THREE ESSAYS ON CORPORATE BANKRUPTCIES AND THEIR PREDICTION

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Chapter 1

Introduction

This thesis comprises three essays on corporate bankruptcies, their prediction, their collection, and their proceedings. In particular, it focuses on (1) the improvement in the performance of bankruptcy prediction models through the construction of a predictor variable, (2) the impact of data quality on the parametrization and the evaluation of bankruptcy prediction models, and (3) the characteristics and implications of a typical bankruptcy proceeding.

Some historical default filings, such as those of General Motors, Lehman Brothers, or WorldCom, have been associated with serious financial losses. Thus, bankruptcies have the power to affect entire economies to a high degree. Particularly, the forecast of bankruptcies is of great interest to financial agents: prediction models are used by investors to decide how to allocate their assets, by managers to determine corrective actions to be taken, by banks to decide whom to grant loans to, by rating agencies to develop their ratings, and by supervisors to monitor the financial health of banks, insurance companies, and other institutions (e.g., Tian and Yu, 2017). Likewise, these forecasts serve as an input for pricing models of, e.g., defaultable bonds or credit derivatives (e.g., Jarrow and Turnbull, 1995; Linetsky, 2006; Carr and Wu, 2010). Therefore, all three essays in this thesis deal with corporate bankruptcies and their prediction.

The extensive literature on predicting corporate bankruptcies starting with the study of Beaver (1966) can be broadly divided into four approaches. First, traditional models mostly use accounting information and a classification technique. For instance, Altman (1968) and Blum (1974) use discriminant analyses and Ohlson (1980) uses logistic regressions. As these classification techniques require the independence of firm-years, these studies match a single bankrupt firm-year of a firm with a single non-bankrupt firm-year of another firm. Zmijewski (1984), for instance, argues that using this matched pair sample yields biased estimates, because it typically oversamples bankrupt firms. Thus, second, more recent models use hazard models that allow the use of the entire firm history instead of one observation per firm (e.g., Shumway, 2001; Chava and Jarrow, 2004). Typically, such models also include predictor variables that are based on stock market movements. Third, structural models apply Merton’s (1974) option pricing theory and view the market value of equity as a call option on the market value of assets (e.g., Vassalou and Xing, 2004; Hillegeist, Keating, Cram, and Lundstedt, 2004; Bharat and Shumway, 2008; Charitou, Dionysiou, Lambertides, and Trigeorgis, 2013). Fourth, studies since the 1990s apply artificially intelligent systems such as support vector machines, neural networks, or random forests to predict bankruptcies (e.g., Boritz, Kennedy, and Albuquerque, 1995; Neves and Vieira, 2006; Jones, Johnstone, and Wilson, 2017).

All these bankruptcy prediction models use a statistical method along with a set of predictor variables. For calibrating and evaluating bankruptcy prediction models, bankruptcy information is a critical input. The first essay uses existing bankruptcy databases but does not collect or investigate bankruptcy information. Instead, it improves the prediction methodology by developing a model that enhances the accuracy of state-of-the-art models, simultaneously expanding their scope of application. The second essay then deals with bankruptcy information. It describes a methodology to gather accurate details of bankruptcy events from public sources and analyzes the impact of data quality on the estimation and evaluation of bankruptcy prediction models. At the same time, it moves away from U.S. corporations, which have been the focus of the literature and investigates German public firms. Meanwhile, the third essay gathers information of privately held firms as well. It predicts their bankruptcies, analyzes the impact of firm size on the prediction, and examines the course of bankruptcy proceedings, even after the initial filing.

The first essay (chapter 2) is based on the working paper “Predicting Bankruptcy via Cross-Sectional Earnings Forecasts” (2019), co-authored by Dieter Hess. In this paper, we develop a bankruptcy prediction model. There have been considerable efforts to improve the performance of bankruptcy prediction models. Altman (1968) was the first to introduce a multivariate model by using a linear discriminant analysis and five accounting-based variables. Ohlson (1980) points out that the assumptions needed for discriminant analyses[1] are violated and suggests using a logistic regression along with nine accounting-based variables. To overcome the shortcomings of matched pair samples, Shumway (2001) uses hazard models along with five accounting-based and market-based predictor variables. Bharath and Shumway (2008) compute default probabilities that are based on a firm’s market equity and use six variables in total. However, recent performance boosts associated with models relying on market data come at a high cost, because the use of these models is limited to firms that have access to capital markets. Altman, Iwanicz-Drozdowska, Laitinen, and Suvas (2017) point out that predicting the bankruptcies of private firms is equally important, for example, for the task of managing large loan portfolios. We add to this stream of literature by improving the out-of-sample performance, simultaneously providing a model that can also be applied to the vast number of privately held firms.

We develop a model to predict bankruptcies, exploiting that negative book equity is a strong indicator of financial distress. Accordingly, our key predictor of bankruptcy is the probability that a firm’s book equity becomes negative. In other words, we derive a closed formula for calculating the probability that future losses will deplete a firm’s book equity. For this purpose, we use the distribution of earnings forecasts that is obtained from cross-sectional regression models in the spirit of Hou, van Dijk, and Zhang (2012). Their approach comprises the use of lagged variables of all sample firms to gain earnings forecasts for an individual firm. We present three bankruptcy prediction models: our negative book equity model includes only the probability of negative book equity. Our accounting model accounts for the possibility of firms intentionally operating on negative book equity without being financially distressed. Thus, it adds accounting variables, that we find to discriminate between healthy and bankrupt negative book equity firms. Our market model finally adds two stock market variables.

[1] These assumptions are, for example, the multivariate normal distribution of the independent variables and the equality of their variance-covariance matrix.

The main results confirm that a firm’s negative book equity is closely related to its bankruptcy risk. In particular, book equity and earnings diminish in the years before bankruptcy, most severely in the final year before bankruptcy. Accordingly, using a rolling evaluation technique, we show that the out-of-sample performance of our accounting model is better than the alternatives that solely use accounting variables, and our market model outperforms other models that allow market information to be included. Importantly, the performance of our accounting model is close to that of state-of-the-art market-based models. In addition, we show that the explanatory power of book equity and earnings forecasts does not change over time. Our study most closely relates to the paper of Correia, Kang, and Richardson (2018), who also use earnings figures to predict bankruptcy. Specifically, they show that earnings’ volatility measures have incremental predictive power regarding bankruptcy. However, they focus solely on the earnings’ volatility. We also use the earnings forecasts themselves and develop a new predictor variable by associating earnings forecasts and their volatilities with book equity. Additionally, we show that the inclusion of additional variables that are chosen based on this new predictor variable yields a higher accuracy than state-of-the-art models.

The findings of the first essay suggest that our accounting model performs best if the situation demands a model to be applicable to private firms. Meanwhile, our market model produces the best results if market-based predictors are allowed. Using our accounting model, we can provide accurate bankruptcy predictions for a wide range of firms, including firms that have no access to capital markets. Our work thus contributes to both researchers and practitioners, as it provides a model that is not restricted to publicly traded firms and simultaneously performing as well as benchmark market models. The empirical analysis of this essay is only based on public firms for consistency with literature. To show that our accounting model outperforms existing models for privately-held firms as well, the third essay (chapter 4) finally includes private firms in the sample. We further contribute to the discussion on whether the credit relevance of accounting measures has changed over the past decades (e.g., Collins, Maydew and Weiss, 1997; Lev and Zarowin, 1999; Beisland and Hamberg, 2013) by showing that book equity and earnings are still useful predictors.

The second essay (chapter 3) is based on the working paper “The Quality of Bankruptcy Data and its Impact on the Evaluation of Prediction Models: Creating and

Testing a German Database" (2019), co-authored by Tobias Lorsbach. While the first essay focuses on the methodology of bankruptcy prediction models, the second essay concentrates on bankruptcy information as a critical input for these models. In particular, we investigate the quality of the commonly used bankruptcy databases and its impact on the estimation and the evaluation of bankruptcy prediction models. The methodology and the choice of predictor variables for prediction models have been intensively addressed. However, previous studies have paid little attention to the quality of bankruptcy data. One related stream of literature analyzes the data providers' quality of financial information, which is crucial for the reliable decision making of both practitioners and academics (e.g., Allen, Cho, and Jung, 1997). Obviously, there should be no differences between the financial statement and the data provided by commercial data providers. However, several studies have investigated the accuracy of commercial data providers and found significant differences between these two. For instance, Rosenberg and Houglet (1974) and Bennin (1980) compare price information of U.S. firms between the Compustat and CRSP databases. Kinney and Swanson (1993) compare tax items extracted from Compustat directly with the official figures in financial statements. San Miguel (1977) does the same for research and development costs; Kern and Morris (1994) for sales and total assets; and Tallapally, Luehlfing, and Motha (2011) for cost of goods sold. Furthermore, Nam, No, and Lee (2017) show the importance of data quality by investigating the impact of faulty financial information on the performance of Ohlson's (1980) bankruptcy prediction model. However, all these evidences are restricted to information of financial statements. To the best of our knowledge, there has been no study to analyze the quality of bankruptcy information. We investigate whether high-quality data on bankruptcy events is as crucial for an effective decision making as is financial data. We add to this stream of literature by answering the following research questions: (i) is the bankruptcy information provided by commercial databases reliable and (ii) if there are data differences between public sources and commercial providers, do these differences impact the estimation and evaluation of bankruptcy prediction models?

To this end, we develop a systematic methodology to obtain bankruptcy information from free-access online sources. We develop a bankruptcy database by crawling mainly two information sources.[2] First, we parse financial disclosures of ad-hoc news providers

[2] The term "crawling" refers to the use of computer programs to systemically browse and analyze websites. The General Appendix shows an exemplary Python program to crawl the German business register.

for bankruptcy-related key words; second, we crawl official online releases made by bankruptcy courts. We apply this methodology to Germany for two reasons. First, for Germany, none of the commonly used bankruptcy databases stream their data directly from public sources, like, for example, the United States' LoPucki Bankruptcy Research Database. Second, Germany is one of the largest stock markets in Europe. We compare our database with Compustat Global and Bureau van Dijk (BvD) data in terms of the completeness and correctness of bankruptcy events and dates. We then use our bankruptcy data to conduct two empirical analyses. First, we compare our database with BvD data and investigate whether the quality of bankruptcy data affects the parameter estimates as well as the out-of-sample evaluation of bankruptcy prediction models.[3] Second, we compare the performance of several bankruptcy prediction models on the German market. While the number of studies that predict bankruptcies for U.S. firms is large, the literature on international firms is sparse (e.g., Altman et al., 2017; Tian and Yu, 2017; Dahiya and Klapper, 2007). However, a domino effect of bankruptcies may trigger a global financial crisis and, thus, prediction models for international markets are important as well (e.g., Srivastava, Lin, Premachandra, and Roberts, 2016; Tian and Yu, 2017).

We find that our bankruptcy database includes a higher number of bankruptcy events than those in the frequently used databases of BvD and Compustat Global. While our database includes 277 bankruptcy events in total, BvD and Compustat cover 63 and 27 events, respectively. For example, BvD does not include the 2009 bankruptcy case of Arcandor AG, a warehouse business valued at 500 million euros. Furthermore, our database carries more accurate bankruptcy dates than those in BvD and Compustat Global. For 25% of the firms, our database reports bankruptcies two months earlier than BvD and, for 50% of the firms, our database reports bankruptcies 24 months earlier than Compustat Global. Importantly, we show that the higher quality of bankruptcy data has a significant impact on the size and significance of parameter estimates and, finally, on the out-of-sample evaluation of bankruptcy prediction models. For example, the use of BvD bankruptcy data would suggest a similar performance for Altman (1968) and Ohlson (1980), whereas the use of our information shows that Ohlson's model significantly outperforms Altman's. Furthermore, we show that market-based bankruptcy prediction models outperform accounting-based models for German public firms.

[3] Since Compustat Global includes too few bankruptcy events, we cannot provide a thorough comparison of our dataset with that of Compustat Global.

This study is the first to show that crawling public sources free of charge creates a database of bankruptcy events with a higher quality than those of Compustat Global and BvD. As such, it is also the first to be able to make a broad comparison of bankruptcy prediction models for Germany using an accurate database. Importantly, we speak to the consequences of training bankruptcy prediction models with noisy bankruptcy data. By showing that the quality of bankruptcy data significantly impacts the interpretation of the results, we prove the sensitivity of prediction models with respect to data. Therefore, the evidence presented by studies that use bankruptcy data from Compustat Global and BvD may need to be revised. It may be the case that those studies present biased parameters and, as a result, uninformative out-of-sample assessments. Moreover, accurate bankruptcy information is crucial for several other applications, for example, analyzing systemic risks or credit spreads. We contribute to the literature on data quality by showing that not only high-quality financial data, but also high-quality bankruptcy event data is essential for an effective decision-making. Another contribution is that we add to the sparse evidence on bankruptcy prediction for the international market by finding models that perform best for German public corporations.

The third essay (chapter 4) is based on the single-authored working paper “Bankruptcy Proceedings, Annual Report Timing, and Bankruptcy Prediction: Crawling the German Business Register” (2019). While the second essay focuses on publicly traded firms, the third essay also analyzes privately held firms. Collecting a database of German bankruptcy events that also include private firms, I can analyze the properties of German bankruptcy proceedings, the implications of a bankruptcy filing for the publication of annual reports, as well as the impact of firm size on bankruptcy prediction. As stated above, there have been many studies on how to improve the prediction of bankruptcies. However, few studies investigate bankruptcy proceedings themselves after bankruptcy has already been filed (e.g., Crhova and Pasekova, 2013). Bankruptcy proceedings are important constructions that serve mainly two goals: first, satisfying the creditors and, second, bringing productive assets back to the productive process (e.g., Crhova, Fiserova, and Pasekova, 2016). I choose to analyze the proceedings of German private firms for two reasons. First, most bankruptcy studies focus on publicly traded firms and, thus, mostly on very large firms. However, considering the relatively few number of listed firms, one can state that private firms are crucial to most economies, thereby requiring specific research (e.g., Dietsch and Petey, 2004; Filipe, Grammatikos, and Michala, 2016; Altman et al., 2017). Second, the literature on non-U.S. firms is sparse (e.g., Tian and Yu, 2017; Dahiya and Klapper, 2007; Lohmann and Ohliger, 2017).

I crawl the German business register to collect bankruptcy events of German firms. In contrast to the second essay, which concentrates on public firms, the third essay also takes privately held firms into account. I compare the number of bankruptcy events in the business register and in BvD with the official figures from Destatis ("*Statistisches Bundesamt*"). While the second essay quantifies the impact of the limited bankruptcy information contained in traditionally used data sources on the parametrization and the evaluation of models, the third essay makes an analysis of the German business register events. In particular, it investigates the different types of events, their respective number, their order, and the duration between certain events. I further extract the annual report publishing dates from the business register. By combining them with bankruptcy dates, I analyze the relationship between bankruptcy events and the timing of publishing annual reports. Moreover, I use the large sample to compare bankruptcy prediction models for the German market. Finally, splitting the sample into small, medium-sized and large firms, I analyze the impact of firm size on the results of prediction models.

For recent years, the business register includes more events than BvD. However, the coverage of the business register for earlier years is low because details of bankruptcy proceedings must be deleted six months after their termination. Furthermore, I find significant differences between public and private firms: while for limited liability firms, bankruptcy proceedings are opened 75.2 days on average after the court orders protective measures, this duration is significantly higher for joint-stock firms (86.0 days). Moreover, limited liability firms are refused bankruptcy proceedings due to insufficient assets more often than joint-stock companies are. In addition, filing for bankruptcy significantly impacts the timing of the subsequent annual report: firms take more time to publish an annual report after bankruptcy proceedings have been opened. Moreover, I show that Hess and Huettemann's (2019) accounting model performs best among the accounting-based models for the German market. As the empirical analysis of this essay uses privately-held firms, I validate that the accounting model of the first essay outperforms existing accounting-based models not only for the scope of public firms, but also for private firms. Finally, I show that the bankruptcies of large firms can be predicted more accurately than those of small and medium-sized firms. Thus, firm size affects the results of prediction models.

The findings of the third essay help understand a typical German bankruptcy proceeding. In particular, I show differences in proceedings for public and private firms. Moreover, to the best of my knowledge, this is the first study to find a relationship between bankruptcy dates and annual report dates. I contribute to the literature on non-listed and international firms by investigating their typical bankruptcy proceedings and by predicting their bankruptcies. I further show that regularly crawling the business register yields a bankruptcy dataset that is more complete than BvD. This is highly relevant to the practitioners and academics who conduct firm-level distress analyses. In addition, I add to the sparse literature on the choice of bankruptcy prediction models for the German market and for private firms. I further provide first evidence for a positive correlation between firm size and the accuracy of prediction models.

Taken together, the three essays in this thesis provide new insights into corporate bankruptcies, their prediction, their collection, and their characteristics. First, including the probability of negative book equity enhances the performance of bankruptcy prediction models, simultaneously enlarging their scope of application. Thereby, it adds to the broad literature on the search for a superior model. Second, the quality of bankruptcy information impacts the results of prediction models, which contributes to the literature on the quality of financial data. Third, properties of bankruptcy proceedings differ by company type. In addition, there is a relationship between a bankruptcy filing and the date of the subsequent annual report as well as between firm size and the results of bankruptcy predictions. These results add to the literature on corporate bankruptcy proceedings as well as to the literature on their predictions. All three essays help to identify superior prediction models, not only for public U.S. firms, but also in the context of non-U.S. and privately held firms.

Chapter 2

Predicting Bankruptcy via Cross-Sectional Earnings Forecasts*

2.1 Introduction

General Motors, Lehman Brothers, and WorldCom are only a few examples of bankruptcies that have had huge impacts on capital markets[4]. Therefore, predicting corporate bankruptcies is critical for investors, managers, regulators, and banks. For example, the ability to predict bankruptcies enables investors to avoid specific securities, managers and regulators to take corrective actions, or banks to decide whom they should grant loans. We develop a new bankruptcy prediction model based on the assumption that negative book equity is a good predictor of financial distress.[5] We predict next year's book equity based on a firm's current book equity and its forecasted earnings. Thus, our key

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[4] For example, May (2014) quantifies the costs for firms that lost access to the credit lines committed by Lehman Brothers.

[5] A firm has negative book equity if the value of its assets is below the value of the obligations it must service.

variable is the probability that current book equity is insufficient to cover upcoming losses. Strictly out-of-sample tests show that our approach leads to more accurate predictions than benchmark models.

To calculate the probability of negative equity, we need to estimate the distribution of a firm's future earnings. We build upon cross-sectional earnings regression models proposed by Hou, van Dijk, and Zhang (2012) and Li and Mohanram (2014) to obtain earnings forecasts. In addition, we use the standard errors of these forecasts to obtain a measure for earnings risk, i.e., the range of a firm's possible earnings (or losses). Using this information, we can derive a closed form solution for the probability that a firm's book equity becomes negative. Our approach shares the use of the loss distribution with the value at risk concept. Value at risk is defined as a loss value that is not exceeded by a pre-specified probability. However, we start with a specific value (book equity) and then measure the probability that a firm's loss exceeds this specific value.

Our paper is related to Correia, Kang, and Richardson (2018) who find that different fundamental volatility measures based on both historical and forecasted earnings[6] have incremental out-of-sample predictive power for bankruptcy. We expand this idea. We use both the dispersion of future earnings forecasts and the earnings forecast itself and combine these figures with the current level of equity. By this, we obtain a measure of future over-indebtedness, indicating whether a firm's current risk capital will suffice to survive adverse conditions. Hence, the volatility of earnings forecasts that Correia et al. (2018) use is a subset of the explanatory variables of our model.

In most jurisdictions, illiquidity, i.e., the inability to pay off expired debt, triggers bankruptcy filings. In contrast, over-indebtedness appears to be lower ranking. For example, in the U.S., firms with negative equity are not required to file for bankruptcy. However, in several European countries the inability to offset its debt with assets requires firms to take immediate action. For example, in Germany and Austria, among others, firms are required to inform their lenders immediately, and if they cannot negotiate some agreement, to file for bankruptcy protection. This supports our notion that negative book equity is a good predictor of financial distress. We claim that negative book equity is a strong indication of financial distress independent of the national bankruptcy regulation as

[6] They use the cross-sectional quantile forecast model of Konstantinidi and Pope (2016) that resemble those of Hou et al. (2012).

it makes it less likely for a firm to obtain further credit and ultimately pay its debts when they become due. In fact, we show that our probability measure that a firm's book equity turns negative provides strong out-of-sample predictions for insolvency filings of U.S. firms. Note that, theoretically, negative book equity is an even better predictor of bankruptcy in countries in which it is a formal criterion for bankruptcy.

Firms may experience negative book equity for different reasons (e.g., Ang, 2015). First, they may suffer from persistent losses which is related to a default event. Second, firms may experience a non-recurring shock which could be a write-off or restructuring costs that could be strategically reported by managers. Furthermore, the shock could emerge from share buybacks or accounting rules such as the undervaluation of assets or major goodwill write-offs after takeovers. This non-recurring shock may not be directly related to distress. For firms that become bankrupt, we indeed observe that their book equity decreases successively during the years preceding bankruptcy. This supports the notion that the first case is prevalent, i.e., weakness in earnings drives most firms into bankruptcy. Cross-sectional earnings forecasts are good in capturing a persistence in earnings (or losses), rather than predicting one-time shocks. Thus, the probability of negative book equity (PNBE) covers rather the first case that is relevant to bankruptcy than the second case that is not related to distress. By this, is a good predictor of bankruptcy, not only empirically but also theoretically.

Our paper is also related to approaches that use Merton's (1974) option pricing theory to compute default probabilities, as they use the market value of equity as an indicator for the distance to default (e.g., Vassalou and Xing, 2004; Hillegeist, Keating, Cram, and Lundstedt, 2004; Bharath and Shumway, 2008; Charitou, Dionysiou, Lambertides, and Trigeorgis, 2013). They view the market value of equity as a call option on the market value of assets where the strike price is the book value of liabilities. Thus, if the market value of assets falls below that of liabilities, market equity goes to zero and the firm goes bankrupt. Hence, although the underlying idea is quite different, our probability of negative book equity resembles the distance-to-default (DD) models in the sense that the resulting probability of default is decreasing in equity and increasing in volatility. Studies using DD models show that a decreasing market equity is a trigger of bankruptcy. One motivation of this study is to show that a decreasing book equity is an even better predictor. Focusing on stock prices, DD models and other market-based models (e.g., Duffie, Saita, and Wang, 2007; Giesecke, Longstaff, Schaefer, and Strebulaev, 2011) are only applicable to firms that are actively traded in the stock markets. A strength of our model is that it does not require stock market data, as we focus on the fundamental volatility, i.e., possible fluctuations of earnings. Hence a major advantage of our approach over DD models is, that we can also provide bankruptcy predictions for smaller firms without access to capital markets. In addition, we do not require a closed theory such as option pricing theory, which is accompanied by assumptions and restrictions (e.g., that a firm's assets follow a certain stochastic process or that it has just a single zero-coupon bond outstanding). Furthermore, we use cross-sectional models to forecast earnings, instead of time series models that are used within the DD models. Cross-sectional models exploit the history of all firms and a broader dataset, and by this can provide forecasts for firms with a short or even no history. Thus, we further expand the scope of application compared to the use of time series models in DD models.

We present three versions of our bankruptcy prediction model: The first version includes only our core variable, i.e., the probability of negative book equity. For simplicity, we call it the "negative book equity" model. However, firms with negative book equity do not inevitably become bankrupt. For example, firms might intentionally operate with negative book equity to avoid tax. Therefore, our second model version adds additional accounting variables which allow to better discriminate between negative book equity firms that continue operating and those that become bankrupt. Haowen (2015), for example, finds that non-bankrupt negative book equity firms tend to have a higher book leverage ratio, have more capital expenditure, pay less tax, have lower profitability, and be smaller in size. These findings, however, have not yet been incorporated into bankruptcy prediction models. This version is called the "accounting" model. The third version adds stock market variables, primarily to allow for a fair comparison with other models drawing on such data. In particular, it replaces the book leverage ratio with the market leverage ratio and adds two common market-based variables: excess return and its standard deviation. We call this version the "market" model. For example, Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008) show that market variables improve model performance. In contrast, Reisz and Perlich (2007) and Agarwal and Taffler (2008) show that accounting models perform similarly to market models. We analyze the out-of-sample performance of our three models and compare them to leading alternatives. Specifically, we re-estimate the most popular models: Altman (1968), Ohlson (1980), Shumway (2001), and the best model version of Merton's DD approach, as outlined in Bharath and Shumway (2008). To eliminate the effects of different statistical methods or sample periods, we embed all these models into hazard models that employ firms' entire histories and the same data.

The empirical results of our study can be summarized as follows. First, we find justification for our overall approach of tying a firm's bankruptcy risk to negative book equity. In fact, we show that book equity and earnings diminish in the years before bankruptcy, with the most dramatic fall happening in the last year before bankruptcy. This finding suggests that negative book equity is a good predictor of bankruptcy, even in the United States whose bankruptcy law does not mandate firms to file for bankruptcy if assets fall below liabilities. Second, we provide evidence that the functional form we use for the probability cannot be completely replaced by a linear combination of the variables used to calculate this probability. The functional form remains significant even if we include all components as individual variables in the model. Third, we find strong differences in the means of certain variables for bankrupt versus non-bankrupt firms with negative book equity. While this validates, for example, Haowen's (2015) results for the market leverage ratio, profitability, and size, it also suggests that we can improve our negative book equity model by including further accounting variables. In fact, by means of rolling out-of-sample analyses, we demonstrate that our augmented accounting model outperforms those models that rely solely on accounting information. Fourth, performance can be further improved by adding stock market information. The out-of-sample analysis shows that our market model performs best with respect to all three accuracy measures: the goodness-of-fit deciles, the area under the ROC (receiver operating characteristic) curve, and the economic value. Overall, our market model thus outperforms all leading alternatives of bankruptcy prediction, including those that use market information. Moreover, it shows significantly better results than our accounting model. This finding supports Shumway (2001), Beaver, McNichols, and Rhie (2005), Campbell et al. (2008), and Beaver, Correia, and McNichols (2012) who demonstrate that market variables add explanatory power. However, the performance boost associated with models relying on market data comes at a high cost, as the use of these models is limited to firms that have access to capital markets. Altman, Iwanicz-Drozdowska, Laitinen, and Suvas (2017) point out that predicting bankruptcies of private firms is equally important. Managing large loan portfolios, for example, requires models that can also assess small- and medium-sized firms. Therefore, it is all the more important to note that our accounting model improves out-of-sample performance, coming close to alternative market models, but at the same time not restricting applicability to public firms. Using the rolling regression technique, we further show that our market model performs better not only on average but for most prediction years. Fifth, there is no difference throughout the whole evaluation period in the performance of our negative book equity model compared with the other models. Thus, we demonstrate that book equity and earnings are credit-relevant even in a fair value accounting regime.

The remainder of this chapter is organized as follows. Section 2.2 describes and motivates the variables that we use in our bankruptcy prediction models. In Section 2.3, we describe our sample selection, report the descriptive statistics, and explain our methods. In Section 2.4, we present and discuss our results. Section 2.5 concludes.

2.2 Constructing bankruptcy measures

2.2.1 Negative book equity model

We exploit the fact that negative book equity is a strong indicator of financial distress. Negative book equity may arise because of persistent losses or a non-recurring shock. While the first case is directly related to distress, the second case is not. Thus, we construct a model that only identifies firms as bankrupt if persistent losses diminish the book equity and not if firms experience a shock. As cross-sectional earnings forecasts by nature translate past losses into future losses rather than capture non-recurring shocks, our probability of negative book equity reflects rather the first than the second case. By this, it is a good predictor of bankruptcy.

Our basic model comprises just one variable, the probability that a firm's future losses will deplete its book equity. We call this model our "negative book equity model." Let $\mathrm{BkEq}_{i,t}$ denote the current book equity of firm i. Book equity is equal to a stockholder's equity (Compustat item SEQ). If SEQ is missing, we take common equity (CEQ) plus the value of preferred stock (PSTK). If CEQ or PSTK is missing, book equity is evaluated as total assets (AT) minus total liabilities (LT) minus minority interest (MIB). Further, let $\mathrm{Earn}_{i,t+12m}$ denote future earnings (change in retained earnings) for this firm for the subsequent twelve months, where earnings are equal to net income (NI) minus dividend payments (DVT). We calculate the next year's book equity as the sum of current book equity and earnings. Then, book equity turns negative if future losses (i.e., negative earnings) exceed current book equity:

$$-Earn_{i,t+12m} > BkEq_{i,t}. \tag{2.1}$$

Thus, our key predictor is the probability that a firm's future losses exceed the currently available book equity:

$$PNBE_{i,t} = Prob\left(Earn_{i,t+12m} < -BkEq_{i,t}\right). \tag{2.2}$$

where $PNBE_{i,t}$ represents the probability of negative book equity for firm i at time t. To calculate this probability, we use the mean of an individual firm's conditional earnings estimate, $\mu\left(\widehat{\mathrm{Earn}}_{i,t+12m}\right)$. This estimate is obtained from a rolling cross-sectional regression model in the spirit of Hou et al. (2012) and Li and Mohanram (2014). We describe this approach in detail in Section 2.2.2. The regression also provides us with a measure of the uncertainty of earnings estimates, namely the standard deviation of a firm's conditional earnings estimate, $\sigma\left(\widehat{\mathrm{Earn}}_{i,t+12m}\right)$.[7] Assuming normality of earnings, we can use the means and standard deviations of the earnings estimates to directly calculate the probability that firms' future earnings might fall below a given threshold, i.e., that losses exceed the current book value of equity:

$$\begin{aligned} PNBE_{i,t} &= Prob\left(Earn_{i,t+12m} < -BkEq_{i,t}\right) \\ &= \Phi\left(-\frac{BkEq_{I,t}+\mu\left(\widehat{Earn}_{i,t+12m}\right)}{\sigma\left(\widehat{Earn_{\iota,t+12m}}\right)}\right), \end{aligned} \tag{2.3}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.[8] The probability of default depends on the sum of a firm's current book equity and its mean earnings estimate relative to the standard deviation of its earnings estimate.

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[7] $\sigma\left(\widehat{\mathrm{Earn}_{\iota,t+12m}}\right)$ denotes the standard deviation of a predicted response of an individual firm for given data rather than the standard deviation of the estimated conditional mean. Thus, it yields the prediction interval rather than the confidence interval. In addition to the uncertainty in estimating the conditional mean, $\sigma\left(\widehat{\mathrm{Earn}_{\iota,t+12m}}\right)$ also reflects the variability of an individual observation in this conditional distribution: $\sigma\left(\widehat{\mathrm{Earn}_{\iota,t+12m}}\right) = \hat{\sigma}\sqrt{(1+\widehat{\mathrm{x}_\iota(\mathrm{X}'\mathrm{X})^{-1}}\mathrm{x}_\iota)}$, where $\hat{\sigma} = \sqrt{\frac{1}{n-2}\sum_{i=1}^{n}(y_i-\hat{y_\iota})}$ is the standard deviation of the residuals, x_i is the explanatory vector of firm i, X is the data matrix, y_i is the outcome of firm i, and $\hat{y_\iota}$ is the predicted outcome of firm i.

[8] Linear regression estimates follow a t-distribution with $n - p$ degrees of freedom, where n denotes the number of observations and p the number of independent variables. Owing to the large number of observations, $n - p$ is consistently far above 40. Therefore, the t-distribution is well approximated by a standard normal distribution.

