panel E: Altman (1983)-Model		
RoA (Altman)	Earnings before interest and taxes deflated by total assets.	EBIT / AT
Retained Earnings	Retained earnings relative to total assets.	RE / AT
Working Capital	Working capital relative to total assets.	WCAP / AT
Leverage	A firm's book equity relative to total liabilities.	CEQ / LT

Table A2.2: Results for the Ohlson (1980)-Model and Altman (1983)-Model

This table shows the out-of-sample performance (AUC and 10th performance decile) of one-year ahead bankruptcy forecasts for the Ohlson (1980)-model and the Altman (1983)-model. The variables included in both models are displayed in Table A2.1. Panel A contains the time-series averages for the non-interacted Ohlson (1980)-model. Panel B contains the time-series averages for the size-interacted Ohlson (1980)-model. Analogously, Panel C and Panel D show results for the Altman (1983)-model.

Panel A: Ohlson (1980)-Model

Variable	Ohlson (1980)	Ohlson (1980) Loss Dummy	Ohlson (1980) Loss Prob.	Ohlson (1980) Illiquidity Prob.
AUC	86.68	87.80	88.40	88.38
10th Decile	62.98	65.57	67.76	68.96

Panel B: Size-Interacted Ohlson (1980)-Model

Variable	Ohlson (1980)	Ohlson (1980) Loss Dummy	Ohlson (1980) Loss Prob.	Ohlson (1980) Illiquidity Prob.
AUC	86.68	87.96	88.94	89.01
10th Decile	62.98	65.73	67.82	68.65

Panel C: Altman (1983)-Model

Variable	Altman (1983)	Altman (1983) Loss Dummy	Altman (1983) Loss Prob.	Altman (1983) Illiquidity Prob.
AUC	83.87	86.87	87.39	87.14
10th Decile	58.54	64.47	64.90	66.51

Panel D: Size-Interacted Altman (1983)-Model

Variable	Altman (1983)	Altman (1983) Loss Dummy	Altman (1983) Loss Prob.	Altman (1983) Illiquidity Prob.
AUC	83.87	87.37	88.58	88.48
10th Decile	58.54	64.80	66.66	67.63

Chapter 3

Using the Expected Profitability Distribution to Predict SME Bankruptcy

3.1 Introduction

Worldwide, small and medium enterprises (SMEs) play a crucial role and are considered the backbone of many economies (e.g., Altman and Sabato (2007) or Gupta et al. (2015)). For example, in the 27 member states of the European Union (EU) in 2020, SMEs accounted for more than 99% of all enterprises, contributed to 53% of total value added by enterprises and generated 65% of employment (European Commission (2021)).[31] Given this economic significance, it is important to understand the factors of SME failure. Yet, research focusing on SME failure prediction starts only in recent years with Altman and Sabato (2007). The increased interest in SME failure prediction is motivated by the revised international capital framework (Basel II), as it links minimum capital requirements for credits directly to the customer's level of risk (Ciampi (2015)). It allows banks to use internal measures as inputs for the computation of minimum capital requirements, with the main input being the customer's one-year ahead default probability (e.g., Bhimani et al. (2010) or Calabrese et al. (2016)). Altman and Sabato (2007) provide evidence that using a specific SME failure prediction model instead of a generic corporate model results in more accurate default predictions. Subsequently, they show that this potentially lowers banks' capital requirements, and in turn, lowers SME customers' interest costs. The superior performance of the SME model can be attributed to the fact that there are substantial differences between SMEs and larger, i.e., public, firms. For instance, SMEs are generally riskier, pay higher interest costs, rely mostly on debt financing, face higher financing constraints, and are more leveraged (e.g., Dietsch and Petey (2004), Beck et al. (2006), Brav (2009), or Saunders and Steffen (2011)). These differences suggest that different factors

[31] The numbers refer to firms in the non-financial business sector.

influence the default risk of SMEs and public firms, respectively (Charalambakis and Garrett (2019)). Taken together, SMEs crucial role in economies worldwide, the change in banking regulations, and the fundamental differences to public firms, all highlight the importance of specific SME failure prediction models (Ciampi (2015)).

Given this relevance, following Altman and Sabato (2007), several studies focusing on SME failure prediction have been published (e.g., Altman et al. (2010), Bhimani et al. (2013), Ciampi (2015), Gupta et al. (2015), Filipe et al. (2016), Charalambakis and Garrett (2019), among others). The bigger part of these studies tries to account for the fact that SMEs have fewer disclosure obligations regarding financial statement data and that the published data is often less reliable and accurate (e.g., Altman et al. (2010) or Ciampi and Gordini (2013)). Therefore, the models additionally incorporate variables that go beyond the traditional accounting ratios based on leverage, profitability, coverage, solvency, and activity that are used in public firm failure prediction models (e.g., Altman (1968)). For example, Bhimani et al. (2013) include macroeconomic measures and information about ownership and management, Ciampi (2015) incorporates corporate governance characteristics, and Filipe et al. (2016) account for country-specific business cycles, credit conditions, and insolvency codes.

A further point to consider is that traditional accounting ratios are backward-looking. i.e., they represent past financial statement information. As failure prediction is per se a future-oriented process, a model including expectations about future firm characteristics is potentially more accurate (Vater and Wolf (2022)).

Hence, this paper aims to add to the trend of extending SME failure prediction models beyond traditional accounting ratios by supplementing these models with firm-specific forward-looking measures. Recent literature provides evidence that forward-looking measures based on the expected profitability distribution are related to common risk measures like equity and bond ratings (e.g., Konstantinidi and Pope (2016), Correia et al. (2018), or Chang et al. (2021)). Further, Vater and Wolf (2022) analyze the role of expected profitability distributions in public firm bankruptcy prediction. They show that information about the expected profitability distribution, particularly the area covering expected losses, significantly improves the predictive accuracy of the bankruptcy predictions models by Shumway (2001), Altman (1983), and Ohlson (1980). Given the worldwide importance of SMEs, I use an approach similar to Vater and Wolf (2022) and analyze if measures based on the expected profitability distribution also improve SME bankruptcy prediction accuracy.[32]

[32] While the estimated expected profitability distributions are still based on SME accounting data that is subject to the criticism stated above, research provides evidence that earnings or profitability forecasts based on accounting data show high accuracy (e.g., Hou et al. (2012), Li and Mohanram (2014), or Tian et al. (2021)).

For my analysis, I use a sample of German SMEs for the period from 2010 to 2019. In Germany, 99.40% of firms are SMEs (Federal Statistical Office of Germany (2021)). While US private firms are not obligated to publish their financial statements, in Germany, a substantial proportion of private firms must publish their annual accounts.[33] Additionally, in terms of economic significance, Germany is Europe's biggest and worldwide the fourth biggest economy (International Monetary Fund (2021)). Therefore, Germany seems to be an excellent testing ground for SME related studies (Dierkes et al. (2013)).

For the empirical analysis, I extend the model by Altman and Sabato (2007) by three loss measures based on the expected profitability distribution.[34] To compute these measures, I estimate out-of-sample firm-specific conditional distributions of future profitability following Chang et al. (2021). Using these estimates, I implement a concept similar to value at risk (VaR). VaR is typically defined as a value not exceeded given a certain probability. I rearrange the concept and compute three firm-specific probabilities of expected accounting losses exceeding certain thresholds. First, I measure the probability that a firm will realize losses in general, i.e., that losses are greater than zero. Second, I estimate the probability that losses will consume current cash balances, i.e., a firm is incapable to fulfil its financial obligations. This serves as a proxy for illiquidity. Third, I compute the probability that losses exceed book equity, i.e., that a firm has negative book equity. This signals that a firm's assets no longer cover its liabilities and thus, that the firm is overindebted.

The first two measures are also tested by Vater and Wolf (2022). They argue that firms that are expected to be unprofitable differ from expectedly profitable firms in terms of bankruptcy risk. Thus, the probability to realize losses should improve bankruptcy prediction. Further, they point out that there is potentially a strong relation between expected illiquidity and future bankruptcy, as the inability to fulfil financial obligations is intuitively the economic rationale for bankruptcy filing. This is also reflected in the German insolvency statute (section 17 to 19). Section 17 states that illiquidity is the general reason to file for bankruptcy and that a debtor is illiquid if he cannot pay his mature obligations. Moreover, section 18 says that imminent illiquidity, i.e., the likely inability to pay obligations on the date of their future maturity, is also a reason for bankruptcy filing. Hence, I expect that there is a strong link between illiquidity and bankruptcy filing for German firms, too. A novelty of this study is the third measure, as it accounts for a special feature of German bankruptcy law that is not present in US bankruptcy law. In Germany, a firm must file for bankruptcy when liabilities exceed

[33] Not all German private firms are obligated to publish their financial statements, but only corporations, i.e., firms with limited liability.

[34] Further, Table A3.3 shows that the tenor of results is unchanged when extending the models by Altman (1983) and Ohlson (1980).

assets, i.e., in case of negative book equity, unless it is highly probable that the firm recovers. This is determined by section 19 of the German insolvency statute. Therefore, I also expect a strong relation between overindebtedness and bankruptcy filing for German firms.

A further aspect addressed by Vater and Wolf (2022) is that smaller firms report losses more frequently than larger firms (e.g., Klein and Marquardt (2006)). They argue that the expected loss measures potentially depend on firm size. Thus, they perform a size analysis by interacting the loss measures with size classes. As the sample used in this study also consists of firms with varying size, I perform a size analysis as well.

I find that, in line with expectations, incorporating the expected loss probability or the expected illiquidity probability significantly improves the accuracy of SME bankruptcy prediction models. For example, including the expected illiquidity probability increases the "10^{th} performance decile" criterion introduced by Shumway (2001) by 3.41 percentage points compared to the initial model by Altman and Sabato (2007). Including the expected loss probability shows an even stronger improvement of 5.38 percentage points. Time-series analysis indicates that the improvements hold for the bigger part of the sample period. This provides evidence for a strong relation between both measures and SME bankruptcy risk. Results for the expected overindebtedness probability are not as significant. The 10^{th} performance decile only increases by 0.38 percentage points, indicating that there is a weaker link to SME bankruptcy risk. A possible explanation is that firms do not immediately file for bankruptcy in case of overindebtedness, as the insolvency statute leaves firms some leeway, i.e., they expect a recovery. Overall, findings indicate that the expected loss probability performs best. In addition, I provide evidence that the results are robust to industries, SME size classes, and location. Using a hypothesized competitive loan market, I also show that banks potentially benefit economically from implementing the expected loss probability.

Further, the size analysis only partly provides evidence for a size effect in the relation between the expected loss measures and SME bankruptcy risk. On the one hand, regression results show that the relevance of the loss signal decreases for firms with more frequent losses, whereas it increases for firms with less frequent losses. On the other hand, this finding does not translate to a significantly increased out-of-sample performance. However, this is in line with the results of Gupta et al. (2015) as they show that there is no need to consider small and medium firms separately when predicting SME bankruptcy.[35]

This paper contributes to the literature as follows. First, I incorporate firm-specific forward-looking measures into SME failure prediction models. To my knowledge, no other

[35] While I only interact the expected loss measures with size classes, untabulated tests show that interacting the full model with size classes does not improve out-of-sample performance either.

SME study incorporates such measures. While public firm failure prediction models are able to incorporate forward-looking information by including market-based variables, SME failure prediction models based on accounting information typically lack this information. Second, I provide evidence that the expected profitability distribution, particularly the area covering losses, is related to SME bankruptcy risk and thus, is a strong predictor for SME bankruptcy filing. This confirms the results of Vater and Wolf (2022) for public firms. Third, I add to the debate whether considering SME size classes separately improves SME bankruptcy prediction accuracy (e.g., Gupta et al. (2015) or El Kalak and Hudson (2016)). I find that interacting the expected loss measures with size classes does not improve out-of-sample accuracy.

To summarize, specifically the expected loss probability shows promising results and banking institutions should incorporate this measure when assessing SME bankruptcy risk. This results in more accurate predictions, potentially leading to lower capital requirements and lower credit costs for SME customers.

The remainder of this paper is structured as follows. Section 3.2 provides a brief overview of related literature. Section 3.3 outlines the methodology, and Section 3.4 depicts the data and variables used for the empirical analysis. Section 3.5 presents the empirical results. Section 3.6 summarizes the findings and concludes.

3.2 Related Literature

This section provides an overview of SME and private firm failure prediction literature. Further, it presents studies that link expected profitability to risk measures.

SME Failure Prediction

With the introduction of Basel II in the early 2000s, SME failure prediction starts gaining popularity.[36] Altman and Sabato (2007) are the first to develop a bankruptcy prediction model for SMEs. Their model includes five variables that cover leverage, liquidity, profitability, coverage, and activity. They find that their model outperforms a generic corporate model, highlighting the fact that SMEs are different from larger corporations regarding credit risk, and that SME specific failure prediction models are needed.

Most studies related to SME failure prediction try to account for the fact that SMEs have fewer disclosure obligations regarding financial statement data and that the data is less reliable

[36] Before, there are only few studies that mainly focus on small firm, e.g., Edmister (1972), Keasey and Watson (1987), or Keasey and Watson (1988).

by additionally incorporating non-financial information (e.g., Altman et al. (2010) or Ciampi and Gordini (2013)). The following passage lists several exemplary studies.[37]

Altman et al. (2010) update the bankruptcy prediction model of Altman and Sabato (2007) to include a wide range of non-financial information, reflecting characteristics such as financial reporting compliance, internal audit, trade credit relationships, age, size, and industry failure rate. They find that including non-financial information significantly increases the model's predictive ability. Bhimani et al. (2010, 2013, and 2014) define several credit default prediction models for private firms using financial, macroeconomic, and non-financial variables. The non-financial variables cover size, age, industry, geographic region, and owner liability status. They find that these variables play an important role in private firm default prediction as they significantly improve the predictive ability of the models. Ciampi (2015) introduces a default prediction model for small firms which incorporates financial and corporate governance data. The corporate governance variables cover CEO duality, board independence, board size, and ownership concentration. He finds that a model containing both financial and corporate governance variables has greater predictive ability than a model based solely on financial ratios. Filipe et al. (2016) develop a distress prediction model for European SMEs that incorporates idiosyncratic and systematic predictors. The idiosyncratic variables include financial ratios and non-financial information, i.e., size, age, legal form, location, industry, and number of shareholders. The systematic variables cover business cycle, credit conditions, and insolvency codes. They provide evidence that SMEs across different European countries are affected by common idiosyncratic factors, but the relevant systematic factors vary by country. Moreover, they find that smaller firms are more vulnerable to systematic factors, and contrary to other studies (e.g., Bhimani et al. (2010)), that industry classifications often show no significance. Altman et al. (2017) analyze the predictive performance of the Z''-Score model introduced by Altman (1983) on a large international dataset of 34 mainly European countries. They show that the model performs reasonably well in an international context, especially when country-specific coefficients are estimated. Additionally, they test various modifications of the model using non-financial variables, i.e., age, size, industry, country specific risk, and year. They conclude that the inclusion of these variables generally increases the predictive ability of the Z''-Score model, but that the strength of the effect is country-dependent.

Accounting for differences between SME size classes, Gupta et al. (2015) develop separate failure prediction models for micro, small and medium sized firms, and for SMEs in general.

[37] Giving a complete literature review would go beyond the scope of this section. There are further studies that use non-financial information but the relation to my research question is limited (e.g., Gupta et al. (2014), Charalambakis and Garrett (2019), among others).

Their results show that there is no need to consider small and medium firms separately from SMEs, as almost the same factors influence default probabilities for these firms. However, they find that micro firms are influenced by different explanatory variables than SMEs. El Kalak and Hudson (2016) follow a similar approach to Gupta et al. (2015) but use US data instead of UK data. They also conclude that micro firms need to be modeled separately from SMEs and that medium firms are not affected by different factors than SMEs. However, contrary to Gupta et al. (2015), they find that small firms are also influenced by different explanatory variables than SMEs in general, and thus, they need to be considered separately when predicting failure, too. Gupta et al. (2018) also take size classes into account and additionally distinguish between bankruptcy and financial distress prediction. For bankruptcy prediction, they find that the factors that influence bankruptcy probabilities vary between size categories and advise to use individual models for each size category. When forecasting financial distress, they provide evidence that the individual size categories are not affected by different explanatory variables compared to SMEs in general.

There are only few studies that primarily focus on Germany.[38] Grunert et al. (2005), using a unique dataset provided by four major German banks, develop a failure prediction model for medium sized firms using financial and non-financial information. The banks provide firm-specific non-financial information regarding rating categories, management quality, and market position. The results suggest that including both financial and non-financial variables yields a significantly higher predictive ability than only using one variable category. Likewise using German data, Dierkes et al. (2013) test whether incorporating business credit information into a private firm default prediction model increases the forecast accuracy. The business credit information includes data about a firm's payment history with business partners, its creditworthiness, its order book, and its business outlook. Further, they use data regarding the credit bureau office that covers the firms. They find that including the information named above significantly improves the accuracy of failure predictions.

Related to the forecasting methodology I use in this study, Gupta et al. (2016) test whether discrete-time or continuous-time hazard models produce more accurate SME failure forecasts. Although the difference in results between both approaches is not fundamental, they conclude that discrete-time hazard models are superior to continuous-time hazard models.

[38] Filipe et al. (2016) and Altman et al. (2017) also cover Germany, but they include several other countries as well.

Risk in Expected Profitability

Hou et al. (2012) introduce model-based earnings forecasts as an alternative to analysts' earnings forecasts. Using a cross-sectional approach, these forecasts minimize firm-specific data history requirements and hence, do not induce survivorship bias in contrast to time-series models. The authors find that their forecasts show larger earnings response coefficients (e.g., Ball and Brown (1968) or Brown et al. (1987)) and lead to more accurate expected return proxies compared to analysts' forecasts. Li and Mohanram (2014) further improve the approach by Hou et al. (2012) by differentiating between the earnings persistence of profit and loss firms, adjusting earnings for special items, and estimating earnings per share instead of firm-level earnings. They find that their model outperforms the model by Hou et al. (2012).

Konstantinidi and Pope (2016) test if measures based on the distribution of future profitability capture risk.[39] Using quantile regressions, they estimate expected level, dispersion, skewness, and kurtosis (i.e., higher moments) of future profitability.[40] They show empirical evidence that these measures are correlated with common risk proxies, e.g., corporate bond spreads and credit risk ratings. Based on these findings on the distributional properties of future earnings, Correia et al. (2018) test if the higher moments of future profitability also improve bankruptcy prediction of bond issuers. They find that mainly the dispersion measure significantly predicts future bankruptcies when also controlling for alternative risk measures. Chang et al. (2021) question the consistency of the estimates by Konstantinidi and Pope 2016 and Correia et al. (2018). They argue that (i) using ad hoc formulas for the calculation of the higher moments, and (ii) quantile crossing, might lead to inconsistencies. Therefore, instead of forecasting selected percentiles to approximate the higher moments, they estimate the entire distribution. This enables them to use general statistical formulas to compute the higher moments. Further, they employ a rearrangement method by Chernozhukov et al. (2010) that prevents quantile crossing. They find that these consistent measures are related to credit spreads and equity prices, providing further empirical evidence on the relevance of forward-looking risk measures.

Using these findings, Vater and Wolf (2022) investigate the role of expected accounting losses in bankruptcy prediction. They argue that the area of the profitability distribution covering losses should be of higher interest when assessing a firm's bankruptcy risk. Following Chang et al. (2021), they estimate firm-specific expected profitability distributions and compute VaR-based loss measures. In contrast to the higher moments that are based on the entire

[39] For their analysis, Konstantinidi and Pope (2016) use earnings scaled by total assets, i.e., profitability.

[40] A recent paper by Tian et al. (2021) provides evidence that earnings forecasts based on quantile regressions, specifically median regressions, outperform those forecasts generated by Ordinary-Least-Squares regressions in predictive accuracy.

distribution, these measures focus solely on the area of the distribution covering losses. They find that particularly the expected probability to realize future losses and the expected probability of future losses consuming current cash balances significantly improves the accuracy of bankruptcy prediction models. Additionally, they provide evidence for a size effect in the relation between expected losses and bankruptcy risk

Given the significant results of Vater and Wolf (2022) for public firm bankruptcy prediction and SMEs' crucial role in economies worldwide, I analyze if measures based on the expected profitability distribution also improve SME bankruptcy prediction.

3.3 Methodology

To conduct my analysis, I follow a three-step approach. First, I forecast firm-specific future profitability distributions. Second, using these distributions, I compute three expected firm-specific probabilities of accounting losses exceeding certain economic thresholds. Third, I test if these measures improve the accuracy of SME bankruptcy prediction models.

Predicting Future Profitability Distributions

Following Chang et al. (2021), I estimate the quantile function of one-year ahead profitability using quantile regressions (e.g., Koenker and Bassett (1978) and Angrist and Pischke (2009)). The quantile function is based on the out-of-sample estimation of 150 quantiles evenly spread between 0 and 1. To obtain the individual quantile estimates, quantile regression solves the following minimization problem:

$$\begin{aligned} Q_\tau\left(\mathrm{Prof}_{i,t+1} \middle| X_{i,t}\right) &= \arg_{\beta_\tau} \min E\left[\rho_\tau\left(\mathrm{Prof}_{i,t+1} - X'_{i,t}\beta_\tau\right)\right] \\ &= \arg_{\beta_\tau} \min E\left[\rho_\tau\left(u_{i,t+1}\right)\right] \\ &= \arg_{\beta_\tau} \min E\left[\tau \cdot \left|u_{i,t+1}\right|_{u_{i,t+1}>0} + (1-\tau) \cdot \left|u_{i,t+1}\right|_{u_{i,t+1}\leq 0}\right] \end{aligned} \tag{3.1}$$

where Q_τ is the τ^{th} percentile of expected profitability $\mathrm{Prof}_{i,t+1}$, conditional on the information set $X_{i,t}$. It is derived by minimizing the check function $\rho_\tau(u_{i,t+1})$ that weighs the forecast errors $u_{i,t+1}$ asymmetrically.[41] Subsequently, I generate firm-specific cumulative distribution functions by inverting the estimated quantile functions.

Using this approach, quantile crossing is an issue that might occur. Due to estimation errors, the estimated percentiles are not monotonously increasing, i.e., lower percentiles might

[41] See Konstantinidi and Pope (2016) for a more detailed description of the approach.

exceed higher percentiles. This appears mainly in the tails of the distribution and leads to inconsistent quantile functions. To solve this problem, Chernozhukov et al. (2010) introduce a rearrangement method that results in consistent quantile functions. In line with Chang et al. (2021), I implement this method and thus, ensure that the three probability measures are based on consistently estimated quantile functions.

