Financial Distress and Relationship Lending

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1 Introduction

1.1 Motivation

Corporate governance mechanisms are economic and legal institutions addressing agency problems based on the separation of ownership and control, typical for large corporations (see Coase (1937), Jensen/ Meckling (1976), Fama (1980), Fama/ Jensen (1983a) and (1983b)). Especially in the situation of financial distress corporate governance mechanisms play an important role: A control of management can contribute to a correction of strategic deficits and false developments. Management can be urged to align their actions by means of performance-based compensations. Varying across countries, shareholders have legal protection rights, such as voting rights on major firm issues, the right to transfer ownership, the right of dividend entitlement, and information rights. However, even if these rights can be considered as improvements in terms of the agency problem, there is still room for the management to follow its self-interest ("moral hazard", see Stiglitz (1975)). On the one hand, the information right is of limited scale. On the other hand, small investors have limited control due to their limited influence.

To evaluate the mechanism of incentive contracts, Jensen/ Murphy (1990) investigate the sensitivity of management payments to firm performance. Their analysis of firm performance and top-management incentives indicates that the relationship between CEO compensation and shareholder return is small. They hypothesize that these findings are a sign of inefficient contracts. The result indicates that there is still a growing necessity for improvement. The managerial investment decisions seem to reflect the personal interest of the manager rather than those of the financiers.

In the case of multiple small investors the free rider effect might occur as a further problem, leading to less control of the management (see Grossman/ Hart (1980)). But a large equity investor has enough voting rights and the incentive to monitor and therewith addresses the agency problem. Empirical evidence for this hypothesis is provided by Shleifer/ Vishny (1986) and Wright/ Ferris/ Sarin/ Awasthi (1996). They observe that institutional investors can provide monitoring and enhance corporate performance as active participants in a corporation's governance.

A large creditor also serves as an example of an important investor. Due to high investments, incentives to monitor exist. Additionally, the main creditor also has a high negotiation power. In the case of credit prolongation or at the end of a fixed interest rate period, the debtor firm relies on the main banks refinancing due to high switching costs (Sharpe (1990) and Rajan (1992)). Especially in the case of financial distress main creditors can have extensive information and control rights. As covenant breaches often occur in times of financial distress, the bank gains further negotiation power at that point (Sheard (1994)). As a result, large creditors have the ability to interfere with the main management decisions of its debtor. Furthermore, they have the possibility to provide loans for workout investments. Kaplan/ Minton (1994) and Kang/ Shivdasani (1995) provide empirical evidence of the role of large creditors. They observe more management turnover as a response to poor performance at companies with one strong bank relationship.

There is a broad literature on banks being “special”, because they generate proprietary information about the borrowers in the course of lending (see e.g. Diamond (1984), Ramakrishnan/ Thakor (1984), Fama (1985), Rajan (1992)). A special form of a large creditor is the “relationship lender”. A relationship lender is defined as the premier lender of a firm, being equipped with more reliable and more timely information than any “normal” non-relationship-lender institution (e.g. Fischer (1990), Elsas/ Krahnen (1998), Boot (2000), Elsas (2005)). Thus, a relationship lender might carry out corporate governance functions. As a large lender, a relationship lender has an incentive to monitor and, due to its strong negotiation power, also the right to monitor. Consequently the principal agent problem of managerial behaviour might be reduced. Overall, the customer can benefit through better loan terms (Berger/ Udell (1995) and Petersen/ Rajan (1995)), more easily attainable capital (Petersen (1999)), and liquidity assurance (Elsas/ Krahnen (1998)). These considerations indicate that having a relationship lender might reduce a firm’s probability of financial distress or influence the outcome of a financial distress period in a positive way.

In contrast thereto, having a strong bank relationship might lead to costs for the borrower. Having a relationship lender gives an information monopoly to the lender and might lead to high switching costs for the borrowing firm (Sharpe (1990), Rajan (1992)). If the monopoly position is used in favour of the bank’s advantage and at the expense of the borrower, having a relationship lender might negatively influence the firm’s probability of financial distress.

Finally studies exist indicating that a relationship lender has no influence on corporate profitability. For the German market Agarwal/ Elston (2001) analyse a sample of large listed and unlisted firms. They observe that firms with a strong bank relationship in Germany do benefit from an increased access to capital. However, they find no evidence to support the hypothesis of either higher profitability or growth for bank-influenced firms. Chirinko/ Elston (2006) use a sample of 91 listed German firms. They observe that a strong bank influence is not related to a reduction in financing costs or a change in profitability of a firm.

To explain the effect of no influence by the relationship lender, the analysis of the results of an ownership-structure study performed by Demsetz (1983) and Demsetz/ Lehn (1985) is considered. According to Demsetz (1983) there is no cross-sectional relationship between the firm’s value and the concentration of ownership, since the ownership structure that “emerges is an endogenous outcome of competitive selection in which various cost advantages and disadvantages are balanced to arrive at an equilibrium organisation of the firm”. Shareholder return maximisation may require a diffuse external ownership structure in one case whereas a large outside equity block is optimal in another firm case. Consequently, one cannot deduce differences in firm values from differences in size of insider stakes across firms. Demsetz/ Lehn (1985) support this view in their empirical investigation of U.S. firms. The equilibrium structure argument by Demsetz (1983) would support the hypothesis that having a relationship lender is an endogenous outcome of a selection of advantages and disadvantages of having a relationship lender, arrived at a bank-relationship-structure equilibrium. Consequently, it is reasonable to argue that having a relationship lender might have no effect on the firm's probability of financial distress or the outcome of a financial distress period.

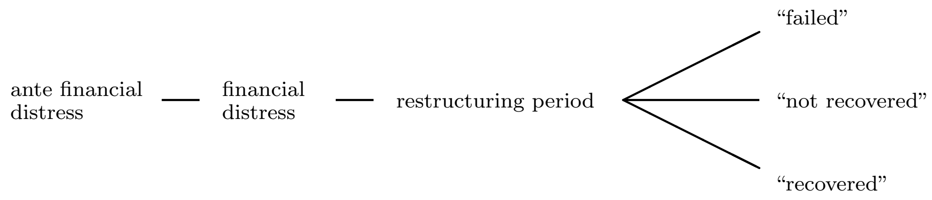
The theoretical considerations about relationship lending and financial distress do not provide a final answer. As far as I know, an empirical investigation on the influence of a relationship lender on firm's probability of financial distress and the outcome of a financial distress period has not been performed. Thus this thesis performs an empirical investigation on financial distress and relationship lending to contribute to this research area.

1.2 Course of examination and contribution to the literature

The following thesis is divided into three working papers. While the topics are connected, each working paper is set up separately. The working papers are connected as follows: The Working Paper (I) "Identification of financial distress" investigates different financial distress identification models in order to develop an identification criterion for the following relationship lending investigation. The identification method should be able to measure the point in time a firm enters financial distress as well as the outcome of a restructuring period. Using the developed criterion, Working Paper (II) "The effect of relationship lending on a firm's probability of financial distress" examines whether or not having a relationship lender affects the firm's probability of financial distress. This study deals with the period in which the financial distress state is entered. Working Paper (III) "Does relationship lending matter in financial distress?" examines the effect a relationship lender might have on the outcome of a financial distress period. The Figure (1) presents an overview of the different time periods covered by this thesis.

In the following, I briefly review the three working papers and emphasise the main findings. In Working Paper (I) different distress identification models to develop a financial distress criterion for the following relationship lending investigation are discussed and empirically investigated. After discussing different types of distress identification methods used in literature, the empirical part of the study focuses on the widely-known logit regression model (see Ohlson (1980)) and the Merton model (Merton (1974)). My sample basis consists of panel data for 1,265 German publicly listed firms between 1993-2007. The applied logit regression model is, as commonly applied, based on annual report data (e.g. Griffin/ Lemmon (2002)). The Merton model includes the share price of a firm as well as the share price volatility and therewith consid-

Fig. 1. Financial distress and relationship lending investigation



Notes. The figure shows the different time periods the three working papers cover. Working Paper (I) deals with the identification of financial distress. The developed criterion allows identifying the point in time a firm enters financial distress. This point in time is relevant for Working Papers (II) and (III). It also allows the classification “recovered” and “not recovered” as the outcome of a financial distress period. This information is applied in Working Paper (III).

ers future market expectations concerning the firm and risk. A ROC (receiver operating characteristic) curve analysis expresses the superiority of the Merton model over the logit regression model. A superiority of the Merton model compared to the logit regression model is also found by Hillegeist/ Keating/ Cram/ Lundstedt (2004).

In a next step, the explanatory power of the Merton model explaining legal bankruptcy is tested using a regression model. The Merton model shows significant explanatory power. Thus, the study uses the Merton model to develop a financial distress identification criterion for a relationship lending investigation. As firms which apply a private restructuring instead of filing for bankruptcy are also of interest for the following investigation, observed restructuring measures serve as an instrument to calibrate and validate a financial distress identification criterion. Bankruptcy and restructuring information indicate that the final developed Merton model-based criterion is a reasonable criterion to identify financial distress.

Working Paper (II) examines whether or not having a relationship lender affects the firm’s probability of financial distress. I use German Credit Register information provided by the German central bank for the period 1993-2007 to identify the relationship lending state of a firm. The Merton model-based financial distress criterion developed in Working Paper (I) is used to identify whether a firm is in financial distress. A sample of 1,265 German equity market-listed firms with available market, annual report and Credit Register Report data is applied. Panel data for the time period 1993-2007 is used. I apply probit regression models for panel data to identify determinants of financial distress. However, a relationship lender might as likely influence the firm’s probability of financial distress as the firm’s probability of financial distress might influence the bank relationship. Thus, the potential endogeneity between relationship lending and the firm’s probability of financial distress is taken into account. A bivariate probit regression using the determinants of relationship lending as a first stage equation is applied to address the endogeneity. The regression models indicate that having a relationship lender has no significant influence on the firm's probability of financial distress. This finding supports the equilibrium structure hypothesis according to Demsetz (1983). Consequently, it is reasonable to argue that having a relationship lender might have no effect on the firm's probability of financial distress.

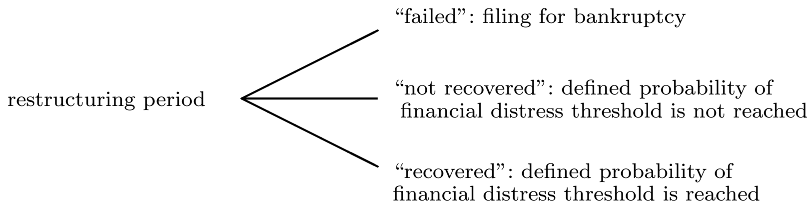
The regression models further suggest that the industry average level of the probability of financial distress has explanatory power. The higher the average probability of financial distress of the industry, the lower is the probability of financial distress of the single firm. This underlines the fact that a lower industry level of the probability of financial distress might indicate that the firm belongs to a more risky industry which is inclined to enter financial distress. Additionally, the firm's profitability has significant negative influence on reaching financial distress, as do liquidity and efficiency. The more profitable and efficient the firm is and the higher its liquidity is, the lower is the probability of entering financial distress. This indicates that high profitability, liquidity and efficiency protect the firm from entering financial distress.

The investigation conducted in Working Paper (III) focuses on the period which starts at the point in time the firm enters financial distress. By using German Credit Register reports provided by the German central bank, German publicly-listed firms are analysed to determine the effect of relationship lending on the outcome of a financial distress period. To identify the sample of financially distressed firms, the criterion derived in Working Paper (I) is used. 295 financially distressed firms are identified from 1,265 firms listed on a German stock exchange between 1993 and 2007. To analyse if a relationship lender has an influence on the outcome of a financial distress period, the following hypotheses are examined: Hypothesis (1) investigates if firms which have a relationship lender when entering financial distress are more likely to show a positive outcome after a restructuring period. Hypothesis (2) examines the question whether firms which have a relationship lender are more likely to get financial support within a restructuring period. Hypothesis (3) deals with the question if firms, which receive financial support of a relationship lender within a restructuring period, are more likely to show a positive outcome after the restructuring period.

To explore the hypotheses probit and ordered probit regression models are used. The dependent variable used in the probit models indicates "recovery" (1) after a period of 375 trading days or "no recovery" (0). In the ordered probit regression three possible outcomes are taken into account presented in Figure (2).

To control for factors which might influence the firm's outcome of a financial distress period, workout measures and firm characteristic variables are applied. To control for workout measures the increase in the firm's debt is included. In addition, a variable to control for ownership change and changes in management is applied. To control for further firm characteristics, the firms probability of financial distress before entering financial distress according to the Merton model is considered. Firm size controls for the firm's level of public perception and for the ability of the firm to survive financial distress. Analyst coverage

Fig. 2. Financial distress period outcome stages



Notes. The figure shows the three outcome stages 375 trading days after the financial distress event is recognised. The stages "failed", if the firm files for bankruptcy within this period, "not recovered" if the firm's probability of financial distress does not reach a defined threshold and "recovered" if the firm's probability of financial distress reaches a defined threshold are distinguished.

is applied as an indicator for publicly available information about the firm. Finally, a variable to control for assets-intensive industries is also included.

The regression results indicate that having a relationship lender when entering a financial distress situation does not affect the outcome of a restructuring period (Hypothesis (1)). For our sample the models indicate that firms which have a relationship lender are more likely to get financial support within a restructuring period (Hypothesis (2)). However, the models do not indicate that the financial support of a relationship lender itself leads to a positive outcome after the restructuring period (Hypothesis (3)). The models indicate, the higher the probability of financial distress in the prior quarter, the higher is the probability of recovery (Hypotheses (1) and (3)), and the higher is the probability of financial support (Hypothesis (2)). The increase of the firm's debt ratio has a positive significant influence on the outcome of a restructuring period in all models (Hypotheses (1)-(3)), however, the coefficient is very low.

The three working papers contribute to the literature in several ways. So far only a few investigations were conducted dealing with the question whether or not a relationship lender has a special responsibility in terms of financial distress. From an economic point of view this is a major question due to the fact that real economy and corresponding welfare are directly affected by financial intermediation. Thus, an investigation on the effect of a relationship lender on the firm's probability of financial distress and on the outcome of a financial distress period completes a gap in the literature.

An in-depth analysis of this subject was possibly not performed so far due to the limited usefulness of frequently used accounting data-based distress identification criteria. In addition, the lack of data availability concerning a detailed bank-loan-financing-structure of firms might be a reason. These two aspects are addressed in my thesis: The Merton model is applied to develop a sound financial distress identification criterion. Therewith, a more precise criterion is used compared to commonly applied criteria in the financial distress literature, which are in general based on legal bankruptcy or historical accounting data (DeAngelo/ DeAngelo (1990), Asquith/ Gertner/ Scharfstein (1994), Hoshi/ Kashyap/ Scharfstein (1990), Griffin/ Lemmon (2002), Dahiya/ Saunders/ Srinivasan (2003)). Accounting data are reported only on a quarterly or annual basis and differences in accounting standards might have an influence on this criterion. For the following relationship lending investigations the Merton model is used to develop a classification criterion which does not rely on bankruptcy or historical accounting data. This criterion considers share prices and therewith future expectations of the capital market. It can be calculated on a daily basis and considers cash flows. By considering asset volatility risk is taken into account. The criterion is constituted on a theoretical foundation, as opposed to ad-hoc measures of financial distress. So far only a few articles within the financial distress literature apply a financial distress criterion on the Merton model basis. Vassalou/ Xing (2004) use the Merton model to investigate default risk and equity returns. As far as I know, a Merton model-based criterion has not been applied so far, in order to investigate the effect a relationship lender has in times of financial distress.

As the financial distress criterion is together with the relationship lending criterion the main element of the investigations, an extensive calibration and validation process in terms of the financial distress criterion is performed. For the sample of 1,265 listed German firms extensive research on bankruptcy information is conducted combining multiple sources of information. First, the Hoppenstedt database is used. Second, an extensive keyword search on bankruptcy related terms in the newspaper database LexisNexis and on the firms' homepages is conducted to identify the date of bankruptcy process announcement. As the homepage of bankruptcy firms is often not available, service providers offering deleted web-page information are used. As firms might not file for bankruptcy, however use private restructuring as the way to overcome financial distress, an extensive keyword search on terms related to restructuring in combination with the firm's name is additionally conducted. Again, the LexisNexis database and the firms' homepages are used. The extensive research within these sources proves that the derived Merton model-based criterion is a reliable criterion to identify financial distress.

The German financial system is often viewed as the prototype of a bank-based financial system, where banks play an important role in corporate finance even for large and exchange-listed companies. Hence using German Credit Register Reports provided by the German central bank offers a unique opportunity to learn about the pros and cons of relationship lending.

A firm match comparing firm names, city of head quarters and postal codes to find German listed firms within the German Credit Register reports was conducted. 1,265 and therewith 89% of the firms identified in the database Datastream could be found in the Credit Register Reports. Identifying the majority of the firms proves that using Credit Register information is a reasonable source for an investigation on firms listed on a German stock exchange.

The Credit Register Reports contain quarterly returns from banks which include each provided single large exposure loans to their customers. This non-aggregated data on a single loan basis serves as the basis to identify the relationship lender. Compared to aggregated data provided within the firm's financial statements, the Credit Register Reports serve as an enhanced data basis enabling a unique investigation.

In addition to the single firm loan reports, the Credit Register Reports include the information of risk units. If two firms affect each others financial situation reciprocally, the reports inform about an existing risk unit (a so-called "borrower unit"). An indication for the existence of these borrower units is given by the bank itself. In a first step the banks report the borrower loan information and the possible indication of a borrower unit to the central bank. In a second step, the bank receives the information whether or not the firm is already included in a borrower unit according to other bank reports. Additionally, the central bank informs the banks about the amount of debt provided by other banks to this borrower unit. Thus, the borrower unit information serves as a basis for further credit decisions made by German banks.

A comparison of the firms belonging to a borrower unit and the corporate group according to the German Corporate Group Act is performed in the scope of the following investigations. The subsidiaries reported by the database Amadeus of every firm group within the sample is compared to the members of a borrower unit. The comparison shows that the borrower unit de facto follows a wider definition compared to the corporate group. As mentioned, risk related firms are included in the unit and the information is taken into account in terms of the banks' decision of being a relationship lender. The borrower unit information, not applied in the financial distress literature so far, is thus another aspect making the following investigations outstanding.

Moreover, it should be mentioned that not only loans are reported by banks but also bank-firm off-balance-sheet transactions. Banks are informed about these off-balance-sheet transactions by the central bank and they might influence the bank's decision in terms of being a relationship lender. These off-balance-sheet transactions are also taken into account while identifying a relationship lender in the following investigation. Overall this shows that the German Credit Register information provide an enhanced basis for a relationship lending criterion which has not been applied for a financial distress investigation so far and therefore makes the following investigations unique.