Option pricing models view market equity as a call option on the market value of a firm's assets, where the strike price is the market value of the firm's liabilities. Although this is a different setting than in our model, Vassalou and Xing (2004) and Hillegeist et al. (2004) develop a formula with a similar structure. Their probability of default depends on the ratio of expected future market equity and asset volatility, where future market equity is calculated as the current market value of assets minus current liabilities plus the expected asset changes according to a geometric Brownian motion. Our PNBE and the default probability extracted from option models have in common that a lower volatility and a larger equity lead to the assessment that a default is less likely. As option pricing models largely depend on market information, their use is restricted to firms that are actively traded in stock markets. In contrast, our approach does not require stock market data, as it builds on fundamental figures. Hence, a major advantage of our approach over option pricing models is, that we can also provide bankruptcy predictions for smaller firms without access to capital markets and, thus, enlarge the scope of application.

2.2.2 Earnings forecasts

We use earnings forecasts for the subsequent twelve months to calculate the PNBE.[9] Following Hess, Meuter, and Kaul (2017), who compare the performance of several cross-sectional models, we implement the RI model of Li and Mohanram (2014) on a per-share basis as this model shows a somewhat better performance.[10] To avoid a look-ahead bias all predictor variables are lagged by three months, i.e., we make predictions three months after the fiscal year end. This ensures that we do not use information before it is actually available. However, we differ from previous studies such as Hou et al. (2012) and Li and Mohanram (2014) who make predictions only once a year (i.e., each June), as we run regressions every month to forecast earnings exactly three months after the fiscal year end and not only at end of the following June. This ensures that the estimation is made promptly as soon as all information is at hand. Nevertheless, the forecast horizon is twelve months, and thus, the same as in Hou et al. (2012) and Li and Mohanram (2014). Following Hou et al. (2012), we employ a rolling regression technique based on windows

[9] To forecast the mean and the standard deviation of earnings, we use cross-sectional earnings forecasts models (e.g., Hou et al., 2012; Li and Mohanram, 2014) instead of quantile regression models (Konstantinidi and Pope. 2016) due to their wide acceptance.

[10] We also perform empirical tests that use the cross-sectional earnings forecast model of Hou et al. (2012) and the EP model of Li and Mohanram (2014) and level earnings instead of per-share earnings. The tenor of the results remains unchanged.

that comprise the most recent ten years of accounting data. Every month, we run the following cross-sectional regression:

$$E_{i,t+\tau} = \alpha_0 + \alpha_1 E_{i,t} + \alpha_2 NegE_{i,t} + \alpha_3 NegE_{i,t} \cdot E_{i,t}$$
$$+ \alpha_4 BkEq_{i,t} + \alpha_5 AC_{i,t} + \varepsilon_{i,t+\tau}\,, \tag{2.4}$$

where $\mathrm{E_{i,t}}$ denotes the change in retained earnings per share of firm i at time t, $\mathrm{NegE_{i,t}}$ is a dummy that takes the value of one if firm i reports negative earnings at time t, and $\mathrm{NegE_{i,t} \cdot E_{i,t}}$ is an interaction term. $\mathrm{BkEq_{i,t}}$ is the book value of equity per share, $\mathrm{AC_{i,t}}$ are accruals per share, and $\tau = 1, 2$. We calculate accruals following Hou et al. (2012). Up to 1988, accruals are the change in non-cash current assets (Compustat items ACT and CHE) minus the change in current liabilities (LCT) plus the change in short-term debt (DLC) plus the change in taxes payable (TXP), excluding depreciation and amortization costs (DP). From 1988 onwards, we define accruals as income before extraordinary items (IB) minus cash flow from operations (OANCF). Missing values are set to zero.

Using the coefficients from this regression, we can easily calculate the out-of-sample predictions for the two subsequent fiscal years. Weighting these predictions, we construct earnings forecasts (and corresponding standard deviations) with a horizon of twelve months ahead.[11]

2.2.3 Accounting model

A central assumption in our basic one-variable model version is that negative book equity directly leads to bankruptcy. However, firms with negative equity do not inevitably become bankrupt. Instead, they might intentionally operate with negative book equity to reduce taxes, for example. To further discriminate between healthy and bankrupt firms, we introduce an extended model version, our “accounting model,” which adds independent variables. In particular, we follow Haowen (2015), who finds that non-bankrupt negative book equity firms tend to have a lower leverage ratio, more capital expenditure, pay less tax, have lower profitability, and be smaller than bankrupt negative book equity firms. However, the variables suggested by Haowen have not been incorporated into bankruptcy prediction models yet. Therefore, we perform profile analyses to analyze whether these

[11] As we make estimations three months after the fiscal year-end, the predictions for the next fiscal year-end have a weight of nine-twelfths and the predictions for the fiscal year-end after that have a weight of three-twelfths.

variables can indeed explain differences between bankrupt and non-bankrupt firm-years. The results clearly show that these additional variables increase the predictive power. In contrast to our negative book equity model, which contains only one variable, the augmented accounting model can better discriminate between bankrupt and non-bankrupt firm-years.

Besides the probability that book equity becomes negative, our accounting model therefore comprises the following accounting-based measures: We use a dummy that takes the value one if book equity is negative, and zero otherwise (NegBkEq). Similarly, we add a dummy that equals one if the earnings forecast is negative, and zero otherwise (NegEarnFrc). Moreover, we use the book leverage ratio (BLR), calculated as the sum of long-term debt (Compustat item DLTT) and current debt (DLC) divided by total assets (AT). CAPXTA denotes capital expenditure (CAPX) divided by total assets (AT), TXT is the total amount of paid taxes (TXT), EBITTA is calculated as earnings before interest and taxes (EBIT) divided by total assets, and Size is measured by the logarithm of sales (SALE). EBITTA is also used by Altman (1968) and Size is used by Ohlson (1980).

2.2.4 Market model

There is ongoing debate whether market variables consistently add explanatory power compared with models that solely consider accounting variables. For example, Shumway (2001), Hillegeist et al. (2004), Beaver et al. (2005), Campbell et al. (2008), and Beaver et al. (2012) demonstrate that market variables can improve accuracy. In contrast, Reisz and Perlich (2007), Agarwal and Taffler (2008), and Xu and Zhang (2009) show that accounting-based models have similar performance. To test these hypotheses, we add two market variables that are taken from Shumway (2001) into our accounting model: the stock's past excess return (ER), which is the last year's stock return minus the last year's value-weighted index return, and the standard deviation of the stock's return (STDER). Moreover, we replace the book leverage ratio by the market leverage ratio (MLR), calculated as the sum of long-term debt (Compustat item DLTT) and current debt (DLC) divided by the sum of long-term debt, current debt, and market equity. Market equity is the fiscal year-end equity price (PRCC_F) multiplied by the number of common shares outstanding (CSHO). We call this augmented specification our "market model."

2.3 Data and method

2.3.1 Sample description and summary statistics

We use bankruptcy information taken from Chava and Jarrow (2004), which is updated in Chava (2014) and Alanis, Chava, and Kumar (2016).[12] This data comprises the bankruptcy events between January 1964 and December 2014 of all firms trading on the NYSE, AMEX, or NASDAQ, independent of their size. Bankruptcy is defined as filing for Chapter 7 or Chapter 11. We make earnings forecasts three months after the fiscal year-end to ensure public availability of the information that we use. That is, we predict the book equity of 15 months after the fiscal year-end. Accordingly, we declare a firm will become bankrupt during the subsequent year if the bankruptcy date lies between the last fiscal year-end plus three months (our estimation date) and the last fiscal year-end plus 15 months. Thus, the dependent variable equals one if the firm becomes bankrupt during this period, and zero otherwise. Our bankruptcy forecast horizon is twelve months for all firm-years. In contrast, many previous studies use the fiscal year or calendar year as their horizon. As we have bankruptcies until the end of 2014, our sample comprises observations with a fiscal year-end before or equal to the end of September 2013.

Table 2.1 summarizes the information about these bankruptcy events. The second column shows the number of active firms in a given year, the third column shows the number of firms with a bankruptcy dummy equal to one and the fourth column presents the corresponding percentage. We observe 1,490 bankruptcy events during our sample period. Chava and Jarrow (2004) retain a total of 464 for their sample period from 1963 until 1998 and Shumway (2001) uses 300 bankruptcies between 1962 and 1992. The overall bankruptcy rate is 0.79%, with substantial fluctuation over the years. Bankruptcies were rare until the late 1970s, whereas the bankruptcy rate had a high in 1985 of 1.20% and a peak of 2.47% in 2001.

Our initial sample comprises all firms listed on the NYSE, AMEX, or NASDAQ in the intersection of the annual Compustat North America fundamentals files and the daily and monthly CRSP files between 1958 and 2013. We obtain out-of-sample bankruptcy predictions with a two-step methodology.

[12] We are grateful to Sudheer Chava for kindly providing us with his bankruptcy data.

In the first step, we use a rolling regression technique to obtain earnings forecasts. We obtain the one-year-ahead earnings forecasts for 1969 to 2014, requiring ten years of data for these cross-sectional earnings regressions. The first earnings forecasts are made in 1968 for 1969 using accounting data from 1958 to 1967 and the last forecasts are made in 2013 for 2014 based on data from 2003 to 2012. These forecasts are free of a look-ahead bias as we only use information up to the point in time when the forecasts are made.

Table 2.1 Number of bankruptcies per year

Year	Active Firms	Bankruptcies	(%)	Year	Active Firms	Bankruptcies	(%)
1968	1,210	0	0.00	1991	4,447	41	0.92
1969	1,427	1	0.07	1992	4,592	33	0.72
1970	1,654	3	0.18	1993	4,799	32	0.67
1971	1,867	2	0.11	1994	5,257	22	0.42
1972	1,961	5	0.25	1995	5,505	27	0.49
1973	2,999	10	0.33	1996	5,791	28	0.48
1974	3,284	15	0.46	1997	6,227	35	0.56
1975	3,290	8	0.24	1998	6,293	58	0.92
1976	3,286	11	0.33	1999	5,990	65	1.09
1977	3,245	11	0.34	2000	5,711	112	1.96
1978	3,227	13	0.40	2001	5,501	136	2.47
1979	3,384	15	0.44	2002	5,071	93	1.83
1980	3,502	22	0.63	2003	4,788	64	1.34
1981	3,622	24	0.66	2004	4,515	22	0.49
1982	3,846	36	0.94	2005	4,502	26	0.58
1983	4,001	24	0.60	2006	4,422	16	0.36
1984	4,267	44	1.03	2007	4,326	29	0.67
1985	4,330	52	1.20	2008	4,225	38	0.90
1986	4,383	40	0.91	2009	3,994	21	0.53
1987	4,616	39	0.84	2010	3,829	16	0.42
1988	4,715	53	1.12	2011	3,723	23	0.62
1989	4,519	41	0.91	2012	3,642	20	0.55
1990	4,399	47	1.07	2013	3,577	17	0.48
				Total	187,761	1,490	0.79

This table lists the number of active firms, the number of bankruptcy dummies, and the percentage of bankruptcy dummies among active firms for every year of our sample period of 1968 to 2013. The bankruptcy dummy takes the value of 1 if a firm becomes bankrupt in the three months after the fiscal year-end and 15 months after the fiscal year-end.

In the second step, we use the resulting earnings forecasts to predict bankruptcies. To produce strictly out-of-sample forecasts here as well, we use a rolling estimation technique again. That is, we estimate parameters based on sample windows including the most recent ten years of data and then calculate one-year-ahead out-of-sample predictions. Our first estimation period comprises data from 1968 to 1977 to predict bankruptcies for 1978 and our last period comprises data from 2003 to 2012 to predict bankruptcies for 2013. This rolling regression technique resembles the procedure of practitioners.

As in the earnings regression, all our bankruptcy measures are lagged by three months to ensure that they are observable when we use them for the estimation. That is, we assume that the accounting and market information is available three months after the fiscal year-end. For the bankruptcy predictions, we use those earnings forecasts that are made three months after the fiscal year-end. Accordingly, we make our one-year bankruptcy predictions three months after the fiscal year-end. We delete observations with missing variables that are required in the earnings forecast model or in any bankruptcy prediction model. These include the variable sets of our negative book equity, accounting, and market models as well as those of the models used for benchmarking, namely the Altman (1968), Ohlson (1980), and Shumway (2001) models and the DD model used by Bharath and Shumway (2008).[13] Appendix 2.A describes the variable construction for these bankruptcy prediction models. To reduce the effect of outliers, we winsorize all variables (except the indicator variables and probabilities) annually at the 1st and 99th percentiles.

Table 2.2 provides summary statistics for the variables described above. Panel A presents the measures used to forecast bankruptcy and Panel B presents the measures used to forecast earnings. We report the mean, median, standard deviation, and certain percentiles of the 189,251 firm-years with complete data availability for 1968 to 2013. Most importantly, the overall firm-year average of the probability that losses exceed current book equity (i.e., the PNBE) is 11%. At the same time, only 25% of all firm-years have a PNBE greater than 9%. For 1% of all firm-years, the PNBE is greater than 96% and half the firms have a PNBE that is zero. Based on this, the PNBE might be a good proxy for the probability of default. As the overall bankruptcy rate is only 0.79%, a possible cut-off point of PNBE to discriminate between bankrupt and non-bankrupt firm-years might be

[13] DD models use Merton's (1974) option pricing theory and have been shown to be good predictors of bankruptcy by Hillegeist et al. (2004) and Vassalou and Xing (2004). We use the DD version model that Bharath and Shumway (2008) find to perform best, which they call "Model 7." It comprises their naïve version of Merton's DD probability, the inputs of this probability as individual measures, and the ratio of net income and total assets.

above 50%. For 33% of all firm-years, the cross-sectional earnings models forecast negative earnings. The statistics for EBITTA, ER, and STDER are consistent with former bankruptcy prediction studies such as Shumway (2001).

Table 2.2 Summary statistics (N=189,251)

Panel A: Variables in bankruptcy prediction models

Variable	Model	Mean	STD	1%	25%	Median	75%	99%
$PNBE_t$	NBE / A / M	0.11	0.21	0.00	0.00	0.00	0.09	0.96
$NegEarnFrc_t$	A / M	0.33	0.47	0.00	0.00	0.00	1.00	1.00
BLR_t	A	0.33	0.36	0.00	0.07	0.29	0.50	1.55
$CAPXTA_t$	A / M	0.07	0.07	0.00	0.02	0.05	0.09	0.39
TXT_t	A / M	34.47	145.89	-26.66	0.00	1.45	12.05	708.00
$EBITTA_t$	A / M	0.01	0.34	-1.27	0.00	0.07	0.13	0.35
$Size_t$	A / M	4.83	2.22	0.37	3.23	4.64	6.30	10.35
MLR_t	M	0.26	0.25	0.00	0.03	0.19	0.42	0.90
ER_t	M	0.02	0.64	-0.96	-0.34	-0.07	0.22	2.35
$STDER_t$	M	0.12	0.08	0.00	0.07	0.10	0.15	0.43

Panel B: Variables in earnings forecast models

Variable	Mean	STD	1%	25%	Median	75%	99%
E_t	37.00	274.70	-303.00	-1.65	1.55	13.81	995.00
$NegE_t$	0.34	0.47	0.00	0.00	0.00	1.00	1.00
$NegExE_t$	-14.45	90.29	-303.00	-1.65	0.00	0.00	0.00
$BkEq_t$	579.26	2,444.08	-38.61	10.94	47.93	233.48	9,709.55
AC_t	-78.49	375.50	-1572.00	-23.33	-2.78	0.18	71.00
$EarnFrc_{t+12m}$	6.16	1511.40	-1.84	-0.28	0.33	0.99	5.03
$STDEarnFrc_{t+12m}$	1.81	29.94	1.09	1.46	1.58	1.67	1.88

This table reports the summary statistics of the following forecast variables ($ millions for all values except dummy variables and probability values). For more details, see the data construction in Appendix 2.A. PNBE is the probability that losses deplete current book equity, NegBE is a dummy for negative book equity, NegEarnFrc is a dummy for negative earnings forecast, BLR is the book leverage ratio, CAPXTA are capital expenditures over total assets, TXT are taxes, EBITTA are earnings before interest and taxes over total assets, size is the logarithm of sales, MLR is the market leverage ratio, ER is the excess return, STDER is the standard deviation of the return, E is the change in retained earnings, NegE is a dummy for negative earnings, NegExE is an interaction term of the dummy for negative earnings and earnings, BkEq is the book equity, AC are accruals, EarnFrc is the 12-month earnings per share forecasts, and STDEarnFrc is the corresponding volatility. Panel A shows those variables used to forecast bankruptcy and Panel B shows those variables and the results of earnings forecasts models. Each observation represents one particular firm in one particular year. The reported values are the time series averages of yearly cross sectional means, medians, standard deviations, and respective percentiles. All variables (except indicator variables and probability values) are winsorized annually at the 1^{st} and 99^{th} percentile. The column labeled “Model” indicates in which model the variable is used, with NBE meaning our negative book equity model, A meaning our accounting model and M meaning our market model. The sample period is from 1968 to 2013. Summary statistics are reported for those observations for which all variables of any model are available.

2.3.2 Method

Shumway (2001) demonstrates that the likelihood function of hazard models is equal to that of logistic regressions with multiple observations per firm. We follow Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008) and estimate the hazard model as a multi-period logistic regression. Thus, the probability of a firm becoming bankrupt follows a logistic distribution with the parameters (α, β) and is equal to

$$P_t(y_{it} = 1) = \frac{1}{1+exp(-\alpha-\beta x_{i,t})}, \tag{2.5}$$

where y_{it} is the bankruptcy dummy that equals one if the firm fails in the following twelve months, and zero otherwise, and $x_{i,t}$ is the vector of the explanatory variables known at t, that is, three months after the fiscal year-end. The higher $\alpha + \beta x_{i,t}$, the greater is the estimated probability of bankruptcy. The estimates and their significance levels are calculated using a maximum likelihood technique. Shumway (2001) points out that the test statistics produced by a logistic regression are incorrect for the hazard model. Calculating correct test statistics requires dividing them by the average number of firm-years per firm. The statistics reported in this study have been adjusted accordingly.

Static models (e.g., Altman, 1968; Ohlson, 1980) use a single observation per firm. Arbitrarily selecting only one firm-year might entail sample selection bias. In contrast, the approach of this study allows the use of entire firm histories. Thus, our estimation technique exploits more information and eliminates the sample selection bias. Note that applying such a technique to variable sets used by Altman (1968) or Ohlson (1980) already improves their performance compared with applying their original estimation technique.

2.4 Empirical results

2.4.1 Evolution of book equity and earnings around bankruptcy

In the following, we validate the assumption made for the construction of PNBE that negative book equity is a good indicator of bankruptcy in the sense that the book equity of bankrupt firms diminishes in the years before bankruptcy and is finally depleted by losses in the year of bankruptcy. Table 2.3 reports the means of the variables related to book equity and earnings for bankrupt firms as well as for firms that never became bankrupt. For bankrupt firms, we provide statistics for each of the five years preceding bankruptcy and for the year of bankruptcy. For example, year -1 denotes the year one year before bankruptcy and year 0 denotes the year of bankruptcy. To avoid confounding effects from changes in the sample, we analyze only those 739 bankrupt firms for which we have at least five years of data before their bankruptcy.[14] Of these firms, only 300 also present a balance sheet in the year of their bankruptcy. For comparison we report the statistics for the non-bankrupt firms (corresponding to another 168,297 firm-years).

Table 2.3 Evolution of book equity and earnings in the years around bankruptcy

	Bankrupt Firms						Non-bankrupt Firms
	Years Relative to Bankruptcy						
Variable	-5	-4	-3	-2	-1	0	
$PNBE_t$	0.12	0.13	0.15	0.22	0.41	0.61	0.10
$BkEq_t$	215.00	223.21	198.44	171.59	82.75	-90.07	759.28
$BkEq_t/AssT_t$	0.40	0.38	0.33	0.25	0.03	-0.27	0.48
$NegBE_t$	0.04	0.05	0.07	0.12	0.29	0.55	0.03
$Earn_t$	-0.85	-19.46	-22.92	-45.85	-99.25	-245.63	49.17
$Earn_t/AssT_t$	-0.09	-0.10	-0.10	-0.18	-0.37	-0.52	-0.14
$NegE_t$	0.45	0.49	0.56	0.73	0.89	0.89	0.33
N	739	739	739	739	739	300	168,297

This table reports the summary statistics of bankrupt firms and of firms that never became bankrupt, respectively. For bankrupt firms, we report statistics in the last five years before bankruptcy and in the year after bankruptcy to see the evolution. We only include those bankrupt firms with a history of at least five years before bankruptcy to ensure that we investigate the same firms over time. For non-bankrupt firms, we report statistics for all observations. The variables ($ millions for all the values except the dummy variables and probability values) are the following: PNBE is the probability that losses deplete current book equity, BkEq is book equity, BkEq/AssT is book equity divided by total assets, NegBE is a dummy for negative book equity, Earn is the change in retained earnings, Earn/AssT is the change in retained earnings divided by total assets, and NegE is a dummy for negative earnings. All the variables (except the indicator variables and probability values) are winsorized annually at the 1st and 99th percentiles. The sample period is from 1968 to 2013. Quantities are reported for those observations for which all the variables are available.

For the non-bankrupt firms, we observe a negative book equity only in 3.0% of the firm-years. In contrast, even five years before bankruptcy, 4% of bankrupt firms already have negative book equity. This ratio increases monotonically to 29% in year -1, directly before bankruptcy. Finally, 55% of bankrupt firms have negative book equity in the year in which they go bankrupt (year 0). Note, however, that out of the 739 bankrupt firms only

[14] This restriction is only made for this analysis; all other analyses also include bankrupt firms with a history of four years or less before bankruptcy.

300 are able to present financial statements at that time. Presumably, the situation of the others is even worse, so that the ratio over all bankrupt firms would be even higher. Accordingly, average book equity five years before bankruptcy is 215.00, which is already much smaller than the average of firms that never go bankrupt (759.28). The average book equity for bankrupt firms consistently declines from year -4 on, with the most severe fall from 171.59 in year -2 to 82.75 in year -1. In the year of bankruptcy, average book equity is negative (-90.07). Note that standardizing book equity by total assets does not change the tenor of our observations. Thus, our results confirm that a low book equity is a signifier of bankruptcy even five years before bankruptcy.

Moreover, we find a similar pattern for earnings: Only 33% of non-bankrupt firm-years report negative earnings. In contrast, the ratio of bankrupt firms with negative earnings rises from 45% in year -5 to 89% in year -1. The mean earnings five years before bankruptcy is -0.85, already much smaller than the mean of firms that never become bankrupt (49.17). Average earnings for bankrupt firms show a downward trend from year -5 on and experience the most significant fall from -45.85 in year -2 to -99.25 in year -1. In the year of bankruptcy, average earnings are -245.63 and thus even more negative. Similar results apply to the mean of earnings standardized by total assets. Importantly, average losses in the year before bankruptcy (-99.25) deplete average book equity in the year of bankruptcy (82.75).

On average, our PNBE is monotonically increasing during the years before bankruptcy. In year -5, the mean of the PNBE is 11.7%, which is already higher than the average PNBE of non-bankrupt firm-years (10.0%). In year -2, the PNBE of bankrupt firms is 22.3% and in the year before bankruptcy, it jumps to 41.2% and finally to 60.6% in the year of bankruptcy.

These results strongly support our overall assumption that book equity diminishes in the years before bankruptcy and finally turns negative after bankruptcy. This depletion of book equity is explained by earnings that are negative even five years before bankruptcy and a further decrease in the years preceding bankruptcy. Book equity and earnings experience a dramatic fall, and losses exceed book equity in the year directly before bankruptcy. Accordingly, our variable of the PNBE, which also incorporates the volatility of the earnings estimate, consistently rises during the years before bankruptcy. By this, we find differences between healthy and bankrupt firms already five years before the latter firms go into bankruptcy. That is, diminishing book equity and weak earnings are early warning signals for an impending bankruptcy. It may be somewhat surprising that we find such a relation between book equity and bankruptcy for U.S. firms even though the U.S. bankruptcy law does not require firms to file for bankruptcy when assets fall below liabilities. Therefore, further research should be devoted to the question whether this relation is even stronger in countries whose law explicitly defines negative book equity to trigger a bankruptcy filing.

2.4.2 Profile analysis of bankrupt and non-bankrupt firms

Table 2.4 provides a profile analysis. We report the means and standard deviations of all variables separately for the group of non-bankrupt firm-years and the group of bankrupt firm-years. A bankrupt firm-year is an observation for which the fiscal year-end lies three to 15 months before the bankruptcy; in other words, the bankruptcy dummy is equal to 1. A non-bankrupt firm is an observation for which the bankruptcy dummy is equal to 0. That is, a non-bankrupt firm-year might be an observation of a firm that becomes bankrupt at a later point in time. The column labeled “Diff” shows the mean difference between healthy firm-years and bankrupt firm-years. We further report the results of Welch’s t-test on mean equality.[15]

This t-test is significant for all our bankruptcy model variables which suggests that the hypothesis that bankrupt and non-bankrupt firm-years have the same mean is rejected for all the variables. In firm-years with an impending bankruptcy all the variables experience some mean shift. For most variables the observed differences are as expected. Most importantly, firms that go bankrupt have an average PNBE of 41.3%, which is significantly higher than the probability of 10.4% for the healthy firm group. Thus, the PNBE has strong discriminating power. The untabulated median for the bankrupt group is 39%, close to its mean. However, the distribution of the PNBE is skewed for the non-bankrupt group. Its untabulated median is 0%, which is much smaller than its mean of 10%. Only 25% of the observations for non-bankrupt firms have a PNBE higher than 9% and only 10% have a PNBE higher than 45%. Furthermore, firms in their last year before bankruptcy more often have negative earnings forecasts, a higher leverage ratio, a lower amount of paid taxes, lower profitability measured by EBITTA, a lower excess return, a

[15] Welch’s t-test is a two-sample test for the hypothesis that two populations have the same mean. Unlike the more common Student’s t-test, Welch’s t-test does not assume equal variances or equal sample sizes.

higher return standard deviation, and are smaller in size. Unexpectedly, those firms have higher capital expenditure relative to total assets.

Overall, these variables may help to discriminate between bankrupt and non-bankrupt firm-years; consequently, they directly add to the idea of negative book equity and may increase the explanatory power of PNBE. In Section 2.4.3, we therefore include these variables into our "accounting" and "market" models and investigate whether they are indeed significant predictors of bankruptcy.

Table 2.4 Profile analysis and t-test for mean equality (N=189,251)

		Non-Bankrupt Firm-Years		Bankrupt Firm-Years				
Variable	Model	Mean	STD	Mean	STD	Diff	t-stat	
$PNBE_t$	NBE / A / M	0.10	0.20	0.41	0.36	-0.31	-32.83	***
$NegEarnFrc_t$	A / M	0.33	0.47	0.87	0.34	-0.54	-60.20	***
BLR_t	A	0.33	0.35	0.79	0.73	-0.46	-24.38	***
$CAPXTA_t$	A / M	0.07	0.07	0.08	0.11	-0.01	-4.43	***
TXT_t	A / M	34.71	146.34	4.39	62.28	30.32	18.39	***
$EBITTA_t$	A / M	0.01	0.34	-0.24	0.63	0.25	15.46	***
$Size_t$	A / M	4.83	2.23	4.45	1.96	0.38	7.40	***
MLR_t	M	0.25	0.25	0.58	0.31	-0.33	-40.73	***
ER_t	M	0.02	0.64	-0.45	0.52	0.47	34.90	***
$STDER_t$	M	0.12	0.08	0.19	0.11	-0.07	-27.18	***
N		187,761		1,490				

This table reports the summary statistics of the following forecast variables ($ millions for all the values except the dummy variables and probability values) for the bankrupt and non-bankrupt groups, respectively. For more details, see the data construction in Appendix 2.A. PNBE is the probability that losses deplete current book equity, NegBE is a dummy for negative book equity, NegEarnFrc is a dummy for a negative earnings forecast, BLR is the book leverage ratio, CAPXTA is capital expenditures over total assets, TXT is taxes, EBITTA is earnings before interest and taxes over total assets, size is the logarithm of sales, MLR is the market leverage ratio, ER is the excess return, and STDER is the standard deviation of the return. Each observation represents one particular firm in one particular year. The reported values are the time series averages of the yearly cross-sectional means and standard deviations. All the variables (except the indicator variables and probability values) are winsorized annually at the 1^{st} and 99^{th} percentiles. The column labeled "Model" indicates in which model the variable is used, with NBE meaning our negative book equity model, A meaning our accounting model, and M meaning our market model. The sample period is from 1968 to 2013. Quantities are reported for those observations for which all the variables are available. The column "Diff" shows the difference in the means of the non-bankrupt group and bankrupt group. The t-statistic of Welch's t-test of mean equality is reported, where an independent two-sample and unequal variances are assumed. *** denotes significance at the 1% level.

2.4.3 Estimation results

We use rolling windows that comprise the most recent ten years of data to calculate one-year-ahead out-of-sample predictions. We perform hazard models annually: our first estimation uses data from 1968 to 1977 to predict bankruptcies for 1978, and our last estimation is based on data from 2003 to 2012 to predict bankruptcies for 2013. As outlined in Section 2.3.2, we estimate the hazard model as a multi-period logistic regression and adjust the test statistics accordingly. Table 2.5 presents the coefficients of these hazard models, along with measures to evaluate their out-of-sample performance.

Table 2.5 Rolling hazard models of the bankruptcy prediction models

Panel A: Parameter estimates

Variable	Negative Book Equity Model		Accounting Model		Market Model	
Constant	-5.626	***	-7.449	***	-8.031	***
$PNBE_t$	3.684	***	1.501	***	1.040	***
$NegEarnFrc_t$			1.757	***	1.297	***
BLR_t			1.001	***		
$CAPXTA_t$			0.856		1.672	***
TXT_t			-0.043	***	-0.033	***
$EBITTA_t$			-0.920	***	-1.184	***
$Size_t$			0.192	***	0.111	***
MLR_t					3.023	***
ER_t					-0.669	***
$STDER_t$					2.656	***

Panel B: Goodness-of-fit deciles

Decile	Negative Book Equity	Accounting	Market	Altman (1968)	Ohlson (1980)	Shumway (2001)	Bharath and Shumway (2008)
1	45.29	55.97	65.66	55.69	50.56	58.01	61.38
2	13.62	19.45	16.50	14.12	20.22	17.28	16.15
3	10.60	9.06	6.53	7.58	11.24	8.50	7.23
4	8.50	5.27	4.07	5.27	5.62	5.41	5.48
5	6.46	3.58	2.25	4.07	3.37	3.23	2.60
6	4.42	2.88	1.69	4.63	1.76	2.32	1.90
7	3.23	1.54	1.19	2.39	2.11	1.40	1.47
8	2.95	0.98	0.98	2.53	1.33	1.33	1.05
9	2.11	0.56	0.77	2.11	1.90	1.26	1.69
10	2.81	0.70	0.35	1.62	1.90	1.26	1.05

(continued)

Table 2.5 Rolling hazard models of the bankruptcy prediction models (continued)

Panel C: Area under the ROC curve

	Negative Book Equity	Accounting	Market	Altman (1968)	Ohlson (1980)	Shumway (2001)	Bharath and Shumway (2008)
Mean	0.783	0.862	0.892	0.828	0.841	0.859	0.868

Panel D: Economic value of different misclassification costs

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7
	Negative Book Equity	Accounting	Market	Altman (1968)	Ohlson (1980)	Shumway (2001)	Bharath and Shumway (2008)
Credits	12,316.5	26,834.0	48,459.5	18,472.5	15,194.5	17,792.5	24,841.5
Market share (%)	7.47%	16.27%	29.38%	11.20%	9.21%	10.79%	15.06%
Defaults	383	101	75.5	257	183	129.5	139
Defaults/credits (%)	3.11%	0.38%	0.16%	1.39%	1.20%	0.73%	0.56%
Avg. credit spread (%)	0.51%	0.35%	0.34%	0.45%	0.42%	0.39%	0.39%
Revenue ($m)	37.92	57.46	99.34	50.48	38.85	41.69	58.22
Loss ($m)	117.33	30.94	23.13	78.73	56.06	39.67	42.58
Profit ($m)	-79.41	26.52	76.21	-28.25	-17.22	2.02	15.64
Return on assets (%)	-1.06%	0.16%	0.26%	-0.25%	-0.19%	0.02%	0.10%

This table reports the results of the rolling hazard models. Panel A shows the Newey–West (1987) time series averages of the annual regression coefficients for our negative book equity model, our accounting model, and our market model to predict bankruptcies. PNBE is the probability that losses deplete current book equity, NegBE is a dummy for negative book equity, NegEarnFrc is a dummy for a negative earnings forecast, BLR is the book leverage ratio, CAPXTA is capital expenditures over total assets, TXT is taxes, EBITTA is earnings before interest and taxes over total assets, size is the logarithm of sales, MLR is the market leverage ratio, ER is the excess return, and STDER is the standard deviation of the return. Panel B shows the goodness-of-fit deciles. For every year, we rank firms into deciles based on their fitted bankruptcy probability values, where the firms with the highest values fall into the first decile. We report the percentage of bankrupt firms classified into each probability decile. Panel C reports the Newey–West (1987) time series averages of the yearly means of the area under the ROC curve (AUC). Panel D shows the results of a competitive credit market. The banks reject firms with scores in the bottom 5% based on their respective models, while offering credit to all others at a credit spread derived using equation (2.6). The bank with the lowest credit spread is assumed to grant the loan. Firms are assumed to split their loan equally if banks offer the same credit spread. Market share is the total credit granted divided by the total number of firm-years. Default is the number of firms to which a loan is granted that went bankrupt. Revenue is market size * market share * average credit spread, and loss is market size * prior probability of failure * share of defaulters * loss given default. Profit is revenue - loss. Return on assets are profit divided by market size * market share. For illustrative purposes, we assume the market size to be $100 billion, equal sized loans, the loss given default to be 45%, and the credit spread for the highest quality customers to be 0.30%. The prior probability of failure is taken to be the same as the ex-post failure rate. *** denotes significance at the 1% level.