To generate the quantile estimates, I use the earnings persistence (EP) model by Li and Mohanram (2014):

$$\mathrm{Prof}_{i,t+1} = \beta_0 + \beta_1 \cdot \mathrm{Prof}_{i,t} + \beta_2 \cdot \mathrm{NegProf}_{i,t} + \beta_3 \cdot \mathrm{NegProf}_{i,t} \cdot \mathrm{Prof}_{i,t} + \varepsilon_{t+1} \tag{3.2}$$

where $\mathrm{Prof}_{i,t+1}$and $\mathrm{Prof}_{i,t}$ are asset-scaled earnings, $\mathrm{NegProf}_{i,t}$ is a dummy variable that equals one for firms with negative profitability and 0 otherwise, and $\mathrm{NegProf}_{i,t} \cdot \mathrm{Prof}_{i,t}$ is an interaction term of the dummy variable and profitability.[42] I select the EP model as only earnings and total assets are needed for the estimation. This takes into account that SMEs often have fewer disclosure obligations regarding financial statement data and that no market data is available.

The model estimation is performed annually at the end of December. To estimate the model, I use an increasing time window.[43] That is, in the first iteration, the model is estimated on two years of data, in the second iteration, the model is estimated on three years of data, and so forth. Subsequently, I compute out-of-sample firm-specific estimates for the 150 quantiles by combining the respective quantiles' parameter estimates with current profitability, the respective dummy variable, and the corresponding interaction term. This results in time-varying firm-specific quantile functions and conditional distributions, as profitability and hence, predicted quantiles, change across firms and over time.

Loss Probability Measures

Using the profitability distributions obtained in the previous step, a concept similar to VaR is implemented. However, while a VaR is typically defined as a value not exceeded given a certain probability, the approach is rearranged here. I calculate three expected firm-specific probabilities of accounting losses exceeding certain economic thresholds:[44]

[42] For a detailed variable description, see Section 3.4 or Table A3.1.
[43] The tenor of results is unchanged using a two-year rolling window.
[44] The probability measures are based on a concept introduced by Hüttemann (2019). Assuming a standard normal distribution, he uses the mean and standard deviation of an individual firm's conditional earnings estimate to compute the probability that a firm's future losses exceed currently available book equity. I deviate from this approach by directly estimating the underlying distribution of future earnings and by using losses and current cash balances as additional threshold values.

(i) Loss Probability: $P(E[\mathrm{Prof}_{t+1}] < 0)$

(ii) Illiquidity Probability: $P(E[\mathrm{Prof}_{t+1}] < -\mathrm{Cash\ Balance}_t)$

(iii) Overindebtedness Probability: $P(E[\mathrm{Prof}_{t+1}] < -\mathrm{Book\ Equity}_t)$

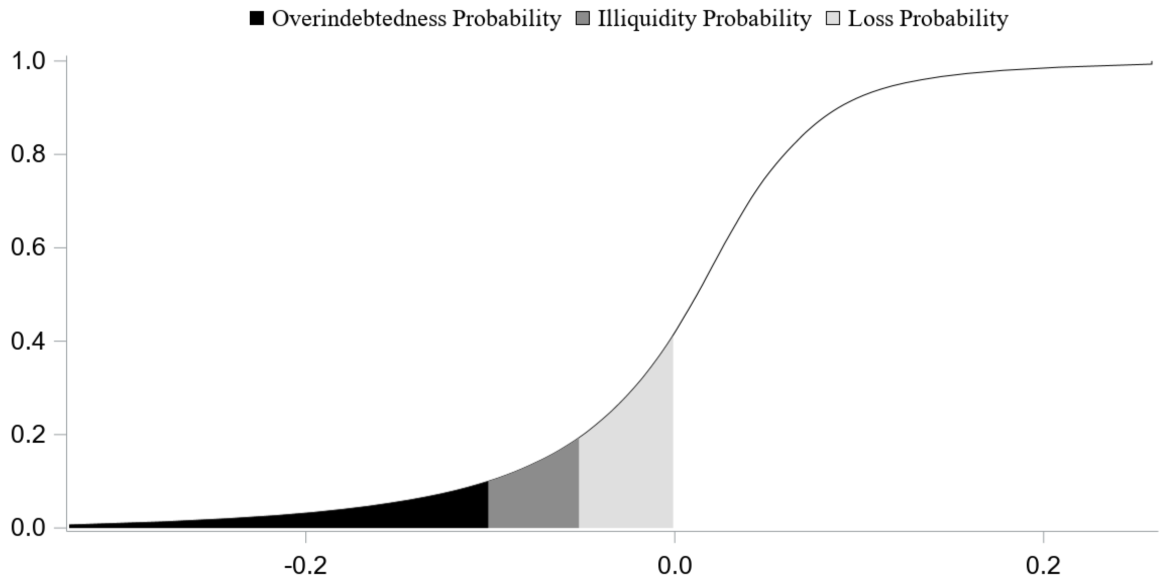
First, Loss Probability is equal to the largest quantile of the profitability distribution with negative profitability, i.e., showing the probability to realize accounting losses in general in the following period. It presents the value of the VaR's inverse function when using future accounting losses as threshold. The rationale for this measure is that bankruptcy risk should differ for expectedly unprofitable and expectedly profitable firms. I expect a positive relation between bankruptcy risk and Loss Probability. Second, Illiquidity Probability is the value of the VaR's inverse function when defining future accounting losses depleting current cash balances as threshold. It serves as a proxy for illiquidity, i.e., a firm's inability to fulfil its financial obligations. There should be a strong relation between expected illiquidity and future bankruptcies, as the inability to fulfil financial obligations is intuitively the economic rationale for bankruptcy filing. This is also reflected in the German insolvency statute. Section 17 of the statute states that illiquidity is the general reason to file for bankruptcy and that a debtor is illiquid if he cannot pay his mature obligations. Moreover, section 18 says that imminent illiquidity, i.e., the likely inability to pay obligations on the date of their future maturity, is also a reason for bankruptcy filing. Therefore, I expect a strong positive relation between Illiquidity Probability and bankruptcy risk. Third, Overindebtedness Probability is the value of the VaR's inverse function when defining future accounting losses depleting current book equity as threshold. This results in negative book equity, signaling that a firm's assets no longer cover its liabilities. Section 19 of the German insolvency statute states that a firm must file for bankruptcy when liabilities exceed assets unless that it is highly probable that the firm recovers. Hence, I also expect a strong relation between Overindebtedness Probability and bankruptcy filing.

Figure 3.1 visualizes the three probability measures using an exemplary cumulative distribution function. The sum of the light gray, dark gray, and black area assesses Loss Probability, i.e., the probability to be unprofitable in the subsequent fiscal year. The combination of the dark gray and black area shows Illiquidity Probability. It moves the reference point from being unprofitable to losses depleting current cash balances. The black area displays Overindebtedness Probability, i.e., the probability that losses deplete book equity.[45]

[45] Note that this is a cumulative distribution function for an exemplary firm. For other firms, current cash balances might exceed book equity, i.e., the dark gray and black area are swapped.

Figure 3.1: Visualization of the Three Probability Measures

This figure visualizes the three probability measures using an exemplary cumulative distribution function. The combined light gray, dark gray, and black area assesses Loss Probability. The combination of the dark gray and black area shows Illiquidity Probability. The black area displays Overindebtedness Probability.



It is important to highlight that Illiquidity Probability only serves as a proxy for illiquidity as actual illiquidity is mainly driven by the net cash outflow over a fiscal period (Vater and Wolf (2022)). A firm faces illiquidity, i.e., it is unable to pay further obligations, if net cash outflow depletes the current cash balance. However, in terms of financial reporting, net cash outflow cannot exceed the current cash balance.[46] Therefore, finding a reliable estimate of future illiquidity is challenging, as the contractual claims that potentially exceed the cash balance are not observable. To address this issue, in line with Vater and Wolf (2022), I use profitability to approximate this risk of becoming unable to pay, as profitability is related to cash flow and not restricted by the cash balance.[47]

Bankruptcy Prediction

In line with previous SME failure prediction literature (e.g., Gupta et al. (2015) or Filipe et al. (2016)), I use a discrete hazard model, i.e., a logistic regression model with multiple observations per firm (Shumway (2001)), to predict firm-specific one-year ahead bankruptcy probabilities:

[46] Reporting a negative cash balance in the balance sheet occurs very rarely. In case a firm overdraws its cash balance, it is typically recognized as a liability position.

[47] Literature provides evidence for a strong relation between earnings and cash flows (e.g., Bowen et al. (1986) or Dechow et al. (1998)). Further, I also test other approximations. I use direct estimates of change in cash balance predicted by an auto-regressive model and cash flow forecasts estimated using specific cash flow forecast models (e.g., Barth et al. (2001)). However, untabulated results show that the alternative proxies lead to noisier estimates, resulting in worse out-of-sample performance compared to the approximation based on profitability.

$$P_{i,t}(y_{i,t} = 1 | X_{i,t}) = \frac{1}{1 + \exp(-X'_{i,t}\beta)} \tag{3.3}$$

where $y_{i,t}$ is a dummy variable indicating if a firm files for bankruptcy within the subsequent twelve months, $X'_{i,t}$ is the set of explanatory variables, and β is the vector of parameters.

To estimate out-of-sample bankruptcy probabilities, I use the model specification of Altman and Sabato (2007) as benchmark. I select this model specification as Altman and Sabato (2007) analyze various financial ratios and select the ones that predict SME failure best. They show that their model exhibits high forecast accuracy and significantly outperforms a generic corporate model. Further, only basic financial statement data is needed. Analogous to the profitability forecast model, this takes into account that SMEs often have fewer disclosure obligations and that no market data is available. The linear regression model is denoted by the following equation:

$$\begin{aligned} X'_{i,t}\beta = {} & \beta_0 + \beta_1 \cdot \mathrm{EBITDA/TA}_{i,t} + \beta_2 \cdot \mathrm{STD/BKEQ}_{i,t} + \beta_3 \cdot \mathrm{RE/TA}_{i,t} \\ & + \beta_4 \cdot \mathrm{CASH/TA}_{i,t} + \beta_5 \cdot \mathrm{EBITDA/INT}_{i,t} \end{aligned} \tag{3.4}$$

where $\mathrm{EBITDA/TA}_{i,t}$ is EBITDA divided by total assets, $\mathrm{STD/BKEQ}_{i,t}$ is short-term debt divided by book equity, $\mathrm{RE/TA}_{i,t}$ is retained earnings divided by total assets, $\mathrm{CASH/TA}_{i,t}$ is cash balance divided by total assets, and $\mathrm{EBITDA/INT}_{i,t}$ is EBITDA divided by interest expense.[48] The variables represent the categories profitability, leverage, coverage, liquidity, and activity, respectively. All variables but short-term debt divided by book equity are expected to have a negative relation to SME bankruptcy risk.

To test if the three probability measures based on out-of-sample estimated profitability distributions add value to SME bankruptcy prediction, I extend the benchmark model univariately with the three measures. For simplicity, in the following equation, the explanatory variable $Z_{i,t}$ is representative for each of the three probability measures.

$$\begin{aligned} X'_{i,t}\beta = {} & \beta_0 + \beta_1 \cdot \mathrm{EBITDA/TA}_{i,t} + \beta_2 \cdot \mathrm{STD/BKEQ}_{i,t} + \beta_3 \cdot \mathrm{RE/TA}_{i,t} \\ & + \beta_4 \cdot \mathrm{CASH/TA}_{i,t} + \beta_5 \cdot \mathrm{EBITDA/INT}_{i,t} + \beta_6 \cdot Z_{i,t} \end{aligned} \tag{3.5}$$

[48] Detailed variable definitions are presented in Section 3.4 and Table A3.1.

Analogous to the prediction of the profitability distribution, the models are estimated annually at the end of December using an increasing time window. I compute out-of-sample firm-specific bankruptcy probabilities by combining the respective parameter estimates with current financial data.

Performance Evaluation

To evaluate if the three probability measures improve the in-sample fit of the regression model, I use the Akaike (1974) Information Criterion (AIC) (e.g., Gupta et al. (2016)). It is used to compare competing model specifications applied to the same task (i.e., SME bankruptcy prediction) on the same data set while controlling for model complexity. It helps to provide evidence that the three probability measures in fact capture SME bankruptcy risk. AIC is given by the following equation:

$$\mathrm{AIC} = -2 \cdot \mathrm{Log\ L} + 2 \cdot \mathrm{p} \tag{3.6}$$

where Log L equals the log likelihood and p equals the number of explanatory variables including the intercept. Lower AIC values indicate a better model fit while avoiding overfitting.

To evaluate the out-of-sample performance, i.e., to assess if the three probability measures improve predictive accuracy, I use two test statistics commonly employed in bankruptcy prediction literature (e.g., Shumway (2001), Altman et al. (2010), or Filipe et al. (2016)). First, I use the "Area Under the Receiver Operating Characteristics Curve" (AUC). Based on the predicted bankruptcy probabilities, the "Receiver Operating Characteristics" (ROC) curve plots true positive rates against false positive rates for all classification cut-off values between 0 and 1. The area under this curve measures how well the model discriminates between bankrupt and non-bankrupt firms. A value of 0.5 stands for a random allocation (i.e., no predictive ability) and a value of 1.0 implies perfect discrimination. Second, I use the performance decile measure introduced by Shumway (2001). To compute the measure, observations are sorted into deciles based on their predicted bankruptcy probability. After actual bankruptcies become observable in the subsequent twelve months, the share of actual bankruptcies in each decile is calculated. I mainly focus on the 10$^{\text{th}}$ decile. The higher the fraction of bankrupt firms in deciles with the highest predicted bankruptcy probabilities, the better the predictive performance of a model. From a practitioner's point of view, it shows the number of defaults a bank can potentially avoid if it does not grant loans to firms with high bankruptcy probabilities. I calculate AUC and the performance deciles annually and report time-series averages.

However, both AUC and the performance decile measure do not take into account that for banks in practice, the cost of a type I error (classifying a bankrupt firm as non-bankrupt) and of a type II error (classifying a non-bankrupt firm as bankrupt) substantially differs. In case of a type I error, a bank can potentially lose the total loan amount, while a type II error only leads to a revenue loss (Blöchlinger and Leippold (2006)). To account for the differing misclassification costs and to link the predictive accuracy of a bankruptcy prediction model to its economic impact on a bank's credit business, I employ an approach similar to Agarwal and Taffler (2008). I assume two competing banks in a loan market worth EUR 100 billion.[49] Further, all loans are of the same size. To assess a customer's credit risk, one bank uses the initial model by Altman and Sabato (2007) and the other bank uses the best performing extended model.[50] Potential customers are the German SMEs analyzed in this study. Banks reject the 5% of firms with the highest bankruptcy probability according to the respective model. For the remaining SMEs, each bank quotes a credit spread based on the following equation derived by Blöchlinger and Leippold (2006):

$$R_{i,t} = \frac{P_{i,t}(Y = 1)}{P_{i,t}(Y = 0)} \cdot LGD + k \tag{3.7}$$

where $R_{i,t}$ is the credit spread, $P_{i,t}(Y = 1)$ is the calculated probability of bankruptcy, $P_{i,t}(Y = 0)$ is the calculated probability not to file for bankruptcy, LGD is the loan loss given default, and k is the credit spread for the highest quality loan. In line with Agarwal and Taffler (2008), I set LGD to 45.00% and k to 0.30%. Customers choose the bank that quotes the lowest spread. Based on the resulting loan distribution between both banks, I report the corresponding market share, default share, average credit spread, revenue, loss, profit, and return on assets for the total sample period.

3.4 Data and Variables

The sample used for the empirical analysis is taken from Bureau van Dijk's (BvD) Amadeus database. It covers the period from 2010 to 2019 and consists of private German SMEs. Banks and insurance companies are generally excluded from the Amadeus database. In line with recent literature (e.g., Filipe et al. (2016) or Gupta et al. (2016)), SMEs are defined

[49] The size of the loan market is analogous to Agarwal and Taffler (2008). Relative results between both banks are invariant to the size of the loan market.
[50] The performance is evaluated using AUC and 10th performance decile values.

Table 3.1: Number of Bankrupt and Non-Bankrupt Firms per Year

This table contains the number of non-bankrupt and bankrupt firm-years and the corresponding bankruptcy rates in the sample period from 2010 to 2019.

Year	Non-Bankrupt Firm-Years	Bankrupt Firm-Years	Bankruptcy Rate (%)
2010	30,418	-	-
2011	32,419	185	0.57
2012	34,507	303	0.87
2013	35,886	112	0.31
2014	35,705	142	0.40
2015	26,030	112	0.43
2016	23,513	98	0.42
2017	22,779	44	0.19
2018	22,278	114	0.51
2019	22,312	124	0.55
Total	285,847	1,234	0.48

based on the guidelines of the European Commission (2003), i.e., medium-sized (small-sized) enterprises encompass firms with total assets between EUR 10 million and EUR 43 million (EUR 2 million and EUR 10 million). Further, owners must have limited liability (e.g., Altman et al. (2017)).[51] Based on section 325 of the German commercial code, I implement a 12-month reporting lag for firm fundamentals to become publicly available. Information about bankruptcies is also taken from BvD. Firm observations are marked as bankrupt, if the legal status is “Active (insolvency proceedings)” and the corresponding legal status date is in the twelve months following the lagged financial statement publishing date. In addition, from 2018 onwards, the bankruptcy data included in the BvD Amadeus database is supplemented by a bankruptcy database provided by Dieter Hess.[52] This database is compiled by crawling the daily official online releases on the website of the German business register. Therefore, it contains a virtually complete list of all German bankruptcies. Further, observations of bankrupt firms after the bankruptcy filing date are deleted (e.g., Correia et al. (2018)), and in case of multiple bankruptcy entries for a single firm, I keep only the first filing. Moreover, it is worth highlighting that BvD only provides information for the eight most current years, and that most variables have only the most recent information available, i.e., they are not historical. I overcome this issue by additionally using vintage BvD datasets obtained between 2013 and 2017.[53]

[51] In detail, the following German firm types are included: AG, AG & Co. KG, GmbH, GmbH & Co. KG, UG, and UG & Co. KG.

[52] I am grateful to Dieter Hess for providing the database. The database may be obtainable from Dieter Hess on request.

[53] Researchers may contact BvD for historical snapshots. I am grateful to Dieter Hess for providing me with BvD vintage datasets.

Table 3.2: Descriptive Statistics

This table contains descriptive statistics for the pooled cross-section from 2011 to 2019. Panel A displays summary statistics for the variables of the bankruptcy prediction model by Altman and Sabato (2007) as well as for the three probability measures. Panel B shows the respective cross-correlations following Pearson (Spearman) below (above) the diagonal. All correlations are statistically significance at the 1% significance level.

Panel A: Summary Statistics

Variable	N	Mean	STD	Min	1%	25%	Median	75%	99%	Max
EBITDA/TA	256,663	0.13	0.13	-0.31	-0.26	0.06	0.11	0.19	0.56	0.60
STD/BKEQ	256,663	0.53	2.01	-2.83	-0.96	0.00	0.00	0.20	11.59	19.65
CASH/TA	256,663	0.13	0.16	0.00	0.00	0.01	0.06	0.19	0.68	0.72
EBITDA/INT	256,663	384.88	2,234.34	-121.49	-69.07	3.40	9.53	33.61	16,771.94	23,765.84
RE/TA	256,663	0.27	0.28	-0.89	-0.38	0.05	0.23	0.47	0.88	0.91
Loss Prob.	256,663	0.13	0.19	0.04	0.04	0.04	0.05	0.05	0.70	0.72
Illiquidity Prob.	256,663	0.07	0.15	0.00	0.00	0.00	0.01	0.03	0.64	0.66
Overind. Prob.	256,663	0.06	0.21	0.00	0.00	0.00	0.00	0.00	0.99	0.99

Panel B: Correlation Analysis

Variable	EBITDA/ TA	STD/ BKEQ	CASH/ TA	EBITDA/ INT	RE/ TA	Loss Prob.	Illiquidity Prob.	Overind. Prob.
EBITDA/TA	-	-0.02	0.20	0.65	0.19	-0.40	-0.21	-0.20
STD/BKEQ	-0.06	-	-0.26	-0.21	-0.11	-0.04	0.08	-0.12
CASH/TA	0.19	-0.13	-	0.38	0.29	-0.11	-0.69	-0.15
EBITDA/INT	0.14	-0.04	0.13	-	0.42	-0.38	-0.38	-0.33
RE/TA	0.19	-0.20	0.26	0.12	-	-0.16	-0.26	-0.54
Loss Prob.	-0.54	0.04	-0.13	-0.07	-0.23	-	0.44	0.40
Illiquidity Prob.	-0.46	0.07	-0.27	-0.06	-0.26	0.85	-	0.44
Overind. Prob.	-0.30	-0.01	-0.10	-0.04	-0.42	0.48	0.48	-

Table 3.1 displays the number of bankrupt and non-bankrupt firms by year included in the sample. In total, it contains 285,847 non-bankrupt and 1,234 bankrupt firm-years, with a mean annual bankruptcy rate of 0.48%.[54]

For the profitability prediction model, the central variable profitability is defined as "Profit (Loss)" (PL) minus "Extraordinary Profit (Loss)" (EXTR) divided by "Total Assets" (TOAS). For the bankruptcy prediction model, the variables are defined as follows. EBITDA/AT is "EBITDA" (EBTA) divided by "Total Assets", STD/BKEQ is "Current Liabilities: Loans" (LOAN) divided by "Shareholder Funds" (SHFD), RE/TA is "Other Shareholder Funds" (OSFD) divided by "Total Assets", CASH/TA is "Cash and Cash Equivalents" (CASH) divided by "Total Assets", and EBITDA/INT is "EBITDA" divided by "Interest Paid" (INTE). Further, to compute the three probability measures, I use the estimated profitability distributions. To calculate Illiquidity Probability (Overindebtedness Probability), I additionally use "Cash and Cash Equivalents" ("Shareholder Funds").

[54] The non-bankrupt firm-years from 2010 are not included in the calculation of the mean annual bankruptcy rate.

Table 3.3: Analysis of the Probability Measures

This table contains an analysis of the three probability measures and their differences between bankrupt and non-bankrupt firms. Panel A shows the development of the mean values of the probability measures for bankrupt firms up to five years prior to bankruptcy filing and for non-bankrupt firms. Only bankrupt firms with a history of at least five years before bankruptcy are included. Panel B displays the results of a mean equality test between bankrupt and non-bankrupt firms, testing whether annual means of the probability measures are significantly different for both groups. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: Development Prior to Bankruptcy

Variable	Years Prior to Bankruptcy Filing					Non-Bankrupt
	5	4	3	2	1	Firms
Loss Prob.	0.16	0.19	0.25	0.28	0.36	0.13
Illiquidity Prob.	0.10	0.12	0.17	0.20	0.27	0.06
Overind. Prob.	0.09	0.09	0.10	0.14	0.19	0.06
N	189	189	189	189	189	251,031

Panel B: Mean Equality Test

Variable	Bankrupt Firms	Non-Bankrupt Firms	Difference	t-Statistic	Significance
Loss Prob.	0.33	0.13	0.20	13.21	***
Illiquidity Prob.	0.24	0.06	0.17	12.64	***
Overind. Prob.	0.21	0.06	0.15	9.23	***

For the empirical analysis, I require all relevant variables to be non-missing. To mitigate the impact of outlying observations, I winsorize all variables annually at the top and bottom percentiles.