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Identification of financial distress

Working Paper I

Nadine Stephenson

Abstract

This study addresses the question of how to measure financial distress. I discuss different identification models used in the literature in order to develop a criterion for financial distress suitable for investigations in corporate finance such as the question of valuation of restructuring methods. The empirical part of this study focuses on the widely known logit regression models (e.g. Ohlson (1980)) and the Merton model (Merton (1974)) to identify financial distress. Logit regression models used in the literature predominantly apply annual report data-based predictor variables. The main determinant of the Merton model is the firm's leverage ratio and the volatility of the asset value. To estimate the market value of equity in this context, the share price of the firm is used. This considers future expectations of the capital market. By taking asset volatility into account risk is also considered. Application of ROC (receiver operating characteristic) curve analysis indicates a higher predictive power for the Merton model compared to the logit regression model in terms of bankruptcy cases. Furthermore, I find that the Merton model is less sensitive in terms of the accounting policy the management chooses than the logit regression model is. Hence, this study uses the Merton model to develop a financial distress identification criterion. To calibrate and validate the Merton model-based financial distress criterion, I use bankruptcy information as well as information about restructuring. Bankruptcy and restructuring information indicate that the developed Merton model-based criterion is a reasonable criterion to identify a financial distress situation.

1 Introduction

Financial distress identification models are crucial for studies of corporate finance, e.g. dealing with the valuation of restructuring methods in cases of financial distress, such as management measures or financing measures such as equity offerings and bank lending relationships. For this kind of corporate finance investigation an identification method is required to determine if and at what point in time a firm is in financial distress or leaves financial distress. However, this raises the question addressed in this paper of how to measure financial distress.

The literature on financial distress identification is very small and in general the investigated models are based on models initially invented for bankruptcy prediction (Altman (2000), Shinong/ Xianyi (2001)). Altman (2000), for example, presents his Z-Score and Z-Model, initially invented to predict corporate bankruptcy, as a predictor of financial distress. In contrast to the small literature on financial distress, there is a large related literature on prediction of corporate bankruptcy. The literature varies in terms of the variables chosen and the methodology used to predict the probability of bankruptcy. Univariate models consider single financial ratios to separate non-bankruptcy from bankruptcy-threatened firms. Beaver (1966) presents financial ratios as a useful predictor of bankruptcy. The widely known models of Altman (1968) and Ohlson (1980) primarily use accounting data to estimate the probability of bankruptcy in their discriminant and logit regression models. In contrast to these single period models, Shumway (2001) suggests a hazard model with an annual frequency and adds equity market variables, past stock returns and its volatility to the set of accounting data-based variables.

Bankruptcy prediction models are also used in the literature for examinations of financially distressed firms. To analyse dividend the policy of financially distressed firms DeAngelo/ DeAngelo (1990) use an univariate criterion. As a predictor of financial distress Griffin/ Lemmon (2002) apply the Ohlson model-based logit approach (Ohlson (1980)) to examine financial distress risk and stock returns.

In addition to the group of models initially developed to predict bankruptcy, there is a group of so-called structural models. One of the main models in this context is the Merton model (Merton (1974)). Longstaff/ Schwarz (1995) and Leland/ Toft (1996) extend the original Merton model. The main determinants of the Merton model are the firm's leverage ratio and the volatility of the asset value. To estimate the market value of equity in this context, the share price of the firm is used. This considers future expectations of the capital market. By taking asset volatility into account risk is also considered. Vassalou/ Xing (2004) apply the Merton model to identify financial distress and investigate default risk and equity returns.

This study analyses different financial distress identification models to develop a financial distress criterion for a corporate finance investigation such as the investigation of restructuring methods. To conduct this study I start by discussing different identification methods, and focus on the widely known logit regression model (e.g. Ohlson (1980)) and the Merton model in the empirical part of this study. I compare the explanatory power of the logit regression model and the Merton model in terms of bankruptcy cases using a ROC (receiver operating characteristic) curve analysis. I use bankruptcy cases to validate the financial distress identification methods because financial distress itself is not observable. The ROC curve is suggested by the Basel Committee on Banking Supervision (2005) as a validation method for bank internal ratings. The ROC curve analysis indicates a higher predictive power of the Merton model compared to the logit regression model in terms of bankruptcy cases. A following logit regression analysis underlines the explanatory power of the Merton model-based probability of default in terms of explaining bankruptcy. However, as this paper addresses the question of how to measure financial distress, filing for bankruptcy is only used as a calibration criterion in a first step. Further examinations on firm restructuring follow to calibrate the criterion.

A side aspect addressed in this paper in order to compare the logit regression and the Merton model is the following: DeAngelo/ DeAngelo/ Skinner (1994) observe the application of systematic accounting policy measures in order to influence performance indicators in favour of the management. The sensitivity of the models in terms of different accounting policies potentially chosen by the management is the subject of an empirical analysis. To assess the sensitivity in terms of accounting policies, German Accounting Standard data (HGB) and international accounting standard (IFRS) data are applied for the years of an accounting standard conversion. The firm's probability of default is calculated, applying the Merton model and the logit regression model under consideration of the two accounting standards information. I observe that the Merton model is less sensitive in terms of changes of the accounting standard than the logit regression model is.

Due to the above-mentioned aspects, the Merton model is used as a basis to develop a financial distress criterion. I apply a dataset of 1,265 German publicly traded firms with market data available on Datastream and balance sheet data available on Hoppenstedt. Information about restructuring measures is used to calibrate and validate the financial distress criterion. A calibration matrix using bankruptcy information supports the calibration process. A logit regression is applied to investigate whether or not the derived financial distress criterion has additional explanatory power compared to the distance to default calculated by using the Merton model. Restructuring information is used to finally validate the criterion and underline whether the Merton model-based criterion developed in this paper is reasonable for the identification of a financial distress situation.

The remainder of this paper is organised as follows: Section 2 begins with a literature survey concerning financial distress definitions and financial distress identification methods used in the corporate finance literature. Section 3 includes the empirical implementation of the Merton model as the basis for a financial distress identification criterion. Section 4 investigates the accounting policy sensitivity of financial distress identification methods. Section 5 deals with the empirical comparison of financial distress identification criteria and finally calibrates and validates a criterion through consideration of bankruptcy and restructuring information. Section 6 concludes.

2 The notion of financial distress

2.1 Financial distress, economic distress and bankruptcy

A variety of definitions exist in the economic literature for the notion of financial distress. One definition provided by Altman/ Hotchkiss (2006) uses the term "insolvency" in a technical sense to define financial distress and in the sense of bankruptcy to define economic distress:

- Insolvency in a technical sense is the case when a firm **fails to meet its current obligations**.
- Insolvency in a bankruptcy sense means that **the fair value of the firm's total liabilities exceeds its fair value of total assets**. Therefore, the firm's real net present value is negative.
- Bankruptcy is the firm's **formal declaration of bankruptcy** in federal court, combined with a petition for liquidation (Chapter 7 US bankruptcy code) or for a recovery program (Chapter 11 US bankruptcy code).[1]

Consistent with this definition, Sharpe/ Alexander/ Bailey (1990) use the notion "technical insolvency" and define it as a situation in which a company is unable to meet its current debt payments. They discuss insolvency in a legal sense if the present value of the firm's assets is not in excess of its liabilities. This indicates the heterogeneity of distress-related definitions, ranging from legal bankruptcy, through negative net present value to a situation in which a firm is not able to meet its current debt obligations. Zmijewski (1984) defines financial distress as the act of filing petition for bankruptcy. Edwards/ Fischer (1994) define financial distress as a situation in which bankruptcy is imminent but has not yet occurred. According to Gilson (1990) financial distress occurs either if a firm is in default on its debt, a firm is bankrupt or if the firm is restructuring its debt to avoid bankruptcy. Greenbaum/ Thakor (1995) classify financial distress as "mild financial distress", "moderate financial distress" and "severe financial distress". They call a situation "mild financial distress" if the borrower faces the prospect of a temporarily insufficient cash flow to serve its

[1] Concerning the notion of bankruptcy, reference shall also be made to the German insolvency code. According to §17-19 of the German insolvency code (Insolvenzordnung - InsO) an insolvency proceeding has to be initiated if either contractually guaranteed payment obligations cannot be fulfilled (illiquidity/ imminent illiquidity in accordance to §17 and §18 InsO) or the company's assets do not cover the total liabilities (over-indebtedness according to §19 InsO based on book values).

outstanding debt obligations, but the economic value of the firm comfortably exceeds its repayment obligations. “Moderate financial distress” is a situation in which default is imminent without debt restructuring. Given the existing debt repayment obligations, the economic value of the firm’s assets is less than its repayment obligations. However, in this situation it is possible to restructure the debt, so the economic value of the firm’s assets would exceed the value of restructured debt. “Severe financial distress” is defined as a situation in which the borrower actually defaults on some debt obligations. A debt restructuring plan may be worked out to preclude formal bankruptcy proceedings.

The definitions presented above are the basis for the definitions of distress this study follows. However, some variations will be considered:

- **Financial distress** is defined as a situation in which the firm cannot meet its current obligations or if a sufficient likelihood is given concerning the inability to meet the current obligations.
- The situation in which the firm’s present value of liquidation is higher than the present value of going concern will be called **economic distress**.
- The notion **bankruptcy** is defined as the firm’s formal declaration of bankruptcy in federal court.

A company can be economically distressed and nevertheless be able to pay its obligations, meaning that the firm is not in financial distress (see also Elsas (2001)). Furthermore, a firm may be in financial and economic distress, however, the legal bankruptcy proceedings are not yet commenced. The definitions this paper follows are summarized in Table 1.

Table 1
Overview of distress definitions

Bankruptcy	**Financial Distress**		**Economic Distress**
Legal Proceedings: Formal declaration of bankruptcy in federal court.	Illiquidity: A firm cannot meet its current obligations.	Sufficient likelihood of illiquidity.	Present value of liquidation is higher than present value of going concern.

2.2 Financial distress identification methods

After discussing the definition of financial distress, the following subsection deals with different financial distress identification methods used in literature. External company observers face a special problem regarding the identification of financial distress due to a lack of information. Annual report data, the share price, public press data and in some cases firm ratings are available and consequently these form the commonly used data basis to identify financial distress. The problem of how to identify financial distress is difficult to solve and the literature on financial distress identification models is sparse. The models to identify financial distress are often based on models initially invented for bankruptcy prediction. In contrast to the sparse literature on identification of financial distress, the literature on identification of corporate bankruptcy is large. The main models and their use in the bankruptcy and financial distress literature are presented in the following in order to consider whether or not any such model appears appropriate to identify financial distress.

A famous model within the quantitative research on bankruptcy prediction is the Z-score model by Altman (1968) and Altman/ Haldemann/ Narayanan (1977). The method is based on a multivariate discriminant analysis of non-bankruptcy and bankruptcy-threatened firms. The crisis indicator is based on the weighting of a company's performance indicators in order to enable a classification of companies into threatened and not threatened. The result of the discriminant analysis is a proxy of the bankruptcy probability of the company. The Altman Z-score formula for manufacturing companies displayed below primarily consists of annual report data-based ratios. Beside one market data-influenced variable (market value equity divided by book value liabilities), balance sheet, income statement and cash flow ratios such as working capital and sales divided by total assets are used to calculate the overall index:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{1}$$

with
X_1 = working capital divided by total assets
X_2 = retained earnings divided by total assets
X_3 = earnings before interest and taxes divided by total assets
X_4 = market value of preferred and common equity divided by book value of total liabilities
X_5 = sales divided by total assets
Z = overall index

Although the method was developed in the late 1960s it is still commonly used. Aharony/ Jones/ Swary (1980) test the discriminant analysis for bankruptcy perdiction. They investigate whether market data within the identification model leads to a higher accuracy than using purely annual financial statement data. They find that using market data increases the accuracy in terms of bankruptcy prediction. As a predictor of financial distress Altman (2000) and Frydman/ Altman/ Kao (1985) investigate discriminant models initially implemented to identify bankruptcy.

The discriminant model also serves as the basis for the widely known logit regression models. Ohlson's O-score is one of the main models known in this context. This model is also based on accounting data. A logit regression model is for example used by Mutchler/ Hopwood/ McKeown (1997) to analyse the impact of information asymmetry on potentially bankrupt firms. Dichev (1998) applies the Ohlson model (Ohlson (1980)) as well as the Altman model (Altman (1968)) to investigate whether the risk of bankruptcy is a systematic risk. Begley/ Ming/ Watts (1996) analyse the Altman model and Ohlson model for bankruptcy prediction. Their investigation indicates that the Ohlson model is superior to the Altman model in terms of potential misclassification of the firms. In the financial distress literature Griffin/ Lemmon (2002) use the

Ohlson model as a predictor of financial distress to investigate financial distress risk and stock returns.

In addition to those multivariate analysis methods univariate analysis methods exist. These models consider single financial ratios to separate non-bankruptcy from bankruptcy-threatened companies. Beaver (1966) presents financial ratios as a useful predictor of bankruptcy. In the literature on financial distress the univariate models are often used. To investigate the dividend policy of financially distressed firms DeAngelo/ DeAngelo (1990) apply an univariate criterion. They classify a firm as financially distressed if the firm experiences annual losses for three years in succession. Asquith/ Gertner/ Scharfstein (1994) use the interest coverage ratio to examine how bond issuers facing financial distress try to avoid bankruptcy filing via debt restructuring. Hoshi/ Kashyap/ Scharfstein (1990) also use the interest coverage ratio to investigate the role of banks in reducing the costs of financial distress in Japan. Dahiya/ Saunders/ Srinivasan (2003) investigate bank lending relationships of financially distressed firms and classify a firm as financially distressed if its cash flow is insufficient to meet the debt payments. Moreover, Whitaker (1999) uses the firm's ability to meet contractual debt obligations (cash flow to current maturities of long-term debt) to investigate managerial behaviour in financially distressed firms. To identify firms in financial distress Opler/ Titman (1994) use poor stock performance and negative sales growth for two years in succession. They investigate corporate market performance and financial distress. Poor stock performance is also used by Clark/ Ofek (1994) as an identification criterion to investigate mergers after financial distress.

Besides the aforementioned group of prediction models, the group of structural models or option pricing/ contingent claims methods should be mentioned. One of the main models in this context is the Merton model (Merton (1974)). The main determinants of this model are the firm's leverage ratio and the volatility of the asset value. To estimate the market value of equity in this context, the share price of the firm is used, reflecting the aggregated capital market expectations concerning the firm's future development. Another advantage in this regard is the daily availability of share price data. This allows a daily update on the firm's financial situation. Moreover, the criterion allows researchers to identify not only the financial distress stage itself but also the ante- and post-financial distress stage on a daily basis and is thus very precise. Furthermore, the criterion considers the asset volatility and therewith risk. Hillegeist/ Keating/ Cram/ Lundstedt (2004) compare Altman's and Ohlson's models to the contingent claims approach proposed by Merton in their article "Assessing the Probability of Bankruptcy". They find that the Merton model is superior compared to the predominantly accounting data-based models. In the financial distress literature Vassalou/ Xing (2004) use the Merton model-based contingent claim approach to investigate default risk and equity returns.

Another well-used criterion in the literature to investigate firms facing financial difficulties is observed filing for bankruptcy. Filing for bankruptcy is used by Altman (1984) in his investigation on bankruptcy costs. Eberhard/ Altman/ Aggarwal (1999) apply filing for bankruptcy as a criterion in their analysis of equity performance of firms emerging from bankruptcy. Ang/ Chua/ McConnell (1982) use bankruptcy in their investigation of the administrative costs of corporate bankruptcy. Bankruptcy information is also used by Dawkins/ Smith Bamber (1998) in investigating market reactions, Gosnell/ Keown/ Pinkerton (1992) in analysing insider trading, Hotchkiss (1995) in analysing management turnover, Lawrence (1983) in observing reporting delays, Loderer/ Sheehan (1989) in investigating managerial behaviour as well as Maksimovic/ Phillips (1998) in analysing efficiency of reorganisation, and Strömberg (2000) in analysing inefficient liquidations. Filing for bankruptcy is also used in the financial distress literature. For example Khanna/ Poulsen (1995) use filing for bankruptcy as a criterion in their analysis of accountability in management in financial distress. Gilson/ Vetsuypens (1993) and Gilson (1997) use bankruptcy filing information to examine CEO compensation in financially distressed firms.

As firms which apply a private restructuring and do not file for bankruptcy might also be of interest, observing restructuring measures might serve as a reasonable identification criterion. Gilson (1990) uses private debt restructuring information to identify a firm's potentially filing for bankruptcy and investigates block holder and firm boards. In the financial distress literature Clark/ Ofek (1994) use, in addition to poor stock performance, restructuring information as a criterion to identify financially distressed firms. A key word search for restructuring information is also used by James (1996) for his investigation on bank debt restructuring in financial distress. Also Andrade/ Kaplan (1998) use a key word search on restructuring terms to measure how costly financial distress is. Moreover, Gilson/ Vetsuypens (1993) and Gilson (1997) combine a restructuring key word search with bankruptcy filing information to examine CEO compensation in financially distressed firms and capital structure choice respectively.

Finally, using the ratings of rating agencies should be mentioned as a criterion used in the literature to identify firms facing financial difficulties. Castanias (1983) applies rating information to categorise potentially bankrupt firms. In the financial distress literature Molina (2005) uses external ratings to investigate the effect of leverage on the default probability and Helwege (1999) uses speculative-grade-rated firms to investigate how long their bonds remain in default. Nevertheless, a critical point about this criterion is the fact that ratings are available only for a relatively small number of firms. Furthermore, the process of rating adjustments is often a long-term process.

Table 2 provides an overview of the main bankruptcy prediction models used in the literature. The table differentiates between the use of the models in bankruptcy literature and financial distress literature.