Panel A in Table 2.5 reports the Newey and West (1987) time series averages of the annual regression coefficients for our three model versions, the negative book equity, the accounting, and the market model. The coefficients of our negative book equity model confirm that the PNBE on its own is a significant bankruptcy predictor. All the variables that are added to our accounting model except for CAPXTA are also statistically significant and thus may help increase the predictive power of the PNBE. In our market model, all the measures are significant. The fact that the market-based variables are significant supports the hypothesis that a combination of accounting- and market-based variables can improve the accuracy of bankruptcy prediction models. The signs of most coefficients are consistent with economic intuition: Firms with a higher PNBE and firms with negative earnings forecasts (NegEarnFrc) are more likely to fail. The higher the book leverage ratio (BLR), market leverage ratio (MLR), and volatility of returns (STDER), the higher is the estimated probability of bankruptcy. The lower the tax (TXT) and excess return (ER), the higher is the estimated probability of bankruptcy. Unexpectedly, higher capital expenditure (CAPXTA) and larger size (Size) lead to the assessment that bankruptcy is more likely.

2.4.4 Out-of-sample results

Panels B, C, and D of Table 2.5 assess the out-of-sample predictive ability of the different models. We compare our negative book equity, accounting, and market models with the common alternatives of Altman (1968), Ohlson (1980), and Shumway (2001). Furthermore, we estimate Merton's DD model in its best version as found by Bharath and Shumway (2008). Note that we re-parametrize all these models using a hazard model and the same data to eliminate the effects of statistical methods or different sample periods. Differences in the out-of-sample results compared with other studies such as Shumway (2001) and Bharath and Shumway (2008) are because we use an augmented period of time and a rolling estimation technique.

2.4.4.1 Goodness-of-fit deciles

Panel B of Table 2.5 reports the goodness-of-fit deciles. Following Shumway (2001), we rank firms into deciles based on their fitted bankruptcy probability values for every year of our validation period (1978 to 2013). That is, firms that will most likely default in the subsequent year according to the respective model are sorted into the first decile and firms with the lowest estimated default probabilities are assigned to the 10^{th} decile. Since our negative book equity model is univariate, there is no difference if the firms are ranked with the probability estimated by the hazard model or directly with the PNBE. We report the percentages of bankrupt firms that fall into each of the ten probability deciles. A model is accurate if it yields high default probability estimates for bankrupt firm-years and thus assigns many bankrupt firms into the first decile.

Our accounting model classifies 55.97% of all bankrupt firm-years into the highest default probability decile (decile one). That is, a bank can exclude 55.97% of all bankruptcies if it does not lend money to the 10% of firms with the highest expected default measures. Based on this, the model outperforms the Altman (55.69%) and Ohlson (50.56%) models, which also use accounting information.[16] Even our negative book equity model identifies 45.29% of bankruptcies correctly (in the first decile). Given that it has only one variable, it performs surprisingly well. For the top two deciles (in aggregate), 75.42% of the bankruptcies are predicted accurately by our accounting model. That is, if a bank does not lend money to the 20% of firms with the highest default probabilities, it excludes 75.42% of all bankruptcies. Again, our accounting model performs better than the Altman (69.80%) and Ohlson (70.79%) models. Importantly, the accounting model achieves better out-of-sample performance than all other accounting-based models, i.e., other models that do not require market variables.

If we limit the scope of application of our models by adding market information, we can further significantly improve performance; our market model classifies 65.66% of all bankrupt firm-years into the highest default probability decile (decile one). In contrast, Shumway (2001) and Bharath and Shumway (2008) only classify 58.01% and 61.38% of bankrupt firms into the first decile, respectively, For the top two deciles (in aggregate), the correct predictions of our market model are 82.16% versus 75.28% for Shumway and 77.53% for Bharath and Shumway. Importantly, our market model significantly outperforms all leading alternatives, including those that also exploit market information. Furthermore, the fact that our market model performs significantly better than our

[16] The version of the model in Altman (1968) requires stock price information and thus is not purely accounting-based. We are aware of the applications of Altman's (1983) z'-score (e.g., in Altman et al., 2017) and the applications of Altman, Hartzell, and Peck's (1995) z''-score (e.g., in Megginson, Meles, Sampagnaro, and Verdoliva, 2016) for private firms in which market equity is replaced by book equity. However, we use Altman's (1968) model because of its wide adoption (e.g., Almamy, Aston, and Ngwa, 2016) and acceptance.

accounting model supports the previous findings of Shumway (2001), Hillegeist et al. (2004), and Campbell et al. (2008) that market variables add explanatory power.

2.4.4.2 Receiver operating characteristics

An alternative overall classification measure used to evaluate bankruptcy prediction models is the area under the Receiver Operating Characteristics (ROC) curve, also referred to as the AUC (area under the curve; see Sobehart and Keenan, 2001). The ROC curve plots the true positive rate (the correctly predicted positive cases) of a model against the false positive rate (the misclassified positive cases). The AUC is then interpreted as the probability that a randomly chosen defaulting firm has a greater predicted probability of default than a randomly chosen surviving firm. A value of 0.5 indicates a random model with no predictive ability and a value of 1.0 indicates perfect discrimination. Note that the AUC evaluates both type I and type II errors. To compute the AUC, we estimate the parameters for each model based on the training samples and then use these parameters to predict bankruptcies for the subsequent year.

Panel C of Table 2.5 reports the Newey–West (1987) time series averages of the means of the AUC. The AUC results are consistent with the results reported using the goodness-of-fit deciles. Our accounting model has an average AUC of 0.862, again significantly higher than the average AUCs of 0.828 of Altman’s (1968) model and 0.841 of Ohlson’s (1980) model. Our accounting model’s performance is even similar to the market-based models of Shumway and Bharath and Shumway with average AUCs of 0.859 with 0.868, respectively. Note that Bharath and Shumway’s model has a higher accuracy than Shumway which is in line with the results of Campbell, Hilscher, and Szilagyi (2011). Importantly, our market model has the highest average AUC (0.892) and thus outperforms all other models.

2.4.4.3 Economic value for differing misclassification costs

In practice, the costs associated with type I error and type II error are different. Refusing to grant a loan to a non-bankrupt firm leads to the loss of revenue, whereas lending money to a firm that turns bankrupt may lead to the loss of the total loan amount. To account for the differing misclassification costs, we follow the approach of Agarwal and Taffler (2008) to assess the economic impact of using different bankruptcy prediction models in a competitive market. To link the power of prediction models and loan pricing, we follow Stein (2005) and Blöchlinger and Leippold (2006) and derive the credit spread as a function of the credit score (S) by

$$R = \frac{P_t(Y=1|S=t)}{P_t(Y=0|S=t)} LGD + k, \tag{2.6}$$

where R is the credit spread, $P_t(Y = 1|S = t)$ is the conditional probability of bankruptcy for a score of t, $P_t(Y = 0|S = t)$ is the conditional probability of non-bankruptcy for a score of t, LGD is the loan loss given default, and k is the credit spread for the highest quality loan.

We evaluate the economic scenario described in Agarwal and Taffler (2008) and Bauer and Agarwal (2014) with a simple loan market worth $100 billion. Each bank uses a different bankruptcy prediction model and competes for customers that are represented by firms in our sample. We assume that all loans are of the same size and are unsecured senior debt (i.e., the loss given default is 45%). Further, we assume the risk premium for a high-quality customer (k) to be 0.30%. Each year, we rank our sample firms into 20 categories based on their fitted bankruptcy probability values. The banks reject those customers that fall in the bottom 5%, which is the lowest category, according to the model they use. For all other customers, they quote a spread based on equation (2.6). The customer then chooses the bank that quotes the lowest spread. If multiple banks quote equal minimum spreads, the customer randomly chooses one of those banks (or equivalently, the business is split equally). In this regime, some customers may be refused credit by all banks and thus the market share may not sum to 1.

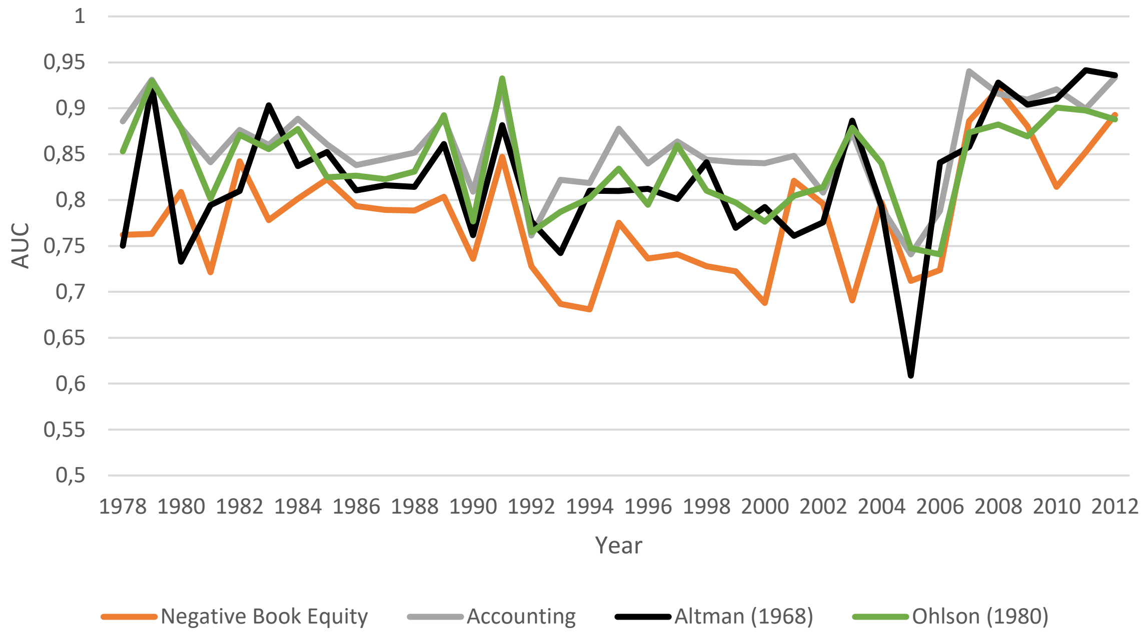
Panel D of Table 2.5 presents the revenue, profitability, and other statistics for all banks in the competitive loan market. The bank that uses our market model has clearly the largest market share of 29.38% followed by our accounting model (16.27%), Bharath and Shumway (15.06%), Altman (11.20%), Shumway (10.79%), Ohlson (9.21%), and our negative book equity model (7.47%). That is, the bank that makes its loan decision based on our market model holds the greatest amount of loans. In addition, the quality of loans granted by our market model is the best: only 0.16% of its customers default compared with 0.38% for a bank that uses our accounting model, 0.56% for Bharath and Shumway, 0.73% for Shumway, 1.20% for Ohlson, 1.39% for Altman, and 3.11% for our negative book equity model. The highest amount of loans combined with the highest loan quality directly translate into the highest profitability of 0.26% for the bank that uses our market model. In other words, this bank makes a net income of $0.26 per $100 loan. This profitability is higher than when using our accounting model (0.16%), Bharath and Shumway (0.10%), and Shumway (0.02%). The profitability of banks that use Ohlson (-0.19%), Altman (-0.25%), and our negative book equity model (-1.06%) is even negative. In conclusion, our market model and our accounting model outperform all other models in all statistics of the competitive loan market scenario that assumes misclassification costs that are different for type I and type II errors.

In summary, the rolling regression technique yields strong evidence for the better performance of our bankruptcy prediction models. Our accounting model performs better than Altman and Ohlson with respect to the goodness-of-fit deciles and it has a higher average AUC than Altman and Ohlson and even than the market-based model of Shumway. For the economic value, our accounting model even outperforms all other benchmark models, including those that use market variables. Our market model performs best in all three accuracy measures. We conclude that if the model is restricted to accounting information, our accounting model performs best and that if we allow for market information in the model, our market model performs best.

2.4.5 Evolution of the out-of-sample results over time

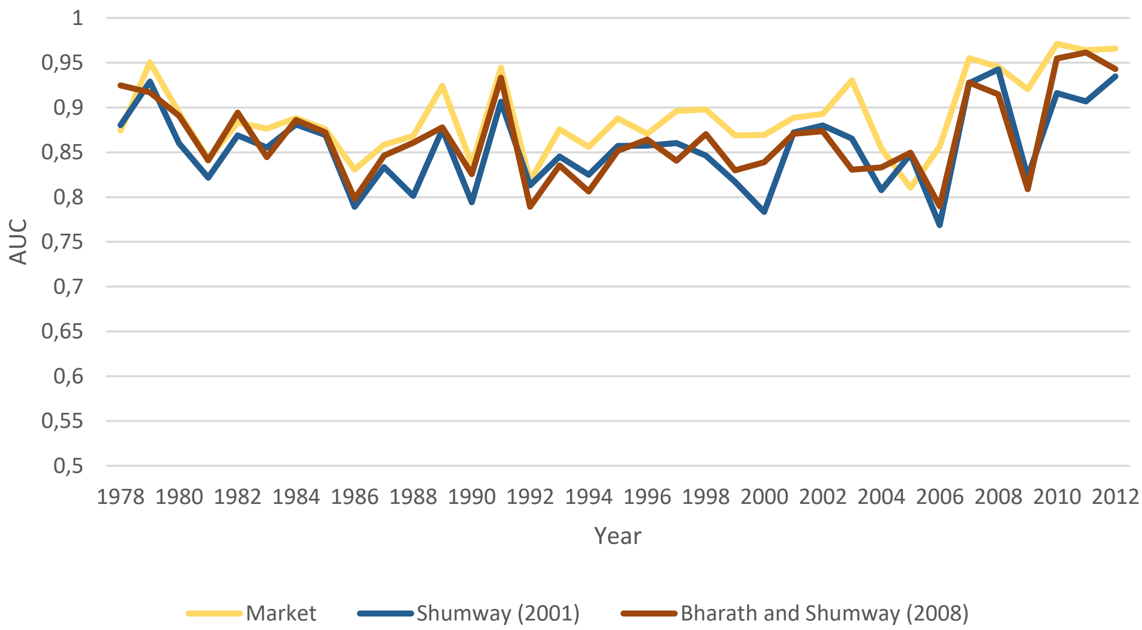
We use a rolling estimation technique that comprise the most recent ten years of data to make one-year predictions. In Section 2.4.4, we evaluate the bankruptcy prediction models for the whole evaluation period (1978-2013). In the following, we show the out-of-sample performance for every year in the evaluation period separately in order analyze the development of accuracies over time.

Figure 2.1 Development of AUCs for accounting models



The figure plots the average AUC per year over the evaluation period (1978-2013) for the accounting-based models. We use rolling windows that comprise the most recent ten years of data to perform hazard models and evaluate the one-year predictions for each model at an annual frequency. Our accounting model performs best among accounting models for 24 of 36 years (67%).

Figure 2.2 Development of AUCs for market models



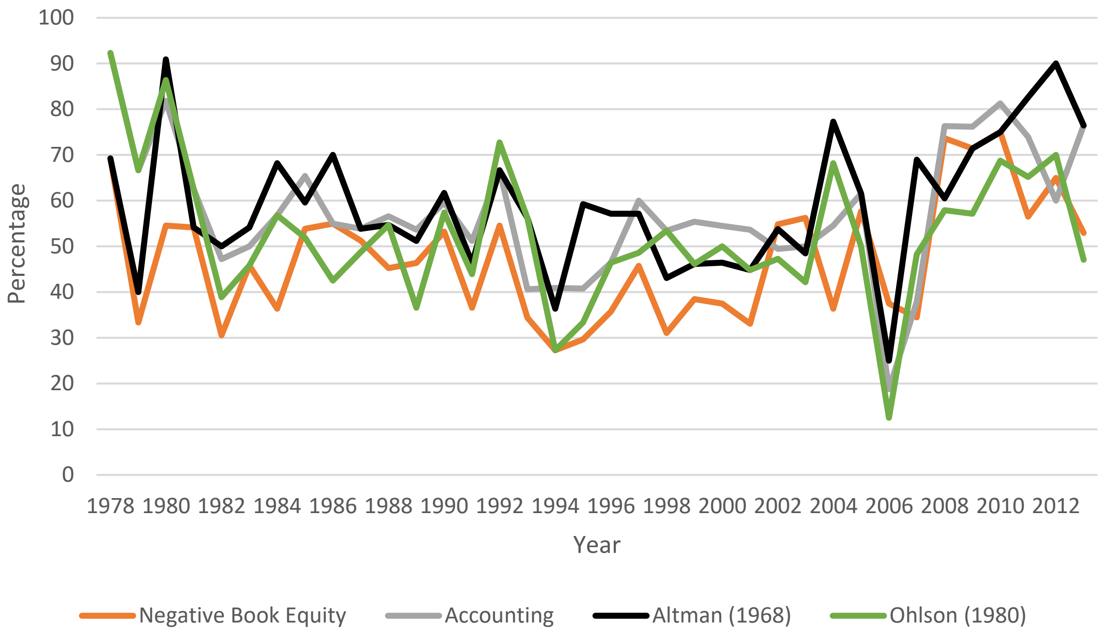
The figure plots the average AUC per year over the evaluation period (1978-2013) for the market-based models. We use rolling windows that comprise the most recent ten years of data to perform hazard models and evaluate the one-year predictions for each model at an annual frequency. Our market model performs best among market models for 33 of 36 years (92%).

Figure 2.1 plots the performance development of accounting-based models by reporting the average AUCs for every year. For all models, there is a high accuracy in the 1970s followed by a downward trend until the mid-1990s and an upward trend from then until 2013. Most importantly, our accounting model does not only perform better on average but shows a higher performance for the majority of evaluation years. It outperforms the models of Altman (1968) and Ohlson (1980) for 24 of 36 years (67%). Figure 2.2 reports the average AUCs for the market-based models. The performance of market-based models is less volatile and higher than that of accounting-based models. We find that our market model performs better than Shumway (2001) and Bharath and Shumway (2008) 33 of 36 years (92%), i.e., for nearly all years.

Figure 2.3 shows the accuracy of accounting-based models over time by plotting the respective percentage of bankrupt firms classified into the first decile for every year. Again, there is a downward trend from the 1970s until the mid-1990s followed by an upward trend from then until 2013. In year 2006, the performance of all accounting models falls dramatically.[17] Again, our accounting model outperforms Altman (1968), Ohlson (1980) and our negative book equity model for a majority of evaluation years (53%). Our negative book equity model outperforms all other models (including our accounting model) for another 8%. That is, our models have the highest performance for 61% of the years. Figure 2.4 plots the respective percentage of bankrupt firms classified into the first decile for market-based models. Again, their performance is less volatile than that of accounting-based models. For example, in 2006, while the performance of accounting models has a shock, the performance of models using the market variables remains stable. Importantly, our market model shows better performance than Shumway (2001) and Bharath and Shumway (2008) for 25 of 36 years (69%).

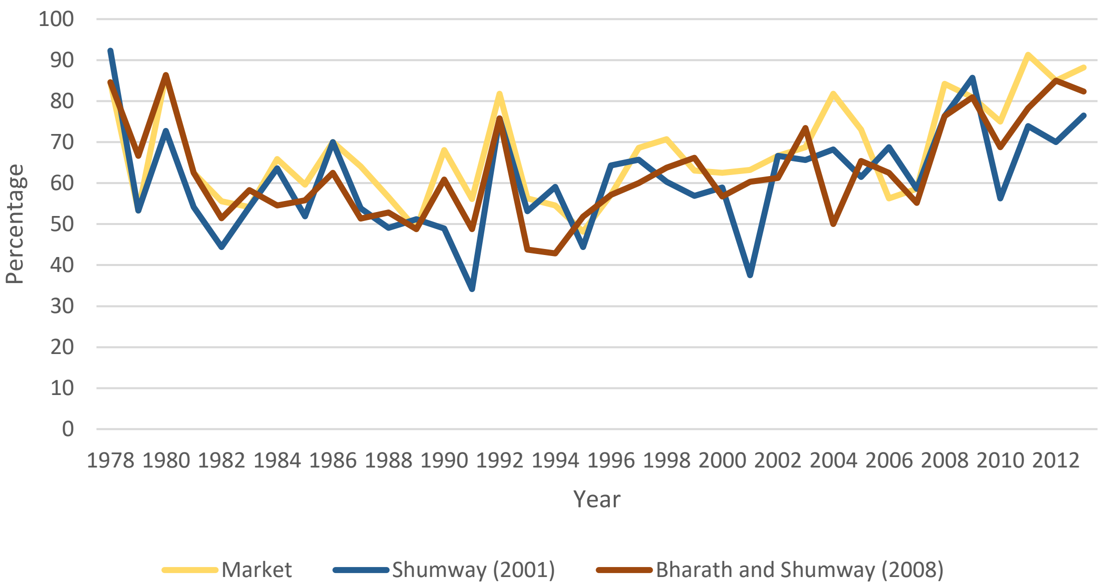
[17] Interestingly, the negative book equity model is most stable in 2006 among the accounting-based models.

Figure 2.3 Development of goodness-of-fit deciles for accounting models



The figure plots the percentage of bankruptcies classified into the highest probability decile per year over the evaluation period (1978-2013) for the accounting-based models. We use rolling windows that comprise the most recent ten years of data to perform hazard models and evaluate the one-year predictions for each model at an annual frequency. Our accounting model performs best among accounting models for 19 of 36 years (53%).

Figure 2.4 Development of goodness-of-fit deciles for market models



The figure plots the percentage of bankruptcies classified into the highest probability decile per year over the evaluation period (1978-2013) for the market-based models. We use rolling windows that comprise the most recent ten years of data to perform hazard models and evaluate the one-year predictions for each model at an annual frequency. Our market model performs best among market models for 25 of 36 years (69%).

Furthermore, we find that our negative book equity model, which only incorporates information about book equity and earnings forecasts, performs similarly compared to the other models throughout the evaluation period. In other words, the performance difference between our negative book equity and all other models remains stable for all evaluation years. There is no evident difference between the 1970s and recent years. Thus, book equity and earnings figures are as valuable for the task of predicting corporate bankruptcies as in the 1970s; they are still credit relevant. Many studies claim that earnings have lost relevance. For example, Collins, Maydew, and Weiss (1997), Lev and Zarowin (1999), and Beisland and Hamberg (2013) show that accounting effects and effects related to new types of firms have important consequences for the application of accounting measures as predictors. Furthermore, accounting has moved from an earnings-oriented "historical cost regime" toward a balance sheet-oriented "fair value regime." Nissim and Penman (2008) claim that in a perfect fair value accounting regime, earnings are nothing more than value changes that are expected to follow a random walk. This strand of literature focuses on the value relevance of accounting information. We add to the discussion of its credit relevance by showing that book equity and earnings are useful predictors of bankruptcy even in today's fair value accounting regime.

2.4.6 Functional form of PNBE

To calculate the probability of negative book equity, we use a non-linear functional form with three inputs. In the following, we test whether this functional form has incremental predictive power compared to its components. To assess the importance of this rigid functional form, we compare two models, again using a rolling regression technique. Model 1 comprises all the components of the PNBE: current book equity, the earnings forecast, and the inverse of its standard deviation. It adds the PNBE, that is, the non-linear combination of these variables. Model 2 only comprises the three single components of PNBE but does not compress these variables into a single variable. Table 2.6 reports the results of these two models.

Table 2.6 Functional form of PNBE

Panel A: Parameter estimates				
Variable	Model 1		Model 2	
Constant	-6.315	***	-4.248	***
$PNBE_t$	3.304	***		
$BkEq_t$	-0.002	**	-0.004	***
$EarnFrc_t$	-0.590	***	-0.835	***
1/sigma(EarnFrc)	2.965		-0.398	

Panel B: Goodness-of-fit deciles		
Decile	Model 1	Model 2
1	46.14	37.22
2	13.34	14.68
3	10.53	9.62
4	7.65	9.06
5	6.11	8.57
6	3.58	6.67
7	3.30	5.06
8	4.07	4.21
9	3.51	3.30
10	1.76	1.62

Panel C: Area under the ROC curve		
	Model 1	Model 2
Mean	0.789	0.754

Panel D: Economic value of different misclassification costs		
	Bank 1	Bank 2
	Model 1	Model 2
Credits	103,077	56,762
Market share (%)	62.49%	34.41%
Defaults	528	536
Defaults/credits (%)	0.51%	0.94%
Avg. credit spread (%)	0.53%	0.56%
Revenue ($m)	329.86	191.36
Loss ($m)	192.77	195.69
Profit ($m)	137.09	-4.33
Return on assets (%)	0.22%	-0.01%

(continued)

Table 2.6 Functional form of PNBE (continued)

This table shows the importance of the functional form of the PNBE. Panel A shows the Newey–West (1987) time series averages of the annual regression coefficients. PNBE is the probability that losses deplete current book equity, BkEq is book equity, EarnFrc is the earnings forecast, and 1/sigma(EarnFrc) is the inverse value of the earnings forecast's volatility. Panel B shows the goodness-of-fit deciles. For every year, we rank firms into deciles based on their fitted bankruptcy probability values, where the firms with the highest values fall into the first decile. We report the percentage of bankrupt firms classified into each probability decile. Panel C reports the Newey–West (1987) time series averages of the yearly means of the area under the ROC curve (AUC). Panel D shows the results of a competitive credit market. The banks reject firms with scores in the bottom 5% based on their respective models, while offering credit to all others at a credit spread derived using equation (2.6). The bank with the lowest credit spread is assumed to grant the loan. Firms are assumed to split their loan equally if banks offer the same credit spread. Market share is the total credit granted divided by the total number of firm-years. Default is the number of firms to which a loan is granted that went bankrupt. Revenue is market size * market share * average credit spread, and loss is market size * prior probability of failure * share of defaulters * loss given default. Profit is revenue - loss. Return on assets are profit divided by market size * market share. For illustrative purposes, we assume the market size to be $100 billion, equal sized loans, the loss given default to be 45%, and the credit spread for the highest quality customers to be 0.30%. The prior probability of failure is taken to be the same as the ex-post failure rate. *** and ** denote significance at the 1% and 5% levels, respectively.

Panel A reports the Newey–West (1987) time series averages of the annual regression coefficients for model 1 and model 2. In model 2, firms with lower book equity and a lower earnings forecast are more likely to fail. The inverse value of the earnings forecast's volatility is not significant. Model 1 shows the same intuitive signs for book equity and the earnings forecast as model 2 and again a non-significant coefficient for the forecast's volatility. Importantly, the PNBE is a significant predictor of bankruptcy, although all the components required to construct the PNBE are also included as individual variables. This finding suggests that the functional form we use for constructing the probability provides value beyond the information contained in the individual variables used to calculate it.

This incremental predictive power of PNBE over its inputs is supported by the out-of-sample results that are presented in Panels B, C, and D. Panel A shows that model 1 classifies 46.14% of all bankruptcies into the highest probability decile and thus outperforms model 2 (37.22%). This means that adding PNBE increases the out-of-sample accuracy although its three components are already included as single variables. Accordingly, panel C shows that the average AUC of model 1 (0.789) exceeds that of model 2 (0.754). Again, this shows that the closed functional form of PNBE has incremental power compared to its inputs. Panel D finally presents statistics for two banks in a competitive loan market that use model 1 and model 2, respectively. The bank that makes its loan decisions based on model 1 has a market share of 62.49%, which is far larger than that of model 2 (34.41%). In addition, the quality of loans granted by model 1 is better, as only 0.51% of their customers default compared with 0.94% of the customers of the bank that uses model 2. This translates into a higher profitability of the bank that uses model 1 (0.22%) compared to the bank that uses model 2 (-0.01%). Thus, model 1 outperforms model 2 in all statistics of the competitive loan market scenario. This again supports the notion that PNBE has incremental predictive power over its components. In conclusion, the results provide support for the concept that the functional form of the PNBE is a valuable construct for predicting bankruptcy, beyond the information contained in its individual variables.

2.5 Conclusions

We develop a new framework for predicting bankruptcies, focusing on the economically intuitive idea that future losses deplete a firm's book equity. Hence, the probability that book equity may become negative is a central variable in our model versions. Previously, major improvements in bankruptcy prediction models have been achieved by the inclusion of stock market data. In contrast, we focus on risk measures extracted from accounting data, in particular, earnings risk. This improves the performance of bankruptcy predictions without excluding private firms. Nevertheless, for firms listed on the stock market we provide a model version that picks stock market information, as well. We find that both our accounting and our market models outperform leading alternatives that use corresponding information. Our accounting model performs best for predicting the bankruptcy of a non-public firm where stock market information is unavailable, while our market model produces the best results for predicting the bankruptcy of a publicly traded firm. We further show that book equity and earnings have been useful predictors throughout the whole evaluation period, including more recent years. By this, we contribute to the ongoing discussion whether the credit relevance of accounting measures has decreased in the course of the shift from a historical cost accounting regime towards a fair value regime.

We focus on predictions with a horizon of twelve months. However, our analyses indicate that a firm's earnings weakness and negative book equity may signal financial distress much earlier. Thus, it appears promising to devote further research to creating multi-period bankruptcy prediction models using multi-period earnings forecasts as described in Hou et al. (2012). Alternatively, one could use analysts' earnings forecasts instead of mechanical forecasts to model the changes in book equity. However, this would restrict the scope of the application, as analysts only provide earnings forecasts for (selected) publicly traded firms. Moreover, further research could account for the dynamic aspects of the data, e.g., by using survival analysis techniques whose dependent variable is not binary but the number of years in the non-bankrupt group. In addition, further research could aim at grasping the imperfect relationship between firms with negative book equity and bankrupt firms. First, developing alternative approaches to discriminate between bankrupt and non-bankrupt firms with negative book equity appears to be promising. Second, one could refrain from using the formal definition of negative book equity as a predictor of bankruptcy. Instead, the components that belong to the definition of book equity but do not influence bankruptcy could be removed. Furthermore, a cross-country comparison of the performance of our models would help to understand to what extent specific national regulations, such as the requirement to file for bankruptcy in the case of negative book equity, facilitates better bankruptcy predictions.