Table 3.2 contains descriptive statistics (Panel A) and correlation analyses (Panel B) for the variables of the model by Altman and Sabato (2007) and for the three probability measures. Results for the variables by Altman and Sabato (2007) are in line with previous studies that employ similar variables (e.g., Gupta et al. (2015) or Filipe et al. (2016)).[55] Examining the three probability measures, Panel A shows that all firms have a positive probability to realize future losses (Loss Probability) and that all measures are skewed to the right. Untabulated tests reveal that for Illiquidity Probability, positive probabilities start at the 45th quantile (22nd quantile) for non-bankrupt (bankrupt) firms, and for Overindebtedness Probability, they start at the 79th quantile (49th quantile), respectively. This shows that on average for the cross-section of firms, book equity is larger than cash balances, i.e., expected losses must be more severe to deplete book equity than to consume cash balances. Correlations in Panel B illustrate that the three probability measures are only moderately correlated. The only exception is the rather high Pearson correlation between Loss Probability and Illiquidity Probability.

Table 3.3 illustrates differences between bankrupt and non-bankrupt firms with respect to the three probability measures. Panel A shows how the measures develop in the five years

[55] Altman and Sabato (2007) do not report these statistics. Thus, a comparison to the initial study is not possible.

before a firm's bankruptcy filing date.[56] I only include bankrupt firms with a history of at least five years before bankruptcy to ensure that I analyze the same firms over time. All measures are monotonously increasing while approaching bankruptcy. Loss Probability and Overindebtedness Probability roughly double in the five years leading to bankruptcy, while Illiquidity Probability nearly triples. Further, a test for equality of means in Panel B reveals that non-bankrupt and bankrupt firms show statistically significant differences in the three probability measures. All measures are significantly higher for bankrupt firms than for non-bankrupt firms. In consequence, Table 3.3 provides first evidence that the three probability measures potentially help to differentiate between bankrupt and non-bankrupt SMEs.

3.5 Empirical Results

This section provides empirical evidence that the three probability measures based on expected profitability distributions improve SME failure prediction accuracy. First, I show in-sample results of annual logistic regressions. I compare the initial model by Altman and Sabato (2007) to the univariate extensions of the model with the three probability measures and provide evidence on the discriminative power of the probability measures for SME bankruptcies. Second, using AUC and the performance decile measure, I test if the discriminative power persists out-of-sample and how it develops throughout the sample period. Further, using a hypothesized competitive SME loan market, I show how banks would benefit from implementing the best performing probability measure. Third, I analyze a potential size effect in the relation between the three probability measures and SME bankruptcy risk. Fourth, I show that the results are robust to industries, SME size classes, and locations.

3.5.1 In-Sample Analysis

Table 3.4 presents results of the annual logistic regression. It shows time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and AIC values of the four model specifications tested. Multiple findings are worth highlighting. First, in all model specifications, the variables of the model by Altman and Sabato (2007) are significant and show the correct sign, i.e., bankruptcy probability is increasing with increasing STD/BKEQ and decreasing with increasing values for all other variables. Second, the three probability measures are also significant, and the sign is in line with expectations. When either of the measures increases, the bankruptcy probability increases, too. It is interesting that the strength of the effect seems to

[56] Year 1 indicates that the financial statement information is released at maximum twelve months before filing for bankruptcy.

Table 3.4: Parameter Estimates of Logistic Regressions

This table contains time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and AIC values for the annual logistic regressions of the model by Altman and Sabato (2007) and the extended models. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Variable	Altman/Sabato (2007)	Altman/Sabato (2007) Loss Prob.	Altman/Sabato (2007) Illiquidity Prob.	Altman/Sabato (2007) Overind. Prob.
Intercept	-4.2028 ***	-4.7619 ***	-4.5871 ***	-4.3000 ***
	(-53.33)	(-61.30)	(-54.65)	(-73.76)
EBITDA/TA	-4.3563 ***	-2.0858 ***	-2.7413 ***	-4.0234 ***
	(-43.90)	(-34.12)	(-25.93)	(-50.54)
STD/BKEQ	0.0361 ***	0.0376 ***	0.0374 ***	0.0395 ***
	(8.15)	(8.56)	(8.51)	(8.89)
CASH/TA	-4.4911 ***	-4.3386 ***	-3.6314 ***	-4.4779 ***
	(-127.42)	(-136.10)	(-126.10)	(-120.72)
EBITDA/INT	-0.0001 ***	-0.0001 ***	-0.0001 ***	-0.0001 ***
	(-8.00)	(-7.85)	(-8.17)	(-8.04)
RE/TA	-1.9760 ***	-1.7540 ***	-1.8198 ***	-1.7873 ***
	(-11.52)	(-10.64)	(-10.51)	(-13.35)
Loss Prob.		1.6389 ***		
		(29.31)		
Illiquidity Prob.			1.3528 ***	
			(35.24)	
Overind. Prob.				0.3051 ***
				(4.83)
AIC	8,565.19	8,510.67	8,533.74	8,563.17

decrease with increasing loss severity, i.e., Loss Probability shows the highest parameter estimate (1.6257) and Overindebtedness Probability the lowest (0.2312).[57] Further, when looking at the effect on the initial variables of Altman and Sabato (2007), Loss Probability and Illiquidity Probability have the highest influence on EBITDA/TA, as it decreases from -4.2887 to -2.0470 and -2.6990, respectively. The relation is also reflected in the correlation analysis in Table 3.2, as both probability measures show the highest Pearson correlations to EBITDA/TA. This is unsurprising, as EBITDA/TA is a profitability measure (Altman and Sabato (2007)), and the probability measures are based on profitability distributions. Further, Illiquidity Probability influences the parameter estimate of CASH/AT. Again, this is related to the computation of Illiquidity Probability and also reflected in the correlation analysis. In contrast, Overindebtedness Probability only has a minor influence on the variables of the model by Altman and Sabato (2007). Third, the overall goodness-of-fit criterion confirms that each loss probability measure improves in-sample model fit, as all models show decreased AIC values compared to the initial model by Altman and Sabato (2007). Loss Probability shows the highest reduction in AIC, i.e., it improves model fit the most, while Overindebtedness Probability only slightly reduces AIC.

[57] I further elaborate on this in the following section.

To summarize, results in Table 3.4 provide empirical evidence for a significant positive relation between the three probability measures and SME bankruptcy risk. However, the strength of the relation seems to vary depending on the threshold. This is in line with the findings of Vater and Wolf (2022) for public firm bankruptcy prediction.

3.5.2 Out-of-Sample Analysis

I use strict out-of-sample tests to evaluate if the three probability measures in fact improve SME bankruptcy prediction, i.e., if the relation documented in the previous part translates to real forecast scenarios. Table 3.5 shows time-series averages of AUC (Panel A) and performance decile (Panel B) values for the model by Altman and Sabato (2007) and the models extended by the probability measures. Further, Panel C displays time-series averages of differences in AUC and 10th performance decile values and the corresponding Newey-West (1987) t-statistics for pairwise model specification comparisons.

Mean AUC values in Panel A provide evidence that information about expected losses improves SME bankruptcy prediction. Compared to the initial model by Altman and Sabato (2007) with an AUC of 77.94, all probability measures improve performance. While Overindebtedness Probability only shows minor improvements (78.02), Illiquidity Probability substantially boosts performance with an AUC of 78.64, and Loss Probability increases it even further to 79.08. That means, e.g., for Loss Probability, the probability that a randomly picked bankrupt firm has a higher predicted bankruptcy probability than a randomly picked non-bankrupt firm increases by 1.14 percentage points. Panel C confirms that the performance improvements are statistically significant for Loss Probability and Illiquidity Probability, whereas they are statistically insignificant for Overindebtedness Probability. Further, it shows that the superior performance of Loss Probability compared to Illiquidity Probability is statistically significant as well.

Mean values for the performance deciles in Panel B, specifically the 10th decile, display a similar pattern. All probability measures improve performance compared to the model by Altman and Sabato (2007). Adding Overindebtedness Probability only slightly increases performance (36.80 to 37.18), while Loss Probability and Illiquidity Probability substantially boost performance to 42.18 and 40.21, respectively. That means, e.g., for Loss Probability, a bank can avoid additional 5.38 percentage points of credit defaults if it does not grant credits to firms in the 10th decile. Again, Panel C confirms that the performance improvements are statistically significant for Loss Probability and Illiquidity Probability and statistically insignificant for Overindebtedness Probability. However, for the 10th performance decile, the

Table 3.5: Performance Evaluation of One-Year Ahead Bankruptcy Forecasts

This table shows the out-of-sample performance of one-year ahead bankruptcy forecasts. Panel A (Panel B) contains time-series averages of AUC (performance decile) values for the model by Altman and Sabato (2007) and for the extended models. Panel C shows the difference (y-axis minus x-axis) in out-of-sample performance of the one-year ahead bankruptcy forecasts. It contains time-series averages of differences in AUC (above the diagonal) and 10th performance decile (below the diagonal) and the corresponding Newey-West (1987) t-statistics. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: AUC

Variable	Altman/Sabato (2007)	Altman/Sabato (2007) Loss Prob.	Altman/Sabato (2007) Illiquidity Prob.	Altman/Sabato (2007) Overind. Prob.
AUC	77.94	79.08	78.64	78.02

Panel B: Performance Deciles

Decile	Altman/Sabato (2007)	Altman/Sabato (2007) Loss Prob.	Altman/Sabato (2007) Illiquidity Prob.	Altman/Sabato (2007) Overind. Prob.
1	1.21	1.14	0.92	1.21
2	1.12	1.18	1.57	1.21
3	2.79	2.37	2.55	2.66
4	1.86	2.18	2.22	2.38
5	3.77	3.92	3.65	3.27
6	6.34	5.95	6.19	6.12
7	8.98	8.46	8.48	8.81
8	15.76	12.39	13.38	15.38
9	21.38	20.24	20.83	21.79
10	36.80	42.18	40.21	37.18

Panel C: Differences in AUC (Above the Diagonal) and 10th Decile (Below the Diagonal)

Variable	Altman/Sabato (2007)	Altman/Sabato (2007) Loss Prob.	Altman/Sabato (2007) Illiquidity Prob.	Altman/Sabato (2007) Overind. Prob.
Altman/Sabato (2007)	-	-1.1400 ***	-0.7000 ***	-0.0800
		(-6.03)	(-4.02)	(-1.01)
Altman/Sabato (2007) Loss Prob.	5.3800 ***	-	0.4400 ***	1.0600 ***
	(4.80)		(4.14)	(5.54)
Altman/Sabato (2007) Illiquidity Prob.	3.4100 **	-1.9700	-	0.6200 ***
	(3.15)	(-1.80)		(3.63)
Altman/Sabato (2007) Overind. Prob.	0.3800	-5.0000 ***	-3.0300 *	-
	(0.94)	(-4.40)	(-2.30)	

superior performance of Loss Probability compared to Illiquidity Probability is not statistically significant.

Overall, results from Table 3.5 indicate that Loss Probability improves performances the most compared to the initial model by Altman and Sabato (2007).[58] This is surprising, as it only shows the probability to realize future losses, i.e., to have negative profitability. Illiquidity Probability and Overindebtedness Probability, on the other hand, also account for the severity of future losses by using cash balance or book equity as thresholds. Further, they are linked to the reasons to file for bankruptcy stated in the German bankruptcy statute. However, regarding

[58] Untabulated results show that including a combination of the three probability measures does not increase performance further.

Overindebtedness Probability, the insolvency statute leaves firms some leeway, i.e., if a firm expects a recovery from overindebtedness, it does not have to file for bankruptcy immediately. Untabulated statistics show that 5.05% of firm-years in the sample report negative equity but do not file for bankruptcy.[59] This could potentially explain the weak performance of Overindebtedness Probability. The superior performance of Loss Probability compared to Illiquidity Probability could be related to the fact that a variable based on cash balance, i.e., CASH/AT, is already included in the model by Altman and Sabato (2007). Table 3.2 confirms a rather high relation between both variables with a Spearman correlation of -0.69. Further, Table A3.3 shows results when extending the model by Altman (1983) and the model by Ohlson (1980) with the three probability measures. Both models initially do not include a measure related to cash balances. While Overindebtedness Probability still performs rather weak, Loss Probability and Illiquidity Probability again show substantial improvements. However, for both the Altman (1983) and the Ohlson (1980) model, Illiquidity Probability outperforms Loss Probability. This is also in line with the findings of Vater and Wolf (2022) for public firms. Thus, depending on whether the SME bankruptcy prediction model already includes a measure related to cash balance, including Loss Probability or Illiquidity Probability is potentially the better choice. However, since the model by Altman and Sabato (2007) is the benchmark for this study, results provide evidence that Loss Probability performs best.

Next, I analyze the performance of the three probability measures throughout the sample period. Figure 3.2 displays the time-series of differences in AUC (left graphs) and 10th performance decile (right graphs) values between the initial model by Altman and Sabato (2007) and the models extended by the probability measures. Panel A shows that the model extended by Loss Probability outperforms the initial model for both evaluation measures in every year throughout the sample period, i.e., the superior performance is not driven by single years. Differences for AUC and 10th performance decile look somewhat similar for Illiquidity Probability in Panel B. However, in 2016, both evaluation measures show a worse performance for the extended model, making the results not as consistent as for Loss Probability. Results for Overindebtedness Probability in Panel C show the weakest results, as the initial model performs better in terms of AUC (10th performance decile) between 2014 and 2016 (2013 and 2014). In total, Figure 3.2 suggest that the model extended by Loss Probability is the best and most consistently performing model.

As pointed out in Section 3.3, AUC and the performance deciles do not consider the differing misclassification costs of type I and type II errors. To verify that the overall best

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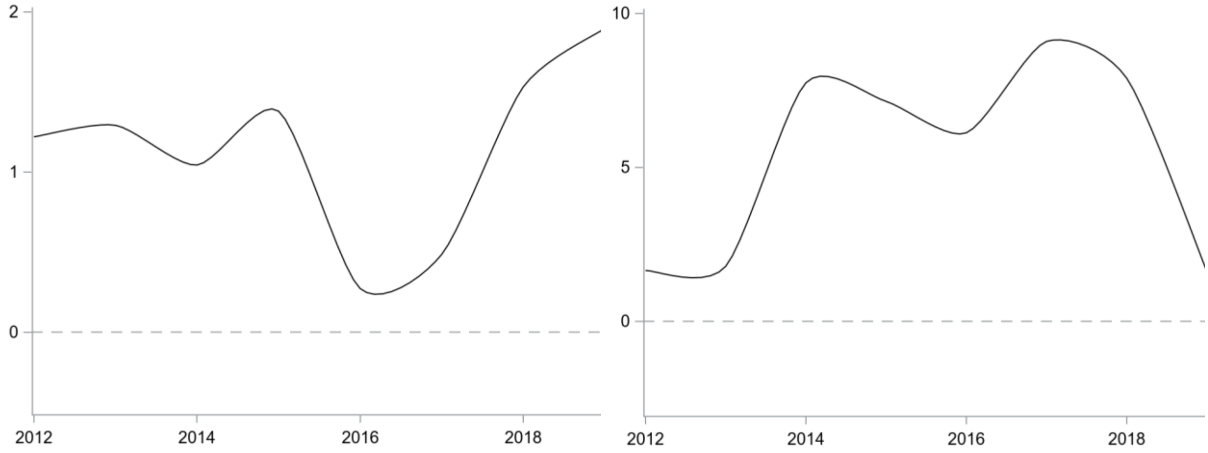
[59] For comparison, in the year preceding bankruptcy, 16.35% of firms report negative book equity.

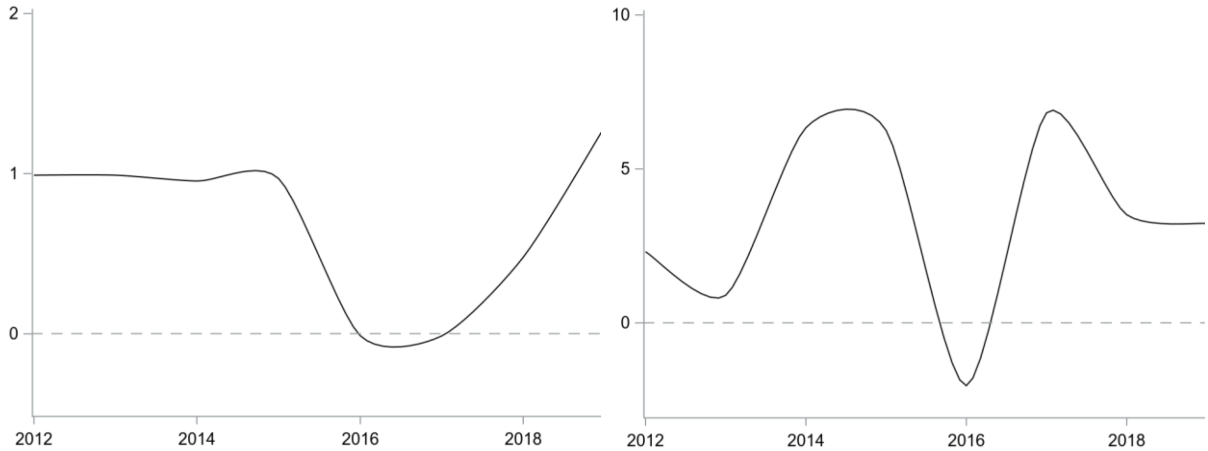
Figure 3.2: Differences in Out-of-Sample Performance Over Time

This figure contains the percentage point differences in out-of-sample performance between the model by Altman and Sabato (2007) and the models extended by the three probability measures throughout the sample period. Panel A displays results for Loss Probability, Panel B for Illiquidity Probability, and Panel C for Overindebtedness Probability. In each Panel, the left graph displays differences in AUC and the right graph shows differences in 10th performance decile values.

Panel A: Loss Probability (Left: AUC / Right: 10th Decile)



Panel B: Illiquidity Probability (Left: AUC / Right: 10th Decile)



Panel C: Overindebtedness Probability (Left: AUC / Right: 10th Decile)

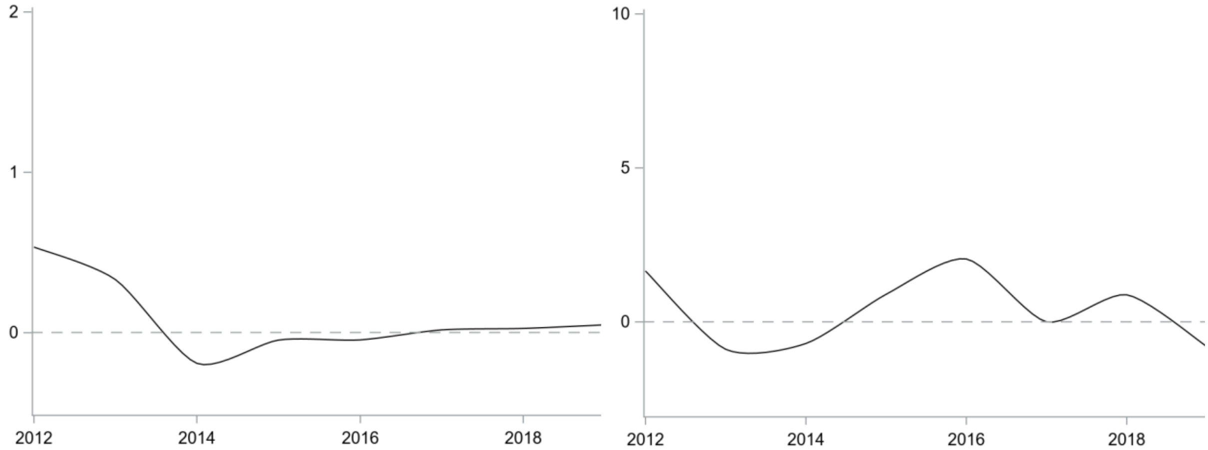


Table 3.6: Economic Value of Differing Misclassification Costs

This table shows results of a competitive SME credit market with a market size of EUR 100 billion. Evaluation takes place at the end of the sample period. Credit spreads of Bank 1 are based on the initial model by Altman and Sabato (2007) and credits spreads of Bank 2 are based on the model extended by Loss Probability. The bank with the lower credit spread is assumed to grant the loan. Credits is the total number of credits granted per bank. Market Share is Credits divided by total number of credits. Defaults is the total number of bankruptcies, i.e., credit defaults, per bank. Avg. Credit Spread is the mean credit spread for all loans granted. Revenue is market size * Market Share * Avg. Credit Spread. Loss is market size * total number of credits * Defaults * LGD (0.45%). Profit is Revenue - Loss. Return on Assets is Profit / (market size * Market Share).

Variable	Bank 1: Altman/Sabato (2007)	Bank 2: Altman/Sabato (2007) Loss Probability
Credits	94,430	119,770
Market Share (%)	44.08	55.92
Defaults	410	431
Defaults/Credits (%)	0.43	0.36
Avg. Credit Spread (%)	0.45	0.49
Revenue (EUR m)	200.25	271.91
Loss (EUR m)	86.13	90.55
Profit (EUR m)	114.11	181.37
Return on Assets (%)	0.26	0.32

performance of the model extended by Loss Probability compared to the initial model by Altman and Sabato (2007) holds when explicitly considering the differing misclassification costs, I use a hypothesized competitive loan market similar to Agarwal and Taffler (2008). Table 3.6 presents the results. Credit spreads of Bank 1 (Bank 2) are based on the initial model by Altman and Sabato (2007) (the model extended by Loss Probability). Bank 2 has a market share of 55.92% compared to 44.08% for Bank 1. Hence, more SMEs choose to take loans from Bank 2 due to lower credit spreads. Further, the number of defaults relative to total credits granted is lower for Bank 2. This is a sign for an overall higher credit quality (Agarwal and Taffler (2008)). The higher market share in combination with higher loan quality translates into a substantially higher revenue for Bank 2 compared to Bank 1, with values of 271.91 and 200.25, respectively. Since losses are only slightly higher for Bank 2, profits are also substantially higher for Bank 2 (181.37 compared to 114.11 for Bank 1). The superior performance of Bank 2 is also reflected in a higher return on assets.

To summarize, Table 3.6 provides evidence that the model extended by Loss Probability outperforms the initial model by Altman and Sabato (2007) in economic terms when considering the differing misclassification costs. Hence, banks would potentially benefit from incorporating Loss Probability into their SME bankruptcy prediction models.

3.5.3 SME Size Class Analysis

Vater and Wolf (2022) argue that the relation between expected accounting losses and bankruptcy risk possibly depends on firm size as small firms tend to have accounting losses at a higher frequency compared to larger firms (Klein and Marquardt (2006)). Further, if bankruptcies do not occur proportionally more frequently for smaller firms, the relevant loss causing bankruptcy filing is more challenging to identify. Hence, they state that pooling all firms together could negatively affect model fit and prediction accuracy. To account for this, they run a size analysis by interacting the loss probability measures with three size classes. First, they show that in their sample, losses and bankruptcies occur more frequently for smaller firms. However, the relation of losses to bankruptcies is much higher for smaller firms compared to larger firms. Second, they provide empirical evidence that prediction accuracy is improved by interacting the loss probability measures with size classes. Therefore, they argue that there is a size effect in the relation between expected accounting losses and bankruptcy risk.