The variety of models used in the literature indicates, that possibly related to the information asymmetry problem between management and capital market participants, the symptoms of financial distress are not easy to detect. Signs of financial distress might be even hidden by the management. DeAngelo/ DeAn-

Table 2
Overview of bankruptcy and financial distress literature

Identification models	Bankruptcy literature	Financial distress literature
Univariate analysis	Beaver (1966)	Asquith/ Gertner/ Scharfstein (1994), Clark/ Ofek (1994), Dahiya/ Saunders/ Srinivasan (2003), DeAngelo/ DeAngelo (1990), Hoshi/ Kashyap/ Scharfstein (1990), Opler/ Titman (1994), Whitaker (1999)
Discriminant analysis	Aharony/ Jones/ Swary (1980), Altman (1968), Begley/ Ming/ Watts (1996), Hillegeist/ Keating/ Cram/ Lundstedt (2004)	Altman (2000), Frydman/ Altman/ Kao (1985)
Logit/probit regression models	Begley/ Ming/ Watts (1996), Dichev (1998), Hillegeist/ Keating/ Cram/ Lundstedt (2004), Mutchler/ Hopwood/ McKeown (1997), Ohlson (1980)	Griffin/ Lemmon (2002)
Contingent claims approach/ structered models	Hillegeist/ Keating/ Cram/ Lundstedt (2004)	Merton (1974), Vassalou/ Xing (2004)
Filing for bankruptcy	Altman (1984), Ang/ Chua/ McConnell (1982), Dawkins/ Smith Bamber (1998), Eberhart/ Altman/ Aggarwal (1999), Gosnell/ Keown/ Pinkerton (1992), Hotchkiss (1995), Lawrence (1983), Loderer/ Sheehan (1989), Maksimovic/ Phillips (1998), Strömberg (2000)	Gilson (1997), Gilson/ Vetsuypens (1993), Khanna/ Poulsen (1995)
Restructuring information	Gilson (1990)	Andrade/ Kaplan (1998), Clark/ Ofek (1994), Gilson (1997), Gilson/ Vetsuypens (1993), James (1996), Khanna/ Poulsen (1995)
Rating information	Castanias (1983)	Helwege (1999), Molina (2005)

Notes. The table shows the main models used to identify firms in financial distress. The column "Bankruptcy literature" displays their usage in the bankruptcy literature, the column "Financial distress literature" their usage in the financial distress literature.

gelo/ Skinner (1994) observe the application of systematic accounting policy measures in order to influence performance indicators in favour of the management. The studies mentioned that use discriminant and logit regression models all have in common that each applies a criterion that classifies companies primarily on the basis of historical financial statements. The problem arises that the required data is published only after a certain time lag and is only reported on a quarterly or annual basis. Depending on the defined classification threshold, five financial statements were required for the above-mentioned studies, leading to an additional time lag. A criterion based only on annual report data does not appear to be sufficiently precise. In addition, differences in accounting standards might reduce the predictive power of the annual figures and the classification is primarily based on the historical performance. Finally, risk is not considered. Most of the ratios used for the univariate classification method are also based on financial statement ratios. Thus the same aspects as the one for the financial statement data-based discriminant and logit regression models can be mentioned regarding this method. Moreover, the classification only on one ratio appears not to be adequate as there is more than one influencing factor that might lead to financial distress.

Structural models such as the Merton model consider the share price reflecting the capital market's future expectations in terms of the firm. Due to the daily availability of the share price, a daily update of the firm's financial distress condition is possible. The model considers asset volatility and therewith risk. An ante-distress stage, a distress stage and a post-distress stage can be identified on a daily basis and therefore very precisely. Due to these aspects special attention will be paid to this criterion in the following.

In terms of using the legal filing for bankruptcy to identify financial distress it has to be said that depending on the objective of the corporate finance investigation it does not appear adequate to limit the company selection to firms which filed for bankruptcy. Furthermore, companies which did not choose to file for bankruptcy but chose a private debt-restructuring as the way to overcome the financial distress might be of interest. Furthermore, the identification is dependent on the prevalent national bankruptcy law. In addition, for a corporate finance investigation such as the question of valuation of restructuring methods a criterion is needed to identify if the firm leaves financial distress after a certain time period. The criterion of filing for bankruptcy does not enable the identification of this.

Using a restructuring key word search might lead to a time lag in terms of financial distress identification. Restructuring measures have to be discussed and decided and reported by the management. In addition, a press key word search is very time consuming. Nevertheless, in terms of the validation of a financial distress criterion restructuring information appears applicable. After identifying firms in financial distress, the post-distress period can be examined in terms of reported restructuring to validate whether or not the firm has faced financial difficulties. This method is applied in this study to validate the financial distress criterion which is to be developed.

The critical point about using rating agency ratings is that ratings are available only for a relatively small amount of firms and face the problem of slow adjustments. Considering all these aspects, the Merton model forms the focus of this study. In a first step, the Merton model is compared with a logit identification criterion also using a market data-based criterion.

3 Empirical implementation of the Merton model

3.1 Theoretical foundation of the Merton model

Due to the aforementioned aspects, this paper investigates an identification criterion based on the Merton model in the following. In 1974 Merton applied the option pricing theory, developed by Black/ Scholes (1973) and Merton (1973), to the evaluation of debt capital. The model supposes that the shareholders will not pay back the raised debt capital at the maturity date if the asset value falls below the debt value. Hence, the equity can be regarded as a call option on the company's assets. In case the shareholder does not exercise the option, the risky assets will be transferred to the debt capital provider, who therefore can be considered as an option writer.

In particular, the Merton model makes two main assumptions. The first assumption is that the asset value (A) is assumed to follow a geometric Brownian motion, i.e.

$$dA = \mu_A A dt + \sigma_A A dW, \tag{2}$$

where μ_A is the expected continuously compound return on A, σ_A is the volatility of the firm value and dW is the standard Wiener process. The second assumption of the Merton model is that the firm has issued one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying firm asset value with a strike price equal to the firm's debt face value and a time-to-maturity of T. The value of equity as a function of the firm's asset value can be described by using the Black-Scholes-Merton formula:

$$E = AN(d_1) - De^{-rT}N(d_2), \tag{3}$$

where E is the firm's equity value, D the firm's debt face value, r the instantaneous risk-free rate, $N(\cdot)$ denotes the cumulative standard normal distribution function and d_1 and d_2 are given by

$$d_1 = \frac{ln\left(\frac{A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \quad and \;\; d_2 = d_1 - \sigma_A\sqrt{T}. \tag{4}$$

Under the assumption of the Merton model the value of equity is a function of the value of the firm and time, and thus it follows directly from Ito's lemma that

$$\sigma_E = \left(\frac{A}{E}\right)\frac{\delta E}{\delta A}\sigma_A. \tag{5}$$

In the Merton model it can be shown that $\frac{\delta E}{\delta A} = N(d_1)$ and under the Merton model's assumptions the volatility of the firm equity can be calculated as

$$\sigma_E = \frac{A}{E}N(d_1)\sigma_A. \tag{6}$$

The asset volatility (σ_A) is thus given by:

$$\sigma_A = \frac{E}{AN(d_1)}\sigma_E. \tag{7}$$

$N(d_2)$ in Equation (4) declares the probability that the equity holder exercises the call option and pays back the credit. $1 - N(d_2) = N(-d_2)$ is the probability that the call option is not exercised and no repayment of the credit takes place.

$N(-d_2)$ accordingly is called the probability of default (PD). Following Merton (1973) and Merton (1974), the probability of default can be written as:

$$PD = N\left(-\left(\frac{ln\left(\frac{A}{D}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right)\right). \tag{8}$$

Alternatively, the distance to default (DD), measuring how many standard deviations the asset value needs to drop to meet the debt value, can be calculated as:

$$DD = \frac{ln\left(\frac{A}{D}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}. \tag{9}$$

One way to implement the Merton model is to use the two non-linear Equations (3) and (7), in order to translate the value and volatility of a firm's equity into an implied probability of default or distance to default. The firm's equity value E is easy to observe in the marketplace. The volatility of the equity (σ_E) can be calculated using historical stock return data or implied volatility data. A forecasting time horizon has to be assumed (e.g. T=1) and the book value of debt can be taken as the face value of the firm's debt. Inter-banking market rates serve as a risk-free rate (e.g. EURIBOR or LIBOR). However, the asset value A is not observable and A and σ_A must be inferred. One way to calculate the firm's asset value and volatility is to solve Equations (3) and (7) simultaneously for numerical values of A and σ_A (this approach is called the "instantaneous method" in the following).

To investigate the accuracy of the solving algorithm, 1,000 evaluations are executed in terms of a Monte Carlo simulation generating 250 simulated asset and equity values per evaluation. Based on the equity values the asset values are determined by solving Equation (3) and (7) simultaneously and the resulting asset values are compared with the simulated values. As fixed parameters a risk-free interest rate of 0.03, an asset starting value of 100 and μ of 0.1 is assumed. The applied varying parameters are the debt value and the volatility of the asset value. The debt value and the volatility of the asset value are subsequently increased in order to examine if the precision of the two solving algorithms differ among different debt values and volatilities. The simulation results are displayed in Table 3, showing the mean square deviation in percent for varying volatility and debt values.

In case of high volatility and debt values the instantaneous solution algorithm leads to high deviations. As Table 3 shows, the mean squared deviation is very high, at 796%. As the identification of distressed firms is the objective of this investigation, are especially of interest cases with high volatility and debt values are of interest. Thus, using the instantaneous approach would lead to misclassifications.

Table 3
Mean square deviation from simulated values in percent using the instantaneous method

		Volatility				
		0.2	0.4	0.6	0.9	1
	10	0%	0%	0%	0%	1%
Debt	30	0%	0%	**1%**	**6%**	**40%**
	60	0%	1%	**9%**	**57%**	**283%**
	90	0%	7%	**43%**	**196%**	**796%**

Notes. The table shows the mean square deviation in percent from simulated values using the instantaneous method for different debt starting values (10, 30, 60, 90) and equity volatility values (0.2, 0.4, 0.6, 0.9, 1).

To address this problem, I follow Moody's KMV (Crosbie/ Bohn (2003)) by implementing an iterative procedure. I start with an initial asset volatility value σ_A of $(\sigma_A = \sigma_E/(E + F))$ as a starting value to infer the market value of the firm's assets on a daily basis. E denotes the firm's equity market value, σ_E the volatility of the firm's equity, and F the firm's book debt value. For each point in time t, the preceding 250 trading days are used to estimate σ_E as an initial guess for the asset volatility, σ_A. Applying the Black-Scholes-Merton formula (Equation (3)), this leads to a series of asset values, A_t. These are in turn used to arrive at an updated estimate of σ_A. This estimate is used for the next iteration, and the procedure is continued until the σ_A estimate converges with a tolerance level of $10e - 6$. The final volatility estimate is then used to calculate the asset value estimate, using again Equation (3). I again investigate the estimation accuracy as described above. Table 4 shows the results.

Table 4
Mean square deviation in percent from simulated values using the iteration method

		Volatility				
		0.2	0.4	0.6	0.9	1
	10	0.00%	0.00%	0.00%	0.00%	0.01%
Debt	30	0.00%	0.00%	0.00%	0.03%	0.11%
	60	0.00%	0.01%	0.09%	0.26%	0.56%
	90	0.01%	0.13%	0.41%	0.84%	1.43%

Notes. The table shows the mean square deviation in percent from simulated values using the iteration method for different debt starting values (10, 30, 60, 90) and equity volatility values (0.2, 0.4, 0.6, 0.9, 1).

In contrast to the instantaneous approach, the iteration approach is more precise even at high debt and volatility values. The mean square deviation in percent of only 1.43% even at high debt and volatility levels proves this. Because companies in financial distress normally exhibit high debt ratios and high equity volatility, the application of the instantaneous approach does not appear feasible. Thus the probability of default by the considered companies is calculated by applying the iteration approach. For futher information on estimation approaches, see Breitkopf (2010) and Ericsson/ Reneby (2005).

3.2 Sample selection and implementation of the Merton model

As the share price is the main input for the selected Merton classification criterion, companies listed in Germany between January 1, 1993 and December 31, 2007 are considered in the investigation. In terms of the required debt data, a comparison of data provided by the databases Hoppenstedt and Datastream is made. This shows that Hoppenstedt, a database for German financial statement information, shows better coverage and is more reliable for German companies. One of the reasons for this is the distinction of different accounting standards in Hoppenstedt. This is an important issue for a German stock market investigation, as listed German firms used to disclose their financial statement according to the German accounting standard (HGB). For accounting years starting after January 1, 2005, German-listed parent companies have to draw up their financial statements according to international accounting standards. Balance sheet data provided by Datastream does not include information about the underlying accounting standard. Different accounting standard data is combined in one scheme and is partially irreproducible. Therefore Hoppenstedt data is used for balance sheet information.

Finally, 1,265 companies were included in the sample, for which all required market data from Datastream and the financial statement data from Hoppenstedt is available. The sample includes currently operating companies as well as delisted companies.

To implement the Merton model in accordance with Moody's KMV the short-term debt was considered at 100% while the long-term debt is only considered at 50% (Crosbie/ Bohn (2003)). The FIBOR and later the EURIBOR are applied as the risk-free interest rate in the Merton model.

To determine the equity volatility the return index provided by Datastream serves as a basis. The return index contains corrections regarding dividend payments and capital measures and thus represents the applicable measurement for the determination of the equity volatility. The equity volatility is calculated on a daily basis corresponding to a time period of 250 days. The applied time to maturity T is set to $T = 1$. The asset mean used for the probability of default and distance to default determination is computed by applying the logarithm of asset returns on a 250 day basis. The minimum level of the asset returns is the risk-free rate. The probability of default is calculated by applying the standard normal distribution. Alternatively, the probability of default on the basis of the Student-t distribution with three degrees of freedom is applied. The Student-t distribution with three degrees of freedom is wider at the boundaries and is more beneficial to meet the actual distribution of the default probability on the basis of the historical data in accordance with a study conducted by Moody's KMV (Crosbie/ Bohn (2003)).

3.3 Descriptive statistics

The distance to default and the probability of default according to the Merton model are calculated for all German publicly listed companies between January 1, 1993 and December 31, 2007 for which Datastream provides data.

The sample composition in terms of industry sector as well as the mean of the distance to default are displayed in Appendix A.1.

The distances to default of the German market are compared to the US market. The US data is provided by Vassalou/ Xing (2004). To compare German data to US data the values are divided into percentiles. For the German market I use the normal (N) and the Student-t (T) distribution to calculate the probability of default. Table 5 shows the comparison of the German and the American market.

Table 5
Probability of default (PD) comparison of the German and the American market

Percentile	PD USA	PD Germany (Student-t distribution)	PD Germany (Normal distribution)
0.01	0.0000	0.0000	0.0000
0.05	0.0000	0.0000	0.0000
0.10	0.0000	0.0000	0.0000
0.25	0.0000	0.0001	0.0006
0.50	0.0000	0.0082	0.0047
0.75	**0.0075**	**0.0858**	**0.0224**
0.90	0.1585	0.2136	0.0927
0.95	0.3917	0.3261	0.1999
0.99	**0.8281**	**0.6211**	**0.4225**
PD mean	0.0533	0.0336	0.0280
Standard deviation	0.1548	0.0781	0.1097
No. of observations	964252 (monthly)	126535 (monthly)	126535 (monthly)

Notes. The table compares the probability of default (PD) of the American market with the German market for a time period from 1993 to 1999. The American market data are provided by Vassalou/ Xing (2004).

The results illustrate a lower probability of default for the German market in terms of the 0.99 percentile and the 0.95 percentile. In contrast, the probability of default for other percentiles is higher for the German market. An overall comparison of the mean probability of default for the German and American market is also displayed in the table, showing a lower mean probability of default overall for the German market.

To achieve a first impression of the adequacy of distance to default and probability of default as proxies for financial distress, the distance to default of companies that went formally bankrupt is calculated in relation to their date of bankruptcy (measured as days before bankruptcy) within the time period 1993 and 2007. The results can be seen in Table 6.

The distance to default decreases the closer the date is to formal bankruptcy. This indicates that the distance to default provided by the Merton model is a reasonable indicator for financial distress (see Figure 1).

4 Financial distress identification methods and accounting policy sensitivity

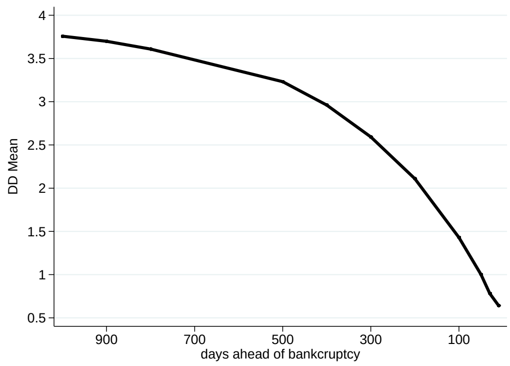
DeAngelo/ DeAngelo/ Skinner (1994) observe the application of systematic accounting policy measures in order to influence performance indicators in

Table 6
Distance to default probability of default related to the formal date of bankruptcy

Distance to legal bankruptcy	DD mean	PD mean (Student-t distribution)	PD mean (normal distribution)	Number of observations
801-1000 days	3.7002	0.0738	0.0914	560
501-800 days	3.6295	0.1187	0.1281	997
251-500 days	2.7796	0.1397	0.1449	977
101-250 days	1.9445	0.2024	0.1915	625
51-100 days	1.1459	0.2827	0.2239	205
11-50 days	0.8344	0.3618	0.2592	165
5-10 days	0.3678	0.4121	0.3687	23
1-5 days	0.7086	0.3773	0.2590	36

Notes. The table is based on bankruptcy information according to Hoppenstedt, LexisNexis and the firms' homepages. The distance to default (DD) and probability of default (PD) mean is calculated using the Merton model. The values are measured for certain time periods before the bankruptcy event occurred. The table is based on bankruptcy events within the time period January 1, 1993 and December 31, 2007.

Fig. 1. Distance to default relative to the bankruptcy date



Notes. The figure shows the development of the distance to default according to the Merton model. The bankruptcy date information is based on LexisNexis, Hoppenstedt and the firms' homepages. The graph shows the distance to default in relation to the time before the bankruptcy event occurred. The figure is based on data for a time period between 1993 and 2007.

favour of the management. Thus, accounting policies might be used to hide a financial distress situation. As the Merton model is essentially influenced by the stock price and its volatility, a lower sensitivity in terms of accounting policies is expected.

The sensitivity of the financial distress models in terms of accounting policies is empirically investigated in the following by comparing the logit versus the Merton model. To address this aspect, reported German Accounting Standard (HGB) and international accounting standard firm data within the year of an accounting standard conversion is applied.

According to the German Capital Raising Facilitation Act (Kapitalaufnahmeerleichterungsgesetz KapAEG) from April 20, 1998 German stock-exchange listed firms were able to choose between disclosing their consolidated financial statement according to international accounting standards (IFRS or US-GAAP) or the German accounting standard (HGB). For accounting years starting after January 1, 2005, German-listed firms must draw up their consolidated group statement according to IFRS (see EG-regulation no. 1606/ 2002).

For 319 publicly listed German firms the Hoppenstedt database provides IFRS/ US-GAAP and HGB data reported for the same year. I test whether or not the Merton model leads to fewer changes in the ranking of the probability of default than a logit regression model does in case of accounting standard conversion. For the Merton model the steps explained in Section 3.1 are performed with the firm's debt value reported according to the HGB and the international accounting standard.

To calculate the HGB and international accounting standard-based probability of default according to the logit regression model, the following steps are executed. A logit regression for the German market is executed using the firm's bankruptcy status as a dependent variable ($P(bankruptcy)_{it}$, a dummy variable with the value 1 if the firm enters bankruptcy in the reported year and 0 if not).

$$\begin{aligned} P(bankruptcy)_{it} &= \beta_0 + \beta_1\ working\ capital/assets_{it} \\ + \beta_2\ retained\ earnings/assets_{it} &+ \beta_3\ return\ on\ assets_{it} \\ + \beta_4\ leverage_{it} + \beta_5\ asset\ turnover_{it} &+ \beta_6\ year_{it} + u_{it} \end{aligned} \tag{10}$$

The variables with which to explain the bankruptcy status are chosen according to Altman (1968) and Altman/ Hotchkiss (2006) and the Moody's rating for non-listed firms (Dwyer/ Kocagil/ Stein (2004)). The subscripts refer to the firm's working capital divided by total assets ($working\ capital/assets_{it}$), retained earnings divided by total assets ($retained\ earnings/assets_{it}$), earnings before interest and tax divided by total assets ($return\ on\ assets_{it}$), the leverage ratio as the book value of total liabilities divided by total assets ($leverage_{it}$) and sales divided by total assets ($asset\ turnover_{it}$). The sample includes firms which filed for bankruptcy with firm data for the year ending before the bankruptcy filing occurs. Furthermore, I include firms which did not file for bankruptcy. Overall panel data for a firm sample of 1,265 firms (i) including 164 firms which filed for bankruptcy serves as the database for a time period 1993-2007 (t). I perform a random effects logit regression model to calculate the coefficients for the different variables. As a robustness check a pooled OLS regression is performed. This does not lead to a significant change in the final results.