2.A Construction of variables of earlier bankruptcy prediction models

We discuss the construction of variables used in Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway's (2008) best-performing model.

Altman (1968) obtains a Z-score using a linear weighted sum of five ratios:

$$Z = \beta_0 + \beta_1 \cdot WCTA + \beta_2 \cdot RETA + \beta_3 \cdot EBITTA + \beta_4 \cdot METL + \beta_5 \cdot STA, \tag{2.7}$$

where WCTA is working capital (Compustat item WCAP) divided by total assets (AT), RETA is retained earnings (RE) divided by total assets (AT), EBITTA is earnings before interest and taxes (EBIT) divided by total assets (AT), METL is the market value of equity (PRCC_F multiplied by CSHO) divided by the book value of total debt (LT), STA is sales (SALE) divided by total assets (AT) and Z is the Z-score (overall index). WCTA is a proxy for a firm's liquidity, RETA is a proxy for firm age, and EBITTA measures profitability. METL is a widely used measure of leverage and STA describes the firm's efficiency in using assets to generate sales. The Z-score characterizes the financial strength of a firm by aggregating the abovementioned five accounting ratios into one figure using the estimated coefficients $\beta_1, \dots, \beta_5$.

Ohlson (1980) finds nine variables to be significant and defines his O-score model as

$$
\begin{aligned}
O = {} & \beta_0 + \beta_1 \cdot SIZE + \beta_2 \cdot TLTA + \beta_3 \cdot WCTA \\
& + \beta_4 \cdot CLCA + \beta_5 \cdot OENEG + \beta_6 \cdot NITA \\
& + \beta_7 \cdot FUTL + \beta_8 \cdot INTWO + \beta_9 \cdot CHIN,
\end{aligned} \tag{2.8}
$$

where Size is the logarithm of total assets (AT), TLTA is total liabilities (LT) over total assets (AT), WCTA is working capital (WCAP) over total assets (AT), CLCA is current liabilities (LCT) over current assets (ACT), OENEG is a dummy that takes the value of one if total liabilities (LT) exceed total assets (AT) and zero otherwise, NITA is net income (NI) over total assets (AT), FUTL is funds provided by operations[18] (PI plus DP) over total liabilities (LT), INTWO is a dummy that takes the value of one if the net income (NI) was negative for the past two years and zero otherwise, CHIN is the change in net income (NI) and O is the O-score (overall index). WCTA and CLCA measure liquidity. NITA, FUTL, INTWO, and CHIN capture the different aspects of profitability. TLTA and OENEG describe the capital structure. Size is a measure of firm size.

In addition to selected financial ratios used by Ohlson, Shumway (2001) adds two market variables, the excess return and its standard deviation:

$$
\begin{aligned}
S = {} & \beta_0 + \beta_1 \cdot RSIZE + \beta_2 \cdot TLTA + \beta_3 \cdot NITA \\
& + \beta_4 \cdot ER + \beta_5 \cdot STDER,
\end{aligned} \tag{2.9}
$$

where RSIZE is the logarithm of market equity divided by value-weighted market equity of the index, TLTA is total liabilities (LT) over total assets (AT), NITA is net income (NI) over total assets (AT), ER is excess returns calculated as the difference between the previous year's returns and risk-free rate, STDER is the standard deviation of the returns, and S is the S-score (overall index). TLTA measures solvency and describes the capital structure. Profitability is captured by NITA. ER measures the profit of an investment, where STDER determines the variability of excess returns. Returns are calculated as the present year's adjusted stock price (PRCCD multiplied by TRFD and

[18] Funds provided by operations are not reported anymore. We use an approximation by summing pretax income and depreciations and amortization.

divided by AJEXDI) divided by the previous year's adjusted stock price minus one. RSIZE is a measure of firm size.

Bharath and Shumway (2008) extend the distance-to-default models that Vassalou and Xing (2004) and Hillegeist et al. (2004) construct. Applying Merton's (1974) option pricing theory yields the probability of bankruptcy as

$$PD_{Merton} = N\left(-\left(\frac{ln(V/F)+(\mu-0.5\sigma_V{}^2)}{\sigma_V}\right)\right), \quad (2.10)$$

where V is the market value of a firm's assets, σ_V its standard deviation, μ is the expected return on assets, F is the market value of the firm's debt, and $N(\cdot)$ is the cumulative standard normal distribution function. Vassalou and Xing (2004) numerically compute V and σ_V by applying an iterative procedure. Bharath and Shumway, however, propose a naïve approach. They approximate the market value of debt using the book value of debt and thus, calculate F as debt in current liabilities plus one half of long-term debt. Furthermore, the volatility of a firm's debt is approximated by

$$\sigma_F = 0.05 + 0.25 \cdot \sigma_E, \quad (2.11)$$

where σ_E is the volatility of the market return. An approximation of the volatility of the firm's assets is then given by

$$\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}\sigma_F. \quad (2.12)$$

The expected return on assets μ is approximated using the previous year's return on assets. In addition, the market value of assets is approximated by the sum of the market value of equity and book value of debt. The best model in Bharath and Shumway is constructed as:

$$\begin{aligned} BS = {} & \beta_0 + \beta_1 \cdot PD_{Merton} + \beta_2 \cdot LNE + \beta_3 \cdot LNF \\ & + \beta_4 \cdot 1/\sigma_E + \beta_5 \cdot ER + \beta_6 \cdot NITA, \end{aligned} \quad (2.13)$$

where PD_{Merton} is the probability constructed above, LNE is the logarithm of market equity E (PRCC_F multiplied by CSHO), LNF the logarithm of the book value of debt F calculated as current debt (DLC) plus one half of long-term debt (DLTT), $1/\sigma_E$ is the inverse of the volatility of market equity, ER is the excess return calculated as the difference of last year’s return and last year’s value-weighted index return, and NITA as the ratio of net income (NI) and total assets (TA).

Chapter 3

The Quality of Bankruptcy Data and its Impact on the Evaluation of Prediction Models: Creating and Testing a German Database*

3.1 Introduction

For decades, academics and practitioners have been tasked with the prediction of corporate bankruptcies. While considerable efforts have been made to improve the methodologies used in bankruptcy prediction models (e.g., Altman, 1968; Ohlson, 1980; Shumway, 2001; Vassalou and Xing, 2004), previous studies have paid little attention to the quality of the underlying bankruptcy data. In this regard, quality can be defined as the completeness and correctness of information of bankruptcy events and explicit bankruptcy

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dates. Accurate bankruptcy data is crucial for two main reasons. First, it helps to obtain unbiased parameter estimates for bankruptcy models; incorrect data can affect the significance and size of the coefficients and, thus, the variable setup of models. Second, the validation of bankruptcy prediction models strongly depends on the integrity of the bankruptcy data. In fact, inaccurate information can affect the evaluation of out-of-sample performance. Thus, we investigate the impact of data quality on the evaluation of bankruptcy prediction models.

Studies commonly use commercial databases to collect bankruptcy information. The most common data providers in the U.S. are the SDC Platinum Database, Moody's Default and Recovery Database, and Capital IQ. Of these, Capital IQ includes only bankrupt firms that are located in the U.S,[19] while the SDC Platinum Database and Moody's Default and Recovery Database contain data on European bankruptcies. However, their data availability for non-U.S. firms is relatively sparse: SDC Platinum[20] reports only 250 recent bankruptcies that are outside the U.S. and Moody's Default and Recovery Database[21] lists only 108 bankruptcy events in Germany since 1980. Therefore, we focus on the most frequently used European databases: Compustat Global (e.g., Dahiya and Klapper, 2007; Tian and Yu, 2017) and Bureau van Dijk (BvD) (e.g., Altman, Iwanicz-Drozdowska, Laitinen, and Suvas, 2017; Filipe, Grammatikos, and Michala, 2016; Lohmann and Ohliger, 2017). Few studies have examined the quality of these popular bankruptcy databases. In fact, BvD deletes bankruptcy information after five years of inactivity. Moreover, requesting data directly from Creditreform, BvD's provider of bankruptcy information for German firms, would not rectify this fundamental limitation since Creditreform also deletes a firm's bankruptcy information after bankruptcy proceedings are terminated. Therefore, one aim of this study is to quantify the amount of erroneous bankruptcy information in the databases largely used in earlier bankruptcy studies.

Unlike commercial databases such as BvD and Compustat Global, the UCLA-LoPucki Bankruptcy Research Database (BRD)[22] consists of U.S. bankruptcy data that is retrieved directly from public sources such as court files or Securities and Exchange

[19] We directly contacted S&P Global to clarify the availability of bankruptcy events.
[20] Thomson Reuters: https://financial.thomsonreuters.com/en/products/data-analytics/market-data/sdc-platinum-financial-securities.html (accessed July 20, 2018).
[21] Moody's Analytics: https://www.moodys.com/sites/products/productattachments/drd_brochure.pdf (accessed July 20, 2018).
[22] UCLA-LoPucki Bankruptcy Research Database: http://lopucki.law.ucla.edu/ (accessed July 20, 2018).

Commission (SEC) filings. However, there are no guidelines for producing such a bankruptcy database that derives information from public sources. This study constructs these guidelines by describing a methodology to systematically collect accurate bankruptcy data from public sources and applying it to the German market. We focus on one country because parameter estimates may differ across countries for two reasons. First, the definition of bankruptcy may vary depending on regulatory requirements. Second, administrative firm-level data and thus, the definition of variables used for bankruptcy prediction, differ by country. For example, Altman et al. (2017) argue that differences in financial statements can be attributed to variances in fiscal systems across countries. Nevertheless, Altman et al. (2017) and other previous studies must use the entire European market to obtain sufficient bankruptcy data. We choose Germany as a case country for two reasons. First, Germany lacks an academic bankruptcy database that contains data from public sources, similar to the U.S. data in the UCLA-LoPucki BRD. Second, Germany is one of the largest stock markets in Europe. It is noteworthy that while our methodology can be applied to other countries, it is critical that disclosure obligations and their public availability be checked when doing so. In the case of the United States and United Kingdom, this would mean referring to SEC filings and the Regulatory News Service (RNS) as the national news providers, respectively.

Then, we compare our bankruptcy database (hereafter, HL) with the most commonly used databases for German bankruptcies, Compustat Global and BvD. In particular, we analyze the completeness and correctness of the information on bankruptcy events and dates. We then conduct a two-part empirical analysis of public German firms. In the first part, we compare the bankruptcy prediction models of Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway (2008), and Hess and Huettemann (2019). There is voluminous bankruptcy prediction research, but a majority of existing studies focuses on U.S. corporations, while research that presents international evidence remains relatively sparse. For example, Altman et al. (2017) assess the performance of Altman’s (1983) Z-score for 31 European and three non-European countries. Tian and Yu (2017) investigate the significance of ratios for bankruptcy prediction in Japan and selected European countries, and Dahiya and Klapper (2007) compare key industrial nations. These studies use the commercial databases of BvD or Compustat Global. Note that because we have a sufficient number of bankruptcy events, we can focus on a single European country, giving our study the advantages noted above. In the second part, we investigate how using the HL database, instead of BvD data, affects the results of bankruptcy prediction models. More specifically, we analyze the parameter estimates and out-of-sample performance when we use our bankruptcy data compared to BvD data. We also compare the ability of the respective bankruptcy datasets to produce unbiased parameter estimates by applying the estimates to a validation sample with the same bankruptcy dummies. Note that the fact that BvD deletes firm information after five years of inactivity does not alter the results of this comparison as we restrict our sample to the period with full BvD data coverage.

The empirical results of this study are as follows. First, more than 80% of all public German firms' bankruptcies can be extracted from easily accessible corporate disclosures. Second, HL bankruptcy events are more complete and more accurate than those listed by BvD and Compustat Global. While our HL database comprises 277 bankruptcies, BvD and Compustat cover only 63 and 27 events, respectively. BvD and Compustat Global's incomplete data applies not only to small- and medium-sized firms but also to large firms. For example, BvD does not include the 2009 bankruptcy case of Arcandor AG, a warehouse business valued at 500 million euros. Surprisingly, BvD declares bankruptcy for firms that never filed for insolvency and continue to exist, such as Suedzucker AG. While there are many bankruptcies exclusively captured by HL, only a few events are solely captured by Compustat Global or Bureau van Dijk and not by HL. Third, the bankruptcy dates for HL-listed events are more accurate than those contained in BvD and Compustat Global. For 25% of firms, HL reports bankruptcies two months earlier than BvD, and for 50% of firms, HL reports bankruptcies 24 months earlier than Compustat Global. Fourth, the choice of bankruptcy database affects parameter estimates. If we use the inaccurate bankruptcy events reported in BvD instead of events in HL, the parameters change in terms of significance and size. We further show that HL information produces more realistic parameter estimates than BvD data. Fifth, we demonstrate that using HL data, instead of BvD information, has a major impact on out-of-sample results. When researchers use models estimated based on BvD data, they cannot effectively predict true bankruptcy outcomes, that is, out-of-sample results for bankruptcies in the HL database. For example, using BvD bankruptcy information would yield similar out-of-sample performances for the Altman (1968) and Ohlson (1980) models. However, using HL's more precise information reveals that Ohlson's model significantly outperforms that of Altman. Finally, we show that, opposed to models that only use accounting-based variables, market-based bankruptcy prediction models (Bharath and Shumway, 2008; Hess and Huettemann, 2019; Shumway, 2001) are a better fit for the German market when HL data is used.

For our scope of application, we find that the quality of bankruptcy data has a significant impact on the interpretation of results of bankruptcy prediction models. Specifically, we speak to the consequences of training bankruptcy models with noisy bankruptcy data. For example, using BvD information instead of HL data would suggest that other bankruptcy prediction models may be more appropriate. This study is the first to show that the frequently used commercial bankruptcy databases of Compustat Global (e.g., Dahiya and Klapper, 2007; Tian and Yu, 2017) and BvD (e.g., Altman et al., 2017; Filipe et al., 2016; Lohmann and Ohliger, 2017) are inaccurate. We describe a systematic methodology to gather more precise bankruptcy information free of charge and create the first academic bankruptcy database for Germany. Furthermore, using this database, we are the first to compare bankruptcy prediction models for Germany based on valid bankruptcy data.

The remainder of this chapter is organized as follows. Section 3.2 describes the methodology to gather bankruptcy information from public sources. It further compares the resulting database with commercial bankruptcy databases. In Section 3.3, we describe our sample selection, report the descriptive statistics, and explain our methods. In Section 3.4, we present and discuss our empirical results. Section 3.5 concludes.

3.2 Our bankruptcy database

3.2.1 German insolvency proceedings

According to Germany's 2009 insolvency statute (*"Insolvenzverordnung"*), a company or a creditor have the right to file a request at the local court (*"Amtsgericht"*), which is the court of first instance, if there are reasons for insolvency.[23] Such reasons could be a company's illiquidity (inability to meet the obligations that are due), imminent illiquidity, or over-indebtedness (obligations exceed assets). The company is obliged to file for insolvency within the first three weeks of experiencing illiquidity or over-indebtedness.

After a company files for insolvency, the responsible court may take protective measures, which include the appointment of an interim insolvency administrator. If the

[23] Hereafter, insolvency and bankruptcy are used synonymously.

administrator verifies that the company's funds are sufficient to cover the costs of a proceeding, he or she initiates insolvency proceedings; otherwise, the company is liquidated. The insolvency administrator takes over the company's administration and is responsible for restructuring measures, liquidating business units, and collecting outstanding receivables to partially service creditors' claims. Exchange-listed firms are required to immediately report material events to their stakeholders and the public. They must submit ad-hoc statements when insolvency is imminent, or an application is submitted to the corresponding court. The corresponding court issues additional statements when taking proactive actions, openings, or further information on bankruptcy proceedings.

3.2.2 Extracting German bankruptcy data from public sources

The most commonly used database for German companies in the finance and accounting literature stems from Compustat Global or BvD. However, using both databases for bankruptcy prediction raises several issues. For instance, Compustat Global only contains delisting dates and the reasons for the delisting. However, a delisting is often requested at a later stage during the bankruptcy proceedings. Thus, delisting dates are often determined several years after a firm has applied for bankruptcy. More recent studies predominantly use the BvD database, which deletes a firm's financial data when it has not published annual reports for five consecutive years. This may apply to firms in bankruptcy proceedings and it is likely that the database excludes firms that filed for bankruptcy more than five years ago. Evidence of this point is the study conducted by Filipe et al. (2017), who use 2000–2009 as the sample period but find no bankruptcies for 2000. In fact, studies that apply BvD's bankruptcy information can use only the training and validation samples from the past five years. To obtain a sufficient number of observations for a coherent bankruptcy prediction analysis, previous studies have used data from various countries, although the definition for bankruptcy events and prediction variables tend to differ by country.

This study is the first to describe a methodology to systematically collect accurate bankruptcy data from public sources and apply it in the context of Germany. We aggregate our bankruptcy data from multiple online and free-access sources: (i) financial disclosures from *"Deutsche Gesellschaft für Ad-hoc-Publizität mbH"* (DGAP) and *"APA Originaltext-Service GmbH"* (APA OTS), (ii) the German business register, and (iii)

InsolNet, which is specifically a bankruptcy online database. Our approach is straightforward and follows three steps. First, we parse corporate news releases for bankruptcy-related news. Second, we use a web crawler[24] on online releases by German bankruptcy courts, which are compiled in the German business register. Finally, we validate our results by obtaining data from an explicit bankruptcy database. To apply this methodology to other countries, it is important to check for public availability of the disclosure statements.

3.2.2.1 Corporate news releases

In regulated stock markets, companies must immediately inform investors about material events, particularly when they apply for bankruptcy. Financial disclosures and company news releases are mainly distributed by professional ad-hoc service providers. The German market is highly concentrated in the DGAP, which currently distributes approximately 98% of all news releases in Germany. Further, we use APA OTS as an additional source for corporate news releases because it covered several German firms from 2007 to 2011 before it stopped reporting on German firms in 2013. One advantage of corporate disclosures and news releases by ad-hoc providers is that they are free of charge.

In the first step, we use Python, a script-based programming language, to direct web queries to the DGAP and APA OTS web servers. We request all news releases and download the full-text information of each document. We collect the complete archives for both DGAP and APA OTS, containing 363,282 news releases for listed companies from 1997 to 2016. For each article, we process the full document into tokens of single words to evaluate if the wording is related to bankruptcy news. We use dynamic regular expressions to test if the root of each word contains insolvency wording. These regular expressions create a word list of 150 German words connected to news releases about bankruptcy (see Appendix 3.B for the full list). This procedure reduces the overall set of documents to a concise sample of 462 disclosures. We then manually check the news releases to aggregate the bankruptcy information, most importantly, the dates of bankruptcy filings and openings.

[24] A web crawler is a computer program used to systemically browse and analyze websites. The General Appendix shows an exemplary Python program to crawl the German business register.

3.2.2.2 German business register (Unternehmensregister)

The German business register is a government entity that provides free public access to key corporate information such as annual reports, court statements, or register keys. It is the central platform for storing company data. The register also serves as a distributor of key statements from bankruptcy courts containing information about bankruptcy dates, decisions, status, meetings, and further proceedings. Notably, information is available for both public and private firms. However, researchers should be aware of the official deletion of proceedings of online bankruptcy statements.[25] To process this information, we automatically create web queries for information about each firm to check for any bankruptcy court statements. In addition, we manually review the results obtained from our automated web queries.

3.2.2.3 InsolNet

As a robustness check, we submit similar web requests for each firm to InsolNet.de's web servers. InsolNet is a commercial data provider that compiles statements from bankruptcy courts and presents them in a structured manner. Therefore, we examine the correctness and completeness of our bankruptcy data using InsolNet. However, since it provides only the opening date for bankruptcy proceedings, we prefer data from other sources to obtain the initial dates when bankruptcy information was made public, if available.

Even though this study focuses on companies listed on stock exchanges to include bankruptcy prediction models requiring capital market information such as Shumway (2001), our data collection approach can be used to extract bankruptcy information for all private and public companies in Germany.

3.2.3 Summary statistics

We use a straightforward definition for bankruptcy: a firm is bankrupt if it has filed a request to initiate an insolvency proceeding. We generally use the date of bankruptcy filing as an indicator because it is the earliest mention of a company's financial distress. Further, we exclude firms in liquidation because they may have ceased activities for reasons other than failure, for example, shareholder decisions, mergers, or discontinuation of operations

[25] Bankruptcy statements are deleted six months after the bankruptcy proceedings are completed.

by an allied company or foreign branch. Thus, we only include firms that explicitly indicate financial distress.

Table 3.1 illustrates the bankruptcy data we collected from multiple sources and used for our sample. We include the 1,711 securities listed in the Compustat Global company and security files, either incorporated or headquartered in Germany. To perform web queries with the German business register and InsolNet, we use the international securities identification number (ISIN) to merge corporate news releases with the explicit company name. Since we focus on public firms, we find that most firms release public statements when applying for bankruptcy. Over 80% of our bankruptcy data originates from corporate disclosures by the DGAP and APA OTS. This result suggests that researchers should also closely examine corporate news in other countries to likewise obtain more reliable data. Nevertheless, it is noteworthy that the business register is an interesting source for non-public firm bankruptcies because it covers all disclosures made by bankruptcy courts. Firm-level bankruptcy information data compiled by us is available upon request.

Table 3.1 HL bankruptcy data sources

		All Firms		Sample Firms	
ID	Source	N	%	N	%
1	DGAP & APA OTS news releases, Filing date	230	83.0%	135	97.1%
2	Unternehmensregister, Filing date	9	3.2%	1	0.7%
3	Unternehmensregister, Earliest date	16	5.8%	3	2.2%
4	DGAP & APA OTS news releases, Opening date	6	2.2%		0.0%
5	Unternehmensregister, Opening date	4	1.4%		0.0%
6	Insolnet, Opening date	8	2.9%		0.0%
7	Insolnet, Opening date (with historical names)	3	1.1%		0.0%
8	Web search	1	0.4%		0.0%
	Total Bankruptcies	277	19.3%	139	20.6%
	Total Non-bankruptcies	1,434		674	

This table reports the data sources used to create the HL bankruptcy. It shows the number of firm bankruptcies that were extracted from the respective source, along with their proportions. The columns “All firms” include all entities in Compustat Global that are either incorporated or headquartered in Germany (i.e., 1,711). Similarly, the columns “Sample firms” include companies with sufficient accounting and stock market data to predict several bankruptcy models. In general, bankruptcy data is either from ad-hoc disclosure (e.g., DGAP or APA OTS) or bankruptcy notifications in Unternehmensregister or Insolnet. We consistently use the earliest available bankruptcy notification data (i.e., filing for bankruptcy proceedings). Since most of our observations are obtained directly from ad-hoc disclosures, our bankruptcy data commonly refers to the date of filing for insolvency proceedings.

3.2.4 Comparison with other bankruptcy databases

We evaluate our collected bankruptcy data (HL data) against the predominantly used data sources, that is, the delistings on Compustat Global and BvD status codes.

Table 3.2 Number of bankruptcies across databases

	All firms			Sample firms		
	Compustat Global	Bureau van Dijk	HL	Compustat Global	Bureau van Dijk	HL
	Delisting (Liquidation, Bankruptcy)	*Status Code (Bankruptcy proceedings)*		*Delisting (Liquidation, Bankruptcy)*	*Status Code (Bankruptcy proceedings)*	
1996	1	-	-	-	-	-
1997	1	-	1	-	-	-
1998	1	-	-	-	-	-
1999	-	-	3	-	-	-
2000	1	-	3	-	-	-
2001	1	-	23	-	-	10
2002	2	-	44	-	-	23
2003	1	-	20	1	-	11
2004	2	-	16	2	-	11
2005	-	-	6	-	-	5
2006	3	-	7	2	-	3
2007	1	-	8	1	-	5
2008	2	-	16	-	-	10
2009	-	5	27	-	2	15
2010	1	6	20	-	5	12
2011	2	6	11	-	4	5
2012	2	12	15	1	5	6
2013	2	12	19	-	4	8
2014	1	10	12	1	3	5
2015	2	8	16	1	6	6
2016	1	4	10	-	2	4
	27	63	277	9	31	139

This table reports the number of corporate bankruptcies in each year using different databases (i.e., Compustat delisting codes, Bureau van Dijk status codes, and HL). Compustat delisting codes for liquidation or bankruptcy are obtained from Compustat Global. Bureau van Dijk data is sourced with a subscription to the Amadeus database. The HL database is created using the approach described in this study. While information from BvD is available only for the most recent years, data from Compustat and HL date back to 1996 and cover large bankruptcies that occurred during the recessions of the early 2000s.

Compustat Global provides delisting dates and the reasons for delisting. We follow Dahiya and Klapper (2007) and Tian and Yu (2017), who classify bankrupt firms based on reason 2 (“bankruptcy”) and reason 3 (“liquidation”). Altman et al. (2017) and Filipe et al.

(2016) use BvD's status code to indicate if firms are in liquidation or bankruptcy proceedings. We call a firm bankrupt if it has been assigned the BvD status code "Active (insolvency proceedings)." There are two reasons we do not use the status levels "Active (default of payment)," "Active (dormant)," "Dissolved," "Dissolved (liquidation)," or "In liquidation," which also apply to German public firms. The notional reason is that we aim for a consistent definition of bankruptcy across all databases, that a firm is bankrupt if it has filed for bankruptcy. The practical reason is that BvD does not provide any date for status levels other than "Active (insolvency proceeding)." We first examine whether the data sources indicate firm bankruptcies correctly and completely and then test the accuracy of the bankruptcy dates.

Table 3.2 summarizes the distribution of bankruptcies from 1996 to 2016. Our approach identifies 277 bankrupt firms, whereas BvD comprises 63 bankrupt firms and Compustat provides only 27 delistings. Note that, for this study, we gather bankruptcy information only for firms covered by Compustat. Thus, the difference in number of bankruptcies cannot be attributed to different firm coverage. Our final sample, constructed in Section 3.3.1, has 139, 31, and 9 bankruptcies that arise from data collected from HL, BvD, and Compustat, respectively. Table 3.2 clearly shows that Compustat Global delisting codes cannot be used to conduct a valid bankruptcy prediction analysis. Delisting codes are generally a bad proxy for bankruptcies. Foremost, Compustat Global categorizes many firms as delisted for "Other reasons" without providing further details. In addition, some firms experienced turnaround under bankruptcy administration and restructuring and thus, were not delisted. Vice versa, Compustat does not delist several bankrupt firms undergoing bankruptcy proceedings because they still trade at penny levels. BvD provides somewhat better bankruptcy data, although the coverage is less than 50% of our bankruptcy data. BvD deletes firm history five years after bankruptcy and, thus, BvD data that is requested in 2017 contains only bankruptcies between 2013 and 2017. Note that this limitation does not affect the results of our comparison analysis in Section 3.4.2, since it only uses the time period covered by BvD bankruptcies. Since we also have access to BvD's vintage data that we extracted in the years 2013, 2014, 2015, and 2016, we can artificially extend BvD's horizon and identify bankruptcies in earlier years. This vintage data can no longer be requested through WRDS or directly from BvD.[26] Despite these measures, our methodology yields significantly more bankruptcies than those identified in Compustat and BvD.

Table 3.3 Number of bankruptcies not captured by HL

	All firms		Sample firms	
	Compustat Global	Bureau van Dijk	Compustat Global	Bureau van Dijk
	Delisting (Liquidation, Bankruptcy)	*Status Code (Bankruptcy proceedings)*	*Delisting (Liquidation, Bankruptcy)*	*Status Code (Bankruptcy proceedings)*
1996	1	-	-	-
1997	1	-	-	-
1998	1	-	-	-
1999	-	-	-	-
2000	-	-	-	-
2001	1	-	-	-
2002	-	-	-	-
2003	-	-	-	-
2004	-	-	-	-
2005	-	-	-	-
2006	1	-	-	-
2007	-	-	-	-
2008	2	-	-	-
2009	-	-	-	-
2010	1	-	-	-
2011	2	-	-	-
2012	-	1	-	-
2013	1	-	-	-
2014	-	1	-	-
2015	-	-	-	-
2016	1	-	-	-
	12	2	-	-

This table reports the number of corporate bankruptcies for each year that are listed in Compustat (delisting codes) and Bureau van Dijk (status codes) respectively, but that are not captured by the HL database. Compustat delisting codes for liquidation and bankruptcy are obtained from Compustat Global. Bureau van Dijk data is taken from the Amadeus subscription. The HL database is created using the approach described in this study. While information from BvD is available only for the most recent years, data from Compustat and HL date back to 1996 and cover large bankruptcies that occurred during the recessions of the early 2000s.

[26] In fact, several items of information on German firms within BvD are obtained from Creditreform as the original data provider. We also directly contacted Creditreform to request bankruptcy information, however, Creditreform also deletes bankruptcy information three years after a firm's bankruptcy.

Table 3.3 shows the number of bankruptcies that are captured by Compustat Global and BvD respectively, but that are not by the HL database. Compustat Global reports 12 such firms[27], which means that HL and Compustat share 15 bankruptcies. In other words, HL exclusively captures 262 firms. We further find that BvD captures data for two firms that are not present in the HL database, which means that HL and BvD have 61 bankruptcies in common. One of the two companies is Suedzucker AG, a renowned MDAX company. An extensive analysis of Suedzucker AG discloses no bankruptcy application, filing, or statement for the firm. In other words, HL exclusively captures 216 firms. In our final sample, neither Compustat Global nor BvD exclusively capture any bankruptcy.

Table 3.4 provides further details on the firms that go bankrupt over the years. We report the largest bankrupt firms in terms of market equity at the preceding fiscal year end. While Compustat Global delistings do not provide valid bankruptcy data (not even for large-scale firms), BvD is somewhat consistent with data for certain years. For example, in 2013, the largest bankruptcy reported in the BvD database is that of Praktiker AG, and this is consistent with our HL database. However, unlike HL, BvD does not account for Arcandor AG, which filed for bankruptcy in 2009. We also note that BvD data has some serious errors. For Solar Millennium AG, BvD reports 2012 as the bankruptcy year, whereas the company went bankrupt in 2011. Similarly, it claims that Suedzucker AG, a renowned MDAX company, had been going through bankruptcy proceedings since 2012, although it never filed for bankruptcy. The results show that our approach not only provides additional bankruptcy data for small-scale firms but also proves that commercial data sources are inaccurate for even the largest firms.

[27] Note that Compustat Global reports delistings which may not be due to bankruptcy events.

Table 3.4 Comparison across databases (largest bankruptcies)

Panel A: Largest bankruptcies in Germany - HL versus Bureau van Dijk

	HL		Bureau van Dijk	
	Company name	MkEq	Company name	MkEq
2001	Kinowelt Medien AG	1,542.2	-	-
2002	Ision Internet AG	775.3	-	-
2003	Media AG	77.0	-	-
2004	Agiv Real Estate AG	108.6	-	-
2005	Pgam Advanced Techn. AG	46.3	-	-
2006	Hucke AG	22.9	-	-
2007	Koehler & Krenzer Fashion AG	35.8	-	-
2008	Thielert AG	354.1	-	-
2009	Arcandor AG	5,188.4	EDOB Abwicklungs AG	478.3
2010	Primacom AG	189.6	Primacom AG	189.6
2011	Solar Millennium AG	272.3	Agiv Real Estate AG	108.6
2012	Centrotherm International AG	570.1	Solar Millennium AG	272.3
2013	Praktiker AG	79.3	Praktiker AG	79.3
2014	Hansa Group AG	144.2	MIFA Mitteldeutsche Fahrrad	73.4
2015	Joyou AG	307.3	Joyou AG	307.3
2016	KTG Energie AG	72.5	Heliocentris Fuel Energy Sol	53.5

Panel B: Largest bankruptcies in Germany - HL versus Compustat Global

	HL		Compustat Global	
	Company name	MkEq	Company name	MkEq
2001	Kinowelt Medien AG	1,542.2	-	-
2002	Ision Internet AG	775.3	-	-
2003	Media AG	77.0	Telesens KSCL AG	616.0
2004	Agiv Real Estate AG	108.6	Das Werk AG	245.0
2005	Pgam Advanced Techn. AG	46.3	-	-
2006	Hucke AG	22.9	Umweltkontor Renewable Energy	66.4
2007	Koehler & Krenzer Fashion AG	35.8	Adori AG	17.3
2008	Thielert AG	354.1	-	-
2009	Arcandor AG	5,188.4	-	-
2010	Primacom AG	189.6	-	-
2011	Solar Millennium AG	272.3	-	-
2012	Centrotherm International AG	570.1	Phenomedia AG	96.6
2013	Praktiker AG	79.3	-	-
2014	Hansa Group AG	144.2	Conergy AG	50.3
2015	Joyou AG	307.3	TRIA IT-solutions AG	3.2
2016	KTG Energie AG	72.5	-	-

(continued)

Table 3.4 Comparison across databases (largest bankruptcies) (continued)

This table contrasts the largest bankruptcy in our HL database against existing commercial databases (i.e., BvD and Compustat Global) for each calendar year. This analysis exclusively covers our sample firms to provide scalable data on the economic relevance and size of bankrupt firms. Most importantly, the test provides information on whether the coverage of databases is restricted by size and years and proves that the extensive coverage of our HL database is not created by solely considering the bankruptcies of smaller firms with less economic relevance.