Table 3.7 presents results for the SME sample used in this study. Panel A provides empirical evidence for the disproportionate relation of (expected) losses and bankruptcies for small and medium firms. 56.44% of firm-years that report losses belong to small firms, while 43.56% belong to medium firms. Values for expected losses are nearly identical.[60] However, small firms account for 62.64% of bankruptcies, whereas medium firms are responsible for 37.36% of bankruptcies. These relations show that for small firms, the relevant loss causing bankruptcy filing should be more challenging to identify. In consequence, fitting the three probability measures individually for small and medium firms when assessing bankruptcy risk potentially improves accuracy. Therefore, I interact the measures with SME size classes and rerun the bankruptcy predictions. Panel B presents the regression results for the interacted models. Parameter estimates of the variables of the model by Altman and Sabato (2007) are nearly unaffected compared to Table 3.4. For the three probability measures, in line with expectations, all interaction parameter estimates are statistically significant and increasing in size. In contrast to the non-interacted models in Table 3.4, the effect, i.e., the magnitude of the parameter estimates, is reduced for small firms in comparison to medium firms. This confirms the finding from Panel A, that for medium firms, expected losses should be a stronger sign for bankruptcy filing. Further, AIC values are slightly lower, i.e., model fit improves compared to the results in Table 3.4. Panel C contains out-of-sample evaluation results. All AUC and 10th performance decile values show improvements compared to Table 3.5, except for the 10th performance decile of Loss Probability. However, untabulated results show that the improvements compared to Table 3.5 are statistically insignificant. This is in contrast to the results of Vater and Wolf (2022). They find that the size interaction significantly improves results. A possible reason could be that the disproportionate relation of losses and bankruptcies

[60] A firm expects losses if the median profitability forecast is negative.

Table 3.7: Relation Between the Probability Measures and SME Size Classes

This table analyzes the relation between the three probability measures and SME size classes, i.e., small and medium size. Panel A shows the disproportionality in size of realized losses, expected losses, and bankruptcy filings. Panel B displays time-series averages of parameter estimates, Newey-West (1987) t-statistics, and AIC values for the annual logistic regressions of the size interacted models. Panel C presents results for AUC and 10th performance decile. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: (Expected) Losses and Bankruptcies in SME Size Classes

Size Class	Small	Medium
% Realized Losses	56.44	43.56
% Expected Losses	57.72	42.28
% Bankruptcies	62.64	37.36

Panel B: Logistic Regression Results for SME Size Class Interaction

Variable	Altman/Sabato (2007) Interacted Loss Prob.	Altman/Sabato (2007) Interacted Illiquidity Prob.	Altman/Sabato (2007) Interacted Overind. Prob.
EBITDA/TA	-2.1745 ***	-2.8092 ***	-4.0626 ***
	(-36.50)	(-28.29)	(-50.38)
STD/BKEQ	0.0365 ***	0.0365 ***	0.0386 ***
	(8.27)	(8.24)	(8.59)
CASH/TA	-4.3370 ***	-3.6531 ***	-4.5018 ***
	(-130.06)	(-117.68)	(-119.54)
EBITDA/INT	-0.0001 ***	-0.0001 ***	-0.0001 ***
	(-7.91)	(-8.21)	(-8.06)
RE/TA	-1.6914 ***	-1.7610 ***	-1.7393 ***
	(-10.27)	(-10.12)	(-12.84)
Interaction Terms			
Loss Prob. | Small	1.1349 ***		
	(27.04)		
Loss Prob. | Medium	2.2406 ***		
	(25.35)		
Illiquidity Prob. | Small		1.1363 ***	
		(20.21)	
Illiquidity Prob. | Medium		1.7290 ***	
		(33.00)	
Overind. Prob. | Small			0.2676 ***
			(3.79)
Overind. Prob. | Medium			0.3370 ***
			(6.20)
Size-Specific Intercept	Yes	Yes	Yes
AIC	8,494.42	8,521.99	8,555.63

Panel C: Out-of-Sample Evaluation for SME Size Class Interaction

Measure	Altman/Sabato (2007) Interacted Loss Prob.	Altman/Sabato (2007) Interacted Illiquidity Prob.	Altman/Sabato (2007) Interacted Overind. Prob.
AUC	79.13	78.82	78.16
10th Decile	41.44	40.80	38.13

for different size classes is more pronounced in the sample of Vater and Wolf (2022), thus increasing the strength of the size effect and its impact on out-of-sample results.

Overall, while regression results suggest that there is a size effect in the relation between the three probability measures and SME bankruptcy risk, out-of-sample evaluation results do not confirm this finding. While I only interact the three probability measures with size classes in Table 3.7, untabulated tests show that interacting the full model with size classes does not improve out-of-sample performance either. This adds to the debate whether it is worth considering SME size classes separately when predicting SME bankruptcy (e.g., Gupta et al. (2015), El Kalak and Hudson (2016), or Gupta et al. (2018)). In line with Gupta et al. (2015), my findings suggest that it is not necessary to consider small and medium firm separately for SME bankruptcy prediction.

3.5.4 Robustness Tests

Results in Section 3.5.2 provide evidence that especially the addition of Loss Probability significantly improves the predictive accuracy of the model by Altman and Sabato (2007). This section tests if the superior performance of Loss Probability in terms of AUC and 10th performance decile persists across industries, SME size classes, and locations. Figure 3.3 presents the results for the model by Altman and Sabato (2007) (gray) and the model extended by Loss Probability (black). In each panel, the left (right) graph shows time-series averages of AUC (10th performance decile) values. I use expected bankruptcy probabilities from the initial analysis in section 3.5.2, i.e., grouping is done ex post. Further, Table A3.2 presents a detailed overview of the industry, size, and location classifications.

Panel A shows results for industry groupings according to Chava and Jarrow (2004).[61] Predictive accuracy varies widely across industries, i.e., AUC (10th performance decile) values range between 74.79 and 92.47 (33.10 and 49.32). In general, predictions seem to be most accurate for firms in industry #3 (Construction Industries), and least precise for industry #8 (Finance, Insurance, and Real Estate).[62] In terms of model comparison, for industries #4 (Manufacturing; 460 bankruptcies), #6 (Wholesale Trade; 163 bankruptcies), #7 (Retail Trade; 94 bankruptcies), and #9 (Service Industries; 139 bankruptcies), the model extended by Loss Probability outperforms the initial model by Altman and Sabato (2007) in both evaluation criteria. For industries #5 (Transportation, Communications, and Utilities; 65 bankruptcies) and #8 (Finance, Insurance, and Real Estate; 33 bankruptcies), results are mixed, whereas in industry #3 (Construction Industries; 94 bankruptcies), the initial model performs better. In

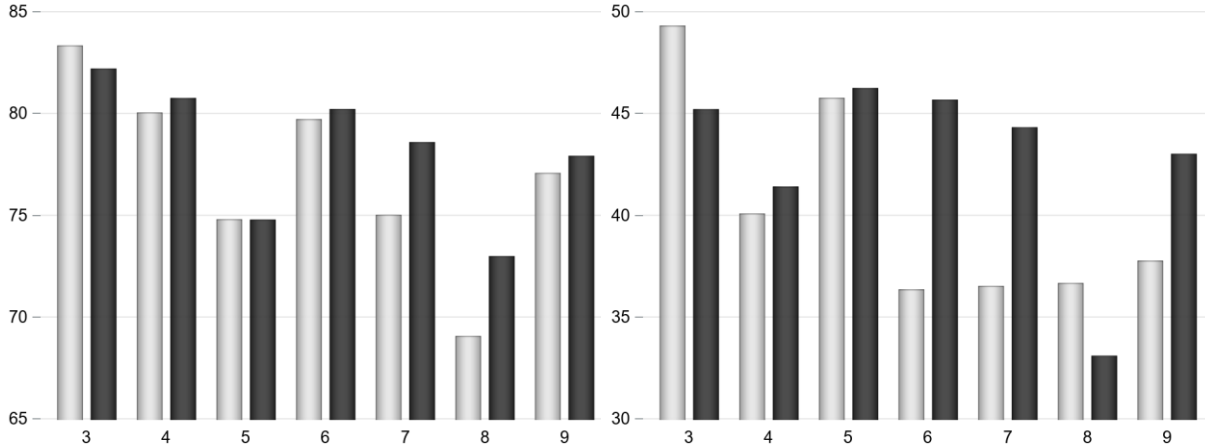
[61] Industries #1 (Agriculture, Forestry, and Fisheries), #2 (Mineral Industries), and #10 (Public Administration) are excluded from the analysis due to the lack of bankruptcies in these industries. See Table A3.2 for further details.

[62] As noted in Section 3.4, banks and insurance companies are excluded from the BvD Amadeus database used for this study. Hence, industry #8 only includes real estate firms.

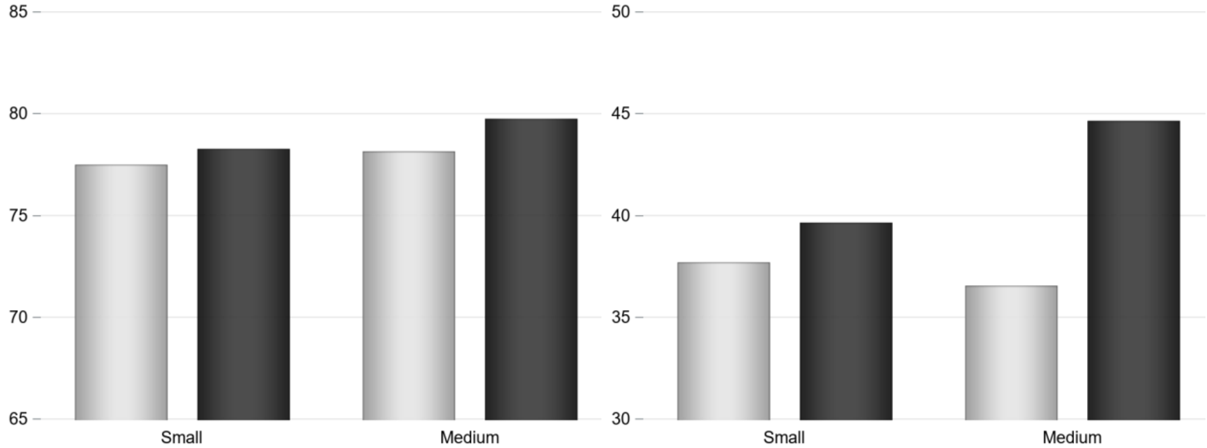
Figure 3.3: Robustness Tests Based on Industries, Size Classes, and Locations

This figure displays robustness checks for the out-of-sample performance of the model by Altman and Sabato (2007) (gray) and the model extended by Loss Probability (black). The robustness tests cover industries (Panel A), SME size classes (Panel B), and locations (Panel C). In each panel, the left (right) graph shows time-series averages of AUC (10th performance decile). In Addition, Table A3.2 presents a detailed description of the industry, size, and location classification.

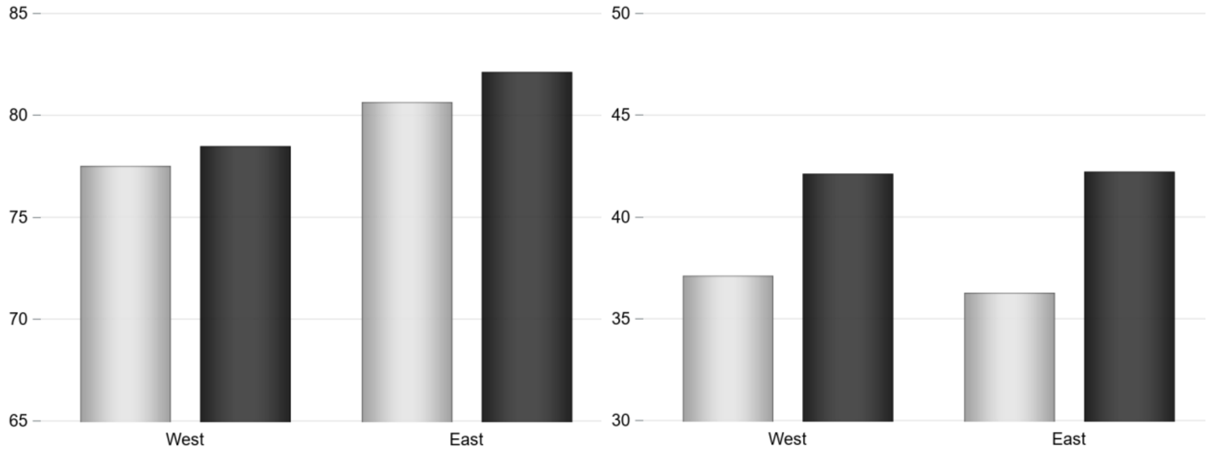
Panel A: Chava/Jarrow 10-Industries (Left: AUC / Right: 10th Decile)



Panel B: Size Classes (Left: AUC / Right: 10th Decile)



Panel C: Location (Left: AUC / Right: 10th Decile)



total, when considering the number of bankruptcies in each industry, the findings suggest that results are robust for the bigger part of firms.

Panel B displays results for SME size classes. The model extended by Loss Probability exhibits superior AUC and 10th performance decile values for both small and medium firms, with more pronounced improvements for medium firms. Specifically for the 10th performance decile, predictions for medium firms compared to small firms are less accurate for the initial model by Altman and Sabato (2007) but are substantially more accurate for the model extended by Loss Probability. Overall, the findings prove that the superior performance is robust across SME size classes and suggest that medium firms benefit the most from the addition of Loss Probability.

Panel C compares results for firms in eastern and western Germany. Eastern Germany contains the federal states that formerly belonged to the German Democratic Republic. These federal states are still in parts economically underdeveloped and structurally weaker in contrast to their western counterparts (e.g., Sinn (2002), Alecke et al. (2010), or Brenke (2014)). Hence, the location in Germany could also be seen as a proxy for the economic strength of a region. Looking at the graph, it is evident that the model extended by Loss Probability outperforms the initial model in both evaluation criteria. For AUC, eastern Germany shows higher values for the initial and the extended model. For the 10th performance decile, eastern Germany's values are slightly lower compared to western Germany, but for the extended model, values are approximately equal. In total, findings are robust regarding a firm's location. Further, Lehmann et al. (2004) provide evidence for a lending gap between eastern and western German SMEs, i.e., firms in eastern Germany face higher loan prices and collateral requirements. Therefore, the increased accuracy of the extended model is especially beneficial for eastern German SMEs, as this potentially decrease banks' capital requirements and in turn lower SMEs' capital cost (Altman and Sabato (2007)).

To summarize, Figure 3.3 provides evidence that the results are robust to (most) industries, SME size classes, and locations. It further highlights the value of Loss Probability for SME bankruptcy prediction and indicates that it should be incorporated into SME bankruptcy prediction models.

3.6 Conclusion

Given SMEs' crucial role in economies worldwide, it is of special interest for banks and investors to assess the financial condition of these firms. Therefore, in this paper, I aim to improve SME bankruptcy prediction models by including forward-looking measures, similar to Vater and Wolf (2022). As bankruptcy prediction is per se future-oriented, a model including expectations about future firm characteristics is potentially more accurate. I analyze the relation of these measures to SME bankruptcy risk and provide empirical evidence that they are a strong predictor for SME bankruptcy filings. In detail, using a sample of German SMEs, I extend the model by Altman and Sabato (2007) by three measures based on expected profitability distributions, particularly the area covering losses. First, I measure the probability that a firm will realize losses in general. Second, I estimate the probability that losses will consume current cash balances, serving as a proxy for illiquidity. Third, I compute the probability that losses exceed book equity, signaling that a firm becomes overindebted.

I find that, in line with expectations, all probability measures are positively related to SME bankruptcy risk. The analysis shows that for bankrupt firms, the probability measures increase substantially in the last five years leading to bankruptcy filing. Also, the differences between bankrupt and non-bankrupt firms for all measures are statistically significant. Regression results reveal a significant and positive relation between all measures and bankruptcy risk. The effect seems to be strongest for Loss Probability and weakest for Overindebtedness Probability with parameter estimates of 1.6389 and 0.3051, respectively. Further, all measures reduce AIC, i.e., they improve model fit. In terms of out-of-sample performance, I find that Loss Probability and Illiquidity Probability significantly improve the accuracy of SME failure prediction models. For instance, Illiquidity Probability significantly increases the 10th performance decile from 36.80% to 40.21% compared to the model by Altman and Sabato (2007). Loss Probability shows an even stronger improvement with a value of 42.18%. This is in line with the findings of Vater and Wolf (2022) and provides evidence for a strong relation between both loss measures and SME bankruptcy risk. In contrast, Overindebtedness Probability shows weaker results. While the 10th performance decile still increases to 37.18%, the difference to the initial model is statistically insignificant, indicating a weaker link to SME bankruptcy risk. A potential reason for this finding is that firms do not have to file for bankruptcy immediately in case of overindebtedness. The insolvency statute leaves firms some leeway, i.e., if a recovery is expected, bankruptcy filing is not necessary. Additional tests show that in contrast to Illiquidity Probability and Overindebtedness Probability, including Loss Probability outperforms the initial model by Altman and Sabato (2007) in every year of the sample period. Taken together, this indicates that out of the three analyzed probability measures, Loss Probability performs best. Further, using a hypothesized competitive SME loan market, I show that banks would economically benefit from implementing Loss Probability, and robustness checks provide evidence that results are consistent across (most) industries, SME size classes and locations.

In addition, previous studies show that smaller firms report losses more frequently than larger firms (e.g., Klein and Marquardt (2006) or Vater and Wolf (2022)). Therefore, I interact the three probability measures with SME size classes to test for a size effect in their relation to bankruptcy risk. Results indicate that the relevance of expected losses grows with firm size, but out-of-sample prediction accuracy does not improve significantly.

In total, my findings contribute to research on SME failure as follows. I show that incorporating firm-specific forward-looking measures into SME bankruptcy prediction models significantly improves forecast accuracy. I provide evidence that the expected profitability distribution, particularly the area covering losses, is a strong predictor for SME bankruptcy filing. To my knowledge, no other SME study incorporates such measures. As “predicting” is per se a forward-looking process, future research could test further forward-looking measures. Moreover, I add to the debate on whether accounting for size classes in SME bankruptcy prediction models improves accuracy (e.g., Gupta et al. (2015), El Kalak and Hudson (2016), or Gupta et al. (2018)). In line with Gupta et al. (2015), I conclude that distinguishing the effects on small and medium firms does not improve predictive accuracy. Lastly, I suggest that banking institutions implement the probability measures, particularly Loss Probability, when assessing SME bankruptcy risk. As Altman and Sabato (2007) point out, more accurate predictions lead to lower capital requirements and lower credit costs. This in turn helps to sustain SME financing, i.e., financing for the backbone of most economies.

3.7 Appendices

Table A3.1: Variable Descriptions

This table contains the descriptions of the variables used throughout Chapter 3. All variables refer to the current period if not noted otherwise. Panel A contains the variable descriptions of the EP-model by Li and Mohanram (2014) used for the prediction of future profitability distributions. Panel B contains the definitions of the three probability measures. Panel C, Panel D, and Panel E describe the explanatory variables used in the bankruptcy prediction models by Altman and Sabato (2007), Altman (1983), and Ohlson (1980), respectively.

Variable	Description	Bureau van Dijk Variable
	Panel A: Li and Mohanram (2014) EP-Model	
Profitability	Income before extraordinary items scaled by total assets.	(PL - EXTR) / TOAS
Loss Dummy	Variable that indicates whether the firm realized losses in the past period.	$f(\text{Prof}) = \begin{cases} 1, & \text{Prof} < 0 \\ 0, & \text{Prof} \geq 0 \end{cases}$
Loss Interaction	Interaction term between profitability and the loss dummy.	Prof · Loss Dummy
	Panel B: Loss Probability Measures	
Loss Prob.	Probability that a company will realize losses in the next period.	$P(E[\text{Prof}] < 0)$
Illiquidity Prob.	Probability that a company will realize losses that will consume the current cash balance in the next period.	$P(E[\text{Prof}] < -CASH)$
Overind. Prob.	Probability that a company will realize losses that will consume book equity in the next period.	$P(E[\text{Prof}] < -SHFD)$
	Panel C: Altman and Sabato (2007)-Model	
EBITDA/TA	Earnings before interest, taxes, depreciation, and amortization relative to total assets.	EBTA / TOAS
STD/BKEQ	Short-term debt relative to book equity.	LOAN / SHFD
CASH/TA	Current cash balance relative to total assets.	CASH / TOAS
EBITDA/INT	Earnings before interest, taxes, depreciation, and amortization relative to interest expenses.	EBTA / INTE
RE/TA	Retained earnings relative to total assets.	OSFD / TOAS
	Panel D: Altman (1983)-Model	
RoA	Earnings before interest and taxes relative to total assets.	EBIT / TOAS
Retained Earnings	Retained earnings relative to total assets.	OSFD / TOAS

(continued)

Table A3.1: Variable Descriptions (continued)

Working Capital	Working capital relative to total assets.	WKCA / TOAS
Leverage	A firm's book equity relative to total liabilities.	SHFD / TOLI [with TOLI = CULI + NCLI]
	Panel E: Ohlson (1980)-Model	
RoA (Ohlson)	Net income relative to total assets.	PL / TOAS
Debt Ratio	Long-term liabilities relative to total assets.	TOLI/ TOAS
Working Capital	Working capital relative to total assets.	WKCA / TOAS
Current Ratio	Current liabilities relative to current assets.	CULI / CUAS
Size	A firm's size.	log(TOAS)
Overindebted-ness	Dummy that indicates whether total liabilities exceed total assets.	$f(\mathrm{TOLI}-\mathrm{TOAS}) = \begin{cases} 0, \mathrm{TOLI}-\mathrm{TOAS} \leq 0 \\ 1, \mathrm{TOLI}-\mathrm{TOAS} > 0 \end{cases}$
Financial Performance	Funds provided by operations relative to total liabilities.	(PL + DEPR - FIPL) / TOLI
Persistent Loss	Dummy that indicates whether a firm realized losses in two consecutive fiscal years.	$f(\mathrm{PL}_{t,t-1}) = \begin{cases} 1, & \mathrm{PL}_t, \mathrm{PL}_{t-1} < 0 \\ 0, & \mathrm{PL}_t, \mathrm{PL}_{t-1} \geq 0 \end{cases}$
Net Income Change	Scaled change in net income between two consecutive fiscal years.	$\frac{\mathrm{PL}_t - \mathrm{PL}_{t-1}}{\lvert \mathrm{PL}_t \rvert + \lvert \mathrm{PL}_{t-1} \rvert}$

Table A3.2: Industry, SME Size Class, and Location Classification

This table presents information about the industry classification by Chava and Jarrow (2004) (Panel A), SME size classes (Panel B) and the classification in eastern and western Germany (Panel C) used for the robustness checks in Section 3.5.4. Each panel additionally shows the number of firm-years marked as bankrupt and non-bankrupt in each category. The covered period starts with the first bankruptcy predictions in 2012, i.e., total numbers of bankrupt and non-bankrupt firm-years deviate from Table 3.1.