To estimate the coefficients for the HGB data-based probability of default calculation I use only historical German accounting standard data. To estimate the coefficients for the international standard data-based probability of default I use international accounting standard data as soon as the firm reports those and HGB data otherwise. It could be argued that only international accounting standard data should be used for estimating the international standard coefficients. However, firms start at different points of time to change their accounting standard (between 1998 and the end of 2005). Hence, there is insufficient international accounting data available for the German market up to a certain point in time. Consequently it is necessary to use historical data based on different accounting standards to calculate the probability of default using the logit regression model.

In a next step, the calculated HGB data-based coefficients are multiplied with the HGB-based variable values for each firm provided for the year of the standard change. The reported international accounting standard firm values are multiplied with the coefficients based on international accounting and German accounting standard data. To calculate the scores I perform an out-of-sample estimation process. I calculate coefficients on an annual basis and multiply the accounting firm values with the coefficient estimated on historical data. The two *scores* per firm (international standard and HGB-based) resulting from that process are inserted into $(1/(1 + exp(-score)))$ to calculate the probability of default according to the two standards.

I analyse whether the logit model leads more or less often to a change in the firm's probability of default ranking after an accounting standard change than the Merton model. Therefore the ranking changes of the two models are compared. Table 7 displays the mean of the sum of the absolute ranking changes.

As expected, the comparison of the mean change of the probability of default ranking following an accounting standard change is higher for the logit regression model (63.591 compared to 5.311). To investigate if this is a significant difference in means a t-test is performed. The resulting p-value of 0.000 indicates a significance difference in means. I further calculate a Spearman correlation to calculate the correlation between the German and international accounting standard ranks for the Merton model and the logit regression model. Spearman's ρ is 0.9879 for the Merton model-based ranking and indicates a strong positive correlation between the German and the international accounting standard ranking. For the logit regression model I find a much lower correlation of 0.6080 between the rankings. This indicates a higher sensitivity of the logit regression model in terms of accounting policy measures chosen by the management compared to the Merton model.

Table 7
Absolute ranking changes of logit regression model and the Merton model after an accounting standard change

Ranking change	Number of firms	Mean	Standard error	Standard deviation	t-value	p-value	Spearman's ρ	Prob> $\|t\|$
Merton model	319	5.311	0.746	13.304			0.9879	0.000
Logit model	319	63.591	2.972	52.999			0.6080	0.000
Differences	319	-58.279	3.145	56.089	-18.529	0.000		

Notes. The table shows a ranking change comparison of the probability of default ranking according to the Merton model and the logit regression model. The ranking standard change is based on an accounting standard change from the German to an international accounting standard for 319 firms. The data cover a time period 1993-2007.

5 Calibration and validation of the Merton model-based financial distress criterion

5.1 Comparing the Merton and logit regression model prediction accuracy of bankruptcy

As a validation step a ROC (receiver operating characteristic) curve is applied to analyse the predictive power of the Merton model compared to the logit regression model in terms of bankruptcy cases. According to the Basel Committee on Banking Supervision (2005), a credit rating model's performance is better the steeper the ROC curve is at the left end and the closer the ROC curve's position is to the point (0,1). Similarly, the model is better the larger the area under the ROC curve is. To calculate the ROC curve, the firms are sorted by their probability of default at a certain point in time calculated using the Merton model and the logit regression model.

To calculate the probability of default according to the models the steps described in Sections 3.1 and 3.2 for the Merton model and Section 4 for the logit regression model are performed. Thus I use an out-of-sample testing procedure covering an overall time period from 1993 to 2007. I rank the probability of default according to each model separately and divide the ranked probabilities of default into percentiles. In a next step it is measured how many of the firms belonging to the class with the x% highest probability of default filed for bankruptcy within the next year. I use Hoppenstedt and LexisNexis information as well as the firms' homepages to identify bankruptcy. The applied ROC curve illustrates the connection between the number of cases which are correcly classified as "bankruptcy cases" and cases which are misclassified as "bankruptcy cases" for different levels of the probability of default. Misclassified cases are called "alpha error". The ROC curves for the two models are displayed in Figures 2 and 3.

Fig. 2. ROC curve Merton model

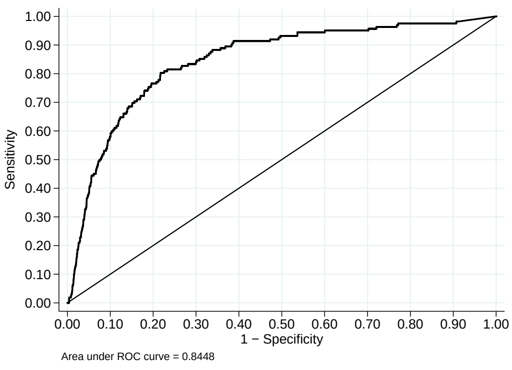
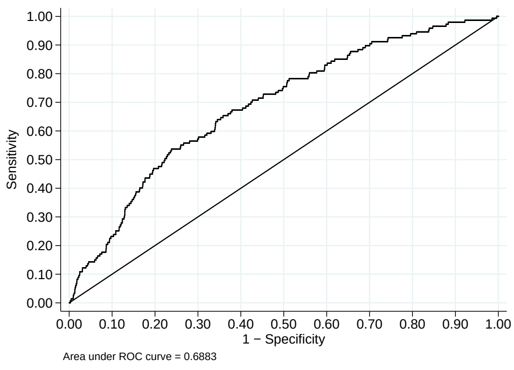


Fig. 3. ROC curve logit regression model



*Notes.*The figures above show ROC curve analysis based on the Merton model probability of default versus the logit regression model. Data for a time period between 1993 to 2007 are used.

The Merton model ROC curve shows a much steeper development compared to the logit curve. The area under the ROC curve for the Merton model totals 0.8448 compared to the logit regression model with 0.6883. Thus the area under the ROC curves illustrate that the Merton model has a higher predictive power than the logit regression model in terms of bankruptcy cases.

Beside the theoretical considerations made in Section 2, the higher predictive accuracy in terms of bankruptcy strengthens the decision to choose the Merton model as a financial distress identification model.

5.2 Regression analysis of the predictive power of the Merton model

To further investigate the predictive power of the Merton model-based distance to default (*dd*) in terms of bankruptcy, a logit regression is performed. A dummy variable measuring legal bankruptcy (0) or no bankruptcy (1) serves as the dependent variable ($P(bankruptcy)_{it}$). The distance to default serves as an explanatory variable.

I use additional explanatory variables in accordance to the variables used in Altman's prediction model (Altman (1968)) and Moody's KMV RiskCalc model (Dwyer/ Kocagil/ Stein (2004)). To control for profitability I use return on assets (measured as EBIT to assets, $return\ on\ assets_{it}$), for liquidity I employ working capital to total assets ($working\ capital/assets_{it}$), for growth I use sales growth (measured as sales growth from one fiscal year to another divided by total assets, $growth_{it}$), and for capital lockup I apply asset turnover (measured as sales divided by assets, $asset\ turnover_{it}$). To control for the firm's equity-debt ratio the firm market value divided by total liabilities ($MV/liabilities_{it}$) is used and for size log sales ($size_{it}$) is used. Further, industry dummies ($industry_{it}$) and year dummies ($year_{it}$) are included. The regression model is displayed below:

$$\begin{aligned} P(bankruptcy)_{it} &= \beta_0 + \beta_1\ dd_{it} + \beta_2\ return\ on\ assets_{it} \\ + \beta_3\ working\ capital/assets_{it} &+ \beta_4\ growth_{it} + \beta_5\ asset\ turnover_{it} \\ + \beta_6\ MV/liabilities_{it} &+ \beta_7\ size_{it} + \beta_8\ industry_{it} + \beta_9\ year_t + u_{it} \end{aligned} \tag{11}$$

Overall panel data for a firm sample of 1,265 firms (i) including 164 firms which filed for bankruptcy serves as the database for a time period 1993-2007 (t). I perform a pooled regression (Table 8 model I), a matched sample regression (Table 8 model II) and a random effect panel data regression (Table 8 model III).

For an additional matched sample regression (Wooldridge (2002), p. 328) one data point per firm is used. For each financially distressed firm approximately six additional non-distressed firm values, with approximately same firm size, measured at the same point in time are included. As a panel data regression model a random effects regression is applied to investigate the predictive power in terms of bankruptcy. As there are no variations of the dependent variable bankruptcy/no bankruptcy for non-bankrupt firms, a fixed effects regression is not implemented. If a firm went bankrupt, the information of the previous year before the firm went bankrupt is considered. 164 firms which went bankrupt are included in the sample. I perform a Wald test (Wooldridge (2002), p. 362) leading to the result that year dummies need to be included.

The three regression models indicate that the distance to default has significant predictive power in terms of explaining the legal bankruptcy. In accordance with the expectations the results show the higher the distance to default is, the lower the probability of a legal bankruptcy process is. Furthermore, other variables such as return on assets, working capital to assets, asset turnover, market equity to liabilities, size and sector variables do have a significant negative coefficient in the panel data regression model. According to expectations I find that the higher the return on assets, working capital to assets, asset turnover, market equity to liabilities, and the bigger the firm is, the lower is the probability of a legal bankruptcy process.

Table 8
Logit regression explaining legal bankruptcy

	Logit regression model		
	I	II	III
	(Pooled regression)	(Matched sample regression)	(Panel regression)
Explanatory variables:			
Distance to default	-0.0974*** (0.000)	-0.0578*** (0.000)	-0.0756*** (0.002)
Return on assets	0.0010 (0.950)	-4.0552*** (0.000)	-0.1603** (0.037)
Working capital to assets	-1.5514*** (0.000)	-1.9189*** (0.001)	-1.8375*** (0.000)
Sales growth	-0.0013*** (0.0026)	-0.0768** (0.016)	-0.0020 (0.430)
Asset turnover	0.0166 (0.332)	0.0002 (0.997)	-0.2057* (0.096)
Market equity to liabilities	-0.0001 (0.785)	-0.1156 (0.104)	-0.0030** (0.012)
Size	-0.0838*** (0.000)	0.0723 (0.104)	-0.1502*** (0.000)
Mining and construction	-0.0770 (0.734)	-1.6371* (0.083)	-4.5357**(0.077)
Manufacturing	0.2802*** (0.000)	1.1439** (0.018)	-2.5517*** (0.000)
Constant	-1.376*** (0.000)	-5.8322*** (0.000)	-12.8353*** (0.000)
Number of observations	41,510	1,265	41,510
Pseudo R^2	0.1590	0.7689	
Number of groups			1,265

Notes. Logit regression explaining legal bankruptcy based on time-series observations for individual firms between 1993 to 2007. Models I - III show the results of a pooled logit regression, a matched sample and a random effect panel data regression. The models include the distance to default as an explanatory variable. Year dummies are included. P-values are in parentheses.

* Significance at the 10% level.

** Significance at the 5% level.

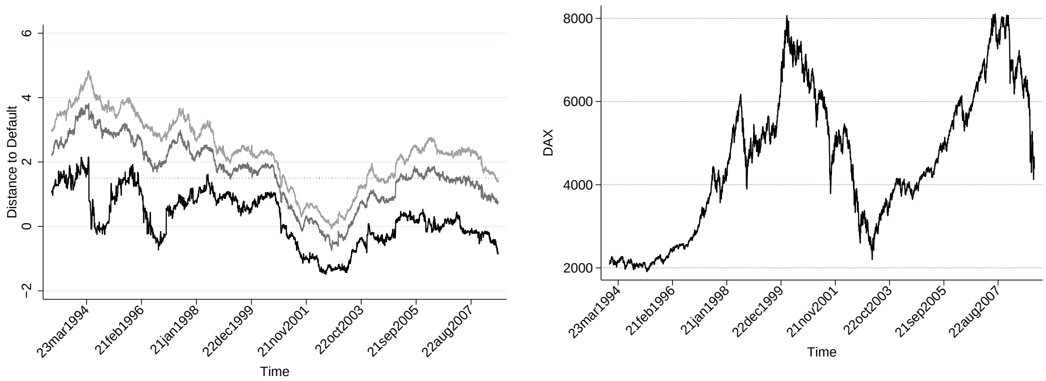
*** Significance at the 1% level.

The presented regression models lead to the conclusion that the distance to default has significant explanatory power on a 1% level to explain legal bankruptcy. Other variables also explain the legal bankruptcy state. However, as the aim is to explain a financial distress situation which includes situations in which a firm was able to avoid the bankruptcy status, e.g. due to workout investments, I suggest applying a Merton model-based criterion to identify non-bankruptcy firms as well. To calibrate such a criterion identifying non-bankruptcy firms I use restructuring information in the following.

5.3 Calibration of the Merton model-based financial distress identification criterion

In this subsection further analyses on the Merton model-based distance to default follow to calibrate a financial distress criterion. To gain further knowledge about the distance to default, an analysis of the distance to default over a certain time period is conducted. Therefore I rank the distance to defaults of all firms on a daily basis and cluster the distance to default into percentiles. Moreover, different distance to default percentile values are observed over time. The development of different percentile values (0.10/ 0.05/ 0.01) in comparison to the German stock index (DAX) is displayed in Figure 4.

Fig. 4. DD percentile values and the German stock index DAX over time



Notes. The figure on the left shows the Merton model-based distance to default development of the 0.10 (upper line), the 0.05 (middle line) and 0.01 (lower line) distance to default percentile values. The figure on the right shows the development of the German stock index (DAX) in comparison.

On the left hand side Figure 4 displays the development of the 0.10 (upper line), the 0.05 (middle line) and 0.01 (lower line) distance to default percentile values. It illustrates that the distances to default of different percentiles vary over time. In a situation of moderate market conditions even higher percentiles show a low distance to default. This reflects that in bad market condition a higher number of firms are potentially in danger of entering financial distress. In good market conditions, even the lower 0.01 percentile shows a distance to default higher than 1.5. This reflects that in good market conditions less firms are in danger of entering financial distress. In terms of the classification criterion this indicates that not only a relative criterion should be chosen. Thus, a threshold of an absolute distance to default value of 1.5 is included in the financial distress criterion.

A matrix displaying different combinations of distance to default percentiles and the number of days in a row a company stayed within this class combined with the threshold of an absolute distance to default of 1.5 is applied to further calibrate the criterion. It displays how many companies belonging to a certain percentile for a certain time period filed for bankruptcy. To validate the financial distress criterion, it is of interest how many firms are correctly classified as financially distressed, how many are misclassified as financially distressed (alpha error) and how many firms are misclassified as not financially distressed (beta error). Nevertheless, there is no observable identification criterion to measure the two error types. Bankruptcy information is thus used as a first indicator to identify the error types. A further assessment including restructuring information follows in Section 5.5.

The percentile matrix for the financial distress criterion thereby developed (distance to default lower or equal to 1.5 and belonging to a certain percentile for a certain time period) is displayed in Table 9. The analysis shows that multiple firms fall below the threshold more than once. The data of a company which falls below the threshold twice are fully included in the sample data, if the distance-period between the two events exceeds 750 trading days (approximately three years). If the distance between the events is less than 750 trading days, the company will be included in the distress sample only with the first event. The 750 trading days are chosen on the basis of an examination of how long it takes a firm on average to get out of the 0.05 distance to default percentile. The investigation shows that 95% of the firms left the 0.05 percentile after a maximum of 375 trading days in a row within the percentile. To leave enough time for the firm to recover, I choose a period of 750 trading days for the re-inclusion of a firm into the sample.

Using a financial distress criterion of:

- a distance to default lower or equal to 1.5 and
- belonging for at least 10 days in a row
- to the 0.05 percentile

leads to 382 distress cases overall. 49 companies never belong to the category "at least 10 days in a row within the 0.5 percentile" but went bankrupt. 860 companies never belong to the category "at least 10 days in a row within the 0.5 percentile" and also never went bankrupt. 268 cases occurred in which a company belong to the category "at least 10 days in a row within the 0.5 percentile" and never went bankrupt. 114 firm cases are detected in which a company belong to the category "at least 10 days in a row within the 0.5 percentile" and went bankrupt after this event occurred. This covers 75% of the bankruptcy cases. Taking also the other classification categories into account, the criterion appears as a reliable criterion.

Figure 5 shows the number of financial distress cases per year for the derived financial distress criterion (distance to default lower or equal to 1.5 and belonging for at least 10 days in a row to the 0.05 percentile) and Figure 6 shows as a comparison the amount of legal bankruptcy cases per year. The figure underlines that combining the relative distance to default level and the absolute distance to default into a financial distress criterion reflects economic up- and downturns.

Whereas Figure 5 has its peak of a first recognition of a financial distress situation in 2001, the peak of legal bankruptcy processes occurred in 2002. This might be the case because the financial distress situation is on aver-

Table 9
Default sample using a Merton-based financial distress criterion

Percentile	Days in a row	Financially distressed & ahead of bankruptcy	Not financially distressed & bankrupt	Not financially distressed & no bankruptcy	Financially & no bankruptcy	Overall number of financial distress
0.05	22	106	57	875	253	359
	20	108	56	874	254	362
	14	108	56	863	267	375
	12	110	52	861	267	377
	10	**114** (75% of bankruptcy firms)	**49**	**860**	**268**	**382** (30% of all firms)
	9	115	48	859	269	384
	8	116	48	857	271	387
	4	116	45	854	276	392
	3	119	42	852	277	396
	1	121	42	847	285	406
0.03	22	86	78	918	204	290
	20	87	77	914	207	294
	13	93	72	914	211	304
	12	92	73	910	215	307
	10	95	70	908	220	315
	9	98	67	906	222	320
	8	100	67	906	224	324
	4	105	61	903	225	330
	3	106	60	898	227	333
	1	113	53	884	242	355
0.01	4	63	97	974	143	206
	3	63	95	971	146	209
	1	70	89	964	154	224

Notes. The table shows the percentile matrix based on the combined Merton model-based criterion. Multiple company cases are allowed, which means a firm might be classified more than once as financially distressed. The table is based on a daily percentile classification for a time period 1993-2007. The table shows how many firms fall for certain days in a row into a certain percentile class, having a distance to default of 1.5 or lower (and are therewith classified as financially distressed) and filed for bankruptcy or not.