Table 3.5 highlights the differences in bankruptcy dates by database. Panel A reports the results for the full sample, while Panel B contrasts the results for the sample used for the bankruptcy models. The median difference in the dates between Compustat and HL is 24 months for all firms and 35 months for sample firms. That is, for half the firms, Compustat reports a bankruptcy date that is more than 24 months (35 months) after the bankruptcy date registered in our database. The 75th percentile is 46 months for all firms and 59 months for the sample firms. That is, for 25% of the sample firms, Compustat reports a delisting date that is 59 months or more after our date. This is because stock delistings generally happen several years after a firm files for bankruptcy. For bankruptcy events in BvD, half the dates are somewhat congruent with those in our HL database; the median distance between the BvD and HL bankruptcy dates is two days for the full sample and one day for our sample. This small lag is because BvD relies on court announcements that slightly lag the direct corporate announcements that are also used to determine the bankruptcy filing dates in the HL database. However, the 75th percentile is 56 days for all firms and 69 days for the sample firms; thus, BvD dates substantially lag behind the data we collected. Note that we can compare only a few HL events with those in BvD, given the poor coverage of the latter. For this comparison, we can use 31 of the 139 bankruptcies (22%) in the HL dataset for our sample. The results in Table 3.5 support the idea that commercial bankruptcy data is inaccurate in terms of bankruptcy dates.

Overall, the HL bankruptcy dataset outperforms both BvD and Compustat in terms of coverage, correctness of bankruptcy events, and accuracy of bankruptcy dates. This shows that our dataset cannot be reproduced by simply gathering information from the two commercial bankruptcy databases. In Section 3.4.2, we investigate if this higher quality of bankruptcy information influences the interpretation of results of bankruptcy prediction models.

Table 3.5 Differences in bankruptcy dates across databases

Panel A: Time differences for all firms

	Differences in days		Differences in month	
	HL vs. Compustat Global	HL vs. Bureau van Dijk	HL vs. Compustat Global	HL vs. Bureau van Dijk
Mean	1,064	259	35	9
P1	145	-95	5	-3
P25	354	0	12	0
Median	723	2	24	0
P75	1,374	56	46	2
P99	3,870	3,599	129	120
Std	1,111	817	37	27
N	15	61	15	61

Panel B: Time differences for sample firms

	Differences in days		Differences in month	
	HL vs. Compustat Global	HL vs. Bureau van Dijk	HL vs. Compustat Global	HL vs. Bureau van Dijk
Mean	1,219	261	35	9
P1	354	0	12	0
P25	723	0	12	0
Median	816	1	35	0
P75	1,374	69	59	2
P99	3,870	3,378	59	113
Std	1,089	787	33	9
N	9	31	9	31

This table shows the differences between the reported dates of initial bankruptcy filings across databases. We compare the lags in days and months between the explicit dates of bankruptcy announcements by different databases. Compustat delisting codes for liquidation or bankruptcy are obtained from Compustat Global. Bureau van Dijk data is taken from the Amadeus subscription. The HL database is created using the approach described in this study.

3.3 Data and method

3.3.1 Sample description and summary statistics

Our initial sample comprises all firms listed in Compustat Global's company and security files that are either incorporated or headquartered in Germany between 1995 and 2015. We delete observations with missing variables that are required for any bankruptcy prediction model. These include the variable sets in Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway (2008), and Hess and Huettemann (2019).

Appendix 3.A describes the variable construction for these bankruptcy prediction models. To reduce the effect of outliers, we winsorize all variables (except indicator variables and probabilities) annually at the 1st and 99th percentiles. Since we require five years of training data to perform cross-sectional earnings regressions for Hess and Huettemann (2019), which are based on Hou, van Dijk, and Zhang (2012) and Li and Mohanram (2014), our sample for bankruptcy prediction begins in 2000.

For each firm-year observation, we construct twelve monthly observations to enable market participants to perform bankruptcy predictions for each month. All bankruptcy measures are lagged by three months to ensure that they are observable when used for estimation. For example, the first observation for a firm-year with a fiscal year end of December 31, 2009 has an estimation date of March 31, 2010, and the last observation for the respective firm-year has an estimation date of February 28, 2011. A firm observation is defined as bankrupt if the firm files for bankruptcy exactly twelve months after the date of estimation; in such cases, the dependent variable equals one and otherwise it equals zero. Since we account for bankruptcies until the end of 2016, our sample comprises firm months with an estimation date before or at the end of December 2015.

Table 3.6 provides the summary statistics for all variables used to forecast bankruptcy. We report the mean, median, standard deviation, and certain percentiles of 95,431 firm months with complete data availability for 2000–2015. The results indicate a significant cross-sectional variation among these variables. For example, RETA has a standard deviation of 1.07. In addition, its 1st and 99th percentiles are −5.95 and 0.60, respectively. Interestingly, the probability of book equity becoming negative, PNBE, has a mean of 0.21, which is twice that found in Hess and Huettemann's (2019) study of U.S. firms (0.11). This suggests that German firms operate with negative book equity more frequently than U.S. firms do.

Table 3.6 Summary statistics (N=95,431)

Variable	Model	Mean	STD	1%	25%	Median	75%	99%
$WCTA_t$	A / O	0.22	0.26	-0.52	0.06	0.22	0.38	0.83
$RETA_t$	A	-0.14	1.07	-5.95	-0.02	0.03	0.17	0.60
$EBITTA_t$	A / HH	0.01	0.19	-0.78	-0.01	0.05	0.09	0.32
$METL_t$	A	2.86	7.14	0.04	0.45	1.02	2.46	30.27
STA_t	A	1.18	0.72	0.02	0.72	1.08	1.48	3.92
$Size_t$	O / HH	5.21	2.10	1.18	3.77	4.93	6.33	11.55
$TLTA_t$	O / S	0.57	0.24	0.07	0.40	0.58	0.72	1.24
$CLCA_t$	O	0.71	0.61	0.06	0.38	0.59	0.85	3.33
$OENEG_t$	O	0.02	0.15	0.00	0.00	0.00	0.00	1.00
$NITA_t$	O / S / BS	-0.03	0.20	-1.02	-0.03	0.02	0.06	0.26
$FUTL_t$	O	-0.01	0.63	-2.88	-0.04	0.06	0.17	1.34
$INTWO_t$	O	0.21	0.40	0.00	0.00	0.00	0.00	1.00
$CHIN_t$	O	0.01	0.60	-1.00	-0.36	0.04	0.35	1.00
$RSIZE_t$	S	-25.38	2.64	-31.16	-27.05	-25.54	-23.88	-18.62
ER_t	S / BS / HH	-0.38	0.73	-1.71	-0.81	-0.40	-0.04	2.18
$STDER_t$	S / HH	0.12	0.11	0.02	0.06	0.09	0.14	0.46
$PNBE_t$	HH	0.21	0.20	0.00	0.00	0.17	0.39	0.70
Neg $EarnFrc_t$	HH	0.35	0.48	0.00	0.00	0.00	1.00	1.00
$CAPXTA_t$	HH	0.05	0.05	0.00	0.02	0.04	0.06	0.27
TXT_t	HH	40.82	169.45	-13.31	0.04	1.50	10.07	979.00
MLR_t	HH	0.49	0.25	0.03	0.28	0.49	0.69	0.97
PD-$Merton_t$	BS	0.32	0.32	0.00	0.01	0.22	0.58	1.00
$LNME_t$	BS	4.59	2.11	0.69	3.11	4.24	5.78	10.48
$LNBD_t$	BS	4.53	2.30	0.02	2.91	4.31	5.83	11.26
$VOLME_t$	BS	0.73	0.56	0.12	0.38	0.59	0.90	3.23

This table reports the summary statistics for the following forecast variables (all values except dummy variables and probability values are in million dollars). Each observation represents one firm in a given year. Specifically, it shows variables used to forecast bankruptcy. For more details, see the data construction in Appendix 3.A. WCTA is working capital over total assets, RETA is retained earnings over total assets, EBITTA is earnings before interest and taxes over total assets, METL is the market value of equity over the book value of total debt, STA is sales over total assets, Size is the logarithm of total assets, TLTA is total liabilities over total assets, CLCA is current liabilities over current assets, OENEG is a dummy that equals one if total liabilities exceed total assets and zero otherwise, NITA is net income over total assets, FUTL is funds provided by operations over total liabilities, INTWO is a dummy that equals one if net income has been negative for the past two years and zero otherwise, CHIN is change in net income, RSIZE is the logarithm of market equity divided by the value-weighted market equity of the index, ER is excess return, STDER is the standard deviation of return, PNBE is the probability that losses deplete current book equity, NegEarnFrc is a dummy for negative earnings forecast, CAPXTA is capital expenditure over total assets, TXT is taxes, MLR is the market leverage ratio, PD-Merton is the KMV probability, LNME is the logarithm of market equity, LNBD is the logarithm of the book value of debt, and VOLME is the inverse of market equity volatility. The reported values are the time series averages of yearly cross-sectional means, medians, standard deviations, and respective percentiles. To treat extreme outliers and data errors, all variables (except indicator variables and probability values) are winsorized annually at the 1st and 99th percentiles. The column labeled "Source" indicates the model in which the variable is used, where "A" is Altman (1968), "O" is Ohlson (1980), "S" is Shumway (2001), "BS" is Bharath and Shumway (2008), and "HH" is Hess and Huettemann (2019). The sample period is 2000–2015. The summary statistics are reported for observations in which all model variables are available.

3.3.2 Method

Shumway (2001) demonstrates that the likelihood function of hazard models is equivalent to that of logistic regressions with multiple observations per firm. We follow Shumway (2001), Chava and Jarrow (2004), and Campbell, Hilscher, and Szilagyi (2008) and estimate the hazard model as a multi-period logistic regression. Thus, the probability of a firm becoming bankrupt follows a logistic distribution with parameters (α, β) and is equal to

$$P_t(y_{it} = 1) = \frac{1}{1+exp(-\alpha-\beta x_{i,t})}, \quad (3.1)$$

where y_{it} is a bankruptcy dummy that equals one if the firm fails in twelve months and zero otherwise,[28] and $x_{i,t}$ is the vector of explanatory variables that are known at time t. The higher the term $\alpha + \beta x_{i,t}$, the greater the estimated probability of bankruptcy. The estimates and their significance levels are calculated using a maximum likelihood technique. Shumway (2001) points out that the test statistics produced by a logistic regression are incorrect for the hazard model; correct test statistics are calculated by dividing them by the average number of observations per firm. The statistics reported in this study have been adjusted accordingly.

We conduct two empirical analyses. First, we compare the bankruptcy prediction models. To produce strictly out-of-sample forecasts, we estimate the parameters using 2000–2007 data and use the resulting coefficients to predict bankruptcies from 2008 to 2015. Second, we compare the HL and BvD databases. Given the data restrictions in the BvD database, we are limited to a shorter period. We estimate the parameters with 2009–2012 data and then use the coefficients to predict bankruptcies from 2013 to 2015.

Static models use a single observation per firm and, thus, result in sample selection bias. In contrast, our approach uses all available firm observations to estimate the hazard model, exploiting more information and eliminating any sample selection bias. Note that applying such a technique to Altman's (1968) and Ohlson's (1980) static models already improves their performance as compared to adopting the estimation techniques originally suggested.

[28] We also perform empirical tests that predict bankruptcy for a forecast horizon of one month rather than twelve months and find that the results remain robust regardless of the horizon change.

3.4 Empirical results

3.4.1 Comparison across models

3.4.1.1 Estimation results

Table 3.7 reports the estimation results for the hazard models of Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway (2008), and Hess and Huettemann (2019), including the parameter estimates as well as their significance. In addition, it presents the likelihood ratio test for each model.

The likelihood ratio test is significant for each model. Thus, for all models, the independent variables have explanatory power. Not all variables are statistically significant, which is contrary to studies on U.S. firms. However, if the parameters are statistically significant, the signs of these coefficients are consistent with economic intuition and those found in previous studies. For Altman (1968), lower profitability (EBITTA) yields higher estimated probability of bankruptcy. In the case of Ohlson (1980), the probability of bankruptcy rises if net income is negative for the past two years (INTWO) and if the change in net income (CHIN) is negative. For Shumway (2001), firms that are more leveraged (TLTA), less profitable (NITA), and smaller (RSIZE), are more likely to become bankrupt. For Bharath and Shumway (2008), lower excess return (ER), lower market equity (LNME), and higher PD-Merton yield higher estimated default probability. Finally, for Hess and Huettemann (2019), firms with higher PNBE are more likely to fail. The higher the market leverage ratio (MLR) and the lower the tax (TXT) and excess return (ER), the greater the estimated probability of bankruptcy.

Table 3.7 Parameter estimates of bankruptcy models

Variable	Altman (1968)	Ohlson (1980)	Shumway (2001)	Bharath and Shumway (2008)	Hess and Huettemann (2019)
Constant	-6.16 ***	-6.40 ***	-12.67 ***	-6.78 ***	-8.97 ***
	(622.75)	(71.00)	(77.20)	(145.32)	(211.75)
$WCTA_t$	-0.67	-1.05			
	(2.70)	(1.28)			
$RETA_t$	-0.02				
	(0.02)				
$EBITTA_t$	-1.39 ***				-0.61
	(20.47)				(2.35)
$METL_t$	0.02				
	(1.63)				
STA_t	-0.22				
	(1.59)				
$Size_t$		-0.12			-0.02
		(2.30)			(0.04)
$TLTA_t$		0.87	0.77 *		
		(1.64)	(3.05)		
$CLCA_t$		-0.41			
		(0.91)			
$OENEG_t$		-0.16			
		(0.07)			
$NITA_t$		0.40	-0.81 **	-0.45	
		(0.40)	(6.16)	(1.60)	
$FUTL_t$		-0.23			
		(0.99)			
$INTWO_t$		1.18 ***			
		(18.50)			
$CHIN_t$		-0.72 ***			
		(12.10)			
$RSIZE_t$			-0.18 ***		
			(10.94)		
ER_t			-1.31 ***	-1.04 ***	-1.23 ***
			(49.86)	(38.08)	(35.84)
$STDER_t$			-0.24		0.15
			(0.34)		(0.10)
$PNBE_t$					2.73 ***
					(10.95)
Neg $EarnFrc_t$					0.07
					(0.08)
$CAPXTA_t$					2.13
					(2.69)
TXT_t					-0.01 *
					(3.13)
MLR_t					0.87 *
					(3.63)
PD-$Merton_t$				1.06 **	
				(4.06)	
$LNME_t$				-0.23 **	
				(6.34)	
$LNBD_t$				0.00	
				(0.00)	
$VOLME_t$				-0.44	
				(0.76)	
N	47,738	47,738	47,738	47,738	47,738
LRT	25.97 ***	56.07 ***	93.25 ***	103.30 ***	112.81 ***

(continued)

Table 3.7 Parameter estimates of bankruptcy models (continued)

This table reports the results of the hazard models for the bankruptcy indicators for Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway (2008), and Hess and Huettemann's (2019) market model. Parameter estimates for all variables in each model are reported along with their chi-square statistics in parentheses. The hazard model is estimated for 2000–2007 with 47,738 observations and 78 bankruptcies. The chi-square of the likelihood ratio test for each model is reported in the row labeled LRT. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.4.1.2 Out-of-sample results

Table 3.8 presents the out-of-sample accuracies. Panel A reports the goodness-of-fit deciles. To create this table, we rank firms into deciles based on their fitted bankruptcy probability values for each year in our validation sample (2008–2015). That is, firms most likely to default in the subsequent year are sorted into the first decile and those with the lowest estimated default probabilities are assigned to the tenth decile. We report the percentage of bankrupt firms that fall under each of the ten probability deciles. A model is accurate if it estimates a high default probability for bankrupt firm-years and assigns many bankrupt firms into low deciles.

Hess and Huettemann's (2019) model classifies 59.02% of all bankrupt firms into the highest default probability decile (decile one). That is, a bank can exclude 59.02% of all bankruptcies if it does not lend money to the 10% of firms with the highest expected default measures. Shumway (2001) and Bharath and Shumway (2008) classify 57.38% and 54.1% of all bankrupt firms into the first decile, respectively. As a result, models using a combination of accounting and market information strongly outperform Altman's (39.34%) and Ohlson's (32.79%) accounting-based models. For the top two deciles (in aggregate), the correct predictions are 81.97% for Shumway (2001), 78.69% for Bharath and Shumway (2008), 73.77% for Hess and Huettemann (2019), 57.38% for Ohlson (1980), and 50.82% for Altman (1968).

Panel B reports the distribution of the area under the receiver operating characteristic (ROC) curve, also referred to as area under the curve (AUC), for the validation sample. The ROC curve plots the true positive rate against the false positive rate for all cut-off points. The AUC is measured relative to the area of the unit square. A value of 0.5 indicates a random model with no predictive ability and a value of 1.0 denotes perfect discrimination. To compute the AUC, we estimate the parameters for each model using the training sample (2000–2007) and adopt these parameters to predict bankruptcies in our validation sample (2008–2015). Chi-square tests for the differences in the means of the AUC across all models are shown in Panel C.

Table 3.8 Out-of-sample results: Comparison across models

Panel A: Goodness-of-fit deciles

Decile	Altman (1968)	Ohlson (1980)	Shumway (2001)	Bharath and Shumway (2008)	Hess and Huettemann (2019) - Market
1	39.34	32.79	57.38	54.1	59.02
2	11.48	24.59	24.59	24.59	14.75
3	9.84	16.39	8.2	9.84	11.48
4	6.56	6.56	4.92	6.56	6.56
5	6.56	1.64	0	3.28	1.64
6	3.28	1.64	3.28	0	1.64
7	1.64	3.28	0	0	1.64
8	9.84	1.64	0	0	0
9	6.56	4.92	0	0	0
10	4.92	6.56	1.64	1.64	3.28

Panel B: Area under the ROC curve

Model	Mean	95% Confidence interval		STD
Altman (1968)	0.675***	0.597	0.752	0.039
Ohlson (1980)	0.731***	0.656	0.804	0.037
Shumway (2001)	0.851***	0.804	0.898	0.024
Bharath and Shumway (2008)	0.854***	0.810	0.899	0.023
Hess and Huettemann (2019)	0.842***	0.789	0.895	0.027

Panel C: Comparison of Area under the ROC curve

	Altman (1968)	Ohlson (1980)	Shumway (2001)	Bharath and Shumway (2008)	Hess and Huettemann (2019)
Altman	-	0.057	0.176 ***	0.180 ***	0.167 ***
Ohlson	-0.057	-	0.120 ***	0.123 ***	0.111 ***
Shumway	-0.176 ***	-0.120 ***	-	0.003	-0.009
Bharath and Shumway	-0.180 ***	-0.123 ***	-0.003	-	-0.012
Hess and Huettemann	-0.167 ***	-0.111 ***	0.009	0.012	-

This table compares the out-of-sample accuracy of various bankruptcy prediction models. Parameter estimates from the training sample (2000–2007) are used to predict bankruptcies for the validation period 2008–2015. This validation sample includes 47,693 firm-years and 61 bankruptcies. All models are estimated with a hazard model. For Panel A, firms are ranked into deciles based on their fitted bankruptcy probability values for every year, where firms with the highest values fall into the first decile. We report the percentage of bankrupt firms that are classified into each probability decile. Panel B reports the mean of the area under the ROC curve (AUC) along with its significance to be greater than 0.5, its standard deviation, and the 95% Wald confidence interval. Panel C compares the means of the AUC across models reporting their mean differences and their significance. *** denotes significance at the 1% level.

For each model we test the hypothesis that the AUC is equal to 0.5, that is, that the model is a purely random classifier. This hypothesis is rejected for all models. Bharath and Shumway's (2008) model has an average AUC of 0.854, which is non-significantly higher than 0.851 in Shumway (2001) and 0.842 in Hess and Huettemann (2019). The market-based models significantly outperform the accounting-based ones in Ohlson (1980) and Altman (1968) with an average AUC of 0.731 and 0.675, respectively. These results are consistent with those reported using goodness-of-fit deciles: Shumway (2001), Bharath and Shumway (2008), and Hess and Huettemann (2019) have a similar out-of-sample performance for German firms, followed by Ohlson (1980) and Altman (1968). This study's results are consistent with those in studies such as Shumway (2001), Hillegeist, Keating, Cram, and Lundstedt (2004), and Campbell et al. (2008), who demonstrate that market variables can improve the accuracy of bankruptcy predictions. In contrast, for example, Reisz and Perlich (2007), and Agarwal and Taffler (2008) show that accounting-based models have similar performance.

3.4.2 Comparison across bankruptcy databases

We analyze the effect of different bankruptcy databases on parameter estimation and validation of bankruptcy prediction models. Since the BvD database deletes firm histories, we reduce our sample period to 2009–2015. While this eliminates the effect of BvD's deletion procedure on the analysis results and ensures a fair test, the test includes fewer bankruptcy events for both estimation and validation. In addition, we exclude Compustat Global because it has only two delisting events for this period, which is not sufficient for a reasonable analysis.

3.4.2.1 Estimation results

Table 3.9 reports the hazard model results for all models when using the HL or BvD bankruptcy databases for parameter estimation. In addition, it presents the parameter estimates, their significance, and the likelihood ratio test.

For each model, the chi-square statistic of the likelihood ratio test is higher if we use the HL bankruptcies as opposed to the BvD bankruptcies. For example, in Shumway (2001), HL data yields a chi-square statistic of 70.74 and BvD data produces a value of 24.84.

Table 3.9 Parameter estimates by bankruptcy database

	Altman (1968)		Ohlson (1980)		Shumway (2001)		Bharath and Shumway (2008)		Hess and Huettemann (2019)	
Variable	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD
Constant	-5.80***	-6.85***	-10.50***	-13.40***	-14.46***	-12.68***	-5.11***	-5.98***	-10.10***	-10.88***
	(236.56)	(183.98)	(73.95)	(63.49)	(53.40)	(25.17)	(30.92)	(28.61)	(153.57)	(111.31)
$WCTA_t$	-0.96	-0.23	1.04	3.40**						
	(1.66)	(0.05)	(0.77)	(5.26)						
$RETA_t$	-0.07	-0.05								
	(0.30)	(0.07)								
$EBITTA_t$	-1.57	-1.24							-0.08	0.20
	(2.26)	(0.62)							(0.01)	(0.01)
$METL_t$	-0.78**	-0.57*								
	(6.27)	(2.98)								
STA_t	0.01	0.25								
	(0.00)	(0.82)								
$Size_t$			-0.05	0.09					0.01	0.20
			(0.24)	(0.56)					(0.13)	(1.85)
$TLTA_t$			5.09***	6.41***	1.62***	1.74**				
			(18.09)	(14.76)	(8.06)	(5.12)				
$CLCA_t$			0.33	0.69**						
			(1.51)	(5.50)						
$OENEG_t$			-2.81***	-3.86**						
			(8.31)	(6.39)						
$NITA_t$			-0.07	-0.16	-0.60	-0.13	-1.13*	-0.89		
			(0.01)	(0.01)	(1.02)	(0.02)	(3.64)	(1.00)		
$FUTL_t$			-0.46	-0.10						
			(1.25)	(0.01)						
$INTWO_t$			0.62	1.08*						
			(1.99)	(3.65)						
$CHIN_t$			-0.35	-0.48						
			(1.23)	(1.33)						
$RSIZE_t$					-0.22***	-0.14				
					(8.24)	(1.98)				
ER_t					-1.32***	-0.95**	-1.42***	-1.25**	-0.86***	-0.60
					(14.68)	(4.87)	(12.79)	(6.09)	(6.80)	(2.03)

(continued)

Table 3.9 Parameter estimates by bankruptcy database (continued)

$STDER_t$					3.46***	3.24**			2.87**	2.22
					(9.01)	(3.94)			(5.22)	(1.51)
$PNBE_t$									1.60*	2.37**
									(3.76)	(5.21)
$NegEarnFrc_t$									0.51	-0.10
									(0.97)	(0.02)
$CAPXTA_t$									2.43	-3.07
									(0.52)	(0.25)
TXT_t									-0.01	-0.01
									(0.80)	(0.98)
MLR_t									3.26***	3.11**
									(8.94)	(4.93)
$PD\text{-}Merton_t$							-0.61	-1.35		
							(0.41)	(1.15)		
$LNME_t$							-0.72***	-0.73***		
							(25.13)	(15.30)		
$LNBD_t$							0.56***	0.72***		
							(16.66)	(16.00)		
$VOLME_t$							-3.09**	-2.64*		
							(6.24)	(3.61)		
LRT	32.88***	11.18***	47.84***	30.49***	70.74***	24.84***	83.03***	34.80***	81.10***	36.77***
Wilks' Lambda F-value	2.59**		2.94**		7.46***		5.22***		4.48***	

This table reports the results of the hazard models of the bankruptcy indicators for the market models proposed by Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway (2008), and Hess and Huettemann's (2019) market model. Parameter estimates for all variables in each model are reported along with their chi-square statistics in parentheses. The hazard model is estimated for 2009–2012 with 24,578 observations. In the training sample, there are 31 bankruptcies for the HL database and 18 bankruptcies for the BvD database. The chi-square of the likelihood ratio test for the hypothesis that each parameter is equal to zero is reported. Furthermore, the F-value of Wilks' Lambda for the hypothesis that the parameter estimates created by HL data and BvD data are equal is reported. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

For Ohlson (1980), the variables WCTA, CLCA, and INTWO are only significant if we use the BvD database for the estimation. As for Shumway (2001), the variable RSIZE is significant if we use HL bankruptcy events for estimation, but not if we use BvD bankruptcies. In Bharath and Shumway (2008), the variable NITA is significant if we use HL for parameter estimation, but not if we use BvD data. In Hess and Huettemann (2019), the variables ER and STDER are significant if we use HL for parameter estimation, while they are not significant, if we use BvD for estimation.

We conduct formal tests on the differences of the coefficients across the two training samples. We test the hypothesis that parameters emerging from use of the HL data equal those from the use of the BvD data. This hypothesis is rejected for all bankruptcy prediction models. That is, the choice of bankruptcy database affects the parameter estimates. If we use the inaccurate BvD bankruptcy events instead of HL data, the parameters are different in terms of significance and size. In the next subsection, we investigate if these different parameter estimates translate into different out-of-sample performances, that is, if the parameters estimated using the HL data outperform those estimated by BvD.

3.4.2.2 Out-of-sample results

Table 3.10 presents the out-of-sample accuracies for all models. The parameters are estimated using a training sample and the accuracy is evaluated with a validation sample. Both samples warrant bankruptcy dummies as the dependent variable. Dummies that emerge from the two bankruptcy databases, HL and BvD, are used for both parameter estimation and validation of the models. Thus, we have four out-of-sample results for each model, with which we conduct two empirical tests.

First, we evaluate the ability of each database to produce unbiased parameter estimates. If the parameter estimates from the bankruptcy dummies of one dataset yield better out-of-sample results, we can conclude that this bankruptcy dataset produces better parameter estimates. To derive this information, we compare the two results obtained using different bankruptcy dummies in the training sample but the same HL bankruptcy dummies in the validation sample.

Table 3.10 Out-of-sample results: Comparison across bankruptcy databases

Panel A: Goodness-of-fit deciles

Decile	Altman (1968)				Ohlson (1980)				Shumway (2001)				Bharath and Shumway (2008)				Hess and Huettemann (2019) - Market			
Training	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD	HL	BvD
Validation	HL		BvD		HL		BvD		HL		BvD		HL		BvD		HL		BvD	
1	40	33.33	33.33	33.33	33.33	20	25	16.67	60	53.33	75	66.67	46.67	33.33	58.33	41.67	46.67	33.33	50	41.67
2	6.67	13.33	8.33	8.33	20	20	25	16.67	13.33	20	8.33	16.67	20	26.67	16.67	25	20	6.67	25	8.33
3	6.67	6.67	0	0	26.67	20	25	16.67	13.33	6.67	8.33	8.33	6.67	13.33	0	8.33	13.33	26.67	0	16.67
4	6.67	6.67	8.33	8.33	0	0	0	0	0	13.33	0	0	6.67	13.33	8.33	8.33	13.33	20	16.67	25
5	6.67	6.67	8.33	8.33	6.67	13.33	0	16.67	6.67	0	0	0	13.33	6.67	8.33	8.33	0	6.67	0	0
6	6.67	6.67	8.33	16.67	0	13.33	8.33	16.67	0	0	0	0	0	0	0	0	6.67	6.67	8.33	8.33
7	13.33	20	16.67	8.33	0	0	0	0	6.67	0	8.33	0	0	0	0	0	0	0	0	0
8	6.67	0	8.33	8.33	0	6.67	0	8.33	0	6.67	0	8.33	6.67	0	8.33	0	0	0	0	0
9	6.67	6.67	8.33	8.33	6.67	6.67	8.33	8.33	0	0	0	0	0	6.67	0	8.33	0	0	0	0
10	0	0	0	0	6.67	0	8.33	0	0	0	0	0	0	0	0	0	0	0	0	0

Panel B: Area under ROC curve

Model	Mean					
Training	HL	BvD		HL	BvD	
Validation	HL		Diff	BvD		Diff
Altman (1968)	0.670	0.682	-0.011	0.622	0.630	-0.008
Ohlson (1980)	0.733	0.673	0.060 *	0.690	0.630	0.060 **
Shumway (2001)	0.841	0.827	0.014	0.870	0.861	0.010
Bharath and Shumway (2008)	0.800	0.782	0.017	0.821	0.795	0.026 **
Hess and Huettemann (2019)	0.831	0.775	0.056 **	0.842	0.803	0.039 *

This table compares the out-of-sample accuracy for various bankruptcy prediction models with yearly observations. We estimate and validate the sample with HL and BvD bankruptcy events. The parameter estimates from the training sample (2009–2012) are used to predict bankruptcies for the validation period 2013–2015. This validation sample includes 16,629 firm-years and 15 bankruptcies in the HL database and 12 bankruptcies in the BvD database. All models are estimated using a hazard model. For Panel A, firms are ranked into deciles based on their fitted bankruptcy probability values for every year, where firms with the highest values are categorized as the first decile. We report the percentage of bankrupt firms that are classified into each probability decile. Panel B reports the mean of the area under the ROC curve (AUC), the differences, and the significance of the differences. ** and * denote significance at the 5% and 10% levels, respectively.