Panel A: Industry Classification

Industry	Description	SIC Codes	Non-Bankrupt	Bankrupt
1	Agriculture, Forestry, and Fisheries	< 1000	1,741	0
2	Mineral Industries	1000 - 1500	808	1
3	Construction Industries	1500 - 1800	15,695	94
4	Manufacturing	2000 - 4000	66,374	460
5	Transportation, Communications, and Utilities	4000 - 5000	21,167	65
6	Wholesale Trade	5000 - 5200	38,547	163
7	Retail Trade	5200 - 6000	17,166	94
8	Finance, Insurance, and Real Estate	6000 - 6800	15,322	33
9	Service Industries	7000 - 8900	45,650	139
10	Public Administration	9100 - 10000	540	0

Panel B: SME Size Classes

Size Class	Description	Non-Bankrupt	Bankrupt
Small	EUR 2 m < Total Assets ≤ EUR 10 m	117,906	646
Medium	EUR 10 m < Total Assets ≤ EUR 43 m	105,104	403

Panel C: Location

Location	Description	Non-Bankrupt	Bankrupt
West	Registered in Old German Federal States	184,231	850
East	Registered in New German Federal States + Berlin	38,779	199

Table A3.3: Results for the Models by Altman (1983) and Ohlson (1980)

This table shows the time-series averages of annual out-of-sample performance (AUC and 10th performance decile) of the one-year ahead bankruptcy forecasts for the models by Altman (1983) (Panel A) and Ohlson (1980) (Panel B). The variables included in both models are presented in Table A3.1.

Panel A: Altman (1983)

Variable	Altman (1983)	Altman (1983) Loss Prob.	Altman (1983) Illiquidity Prob.	Altman (1983) Overind. Prob.
AUC	76.29	77.30	77.49	76.27
10th decile	36.55	39.61	40.77	36.69

Panel B: Ohlson (1980)

Variable	Ohlson (1980)	Ohlson (1980) Loss Prob.	Ohlson (1980) Illiquidity Prob.	Ohlson (1980) Overind. Prob.
AUC	77.99	78.67	78.74	78.00
10th decile	39.08	42.76	43.53	38.89

Chapter 4

The Relation Between Earnings Management and Model-Based Earnings Forecast Accuracy

4.1 Introduction

Earnings are a central measure of a firm's performance. Hence, it is of special interest for investors, analysts, and firms themselves to obtain accurate information about future earnings (Tian et al. (2021)). For practitioners and academics alike, earnings forecasts are an important input for firm valuation, asset allocation, or cost of capital calculation (Azevedo et al. (2021)). In recent years, research on cross-sectional model forecasts as an alternative to analysts' earnings forecasts emerged, particularly focusing on the computation of the implied cost of capital (ICC). The ICC is an expected return proxy, and it is computed as the discount rate that equates expected future cash flows to current stock price. Several studies provide evidence that model-based ICCs are more reliable expected return proxies than analyst-based ICCs (e.g., Hou et al. (2012) and Hess et al. (2019)).

A common denominator in most earnings forecast models is that last period's reported earnings are a key explanatory variable for future earnings (e.g., Hou et al. (2012) and Li and Mohanram (2014)). This is unsurprising, as previous literature finds that earnings are highly persistent (e.g., Fama and French (2006) and Hou and van Dijk (2019)). Thus, the reliability of the reported earnings figure is presumably related to the predictive ability of the forecast models. However, one factor affecting reported earnings, and in turn earnings forecasts, has not been covered by research on model-based earnings forecasts yet. This factor is the extent of a firm's earnings management (EM). A widely accepted definition of EM in academic literature is that EM is an adjustment of financial reports in order to deceive certain stakeholders about a firm's economic performance or to affect contractual obligations that are based on reported financial numbers (e.g., Healy and Wahlen (1999), Dechow and Skinner (2000), and Lo (2008)).

Hence, the occurrence of EM, i.e., intentionally misstating earnings, should intuitively compromise the reliability of reported earnings. This assumption is further supported when looking at managers' incentives to manipulate earnings (Dechow et al. (1996) and Dechow and Schrand (2004)). For instance, managers use EM to increase stock prices before initial public offerings, meet analysts' earnings targets, or maximize bonuses that are based on the respective earnings. Literature provides evidence for the occurrence of EM in relation to these incentives (e.g., Healy (1985), Perry and Williams (1994), Teoh et al. (1998) and Doyle et al. (2013)). Therefore, this all points to EM impairing the reliability of reported earnings and in turn, negatively affecting the accuracy of model-based earnings forecasts.

Consequently, with our paper, we aim to examine the effect of EM on the predictability of future earnings. The motivation for our study stems from the assumption of a significantly negative relationship between the extent of a firm's EM and the ability to forecast its respective earnings figure. Further, we seek to use this relation to improve the predictive ability of earnings forecasts models. That is, we incorporate information about firms' EM in the earnings forecast approach and evaluate if this results in more accurate forecasts and more reliable ICC estimates.

For our analysis, we require measures of (i) earnings forecast accuracy and (ii) the extent of a firm's EM. To evaluate forecast accuracy, we first generate earnings forecasts for up to three years ahead using the residual income (RI) model by Li and Mohanram (2014), and then we calculate the price-scaled absolute forecast error (PAFE). Next, firms manage earnings either through the manipulation of cash flows or accruals (Dechow and Schrand (2004)). In line with the bigger part of previous literature, we focus on the accruals component and use absolute discretionary accruals to measure firms' EM (e.g., Frankel et al. (2002), Klein (2002), Bergstresser and Philippon (2006), among others). Discretionary accruals are defined as the residuals from the estimation of an accruals model, and we use the modified Jones (1991) model by Dechow et al. (1995) for the estimation.[63]

The results of the empirical analysis support our expectations, i.e., we provide evidence for a negative relationship between the extent of a firm's EM and the ability to accurately forecast its respective earnings. When running annual cross-sectional regressions of PAFE on the EM measure for one-, two-, and three-year ahead earnings forecasts, we find significantly positive average parameter estimates of 0.0204, 0.0189, and 0.0182, respectively. In other words, we provide empirical evidence that a higher level of EM corresponds to less accurate model-based earnings forecasts. Subsequently, we capitalize on this finding and use the relation between EM and the predictability of future earnings to improve forecast accuracy. We annually

[63] We further elaborate on the selection of the specific earnings forecast model and accruals model in Section 4.2.

rank firms into quintiles based on the extent of a firm's EM and create five dummy variables that indicate a firm's respective quintile. We then interact the earnings forecast model with the EM quintile dummy variables. Again, we generate earnings forecasts for up to three years ahead and find that the forecasts of the interacted model show significantly lower PAFEs compared to the initial model.[64] For instance, for one-year (two-year, three-year) ahead forecasts, the median PAFE of the initial model is 3.72% (4.88%, 6.41%), whereas the PAFE of the interacted model is 3.18% (4.58%, 5.64%). Further, analogous to the methodology used in previous studies (e.g., Hou et al. (2012) and Li and Mohanram (2014)), we implement an ICC analysis and provide evidence that ICCs based on the interacted model are more reliable expected return proxies in comparison to ICCs based on the initial model. For the cross-section of firms, we annually regress realized future returns on ICCs. We show that ICCs based on the interacted model exhibit higher correlations to realized future returns. For example, for one-year ahead forecasts, the initial model shows an average parameter estimate of 0.1904 and an R^2 of 10.70%, while the interacted model shows values of 0.2176 and 12.80%, respectively. Moreover, we annually rank firms into deciles based on the ICCs and implement a long-short-strategy, i.e., we compute the spread between the highest and lowest decile. We find that this portfolio approach yields higher returns for holding periods of up to three years when using ICCs based on the interacted model (e.g., 12.32% vs. 10.63% for a one year holding period). Lastly, we ensure that our findings are robust to alternative earnings forecast models. We rerun the previous tests and provide evidence that the tenor of results is unchanged when using the earnings persistence (EP) model by Li and Mohanram (2014) and the model by Hou et al. (2012).

Our findings contribute to the literature as follows. First, to our knowledge, we are the first to examine the relation between the extent of a firm's EM and the ability to forecast its respective earnings figure. In line with our expectations, we provide evidence for a significantly negative relationship. That is, when the level of a firm's EM increases, the PAFE increases as well. Second, our results of the interacted model highlight that EM should be considered when generating model-based earnings forecasts. It improves forecast accuracy and results in more reliable ICCs that yield higher investment strategy returns. This is important as it further supports previous research (e.g., Hou et al. (2012) and Hess et al. (2019)) that identifies model-based earnings forecasts as a viable alternative to analysts' earnings forecasts. Third, our findings add to the debate on managers' incentives for EM. Beneish (2001) points out that there are potentially two perspectives on EM. On the one hand, the "informative perspective"

[64] Throughout this paper, we will refer to the RI model by Li and Mohanram (2014) as the "initial model", and we will refer to the RI model that we interact with the EM quintile dummy variables as the "interacted model".

suggests that managerial discretion is used to reveal private expectations about future cash flows to stakeholders. For our analysis, this could improve the information content of reported earnings and lead to more accurate earnings forecasts. However, there is no empirical evidence for this perspective, and our results do not support it either. On the other hand, the "opportunistic perspective" states that managers manipulate earnings to mislead investors with the intention of obtaining some personal gain. This should impair the reliability of reported earnings, resulting in less accurate earnings forecasts. Our findings match this perspective, and therefore support the results of previous studies focusing on opportunistic managers' actions (e.g., Perry and Williams (1994), Teoh et al. (2002), and Bergstresser and Philippon (2006)).

The remainder of this paper is structured as follows. Section 4.2 provides a brief overview of related literature. Section 4.3 outlines the methodology we employ, and Section 4.4 describes the data we use for our empirical analysis. Section 4.5 covers the empirical results, and Section 4.6 concludes.

4.2 Related Literature

This section provides an overview of related literature. First, we present studies focusing on cross-sectional earnings forecasts and their relation to ICCs.[65] Second, we briefly discuss studies that implement models to estimate discretionary accruals as a measure for the extent of a firm's EM.

Model-Based Earnings Forecasts and Implied Cost of Capital

Information about the expected rate of return is crucial in various economic settings, e.g., to ensure an efficient allocation of scarce resources or capital budgeting (e.g., Botosan and Plumlee (2005) and Lee et al. (2021)). There exists a vast amount of literature on different approaches for deriving an estimate of a firm's expected rate of return. It is well documented that using realized returns to proxy for expected returns bears a range of problems and leads to noisy and biased estimates (e.g., Fama and French (1997) and Easton and Monahan (2016)). Thus, in recent years, a stream of literature that approximates the expected rate of return with the ICC emerged (e.g., Gebhardt et al. (2001), Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004)). An advantage of the ICC estimation is that it does not rely on noisy realized returns to derive a proxy for expected returns (Lee et al. (2010)). Although it is an important source of information for researchers and practitioners alike, the ICC of a firm

[65] Throughout this paper, we will use the terms "cross-sectional" and "model-based" earnings forecasts interchangeably.

itself is unobservable. It is defined as the internal rate of return that results equating the current stock price to the present value of expected future cash flows. Whereas the current stock price is directly observable, information about future cash flows has to be approximated. In order to derive a reliable ICC estimate, this approximation relies heavily on the accuracy of the respective input factors, especially unobservable future earnings (Botosan and Plumlee (2005)).

Literature provides two popular options to derive estimates of a firm's future earnings. On the one hand, for a subsample of firms, analyst forecasts of the respective firm's earnings are available. Easton and Monahan (2005) show that more reliable ICCs are the result of more accurate analysts' forecasts. Thus, they provide evidence for the necessity of accurate input factors for the ICC estimation.

However, since analysts mainly cover larger firms, various models to forecast future earnings emerged (e.g., Hou et al. (2012) and Li and Mohanram (2014)). These models allow to cover all firms with available financial statement data. The majority of recent studies on model-based earnings forecasts implements a cross-sectional estimation approach. While the model-based forecasts show lower forecast accuracy, Hou et al. (2012) find that these forecasts beat analysts' earnings forecasts in terms of coverage, forecast bias and earnings response coefficient. Further, ICCs based on cross-sectional earnings forecasts are more reliable expected return proxies than analyst-based ICC estimates. Thus, they supply evidence that suggests deriving ICC estimates from model-based earnings forecasts rather than from analyst forecasts. Whereas Easton and Monahan (2016) question these results, Hess et al. (2019) confirm the superiority of model-based earnings forecast in terms of the achieved reliability of ICC estimates. However, the puzzle why mechanical earnings forecast models result in less accurate forecasts compared to analyst earnings forecasts, but in more reliable ICC estimates, remains unanswered at this point (Hess et al. (2019)). Additionally, Gerakos and Gramacy (2013), as well as Li and Mohanram (2014), note that the forecast errors resulting from the Hou et al. (2012) model are quite similar to or even worse than those derived from a random walk model. They express doubt whether the forecasts from that model should be used at all. Thus, Li and Mohanram (2014) propose two new models to improve the approach of Hou et al. (2012) by differentiating between the earnings persistence of profit and loss firms, adjusting the earnings metric for special items, and estimating earnings per share instead of firm-level earnings. They provide evidence that their adjusted model outperforms the model by Hou et al. (2012) regarding forecast bias, accuracy, earnings response coefficient, and ICC reliability.

Evans et al. (2017) and Tian et al. (2021) show that using the least absolute deviation method, i.e., median regressions, further improves forecast performance. However, since our analysis is mainly concerned with the relation between EM and forecast accuracy, we follow Hou et al. (2012) and Li and Mohanram (2014) and employ the OLS method.[66]

In addition to forecasting mean or median earnings, Konstantinidi and Pope (2016) and Chang et al. (2021) use quantile regressions to estimate the distribution of expected earnings. Using these estimates, they compute the higher moments of future earnings. They argue that these moments are measures of risk in future earnings and provide evidence that they are related to common risk measures such as credit risk ratings or corporate bond spreads. Although they also develop models to forecast future earnings, their work is mainly concerned with forecasting higher moments of future earnings and not with a mean forecast of earnings. Thus, in our study, we will not cover the models suggested by Konstantinidi and Pope (2016) and Chang et al. (2021) due to a deviating research focus.

Throughout our empirical analysis, we focus on the RI model introduced by Li and Mohanram (2014), since previous studies find that it performs best in terms of forecast accuracy. However, we will disclose the results based on the EP model by Li and Mohanram (2014) and the model by Hou et al. (2012) in Table A4.3 and Table A4.4. Our main findings are robust to changes in the underlying earnings forecast model.

Estimation of the Earnings Management Measure

A widely accepted definition of EM in previous studies is that EM is an adjustment of financial reports in order to deceive certain stakeholders about a firm's economic performance or to affect contractual obligations that are based on reported financial numbers (e.g., Healy and Wahlen (1999) and Dechow and Skinner (2000)). However, this concept is difficult to measure directly, as it focuses on unobservable managerial intent (Dechow and Skinner (2000)). The most common approach to measure EM is isolating the discretionary part of accruals (Dechow et al. (2012)). This part of accruals reflects distortions due to active EM, while the non-discretionary part captures adjustments based on fundamental performance (Dechow et al. (2010)). Estimates of discretionary accruals are obtained by directly modeling the accruals process. Widely used accruals models are developed by Jones (1991), Dechow et al. (1995), Dechow and Dichev (2002), and McNichols (2002) (Dechow et al. (2012)).

Jones (1991) analyzes if firms use EM to decrease earnings during import relief investigations. Her model includes total accruals as dependent variable, and change in revenues and property, plants, and equipment as independent variables. The fitted value of the regression represents non-discretionary accruals, and the residual represents discretionary accruals. Jones

[66] Untabulated tests show that our results are unchanged when median regressions are used.

(1991) finds that managers actively decrease earnings to profit from import reliefs. Dechow et al. (1995) point out that the model by Jones (1991) implicitly assumes that revenues are non-discretionary. In consequence, if EM occurs through discretionary revenues, it is not accounted for in the discretionary accruals estimate. Dechow et al. (1995) propose a solution by modifying the model by Jones (1991). They use cash revenue instead of reported revenue, i.e., the change in revenues is adjusted for change in receivables. They provide empirical evidence that the modified model better detects EM compared to the initial model by Jones (1991). Dechow and Dichev (2002) suggest a new measure for accruals and earnings quality. While they do not explicitly intent to measure EM, their measure is based on the standard deviation of the residuals, i.e., discretionary accruals. Their model includes change in working capital as dependent variable and past, current, and future cash flows as independent variables. They find that a larger standard deviation of discretionary accruals results in e.g., less persistent earnings, longer operating cycles, and more volatile cash flows, accruals, and earnings (Dechow et al. (2010)). McNichols (2002) links the approach of Jones (1991) to Dechow and Dichev (2002). She adds the variables of Jones (1991) to the model by Dechow and Dichev (2002) and shows that the explanatory power regarding working capital accruals increases. Moreover, Francis et al. (2005) use this model to compute the accruals quality measure proposed by Dechow and Dichev (2002). However, they further differentiate between accruals quality due to economic fundamentals and due to management choices. They find that lower accruals quality yields higher cost of debt, smaller price multiples on earnings, and larger equity betas. Yet, they conclude that accruals quality driven by economic factors has a larger effect on cost of capital than accruals quality driven by management choices.

In this study, we use the modified Jones (1991) model by Dechow et al. (1995) to compute the EM measure for the following reasons. First, as stated before, Dechow et al. (1995) show that their modified model better detects EM compared to the initial model by Jones (1991). Second, the models by Dechow and Dichev (2002) and McNichols (2002) contain cash flows from period $t + 1$ to estimate discretionary accruals for period t. To prevent a look-ahead-bias in our analysis, we would have to relate the forecast error of current period's earnings forecasts to last period's EM measure. However, we want to avoid such a timing lag between both measures, and additionally, Dechow and Dichev (2002) point out that their model is not specifically intended to estimate firms' EM. Third, the accruals quality measure of Francis et al. (2005) that is driven by management choices requires a seven-year time-series of firm-specific data. This potentially induces a survivorship bias that we intent to avoid.

To the best of our knowledge, we are the first to analyze the relation between the extent of a firm's EM and model-based earnings forecast accuracy. As noted in the previous section, model-based earnings forecasts are an important input in practice as well as in academic studies. Thus, understanding the factors influencing their accuracy is worth investigating further.

4.3 Methodology

This section outlines the methodology we employ in this study. First, it shows how we generate earnings forecasts and the corresponding PAFEs. Second, it presents how we compute the EM measure, i.e., absolute discretionary accruals. Third, it depicts how we (i) examine the relation between the extent of a firm's EM and earnings forecast accuracy, (ii) use information about firms' EM to improve the predictive ability of earnings forecast models, and (iii) test if this information enhances ICC reliability.

Model-Based Earnings Forecasts

To forecast earnings, we use the RI model introduced by Li and Mohanram (2014). The model is defined as follows:

$$\begin{aligned}\mathrm{Earn}_{i,t+\tau} = \beta_0 + \beta_1 \cdot \mathrm{Earn}_{i,t} + \beta_2 \cdot \mathrm{NegE}_{i,t} + \beta_3 \cdot \mathrm{NegE}_{i,t} \cdot \mathrm{Earn}_{i,t} \\ + \beta_4 \cdot \mathrm{BkEq}_{i,t} + \beta_5 \cdot \mathrm{Tacc}_{i,t} + \varepsilon_{i,t+\tau}\end{aligned} \tag{4.1}$$

where $\mathrm{Earn}_{i,t+\tau}$ and $\mathrm{Earn}_{i,t}$ are earnings, $\mathrm{NegE}_{i,t}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise, and $\mathrm{NegE}_{i,t} \cdot \mathrm{Earn}_{i,t}$ is an interaction term of the dummy variable and earnings. Further, $\mathrm{BkEq}_{i,t}$ is book value of equity and $\mathrm{Tacc}_{i,t}$ is total accruals. All variables are scaled by the number of shares outstanding. We forecast earnings for up to five years ahead, i.e., for $\tau = 1 - 5$.[67]

In line with cross-sectional earnings forecast literature (e.g., Hou et al. (2012) and Li and Mohanram (2014)), we use a rolling OLS regression approach with a ten-year window to generate the earnings forecasts.[68] First, at the end of June of each year of our sample period, data from year $t - 9$ to year t is used to estimate the model parameters. Second, we multiply the computed parameters with the independent variables from year t to obtain firm-specific earnings estimates for year $t + \tau$. Out-of-sample earnings forecasts are available from 1979 onwards.

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[67] For our analysis, we primarily use one-, two-, and three-year ahead forecasts. Four- and five-year ahead forecasts are needed for the ICC computation in Section 4.5.3.

[68] To lower data requirements, we start with a five-year window at the beginning of the sample period and expand the window to ten years successively.

To evaluate forecast accuracy, we use the PAFE (e.g., Hou et al. (2012) and Li and Mohanram (2014)). It is defined as follows:

$$\mathrm{PAFE}_{i,t+\tau} = \left| \frac{\mathrm{Earn}_{t+\tau} - \widehat{\mathrm{Earn}}_{t+\tau}}{\mathrm{prc}_t} \right| \tag{4.2}$$

where $\mathrm{Earn}_{t+\tau}$ is realized earnings in year $t + \tau$, $\widehat{\mathrm{Earn}}_{t+\tau}$ is the model-based earnings forecast for year $t + \tau$, and prc_t is the stock price at the end of June of year t.

Earnings Management Measure

In line with previous literature (e.g., Frankel et al. (2002), Klein (2002), and Bergstresser and Philippon (2006)), we use absolute discretionary accruals as a measure for the extent of a firm's EM. Discretionary accruals are defined as the residuals from the estimation of an accruals model. To compute non-discretionary accruals, we use the modified Jones (1991) model by Dechow et al. (1995):

$$\mathrm{TACC}_{i,t} = \beta_0 + \beta_1 \cdot \left(\Delta\mathrm{REV}_{i,t} - \Delta\mathrm{REC}_{i,t}\right) + \beta_2 \cdot \mathrm{PPE}_{i,t} + \varepsilon_{i,t} \tag{4.3}$$

where $\mathrm{TACC}_{i,t}$ is total accruals, $\Delta\mathrm{REV}_{i,t}$ is change in revenue, $\Delta\mathrm{REC}_{i,t}$ is change in receivables, and $\mathrm{PPE}_{i,t}$ is property, plant, and equipment. All variables are scaled by the number of shares outstanding.[69] Further, as specified by Jones (1991) and Dechow et al. (1995), the intercept is also scaled, i.e., the true constant term is suppressed (Peasnell et al. (2000)).

Following more recent studies (e.g., Chung and Kallapur (2003), Francis et al. (2005), Bergstresser and Philippon (2006), among others), we implement a cross-sectional approach instead of time-series analysis initially employed by Jones (1991). Comparing cross-sectional to time-series accruals models, Bartov et al. (2000) find that only cross-sectional models are constantly able to detect EM. Further, accruals models are frequently estimated at industry level (Dechow et al. (2010)). We follow this approach and employ the Fama and French 48 industry classification.[70]

[69] We scale our variables by the number of shares outstanding to be consistent with the variable definition of the earnings forecast model. Thereby, we deviate from the variable definition of Jones (1991) and Dechow et al. (1995). They scale all variables by lagged total assets to reduce heteroscedasticity. Following the approach of Jones (1991), untabulated tests show that the error term of the unscaled accruals model is highly correlated with the number of shares outstanding. This indicates that scaling by the number of shares outstanding is also reasonable.