Fig. 5. Development of the financial distress cases over time

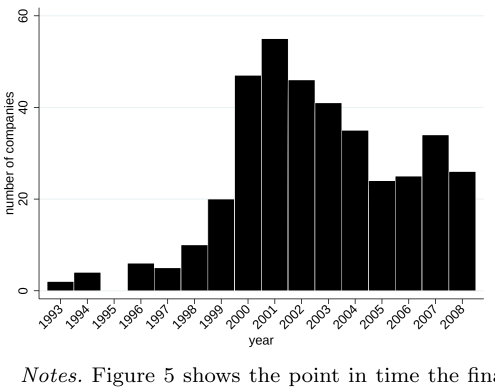
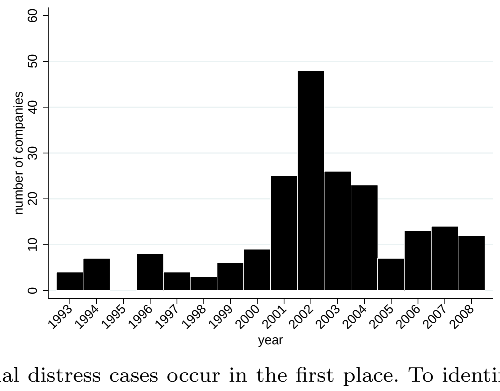


Fig. 6. Development of bankruptcy cases of overall sample firms



Notes. Figure 5 shows the point in time the financial distress cases occur in the first place. To identify financial distress the financial distress criterion is used. Figure 6 shows the point in time sample firms filed for bankruptcy. The bankruptcy information is provided by Hoppenstedt and LexisNexis as well as the firms' homepages.

age potentially recognised before the firm enters a legal bankruptcy process. Furthermore, financial distress occurs more often. This might reflect that companies which did not file for bankruptcy but chose private debt-restructuring as a way to overcome the financial distress are also included in the sample.

5.4 Regression model-based validation of the financial distress criterion

To investigate whether or not using the derived financial distress criterion increases the predictive power of bankruptcy compared to the pure distance to default, a logit regression is performed. A dummy variable measuring legal bankruptcy (0) or no bankruptcy (1) serves as the dependent variable ($P(bankruptcy)_{it}$). The financial distress criterion ($distress\ criterion_{it}$) is applied as an independent variable.

I use further explanatory variables as discussed above, namely the distance to default (dd_{it}), return on assets ($return\ on\ assets_{it}$), working capital to total assets ($working\ capital/assets_{it}$), sales growth ($growth_{it}$), asset turnover ($asset\ turnover_{it}$), the firm's equity-debt ratio ($MV/liabilities_{it}$), and size ($size_{it}$). Furthermore, industry dummies ($industry_{it}$) and year dummies ($year_t$) are included. The regression model is displayed below:

$$\begin{aligned} P(bankruptcy)_{it} &= \beta_0 + \beta_1\ distress\ criterion_{it} + \beta_2\ dd_{it} \\ + \beta_3\ return\ on\ assets_{it} &+ \beta_4\ working\ capital/assets_{it} + \beta_5\ growth_{it} \\ &+ \beta_6\ asset\ turnover_{it} + \beta_7\ MV/liabilities_{it} + \beta_8\ size_{it} \\ &+ \beta_9\ industry_{it} + \beta_{10}\ year_t + u_{it} \end{aligned} \tag{12}$$

Overall panel data for a firm sample of 1,265 firms (i) including 164 firms which filed for bankruptcy serves as the database for a time period 1993-2007 (t). I perform a pooled (Table 10 model I), a matched sample (Table 10 model II) and a panel data regression (Table 10 model III) as described in Section 5.2. I perform a Wald test leading to the result that year dummies need to be included. All three regression models indicate that beside the distance to default the derived financial distress criterion has significant predictive power in terms of explaining the legal bankruptcy. In accordance with the expectations the results show the higher the distance to default is, the lower is the probability of a legal bankruptcy process. Additionally the results show that if a firm is indicated as financially distressed using the financial distress criterion, the probability of bankruptcy is higher. This underlines that the criterion has further explanatory power.

Table 10
Logit regression financial criterion explaining legal bankruptcy

	Logit regression model		
	I	II	III
	(Pooled regression)	(Matched sample regression)	(Panel regression)
Explai variables:			
Financial distress criterion	3.2875*** (0.000)	1.0854*** (0.010)	8.020*** (0.000)
Distance to default	-0.0289*** (0.000)	-0.0523*** (0.000)	-0.0419*** (0.000)
Return on assets	0.0245 (0.230)	-3.7785*** (0.000)	-0.1234** (0.044)
Working capital to assets	-0.7218*** (0.000)	-1.7798*** (0.002)	-1.3515*** (0.003)
Sales growth	-0.0023*** (0.000)	-0.0582** (0.081)	-0.0055** (0.029)
Asset turnover	0.0288 (0.179)	-0.0011 (0.983)	-0.0870 (0.454)
Market equity to liabilities	-0.0002 (0.443)	-0.0873 (0.184)	-0.0046*** (0.001)
Size	-0.1021*** (0.000)	0.0580 (0.177)	-0.1154*** (0.001)
Mining and construction	0.0289 (0.904)	-1.289714 (0.172)	-3.1802**(0.043)
Manufacturing	0.4667*** (0.000)	1.3788*** (0.006)	-1.9292*** (0.000)
Constant	-3.4869*** (0.000)	-6.2281*** (0.000)	-9.5658*** (0.000)
Number of observations	41,510	1,217	41,510
Pseudo R^2	0.3308	0.7759	
Number of groups			1,265

Notes. Logit regression explaining legal bankruptcy based on time-series observations for individual firms between 1993 and 2007. The models I - III show the results of a pooled logit, a matched sample and a panel data logit regression. The financial distress criterion is a dummy variable (level of distance to default is lower or equal to 1.5 and the firm is in the 0.05 distance to default percentile for at least 10 days in a row). Year dummies are included. P-values are in parentheses.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

5.5 *Restructuring information-based validation of the financial distress criterion*

Even if a company never filed for bankruptcy, a classification as financially distressed could be reasonable because the firm might have chosen the way of private restructuring. Thus the financial distress criterion should also identify non-bankruptcy firms avoiding bankruptcy by a private restructuring process. In a final step a search for restructuring terms serves as a validation process. Therefore, potential restructuring methods are considered to define different searching terms.

Altman/ Smith (1999) define restructuring as: "...any substantial change in a firm's assets portfolio or capital structure. Its objectives are usually to increase value to the owners by improving operating efficiency, exploiting debt capacity, and redeploying assets". In this context, several measures can be taken to overcome the financial distress situation and might be relevant for the validation of the criterion. Basically, a differentiation can be made between financial measures and management measures. Internal financial measures in the context of overcoming financial distress comprise measures concerning the fixed assets and working capital. As internal finance measures might not be sustainable, additional sources of financing might be required. Equity measures basically comprise the increase/ decrease in share capital, the deletion/ reduction of dividends as well as the granting of shareholders' loans. Debt-based measures

Fig. 7. Distance to legal insolvency in relation to financial distress date

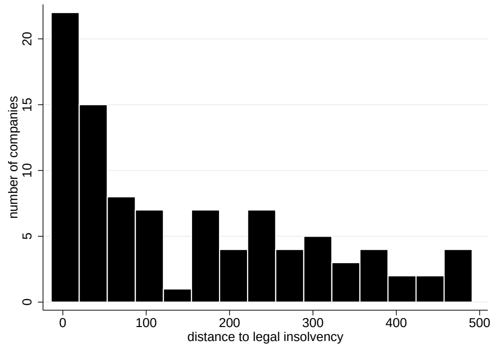
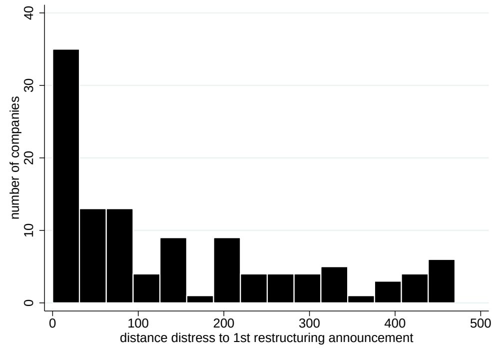


Fig. 8. Distance to 1st restructuring announcement after financial distress



Notes. Figure 7 shows the time range between the point in time of the financial distress event and the event of legal bankruptcy. The financial distress event is identified using the Merton model-based combined criterion. The legal bankruptcy is identified using Hoppenstedt and LexisNexis and the firms' homepages. Figure 8 shows the time range between the point in time the financial distress event is recognised by using the Merton model and a restructuring event reported in LexisNexis. The keyword search in LexisNexis for restructuring events is based on the words reported in Appendix B.

in terms of restructuring include e.g. trade credits, increase of loans, emission of bonds, as well as the deployment of asset-backed securities and leasing.

Furthermore, management measures might be observed as an indicator for financial distress. An increase in management turnover, the reorganisation of business units, the sale of business units as well as changes in the corporate governance mechanism might be indicators for financial distress. The filing for bankruptcy as a court-managed restructuring process can also be seen as a restructuring measure.

To finally validate the criterion I investigate how many of the 382 identified financially distressed firms filed for bankruptcy within a time period of 10 trading days before and 500 days (about 375 trading days) after the financial distress event occurred: 95 of the financially distressed firms filed for bankruptcy within the defined period according to Hoppenstedt, LexisNexis or the firms' homepages. I use LexisNexis to find out more about the remaining firms. I search for words related to restructuring in combination with the company name (for the exact search terms see Appendix B).

I find that an additional 113 firms (in addition to the 95 firms which filed for bankruptcy) report restructuring within that time period. The distance of the legal bankruptcy filing and the first announcement of restructuring after the financial distress event occurred are displayed in Figure 7 and Figure 8. The Figures indicate that the bankruptcy and restructuring information occur close to the financial distress identification date.

Beside searching for the restructuring keywords and the word "bankruptcy", I searched for a reporting of "liquidation". An overview can be found in Table 11. Two of the remaining firms reported an agreement of liquidation in their annual general meeting. The remaining 56 report a change in “management”. A change in management covers a board member change and excludes cases as retirement-related changes or maternity leave. Additionally two firms report a “merger”. A further 13 firms mention a “sale of a business segment/ business unit” or a “sale of a subsidiary”. Furthermore, nine firms filed for “bankruptcy” after a period of more than 500 trading days. The table shows that for 290 out of the 382 firms an event is reported which might be an indicator for a financial distress situation. Thus the derived distress criterion is seen as a reasonable criterion.

Table 11
Descriptives of the financial distress sample

Within 375 trading days:	Number of firms
Rirms identified as financially distressed	382
thereof	
firms which file for **bankruptcy**:	95
	=287 remaining firms
thereof	
firms which **report restructuring terms**:	113
	=174 remaining firms
thereof	
firms which **report liquidation**:	2
	=172 remaining firms
thereof	
firms which **report management change**:	56
	=116 remaining firms
thereof	
firms which **report merger/ takeover**:	2
	=114 remaining firms
thereof	
firms which **report sale of business** unit or subsidiary:	13
	=101 remaining firms
thereof	
firms which file for bankruptcy after more than 375 trading days:	9
	=92 remaining firms without reporting one of the aforementioned events

Notes. Hoppenstedt, LexisNexis and the firms’ homepages are used to discover the bankruptcy information. LexisNexis is the source for the restructuring information and firm liquidation as well as for management change information and sale of business units or subsidiary. Datastream and LexisNexis are the source for takeover and merger information.

6 Conclusion

The objective of this paper is to develop a distress identification criterion for corporate finance investigations such as management turnover, valuation of restructuring methods, equity offerings or the influence of a relationship lender in financial distress. For such corporate finance investigations a financial distress identification method is needed to determine if and at what point in time a firm is in financial distress or leaves the financial distress state.

Section 2 discusses different financial distress definitions and methods used in the literature. This paper defines financial distress as a situation in which the firm cannot meet its current obligations or if a sufficient likelihood is given concerning the inability to meet the current obligations. Different financial distress identification methods used in the literature are discussed in the second section such as the univariate analysis, the discriminant analysis, the logit regression models and structural models as well as the filing for bankruptcy and the use of restructuring information and ratings information.

The section concludes that due to the information asymmetry problem between management and capital market participants, accounting-based identification methods might be less informative. Accounting-data based measures further have the disadvantage of a time lag in identifying the financial distress stage. This may lead to the consequence that a financial distress situation is not identified by the use of a purely accounting-based method. The distance to default according to the Merton model allows us to identify the distress situation on a daily basis. The share price also considers capital market expectations and considers asset volatility and therewith risk. An ante-distress stage, a distress stage and a post-distress stage can be identified on a daily basis and thus very precisely.

The criterion of bankruptcy filing does not include firms which face financial distress but, however, avoid the bankruptcy process by private restructuring. In addition the criterion is not very precise, because a filing for bankruptcy might happen a long time after the firm faces financial difficulties. Furthermore, a potentially post-financial-distress state can not be identified with this criterion. Using restructuring information might also lead to a time lag, as restructuring measures need to be discussed, implemented and reported by the management. However, this information serve as a good validation criterion. The critical point about using rating agency ratings is that ratings are available only for a relatively small number of firms and face the problem of slow adjustments. Thus, the examination of the Merton model constitutes the focus of this study. Section 3 therefore deals with the empirical implementation of the Merton model for the German market.

Section 4 addresses a side aspect, comparing the logit regression model and the Merton model. DeAngelo/ DeAngelo/ Skinner (1994) observe the application of systematic accounting policy measures in order to influence performance indicators in favour of the management. I assess the sensitivity of those models in terms of different accounting policies the management might choose. As an instrument to investigate this aspect I use the German Accounting Standard Data (HGB) and international accounting standard data provided by the Hoppenstedt database for a firm within the year of an accounting standard change. I calculate the firm's probability of default by using the Merton model and the logit regression model considering the two accounting standards information. I observe that the Merton model is less sensitive in terms of accounting standard changes than the logit regression model and therewith the Merton model is more robust in terms of accounting policies the management might choose.

After discussing different distress identification methods the widely known logit regression model (Ohlson (1980)) and the Merton model (Merton (1974)) are compared in Section 5. The explanatory power of the two models is compared using a ROC curve analysis in terms of bankruptcy cases. The ROC curve is suggested by the Basel Committee on Banking Supervision (2005) as a validation method for bank internal ratings. The ROC curve analysis indicates the higher predictive power of the Merton model compared to the logit regression model in terms of bankruptcy cases. I carry out a logit regression in order to underline the superior explanatory power of the Merton model.

The Merton model is applied to develop a financial distress identification criterion. In the following Section 5 focuses on the calibration and validation of a Merton model-based criterion. The dataset consists of 1,265 German publicly traded firms with market data available on Datastream and balance sheet data available on Hoppenstedt. To calibrate and validate the financial distress criterion, bankruptcy information as well as information about restructuring measures as management change, merger/ takeover or the sale of a business unit/ subsidiary is used. LexisNexis, Hoppenstedt and the firms' homepages are the sources for this information. The empirical German market investigation show that a criterion of an absolute distance to default threshold (distance to default lower than or equal to 1.5 standard deviation of asset value) and a relative distance to default threshold (the company belongs to the lowest 0.05 percentile in terms of its distance to default for a certain time period) leads to a criterion which also takes market up- and downturns into account. Restructuring information indicates that the criterion is a reasonable tool with which to identify a financial distress situation. Furthermore a regression analysis shows that the criterion has greater explanatory power in terms of bankruptcy than the pure distance to default.

Overall, the analysis shows that the Merton model is a solid basis for a financial distress criterion. Daily share price data is taken into account which reflects the future capital market's expectations regarding the firm. Due to the daily availability of the share price, a daily update of the firm's distress condition is possible. The criterion is not as sensitive to the chosen accounting policy by the management as accounting data-based methods are. The criterion takes volatility of asset values into account to consider risk. The combination of the relative criterion (belonging to the lowest 0.05 percentile for a certain time period, e.g 10 days in a row) and the absolute criterion (the distance to default is lower than or equals 1.5) leads to a combined criterion considering market up- and downturns. The conducted research shows that the criterion serves as a reasonable basis for an ex-ante-distress, a distress and post-distress situation identification criterion.

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Appendix

A Distance to default descriptive statistics

To investigate the Merton model as a basis for a financial distress criterion, the distance to default and the probability of default are calculated for all German publicly listed companies between January 1, 1993 and December 31, 2007 for which Datastream provides data. I investigated the distance to default for different sectors. The investigation shows that the mean distance to default varies for different sector firms. The sample composition in terms of industry sector and the mean of the distance to default calculated on basis of the Merton model are displayed in Table A.1.

Table A.1
Distance to default and probability of default mean and overall median by industry sector

SICCODE Sector	SIC 1st digits	SECTOR DETAIL	DD Mean	DD Std Dev	Obs. in month	No. firms
Agriculture, Forestry, Fishing	08	Forestry	29.2	34.3	998	6
Construction	15	General Building	14.1	26.7	1,340	13
Construction	16	Heavy Construction	14.4	29	966	7
Construction	17	Special Trade Contractors	17.5	27.1	681	7
Finance, Insur., Real Estate	67	Holding & Other Invest. Offices	26.1	34.1	8,586	97
Finance, Insur., Real Estate	64	Insurance Agents, Brokers & Service	9.4	17.8	393	5
Finance, Insur., Real Estate	63	Insurance Carriers	18.2	21.2	933	7
Finance, Insur., Real Estate	65	Real Estate	27.9	35.9	11,409	99
Finance, Insur., Real Estate	62	Security & Commodity Brokers	12.4	21	1,542	33
Manufacturing	23	Apparel & Other Textile Products	10	14.6	1,745	11
Manufacturing	28	Chemicals & Allied Products	7	10.3	4,095	49
Manufacturing	36	Electrical Equipment & Components	9.6	19.4	6,462	96
Manufacturing	34	Fabricated Metal Products	27.9	36.1	2,139	16
Manufacturing	20	Food & Kindred Product	27.2	33.4	5,883	2
Manufacturing	35	Industrial & Commercial Machinery	15.9	28.7	11,172	94
Manufacturing	31	Leather & Leather Products	9.5	4	331	2
Manufacturing	24	Lumber & Wood Products	13.3	23.5	537	4
Manufacturing	38	Measurement Analysing	13.2	22.5	2,648	30
Manufacturing	39	Misc. Manufacturing Industries	9.7	15.7	1,052	8
Manufacturing	26	Paper & Allied Products	11	18.4	1,298	9
Manufacturing	33	Primary Metal Industries	25.5	34.6	1,828	11
Manufacturing	27	Printing & Publishing	17.7	30.3	1,113	13
Manufacturing	30	Rubber/ Misc. Plastic Products	11	21.3	1,764	15
Manufacturing	32	Stone, Clay, Glass & Concrete Products	16.6	26.3	4,144	25
Manufacturing	22	Textile Mill Products	19.8	31	2,236	14
Manufacturing	37	Transportation Equipment	8.81	16.7	3,580	30
Mining	13	Oil & Gas	22.7	34.5	227	2
Public Administration	99	Nonclassifiable Establishments	3.1	0.4	12	4
Retail Trade	56	Apparel & Accessory Stores	9.7	20.7	581	5
Retail Trade	52	Build. Mat., Hardware, Garden Supp.	2.5	2.1	100	2
Retail Trade	54	Food Stores	8.5	14.8	213	36
Retail Trade	53	General Merchandise Stores	26.1	39.2	367	3
Retail Trade	57	Home Furniture & Equipment Stores	8.8	18.59	546	5
Retail Trade	59	Miscellaneons Retail	8.7	11	863	8
Services	79	Amusement & Recreation Services	28.1	37.9	1,261	13
Services	75	Automotive Repair Services & Parking	7.2	13.7	507	5
Services	73	Business Services	6.5	12.9	12,535	177
Services	82	Educational Services	7.2	5.7	191	2
Services	87	Engineer., Account., Research Managem.	8.2	17.3	2,817	45
Services	80	Health Services	15.8	26.1	1,699	15
Services	70	Hotels, Rooming, Camps & Other Lodging	26.1	35.4	396	4
Services	78	Motion Pictures	3.5	9.4	1,800	26
Services	84	Museums, Art Galleries & Gardens	30.3	33.15	376	2
Services	72	Personal Services	8.1	7.2	186	4
Transp. & Publ. Utilities	48	Communications	6	14.3	1,447	25
Transp. & Publ. Utilities	49	Electric, Gas & Sanitary Services	16.4	20.7	3,924	35
Transp. & Publ. Utilities	41	Local, Suburban Transit	49.4	39.5	1,259	7
Transp. & Publ. Utilities	42	Motor Freight Transportation	31.7	36.6	486	4
Transp. & Publ. Utilities	40	Railroad Transportation	48.9	38.7	362	2
Transp. & Publ. Utilities	45	Transportation By Air	12.3	24	423	4
Transp. & Publ. Utilities	47	Transportation Services	7.4	13	721	9
Transp. & Publ. Utilities	44	Water Transportation	11.8	19.9	830	7
Wholesale Trade	50	Durable Goods	14.1	26.0	5,052	54

Notes. The table above shows the distance to default and probability of default mean calculated according to the Merton model for the listed firms on the German stock market.