Panel A shows the goodness-of-fit deciles. If we use the HL dummies for validation, the rate of bankrupt firms in the highest default probability decile estimated in Altman's (1968) model is 40.00% when using the HL parameter estimates and 33.33% with the BvD estimates. Thus, estimating the parameters with HL rather than BvD bankruptcies produces greater accuracy. Likewise, in Ohlson (1980), the proportion of bankrupt firm-years in decile one is 33.33% if we estimate the parameters with HL dummies, which is higher than the 20% obtained if we estimate parameters with BvD information. We observe the same pattern for Shumway (2001) (HL: 60%, BvD: 53.33%), Bharath and Shumway (2008) (HL: 46.67%, BvD: 33.33%), and Hess and Huettemann (2019) (HL: 46.67%, BvD: 33.33%).

Panel B reports the mean of the area under the ROC curve (AUC) for all models. Again, we use HL information for the validation sample. We also conduct chi-square tests on whether the AUCs differ significantly when the training sample consist of different bankruptcy dummies. Ohlson (1980) has an average AUC of 0.733 if we estimate the parameters with HL data, which significantly exceeds the average AUC of 0.673 when parameters are estimated with BvD data. For Hess and Huettemann (2019), the average AUC is 0.831 with HL estimates, which is significantly higher than the AUC of 0.775 obtained using BvD estimates. The chi-square tests for the differences in AUC in correlated samples show that these two differences are statistically significant. We find the same pattern for Shumway (2001) (HL: 0.841, BvD: 0.827) and Bharath and Shumway (2008) (HL: 0.800, BvD: 0.782). An exception is Altman (1968), where the average AUC is 0.670 with HL estimates and slightly lower than with BvD estimates (0.682).

All in all, we observe higher accuracy when we use HL data instead of BvD data for parameter estimation. Note that we obtain consistent results when using BvD dummies instead of HL dummies in the validation sample. We conclude that the more accurate bankruptcy information in the HL database produces more realistic parameter estimates. This analysis speaks to the consequences of training bankruptcy models with noisy bankruptcy data. When models are estimated using BvD data, researchers cannot effectively predict true bankruptcy outcomes, that is, out-of-sample results for bankruptcies in the HL database.

Second, we compare the out-of-sample results when using HL and BvD information for both parameter estimation and validation, respectively. When performing parameter estimation and validation with the more accurate HL database, Shumway (2001) has the highest average AUC of 0.841, followed by Hess and Huettemann (2019), Bharath and Shumway (2008), Ohlson (1980), and Altman (1968) with 0.831, 0.800, 0.733, and 0.670, respectively. If we perform bankruptcy predictions using the inaccurate BvD database, Shumway (2001) has the highest average AUC of 0.861, followed by Hess and Huettemann (2019) with 0.803, Bharath and Shumway (2008) with 0.795, and Ohlson (1980) and Altman (1968) equally with 0.630.

Thus, previous studies that use BvD information would conclude that Altman and Ohlson’s models have the same out-of-sample performance and are equally effective in predicting bankruptcies. However, we reach a different conclusion when using more accurate HL information: Ohlson has significantly higher performance and, thus, is the more effective bankruptcy prediction model. Likewise, studies using BvD data would conclude that Shumway (2001) significantly outperforms Hess and Huettemann (2019). In reality, however, if we use HL data, both models perform almost equally well. Specifically, data quality significantly affects the reliability of results for bankruptcy prediction models and the inferences from comparing alternative model specifications.

3.5 Conclusions

In this study, we show that the quality of bankruptcy data has a significant impact on the estimation and the evaluation of bankruptcy prediction models. We introduce an alternative database of German bankruptcies by systematically collecting information from public sources. In doing so, we show that our bankruptcy database has more complete and more accurate data on bankruptcy events and dates than the most frequently used databases, BvD and Compustat Global. In other words, our bankruptcy database cannot be reproduced using these two commercial databases. To the best of our knowledge, we are the first to make a comprehensive comparison of several bankruptcy prediction models for the German market using an appropriate database. Most importantly, in our analysis of German public firms, we demonstrate that the higher quality of our bankruptcy database translates into significantly better parameter estimates and better out-of-sample results for bankruptcy prediction models compared to the use of BvD information.

The implication for studies that use bankruptcy information is huge. It is likely that previous studies that use incorrect bankruptcy information provided by BvD or Compustat present biased parameters for factors that are supposed to drive a company's financial condition. As a result, the out-of-sample assessment based on these biased parameters is not informative. For example, BvD information would recommend a model whose performance deteriorates when we use more accurate HL data. Therefore, the conclusions drawn in previous studies may need to be revised in light of accurate bankruptcy data. In addition, accurate bankruptcy information is crucial to several other applications, such as analyzing systemic risks or credit spreads.

Further research could compile the bankruptcy events of German non-public firms and extend our methodology to extract complete bankruptcy information for other countries if regulatory requirements are fulfilled. Furthermore, investigating whether data quality affects results in other countries as well may be of special interest.

3.A Construction of variables for earlier bankruptcy prediction models

We discuss the construction of variables used in Altman (1968), Ohlson (1980), Shumway (2001), Bharath and Shumway's (2008) most effective model, and Hess and Huettemann's (2019) market model.

Altman (1968) obtains a Z-score using a linear weighted sum of five ratios:

$$Z = \beta_0 + \beta_1 \cdot WCTA + \beta_2 \cdot RETA + \beta_3 \cdot EBITTA + \beta_4 \cdot METL + \beta_5 \cdot STA, \tag{3.2}$$

where WCTA is working capital (Compustat item WCAP) divided by total assets (AT), RETA is retained earnings (RE) divided by total assets (AT), EBITTA is earnings before interest and taxes (EBIT) divided by total assets (AT), METL is the market value of equity (PRCC_F multiplied by CSHO) divided by the book value of total debt (LT), STA is sales (SALE) divided by total assets (AT), and Z is the Z-score (overall index). WCTA is a proxy for a firm's liquidity, RETA is a proxy for firm age, and EBITTA measures profitability. METL is a widely used measure of leverage and STA describes the firm's efficiency in using assets to generate sales. The Z-score characterizes the financial strength of a firm by aggregating these five accounting ratios into one figure using the estimated coefficients $\beta_1, \dots, \beta_5$.

Ohlson (1980) finds nine variables to be significant and defines his O-score model as

$$O = \beta_0 + \beta_1 \cdot SIZE + \beta_2 \cdot TLTA + \beta_3 \cdot WCTA$$
$$+ \beta_4 \cdot CLCA + \beta_5 \cdot OENEG + \beta_6 \cdot NITA$$
$$+ \beta_7 \cdot FUTL + \beta_8 \cdot INTWO + \beta_9 \cdot CHIN, \tag{3.3}$$

where Size is the logarithm of total assets (AT), TLTA is total liabilities (LT) over total assets (AT), WCTA is working capital (WCAP) over total assets (AT), CLCA is current liabilities (LCT) over current assets (ACT), OENEG is a dummy that takes the value of one if total liabilities (LT) exceed total assets (AT) and zero otherwise, NITA is net income (NI) over total assets (AT), FUTL is funds provided by operations[29] (PI plus DP) over total liabilities (LT), INTWO is a dummy that takes the value of one if net income (NI) is negative for the past two years and zero otherwise, CHIN is the change in net income (NI), and O is the O-score (overall index). WCTA and CLCA measure liquidity. NITA, FUTL, INTWO, and CHIN capture the different aspects of profitability. TLTA and OENEG describe the capital structure and Size is a measure of firm size.

In addition to selected financial ratios used by Ohlson, Shumway (2001) adds two market variables, the excess return and its standard deviation:

$$S = \beta_0 + \beta_1 \cdot RSIZE + \beta_2 \cdot TLTA + \beta_3 \cdot NITA$$
$$+\beta_4 \cdot ER + \beta_5 \cdot STDER, \tag{3.4}$$

where RSIZE is the logarithm of market equity divided by the value-weighted market equity of the index, TLTA is total liabilities (LT) over total assets (AT), NITA is net income (NI) over total assets (AT), ER is excess returns calculated as the difference between the previous year's returns and the risk-free rate, STDER is the standard deviation of the returns, and S is the S-score (overall index). TLTA measures solvency and describes the capital structure, and profitability is captured by NITA. ER measures the profit of an investment, where STDER determines the variability of excess returns. Returns are calculated as the present year's adjusted stock price (PRCCD multiplied by TRFD and divided by AJEXDI) divided by the previous year's adjusted stock price minus one. RSIZE is a measure of firm size.

[29] Since funds provided by operations are no longer reported, we perform an approximation by summing "pretax income" and "depreciation and amortization."

Bharath and Shumway (2008) extend the distance-to-default models that Vassalou and Xing (2004) and Hillegeist et al. (2004) construct. Applying Merton's (1974) option pricing theory yields the probability of bankruptcy as

$$PD - Merton = N\left(-\left(\frac{ln(V/F)+(\mu-0.5\sigma_V{}^2)}{\sigma_V}\right)\right), \tag{3.5}$$

where V is the market value of a firm's assets, σ_V is its standard deviation, μ is the expected return on assets, F is the market value of firm debt, and N(·) is the cumulative standard normal distribution function. Vassalou and Xing (2004) numerically compute V and σ_V by applying an iterative procedure. Bharath and Shumway, however, propose a naïve approach. They approximate the market value of debt using the book value of debt and, thus, calculate F as debt in current liabilities plus one half of long-term debt. Furthermore, the volatility of a firm's debt is approximated by

$$\sigma_F = 0.05 + 0.25 \cdot \sigma_E, \tag{3.6}$$

where σ_E is the volatility of market equity. Market equity is denoted by E and calculated as the product of share price at the end of the month and the number of outstanding shares. Accordingly, an approximation for the volatility of the firm's assets is denoted by

$$\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}\sigma_F. \tag{3.7}$$

The expected return on assets, μ, is approximated using the previous year's return on assets. In addition, the market value of assets is approximated by the sum of the market value of equity and book value of debt.

Bharath and Shumway's most effective model includes PD-Merton as constructed above; the logarithm of market equity E (PRCC_F multiplied by CSHO); the logarithm of the book value of debt F, calculated as current debt (DLC) plus one half of long-term debt (DLTT); the inverse of market equity volatility; excess returns calculated as the difference between the previous year's returns and the risk-free rate measured by the return on a one-year Treasury Bill from the Board of Governors of the Federal Reserve system; and NITA computed as the ratio of net income (NI) to total assets (AT).

The key idea of Hess and Huettemann's (2019) models is that a firm becomes bankrupt if its book equity becomes negative. Thus, the key bankruptcy predictor is the probability that the sum of a firm's current book equity and earnings forecast for the subsequent month is negative. This probability for firm i at time t can be expressed as

$$PNBE_{i,t} = 1 - \Phi\left(\frac{\widehat{Earn_{i,t+1}} + BkEq_{i,t}}{\sigma\left(\widehat{Earn_{i,t+1}}\right)}\right), \tag{3.8}$$

where $\mathrm{BkEq}_{i,t}$ denotes the current book equity for the previous quarterly or yearly report, $\mathrm{Earn}_{i,t+1}$ is the expected earnings for the subsequent month, $\sigma\left(\widehat{\mathrm{Earn}_{i,t+1}}\right)$ is the corresponding volatility of the individual earnings forecast, and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Book equity is equal to stockholder's equity (SEQ). If SEQ is missing, they include common equity (CEQ) plus the value of preferred stock (PSTK). If CEQ or PSTK are missing, book equity is evaluated as total assets (AT) minus total liabilities (LT) minus minority interest (MIB). Earnings are the change in retained earnings, which equals net income (NI) minus dividend payments (DVT).

To calculate the earnings forecasts and their volatilities, Hess and Huettemann (2019) use cross-sectional models. More specifically, they adopt a rolling regression technique with accounting data from the past five years to estimate the parameters they use for forecasting.

Hess and Huettemann's (2019) market model contains PNBE, the probability that book equity becomes negative; NegBkEq, a dummy that equals one if book equity is negative and zero otherwise; NegEarnFrc, a dummy that equals one if the earnings forecast is negative and zero otherwise; CAPXTA as capital expenditures (CAPX) divided by total assets (AT); TXT as paid taxes (TXT); EBITTA as profitability calculated as earnings before interest and taxes (EBIT) over total assets (AT); Size measured by the logarithm of total assets (AT); and the market leverage ratio (MLR), calculated as the sum of long-term debt (DLTT) and current debt (DLC) divided by the sum of long-term debt, current debt, and market equity. Market equity is the fiscal year-end equity price (PRCC_F) multiplied by the number of common outstanding shares (CSHO). It adds excess returns calculated as the difference between the previous year's returns and the risk-free rate (ER) and the standard deviation of returns (STDER).

3.B List of German words related to bankruptcy

Insolvenzantragspflicht	Insolvenzrecht	Insolvenzgesetzes
Insolvenzankündigung	Insolvenzplänen	Insolvenzgutachtens
lnsolvenz	insolvenzantrag	Insolvenzverfahren
Insolvenzfällen	Insolvenzantragsgründe	Insolvenzerwaltung
Insolvency	Insolvenzfrist	Insolvenzanfechtungs
lnsolvenzverfahrens	Insolvenzgefährdung	Insolvenzplans
Insolvenzeröffhung	Insolvenzanmeldung	Insolvenzgericht
Insolvenzgrund	Insolvenzgeschichte	Insolvenzantrag
Insolvenzverwalterin	insolvenzrechtlich	Insolvenzverwaltern
Insolvenzkanzlei	Insolvenzverwalters	Insolvenzjahr
Insolvenzgerichten	insolvencies	Insolvenzwirtschaft
insolvenzphase	Insolvenzszenario	Insolvenzgefahr
Insolvenzfälle	Insolvenzen	Insolvenzplanes
Insolvenzeröffnungsgutachten	Insolvenzursachen	Insolvenzverfahrens
Insolvenzverordnung	insolvenzverfahrensgestützten	insolvenzgefährdet
insolvenzverfahrens	insolvency	Insolvenzverwaltung
Insolvenzquote	Insolvenzrechtes	Insolvenzverfähren
Insolvenzabwicklung	Insolvenzmassen	insolvenzbedingte
Insolvenzverwalter	Insolvenzbüro	Insolvenzbedingte
Insolvenzforderung	Insolvenzgeldvorfinanzierung	insolvenzbekanntmachungen
Insolvenaverwalter	Insolvenzantrags	Insolvenzanträge
insolvenzliches	Insolvenzplan	Insolvenzverschleppung
Insolvenzvertreter	Insolvenzwelle	Insolvenzzahlen
Insolvenzantrages	Insolvenzstatus	Insolvent
insolvenzsichere	insolvenzähnliche	insolvenzlichen
Insolvenzreife	Insolvenzeröffnung	Insolvenzplanteilnehmer
Insolvenzausfallgeld	Insolvenz	Insolvenzrisiken
Insolvenzgerichts	Insolvenzsituationen	Insolvenzantragsverfahren
Insolvenzeröffnungsverfahrens	Insolvenztatbestände	Insolvenzmanagement
Insolvenzgeldes	Insolvenzantragsprüfung	insolvenzverwalter
Insolvenzgläubigerversammlung	Insolvenzlage	Insolvenzschuldnerin
insolvenzrechtliche	Insolvenzantragverfahrens	Insolvenverfahrens
Insolvenzentwicklung	Insolvenzausgleichsfonds	Insolvenzpläne
insolvent	insolvenzen	Insolvenzplanverfahren
Insolvenzexpertin	Insolvenzgutachten	Insolvenzgründe
Insolvenzantragstellung	Insolvenzprozesses	Insolvenzplanverfahrens
insolvenzverfahren	insolventer	Insolvenzrisiko
Insolvente	Insolvenzantragsgründen	insolvenzplans
insolvenzabwendenden	Insolvenzsituation	insolvenzbefangene
Insolvenzsanierungsplan	Insolvenzeröffnungs	Insolvenzmasse
insolvenztypische	Insolvenzer	Insolvenzkapitel
Insolvenzgläubigern	Insolvenzantragsverfahrens	insolvenzrechtlichen
insolvenzgefährdeten	Insolvenztabelle	Insolvenzgläubiger
Insolvenzrechts	Insolvenzanträgen	Insolvenzantragspflichten
Insolvenzfordcrungen	insolvenz	Insolvenzrechtlich
Insolvenzbedingter	Insolvenzforderungen	Insolvenzspezialisten
Insolvenzordnung	insolvente	Insolvenzschutz
insolvenzbedingten	insolventen	Insolvenzeröffnungsverfahren
Insolvenzeröffnungsbilanz	Insolvenzgeld	Insolvenzgerichtes
Insolvenzverewalter	Insolvenzgeschäft	Insolvenzplansanierung

This list of German words is extracted from all corporate news releases by using dynamic regular expressions to test if the root of each word contains insolvency wording. It is then used to identify the corporate news releases of DGAP and APA OTS that might be related to a firm's bankruptcy.

Chapter 4

Bankruptcy Proceedings, Annual Report Timing, and Bankruptcy Prediction: Crawling the German Business Register*

4.1 Introduction

Bankruptcies are events that may have major negative effects on different groups of stakeholders, such as shareholders, creditors, and competitors. Several studies have made efforts to improve the methodology of predicting corporate bankruptcies (e.g., Altman, 1968; Ohlson, 1980; Shumway, 2001; Bharath and Shumway, 2008). Thus, these studies analyze the time period until a firm has filed for bankruptcy. However, not many have addressed a firm's actions after bankruptcy has already been filed. Specifically, few studies have investigated the characteristics of a bankruptcy proceeding, such as the type and the timing of those events that happen after the bankruptcy opening. For example, Crhova and

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* This chapter is based on Huettemann (2019). I am grateful to Dieter Hess, Tobias Lorsbach, and William Liu for their insightful discussions and suggestions. This paper has also greatly benefitted from comments made by the seminar participants at the University of Cologne.

Pasekova (2013) compare proceedings in France, Germany, and Slovakia by describing national insolvency laws. However, they do not analyze these proceedings empirically.

Moreover, literature on bankruptcy has a clear focus on publicly traded firms. Early bankruptcy prediction models (e.g., Altman, 1968) rely on accounting-based variables. However, recent models require market-based variables, and, by this, can only be applied to public firms (e.g., Bharath and Shumway, 2008; Chava and Jarrow, 2004; Hillegeist, Keating, Cram, and Lundstedt, 2004; Vassalou and Xing, 2004). Thus, recent bankruptcy prediction literature has neglected privately held firms. However, considering the relatively small number of listed and the huge number of non-listed firms, one can posit that an economy greatly depends on private firms. Altman, Iwanicz-Drozdowska, Laitinen, and Suvas (2017) highlight the importance of predicting private firms' bankruptcies, since, for example, managing large loan portfolios requires models that can also assess small and medium-sized firms, which are commonly non-public.

This study aims at filling both of these gaps in the literature: first, by empirically analyzing German firms' bankruptcy proceedings, and second, by using both public and private firms. I perform a web crawler[30] on the German business register to collect a database containing German firms' bankruptcy events; this database is then used in several analyses. First, I compare the number of bankruptcy events extracted from the business register with official numbers from Destatis ("*Statistisches Bundesamt*") and with the number of bankruptcy events of the database of Bureau van Dijk (BvD), a common provider of European financial and bankruptcy information. Second, I analyze the events listed in the business register, such as protective measures, openings, or decisions, in terms of the number of each event type, the order of events, and the time span between certain events. Third, I crawl the business register to extract annual reports' publication dates and merge them with the bankruptcy dates. This allows me to investigate the effect of bankruptcies on annual reports' publication dates. Fourth, I broadly compare accounting-based bankruptcy prediction models for German firms. Many studies conduct bankruptcy predictions among U.S. corporations. However, there is comparatively little research analyzing firms in other countries. For example, Tian and Yu (2017) produce ratios for bankruptcy prediction in Japan and selected European countries, Dahiya and Klapper (2007) compare key industrial nations, and Altman et al. (2017) evaluate Altman's (1983)

[30] A web crawler is a computer program used to systemically browse and analyze websites. The General Appendix shows an exemplary Python program to crawl the German business register.

Z-score for 31 European and three non-European countries. Of these studies, Altman et al. (2017) is the only study that includes private firms. Fifth, I split the sample into subsamples of small, medium-sized, and large firms measured by total assets. I separately perform bankruptcy predictions on each subsample to analyze the impact of firm size on prediction results.

The empirical results are as follows. First, crawling the business register for bankruptcy events creates a bias, since the law requires that bankruptcy statements must be deleted six months after the bankruptcy proceedings have been terminated. Accordingly, the register's coverage is relatively poor for earlier years, and it improves over time. In 2017, the number of openings comes close to the official number from Destatis; thus, crawling the business register yields nearly all events.[31] Importantly, in recent years, the business register covers more bankruptcy events than BvD. Moreover, the business register's coverage is greater for joint-stock firms than for limited liability firms. Second, analyzing the proceedings I find that compared to limited liability firms, only a few joint-stock firms are refused bankruptcy proceedings due to insufficient assets. Furthermore, approximately 90% of all firms start with either an opening event or an event stating protective measures. On average, bankruptcy proceedings open 75.5 days after the court takes protective measures; this lag is higher for joint-stock firms. Third, 14.8% of all firms publish annual reports after bankruptcy proceedings have been opened. On average, firms need 425.9 days to publish their annual reports after their fiscal year-end. This interval increases by 81.4 days for the time after the bankruptcy opening. Fourth, Hess and Huettemann's (2019) bankruptcy prediction model outperforms the models by Altman (1968) and Ohlson (1980) for the scope of private and public German firms. Fifth, each model predicts large firms' bankruptcies more accurately than small and medium-sized firms' bankruptcies. Thus, the size of a firm has an impact on the results of prediction models.

Crawling the German business register makes a detailed analysis of public bankruptcy information possible. By this, I can interpret the type and number of bankruptcy events and analyze typical bankruptcy proceedings. As the sample includes both joint-stock and limited liability firms, this study can show differences between these firm types. For example, joint-stock firms tend to have a longer lasting proceeding, a

[31] Note that Destatis provides no firm-individual information, and thus, cannot be used in individual firm analyses.

longer duration between protective measures and the opening, and are refused an opening due to insufficient funds less often. To the best of my knowledge, this study is the first to combine bankruptcy dates and annual report dates, which facilitates identification of the impact of bankruptcy proceedings on annual reports' publication dates. Furthermore, I quantify the business register bias that arises due to legal deletion requirements. Researchers learn how many bankruptcies are covered when they use business register data. Simultaneously, this study indicates that for recent years, this methodology yields more bankruptcy events than the BvD data. Finally, I find that Hess and Huettemann's (2019) accounting model performs best for public and private German firms. While Hess and Huettemann (2019) base their empirical analysis solely on public firms, I test their model also on privately held firms. By this, I validate that their accounting model indeed outperforms existing accounting-based models for both public and private firms.

The remainder of this chapter is organized as follows. Section 4.2 describes the methodology to collect information on bankruptcies and annual reports from the German business register. In Section 4.3, we describe the limitations of our bankruptcy database, describe our sample selection, report the descriptive statistics, and explain our methods. In Section 4.4, we present and discuss our empirical results. Section 4.5 concludes.

4.2 Collecting data of bankruptcies and annual reports

4.2.1 Bankruptcy database

4.2.1.1 German bankruptcy proceedings

As stated in Huettemann and Lorsbach (2019), a company is obliged to file for bankruptcy ("*Insolvenzantrag*") at the first instance court ("*Amtsgericht*") within the first three weeks after experiencing a reason for insolvency according to Germany's 2009 insolvency statute ("*Insolvenzverordnung*").[32] These reasons include a company's illiquidity, i.e., its inability to serve its due obligations, its imminent illiquidity, or its over-indebtedness, i.e., if its obligations exceed its assets.

After a company files for insolvency, the responsible court may take protective measures ("*Sicherungsmaßnahmen*"), which include the appointment of an interim insolvency administrator. If this administrator verifies that the company's funds are

[32] "Insolvency" and "bankruptcy" are used synonymously in this study.

sufficient to cover the costs of a proceeding, he or she opens an insolvency proceeding ("*Insolvenzeröffnung*"); otherwise, an opening is refused due to insufficient assets ("*Abweisung mangels Masse*") and the company is liquidated. If the proceeding is opened, the insolvency administrator takes over the company's administration and is responsible for restructuring measures, liquidating business units, and collecting outstanding receivables to partially serve creditors' claims. Further, the following may occur: an appointment ("*Termine*"); miscellaneous ("*Sonstiges*"); a distribution schedule ("*Verteilungsverzeichnisse*"); a supervised insolvency plan ("*Überwachte Insolvenzpläne*"); or a decision in the proceeding ("*Entscheidung im Verfahren*"), in the residual debt discharge ("*Entscheidung im Restschuldbefreiungsverfahren*"), or after termination ("*Entscheidung nach Aufhebung des Verfahrens*"). These events are all directed by the courts, published online on the German business register ("*Unternehmensregister*") and deleted six months after the proceeding has been terminated.

4.2.1.2 Extracting German bankruptcy data from public sources

To obtain data for bankruptcies of German companies, studies commonly use the BvD database. However, BvD deletes a firm's financial data when the firm has not published an annual report for five consecutive years. As this may apply to firms in bankruptcy proceedings, it is likely that the database does not include firms that filed for bankruptcy more than five years ago. This fact is documented in previous studies, such as Filipe, Grammatikos, and Michala (2016), who use a sample period of 2000 to 2009, but find no bankruptcies in 2000.

As stated in Huettemann and Lorsbach (2019), the German business register is a government entity that provides public access to key corporate information, such as annual reports, court statements, or register keys. It is the central platform for company data storage, and serves as a distributor of key statements from bankruptcy courts that contain information on bankruptcy dates, decisions, status, meetings, and further proceedings. I systematically collect bankruptcy data by crawling free access online releases published by the bankruptcy courts. Specifically, I create web queries to the website of the German business register. The crawler automatically searches for all firms and all courts to check for any statements. If there are search results, the crawler saves the company name, the court, the register number, the status, the event name, and the event date. Finally, it aggregates the structured information from all events in a comma-separated values (CSV) file.

4.2.2 Extracting annual reports' publication dates

I then extract the annual reports' publication dates to merge them with the bankruptcy event dates as follows: In a first step, I use a web crawler to browse through the German business register. It automatically enters search queries for all available annual reports for every available year, and then saves the HTML codes of all search result pages as text files. In a second step, I use regular expressions to examine these text files: I extract structured information on the annual reports, such as unique company identifiers (i.e., its name, its register number, and the court) as well as the fiscal years, and the respective annual reports' publication dates. The crawler saves a CSV file in which one line represents one annual report. In total, I find 7,167,611 annual reports of 1,152,119 firms.

4.3 Data and method

4.3.1 Usability of business register bankruptcy data

The business register must by law delete bankruptcy statements six months after the bankruptcy proceeding has been terminated or refused to open due to insufficient assets. Thus, analyzing bankruptcy data that is extracted ad-hoc from the business register comes with a limitation. Consequently, when using the business register, one cannot conduct analyses that require a complete bankruptcy database. For example, one cannot compute insolvency ratios or analyze the evolution of the number of refusals due to insufficient assets over the years.

Nevertheless, bankruptcy data extracted from the business register can be used for several analyses that do not necessarily require full coverage. For example, one can analyze the typical features of proceedings, and one can conduct profile analyses to compare firm-years before the bankruptcy opening with firm-years after the opening. Alternatively, a valid analysis may focus on the sample period for which the business register's coverage is complete. For example, one can analyze the number of opening refusals due to insufficient assets for the most recent six months. Finally, regularly crawling the business register for bankruptcy events creates a complete dataset that overcomes these limitations.

4.3.2 Sample description and summary statistics

The initial sample comprises all observations in BvD's financial files for very large, large, and medium-sized firms incorporated in Germany.[33] Firms include joint-stock companies (company types "AG," "KGaA," "AG & Co. KGaA," and "GmbH & Co. KGaA") and limited liability companies (company types "GmbH" and "UG"). BvD only provides information from the ten most recent years. However, this study also uses vintage data requested through Wharton Research Data Services (WRDS) at year-ends 2013 to 2017, which increases the sample period to span 2004 to 2017. Note that this vintage data can no longer be requested through WRDS or directly from BvD.[34] I then delete observations with missing variables that are used in the bankruptcy prediction models of Altman (1968), Ohlson (1980), and Hess and Huettemann (2019). Appendix 4.A describes the variable construction for these bankruptcy prediction models in detail. The effect of outliers is reduced by winsorizing all variables (except the indicator variables and probabilities) annually at the 1st and 99th percentiles. The sample for bankruptcy prediction starts in 2009, as Hess and Huettemann's (2019) cross-sectional earnings regressions, based on Hou, van Dijk, and Zhang (2012) and Li and Mohanram (2014), require five years of training data. All bankruptcy measures are lagged by three months to ensure that they are observable when used for the estimation. For example, an observation for a firm-year with a fiscal year end of December 31, 2009, has an estimation date of March 31, 2010.

I extract all bankruptcy events from the business register for all available legal entities, and merge them with the BvD sample using unique company identifiers, i.e., the commercial register number and the court in charge. I identify bankruptcies in the sample by combining the BvD events with those extracted from the business register. I define a firm as bankrupt if it has filed for bankruptcy, and use the earliest event date as the bankruptcy date. A firm observation is defined as bankrupt if the firm becomes bankrupt in the subsequent twelve months after the estimation date, in which case the dependent variable equals one; otherwise, it equals zero. As I account for bankruptcies until the end of 2017, the sample comprises observations with an estimation date before or at the end of December 2016.

[33] As this study focuses on traditional corporate bankruptcies and not on those of individuals, the "HRB" section in the commercial register (legal entities) is used rather than the "HRA" section (private partnerships).

[34] I am grateful to Dieter Hess for providing me with this vintage Bureau van Dijk data.

Table 4.1 Summary statistics (N=213,455)

Variable	Model	Mean	STD	1%	25%	Median	75%	99%
$PNBE_t$	HH	0.24	0.22	0.00	0.00	0.24	0.43	0.86
$NegEarnFrc_t$	HH	0.18	0.38	0.00	0.00	0.00	0.00	1.00
BLR_t	HH	0.68	0.28	0.08	0.49	0.70	0.88	1.59
TXT_t	HH	504.58	1612.08	-182.25	7.36	55.65	310.69	8453.80
$FIEXTA_t$	HH	0.02	0.02	0.00	0.00	0.01	0.03	0.12
$EBITTA_t$	HH / A	0.08	0.13	-0.37	0.02	0.06	0.12	0.55
$Size_t$	HH / O	15.94	1.82	12.10	14.63	15.92	17.20	20.30
$WCTA_t$	A / O	0.23	0.25	-0.29	0.03	0.18	0.41	0.85
$RETA_t$	A	0.23	0.29	-0.80	0.03	0.20	0.41	0.88
$BETL_t$	A	1.05	2.11	-0.38	0.14	0.42	1.06	13.00
STA_t	A	2.17	1.92	0.01	0.80	1.77	2.98	10.06
$TLTA_t$	O	0.68	0.28	0.07	0.49	0.70	0.88	1.60
$CLCA_t$	O	0.99	3.05	0.01	0.32	0.61	0.92	11.76
$OENEG_t$	O	0.06	0.24	0.00	0.00	0.00	0.00	1.00
$NITA_t$	O	0.05	0.12	-0.43	0.00	0.03	0.09	0.45
$FUTL_t$	O	0.16	0.35	-0.60	0.01	0.07	0.21	1.93
$INTWO_t$	O	0.10	0.30	0.00	0.00	0.00	0.00	1.00
$CHIN_t$	O	0.03	0.57	-1.00	-0.28	0.03	0.37	1.00

This table reports the summary statistics of the following forecast variables (all values except dummy variables and probability values are in million dollars). Each observation represents one firm in a given year. In particular, it shows variables used to forecast bankruptcy. For more details, see the data construction in Appendix 4.A. PNBE is the probability that losses deplete current book equity, NegEarnFrc is a dummy for a negative earnings forecast, BLR is the book leverage ratio, TXT are taxes, FIEXTA are financial expenses over total assets, EBITTA are earnings before interest and taxes over total assets, size is the logarithmic sales, WCTA is working capital over total assets, RETA is retained earnings over total assets, BETL is book equity over total liabilities, STA is sales over total assets, TLTA is total liabilities over total assets, CLCA is current liabilities over current assets, OENEG is a dummy that takes the value of one if total liabilities exceed total assets and zero otherwise, NITA is net income over total assets, FUTL is funds provided by operations over total liabilities, INTWO is a dummy that takes the value of one if the net income was negative for the past two years and zero otherwise, CHIN is the change in net income. The reported values are the time series averages of yearly cross-sectional means, medians, standard deviations, and respective percentiles. All variables (except indicator variables and probability values) are winsorized annually at the 1st and 99th percentile. The column labeled "Model" indicates the model in which the variable has been used, where "HH" is Hess and Huettemann (2019), "A" is Altman (1968) and "O" is Ohlson (1980). The sample period is 2009–2016. The summary statistics are reported for observations in which all models' variables are available.