[70] Untabulated tests show that the tenor of results is unchanged when we do not estimate the accruals model at industry level. However, we follow the approach commonly used in EM literature.

Similar to the model-based earnings forecasts, we use rolling OLS regressions with a ten-year window to estimate the model.[71] First, model parameters are computed using data from year $t-9$ to year t. Second, the computed parameters are multiplied with the independent variables from year t to obtain an estimate of non-discretionary accruals for year t ($\widehat{TACC}_{i,t}$). Lastly, subtracting this estimate from actual total accruals ($TACC_{i,t}$) provides an estimate for discretionary accruals, and the absolute value of discretionary accruals serves as our measure for the extent of a firm's EM ($EM_{i,t}$). It is available from 1975 onwards and defined as follows:

$$EM_{i,t} = |TACC_{i,t} - \widehat{TACC}_{i,t}| \tag{4.4}$$

Empirical Analyses

First, we test the relation between the extent of a firm's EM and model-based earnings forecast accuracy using the following regression equation:

$$PAFE_{i,t+\tau} = \beta_0 + \beta_1 \cdot EM_{i,t} + \sum\nolimits_k \gamma_k \cdot Control_{k,i,t} + \varepsilon_{t+\tau} \tag{4.5}$$

where $PAFE_{i,t+\tau}$ is the forecast error resulting from the forecast made in year t for the year $t+\tau$ and $EM_{i,t}$ is the EM measure for year t. We control for firm size by including the logarithm of total assets and for industry by adding industry dummies according to the Fama and French 48 industry classification.[72] We run annual cross-sectional OLS regressions for $\tau = 1 - 3$.[73]

Second, to inspect if the EM measure helps to improve the predictive ability of earnings forecast models, we use the following approach. We annually rank firms into quintiles based on the extent of a firm's EM and create five dummy variables that indicate a firm's respective quintile. Next, we interact the earnings forecast model with the EM quintile dummy variables, i.e., we run a separate regression for each quintile subsample:

$$\begin{aligned} Earn_{i,t+\tau} = \sum\nolimits_{k=1}^{5} Q_k \cdot \big(&\beta_0 + \beta_1 \cdot Earn_{i,t} + \beta_2 \cdot NegE_{i,t} + \beta_3 \cdot NegE_{i,t} \cdot Earn_{i,t} \\ &+ \beta_4 \cdot BkEq_{i,t} + \beta_5 \cdot Tacc_{i,t} + \varepsilon_{i,t+\tau}\big) \end{aligned} \tag{4.6}$$

[71] Analogous to the earnings forecasts, we start with a five-year window at the beginning of the sample period and expand the window to ten years successively.
[72] Ecker et al. (2013) identify firm size as a potentially important correlated omitted variable in tests for EM.
[73] Using the estimated EM measure as independent variable potentially induces an "error-in-variables" bias. That is, the regression coefficient of the EM measure might be biased towards zero (Griliches and Ringstad (1970)). Hence, our empirical results might understate the true effect of EM on forecast accuracy.

The notation is analogous to equation 1, with the addition of the indicator variable Q_k representing the five EM quintile dummy variables. They are equal to 1 if a firm belongs to a specific quintile, and 0 otherwise. We rerun the analysis of the initial earnings forecast model and compare regression results and PAFEs of the initial model and the interacted model.

Third, we investigate if the earnings forecasts from the interacted model result in more reliable expected return proxies compared to the initial model. In line with earnings forecast literature (e.g., Hou et al. (2012), Li and Mohanram (2014), and Azevedo et al. (2021)), we use ICCs as a proxy for expected returns. The ICC is defined as the discount rate that equates current stock price to the present value of future cash flows (Hou et al. (2012)). The forecasted earnings are used as future cash flow estimates. Hence, more accurate forecast should yield more reliable expected return proxies. Prior research has developed various ICC estimation methods. To guarantee that our results are not affected by any particular method, we follow the earnings forecast literature and use a composite ICC. Our ICC measure is the average of the following four commonly used ICC metrics (Azevedo et al. (2021)). We use two ICCs based on a residual income model, i.e., metrics by Gebhardt et al. (2001) and Claus and Thomas (2001), and two ICCs based on an abnormal earnings growth model, i.e., metrics by Ohlson and Juettner-Nauroth (2005) and Easton (2004). We present a detailed description of the ICC metrics in Table A4.2. To increase coverage, we require only one ICC metric to be available to compute the composite ICC (Hou et al. (2012)). We calculate the firm-specific composite ICC at the end of June of each year.

We analyze the relation of the composite ICC to future returns using two approaches commonly used in earnings forecast studies (e.g., Hou et al. (2012) and Li and Mohanram (2014)). The first approach examines the relation at the firm-level using the following equation:

$$\mathrm{Ret}_{i,t+\tau} = \beta_0 + \beta_1 \cdot \mathrm{ICC}_{i,t} + \varepsilon_{i,t+\tau} \tag{4.7}$$

where $\mathrm{Ret}_{i,t+\tau}$ is realized stock return at the end of June of the year τ and $\mathrm{ICC}_{i,t}$ is the one-year ahead composite ICC calculated at the end of June of the current year. Using this equation, we run annual cross-sectional OLS regressions for $\tau = 1 - 3$. Values of β_1 closer to 1 imply a more reliable expected return proxy (Li and Mohanram (2014)).

The second approach evaluates the relation between the composite ICC and future returns on a portfolio level. In line with Hou et al. (2012), we rank firms into decile portfolios based on the composite ICC at the end of June of each year. Next, we calculate the equally weighted buy-and-hold return for each decile portfolio for holding periods of up to three years. We mainly focus on the spread between the highest and lowest decile, i.e., when implementing a long-short strategy (Azevedo et al. (2021)). We test if this strategy results in significant returns and compare the initial earnings forecast model to the interacted model. The idea behind this strategy is that more reliable ICCs result in a more accurate ranking of firms regarding their expected returns. Consequently, a more accurate ranking will yield higher returns from the long-short strategy.

4.4 Data

The sample we use for our empirical analysis consists of the intersection of the annual COMPUSTAT North American database and the monthly CRSP stock return file. It contains US American firms reporting in US dollar. The total sample period spans from 1971 to 2019. We implement a three-month reporting lag for firm fundamentals to become publicly available. Following previous literature (e.g., Dechow et al. (2012)), we exclude financial firms (SIC codes 6,000 to 6,999) from our analysis as financial statements of these firms are subject to different regulatory frameworks.

The variables for the earnings forecast model are defined as follows. Earnings is income before extraordinary items (IB) minus special items (SPI). Special items are set to zero if missing. Book equity is total common equity (CEQ). Total accruals are defined as income before extraordinary items (IB) minus cash flow from operations (OANCF). Since cash flow from operations is only available from 1988 onwards, we use the accruals definition of Richardson et al. (2005) in case of missing cash flow from operations (Li and Mohanram (2014)).[74] To compute the PAFE, we take the price from the monthly CRSP stock return file (PRC). To estimate the accruals model, we use the following variables. Total accruals are defined analogously to the earnings forecast model. The change in revenue is current period's total revenue (REVT) minus total revenue from the previous period. Likewise, the change in receivables is current period's total receivables (RECT) minus total receivables from the previous period. Property, plant, and equipment is total gross property, plant, and equipment (PPEGT). For both models, all variables are scaled by the number of common shares outstanding (CSHO). We require all relevant variables to be non-missing. Further, to mitigate the effect of outliers, we winsorize all variables annually at the 1st and 99th percentile.

To compute the ICC metrics, we further use the following variables. Earnings are defined analogous to the earnings forecast model. Book equity is total common equity (CEQ), dividends are common dividends (DVC), and total assets are total assets (AT). These variables are scaled

[74] See Table A4.1 for a more detailed description.

Table 4.1: Descriptive Statistics

This table contains descriptive statistics for the pooled cross-section of firms from 1975 to 2019. Panel A displays summary statistics for the variables of the earnings forecast model and for the EM measure resulting from the accruals model by Dechow et al. (1995). Panel B shows the respective cross-correlations following Pearson (Spearman) below (above) the diagonal. All correlations are statistically significance at the 1% significance level.

Panel A: Summary Statistics

Variable	N	Mean	STD	1%	25%	Median	75%	99%
Earn	164,337	1.00	12.84	-3.55	-0.07	0.57	1.65	7.63
NegE	164,337	0.29	0.45	0.00	0.00	0.00	1.00	1.00
NegExE	164,337	-0.24	0.80	-3.55	-0.07	0.00	0.00	0.00
BkEq	164,337	10.11	109.78	-2.62	2.25	6.11	12.82	50.32
Tacc	164,337	0.55	2.89	-6.70	-0.05	0.12	1.14	8.48
EM	164,337	1.09	1.62	0.01	0.21	0.54	1.25	8.73

Panel B: Correlation Analysis

Variable	Earn	NegE	NegExE	Tacc	BkEq	EM
Earn	-	-0.78	0.80	0.71	0.37	0.27
NegE	-0.09	-	-0.98	-0.50	-0.35	-0.16
NegExE	0.09	-0.48	-	0.47	0.35	0.12
BkEq	0.75	-0.04	0.01	-	0.28	0.41
Tacc	0.07	-0.17	0.19	0.04	-	0.02
EM	0.05	-0.06	-0.24	0.07	-0.03	-

by the number of common shares outstanding (CSHO), too. The one-year buy-and-hold return is computed by compounding returns from the monthly CRSP stock return file (RET).

Table 1 presents descriptive statistics for the variables included in the earnings forecast model and for the EM measure.[75] Panel A shows summary statistics (cross-sectional mean, median, standard deviation, select percentiles, and firm-years with complete data) and Panel B displays Pearson and Spearman correlations. Our final sample contains 164,337 firm-year observations. Focusing on the EM measure, Panel A reveals that it is skewed to the right, i.e., the cross-sectional mean (1.09) is approximately twice as large as the median (0.54). Further, Panel B shows that Pearson (Spearman) correlations between the EM measure and the variables included in the earnings forecast model range between -0.16 and 0.41 (-0.24 and 0.07).

4.5 Empirical Results

This section presents the empirical results. First, we provide evidence for a significantly negative relation between the extent of a firm's EM and model-based earnings forecast accuracy. Second, we capitalize on this finding and use the EM measure to improve the predictive ability of earnings forecast models. Third, we show that the increased forecast

[75] Li and Mohanram (2014) do not present descriptive statistics of the variables. Thus, a comparison to the initial study is not possible.

Table 4.2: Relation Between Earnings Management and Forecast Accuracy

This table depicts the relation between EM and model-based earnings forecast accuracy. It contains the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and R^2 values from the annual regressions of PAFE on the EM measure. We control for firm size by including the logarithm of total assets and for industry by adding industry dummies according to the Fama and French 48 industry classification. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
Coefficient	0.0204 ***	0.0189 ***	0.0182 ***
	(8.85)	*(10.51)*	*(9.77)*
Controls	Yes	Yes	Yes
R^2	0.1249	0.1334	0.1352

accuracy results in more reliable expected return proxies. Lastly, we ensure that our findings are robust to different earnings forecast models.

4.5.1 Relation Between Earnings Management and Forecast Accuracy

In this section, we analyze the relation between the extent of a firm's EM and the accuracy of model-based earnings forecasts. We run annual cross-sectional regressions of PAFE on the EM measure while controlling for firm size and industry. Table 4.2 presents the results for forecast horizons of up to three years. It contains the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and R^2 values.

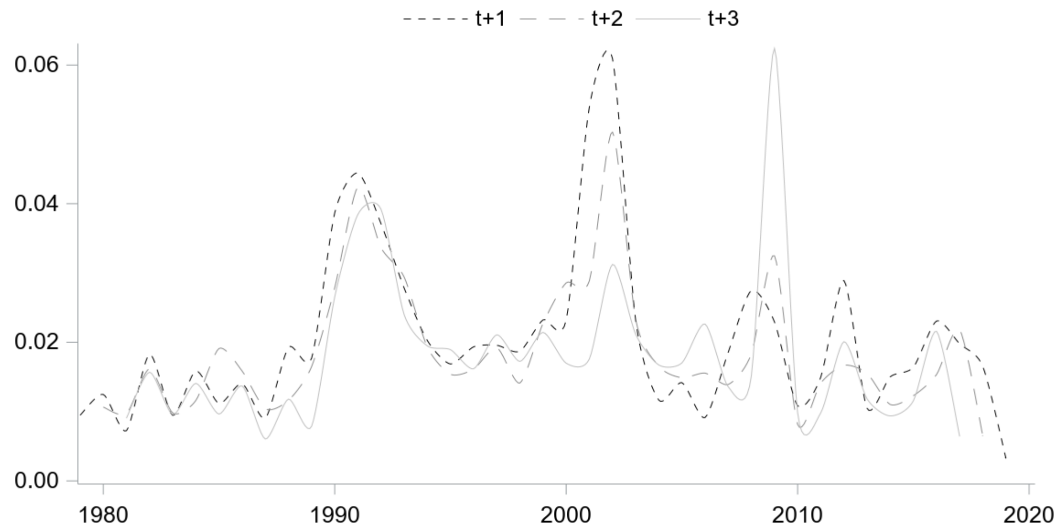
In line with our expectations, the findings provide evidence for a significant positive relation between EM and forecast errors for all forecast horizons. That is, the higher the EM measure, the higher the PAFE, i.e., the lower the forecast accuracy. For one-, two-, and three-year ahead forecast, the coefficient of the EM measure shows values of 0.0204, 0.0189, and 0.0182, respectively. Hence, the strength of the relation slightly decreases with increasing forecast horizon. This could be since earnings forecasts tend to become less accurate the larger the forecast horizon (e.g., Hou et al. (2012) and Li and Mohanram (2014)), and thus, the proportion of the forecast error attributable to management's manipulation of earnings decreases.

In general, the negative relation between EM and forecast accuracy we find indicates that managers' actions lower earnings predictability. As pointed out in Section 4.1, this could be related to an impaired quality of reported earnings due to opportunistic managerial discretion. Hence, our results are in line with previous studies finding that EM is performed with the intention of misleading stakeholders to obtain some personal gain (e.g., Perry and Williams (1994), Teoh et al. (2002), and Bergstresser and Philippon (2006)), instead of aiming to increase the information content of reported earnings (Beneish (2001)).

Additionally, Figure 4.1 plots the annual coefficients of the EM measure for one-, two-, and three-year ahead forecasts. It shows that coefficients approximately range between 0.01

Figure 4.1: Relation Between Earnings Management and Forecast Accuracy Over Time

This figure shows the relation between EM and model-based earnings forecast accuracy. It contains the annual parameter estimates from the annual regressions of PAFE on the EM measure for one-, two-, and three-year ahead forecasts. We further control for firm size and industry.



and 0.06. Most importantly, the figure displays that the coefficients are entirely positive throughout the sample period, i.e., that the sign of the relation between EM and forecast accuracy is consistent. This further strengthens the significance of our findings.

4.5.2 Improving Earnings Forecast Accuracy

In this section, we make use of the insights gained from the previous section, i.e., that a higher level of EM is significantly related to larger earnings forecast errors. Based on this finding, we hypothesize that firms' EM characteristics contain information that is important for predicting future earnings. More specifically, we assume that the parameter estimates of earnings forecast models are influenced by the extent of a firm's EM. As outlined in Section 4.3, we interact the RI model by Li and Mohanram (2014) with the EM quintile dummy variables to account for information about firms' EM. By interacting the model with the dummy variables, we allow for an additional variation of coefficients across EM quintiles. Thus, we expect to obtain more accurate parameter estimates for each subsample. We assume this approach to translate to lower forecast errors on average compared to the initial earnings forecast model.

Table 4.3 presents results for the rolling earnings regressions for one, two, and three years ahead. It contains the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and R^2 values. The first column covers the initial earnings forecast model, whereas

Table 4.3: Parameter Estimates of Earnings Regressions

This table contains the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and R^2 values from the annual earnings regressions. Results are displayed for the initial model and the individual EM quintiles. Further, we show results for one-, two-, and three-year ahead earnings. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Panel A: $Earn_{t+1}$

Variable	Initial Model	EM_{Q1}	EM_{Q2}	EM_{Q3}	EM_{Q4}	EM_{Q5}
Intercept	0.2630 ***	0.1464 **	0.0083	0.0117	0.0079	0.1321 *
	(2.92)	*(2.40)*	*(0.72)*	*(0.84)*	*(0.35)*	*(1.70)*
Earn	0.7927 ***	0.8177 ***	1.0034 ***	0.9626 ***	0.9368 ***	0.8378 ***
	(21.43)	*(14.01)*	*(171.57)*	*(80.19)*	*(168.63)*	*(29.74)*
NegE	-0.4402 ***	-0.2087 ***	-0.0828 ***	-0.0727 ***	-0.0797 ***	-0.2842 ***
	(-5.36)	*(-3.76)*	*(-6.72)*	*(-5.72)*	*(-5.79)*	*(-4.67)*
NegExE	-0.3308 ***	-0.0085	-0.3040 ***	-0.2191 ***	-0.2946 ***	-0.4135 ***
	(-9.00)	*(-0.10)*	*(-5.27)*	*(-3.64)*	*(-14.52)*	*(-11.45)*
BkEq	0.0027	0.0089 ***	0.0064 ***	0.0074 ***	0.0099 ***	0.0115 *
	(0.28)	*(6.42)*	*(3.73)*	*(4.84)*	*(3.83)*	*(1.97)*
Tacc	0.0599 ***	0.0208 ***	-0.0127 ***	0.0144 ***	0.0092 ***	0.0418 ***
	(3.53)	*(4.14)*	*(-4.68)*	*(3.05)*	*(3.73)*	*(3.37)*
R^2	0.6888	0.7721	0.7116	0.6918	0.631	0.6606

Panel B: $Earn_{t+2}$

Variable	Initial Model	EM_{Q1}	EM_{Q2}	EM_{Q3}	EM_{Q4}	EM_{Q5}
Intercept	0.1957 ***	0.1276 ***	0.0039	0.0351 *	0.068 *	0.1574 *
	(3.72)	*(3.09)*	*(0.13)*	*(1.83)*	*(1.99)*	*(1.88)*
Earn	0.7442 ***	0.8553 ***	0.9383 ***	0.9277 ***	0.8820 ***	0.7153 ***
	(22.76)	*(24.15)*	*(56.88)*	*(127.42)*	*(82.63)*	*(20.09)*
NegE	-0.4424 ***	-0.2042 ***	-0.1154 ***	-0.1283 ***	-0.1424 ***	-0.4006 ***
	(-8.29)	*(-5.74)*	*(-4.76)*	*(-7.36)*	*(-5.58)*	*(-5.70)*
NegExE	-0.4868 ***	-0.1736 **	-0.3513 ***	-0.4000 ***	-0.4936 ***	-0.4976 ***
	(-13.19)	*(-2.07)*	*(-5.59)*	*(-9.32)*	*(-15.13)*	*(-10.44)*
BkEq	0.0258 ***	0.0152 ***	0.0278 ***	0.0199 ***	0.0207 ***	0.0333 ***
	(5.13)	*(4.55)*	*(6.26)*	*(10.14)*	*(5.46)*	*(4.97)*
Tacc	0.0074	-0.0008	-0.0381 ***	-0.0064	0.0052	-0.0052
	(0.76)	*(-0.12)*	*(-4.51)*	*(-1.57)*	*(1.10)*	*(-0.63)*
R^2	0.6156	0.6470	0.5392	0.5064	0.4560	0.5496

Panel C: $Earn_{t+3}$

Variable	Initial Model	EM_{Q1}	EM_{Q2}	EM_{Q3}	EM_{Q4}	EM_{Q5}
Intercept	0.4055 ***	0.2292 ***	0.0670 **	0.0719 **	0.1285 ***	0.1463
	(3.64)	*(3.35)*	*(2.18)*	*(2.32)*	*(3.33)*	*(1.47)*
Earn	0.7026 ***	0.7938 ***	0.9810 ***	0.9059 ***	0.8073 ***	0.7797 ***
	(13.43)	*(11.09)*	*(57.68)*	*(65.20)*	*(33.69)*	*(9.82)*
NegE	-0.6284 ***	-0.3254 ***	-0.1787 ***	-0.2508 ***	-0.2168 ***	-0.2618 **
	(-7.67)	*(-4.90)*	*(-5.14)*	*(-9.34)*	*(-5.70)*	*(-2.28)*
NegExE	-0.5734 ***	-0.1752	-0.5069 ***	-0.6136 ***	-0.5807 ***	-0.6256 ***
	(-10.37)	*(-1.54)*	*(-6.70)*	*(-10.78)*	*(-16.98)*	*(-7.98)*
BkEq	0.0253	0.0241 ***	0.0263 ***	0.0311 ***	0.0379 ***	0.0380 ***
	(1.67)	*(6.93)*	*(7.28)*	*(7.34)*	*(7.06)*	*(3.38)*
Tacc	0.0015	-0.0022	-0.0528 ***	-0.0220 ***	-0.0002	-0.0617 ***
	(0.12)	*(-0.27)*	*(-4.80)*	*(-4.33)*	*(-0.05)*	*(-3.59)*
R^2	0.4655	0.5701	0.4443	0.3947	0.3599	0.4706

columns two to six report results for each EM quintile subsample. Looking at the individual parameter estimates for each EM quintile, it becomes evident that they differ across each subsample as well as compared to the parameter estimates of the initial model. For example, for one-year ahead forecasts (Panel A), the initial model shows an earnings parameter estimate of 0.7927, whereas the EM quintiles exhibit larger coefficients ranging between 0.8177 and 1.0034. Similar patterns can be observed for two- and three-year ahead forecasts (Panel B and Panel C, respectively). For the negative earnings dummy, values for the EM quintiles are larger compared to the initial model, too. Values for the interaction term and for book equity vary, i.e., no clear pattern between the EM quintiles and the initial model is visible. Further, for all forecast horizons, the parameter estimate of total accruals is smaller for the EM quintiles in comparison to the initial model. This could be due to the fact that the EM measure is based on accruals, and thus, it already incorporates information about accruals into the model. To summarize, the findings support our assumption that the parameter estimates of earnings forecast models are influenced by firms' EM. That is, parameter estimates vary between the EM quintile subsamples and thus, the relationship between the predictor variables and future earnings differs based on the extent of a firm's EM.

Next, we assume that fitting parameter estimates for each EM quintile translates to lower forecast errors. Table 4.4 shows results of the forecasting performance of the initial model compared to the interacted model. We report mean and median PAFEs for earnings forecasts of up to three years ahead. Furthermore, we report the difference in PAFEs between both models and whether the difference is statistically significant. The table provides evidence that for both mean and median PAFEs, the interacted model significantly improves the predictive ability compared to the initial model. This finding holds for all forecast horizons. Forecasting one-year (two-year, three-year-) ahead leads to a median PAFE of 3.72% (4.88%, 6.41%) for the initial model compared to a significantly lower median PAFE of 3.18% (4.58%, 5.64%) for the interacted model. Results are similar when examining mean PAFE values, although mean PAFE values are generally higher than median PAFE values. Moreover, the differences in PAFEs between the initial and the interacted model are statistically significant at the 1% significance level for forecasts of up to two years ahead and at the 10% significance level for three-year ahead forecasts.