B Validation of the financial distress criterion

To validate a criterion for financial distress appears difficult. As firms might apply private restructuring to leave the financial distress state or to avoid filing for bankruptcy, observing restructuring measures might serve as a reasonable validation criterion. Also, observed restructuring measures might serve as a reasonable validation criterion. Thus, in a final validation step I investigate whether or not the firms identified as financially distressed based on the developed criterion also report restructuring measures. Therefore, I conduct research within data on the German press (LexisNexis database) for a time period of 375 trading days after the financial distress is identified. The searching terms I used to find restructuring measures are displayed below:

- R/restruktur (e.g. Restrukturierung, restrukturieren)
- N/neustruktur (e.g. Neustrukturierung, neustrukturieren)
- S/sanier (e.g. Sanierung, sanieren)
- N/neuausricht (e.g Neuausrichtung, neuausrichten)
- U/umstruktur (e.g. Umstrukturierung, umstrukturieren)
- N/neuorientier (e.g. Neuorientierung, neuorientieren)
- N/neuorganis (e.g. Neuorganisation, neuorganisieren)
- N/neustruktur (e.g. Neustrukturierung, neustrukturieren)
- Strukturveränderung
- Strategiewechsel
- Rationalisierungsprogramm
- Strukturmaßnahmen
- Veränderung /Wechsel Kerngeschäft
- Trennung von Verlustbringern

The effect of relationship lending on a firm's probability of financial distress

Working Paper II

N. Stephenson [1]

Abstract

This paper examines whether or not having a relationship lender affects the firm's probability of financial distress. I use German Credit Register information provided by the German central bank (Deutsche Bundesbank) for the period 1993-2007 to identify the relationship lending status of a firm. To identify financial distress, a criterion based on the Merton model is derived. I apply probit regression models to identify determinants of financial distress and relationship lending. Finally, a bivariate probit regression model is performed, to address the aspect of endogeneity of firm-bank relationships and financial distress. The regression models indicate that having a relationship lender has no significant influence on the firm's probability of financial distress. This finding supports the equilibrium structure hypothesis, stating that having a relationship lender is an endogenous outcome of a selection of advantages and disadvantages of having a relationship lender arrived at a bank-relationship equilibrium. The regression models indicate that profitability, liquidity, size and efficiency lower the probability that a firm will enter financial distress.

[1] The research for this paper was partly conducted while Nadine Stephenson was a visiting researcher at the Deutsche Bundesbank. This working paper represents the author's personal opinion and does not necessarily reflect the views of the Deutsche Bundesbank or its staff. Nadine Stephenson would like to thank the Deutsche Bundesbank most sincerely for its hospitality and for providing its data. Special thanks go to Ingrid Stein for her valuable suggestions and inputs in terms of the Deutsche Bundesbank dataset. Of course, all remaining errors are those of the author.

1 Introduction

The modern theory of financial intermediation emphasises repeated interactions between banks and firms. This dynamic concept is referred to as "relationship lending" and accounts economically for the potential benefits of the German institution of a "Hausbank"(e.g. Sharpe (1990), Fischer (1990), Rajan (1992), Boot (2000) and Elsas (2001)). A relationship lender in a theoretical sense can be characterised by the following attributes: The relationship lender has an information advantage compared to other lenders having no close relationship (arm's length banks). The relationship lender is able to renegotiate credit contracts and possesses a certain degree of negotiating power (Boot (2000) and Elsas (2005)). The relationship lender might accept a loan contract which is not profitable in the short term but leads to profitable contracts in the long term (Boot (2000)). Having a relationship lender might lead to different bank and firm decisions and thus a relationship lender might influence the firm's probability of financial distress. The aim of this paper is to investigate empirically whether or not a relationship lender significantly influences the firm's probability of financial distress.

In the literature the hypothesis can be found that banking relationships reduce information asymmetry by means of continued relationships with their customers (Boot (2000)). Lenders generate information about their borrowing firms and borrowers are more willing to provide information. Thus, information asymmetry is reduced by means of transactions. Having a long term relationship allows firms to enter contracts which are not profitable for the bank in the short term, but are, however, profitable in the long term (Boot (2000)). Furthermore, the information generated by the lender through repeated interactions leads to a reduction of the bank's fixed costs for screening and monitoring (Boot/ Greenbaum/ Thakor (1993)). These fixed cost reductions could partly be passed on to the customer. Additionally, the bank gains sector-specific knowledge that might lead to an increase in investment project values (Boot/ Thakor (2000)) and the firm might profit from this knowledge as well. Moreover, as a relationship lender has an incentive to monitor and, due to its strong negotiation power, also the right to monitor, the principal agent problem of managerial behaviour might be reduced. Overall, the customer can benefit through better loan terms (Petersen/ Rajan (1994) and Berger/ Udell (1995)), more easily attainable capital (Petersen (1999)), and liquidity assurance (Elsas/ Krahnen (1998)). The presented considerations indicate that **having a relationship lender might reduce a firm's probability of financial distress**. An empirical investigation to validate this hypothesis has not, so far, been performed. Only examinations of related hypotheses can be found. For example, Hoshi/ Kashyap/ Scharfstein (1990) investigate financially distressed Japanese firms and observe that firms with strong ties to a main bank invest more and have higher sales than firms without strong bank ties.

In contrast thereto, having a strong bank relationship might lead to costs for the firm. Having a relationship lender gives an information monopoly to the lender and might lead to high switching costs (Sharpe (1990), Rajan (1992)). This indicates that a relationship lender might have a negative impact on the firm's probability of financial distress. A further possible negative effect might linked to the fact that it is especially those firms which are in need of a relationship lender which choose to have one. For example small firms with limited access to the capital market or firms mainly invested in risky assets might choose this type of lender. In the empirical literature Bolton/ Scharfstein (1996) find that managers are more likely to tend to a strategical firm default in order to divert cash to themselves when there is only one creditor. Weinstein/ Yafeh (1998) analyse Japanese firms and find that strong bank ties exhibit slow firm growth rates and low profitability in cases where the access to capital markets is limited. **Having a relationship lender might thus increase a firm's probability of financial distress**. However, the findings could be based on a selection bias. Yosha (1995) observes that more profitable firms prefer bilateral financing to reduce information disclosure. This indicates that the relationship lending status might also be influenced by the firm's financial situation. Consequently, the potential endogeneity between relationship lending and the firm's probability of financial distress is explicitly taken into account within this study. A bivariate probit regression using the determinants of relationship lending as a first stage equation is applied to address the endogeneity between relationship lending and the firm's probability of financial distress.

For the German market Agarwal/ Elston (2001) analyse a sample of large listed and unlisted firms. They observe that firms with a strong bank relationship in Germany do benefit from an increased access to capital. However, they find no evidence to support the hypothesis of either higher profitability or growth for bank-influenced firms. Chirinko and Elston (2006) use a sample of 91 listed German firms. They observe that a strong bank influence is not related to a reduction in financing costs or a change in profitability for the firm. Those studies indicate that a relationship lender has no influence on profitability or firm growth. To explain the effect of no influence by the relationship lender, the analysis of the results of an ownership-structure study performed by Demsetz (1983) and Demsetz/ Lehn (1985) is considered. According to Demsetz (1983) there is no cross-sectional relationship between the firm's value and the concentration of ownership, since the ownership structure that "emerges is an endogenous outcome of competitive selection in which various cost advantages and disadvantages are balanced to arrive at an equilibrium organization of the firm". Shareholder wealth maximization may require a diffuse external ownership structure in one case whereas a large outside equity block is optimal in another firm case. Consequently, one cannot deduce differences in firm values from differences in size of insider stakes across firms. Demsetz/ Lehn (1985) support this view in their empirical investigation of U.S. firms. The equilibrium structure argument by Demsetz (1983) would support the hypothesis that having a relationship lender is an endogenous outcome of a selection of advantages and disadvantages of having a relationship lender arrived at a bank-relationship-structure equilibrium. Consequently, it is reasonable to argue that **having a relationship lender might have no effect on the firm's probability of financial distress**.

This paper is also related to the empirical financial distress literature. In general those papers focus on accounting data to identify the probability of financial distress (e.g. DeAngelo/ DeAngelo (1990), Hoshi/ Kashyap/ Scharfstein (1990), Asquith/ Gertner/ Scharfstein (1994), Dahiya/ Saunders/ Srinivasan (2003), Griffin/ Lemmon (2002)). This study derives a financial distress criterion based on the Merton model, a so-called structural model, to analyse whether having a relationship lender influences the firm's financial situation. The main determinants of the Merton model are the firm's leverage ratio and the volatility of the asset value. To estimate the market value of equity in this context, the share price of the firm is used. This considers future expectations of the capital market. By taking asset volatility into account risk is considered. Thus, this model stands out compared to predominately accounting data-based financial distress identification models such as the discriminant analysis (e.g. Altman (1968)) and logit regression models (e.g. Ohlson (1980)) or the univariate identification models (Beaver (1966)) used in the literature.

To investigate if a relationship lender has a significant influence on the firm's probability of financial distress, I apply a dataset of 1,265 German publicly listed firms with equity market data available on Datastream for a time period between 1993 and 2007. To identify whether or not a firm has a relationship lender, I am able to access German Credit Register reports provided by the German central bank. I use the Herfindahl-Hirschman index as the basis for a criterion to identify a relationship lender.

I apply probit regression models to identify determinants of financial distress and relationship lending. In addition, a bivariate probit regression model is performed to address the aspect of endogeneity of firm-bank relationships and financial distress. The regression models support the equilibrium structure hypothesis (Demsetz (1983)) that a relationship lender has no significant influence on the firm's probability of financial distress. The models further indicate that the average industry distance to default, the firm's profitability, the liquidity situation, and the size as well as the efficiency of the firm have significant explanatory power in terms of the probability of financial distress.

The remainder of this paper is organised as follows. Section 2 provides a literature review and defines the notation of financial distress and relationship lending. Section 3 describes the data set used for the empirical analysis. In Section 4 a criterion to identify financial distress is derived. Section 5 derives a criterion to identify a relationship lender. In Section 6 an univariate analysis and a multivariate analysis of the determinants of financial distress and relationship lending is conducted. Section 7 summarises and concludes.

2 Related literature

2.1 Identification of financial distress

A variety of definitions exist in the economic literature for the notion of financial distress (e.g. Zmijewski (1984), Gilson (1990), Sharpe/ Alexander/ Bailey (1990), Greenbaum/ Thakor (1995), Altman/ Hotchkiss (2006)). In the following, financial distress is defined as a situation in which the firm cannot meet its current obligations, or in which there is sufficient likelihood of its inability to meet current obligations.

The problem of how to identify financial distress is hard to solve and the literature on financial distress prediction models is sparse. The models to identify financial distress are often based on prediction models initially designed for bankruptcy prediction (Altman (2000)). Univariate models consider single financial ratios to separate non-bankruptcy from bankruptcy-threatened companies (Beaver (1966)). In the financial distress literature the univariate models are used by several authors. DeAngelo/ DeAngelo (1990) classify a firm as financially distressed if the firm experiences annual losses for three years in a row. Asquith/ Gertner/ Scharfstein (1994) use the interest coverage ratio to analyse bond issuers facing financial distress. Hoshi/ Kashyap/ Scharfstein (1990), Dahiya/ Saunders/ Srinivasan (2003), and Whitaker (1999) use interest ratios to identify financial distress. Opler/ Titman (1994) use poor stock performance and negative sales growth and Clark/ Ofek (1994) also use poor stock performance as an indicator for financial distress.

The widely known models of Altman (1968) and Ohlson (1980) predominately apply accounting data to estimate the probability of bankruptcy in their discriminant and logit regression models. As a predictor of financial distress Altman (2000) and Frydman/ Altman/ Kao (1985) investigate discriminant models initially implemented to identify bankruptcy. Griffin/ Lemmon (2002) use the Ohlson logit regression model to investigate financial distress risk and stock returns.

Another criterion used in the literature to identify financial distress is filing for bankruptcy (e.g. used by Khanna/ Poulsen (1995)). Observed restructuring measures such as management turnover, financial measures such as equity offerings or debt increases or the sale of important business units are used as an identification criterion for financial distress as well. For example James (1996), Gilson/ Vetsuypens (1993) and Gilson (1997) use a restructuring term key word search to identify financially distressed firms. Moreover, ratings of rating agencies are used in the literature to identify firms facing financial distress and are applied e.g. by Castanias (1983) and Molina (2005).

Beside the group of models originally initialized to predict bankruptcy, there is a group of so-called structural models in the literature which are not based on the aforementioned bankruptcy prediction models. One of the main models in this context is the Merton model (Merton (1974)). The main determinants of the Merton model are the firm's leverage ratio and the volatility of the asset value. To estimate the market value of equity in this context, the share price of the firm is used. This considers future expectations of the capital market. By taking asset volatility into account risk is considered. Vassalou/ Xing (2004) apply the Merton model to identify financial distress and investigate default risk and equity returns.

Comparing the aforementioned identification methods, it can be said that the studies using discriminant and logit regression models all have in common that each applies a criterion that classifies companies primarily on the basis of historical financial statements. Hence, the problem arises that the required data are published only after a certain time lag and are only reported on a quarterly or annual basis. Depending on the defined classification threshold five financial statements were required for the above-mentioned studies, leading to an additional time lag. Concerning the hypothesis this paper examines, a more precise measure for the point of financial distress recognition is required. Therefore, a criterion based only on annual report data does not appear precise enough. In addition, risk is not considered in those accounting data-based models.

Most of the ratios used for the univariate classification method are also based on financial ratios. Moreover, the classification on only one ratio appears not to be adequate as there might be more than one influencing factor that leads to financial distress. In terms of using legal filing for bankruptcy to identify financial distress it has to be said that regarding the objective of this investigation it does not seem adequate to limit the company selection to firms which filed for bankruptcy.

Using a restructuring key word search might lead to a time lag in terms of financial distress identification as well. Restructuring measures have to be discussed, decided and reported by the management. In addition, a press key word search is very time consuming. Nevertheless, in terms of the validation of a financial distress criterion, restructuring information appears applicable and is applied in the following. The critical point about using rating agency ratings is that ratings are available only for a relatively small number of firms and face the problem of slow adjustments. Structural models such as the Merton model consider the share price reflecting the capital market's future expectations in terms of the firm. Due to the daily availability of the share price, a daily update of the firm's probability of financial distress is possible. By considering asset volatility, risk is taken into account. Reflecting these aspects the Merton model is applied to identify financial distress within this study.

2.2 Identification of relationship lending

According to Elsas (2001) a bank-firm relationship is every connection between a bank and its customer that is more than a simple anonymous financial transaction. In this context Boot (2000) defines "relationship banking" as the provision of financial services by a financial intermediary that:

- invests in obtaining customer-specific information, often proprietary in nature; and
- evaluates the profitability of these investments through multiple interactions with the same customer over time and/ or across products.

The definition underlines the two aspects of proprietary information and multiple interactions. Fischer (1990) defines the German "Hausbank relationship", a special relationship lending form, as follows:

- a Hausbank relationship is a long term relationship between the bank and the firm, leading to mutual trust,
- the Hausbank has the largest share of the financial business of the firm, especially of the credit business,
- the Hausbank has an information advantage due to the long term and intensive relationship, and
- the Hausbank has a special responsibility for the firm in times of corporate distress.

Considering these aspects emphasised by Boot (2000) and Fischer (1990), in the following a relationship lender is defined in accordance with the "Hausbank relationship" definition provided by Elsas/ Krahnen (1998). A relationship lender is defined as the premier lender of a firm, being equipped with more reliable and more timely information than any 'normal' non-relationship-lender institution. This definition underlines the aspects of the premier lender, of an information advantage and information asymmetry all of which will be considered in the search for an identification criterion for relationship lending.

To identify a relationship lender, different concepts can be found in the literature. Petersen/ Rajan (1994), Berger/ Udell (1995) and Ongena/ Smith (2001) apply the duration of a firm-bank relationship as a criterion to identify the relationship lender. This approach is based on the idea that the relationship intensity increases with the duration of a relationship. However, Elsas (2005) finds in his empirical investigation that the duration of the firm-bank relationship is not related to the firm-bank relationship status. An example of such a long term relationship with a low intensity would be where a bank keeps only a foreign currency account for a firm for certain foreign transactions. But a firm may enter a credit contract of a certain amount and the bank has to request various information to fulfil guidelines such as the German Banking Act (KWG) §18, which dictates that providing loans of a certain size requires that the borrower discloses its financial circumstances. Thus, duration is not applied to the identification of a relationship lender in this study.

Following the definitions presented above, another potential criterion to identify a relationship lender is the number of bank relationships. Elsas (2005) finds in his empirical study that the number of bank relationships is positive related to the Hausbank status. The idea is that being the premier lender to a firm leads to a close relationship. Nevertheless, being the exclusive lender might be too strict a criterion. Providing the largest proportion of a firm's debt could already lead to strong monitoring power. Consequently, the identification criterion should not only take the number of banks into account. The empirical analysis undertaken by Elsas (2005) further shows that a bank's share of debt financing is related to the Hausbank status. This finding is consistent with the definition of relationship lending this paper follows. Thus, this aspect is considered while choosing an identification criterion for relationship lending.