Table 4.1 provides the summary statistics for all variables used to forecast a bankruptcy. I report the mean, median, standard deviation, and certain percentiles for 213,455 firm-years with complete data availability for 2009 to 2016. The probability of book equity becoming negative (PNBE) has a median of 0.24, which is higher than that noted in Huettemann and Lorsbach's (2019) study of German public firms (0.17). This supports the notion that private firms have a higher distress risk than public firms.

4.3.3 Method

I follow Shumway (2001), Chava and Jarrow (2004), and Campbell, Hilscher, and Szilagyi (2008) to predict bankruptcies by estimating the hazard model as a logistic regression with multiple observations per firm. Thus, the probability of a firm's bankruptcy follows a logistic distribution with parameters (α, β), and is equal to

$$P_t(y_{it} = 1) = \frac{1}{1+exp(-\alpha-\beta x_{i,t})}, \tag{4.1}$$

where y_{it} is a bankruptcy dummy, which equals one if the firm fails in the following twelve months and zero otherwise, and $x_{i,t}$ is the vector of explanatory variables known at time t, that is, three months after the end of the fiscal year. The higher $\alpha + \beta x_{i,t}$, the greater is the estimated probability of bankruptcy. The estimates and their significance levels are calculated using a maximum likelihood technique. Shumway (2001) points out that the test statistics produced by a logistic regression are incorrect for the hazard model. Calculating the correct test statistics requires dividing them by the average number of firm-years per firm. The statistics reported in this study have been adjusted accordingly.

For predicting bankruptcies, I use rolling hazard models to account for coefficients that may change over time. The rolling windows comprise the most recent three years of data to calculate one-year-ahead, out-of-sample bankruptcy predictions. The first estimation period comprises data from 2009 to 2011 and predicts bankruptcies for 2012, and the last estimation period comprises data from 2013 to 2015 to predict bankruptcies for 2016. Thus, the rolling technique evaluates models for the years 2012 to 2016.

4.4 Empirical results

4.4.1 Number of bankruptcies across databases

I compare the number of bankruptcy events listed in the German business register with the BvD database and with official numbers from Destatis. The database on the business register is created using the methodology described above. The BvD database is frequently used by extant research to predict bankruptcies (e.g., Altman et al., 2017; Filipe et al., 2016). To be in line with the bankruptcy definition, which only considers firms in bankruptcy proceedings, for BvD I count firms that have a status of “active (insolvency proceedings),” and omit those with statuses of “active (default of payment),” “active (dormant),” “dissolved,” “dissolved (liquidation),” or “in liquidation,”. For these status BvD does not provide dates for German firms anyway. Note that BvD deletes the entire firm history five years after its bankruptcy; thus, the BvD data requested in 2017 only contain bankruptcies between 2013 and 2017. However, by using historic, vintage BvD data for 2013 to 2016, we come up with bankruptcies from 2009 (this vintage data can no longer be requested through WRDS or directly from BvD). Moreover, Destatis is a federal German authority responsible for collecting, processing, presenting, and analyzing statistical information concerning the economy, society, and the environment. Destatis provides official numbers regarding bankruptcy proceedings that have opened in Germany. In contrast to the business register and BvD, Destatis only provides macroeconomic variables, and no individual firm information. Thus, Destatis cannot be used to conduct firm-specific analyses.

Table 4.2 reports the number of bankruptcies for each database. Panel A in Table 4.2 illustrates the quarterly and annual number of bankruptcy proceeding openings and refusals due to insufficient assets for the years 2007 to 2017. Destatis states that 83,801 proceeding openings occurred from 2007 to 2017; of these, the business register covers 41,832 and BvD covers 16,384 openings for the period of 2009 to 2017. Figure 4.1 plots the number of openings over time, and a peak can be observed in 2009 for Destatis’ official numbers. Importantly, the business register coverage steadily increases over time. According to its aforementioned limitation, crawling the business register on February 23, 2018, discloses no openings for proceedings that were terminated before August 23, 2017. Thus, the business register’s coverage of openings increases over time. In 2007, the business register includes 573 of 6,536 openings (8.8%), and in 2017 the business register includes 6,475 of 6,797 openings (95.3%). While the business register lists nearly all openings for 2017, it covers approximately half of all openings for 2012 (3,829 of 8,006). BvD covers fewer bankruptcy openings than the business register in nearly all quarters. Even for 2010, where crawling the business register only discloses proceedings that last seven years or more, BvD reports 1,877 openings which is less 2,149 in the business register. The coverage of BvD data relative to the business register even decreases over the years; in 2017, BvD has 1,462 openings, while the business register shows 6,475 openings.

Table 4.2 Number of bankruptcies across databases

Panel A: All firms

	Openings of bankruptcy proceedings					Refusals due to insufficient assets		
	Business register		BvD		Destatis	Business register		Destatis
2007	573	8.8%			6,536	2	0.0%	4,643
Q1	93	5.9%			1,580	0	0.0%	1,150
Q2	140	8.7%			1,601	0	0.0%	1,196
Q3	157	9.9%			1,592	1	0.1%	1,232
Q4	183	10.4%			1,763	1	0.1%	1,065
2008	982	14.0%			7,031	3	0.1%	4,109
Q1	227	13.7%			1,661	0	0.0%	1,024
Q2	240	13.1%			1,834	0	0.0%	1,036
Q3	249	13.9%			1,796	2	0.2%	1,101
Q4	266	15.3%			1,740	1	0.1%	948
2009	1,971	22.1%	392	4.4%	8,925	8	0.2%	4,476
Q1	391	19.4%	0	0.0%	2,011	1	0.1%	1,057
Q2	503	21.0%	0	0.0%	2,394	2	0.2%	1,134
Q3	549	22.6%	95	3.9%	2,425	4	0.3%	1,200
Q4	528	25.2%	297	14.2%	2,095	1	0.1%	1,085
2010	2,149	26.2%	1,877	22.9%	8,195	1	0.0%	4,657
Q1	490	23.5%	426	20.5%	2,082	0	0.0%	1,250
Q2	564	26.5%	408	19.2%	2,129	1	0.1%	1,152
Q3	563	27.6%	480	23.6%	2,038	0	0.0%	1,123
Q4	532	27.3%	563	28.9%	1,946	0	0.0%	1,132
2011	2,892	35.9%	2,172	26.9%	8,062	10	0.2%	4,327
Q1	614	31.7%	603	31.1%	1,938	3	0.3%	1,049
Q2	755	35.7%	547	25.8%	2,117	1	0.1%	1,106
Q3	785	38.1%	507	24.6%	2,063	3	0.3%	1,093
Q4	738	38.0%	515	26.5%	1,944	3	0.3%	1,079
2012	3,829	47.8%	2,234	27.9%	8,006	8	0.2%	4,177
Q1	869	42.7%	597	29.4%	2,033	0	0.0%	1,089
Q2	980	46.8%	533	25.4%	2,095	0	0.0%	1,075
Q3	989	50.0%	563	28.5%	1,977	5	0.5%	1,076
Q4	991	52.1%	541	28.5%	1,901	3	0.3%	937
2013	5,114	62.1%	2,398	29.1%	8,233	2	0.0%	4,216
Q1	1,222	59.0%	678	32.8%	2,070	0	0.0%	1,069
Q2	1,291	61.4%	612	29.1%	2,102	1	0.1%	1,041
Q3	1,318	62.9%	537	25.6%	2,096	1	0.1%	1,086
Q4	1,283	65.3%	571	29.1%	1,965	0	0.0%	1,020
2014	5,553	72.9%	2,127	27.9%	7,622	13	0.3%	4,119
Q1	1,320	68.1%	647	33.4%	1,937	3	0.3%	1,098
Q2	1,390	71.8%	467	24.1%	1,937	4	0.4%	1,029
Q3	1,466	77.4%	517	27.3%	1,894	3	0.3%	1,021
Q4	1,377	74.3%	496	26.8%	1,854	3	0.3%	971
2015	5,905	78.4%	2,108	28.0%	7,534	26	0.6%	4,088
Q1	1,563	82.9%	620	32.9%	1,885	14	1.4%	1,036
Q2	1,572	81.3%	506	26.2%	1,934	6	0.6%	1,063
Q3	1,633	85.5%	534	28.0%	1,910	3	0.3%	1,010
Q4	1,137	63.0%	448	24.8%	1,805	3	0.3%	979

(continued)

Table 4.2 Number of bankruptcies across databases (continued)

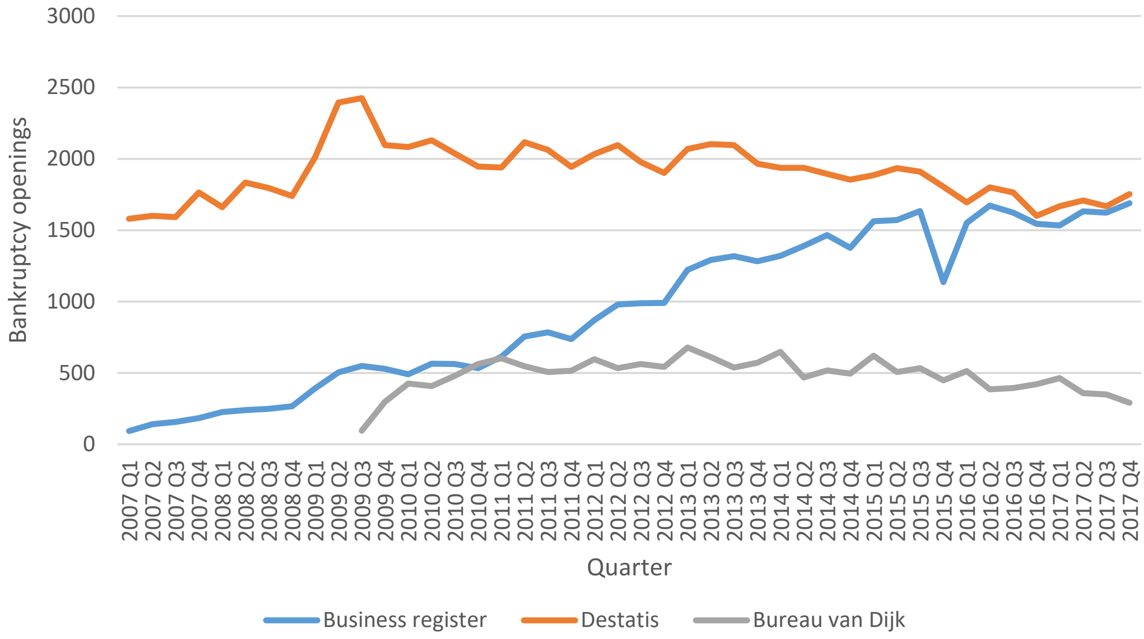
2016	6,389	93.1%	1,714	25.0%	6,860	12	0.3%	3,731
Q1	1,550	91.4%	513	30.3%	1,695	2	0.2%	929
Q2	1,671	92.9%	385	21.4%	1,799	4	0.4%	956
Q3	1,623	92.0%	395	22.4%	1,765	3	0.3%	954
Q4	1,545	96.5%	421	26.3%	1,601	3	0.3%	892
2017	6,475	95.3%	1,462	21.5%	6,797	1,031	27.1%	3,798
Q1	1,532	91.9%	463	27.8%	1,667	4	0.4%	989
Q2	1,632	95.5%	358	20.9%	1,709	11	1.2%	931
Q3	1,622	97.2%	350	21.0%	1,668	307	31.2%	983
Q4	1,689	96.3%	291	16.6%	1,753	709	79.2%	895
	41,832	49.9%	16,484	19.7%	83,801	1,116	2.4%	46,341

Panel B: BvD-covered Firms

	All BvD-covered firms		Sample Firms	
	Business register	BvD	Business register	BvD
	Bankruptcy Event	*Status Code (Bankruptcy proceedings)*	*Bankruptcy Event*	*Status Code (Bankruptcy proceedings)*
2009	234	392	9	2
2010	822	1,877	10	7
2011	1,264	2,172	74	105
2012	1,656	2,234	418	527
2013	1,898	2,398	565	718
2014	1,869	2,127	435	443
2015	1,885	2,108	500	472
2016	2,083	1,714	619	476
2017	2,191	1,462	584	347
	13,902	16,484	3,214	3,097

This table reports the numbers of bankruptcy events listed in different databases (business register events, Destatis (“Statistisches Bundesamt”), and Bureau van Dijk status codes). Panel A shows the numbers of openings of bankruptcy proceedings and the number of refusals of bankruptcy proceeding due to insufficient assets of corporates in each quarter, along with the percentage with regard to Destatis. The business register database is created with the approach described in this study. Due to the legal deletion requirement, the coverage of business register rises by time. Destatis provides official statements on the number of openings and refusals. Bureau van Dijk data is taken from the Amadeus subscription and does not provide data on refusals. Due to its deletion process, BvD data is available only from 2009. As the BvD bankruptcies are restricted to firms covered by BvD, Panel B compares the numbers of bankruptcies of the business register and BvD for all firms covered by BvD and for those firms covered by BvD that are included in our sample as constructed in Section 4.3.2 (sample firms).

Figure 4.1 Openings of bankruptcy proceedings



The figure plots the numbers of openings of bankruptcy proceedings as found in the business register, Destatis and BvD.

Note that bankruptcies in the BvD database are restricted to the firms it covers. Thus, the comparison of BvD's numbers with the absolute numbers of the business register as conducted in Panel A of Table 4.2 is only valid when you consider research that does not require BvD financial information, for example, when you use other financial databases, or when you analyze systemic risk. However, when you require BvD's financial data, you can only use bankruptcies of firms covered by BvD. Thus, it is fair to compare the business register's number of bankruptcies for firms covered by BvD to the number of BvD bankruptcies. Accordingly, Panel B in Table 4.2 compares the numbers of bankruptcy events in the business register and BvD for all firms covered by BvD as well as for our sample firms. Considering all firms covered by BvD, more bankruptcies are extracted from BvD (16,484) than from the business register (13,902). However, BvD includes less bankruptcies in recent years. For example, in 2012 BvD covers 2,234 events, and the business register only comprises 1,656 events. In contrast, the business register demonstrates greater coverage in more recent years: In 2016, more events were found in the business register (2,083) than in BvD (1,714); in 2017, there is an even greater difference between the business register's coverage (2,191) and BvD's (1,462).

For the firms in our sample, crawling the business register yields 3,214 bankruptcy events, more than when using BvD (3,097). From 2011 to 2014, BvD includes more events than the business register. From 2015, BvD includes fewer events; this may be because it does not incorporate all bankruptcy openings, or because incorporating a new status takes time. Note that relatively few bankruptcies occur in 2009 and 2010, as the BvD data we use only covers firms that published annual reports for 2009 onwards. Firms that became bankrupt in 2009 or 2010 may not have published this report.

It has become evident that the business register includes more bankruptcies than BvD in the two or three most recent years, even if the sample is restricted to BvD-listed firms. Consequently, one can build a more complete bankruptcy database by regularly crawling the business register, and, thus, circumventing its deletion process.

Table 4.3 Number of bankruptcies in 2017

	Openings of bankruptcy proceedings			Refusals due to insufficient assets		
	Business Register		Destatis	Business Register		Destatis
January	456	91.4%	499	1	0.3%	352
February	503	92.8%	542	0	0.0%	276
March	573	91.5%	626	3	0.8%	361
April	520	99.6%	522	2	0.7%	282
May	556	93.1%	597	1	0.3%	331
June	556	94.2%	590	8	2.5%	318
July	521	102.4%	509	17	5.0%	337
August	578	96.0%	602	74	22.6%	328
September	523	93.9%	557	216	67.9%	318
October	553	100.0%	553	202	68.5%	295
November	597	94.8%	630	287	82.5%	348
December	539	94.6%	570	220	87.3%	252
2017	6,475	95.3%	6,797	1,031	27.1%	3,798

This table reports the numbers of openings of bankruptcy proceedings and the number of refusals of bankruptcy proceeding due to insufficient assets of corporates in 2017 listed in business register events and Destatis (“Statistisches Bundesamt”), along with the percentage with regard to Destatis. Destatis provides official statements on the number of openings and refusals. The business register database is created with the approach described in this study. It has been crawled end of February 2018. By law, the business register deletes bankruptcy statements six months after the bankruptcy proceedings have been completed. That is, we find all openings whose proceedings have not been terminated by end of August 2017, and all refusals after end of August. Consequently, we find nearly all bankruptcy openings for 2017 and refusals from September 2017.

Table 4.2 also reports the number of bankruptcy filings for which proceedings did not open due to insufficient assets. As BvD provides no information for this event, only the official numbers from Destatis and the business register's results can be compared. According to its limitations, crawling the business register does not yield any notable number of refusals due to insufficient assets before 2017. Table 4.3 shows that the coverage of refusals due to insufficient assets is high only from September 2017 onwards. This confirms that the information is indeed deleted six months after the refusal; thus, BvD does not violate the legal deletion requirements. Table 4.3 also indicates the monthly number of openings for 2017: 6,475 of 6,797 openings, in other words, nearly all openings, are found in the business register for 2017. All 553 openings in October 2017 are covered by the business register, while the register displays 539 of 570 openings for December 2017. This high coverage occurs because very few proceedings that opened in 2017 were terminated before August 23, 2017, six months before the crawling date.

Table 4.4 Number of bankruptcy openings by company type

	Joint-stock firms			Limited liability firms		
	Business Register	Destatis	BvD	Business Register	Destatis	BvD
2007	20	148		553	6,388	
2008	34	153		948	6,878	
2009	99	235	24	1,872	8,690	391
2010	75	191	73	2,074	8,004	1,910
2011	89	166	92	2,803	7,896	2,379
2012	124	197	113	3,705	7,809	2,647
2013	138	182	114	4,976	8,051	2,838
2014	137	163	94	5,416	7,459	2,569
2015	101	132	76	5,804	7,402	2,239
2016	101	108	72	6,288	6,752	1,759
2017	110	124	56	6,365	6,673	1,673
	1,028	1,799	714	40,804	82,002	18,405

This table reports the numbers of openings of bankruptcy proceedings per company type in each year listed in different databases (business register events, Destatis ("Statistisches Bundesamt"), and Bureau van Dijk status codes). Joint-stock companies include the following German types: AG, KGaA, AG & Co. KGaA, and GmbH & Co. KGaA. Limited liability companies include the following German types: GmbH, and UG. The business register database is created with the approach described in this study. Due to the legal deletion requirement, the coverage of business register rises by time. Destatis provides official statements on the number of openings. Bureau van Dijk data is taken from the Amadeus subscription. Due to its deletion process, BvD data is available only from 2009.

Table 4.4 shows the number of openings across the databases for joint-stock and limited liability firms separately. Over the entire sample period, the business register includes 1,028 of 1,799 bankruptcies, or 57.14% of the openings for joint-stock firms. For limited liability firms, crawling the register yields 40,804 of 82,002 openings, or 49.76%. Thus, the business register has a higher coverage for joint-stock firms than for limited liability firms. This higher coverage is more evident in earlier years; in recent years, limited liability and joint-stock firms exhibit similar coverage. One explanation could be that bankruptcy proceedings of limited liability firms are terminated more quickly than proceedings of joint-stock firms. Furthermore, the BvD database's coverage relative to that of the business register is higher for joint-stock firms than for limited liability firms. This may support the notion that commercial databases are biased toward information from firms that is of more interest to their customers.

4.4.2 Bankruptcy proceedings in the German business register

In the following, I aim at identifying typical bankruptcy proceedings in Germany; Table 4.5 reports summary statistics of bankruptcy events extracted from the German business register. Panel A in Table 4.5 shows the number of events: the business register contains 159,696 events from 48,717 firms. Of these, 41,832 are openings (26.2%), and thus, not all firms have an opening event in the business register. This may be because the proceedings had not yet opened and only a filing had occurred so far, or because an opening was refused due to insufficient assets. 36,795 events are appointments (23.0%), 30,308 involve proceedings' decisions (19.0%), and 28,179 contain protective measures (17.6%). Furthermore, 15,269 events are miscellaneous (9.6%), 5,829 contain distribution schedules (3.7%), and 1,116 are refusals due to insufficient assets (0.7%). For joint-stock firms, there are 1,097 decisions in proceeding for 1,211 firms (90.7%), while for limited liability firms, there are only 29,211 proceeding decisions for 47,506 firms (61.5%). For joint-stock firms, there are no decisions after termination (0.0%); for limited liability firms, there are 69 decisions after termination (0.2%). Notably, only twelve refusals occurred due to insufficient assets for the 1,211 joint-stock firms (0.1%), which is significantly lower than the rate of 1,104 refusals for the 47,506 limited liability firms (2.3%). This shows that fewer joint-stock firms have insufficient funds for covering proceeding costs.[35]

[35] Note that these comparisons are valid despite the business register's limitation, as this limitation applies to both joint-stock and limited liability firms.

Table 4.5 Business register events

Panel A: Total number of events

	All firms (N=48,717)		Joint-stock firms (N=1,211)		Limited liability firms (N=47,506)	
	Number	Percentage	Number	Percentage	Number	Percentage
Openings	41,832	26.2%	1,028	21.0%	40,804	26.4%
Appointments	36,795	23.0%	1,231	25.1%	35,564	23.0%
Decisions in proceeding	30,308	19.0%	1,097	22.4%	29,211	18.9%
Protective measures	28,179	17.6%	824	16.8%	27,355	17.7%
Miscellaneous	15,269	9.6%	514	10.5%	14,755	9.5%
Distribution schedule	5,829	3.7%	187	3.8%	5,642	3.6%
Refusals due to insufficient assets	1,116	0.7%	12	0.2%	1,104	0.7%
Decision in residual debt discharge	214	0.1%	8	0.2%	206	0.1%
Insolvency plan	85	0.1%	1	0.0%	84	0.1%
Decision after termination	69	0.0%	0	0.0%	69	0.0%
Total	159,696	100.0%	4,902	100.0%	154,794	100.0%

Panel B: Order of Events

	First Events	
	Number	Percentage
Openings	17,499	35.9%
Appointments	2,427	5.0%
Decisions in proceeding	1,657	3.4%
Protective measures	24,934	51.2%
Miscellaneous	1,008	2.1%
Distribution schedule	138	0.3%
Refusals due to insufficient assets	950	2.0%
Decision in residual debt discharge	26	0.1%
Insolvency plan	51	0.1%
Decision after termination	27	0.1%
Total	48,717	100.0%

(continued)

Table 4.5 Business register events (continued)

Panel C: Time span between protective measures and opening

	All firms	Joint-stock firms	Limited liability firms
N	22,667	638	22,029
Mean	75.53	86.05	75.23
1%	9	8	9
10%	33	36	33
25%	47	52	47
Median	64	70	63
75%	83	89	83
90%	124	140	123
99%	381	510	379

This table reports summary statistics of the events in the business register database which is created with the approach described in this study. Joint-stock companies include the following German types: AG, KGaA, AG & Co. KGaA, and GmbH & Co. KGaA. Limited liability companies include the following German types: GmbH, and UG. Panel A lists the total number of the events for all firms, joint-stock firms, and limited liability firms. Panel B shows the number of events that are first events. Panel C reports summary statistics of the days between protective measures and openings for all, joint-stock, and limited liability firms.

Panel B in Table 4.5 accounts for the chronological order of events in a typical bankruptcy proceeding, indicating the number of events that represent a firm’s first event. Of all firms listed in the business register, 51.2% start with protective measures, while 35.9% of all first events are openings. Thus, these two events together constitute nearly 90% of all first events.

Panel C in Table 4.5 shows the distribution of the time spans between protective measures and opening. On average, an opening occurs 75.53 days after the responsible court takes protective measures. For half the firms, this time span is 64 days or less; for only 10% of these firms, the opening occurs 124 days or more after the protective measures. For joint-stock firms, the average duration between protective measures and the opening is 86.05 days, and thus, longer than for limited liability firms (75.23 days); the median for joint-stock firms (70 days) is also higher than for limited liability firms (63 days). This supports the notion that joint-stock firms’ proceedings are more complex.

4.4.3 Bankruptcy proceedings dates versus annual report dates

Table 4.6 compares the bankruptcy event dates and annual report publication dates. Panel A in Table 4.6 shows that 6,029 of the 40,710 firms (14.8%) publish annual reports after bankruptcy proceedings have opened. These firms have a median of one annual report after the opening. However, the distribution is skewed, with an average of 2.70; 10% of these firms with at least one report after the opening publish seven or more annual reports. Panel B in Table 4.6 analyzes the time span between the fiscal year-end and publishing date of annual reports. On average, firms need 425.91 days to publish their annual reports, with a median of 390 days. Only 10% of the firms manage to publish their reports 261 days or less after the fiscal year-end.

In the following, I analyze the relationship between annual report publishing and bankruptcy timing. When the sample is split into firm-years before and after the opening, there are significant differences in the means. After a bankruptcy opens, firms on average take 81.36 days more than before the opening to publish their annual reports. This mean difference is explained by the 90th percentiles, as publication dates lie 870 days or more after the fiscal year-end for 10% of the firm-years after opening; for firm-years before opening, the 90th percentile is only 563 days. A comparison of joint-stock firms and limited liability firms discloses no significant difference in the means or any percentile of the time span between the fiscal year-end and publishing date.

4.4.4 Bankruptcy prediction models

Table 4.7 displays the estimation and out-of-sample results from the models of Altman (1968), Ohlson (1980), and Hess and Huettemann (2019). Note that I re-estimate all models using a hazard model and an identical sample to eliminate the effects of statistical methods or different sample periods.

4.4.4.1 Estimation results

Panel A in Table 4.7 reports the estimation results for the hazard models, including both the parameter estimates and their significance.

Table 4.6 Bankruptcy event dates versus annual report dates (N=40,710)

Panel A: Number of annual reports after bankruptcy opening

	N	Mean		1%	10%	25%	Median	75%	90%	99%
Firms with report after bankruptcy	6,029	2.70		1	1	1	1	3	7	14

Panel B: Difference between annual report date and fiscal year end date

	N	Mean		1%	10%	25%	Median	75%	90%	99%
All firm-years	165,156	425.91		108	261	354	390	454	586	1,284
Firm-years before bankruptcy opening	149,025	417.97		108	265	355	390	452	563	1,115
Firm-years after bankruptcy opening	16,131	499.32		110	236	337	387	489	870	2,241
Difference		-81.36	***							
Joint-stock firms	4,089	427.33		99	176	312	394	469	629	1,537
Limited liability firms	161,067	425.88		109	264	354	390	454	585	1,276
Difference		1.46								

This table analyzes the relation between bankruptcy event dates and annual report dates listed in the business register. Both databases are created with the respective approach described in this study. Panel A reports summary statistics of the number of annual reports that are published after the bankruptcy opening for all bankrupt firms and firms with at least one report after the opening, respectively. Panel B shows summary statistics of the time span between the annual report and the fiscal year end for all firm-years, firm-years before the bankruptcy opening, firm-years after the opening, for firm-years of joint-stock firms and for firm-years of limited liability firms, respectively. *** denotes significance at the 1% level.

Table 4.7 Rolling hazard models of bankruptcy prediction models

Panel A: Parameter estimates

Variable	Hess and Huettemann (2019)		Altman (1968)		Ohlson (1980)	
Constant	-5.96	***	-5.60	***	-5.41	***
$PNBE_t$	0.91	***				
$NegEarnFrc_t$	0.40	**				
BLR_t	0.86	**				
TXT_t	0.00	**				
$FIEXTA_t$	9.17	**				
$EBITTA_t$	-1.36	***	-2.95	***		
$Size_t$	-0.08	***			-0.13	***
$WCTA_t$			0.29	*	0.26	***
$RETA_t$			0.05			
$BETL_t$			-1.08	**		
STA_t			0.04	***		
$TLTA_t$					1.79	***
$CLCA_t$					-0.06	
$OENEG_t$					-0.29	
$NITA_t$					-0.06	
$FUTL_t$					-2.18	***
$INTWO_t$					0.28	**
$CHIN_t$					0.17	

Panel B: Goodness-of-fit deciles

Decile	Hess and Huettemann (2019)	Altman (1968)	Ohlson (1980)
1	33.44	34.06	30.94
2	21.88	16.56	21.25
3	13.13	13.44	13.44
4	12.50	14.38	15.00
5	6.25	5.00	6.56
6	4.69	6.88	3.75
7	2.81	3.44	4.06
8	1.88	2.81	2.50
9	1.56	2.50	2.19
10	3.44	2.50	1.88

(continued)

Table 4.7 Rolling hazard models of bankruptcy prediction models (continued)

Panel C: Area under the ROC curve

	Hess and Huettemann (2019)	Altman (1968)	Ohlson (1980)
Mean	0.746	0.737	0.749

Panel D: Economic value of different misclassification costs

	Bank 1	Bank 2	Bank 3
	Hess and Huettemann (2019)	Altman (1968)	Ohlson (1980)
Credits	45,425.83	40,565.83	42,971.33
Market share (%)	34.38%	30.70%	32.52%
Defaults	74	120	92
Default/credits (%)	0.16%	0.30%	0.21%
Avg. credit spread (%)	0.36%	0.39%	0.35%
Revenue ($m)	122.98	118.35	114.70
Loss ($m)	28.64	46.45	35.61
Profit ($m)	94.34	71.91	79.10
Return on asset (%)	0.27%	0.23%	0.24%

This table reports the results of the rolling hazard models. Panel A shows the Newey-West (1987) time series averages of annual regression coefficients for Hess and Huettemann (2019), Altman (1968) and Ohlson (1980) to predict bankruptcies. PNBE is the probability that losses deplete current book equity, NegEarnFrc is a dummy for a negative earnings forecast, BLR is the book leverage ratio, TXT are taxes, FIEXTA are financial expenses over total assets, EBITTA are earnings before interest and taxes over total assets, size is the logarithmic sales, WCTA is working capital over total assets, RETA is retained earnings over total assets, BETL is book equity over total liabilities, STA is sales over total assets, TLTA is total liabilities over total assets, CLCA is current liabilities over current assets, OENEG is a dummy that takes the value of one if total liabilities exceed total assets and zero otherwise, NITA is net income over total assets, FUTL is funds provided by operations over total liabilities, INTWO is a dummy that takes the value of one if the net income was negative for the past two years and zero otherwise, CHIN is the change in net income. Panel B shows the goodness-of-fit deciles. For every year, we rank firms into deciles based on their fitted bankruptcy probability values, where the firms with the highest values fall into the first decile. We report the percentage of bankrupt firms that are classified into each probability decile. Panel C reports the Newey-West (1987) time series averages of the yearly means of the area under the ROC curve (AUC). Panel D shows the results of a competitive credit market. The banks reject firms with score in the bottom 5% based on their respective models while offering credit to all others at a credit spread derived using equation (4.2). The bank with the lowest credit spread is assumed to grant the loan. Firms are assumed to split their loan equally if banks offer the same credit spread. Market share is the total number of credits granted divided by total number of firm-years, defaults is the number of firms to whom a loan is granted that went bankrupt. Revenue is market size * market share * average credit spread, and Loss is market size * prior probability of failure * share of defaulters * loss given default. Profit is Revenue - Loss. Return on assets is profit divided by market size * market share. For illustrative purposes, we assume the market size to be $100 billion, equal size loans, loss given default to be 45%, and credit spread for the highest quality customers to be 0.30%. The prior probability of failure is taken to be the same as the ex-post failure rate. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

For Altman (1968), a lower profitability (EBITTA), a higher liquidity (WCTA), a lower leverage calculated as book value of equity divided by the book value of total debt (BETL), and a higher ratio of sales and total assets (STA) yield a higher estimated probability of bankruptcy. The signs of the coefficients for the variables WCTA and STA are inconsistent with Altman's original study of US firms. For Ohlson (1980), the probability of bankruptcy increases if the firm's size decreases (Size), liquidity increases (WCTA), the ratio of total liabilities and total assets (TLTA) increases, the profitability (FUTL) decreases, and if net income has been negative for the past two years (INTWO). The coefficient sign for WCTA is inconsistent with Ohlson's study of US firms. For Hess and Huettemann (2019), firms are more likely to fail with a higher probability that losses will deplete the current book equity (PNBE) and negative earnings forecasts (NegEarnFrc). The higher the financial expenses (FIEXTA), the lower the profitability (EBITTA) and the lower the size (Size), the greater the estimated probability of bankruptcy. The signs of all coefficients are as expected and consistent with previous studies on German public firms, such as with the results from Huettemann and Lorsbach (2019).