In conclusion, we provide evidence that incorporating information about the extent of a firm's EM into cross-sectional earnings forecast models leads to more accurate forecasts. This is notable as it further supports previous research (e.g., Hou et al. (2012) and Hess et al. (2019)) that identifies model-based earnings forecasts as a reasonable alternative to analysts' forecasts.

Table 4.4: PAFE Comparison

This table compares time-series averages of median and mean PAFEs from the initial earnings forecast model and the model interacted with EM quintile dummy variables. One-, two-, and three-year ahead forecasts are analyzed. Further, we test if the difference in PAFE between both models (interacted model minus initial model) is statistically significant. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Model	$Earn_{t+1}$		$Earn_{t+2}$		$Earn_{t+3}$	
	Median	Mean	Median	Mean	Median	Mean
Initial Model	0.0372	0.1330	0.0488	0.1437	0.0641	0.1690
	(18.85)	*(15.46)*	*(23.27)*	*(20.81)*	*(12.72)*	*(11.35)*
Interacted Model	0.0318	0.1176	0.0458	0.1335	0.0564	0.1470
	(21.21)	*(13.96)*	*(19.90)*	*(19.40)*	*(19.33)*	*(21.05)*
Difference	-0.5341 ***	-1.5390 ***	-0.2975 ***	-1.0161 ***	-0.7714 *	-2.2004 *
	(-3.36)	*(-4.34)*	*(-8.04)*	*(-6.15)*	*(-1.90)*	*(-1.97)*

Moreover, it highlights that the extent of a firm's EM is an important predictor for forecasting future earnings.

4.5.3 Evaluation of Implied Cost of Capital Estimates

The previous section provides evidence that interacting the earnings forecast model with quintile dummy variables based on the EM measure improves forecast accuracy. In this section, we follow recent research (e.g., Li and Mohanram (2014) and Hess et al. (2019)) and analyze if the increased forecast accuracy results in more reliable ICCs. In line with ICC literature (e.g., Gebhardt et al. (2001) and Hou et al. (2012)), we evaluate ICCs by assessing their predictive ability for future realized returns. First, we perform firm-level tests to evaluate the relation between the computed composite ICC and realized future returns. Second, we test the predictive power of the composite ICC for future realized returns on a portfolio level.

Table 4.5 presents the results of the firm level-tests, showing the relation between the composite ICC and buy-and-hold returns for one-, two-, and three-years ahead. We annually regress realized future returns on the composite ICC, for both the initial earnings forecast model and the interacted model. The table shows time-series averages of parameter estimates, Newey-West (1987) t-statistics, and R^2 values. We expect a positive and significant coefficient if ICCs are able to predict future returns. Further, a coefficient closer to 1 represents an ICC estimate that is on average closer to realized returns. The table reveals that the coefficients of the interacted model are closer to 1 in comparison to the initial model. For one-year ahead forecasts, the coefficient of the initial model is 0.1904 compared to 0.2176 for the interacted model. For two-year and three-year ahead forecasts, the values are 0.1659 compared to 0.1947 and 0.1472 compared to 0.1896, respectively. Further, the coefficients of the interacted model show higher t-statistics and thus, higher significance. Moreover, for all forecast horizons, R^2 increases when interacting the earnings forecast model with the EM quintile dummy variables. In total,

Table 4.5: ICC Firm-Level Tests

This table depicts the relation between the composite ICC and buy-and-hold returns for one-, two-, and three-years ahead. We compare the initial earnings forecast model with the interacted model. The table show the time-series averages of the parameter estimates, Newey-West (1987) t-statistics, and R^2 values from the annual regressions of realized future returns on the composite ICC. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Model	Ret_{t+1}			Ret_{t+2}			Ret_{t+3}		
	Intercept	ICC	R^2	Intercept	ICC	R^2	Intercept	ICC	R^2
Initial Model	0.1099 *** *(3.91)*	0.1904 ** *(2.62)*	0.0107	0.0484 ** *(2.48)*	0.1659 ** *(2.69)*	0.0129	0.0408 ** *(2.69)*	0.1472 ** *(2.61)*	0.0146
Interacted Model	0.1058 *** *(3.78)*	0.2176 *** *(2.77)*	0.0128	0.0437 ** *(2.26)*	0.1947 *** *(2.91)*	0.0149	0.0355 ** *(2.41)*	0.1896 *** *(3.13)*	0.0164

Table 4.5 provides evidence that ICCs based the interacted model are closer related to realized future returns than ICCs based on the initial model.

Table 4.6 illustrates the results of the portfolio tests for the initial earnings forecast model and the interacted model. We annually rank firms into decile portfolios based on the composite ICC. For each decile portfolio, we calculate annualized equally weighted buy-and-hold returns for holding periods of up to three years. Further, we implement a long-short strategy by calculating the spread between the highest and lowest decile. A positive and significant return spread illustrates that the composite ICC has significant predictive power for future realized returns. Results reveal that for both models, annualized buy-and-hold returns for all holding periods increase almost monotonically from the first to last decile.[76] The corresponding high-minus-low return spreads are positive, statistically significant, and economically meaningful for both models. However, the interacted model outperforms the initial model for all holding periods. For a one-year holding period, the buy-and-hold return spread for the initial model is 10.63%, while the interacted model yields a return spread of 12.32%. For a two-year (three-year) holding period, the return spread of the initial model is 7.20% (6.17%), whereas the interacted model shows a larger return spread of 8.38% (7.94%). Further, return spreads for the interacted model show larger t-statistics for all holding periods.

To summarize, Table 4.6 indicates that ICCs based on the interacted model have stronger predictive power for future realized returns on a portfolio level compared to ICCs based on the initial model. Combined with the results of Table 4.5, the findings provide evidence that the interacted model generates more reliable ICC estimates. Therefore, investors potentially benefit from using earnings forecasts that include information about the extent of a firm's EM. Again, as pointed out in the previous section, this further helps to establish cross-sectional earnings forecasts as an alternative to analysts' forecasts.

[76] With the exception of decile 10 for holding periods of two and three years.

Table 4.6: ICC Portfolio Tests

This table reports time-series averages of annualized buy-and-hold returns of decile portfolios based on the composite ICC for one-, two-, and three-years ahead. We compare the initial earnings forecast model with the interacted model. For the H-L (10th decile minus 1st decile) return spread, we further show Newey-West (1987) t-statistics. ***, **, and * indicate significance at an alpha level of 1%, 5%, and 10%, respectively.

Model	Decile	ICC	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
Initial Model	1	-0.0893	0.1022	0.0066	-0.0035
	2	-0.0200	0.1116	0.0437	0.0355
	3	0.0059	0.1130	0.0532	0.0471
	4	0.0259	0.1142	0.0540	0.0484
	5	0.0436	0.1217	0.0627	0.0575
	6	0.0615	0.1311	0.0748	0.0677
	7	0.0818	0.1363	0.0808	0.0716
	8	0.1095	0.1624	0.0917	0.0808
	9	0.1595	0.1747	0.0935	0.0807
	10	0.4834	0.2085	0.0786	0.0582
	H-L	0.5727 ***	0.1063 ***	0.0720 ***	0.0617 ***
		(13.74)	*(3.24)*	*(3.19)*	*(3.20)*
Interacted Model	1	-0.0948	0.0923	-0.0003	-0.0146
	2	-0.0246	0.1079	0.0365	0.0258
	3	0.0013	0.1128	0.0457	0.0435
	4	0.0209	0.1170	0.0524	0.0476
	5	0.0384	0.1251	0.0610	0.0551
	6	0.0554	0.1327	0.0803	0.0740
	7	0.0739	0.1441	0.0862	0.0757
	8	0.0975	0.1585	0.0970	0.0851
	9	0.1359	0.1698	0.0972	0.0863
	10	0.4461	0.2155	0.0835	0.0648
	H-L	0.5410 ***	0.1232 ***	0.0838 ***	0.0794 ***
		(11.10)	*(3.48)*	*(3.50)*	*(3.94)*

4.5.4 Alternative Earnings Forecast Models

The previous sections provide evidence that the extent of a firm's EM is significantly negatively related to earnings forecast accuracy. We show that information about EM can be used to improve forecast accuracy and that this increased accuracy translates to more reliable ICCs. These findings are based on the RI earnings forecast model by Li and Mohanram (2014). To ensure that the findings are robust to alternative earnings forecast models, we further show results for the EP model by Li and Mohanram (2014) and the model by Hou et al. (HVZ) (2012). Table A4.3 and Table A4.4 display the results for the EP and HVZ model, respectively.

First, Panel A analyzes the relation of the extent of a firm's EM to forecast accuracy, analogous to Table 4.2. For both models, findings are similar to the RI model, i.e., we document a positive and significant relation between EM and forecast accuracy for all forecast horizons. Second, Panel B compares forecast accuracy between the EP (HVZ) model and the EP (HVZ) model interacted with the EM quintile dummy variables. In line with our previous findings from Table 4.4, using the interacted models significantly improves forecast accuracy. Depending on the forecast horizon, the best performing model, i.e., RI, EP, or HVZ model, seems to vary.

However, values for all models are rather close. Third, Panel C shows results for the firm-level ICC tests, analogous to Table 4.5. For both the EP and HVZ model, the interacted models show larger coefficients and t-statistics compared to the initial models. This confirms our previous findings. Further, while R^2 seems to be largest for the HVZ model, coefficients and t-statistics are largest for the RI model. Fourth, Panel D displays findings of the ICC portfolio tests. The results confirm our findings from Table 4.6, i.e., the interacted models yield larger return spreads for all holding periods. The only exception is the EP model for a one-year holding period. In general, return spreads for the RI and HVZ model seem rather similar, while the EP model performs worse.

In summary, Table A4.3 and Table A4.4 provide evidence that our results are robust to alternative cross-sectional earnings forecast models. This further strengthens our findings as it implies that not only the RI model by Li and Mohanram (2014) profits from incorporating information about firms' EM, but cross-sectional earnings forecast models in general.

4.6 Conclusion

Having accurate earnings forecasts is crucial as they are an important input for firm valuation, asset allocation, or ICC calculation. Intuitively, the occurrence of EM, i.e., intentionally misstating earnings, should negatively affect forecast accuracy. Hence, the aim of this paper is to analyze the effect of firms' EM on model-based earnings forecast accuracy.

The analysis is structured as follows. First, we examine the general effect of EM on forecast accuracy. We generate earnings forecasts for up to three years ahead with the RI model by Li and Mohanram (2014) and use the PAFE to evaluate forecast accuracy. Further, we compute the EM measure, i.e., absolute discretionary accruals, using the model of Dechow et al. (1995). We run annual cross-sectional regression of PAFE on the EM measure. In line with our expectations, we find a significantly positive relation between PAFE and EM for all forecast horizons. That is, with increasing EM, PAFE increases, i.e., forecast accuracy decreases. Second, we capitalize on this finding and use the EM measure to improve forecast accuracy. We rank firms annually into quintiles based on the level of EM and create five dummy variables indicating a firm's respective quintile. Next, we interact the earnings forecast model with the EM quintile dummy variables. Again, we generate earnings forecasts for up to three years ahead and find that the forecasts of the interacted model show significantly lower PAFEs compared to the initial model. Third, we provide evidence that ICCs based on the interacted model are more reliable expected return proxies in comparison to the initial model. For the cross-section of firms, we annually regress realized future returns on the ICCs. We show that ICCs based on the interacted model exhibit higher correlations to realized future returns. Moreover, we annually rank firms into deciles based on the ICCs and implement a long-short-strategy, i.e., we compute the spread between the highest and lowest decile. We find that this portfolio approach yields higher returns for holding periods of up to three years when using ICCs based on the interacted model. Fourth, we ensure that the findings are robust to alternative earnings forecast models. We rerun the previous tests and provide evidence that the tenor of results is unchanged when using the EP model by Li and Mohanram (2014) or the model by Hou et al. (2012).

We contribute to the literature by providing first empirical evidence on the significantly negative relation between the extent of a firm's EM and the predictive ability of earnings forecast models. The negative relation indicates that managerial influence on earnings lowers earnings predictability. This is potentially related to an impaired quality of reported earnings due to opportunistic managerial discretion. Therefore, we support the findings of previous studies indicating that EM is performed for opportunistic reasons, i.e., with the intention of misleading stakeholders to obtain some personal gain (e.g., Perry and Williams (1994), Teoh et al. (2002), and Bergstresser and Philippon (2006)), instead of aiming to increase the information content of reported earnings (Beneish (2001)). Further, we show that information about EM should be incorporated into earnings forecast models as it improves accuracy and results in more reliable ICCs that yield higher investment strategy returns. This supports previous research (e.g., Hou et al. (2012) and Hess et al. (2019)) and further establishes cross-sectional earnings forecasts as a viable alternative to analysts' earnings forecasts

In addition, future research on the relation between the extent of a firm's EM and forecast accuracy might focus on EM measures that are not based on accruals models. Some studies (e.g., Guay et al. (1996), McNichols (2000), and Thomas and Zhang (2000)) criticize the use of such EM measures as they argue that these models provide biased and noisy estimates of discretionary accruals. Alternatively, for instance, Stubben (2010) proposes to use revenue models instead of accruals models to estimate firms' EM or Dechow et al. (2012) incorporate reversals of accruals accounting into their model.

To conclude, this study provides evidence that the extent of a firm's EM is significantly negatively related to the predictive ability of earnings forecast models. We use this finding and show that incorporating information about firms' EM into earnings forecast models increases forecast accuracy and improves ICC reliability. Therefore, future studies on model-based earnings forecasts should account for firms' EM.

4.7 Appendices

Table A4.1: Variable Descriptions

This table contains the descriptions of the variables used throughout Chapter 4. All variables refer to the current period and are scaled by number of shares outstanding (COMPUSTAT variable CSHO) if not noted otherwise. Panel A contains the variable descriptions of the earnings forecast models by Li and Mohanram (2014) and Hou, van Dijk, and Zhang (2012). Panel B contains the variable descriptions of the accruals model by Dechow et al. (1995).

Variable	Description	COMPUSTAT Variable
	Panel A: Li and Mohanram (2014) and Hou, van Dijk, and Zhang (2012)	
Earn	Earnings divided by number of shares outstanding.	IB-SPI
NegE	Indicator variable that equals 1 for firms with negative earnings and 0 otherwise.	$\mathrm{f(Earn)} = \begin{cases} 1, & \mathrm{Earn} < 0 \\ 0, & \mathrm{Earn} \geq 0 \end{cases}$
NegExE	Interaction term of Earn and NegE.	$\mathrm{Earn} \cdot \mathrm{NegE}$
BkEq	Book value of equity divided by number of shares outstanding.	CEQ
Tacc	Sum of change in WC, change in NCO, and change in FIN, divided by number of shares outstanding.	WC=(ACT-CHE)-(LCT-DLC) NCO = (AT-ACT-IVAO)-(LT-LCT-DLTT) FIN=(IVST+IVAO)-(DLTT+DLC+PSTK)
Div	Common dividends divided by number of shares outstanding.	DVC
DivD	Indicator variable that equals 1 for dividend payers and 0 otherwise.	$\mathrm{f(Div)} = \begin{cases} 1, & \mathrm{Div} \geq 0 \\ 0, & \mathrm{Div} < 0 \end{cases}$
A	Total assets divided by number of shares outstanding.	AT
	Panel B: Dechow et al. (1995)	
ΔREV-ΔREC	Change in revenues minus change in receivables, divided by number of shares outstanding.	REVT RECT
PPE	Gross total property, plant, and equipment divided by number of shares outstanding.	PPEGT

Table A4.2: ICC Estimates

This table contains the definitions of the individual ICC estimates that are used to compute the composite ICC measure. In detail, it contains the ICC definitions of Gebhardt et al. (2001), Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004). The notation is akin to Hou et al. (2012).

Source	Formulas and Assumptions
Gebhardt et al. (2001)	$M_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[(ROE_{t+\tau} - ICC) \cdot B_{t+\tau-1}]}{(1+ICC)^{\tau}} + \frac{E_t[(ROE_{t+12} - ICC) \cdot B_{t+11}]}{ICC \cdot (1+ICC)^{11}}$ where M_t is market equity in year t, ICC is the implied cost of capital, B_t is book equity, $E_t[]$ are the market expectations based on information available in year t, and $(ROE_{t+\tau} - ICC) \cdot B_{t+\tau-1}$ is the residual income in year $t+\tau$. To estimate expected ROE in years $t+1$ to $t+3$, we use the model-based earnings forecasts and book equity determined based on clean surplus accounting, i.e., $B_{t+\tau} = B_{t+\tau-1} + E_{t+\tau} - D_{t+\tau}$. $E_{t+\tau}$ are earnings and $D_{t+\tau}$ are dividends. For firms with positive earnings, dividends are calculated using the current payout ratio. For firms with negative earnings, the payout ratio is estimated by dividing current dividends by $0.6 \cdot total\ assets$. We assume that following $t+3$, the expected ROE mean-reverts to the industry median value by year $t+11$.
Claus and Thomas (2001)	$M_t = B_t + \sum_{\tau=1}^{5} \frac{E_t[(ROE_{t+\tau} - ICC) \cdot B_{t+\tau-1}]}{(1+ICC)^{\tau}} + \frac{E_t[(ROE_{t+5} - ICC) \cdot B_{t+4}](1+g)}{(ICC-g) \cdot (1+ICC)^{5}}$ where M_t is market equity in year t, ICC is the implied cost of capital, B_t is book equity, $E_t[]$ are the market expectations based on information available in year t, and $(ROE_{t+\tau} - ICC) \cdot B_{t+\tau-1}$ is the residual income in year $t+\tau$. To estimate expected ROE in years $t+1$ to $t+5$ we use the model-based earnings forecasts and book equity determined based on clean surplus accounting, analogous to the ICC metric by Gebhardt et al. (2001). In line with Azevedo (2021), we set g to the 10-year government bond yield minus an assumed real risk-free rate of 3%.
Ohlson and Juettner-Nauroth (2005)	$ICC = A + \sqrt{A^2 + \frac{E_t[E_{t+1}]}{M_t} \cdot (g - (\gamma - 1))}$ where $A = 0.5\left((\gamma - 1) + \frac{E_t[D_{t+1}]}{M_t}\right),$ $g = 0.5\left(\frac{E_t[E_{t+3}] - E_t[E_{t+2}]}{E_t[E_{t+2}]} + \frac{E_t[E_{t+5}] - E_t[E_{t+4}]}{E_t[E_{t+4}]}\right),$ M_t is market equity in year t, ICC is the implied cost of capital, $E_t[]$ are the market expectations based on information available in year t, E_{t+1} are earnings in year $t+1$, and D_{t+1} are dividends in year $t+1$. Dividends are calculated analogous to Gebhardt et al. (2001). g is the short-term growth rate, estimated as the average of forecasted five-year and near-term growth. γ is the perpetual growth rate of abnormal earnings beyond the forecast horizon, computed as 10-year government bond yield minus an assumed real risk-free rate of 3%.
Easton (2004)	$M_t = \frac{E_t[E_{t+2}] + ICC \cdot E_t[D_{t+1}] - E_t[E_{t+1}]}{ICC^2}$ M_t is market equity in year t, ICC is the implied cost of capital, $E_t[]$ are the market expectations based on information available in year t, E_{t+1} and E_{t+2} are earnings in year $t+1$ and $t+2$, respectively. D_{t+1} are dividends in year $t+1$. Dividends are calculated analogous to Gebhardt et al. (2001).

Table A4.3: Results for the EP-Model by Li and Mohanram (2014)

This table presents the main results of Chapter 4 for earnings forecasts generated by the EP-model by Li and Mohanram (2014). The model contains the following variables, displayed in Table A4.1: Earn, NegE, and NegExE. Panel A shows the relation between EM and earnings forecast accuracy, analogous to Table 4.2. Panel B compares the forecast accuracy of the EP-model and the EP-model interacted with EM quintile dummies, analogous to Table 4.4. Panel C and Panel D present results for the ICC tests, analogous to Table 4.5 and Table 4.6.

Panel A: Relation Between Earnings Management and Forecast Accuracy

	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
Coefficient	0.0193 ***	0.0181 ***	0.0165 ***
	(8.28)	*(10.54)*	*(11.19)*
Controls	Yes	Yes	Yes
R^2	0.1198	0.1356	0.1390

Panel B: PAFE Comparison

Model	$Earn_{t+1}$		$Earn_{t+2}$		$Earn_{t+3}$	
	Median	Mean	Median	Mean	Median	Mean
Initial Model	0.0362	0.1278	0.0499	0.1439	0.0614	0.1596
	(23.07)	*(15.18)*	*(21.03)*	*(21.33)*	*(19.62)*	*(20.76)*
Interacted Model	0.0317	0.1163	0.0459	0.1316	0.0566	0.1449
	(21.72)	*(14.21)*	*(19.04)*	*(19.74)*	*(17.90)*	*(20.96)*
Difference	-0.4498 ***	-1.1501 ***	-0.3964 ***	-1.2259 ***	-0.4805 ***	-1.4688 ***
	(-5.59)	*(-6.16)*	*(-11.32)*	*(-8.21)*	*(-10.01)*	*(-6.27)*

Panel C: ICC Firm-Level Test

Model	Ret_{t+1}			Ret_{t+2}			Ret_{t+3}		
	Intercept	ICC	R^2	Intercept	ICC	R^2	Intercept	ICC	R^2
Initial Model	0.1120 ***	0.1484 *	0.0095	0.0541 **	0.0915	0.0106	0.0465 ***	0.0727	0.0112
	(3.90)	*(2.02)*		*(2.61)*	*(1.57)*		*(2.89)*	*(1.45)*	
Interacted Model	0.1099 ***	0.1571 **	0.0106	0.0498 **	0.1302 **	0.0129	0.0413 **	0.1251 **	0.0137
	(3.87)	*(2.07)*		*(2.47)*	*(2.07)*		*(2.68)*	*(2.22)*	

Panel D: ICC Portfolio Test (H-L)

Model	ICC	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
Initial Model	0.5234 ***	0.1114 ***	0.0554 ***	0.0453 **
	(19.99)	*(3.77)*	*(2.72)*	*(2.00)*
Interacted Model	0.5081 ***	0.1069 ***	0.0665 ***	0.0641 ***
	(15.48)	*(3.02)*	*(2.78)*	*(3.00)*

Table A4.4: Results for the Model by Hou, van Dijk, and Zhang (2012)

This table presents the main results of Chapter 4 for earnings forecasts generated by the model by Hou, van Dijk, and Zhang (2012). The model contains the following variables, displayed in Table A4.1: Earn, NegE, A, Div, DivD, and Tacc. Panel A shows the relation between EM and earnings forecast accuracy, analogous to Table 4.2. Panel B compares the forecast accuracy of the model by Hou, van Dijk, and Zhang (2012) and the model interacted with EM quintile dummies, analogous to Table 4.4. Panel C and Panel D present results for the ICC tests, analogous to Table 4.5 and Table 4.6.