A concentration index, e.g. the Herfindahl-Hirschman index, covers the two aspects "high share of debt of one bank" and "number of bank relationships". A concentration index would also address the information asymmetry aspect emphasised in the relationship lending definition this paper follows of "...being equipped with more reliable and timelier information than any normal non-relationship-lending institution". Thus the Herfindahl-Hirschman index (HHI) is chosen as a basis to determine an identification criterion for relationship lender.

3 Data

All companies listed on the German equity capital market between January 1, 1993 and December 31, 2007 with available market data in Datastream are considered in the investigation. The sample includes currently operating companies as well as delisted companies. In terms of the required debt data a comparison of data provided by the databases Hoppenstedt and Datastream is conducted. The outcome shows that Hoppenstedt, a database for information on financial statements by German firms, has a higher coverage and is more reliable for German companies. One of the reasons is the distinction between accounting standards and the provision of different accounting schemes. This is an important issue for a German capital market investigation. Listed German firms used to draw up their financial statements according to the German accounting standard (HGB). Since 2005, German-listed parent companies are required to draw up their financial statements according to international accounting standards. Financial statement data provided by Datastream do not include information about the accounting standard used. Different accounting standard data are combined in a uniform scheme. For this reason data are partially irreproducible. In addition Hoppenstedt provides better information coverage for German firms. Thus, balance sheet, profit & loss and cash flow data are drawn from Hoppenstedt. Sufficient Hoppenstedt data (covering at least one firm year/250 trading days) is provided for 1,265 firms. I collect panel market and annual report data for those firms for the time period between January 1, 1993 and December 31, 2007.

To calibrate and validate the financial distress criterion I use information based on Hoppenstedt data as well as hand-collected data provided by the LexisNexis database and the firm's website. To find information about bankruptcy

I search within the period 1993-2007 for all sample firms. In terms of restructuring information, used for the validation of the financial distress criterion, I investigate a time period of 500 days after a financial distress event occurred.

German Credit Register information held at the German central bank according to the German Banking Act (KWG) §14 is used to determine whether a firm has a relationship lender. The German Credit Register reports are based on loan reports of credit institutions, financial service institutions and financial enterprises or their branches domiciled abroad. The reports contain quarterly announcements of banks regarding loans provided to their customers. The reports are provided by the German central bank.

4 Measures for financial distress

4.1 Theoretical foundation of the Merton model

To identify financial distress, this paper uses an identification criterion based on the Merton model. In 1974 Merton applied option pricing theory, developed by Black/ Scholes (1973) and Merton (1973), to the evaluation of debt capital. The model supposes that the shareholders will not pay back the raised debt capital at the maturity date if the asset value falls below the debt value. Hence, the equity can be regarded as a call option on the company's assets. In case the shareholder does not exercise the option, the risky assets will be transferred to the debt capital provider, who therefore can be considered as an option writer.

In particular, the Merton model makes two main assumptions. The first is that the asset value (A) is assumed to follow a geometric Brownian motion:

$$dA = \mu_A A dt + \sigma_A A dW \tag{1}$$

where μ_A is the expected continuously compound return on A, σ_A is the volatility of the firm value and dW is the standard Wiener process. The second assumption of the Merton model is that the firm has issued one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying firm asset value with a strike price equal to the firm's debt face value and a time-to-maturity of T. The value of equity as a function of the firm's asset value can be described by using the Black-Scholes-Merton formula:

$$E = AN(d_1) - De^{-rT} N(d_2) \tag{2}$$

where E is the firm's equity value, D the firm's debt face value, r the instantaneous risk-free rate, $N(\cdot)$ denotes the cumulative standard normal distribution function and d_1 and d_2 are given by

$$d_1 = \frac{ln\left(\frac{A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \quad and \quad d_2 = d_1 - \sigma_A\sqrt{T}. \tag{3}$$

In the empirical implementation, the unobservable variables σ_A and A_t can be iteratively estimated for each day in the observation period of the stocks (Vassalou/ Xing (2004) and Crosbie/ Bohn (2003)). For each point in time t, the preceding 250 trading days are used to estimate σ_E as an *initial guess* for the asset volatility, σ_A. Applying the Black/ Scholes formula, this leads to a series of asset values, A_t. These are in turn used to get an updated estimate of σ_A. This estimate is used for the next iteration, and the procedure is continued until the σ_A estimate converges with a tolerance level of 10^{-6}. The final volatility estimate is then used to calculate the asset value estimate, again using Equation (2).

$N(d_2)$ in Equation (2) declares the probability that the equity holder exercises the call option and pays back the credit. $1-N(d_2) = N(-d_2)$ is the probability that the call option is not exercised and no repayment of the credit takes place. $N(-d_2)$ accordingly is called the probability of default (PD). Following Merton (1973) and Merton (1974), the probability of default can be written as:

$$PD = N\left(-\left(\frac{ln\left(\frac{A}{D}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right)\right). \tag{4}$$

Alternatively the distance to default (DD), measuring how many standard deviations the asset value needs to drop to meet the debt value, can be calculated as:

$$DD = \frac{ln\left(\frac{A}{D}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}. \tag{5}$$

A lower distance to default translates into a higher probability of default, and vice versa. In the following, I use the distance to default to sort firms on their default risk. In particular this solves the problem that very frequently observed high values of distance to default correspond to very low probability of defaults, which might raise numerical issues in calculations.

The distance to default determined with this model is applied to identify the firm's probability of financial distress. The debt data from Hoppenstedt serve the calculation of the default threshold. In accordance with Moody's KMV the short term debt is considered at 100% while the long term debt is only considered at 50% (Crosbie/ Bohn (2003)). The FIBOR, and later the EURIBOR, are applied as the risk-free interest rate. The applied time to maturity T is set to $T = 1$.

4.2 Calibration and validation of the financial distress criterion

4.2.1 Investigating the Merton model's predicting accuracy

As the financial distress criterion is, alongside the relationship lending criterion, one of the main elements of this study, I perform certain steps to validate and calibrate the criterion. To validate the Merton model, the basis for the financial distress criterion, I use bankruptcy information as a first step. A ROC (receiver operating characteristic) curve is applied to analyse the predictive power in terms of bankruptcy cases of the Merton model-based probability of default. Furthermore, the explanatory power is compared to those of the probability of default calculated on the basis of a logit regression model (e.g. see Ohlson (1980)). According to the Basel Committee on Banking Supervision (2005), a credit rating model's performance is better the steeper the ROC curve is at the left end and the closer the ROC curve's position is to the point (0,1). Similarly, the model is better the larger the area is under the ROC curve. To calculate the ROC curve, the firms are sorted by their probability of default at a certain point in time calculated using the Merton model and the logit regression model.

The probability of default according to the Merton model is calculated as described above. To calculate the probability of default according to a logit regression model I follow Ohlson (1980) (for further information see Stephenson (2010)). The variables to explain the bankruptcy status in the logit regression model are chosen according to Altman (1968) and Altman/ Hotchkiss (2006) and the Moody's rating for non-listed firms (Dwyer/ Kocagil/ Stein (2004)). I use working capital divided by total assets, retained earnings divided by total assets, earnings before interest and tax divided by total assets, the leverage ratio as the book value of total liabilities divided by total assets and sales divided by total assets. To calculate the probability of default I use an out-of-sample testing procedure covering an overall time period from January 1, 1993 to December 31, 2007.

I rank the probability of default according to each model separately and divide the ranked probabilities of default into percentiles. In the next step it is measured how many of the firms belonging to the class with the x% highest probability of default filed for bankruptcy within the next year. I use Hoppenstedt and LexisNexis information as well as the firms' homepages to identify bankruptcy. The applied ROC curve illustrates the connection between the number of cases which are correcly classified as "bankruptcy cases" and cases which are misclassified as "bankruptcy cases" for different levels of the probability of default. Misclassified cases are called "alpha error". The ROC curves for the two models are displayed in Figures 1 and 2.

The areas under the ROC curves above illustrate that the Merton model has higher predictive power compared to the logit regression model in terms of bankruptcy cases. The area under the ROC curve of the Merton model-based probability of default totals 0.8448 compared to the logit regression model with

Fig. 1. ROC curve Merton model

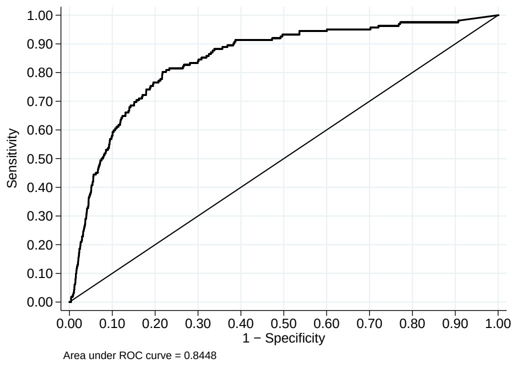
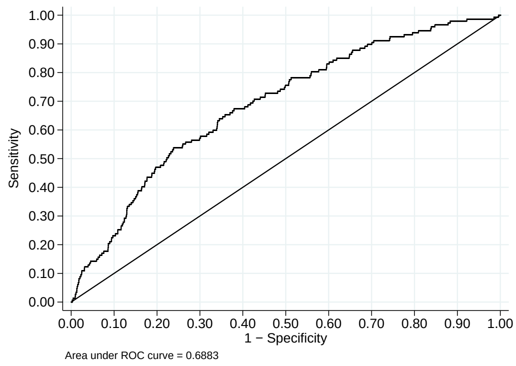


Fig. 2. ROC curve logit regression model



0.6883. The Merton model ROC curve shows a much steeper development compared to the logit ROC curve underlining the higher predictive power in terms of bankruptcy. This underlines that the Merton model serves as a reasonable basis to develop a financial distress criterion.

4.2.2 Developing a financial distress criterion

To compose the financial distress variable I perform further investigations on a Merton model-based classification criterion combining the distance to default percentile of a firm and the distance to default level itself (for a detailed description see Stephenson (2010)). I use bankruptcy information to calibrate and validate the criterion. A migration matrix (see Table 1) suggests that a combined criterion in which the firm's distance to default belongs to the lowest 0.05 percentile for at least 10 days in a row and the absolute level of distance to default is lower than or equal to 1.5, serves as a reasonable criterion to identify firms in financial distress.

However, even if a company never filed for bankruptcy, a classification as financially distressed could be reasonable because the firm might have chosen the way of private restructuring. The financial distress criterion should also identify non-bankruptcy firms avoiding bankruptcy by a private restructuring process. Thus, in a final step a search for restructuring terms serves as a validation process. Potential restructuring methods are considered to derive different searching terms.

To finally validate the derived criterion, I investigate how many of the 382 firms identified as financially distressed report restructuring or bankruptcy as an in-court restructuring process. An overview can be found in Table 2. 95 of the financially distressed firms filed for bankruptcy within the defined period according to Hoppenstedt and LexisNexis or the firms' homepages. I find that an additional 113 firms (in addition to the 95 firms which filed for bankruptcy) report restructuring within that time period. Two of the remaining firms reported an agreement on liquidation at their annual general meeting. The remaining 56 firms report a change in "management". An additional two firms

Table 1
Default sample on a Merton model and dd level basis

Percentile	Days in a row	Financially distressed & ahead of bankruptcy	Not financially distressed & bankrupt	Not financially distressed & no bankruptcy	Financially & no bankruptcy	Overall number of financial distress
0.05	22	106	57	875	253	359
	20	108	56	874	254	362
	14	108	56	863	267	375
	12	110	52	861	267	377
	10	**114** (75% of bankruptcy firms)	**49**	**860**	**268**	**382** (30% of all firms)
	9	115	48	859	269	384
	8	116	48	857	271	387
	4	116	45	854	276	392
	3	119	42	852	277	396
	1	121	42	847	285	406
0.03	22	86	78	918	204	290
	20	87	77	914	207	294
	13	93	72	914	211	304
	12	92	73	910	215	307
	10	95	70	908	220	315
	9	98	67	906	222	320
	8	100	67	906	224	324
	4	105	61	903	225	330
	3	106	60	898	227	333
	1	113	53	884	242	355
0.01	4	63	97	974	143	206
	3	63	95	971	146	209
	1	70	89	964	154	224

Notes. The migrations matrix is based on a comparison of the distance to default over time calculated using the Merton model. The above presented criterion combines the distance to default percentile a firm belongs to with an absolute level lower than or equal to 1.5 as a financial distress criterion.

report a "merger". Another 13 firms mention a "sale of a business segment/ business unit" or a "sale of a subsidiary". Furthermore, nine firms filed for "bankruptcy" after a period of more than 500 trading days. The table shows that for 290 of the 382 firms an event is reported that might be an indicator of a financial distress situation. Thus the derived financial distress criterion can be described as a reasonable criterion and is used in the following to identify firms in financial distress.

5 Calibration of the relationship lending criterion

5.1 Relationship lending data basis

To determine whether a firm has a relationship lender, German Credit Register information held at the German central bank according to the German Banking Act (KWG) §14 is used. Credit institutions, financial service institutions, financial enterprises according to §1 KWG and their branches domiciled

Table 2
Descriptives of the financial distress sample

Within 375 trading days:	Number of firms
Firms identified as financially distressed	382
thereof	
firms which file for **bankruptcy**:	95
	=287 remaining firms
thereof	
firms which **report restructuring terms**:	113
	=174 remaining firms
thereof	
firms which **report liquidation**:	2
	=172 remaining firms
thereof	
firms which **report management change**:	56
	=116 remaining firms
thereof	
firms which **report merger/ takeover**:	2
	=114 remaining firms
thereof	
firms which **report sale of business**	
unit or subsidiary:	13
	=101 remaining firms
thereof	
firms which file for **bankruptcy**	
after more than 375 trading days:	9
	=92 remaining firms without
	reporting one of the aforementioned events

Notes. Hoppenstedt, LexisNexis, and the firms' homepages are used to get the bankruptcy information. LexisNexis is the source for the restructuring information and firm liquidation as well as for management change information and sale of business units or subsidiary. Datastream and LexisNexis are the source for takeover and merger information.

abroad have to report loans of 1.5 million EUR or more to a single borrower or a borrower unit to the German central bank. These reports contain quarterly announcements by banks regarding the loans provided to their customers. According to the German Banking Act a borrower unit includes consolidated groups, risk units and partnerships under the German Civil Code. Hence, a borrower unit is defined more broadly and may defer from the consolidated group according to the German Stock Corporation Act (AktG). An overview of the reasons why a firm would join a borrower unit according to the KWG, and the differences between a borrower unit and a consolidated group according to the AktG, are displayed in Appendix A.1.

To use the firm data provided by the central bank I match the Datastream sample firms with firms within the German Credit Register. A firm is considered as a matched firm if the firm's name, the city of the head office, the legal form and if available, the commercial register number as well as the postal code are identical at a 98% level. Overall, 89% of the stock exchange-listed firms identified in the Datastream database could be matched.

According to the KWG a firm can either be reported as a single firm (if no group, risk unit or partnership exists) or be included into one or more borrower units. Thus the borrower unit to which the matched firm belongs is extracted. Matched firms included in a borrower unit headquartered in a foreign country are excluded. As the German Credit Register reports only include German bank reports and a foreign country based-unit has a high probability of having foreign country bank relationships, I categorise this sort of borrowing unit as "not representative".

As the borrower unit serves as the basis for the relationship lending criterion, I perform further investigations on the borrower unit. I examine whether a difference exists between the borrower unit (KWG) and the corporate group (AktG) only according to the definition or whether a factual difference occurs. I compare the members of the borrower units with the members of the corporate group for a representative time period between 1998 and 2007. By using a string match the subsidiary's name provided by the database Amadeus and the borrower unit member's name are compared. A firm is considered as a match if the names are identical at a 99% level. I compare the reported subsidiaries of the group with the members of the borrower unit. A borrower unit is defined as "consistent" with the corporate group if the subsidiaries accounting for 90% of the firm's reported debt are equal. 514 (45%) of the firms which are related to a borrower unit can be considered as "consistent" with the corporate group. A detailed description can be found in Appendix A.2.

The analysis of the borrower unit shows that the borrower unit differs from the corporate group in 55% of the cases. However, including risk-related firms within the unit appears economically reasonable. In addition, an indication of the borrower unit is given by the bank itself. After reporting the borrower information to the central bank, the bank receives information regarding whether the firm is already included in a borrower unit and is informed about the amount of debt provided by other banks to this borrower unit. Thus the borrower unit information serves as a basis for further credit decisions made by German banks. This aspect underlines that using borrower unit loan data enhances this investigation. Moreover, according to the German Banking Act, not only loans are reported but also guarantees provided by banks, as well as off-balance sheet transactions (for more details see Appendix A.3). As banks are informed about these off-balance sheet transactions, they influence the bank's decision. Thus, this information should be considered in the identification process of a relationship lender. Overall this shows that the borrower unit data provide an enhanced basis for a relationship lending criterion which has so far not been applied in a German capital market investigation to my knowledge.

As the KWG allows a firm to enter more than one borrower unit at once, the number of borrower unit relationships is evaluated before determining the relationship lending criterion. I find that 944 firms belong to a borrower unit once. Only 39 firms belong to more than one borrower unit once. If the firm is one of the few firms which belong to more than one borrower unit, I exclude the firm if the different borrower units the firm belongs to show a different relationship lending status.

Furthermore, I investigate the development of borrower unit relationships between 1993 and 2007. The examination shows that only 176 firms of the

944 firms included in a borrower unit do not change their borrower unit. 364 firms change their borrower unit once, 215 firms change twice (for a detailed overview see Appendix A.4). The change of a borrower unit is used as an indicator variable for a change of the firm's ownership. As German banks consider this risk unit in their loan decisions, using borrower unit change as an explanatory variable seems reasonable.

5.2 Relationship lending indicator variable

As described above, the Herfindahl-Hirschman index (HHI) is chosen as a basis for a relationship lender criterion. To identify a relationship lender, the HHI is calculated by using the absolute reported loan amount according to the German Credit Register Reports provided by each single bank (FA_i). The index is calculated by dividing the sum of the squared reported loan amounts by the squared sum of the reported loan amounts:

$$HHI = \frac{\sum\limits_{i=1}^{N} (FA_i)^2}{\left(\sum\limits_{I=1}^{N} FA_i\right)^2}. \tag{6}$$

For a robustness check, I define a bank as a relationship lender if the borrower holds more than 70% of the firm's debt. While investigating the number of bank relationships for the sample firms, I find that within the German market 8% (1996) to 15% (2007) of the borrower units have only one bank relationship. As the study focusses on listed firms, the ratio occurs relatively high. A descriptive statistic of the sample firms' borrower units number of bank relationships can be found in Table 3 for the years 2003 and 2007.

For the investigation it is also taken into account that a firm may have a relationship lender according to one of the aforementioned criteria, but is mainly financed by equity. In this case, the identified relationship lender does not have the influencing power described above. Consequently a bank is considered as a "non-relationship-lender" if the debt ratio (debt to asset book value) is lower than 10%.