4.4.4.2 Out-of-sample results

4.4.4.2.1 Goodness-of-fit deciles

To evaluate the quality of bankruptcy prediction models, I follow Shumway (2001) and rank firms into deciles based on their fitted bankruptcy probability values for every year of the validation sample (2012 to 2016). Specifically, the firms that will most likely default in the subsequent year according to each respective model are sorted into the first decile, and firms with the lowest estimated default probabilities are assigned to the tenth decile. I report the percentages of bankrupt firms that fall into each of the ten probability deciles. A model is accurate if it yields high default probability estimates for bankrupt firm-years, and thus, assigns many bankrupt firms into the first deciles.

Panel B in Table 4.7 reports the goodness-of-fit deciles. Altman's (1968) model classifies 34.06% of all bankrupt firms into the highest default probability decile. That is, a bank can exclude 34.06% of all bankruptcies if it does not lend money to the 10% of firms with the highest expected default measures. The performance of Altman's model is similar to that of Hess and Huettemann's (2019) model, with a score of 33.44%, and Ohlson's (1980) model, with 30.94%. For the top two deciles in aggregate, the percentage of correct predictions is as follows: 55.31% for Hess and Huettemann, 52.19% for Ohlson, and

50.63% for Altman. The results are consistent with those from public firms in Huettemann and Lorsbach (2019) in terms of the percentage of correct predictions.

4.4.4.2.2 Receiver operating characteristics

I consider both type I and type II errors by using an alternative measure to evaluate bankruptcy prediction models: the area under the receiver operating characteristic (ROC) curve, also referred to as the area under the curve (AUC) (e.g., Sobehart and Keenan; 2001). The AUC is interpreted as the probability that a randomly chosen defaulting firm has a greater predicted probability of default than a randomly chosen surviving firm. A value of 0.5 indicates a random model with no predictive ability, and a value of 1.0 indicates perfect discrimination. Panel C in Table 4.7 reports the Newey-West (1987) time-series averages of the means of the AUC. Ohlson (1980) has an average AUC of 0.749, which is similar to the average of 0.746 from Hess and Huettemann (2019) and 0.737 from Altman (1968).

4.4.4.2.3 Economic value for differing misclassification costs

To account for differing type I and type II error costs, I use Agarwal and Taffler's (2008) approach to assess the economic impact of using different bankruptcy prediction models in a competitive market. To link the power of prediction models and loan pricing, I follow Stein (2005) and Blöchlinger and Leippold (2006) to derive the credit spread as a function of the credit score (S) by

$$R = \frac{P_t(Y=1|S=t)}{P_t(Y=0|S=t)} LGD + k, \tag{4.2}$$

where R is the credit spread, $\mathrm{P_t(Y = 1|}S = \mathrm{t)}$ is the conditional probability of bankruptcy for a score of t, $\mathrm{P_t(Y = 0|}S = \mathrm{t)}$ is the conditional probability of non-bankruptcy for a score of t, LGD is the loss in a loan given default, and k is the credit spread for the highest quality loan.

I then evaluate an economic scenario as described by Agarwal and Taffler (2008) and Bauer and Agarwal (2014) under a simple loan market worth $100 billion. Each bank uses a different bankruptcy prediction model and competes for customers that are represented by the sample firms. I assume that all loans are of the same size and are unsecured senior debt; specifically, the loss given default is 45%. Further, I assume the risk premium for a high-quality customer (k) is 0.30%. I rank the sample firms for each year into 20 categories based on their fitted bankruptcy probability values. The banks reject customers that fall in the bottom 5%, the lowest category, according to the respective prediction model they use. They quote spreads for all other customers based on equation (4.2), and the customer chooses the bank that quotes the lowest spread. If multiple banks quote equal minimum spreads, the customer randomly chooses one of these banks, or equivalently, the business is split equally. As this regime may include customers who are refused credit by all banks, the market share may not sum to one.

Panel D in Table 4.7 presents the revenue, profitability, and other statistics for all banks in the competitive loan market. The bank that uses Hess and Huettemann's model has the largest market share of 34.38%, followed by Ohlson (1980) with 32.52%, and Altman (1968) with 30.70%. Additionally, loans granted by the bank that uses Hess and Huettemann's model have the best quality, as only 0.16% of their customers default; this is lower than the banks that use Ohlson's (0.21%) and Altman's models (0.30%). The high market share of the bank that uses Hess and Huettemann's model, combined with low default losses due to the high-quality portfolio, translates into the highest profit ($94.34 million) and highest return on assets (0.27%). The revenue for the bank that uses Ohlson's model is similar, due to similar market share and similar average credit spread. However, using Ohlson's and Altman's models causes banks to experience greater losses, which translates into a lower profit for Ohlson's ($71.19 million) and Altman's ($79.10 million) models, as well as a lower return on assets for both (Ohlson: 0.23% and Altman: 0.24%).

When considering only type I errors, or when assuming equal type I and type II error costs, all three models show similar out-of-sample performance. However, when allowing for differing misclassification costs, Hess and Huettemann's (2019) accounting model outperforms both Altman's (1968) and Ohlson's (1980).

4.4.5 Bankruptcy prediction models for different firm sizes

For each year, firms are ranked into three equally-sized groups according to the amount of their total assets. Combining each of the three groups that contain the firms with the smallest, medium-sized, and largest total assets over the whole sample period yields subsamples with small, medium-sized, and large firms, respectively. I separately perform rolling hazard models for the Altman (1968), Ohlson (1980), and Hess and Huettemann (2019) models using these three subsamples.

Table 4.8 Rolling hazard models of bankruptcy prediction models split into firm sizes

Panel A: Parameter estimates

Variable	Hess and Huettemann (2019)			Altman (1968)			Ohlson (1980)		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Constant	-9.71 ***	3.05 *	-4.36 **	-5.29 ***	-5.39 ***	-6.06 ***	-9.35 ***	2.28	-4.96 **
PNBE$_t$	-1.50 **	-2.24 ***	-0.06						
NegEarnFrc$_t$	0.45 *	0.32 **	0.91 ***						
BLR$_t$	1.52 ***	2.90 ***	0.78 **						
TXT$_t$	0.00 ***	0.00 ***	0.00						
FIEXTA$_t$	3.98	9.94 ***	15.11 ***						
EBITTA$_t$	-0.57 **	-1.33 **	-3.71 ***	-2.05 ***	-3.23 ***	-6.24 ***			
Size$_t$	0.25 *	-0.69 ***	-0.19 *				0.17	-0.65 ***	-0.17
WCTA$_t$				0.27	0.39 ***	-0.60 ***	0.29 *	0.34 ***	-0.49 ***
RETA$_t$				0.68	0.91 ***	-0.84 ***			
BETL$_t$				-1.44 *	-2.25 ***	-0.26 *			
STA$_t$				0.02 **	-0.03 *	0.07 **			
TLTA$_t$							1.60 ***	2.23 ***	1.95 ***
CLCA$_t$							-0.03	-0.09 **	-0.05 **
OENEG$_t$							-0.24	-0.02	-0.54
NITA$_t$							-0.53	0.34	-0.58
FUTL$_t$							-1.07 *	-3.30 ***	-3.17 **
INTWO$_t$							0.35 ***	-0.21 *	0.60 **
CHIN$_t$							0.30 **	0.19	-0.20

(continued)

Table 4.8 Rolling hazard models of bankruptcy prediction models split into firm sizes (continued)

Panel B: Goodness-of-fit deciles

Decile	Hess and Huettemann (2019)			Altman (1968)			Ohlson (1980)		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
1	27.08	36.61	46.38	29.17	29.46	46.38	27.78	26.79	42.03
2	20.83	23.21	18.84	15.97	16.96	18.84	16.67	21.43	18.84
3	18.75	13.39	13.04	15.97	14.29	5.80	12.50	16.96	8.70
4	8.33	11.61	1.45	7.64	12.50	11.59	11.11	13.39	10.14
5	6.25	5.36	7.25	11.81	10.71	0.00	9.72	9.82	5.80
6	5.56	5.36	0.00	6.94	6.25	2.90	9.03	3.57	5.80
7	6.94	0.00	4.35	5.56	0.89	2.90	6.25	2.68	2.90
8	3.47	0.89	2.90	3.47	6.25	4.35	2.78	2.68	0.00
9	0.00	0.89	2.90	0.69	2.68	1.45	0.69	0.89	4.35
10	2.78	2.68	2.90	2.78	0.00	5.80	3.47	1.79	1.45

Panel C: Area under the ROC curve

	Hess and Huettemann (2019)			Altman (1968)			Ohlson (1980)		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Mean	0.729	0.765	0.785	0.734	0.710	0.781	0.720	0.706	0.769

(continued)

Table 4.8 Rolling hazard models of bankruptcy prediction models split into firm sizes (continued)

Panel D: Economic value of different misclassification costs

	Bank 1			Bank 2			Bank 3		
	Hess and Huettemann (2019)			Altman (1968)			Ohlson (1980)		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Credits	17,251.00	15,261.17	16,673.83	15,908.00	15,458.67	13,477.83	10,197.00	12,542.17	12,796.33
Market share (%)	39.17%	34.65%	37.86%	36.12%	35.10%	30.60%	23.15%	28.48%	29.06%
Defaults	43.00	26.50	16.83	48.00	42.00	15.33	48.00	34.50	24.83
Default/credits (%)	0.25%	0.17%	0.10%	0.30%	0.27%	0.11%	0.47%	0.28%	0.19%
Avg. credit spread (%)	0.38%	0.36%	0.32%	0.39%	0.38%	0.32%	0.39%	0.34%	0.33%
Revenue ($m)	148.60	123.75	122.31	141.21	132.09	99.36	90.59	97.83	96.94
Loss ($m)	45.52	29.44	20.82	50.81	46.67	18.97	50.81	38.33	30.72
Profit ($m)	103.08	94.30	101.49	90.40	85.42	80.39	39.78	59.50	66.22
Return on asset (%)	0.26%	0.27%	0.27%	0.25%	0.24%	0.26%	0.17%	0.21%	0.23%

This table reports the results of the rolling hazard models for small, medium-sized and large firms respectively. Each year, the firms are ranked into groups based on the amount of their total assets. The group containing the firms with the smallest, medium and largest amount of total assets constitutes the group of small, medium-sized and large firms, respectively. Panel A shows the Newey-West (1987) time series averages of annual regression coefficients for Hess and Huettemann (2019), Altman (1968) and Ohlson (1980) to predict bankruptcies. PNBE is the probability that losses deplete current book equity, NegEarnFrc is a dummy for a negative earnings forecast, BLR is the book leverage ratio, TXT are taxes, FIEXTA are financial expenses over total assets, EBITTA are earnings before interest and taxes over total assets, size is the logarithmic sales, WCTA is working capital over total assets, RETA is retained earnings over total assets, BETL is book equity over total liabilities, STA is sales over total assets, TLTA is total liabilities over total assets, CLCA is current liabilities over current assets, OENEG is a dummy that takes the value of one if total liabilities exceed total assets and zero otherwise, NITA is net income over total assets, FUTL is funds provided by operations over total liabilities, INTWO is a dummy that takes the value of one if the net income was negative for the past two years and zero otherwise, CHIN is the change in net income. Panel B shows the goodness-of-fit deciles. For every year, we rank firms into deciles based on their fitted bankruptcy probability values, where the firms with the highest values fall into the first decile. We report the percentage of bankrupt firms that are classified into each probability decile. Panel C reports the Newey-West (1987) time series averages of the yearly means of the area under the ROC curve (AUC). Panel D shows the results of a competitive credit market. The banks reject firms with score in the bottom 5% based on their respective models while offering credit to all others at a credit spread derived using equation (4.2). The bank with the lowest credit spread is assumed to grant the loan. Firms are assumed to split their loan equally if banks offer the same credit spread. Market share is the total number of credits granted divided by total number of firm-years, defaults is the number of firms to whom a loan is granted that went bankrupt. Revenue is market size * market share * average credit spread, and Loss is market size * prior probability of failure * share of defaulters * loss given default. Profit is Revenue - Loss. Return on assets is profit divided by market size * market share. For illustrative purposes, we assume the market size to be $100 billion, equal size loans, loss given default to be 45%, and credit spread for the highest quality customers to be 0.30%. The prior probability of failure is taken to be the same as the ex-post failure rate. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A in Table 4.8 reports the parameter estimates and their significance for the hazard models of the three models. The coefficients of all three models differ when applied to firms of different sizes. For example, liquidity (WCTA) is a highly significant predictor when Altman’s model is applied to medium-sized or large firms, whereas it is not significant for small firms. The same pattern applies for CLCA, another measure of liquidity, for Ohlson’s model. One reason for this observation might be the positive relationship between firm size and liquidity (e.g., Gupta, 1969): as small firms tend to have low liquidity anyway, its power to discriminate between bankrupt and non-bankrupt small firms is low.

Panel B in Table 4.8 reports the goodness-of-fit deciles. For all three models, the percentage of correct predictions in the first decile is higher for large firms than for small and medium-sized firms. Altman’s (1968) re-estimated model classifies 46.38% of all bankrupt firms into the highest default probability decile for large firms. The percentage of correct predictions for small (29.17%) and medium-sized firms (29.46%) is lower. Ohlson’s (1980) model assigns 42.03% of all large firms’ bankruptcies into the first decile, which is higher than for small (27.78%) and medium-sized firms (26.79%). The same pattern applies to Hess and Huettemann’s (2019) model (small firms: 27.08%; medium-sized firms: 36.61%; large firms: 46.38%). Interestingly, Hess and Huettemann (2019) outperform both other models for medium-sized firms, whereas its performance for small and large firms is similar.

Panel C in Table 4.8 reports the Newey-West (1987) time-series averages of the means of the AUC. Altman (1968) has an average AUC of 0.781 for large firms which is larger than for small (0.734) and medium-sized firms (0.710). Applying Ohlson (1980) to large firms yields an average AUC of 0.769, which exceeds the average AUC for small (0.720) and medium-sized firms (0.706). The same pattern is observed when applying Hess and Huettemann’s (2019) model (small firms: 0.729; medium-sized firms: 0.765; large firms: 0.785). Again, Hess and Huettemann (2019) outperform the other models when predicting medium-sized firms’ bankruptcies.

Panel D in Table 4.8 presents revenue, profitability, and other statistics for all banks in the competitive loan market. While goodness-of-fit deciles and areas under the ROC curve (AUC) measure the predictive abilities of models in absolute terms, this experiment assumes a competitive market and, thus, measures the predictive power of a bankruptcy prediction model relative to other models. Thus, its results can be used to compare different models for each firm size. However, these results cannot be used to compare the impact of firm sizes for the same model. For small firms, applying Hess and Huettemann’s (2019) model yields the highest market share of 39.17% (Altman: 36.12%; Ohlson: 23.15%) and the best loan quality, as only 0.25% of their customers default compared to 0.30% for Altman and 0.47% for Ohlson. This translates into the highest profit of $103.08 million compared to Altman ($90.40 million) and Ohlson ($39.78 million). The return on assets for Hess and Huettemann’s model is 0.26% and thus similar to Altman’s (0.25%) and higher than Ohlson’s (0.17%). The same pattern is observed in its application to large firms, in which Hess and Huettemann has the highest market share of 37.86% (Altman: 30.60%; Ohlson: 29.06%) and the lowest default rate of 0.10% (Altman: 0.11%; Ohlson: 0.19%). However, the return on assets is similar for all models (Altman: 0.26%; Ohlson: 0.23%; Hess and Huettemann: 0.27%). For medium-sized firms, the bank that uses Hess and Huettemann’s model again has the best-quality loans with a default rate of 0.17% compared to 0.27% and 0.28% for Altman’s and Ohlson’s models, respectively, and the highest profit of 94.30 million (Altman: $85.42 million; Ohlson: $59.50 million). This time, the highest absolute profit also translates into the highest return on assets of 0.27% compared to 0.24% and 0.21% for Altman and Ohlson, respectively.

Taken together, firm size has an impact on the coefficients and results of prediction models. In particular, each model provides better accuracy when applied to large firms compared to small and medium-sized firms. Thus, large firms’ bankruptcies can be predicted more easily. In addition, Hess and Huettemann’s (2019) model outperforms both other models in predicting bankruptcies of medium-sized firms.

4.5 Conclusions

By crawling the German business register, this study creates a bankruptcy database for German firms that includes more bankruptcy events in recent years and more details about the proceedings than the BvD database. Simultaneously, this study quantifies the bias of using ad-hoc data requests from the business register, which are limited due to the legal deletion requirement; however, this bias can be eliminated by regularly crawling the business register and storing data requests. Analyzing this dataset helps interpret the typical German procedures for bankruptcy proceedings by identifying first events and by analyzing the event order. Furthermore, it shows differences in the proceedings of joint-stock and limited liability firms as joint-stock firms typically have a longer lasting proceeding, a longer duration between protective measures and the opening, and are refused an opening due to insufficient funds less often. By combining bankruptcy dates and annual report dates, I compute the ratio of firms that publish annual reports after bankruptcy. Furthermore, I show that opening a bankruptcy proceeding decelerates annual report publication. Finally, this study compares bankruptcy prediction models for a broad range of German public and private firms. It also shows that predictions for large firms are more accurate than those for small and medium-sized firms which means that firm size has an impact on the prediction results.

This study has substantial implications for researchers who analyze or use typical bankruptcy procedures. Bankruptcy prediction models could be improved based on the results of this study. First, further research could use bankruptcy data extracted from the business register instead of BvD status codes to gather more events. Second, annual report publication dates could be empirically tested to serve as an indicator of a bankruptcy filing. Future research could also further investigate the properties of typical bankruptcy proceedings by calculating additional summary statistics or by applying regression setups, if appropriate. Moreover, further research could gather publicly available bankruptcy event information for other countries, and thus, analyze country-specific typical bankruptcy proceedings.

4.A Construction of variables for bankruptcy prediction models

The appendix discusses the construction of variables used in Altman (1968), Ohlson (1980), and Hess and Huettemann's (2019) accounting model.

Altman (1968) obtains a Z-score using a linear weighted sum of five ratios:

$$Z = \beta_0 + \beta_1 \cdot WCTA + \beta_2 \cdot RETA + \beta_3 \cdot EBITTA + \beta_4 \cdot BETL + \beta_5 \cdot STA, \tag{4.3}$$

where WCTA is working capital (BvD item WKCA) divided by total assets (TOAS), RETA is retained earnings[36] (OSFD) divided by total assets (TOAS), EBITTA is earnings

[36] Since BvD does not have a variable for retained earnings, I approximate the variable by using "Other Shareholders Funds".

before interest and taxes (EBIT) divided by total assets (TOAS), BETL[37] is the book value of equity (SHFD) divided by the book value of total debt (NCLI plus CULI), STA is sales (TURN) divided by total assets (TOAS) and Z is the Z-score (overall index). WCTA is a proxy for a firm's liquidity, RETA is a proxy for firm age, and EBITTA measures profitability. BETL is a widely used measure of leverage and STA describes the firm's efficiency in using assets to generate sales. The Z-score characterizes the financial strength of a firm by aggregating the abovementioned five accounting ratios into one figure using the estimated coefficients $\beta_1, \dots, \beta_5$.

Ohlson (1980) finds nine variables to be significant and defines his O-score model as

$$\begin{aligned} O = {} & \beta_0 + \beta_1 \cdot SIZE + \beta_2 \cdot TLTA + \beta_3 \cdot WCTA \\ & + \beta_4 \cdot CLCA + \beta_5 \cdot OENEG + \beta_6 \cdot NITA \\ & + \beta_7 \cdot FUTL + \beta_8 \cdot INTWO + \beta_9 \cdot CHIN, \end{aligned} \tag{4.4}$$

where Size is the logarithm of total assets (TOAS), TLTA is total liabilities (NCLI plus CULI) over total assets (TOAS), WCTA is working capital (WKCA) over total assets (TOAS), CLCA is current liabilities (CULI) over current assets (CUAS), OENEG is a dummy that takes the value of one if total liabilities (NCLI plus CULI) exceed total assets (TOAS) and zero otherwise, NITA is net income (PL) over total assets (TOAS), FUTL is funds provided by operations[38] (PLBT) over total liabilities (NCLI plus CULI), INTWO is a dummy that takes the value of one if the net income (NI) was negative for the past two years and zero otherwise, CHIN is the change in net income (PL) and O is the O-score (overall index). WCTA and CLCA measure liquidity. NITA, FUTL, INTWO, and CHIN capture the different aspects of profitability. TLTA and OENEG describe the capital structure. Size is a measure of firm size.

The key idea of Hess and Huettemann's (2019) models is that a firm becomes bankrupt if its book equity turns negative. Thus, the key predictor of bankruptcy is the probability that the sum of a firm's current book equity and earnings forecast for the subsequent month is negative. This probability for firm i at time t can be expressed as

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[37] The version of the model in Altman (1968) requires stock price information and thus is not purely accounting-based. I use Altman's (1983) z'-score applications (e.g., in Altman, 1993 and Altman et al., 2017) and Altman, Hartzell, and Peck's (1995) z''-score applications (e.g., in Megginson, Meles, Sampagnaro, & Verdoliva, 2016) for private firms where market equity is replaced by book equity.

[38] Since funds provided by operations are no longer reported, I perform an approximation by using "profit before taxation".

$$PNBE_{i,t} = 1 - \Phi\left(\frac{\widehat{Earn_{i,t+1}} + BkEq_{i,t}}{\sigma\left(\widehat{Earn_{i,t+1}}\right)}\right), \tag{4.5}$$

where $\mathrm{BkEq}_{\mathrm{i,t}}$ denotes the current book equity, $\mathrm{Earn}_{\mathrm{i,t+1}}$ is the expected earnings for the subsequent month, $\sigma\left(\widehat{\mathrm{Earn}_{\mathrm{i,t+1}}}\right)$ is the corresponding volatility of the individual earnings forecast, and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Book equity is equal to shareholders' funds (SHFD). Earnings are net income (PL). To calculate the earnings forecasts and their volatilities, Hess and Huettemann (2019) use cross-sectional models. More specifically, they adopt a rolling regression technique with accounting data from the past five years to estimate parameters they use for forecasting.

Hess and Huettemann's (2019) accounting model contains PNBE, the probability that book equity turns negative; NegEarnFrc, a dummy that assumes the value of one if the earnings forecast is negative and zero otherwise; FIEXTA[39] as financial expenses (FIEX) divided by total assets (TOAS); TXT as paid taxes (TAXA); EBITTA as profitability calculated by earnings before interest and taxes (EBIT) over total assets (TOAS); Size measured by logarithmic total assets (TOAS); book leverage ratio (BLR) calculated as total liabilities (NCLI plus CULI) divided by the sum of total liabilities (NCLI plus CULI), and book equity.

[39] Hess and Huettemann (2019) use capital expenditures. As this variable is not included in BvD, I use financial expenses instead.

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General Appendix: Python Code for a Web Crawler

This appendix illustrates the overall methodology of a web crawler by showing an exemplary program that crawls the German business register. It is written in the programming language Python.

This program automatically starts a web browser and opens the search mask for bankruptcy events of the business register. The program then fills in certain arrays of this mask: the company name, the court and search time period. The company name is read in from a list from a text file, the court is read in from a list inside the code and the dates are directly set within the code. The program submits a search request for every possible combination of company name and court. It extracts the information whether any bankruptcy event was found for the corresponding combination and finally exports this information into a csv-file.

```
import mechanicalsoup
from datetime import datetime

import urllib
import string
import os
import sys
import time
import csv
import re
from urllib.request import FancyURLopener
from bs4 import BeautifulSoup

# User defined output file
OUTPUT_FILE = r'Path/File1.csv'
OUTPUT_FIELDS = ['Company Name', 'Amtsgericht', 'Results']

# User defined tab-delimited list of Company Names
COMN_FILE = r'Path/File2.txt'

a = [
"Aachen", "Aalen", "Alzey", "Amberg", "Ansbach", "Arnsberg", "Aschaffenburg", "Augsburg", "Aurich",
"Bad Hersfeld", "Bad Homburg", "Bad Kreuznach", "Bad Neuenahr-Ahrweiler", "Baden-Baden", "Bamberg", "Bayreuth", "Bersenbrück", "Betzdorf", "Bielefeld", "Bingen am Rhein", "Bitburg", "Bochum", "Bonn", "Braunschweig", "Bremen", "Bremerhaven", "Bückeburg",
```

```
"Celle", "Charlottenburg", "Chemnitz", "Cloppenburg", "Coburg", "Cochem", "Cottbus","Crailsheim", "Cuxhaven",
"Darmstadt", "Deggendorf", "Delmenhorst", "Dessau", "Detmold", "Dortmund", "Dresden", "Duisburg", "Düsseldorf",
"Erfurt", "Eschwege", "Essen", "Esslingen", "Eutin",
"Flensburg", "Frankfurt", "Frankfurt/Oder", "Freiburg", "Friedberg", "Fritzlar", "Fulda", "Fürth",
"Gera", "Gießen", "Gifhorn", "Göppingen", "Goslar", "Göttingen",
"Hagen", "Halle/Saalkreis", "Hamburg", "Hameln", "Hanau", "Hannover", "Hechingen", "Heidelberg", "Heilbronn", "Hildesheim", "Hof", "Hohenschönhausen", "Holzminden", "Husum",
"Idar-Oberstein", "Ingolstadt", "Itzehoe",
"Kaiserslautern", "Karlsruhe", "Kassel", "Kempten", "Kiel", "Kleve", "Koblenz", "Köln", "Königstein", "Konstanz", "Köpenick", "Korbach", "Krefeld",
"Landau in der Pfalz", "Landshut", "Leer", "Leipzig", "Lichtenberg", "Limburg", "Lingen", "Lörrach", "Lübeck", "Ludwigsburg", "Ludwigshafen am Rhein", "Lüneburg",
"Magdeburg", "Mainz", "Mannheim", "Marburg", "Mayen", "Meiningen", "Meldorf", "Memmingen", "Meppen", "Mitte", "Mönchengladbach", "Montabaur", "Mosbach", "Mühldorf", "Mühlhausen", "München", "Münster",
"Neu-Ulm", "Neubrandenburg", "Neukölln", "Neumünster", "Neuruppin", "Neustadt an der Weinstraße", "Neuwied", "Niebüll", "Nordenham", "Norderstedt", "Nordhorn", "Nördlingen", "Nürnberg",
"Offenbach", "Offenburg", "Oldenburg", "Osnabrück", "Osterode",
"Paderborn", "Pankow/Weißensee", "Passau", "Pforzheim", "Pinneberg", "Pirmasens", "Potsdam",
"Ravensburg", "Regensburg", "Reinbek", "Rosenheim", "Rostock", "Rottweil",
"Saarbrücken", "Schöneberg", "Schwarzenbek", "Schweinfurt", "Schwerin", "Siegen", "Spandau", "Stade", "Stendal", "Stralsund", "Straubing", "Stuttgart", "Syke",
"Tempelhof-Kreuzberg", "Tiergarten", "Tostedt", "Traunstein", "Trier", "Tübingen",
"Uelzen", "Ulm",
"Vechta", "Verden", "Villingen-Schwenningen",
"Waldshut-Tiengen", "Walsrode", "Wedding", "Weiden", "Weilheim", "Wetzlar", "Wiesbaden", "Wilhelmshaven", "Wittlich", "Wolfratshausen", "Wolfsburg", "Worms", "Wuppertal", "Würzburg",
"Zweibrücken"
]

class MyOpener(FancyURLopener):
    version = 'Mozilla/5.0 (Windows NT 6.1) AppleWebKit/537.17 (KHTML, like Gecko) Chrome/24.0.1312.57 Safari/537.17'

myopener = MyOpener()
url = 'https://www.unternehmensregister.de/ureg/search1.7.html;jsessionid=0446F6EC73AA04F2909204697AB9DB40.web02-1'

def CheckInsolNet(com_name, A_Gericht):

    # Catch errors from server timeouts
    number_of_tries = 5
    sleep_time = 10

    for i in range(1, number_of_tries + 1):
        try:
            # initialise browser
            br = mechanicalsoup.StatefulBrowser()
            br.addheaders = [('User-agent', 'Firefox')]
            br.open('https://www.unternehmensregister.de/ureg/search1.7.html')

            print(br)

            # fill in web form of website with options from above
```

```
            br.select_form('#searchInsolvencyForm')
            br['searchInsolvencyForm:bankruptciesCourtId'] = A_Gericht
            br['searchInsolvencyForm:bankruptciesDepitorName'] = com_name
            br['searchInsolvencyForm:bankruptciesPublicationsStartDateDay'] = 1
            br['searchInsolvencyForm:bankruptciesPublicationsStartDateMonth'] = 1
            br['searchInsolvencyForm:bankruptciesPublicationsStartDateYear'] = 2007
            br['searchInsolvencyForm:bankruptciesPublicationsEndDateDay'] = 31
            br['searchInsolvencyForm:bankruptciesPublicationsEndDateMonth'] = 12
            br['searchInsolvencyForm:bankruptciesPublicationsEndDateYear'] = 2017
            br.submit_selected()
            page = br.get_current_page()
            page = str(page)

            # HTML Cleaner
            soup = BeautifulSoup(page, "html.parser")
            clean_data = soup.get_text()
            return clean_data

        except Exception as exc:
            if i == 1:
                print('\n==>urlretrieve error in download_to_file.py')
            print('  {0}. _url:  {1}'.format(i, com_name))
            print('  {0}. _url:  {1}'.format(i, A_Gericht))
            print('     Warning: {0}  [{1}]'.format(str(exc), time.strftime('%c'))
)
            if '404' in str(exc):
                break
            print('     Retry in {0} seconds'.format(sleep_time))
            time.sleep(sleep_time)
            sleep_time += sleep_time

    return

def main():

    f_out = open(OUTPUT_FILE, 'w')
    wr = csv.writer(f_out, lineterminator='\n')
    wr.writerow(OUTPUT_FIELDS)

    with open(COMN_FILE) as f_in:
        for line in f_in:
            print(line)

            line = re.sub(r'\n',' ', line)

            # We run the request for each Amtsgericht
            j = 0 # Amtsgericht
            jmax = len(a)

            for j in range(0, jmax):

                _odata = [0] * 4

                #Save Company Name;
                _odata[0] = line
                _odata[1] = a[j]

                Insolrequest = CheckInsolNet(line, a[j])
                if Insolrequest:
                    m = re.search('No data found for entered search
                                   criteria', Insolrequest)
```

```
                    if m:
                        _odata[2] = 0
                    else:
                        _odata[2] = 1
                else:
                    _odata[2] = 2

                print(_odata)
                wr.writerow(_odata)

if __name__ == '__main__':
    main()
```