Panel A: Relation Between Earnings Management and Forecast Accuracy

	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
Coefficient	0.0211 ***	0.0216 ***	0.0196 ***
	(8.69)	*(10.78)*	*(9.18)*
Controls	Yes	Yes	Yes
R^2	0.1230	0.1304	0.1332

Panel B: PAFE Comparison

Model	$Earn_{t+1}$		$Earn_{t+2}$		$Earn_{t+3}$	
	Median	Mean	Median	Mean	Median	Mean
Initial	0.0356	0.1282	0.0474	0.1389	0.0595	0.1574
Model	*(19.14)*	*(13.58)*	*(21.03)*	*(18.22)*	*(20.63)*	*(16.88)*
Interacted	0.0314	0.1162	0.0454	0.1357	0.0558	0.1479
Model	*(21.47)*	*(13.99)*	*(19.49)*	*(18.32)*	*(18.95)*	*(19.86)*
Difference	-0.4235 ***	-1.1981 ***	-0.2007 ***	-0.3209 ***	-0.3757 ***	-0.9531 **
	(-4.07)	*(-3.72)*	*(-6.14)*	*(-3.43)*	*(-3.45)*	*(-2.47)*

Panel C: ICC Firm-Level Test

Model	Ret_{t+1}			Ret_{t+2}			Ret_{t+3}		
	Intercept	ICC	R^2	Intercept	ICC	R^2	Intercept	ICC	R^2
Initial	0.1124 ***	0.1588 **	0.0114	0.0503 **	0.1465 **	0.0139	0.0422 **	0.1347 **	0.0149
Model	*(3.92)*	*(2.07)*		*(2.50)*	*(2.23)*		*(2.70)*	*(2.35)*	
Interacted	0.1093 ***	0.2007 **	0.0120	0.0461 **	0.1930 ***	0.0161	0.0381 **	0.1805 ***	0.0170
Model	*(3.79)*	*(2.50)*		*(2.33)*	*(2.75)*		*(2.50)*	*(2.96)*	

Panel D: ICC Portfolio Test (H-L)

Model	ICC	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
Initial	0.6100 ***	0.1029 ***	0.0559 **	0.0503 **
Model	*(13.80)*	*(3.12)*	*(2.35)*	*(3.00)*
Interacted	0.5688 ***	0.1238 ***	0.0884 ***	0.0794 ***
Model	*(7.73)*	*(3.45)*	*(3.61)*	*(4.00)*

Bibliography

Agarwal, V., Taffler, R., 2008, Comparing the Performance of Market-Based and Accounting-Based Bankruptcy Prediction Models, *Journal of Banking and Finance* 32 (8), 1541-1551.

Akaike, H., 1974, A New Look at the Statistical Model Identification, *IEEE Transactions on Automatic Control* 19 (6), 716-723.

Alanis, E., Chava, S., Kumar, P., 2018, Shareholder Bargaining Power, Debt Overhang, and Investments, *The Review of Corporate Finance Studies* 7 (2), 276-318.

Alecke, B., Mitze, T., Untiedt, G., 2010, 20 Jahre deutsche Einheit – Ist die ostdeutsche Wirtschaft immer noch „krank"?, *List Forum für Wirtschafts- und Finanzpolitik* 36 (1), 1-26.

Altman, E., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *The Journal of Finance* 23 (4), 589-609.

Altman, E., 1983, Corporate Distress: A Complete Guide to Predicting, Avoiding and Dealing with Bankruptcy, New York, John Wiley & Sons.

Altman, E., Haldeman, R., Narayanan, P., 1977, ZETA™ Analysis: A New Model to Identify Bankruptcy Risk of Corporations, *Journal of Banking and Finance* 1 (1), 29-54.

Altman, E., Iwanicz-Drozdowska, M., Laitinen, E., Suvas, A., 2017, Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model, *Journal of International Financial Management and Accounting* 28 (2), 131-171.

Altman, E., Sabato, G., 2007, Modelling Credit Risk for SMEs: Evidence from the U.S. Market, *ABACUS* 43 (3), 332-357.

Altman, E., Sabato, G., Wilson, N., 2010, The Value of Non-Financial Information in Small and Medium-Sized Enterprise Risk Management, *The Journal of Credit Risk* 6 (2), 1-33.

Angrist, J., Pischke, J., 2009, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton, Princeton University Press.

Azevedo, V., Bielstein, P., Gerhart, M., 2021, Earnings Forecasts: The Case for Combining Analysts' Estimates with a Cross-Sectional Model, *Review of Quantitative Finance and Accounting* 56 (2), 545-579.

Ball, R., Brown, P., 1968, An Empirical Evaluation of Accounting Income Numbers, *Journal of Accounting Research* 6 (2), 159-178.

Barth, M., Cram, D., Nelson, K., 2001, Accruals and the Prediction of Future Cash Flows, *The Accounting Review* 76 (1), 27-58.

Bartov, E., Gul, F., Tsui, J., 2001, Discretionary-Accruals Models and Audit Qualification, *Journal of Accounting and Economics* 30 (3), 421-452.

Bauer, J., Agarwal, V., 2014, Are Hazard Models Superior to Traditional Bankruptcy Prediction Approaches? A Comprehensive Test, *Journal of Banking and Finance* 40 (1), 432-442.

Beaver, W., Correia, M., McNichols, M., 2012, Do Differences in Financial Reporting Attributes Impair the Predictive Ability of Financial Ratios for Bankruptcy?, *Review of Accounting Studies* 17 (4), 969-1010.

Beaver, W., McNichols, M., Rhie, J., 2005, Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy, *Review of Accounting Studies* 10 (1), 93-122.

Beck, T., Demirgüç-Kunt, A., Laeven, L., Maksimovic, V., 2006, The Determinants of Financing Obstacles, *Journal of International Money and Finance* 25 (6), 932-952.

Beneish, M., 2001, Earnings Management: A Perspective, *Managerial Finance* 27 (1), 3-17.

Bergstresser, D., Philippon, T., 2006, CEO Incentives and Earnings Management, *Journal of Financial Economics* 80 (3), 511-529.

Bhimani, A., Gulamhussen, M., Da-Rocha Lopes, S., 2010, Accounting and Non-Accounting Determinants of Default: An Analysis of Privately-Held Firms, *Journal of Accounting and Public Policy* 29 (6), 517-532.

Bhimani, A., Gulamhussen, M., Da-Rocha Lopes, S., 2013, The Role of Financial, Macroeconomic, and Non-financial Information in Bank Loan Default Timing Prediction, *European Accounting Review* 22 (4), 739-763.

Bhimani, A., Gulamhussen, M., Da-Rocha Lopes, S., 2014, Owner Liability and Financial Reporting Information, *Review of Accounting Studies* 19 (2), 769-804.

Blöchlinger, A., Leippold, M., 2006, Economic Benefit of Powerful Credit Scoring, *Journal of Banking and Finance* 30 (3), 851-873.

Botosan, C., Plumlee, M., 2005, Assessing Alternative Proxies for the Expected Risk Premium, *The Accounting Review* 80 (1), 21–53.

Bowen, R., Burgstahler, D., Daley, L., 1986, Evidence on the Relationships between Earnings and Various Measures of Cash Flow, *The Accounting Review* 61 (4), 713-725.

Brav, O., 2009, Access to Capital, Capital Structure, and the Funding of the Firm, *The Journal of Finance* 64 (1), 263-307.

Brenke, K., 2014, Eastern Germany Still Playing Economic Catch-Up, *DIW Economic Bulletin* 4 (11), 6-23.

Brown, L., Hagerman, R., Griffin, P., Zmijewski, M., 1987, An Evaluation of Alternative Proxies for the Market's Assessment of Unexpected Earnings, *Journal of Accounting and Economics* 9 (2), 159-193.

Calabrese, R., Marra, G., Osmetti, S., 2016, Bankruptcy Prediction of Small and Medium Enterprises Using a Flexible Binary Generalized Extreme Value Model, *Journal of the Operational Research Society* 67 (4), 604-615.

Campbell, J., Hilscher, J., Szilagyi, J., 2008, In Search of Distress Risk, *The Journal of Finance* 63 (6), 2899-2939.

Chang, W., Monahan, S., Ouazad, A., Vasvari, F., 2021, The Higher Moments of Future Earnings, *The Accounting Review* 96 (1), 91-116.

Charalambakis, E., Garrett, I., 2019, On Corporate Financial Distress Prediction: What Can We Learn from Private Firms in a Developing Economy? Evidence from Greece, *Review of Quantitative Finance and Accounting* 52 (2), 467-491.

Chava, S., 2014, Environmental Externalities and Cost of Capital, *Management Science* 60 (9), 2223-2247.

Chava, S., Jarrow, R., 2004, Bankruptcy Prediction with Industry Effects, *The Review of Finance* 8 (4), 537-569.

Chava, S., Stefanescu, C., Turnbull, S., 2011, Modelling the Loss Distribution, *Management Science* 57 (7), 1267-1287.

Chernozhukov, V., Fernandez-Val, I., Galichon, A., 2010, Quantile and Probability Curves Without Crossing, *Econometrica* 78 (3), 1093-1125.

Chung, H., Kallapur, S., 2003, Client Importance, Nonaudit Services, and Abnormal Accruals, *The Accounting Review* 78 (4), 937-955.

Ciampi, F., 2015, Corporate Governance Characteristics and Default Prediction Modeling for Small Enterprises. An Empirical Analysis of Italian Firms, *Journal of Business Research* 68 (5), 1012-1025.

Ciampi, F., Gordini, N., 2013, Small Enterprise Default Prediction Modeling through Artificial Neural Networks: An Empirical Analysis of Italian Small Enterprises, *Journal of Small Business Management* 51 (1), 23-45.

Claus, J., Thomas, J., 2001, Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets, *The Journal of Finance* 56 (5), 1629-1666.

Correia, M., Kang, J., Richardson, S., 2018, Asset volatility, *Review of Accounting Studies* 23 (1), 37-94.

Dechow, P., Dichev, I., 2002, The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors, *The Accounting Review* 77, 35-59.

Dechow, P., Ge, W., Schrand, C., 2010, Understanding Earnings Quality: A Review of the Proxies, Their Determinants and Their Consequences, *Journal of Accounting and Economics* 50 (2-3), 344-401.

Dechow, P., Hutton, A., Kim, J., Sloan, R., 2012, Detecting Earnings Management: A New Approach, *Journal of Accounting Research* 50 (2), 275-334.

Dechow, P., Kothari, S., Watts, R., 1998, The Relation Between Earnings and Cash Flows, *Journal of Accounting and Economics* 25 (2), 133-168.

Dechow, P., Schrand, C., 2004, Earnings Quality, Charlottesville, Research Foundation of CFA Institute.

Dechow, P., Skinner, D., 2000, Earnings Management: Reconciling the Views of Accounting, Practitioners, and Regulators, *Accounting Horizons* 14 (2), 235-250.

Dechow, P., Sloan, R., Sweeney, A., 1995, Detecting Earnings Management, *The Accounting Review* 70 (2), 193-225.

Dechow, P., Sloan, R., Sweeney, A., 1996, Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC, *Contemporary Accounting Research* 13 (l), 1-36.

Dierkes, M., Erner, C., Langer, T., Norden, L., 2013, Business Credit Information Sharing and Default Risk of Private Firms, *Journal of Banking and Finance* 37 (8), 2867-2878.

Dietsch, M., Petey, J., 2004, Should SME Exposures Be Treated as Retail or Corporate Exposures? A Comparative Analysis of Default Probabilities and Asset Correlations in French and German SMEs, *Journal of Banking and Finance* 28 (4), 773-788.

Doyle, J., Jennings, J., Soliman, M., 2013, Do Managers Define Non-GAAP Earnings to Meet or Beat Analyst Forecasts?, *Journal of Accounting and Economics* 56 (1), 40-56.

Easton, P., 2004, PE Ratios, PEG Ratios, and Estimating the Implied Expected Rate of Return on Equity Capital, *The Accounting Review* 79 (1), 73-95.

Easton, P., Monahan, S., 2005, An Evaluation of Accounting-Based Measures of Expected Returns, *The Accounting Review* 80 (2), 501-538.

Easton, P., Monahan, S., 2016, Review of Recent Research on Improving Earnings Forecasts and Evaluating Accounting-Based Estimates of the Expected Rate of Return on Equity Capital, *Journal of Accounting, Finance and Business Studies* 52 (1), 35-58.

Ecker, F., Francis, J., Olsson, P., Schipper, K., 2013, Estimation Sample Selection for Discretionary Accruals Models, *Journal of Accounting and Economics* 56 (2-3), 190-211.

Edmister, R., 1972, An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction, *The Journal of Financial and Quantitative Analysis* 7 (2), 1477-1493.

Eisenbeis, R., 1977, Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics, *The Journal of Finance* 32 (3), 875-900.

El Kalak, I., Hudson, R., 2016, The Effect of Size on the Failure Probabilities of SMEs: An Empirical Study on the US Market Using Discrete Hazard Model, *International Review of Financial Analysis* 43 (4), 135-145.

European Commission, 2003, Commission Recommendation of 6 May 2003 Concerning the Definition of Micro, Small and Medium-Sized Enterprises, URL: https://eur-lex.europa.eu/eli/reco/2003/361/oj (06.10.2021).

European Commission, 2021, Annual Report on European SMEs 2020/2021, Digitalisation of SMEs, SME Performance Review 2020/2021, URL: https://ec.europa.eu/docsroom/documents/46062/attachments/1/translations/en/renditions/native (31.08.2021).

Evans, M., Njoroge, K., Yong, K., 2017, An Examination of the Statistical Significance and Economic Relevance of Probability and Earnings Forecasts from Models and Analysts, *Contemporary Accounting Research* 34 (3), 1453-1488.

Fama, E., French, K., 1997, Industry Costs of Equity, *Journal of Financial Economics* 43 (2), 153-193.

Fama, E., French, K., 2006, Profitability, Investment and Average Returns, *Journal of Financial Economics* 82 (3), 491-518.

Federal Statistical Office of Germany, 2021, Shares of Small and Medium-Sized Enterprises in Selected Variables (2019), URL: https://www.destatis.de/EN/Themes/Economic-Sectors-Enterprises/Enterprises/Small-Sized-Enterprises-Medium-Sized-Enterprises/Tables/total-cik.html?nn=22584 (02.09.2021).

Feltham, G., Ohlson, J., 1995, Valuation and Clean Surplus Accounting for Operating and Financial Activities, *Contemporary Accounting Research* 11 (2), 689-731.

Filipe, S., Grammatikos, T., Michala, D., 2016, Forecasting Distress in European SME Portfolios, *Journal of Banking and Finance* 64 (1), 112-135.

Financial Accounting Standard Board, 2014, Presentation of Financial Statements – Going Concern (Subtopic 205-40), No. 2014-15, FASB, Stamford Connecticut.

Francis, J., LaFond, R., Olsson, P., Schipper, K., 2005, The Market Pricing of Accruals Quality, *Journal of Accounting and Economics* 39 (2), 295-327.

Frankel, R., Johnson, M., Nelson, K., 2002, The Relation Between Auditors' Fees for Nonaudit Services and Earnings Management, *The Accounting Review* 77, 71-105.

Gebhardt, W., Lee, C., Swaminathan, B., 2001, Toward an Implied Cost of Capital, *Journal of Accounting Research* 39 (1), 135-176.

Gerakos, J., Gramacy, R., 2013, Regression-Based Earnings Forecasts, Chicago Booth Research Paper No. 12-26.

Griliches, Z., Ringstad, V., 1970, Error-in-the-Variables Bias in Nonlinear Contexts, *Econometrica* 38 (2), 368-370.

Grunert, J., Norden, L., Weber, M., 2005, The Role of Non-Financial Factors in Internal Credit Ratings, *Journal of Banking and Finance* 29 (2), 509-531.

Guay, W., Kothari, S., Watts, R., 1996, A Market-Based Evaluation of Discretionary Accrual Models, *Journal of Accounting Research* 34, 83-105.

Gupta, J., Barzotto, M., Khorasgani, A., 2018, Does Size Matter in Predicting SME Failure?, *International Journal of Finance and Economics* 23 (4), 571-605.

Gupta, J., Gregoriou, A., Ebrahimi, T., 2016, Empirical Comparison of Hazard Models in Predicting SMEs Failure, *Quantitative Finance* 18 (3), 437-466.

Gupta, J., Gregoriou, A., Healy, J., 2015, Forecasting Bankruptcy for SMEs Using Hazard Function: To What Extent Does Size Matter?, *Review of Quantitative Finance and Accounting* 45 (4), 845-869.

Gupta, J., Wilson, N., Gregoriou, A., Healy, J., 2014, The Effect of Internationalisation on Modelling Credit Risk for SMEs: Evidence from UK Market, *Journal of International Financial Markets, Institutions and Money* 31 (1), 397-413.

Healy, P., 1985, The Effect of Bonus Schemes on Accounting Decisions, *Journal of Accounting and Economics* 7 (1-3), 85-107.

Healy, P., Wahlen, J., 1999, A Review of the Earnings Management Literature and Its Implications for Standard Setting, *Accounting Horizons* 13 (4), 365-383.

Hess, D., Hüttemann, M., 2019, Predicting Bankruptcy via Cross-Sectional Earnings Forecasts, Working Paper, University of Cologne.

Hess, D., Meuter, M., Kaul, A., 2019, The Performance of Mechanical Earnings Forecasts, Working Paper, University of Cologne, Saarland University.

Hillegeist, S., Keating, E., Cram, D., Lundstedt, K., 2004, Assessing the Probability of Bankruptcy, *Review of Accounting Studies* 9 (1), 5-34.

Hou, K., van Dijk, M., Zhang, Y., 2012, The Implied Cost of Capital: A New Approach, *Journal of Accounting and Economics* 53 (3), 504-526.

Hou, K., van Dijk, M., 2019, Resurrecting the Size Effect: Firm Size, Profitability Shocks, and Expected Stock Returns, *The Review of Financial Studies* 32 (7), 2850-2889.

Hüttemann, M., 2019, Three Essays on Corporate Bankruptcies and Their Prediction, Dissertation, University of Cologne.

International Monetary Fund, 2021, World Economic Outlook Database (April 2021), URL: https://www.imf.org/en/Publications/WEO/weo-database/2021/April/download-entire-database (02.09.2021).

Jones, J., 1991, Earnings Management During Import Relief Investigations, *Journal of Accounting Research* 29 (2), 193-228.

Joy, O., Tollefson, J., 1975, On the Financial Applications of Discriminant Analysis, *Journal of Financial and Quantitative Analysis* 10 (5), 723-739.

Keasey, K., Watson, R., 1987, Non-Financial Symptoms and the Prediction of Small Company Failure: A Test of Argenti's Hypotheses, *Journal of Business Finance and Accounting* 14 (3), 335-354.

Keasey, K., Watson, R., 1988, The Non-Submission of Accounts and Small Company Financial Failure Prediction, *Accounting and Business Research* 19 (73), 47-54.

Klein, A., 2002, Audit Committee, Board of Director Characteristics, and Earnings Management, *Journal of Accounting and Economics* 33 (3), 375-400.

Klein, A., Marquardt, C., 2006, Fundamentals of Accounting Losses, *The Accounting Review* 81 (1), 179-206.

Koenker, R., Bassett, G., 1978, Regression Quantiles, *Econometrica* 46 (1), 33-50.

Konstantinidi, T., Pope, P., 2016, Forecasting Risk in Earnings, *Contemporary Accounting Research* 33 (2), 487-525.

Lee, C., So, E., Wang, C., 2010, Evaluating Implied Cost of Capital Estimates, Working Paper, Stanford University.

Lee, C., So, E., Wang, C., 2021, Evaluating Firm-Level Expected-Return Proxies: Implications for Estimating Treatment Effects, *The Review of Financial Studies* 34 (4), 1907-1951.

Lehman, E., Neuberger, D., Räthke, S., 2004, Lending to Small and Medium-Sized Firms: Is There an East-West Gap in Germany?, *Small Business Economics* 23 (1), 23-39.

Li, K., 2011, How Well Do Investors Understand Loss Persistence?, *Review of Accounting Studies* 16 (3), 630-667.

Li, K., Mohanram, P., 2014, Evaluating Cross-Sectional Forecasting Models for Implied Cost of Capital, *Review of Accounting Studies* 19 (3), 1152-1185.

Lo, K., 2008, Earnings Management and Earnings Quality, *Journal of Accounting and Economics* 45 (2-3), 350-357.

McNichols, M., 2000, Research Design Issues in Earnings Management Studies, *Journal of Accounting and Public Policy* 19 (4-5), 313-345.

McNichols, M., 2002, Discussion of The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors, *The Accounting Review* 77, 61-69.

Newey, W., West, K., 1987, Hypothesis Testing with Efficient Method of Moments Estimation, *International Economic Review* 28 (3), 777-787.

Ohlson, J., 1980, Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research* 18 (1), 109-131.

Ohlson, J., Juettner-Nauroth, B., 2005, Expected EPS and EPS Growth as Determinants of Value, *Review of Accounting Studies* 10 (2), 349-365.

Peasnell, K., Pope, P., Young, S., 2000, Detecting Earnings Management Using Cross-Sectional Abnormal Accruals Models, *Accounting and Business Research* 30 (4), 313-326.

Perry, S., Williams, T., 1994, Earnings Management Preceding Management Buyout Offers, *Journal of Accounting and Economics* 18 (2), 157-179.

Richardson, S., Sloan, R., Soliman, M., Tuna, I., 2005, Accrual Reliability, Earnings Persistence and Stock Prices, *Journal of Accounting and Economics* 39 (3), 437-485.

Saunders, A., Steffen, S., 2011, The Costs of Being Private: Evidence from the Loan Market, *The Review of Financial Studies* 24 (12), 4091-4122.

Shumway, T., 2001, Forecasting Bankruptcy More Accurately: A Simple Hazard Model, *The Journal of Business* 74 (1), 101-124.

Sinn, H., 2002, Germany’s Economic Unification: An Assessment after Ten Years, *Review of International Economics* 10 (1), 113-128.

Stubben, S., 2010, Discretionary Revenues as a Measure of Earnings Management, *The Accounting Review* 85 (2), 695-717.

Teoh, S., Welch, I., Wong, T., 1998, Earnings Management and the Long-Run Market Performance of Initial Public Offerings, *The Journal of Finance* 53 (6), 1935-1974.

Thomas, J., Zhang, X., 2000, Identifying Unexpected Accruals: A Comparison of Current Approaches, *Journal of Accounting and Public Policy* 19 (4-5), 347-376.

Tian, H., Yim, A., Newton, D., 2021, Tail-Heaviness, Asymmetry, and Profitability Forecasting by Quantile Regression, *Management Science* 67 (8), 5209-5233.

Vater, T., Wolf, S., 2022, Analyzing Expected Accounting Losses in the Context of Bankruptcy Prediction, Working Paper, University of Cologne.

Zmijewski, M., 1984, Methodological Issues Related to the Estimation of Financial Distress Prediction Models, *Journal of Accounting Research* 22, 59-82.