To calibrate the HHI-related relationship lending criterion I perform further analyses on the HHI. To find out how many bank relationships firms with a high HHI level have, different HHI levels and the related number of bank relationships are investigated. Table 4 shows how many bank relationships firms with a certain HHI have, taking as an illustrating example the second quarter of 2007. It can be seen that for HHI levels of 0.41 to 0.50 the number of bank relationships is three or less for 25% of the sample firms. However, this low number could also include the case that two banks hold an equal share of the firm's debt. In this case the asymmetry of power which leads to the advantages of a relationship lender does not exist. To find out whether asymmetry in bank relationships exists at a HHI level higher than 0.40, I investigate how high the

Table 3
Number of bank relationships per borrower unit 2003/ 2007 first quarter

Bank relationships per BU first quarter 2003				
No. of banks	No. of firms	%	Observations	755
1	112	14.80	Mean	32
2	70	9.25	Std. dev.	154
3	61	8.06		
4-8	217	28.67		
9-12	69	9.11		
13-20	65	8.59		
21-30	52	6.87		
31-50	44	5.81		
>=51	67	8.85		

Bank relationships per BU first quarter 2007				
No. of banks	No. of firms	%	Observations	739
1	111	15.02	Mean	32
2	91	12.31	Std. dev.	142
3	60	8.12		
4-8	182	24.63		
9-12	75	10.15		
13-20	82	11.10		
21-30	32	4.33		
31-50	35	4.74		
>=51	71	9.61		

Notes. The table above is based on German Credit Register data and shows how many bank relationships the sample firms have within the first quarter in 2003/ 2007. E.g. according to the central bank's large exposure loans 111 firms have one bank relationship in 2007. This represents 15.02% of the sample firms.

debt share of the major lender is in these cases. The results for an HHI level of 0.41-0.50 and 0.51-0.60 are displayed in Table 5 by way of illustration. If a firm has an HHI of 0.41 or higher, the share of debt of the largest debt provider is 45% or more. Holding the major share of 45% or more of the debt provides asymmetric power to a bank. Consequently, I consider a bank as a relationship lender if it is the firm's largest lender and the firm's HHI is higher than 0.40.

Table 4
Distribution of number of banks for different HHI level

HHI 0.41-0.50: Distribution of number of banks			
No. of banks	Percentile	Observations	58
2	1%	Mean	8.05
3	25%	Std. dev.	10.89
5	50%		
7	75%		
14	90%		
33	95%		
67	99%		

HHI 0.51-0.60: Distribution of number of banks			
No. of banks	Percentile	Observations	88
2	50%	Mean	3.05
3	75%	Std. dev.	1.97
5	90%		
8	95%		
13	99%		

Notes. The table is based on German Credit Register data and shows that 1% of the firms which do have an HHI between 0.41 and 0.50 have 2 or fewer bank relationships. 50% of the firms have five or fewer relationships. 50% of the firms which have a HHI between 0.51 and 0.60 have 2 or fewer bank relationships. 90% of the firms have five or fewer relationships.

Using the relationship lending criterion of an HHI>0.40 and alternatively the criterion "the relative share of a bank's debt is higher than 0.7", I investigate how many of the sample firms have a relationship lender. The results for time periods between 1996 and 2007 are displayed in Table 6.

The analysis shows that between 29% and 39% (1996-2007) of the firms have a relationship lender according to the HHI-based criterion. According to the relative criterion between 17% and 24% (1996-2007) of the firms have a relationship lender. The number of relationship lenders increases over time, which might be related to consolidation activities in the German banking market. I also compare how many of the firms have a relationship lender according to the relative relationship lending criterion and the HHI-based criterion at the same time. The estimation matrix in Appendix A.5 provides an overview. The

Table 5
Distribution of major share of debt per bank

HHI of 0.41-0.50: Firms largest debt share			
Largest share	Percentile	Observations	58
0.45	1%	Mean	0.57
0.48	5%	Std. dev.	0.057
0.49	10%		
0.53	25%		
0.59	50%		
0.62	75%		
0.64	90%		
0.66	95%		
0.67	99%		

HHI of 0.51-0.60: Firms largest debt share			
Largest share	Percentile	Observations	89
0.50	1%	Mean	0.63
0.51	5%	Std. dev.	0.07
0.52	10%		
0.55	25%		
0.65	50%		
0.69	75%		
0.72	90%		
0.73	95%		
0.75	99%		

Notes. The table is based on German Credit Register data and shows that if a firm has an HHI of 0.41 or higher the share of debt of the largest debt provider is 45% or more. Holding the major share of 45% or more of the debt provides asymmetric power to a bank.

Table 6
Empirical relationship lending criterion investigation on a borrower unit (BU) basis

RL relative criterion first quarter 1996

	Number of BUs	In percent
0	450	83
1	95	17
	545	100

RL relative criterion first quarter 1998

	Number of BUs	In percent
0	522	81
1	119	19
	641	100

RL HHI criterion first quarter 1996

	Number of BUs	In percent
0	386	71
1	159	29
	545	100

RL HHI criterion first quarter 1998

	Number of BUs	In percent
0	437	68
1	204	32
	641	100

RL relative criterion first quarter 2003

	Number of BUs	In percent
0	584	77
1	171	23
	755	100

RL relative criterion first quarter 2007

	Number of BUs	In percent
0	558	76
1	181	24
	739	100

RL HHI criterion first quarter 2003

	Number of BUs	In percent
0	496	66
1	259	34
	755	100

RL HHI criterion first quarter 2007

	Number of BUs	In percent
0	451	61
1	288	39
	739	100

Notes. The relationship lending indicators used above are “the relative share of the largest lender is >=0.70” (RL relative) and “the HHI is >0.40” (RL HHI). The relationship lending criterion is measured on the basis of the borrower units for a time period between first quarter 1996 and second quarter 2007.

matrix underlines that the developed HHI-based criterion includes all firms identified as having a relationship lender by using the relative criterion and covers further firms. As the examination of the major borrower share for the HHI>0.40 shows, the major borrower holds 45% and more (see Table 5). From this perspective asymmetry of influencing power exists (e.g. in case a bank holds only a 45% loan share, and the rest is provided by two other banks). The relative relationship lending criterion of >=0.70 thus seems to be too narrow a definition. Consequently, I use the HHI as a basis for a relationship lending criterion and consider a firm as having a relationship lender if the HHI is > 0.40.

6 Determinants of financial distress and relationship lending

6.1 Methodology

To determine the effect a relationship lender has on the firm's probability of financial distress, this paper starts by regressing a measure for the probability of financial distress on a measure of bank relationship. The dependent dummy variable financial distress indicates whether a firm is in financial distress. The variable has the value 1 if the defined financial distress criterion indicates financial distress and is 0 otherwise. I control for firm characteristics such as size and whether the firm belongs to a borrower unit. Size is expected to have a negative sign, as the public awareness of the firm might lead to the fact that big firms are supported in times of financial difficulties. The firm's assignment to a borrower unit is expected to have a negative sign as borrower unit relationships might lead to internal credit access and prevent the firm from entering financial distress. Additionally, I include the distance to default level of the industry the firm belongs to. This variable is expected to have a negative sign, as a lower industry distance to default level might indicate that the firm belongs to a more risky industry more inclined to enter financial distress. Moreover, financial characteristics such as profitability and liquidity as well as efficiency are included. I expect a negative sign for those characteristics. High profitability, liquidity and efficiency might protect the firm from entering financial distress. An interaction term of the firm's distance to default and the relationship lending status is included to indicate whether strong firm-bank relationships influence the borrower's probability of financial distress. The applied model is displayed below:

$$\begin{aligned} P(distress)_{it} = \beta_0 + \beta_1\ RL_{it} + \beta_2\ borrower\ unit_{it} + \beta_3\ dd\ industry_{it} \\ + \beta_4\ profitability_{it} + \beta_5\ liquidity_{it} + \beta_6\ size_{it} + \beta_7\ efficiency_{it} \\ + \beta_8\ dd\ RL_{it} + \beta_9\ year_t + u_{it} \end{aligned} \tag{7}$$

The subscripts refer to the firm's probability of financial distress ($P(distress)_{it}$), the relationship lending status (RL_{it}), the assignment of the firm to a borrower unit ($borrower\ unit_{it}$), the industry average of the distance to default ($dd\ industry_{it}$), the profitability ($profitability_{it}$, measured as EBIT to assets), the liquidity ($liquidity_{it}$, measured as working capital to total assets), the size ($size_{it}$), sales divided by total assets as a measure for efficiency ($efficiency_{it}$), the interaction term of relationship lending and the distance to default ($dd\ RL_{it}$) and the error term (u_{it}). A Wald test (Wooldridge (2002), p. 362) indicates that year dummies have to be included ($year_t$). Overall panel data for a firm sample of 1,265 firms (i) serve as the database for a period 1993-2007 (t).

The regression model presented above assumes that the choice of having a relationship lender does not depend on the firm's probability of financial distress. However, a relationship lender might as likely influence the firm's probability of financial distress as the firm's probability of financial distress might influence the bank relationships. Ignoring this fact might lead to misleading results as discussed above. Thus, the potential endogeneity between relationship lending and the firm's probability of financial distress is taken into account. A bivariate probit regression using the determinants of relationship lending as a first stage equation is applied to address the endogeneity. To analyse the determinants of having a relationship lender in a first step ($P(RL)_{it}$), the following regression model is run:

$$\begin{aligned} P(RL)_{it} &= \beta_0 + \beta_1\ dd\ average_{it} + \beta_2\ borrower\ unit_{it} + \beta_3\ size_{it} \\ &+ \beta_4\ leverage_{it} + \beta_5\ cash\ strength_{it} + \beta_6\ leverage\ industry_{it} \\ &+ \beta_7\ information\ asymmetry_{it} + \beta_8\ year_t + u_{it} \end{aligned} \tag{8}$$

As explanatory variables the moving average of the distance to default ($dd\ average_{it}$) is used to measure the firm's average level of distance to default. As Yosha (1995) observes that more profitable firms prefer bilateral financing to reduce information disclosure, firms with a higher distance to default also might prefer bilateral lending. Therefore, a positive sign is expected. Further, the assignment of the firm to a borrower unit ($borrower\ unit_{it}$) is applied as a control variable. I expect to find a negative relation between this variable and the relationship lending status as borrower unit relationships might lead to internal credit access and bank ties might be less strong. Firm size ($size_{it}$) is included in the model and it is expected that this variable will have a negative sign, as big firms might have better access to the capital market.

The firm's leverage ($leverage_{it}$, measured as the firm's total bank loans divided by total assets according to Hoppenstedt and alternatively according to the German Credit Register reports as a robustness check) is added as a control variable. The more the firm depends on debt, the higher the probability of having a relationship lender is expected to be. To measure the firm's individual cash ratio, operative cash flow divided by total assets ($cash\ strength_{it}$) is used. A negative correlation between the cash ratio and the relationship lending status is expected, as firms with a high operative cash flow are not as dependent on cash provided by bank loans. The bank loan ratio of the industry is used to reflect how dependent the firm's industry is on credit financing ($leverage\ industry_{it}$). I expect to find that this variable has a positive influence. The more dependent the industry is on bank loans, the higher is the firm's probability of having a relationship lender. To measure information asymmetry the volatility of the firm's idiosyncratic risk ($information\ asymmetry_{it}$) is applied. I expect to find a positive sign in terms of this variable as a higher information asymmetry might restrict the access to the capital market. A Wald test indicates that year dummies have to be included ($year_t$). Overall panel data for a firm sample of 1,265 firms (i) serves as the database for a time period 1993-2007 (t). Table 7 provides an overview of the variables used and the expected signs.

Table 7
Definition of variables

Variable	Definition	Construction	Expected sign on (RL/distress)
RL HHI	Relationship lender according to Credit Register information	Dummy (1 if HHI>0.40)	(n.a./(+),(-),"no influence")
RL relative	Relationship lender according to Credit Register information	Dummy (1 if relative share of a single bank is >=0.70)	(n.a./(+),(-),"no influence")
Borrower unit	Does the firm belong to a borrower unit according to the Credit Register?	Dummy	(-/+)
DD industry	Distance to default level industry	Mean of distance to default per industry measured on a quarterly basis	(n.a./-)
Profitability	Firm's profitability	(EBIT)/(total assets)	(n.a./-)
Liquidity	Firm's liquidity	(Working capital)/(total assets)	(n.a./-)
Size	Firm size	log (assets)	(-/-)
Efficiency	Measure of firm efficiency	(Sales)/(total assets)	(n.a./-)
Leverage	Total bank debt measured using balance sheet data and Credit Register information alternatively	(Total bank debt)/(total assets)	(+/+)
Equity	Equity ratio	(Book value equity)/(total assets)	(n.a./+)
Interaction DD RL	Interaction term of relationship lending and distance to default	(RL dummy)x(dd)	(n.a./n.a.)
DD average	Firm's average default level	Rolling 10 day distance to default average for each firm	(+/-)
Cash strength	Cash availability	(Operat. cash flow)/(total assets)	(-/-)
Leverage industry	Industry bank debt measured using balance sheet data and Credit Register information alternatively	Industry mean of (total bank debt)/ (total assets)	(+/-)
Information asymmetry	Information asymmetry concerning each firm	Volatility of the firm's idiosyncratic risk	(+/-)

Notes. RL HHI and RL relative indicate the relationship lending status according to the German Credit Register reports. The expected signs denote the expected influence on relationship lending or the probability of financial distress in parentheses, starting with the sign for the influence on relationship lending (RL), the expected sign on the probability of financial distress follows (distress).

To address the potential endogeneity of financial distress and relationship lending, a simultaneous equation model is run. In the first stage equation the determinants of having a relationship lender ($P(RL)_{it}$) are modelled (see Equation (2)). In the second stage equation the influencing factors of the firm's probability of default are modelled (see Equation (1)). As an instrumental variable (Wooldridge (2002), p. 84) the bank loan ratio of the industry ($leverage\ industry_{it}$) is used in the first stage equation. This variable measures industry dependence on external finance. The empirical analysis shows that the average industry loan ratio has no significant explanatory power regarding the individual firm's probability of financial distress but does have explanatory power regarding the relationship lending status. A measure for efficiency (sales divided by total assets and personal expenses divided by total assets as a robustness check) is used as an instrument variable within the second stage equation. I expect a negative influence of efficiency on the firm's probability of financial distress. Nevertheless, the efficiency of the firm's production process is not expected to influence the number of bank relationships. The empirical investigation confirms this hypothesis for my dataset.

As both dependent variables are dummy variables, a bivariate probit regression model is used to estimate the two equations simultaneously. According to the result of a Wald test, year dummies and alternatively the growth rate of the annual Gross Domestic Product are included. First, I apply a bivariate probit regression for a matched firm sample (Wooldridge (2002), p. 328). For each financially distressed firm three additional non-distressed firms, with approximately the same firm size, measured at the same point in time, are included in the sample (note, though, that three additional firms of approximately the same size are not available for every point in time). Second, a bivariate probit regression model with standard errors adjusted for firm clusters is performed (Wooldridge (2002), p. 134).

6.2 Univariate analysis

As described above, the sample considers publicly listed German firms. The median of total assets of 8.67 bn EUR of the sample firms, and the mean of 1.65 bn EUR, indicate that the sample mainly consist of non-small and medium-sized enterprises (see SME definition by the European Commission (2008)). As large firms might face less information asymmetry on the market and have more access to finance sources, an examination of the lender relationship for these kinds of firms is of especial interest. An assessment of the average distance to default (mean 17.209, median 6.199 and standard deviation 28.071) shows that the sample includes firms with a distance to default ranging from a high to a low level. It has to be mentioned that the high distance to default mean is driven by firms with a very high distance to default. However, this includes already a limitation of the distance to default to a maximum of 100.

I investigate whether the mean and standard deviation of certain variables of the group of firms with a relationship lender differ from the group of sample firms without a relationship lender. The relationship lending status is measured using the HHI-based criterion. The variable mean and the standard deviation of the two groups is displayed in Table 8. The reported statistics are based on pooled data available for each firm for the time period 1993-2007. A t-test is performed to investigate whether there is a difference in means between the groups. The results are displayed in the column "p-value of t-test" in Table 8.

The univariate analysis suggests that firm groups with and without a relationship lender are different with respect to size. As expected, bigger firms

Table 8
Descriptive statistics for firm group relationship lender and no relationship lender

Variable	Number of Observations	Mean	Standard deviation	p-value of t-test
Average DD group no RL	30,122	17.530	28.417	0.000***
Average DD group RL	7,281	15.987	26.903	
Total assets group no RL	30,122	2.014 bn EUR	12.25 bn EUR	0.000***
Total assets group RL	7,281	123.4 mio EUR	695 mio EUR	
Market value group no RL	30,122	1.11 bn EUR	5.69 bn EUR	0.000***
Market value group RL	7,281	148 mio EUR	1.06 bn EUR	
Credit strength group no RL	30,122	0.170	0.110	0.000***
Credit strength group RL	7,281	0.163	0.106	
Profitability group no RL	30,122	0.024	0.240	0.000***
Profitability group RL	7,281	0.003	0.237	
Liquidity group no RL	30,122	0.0577	1.856	0.006***
Liquidity group RL	7,281	0.0523	0.3644	

Notes. All calculations are based on averages of observations for individual firms between 1993 and 2007. For variable definitions see Table 7. Significance denotes the p-values of simple t-test of differences in means.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

tend not to have, while smaller firms tend to have, a relationship lender. The total asset book value mean of the group without a relationship lender is, in addition to the market value of equity, higher than for the group with a relationship lender. The t-test suggests a significant difference for both book value of total assets and equity market value. For other variables as well the univariate analysis shows a statistical difference (p-value of t-test), however, there is no difference from an economic perspective (e.g. distance to default average of 17.530 compared to 15.987). Table 9 shows the investigation of whether or not the mean of certain variables of the group of firms which entered financial distress differs from the group of sample firms which do not enter financial distress. To measure if a firm is in financial distress, the above-described financial distress identification criterion is used. The variable mean and the standard deviation of the two groups is displayed in Table 9. Further, the results of a mean comparison t-test are displayed in the column “p-value of t-test”.

As expected, the univariate analysis shows that the distance to default mean of the financially distressed group is much lower (0.6188) than the mean of the non-distressed group (17.366). The analysis further suggests that non-distressed firms are bigger in terms of the total asset mean book value and tend to have a higher market value of equity. The t-test suggests a significant difference for both book value of total assets and equity market value. Furthermore, the univariate analysis indicates that profitability and liquidity is significantly lower. However, this might be driven by another factor which is correlated to these factors. A difference in size, in profitability and liquidity

Table 9
Descriptive statistics for firm group relationship lender and no relationship lender

Variable	Number of observations	Mean	Standard deviation	p-value of t-test
Average DD group no distress	37,113	17.366	28.206	0.000***
Average DD group distress	290	0.6188	0.884	
Total assets group no distress	37,113	1.65 bn EUR	11.10 bn EUR	0.0463**
Total assets group distress	290	959 mio EUR	5.810 bn EUR	
Market value group no distress	37,113	927 mio EUR	5.16 bn EUR	0.000***
Market value group distress	290	305 mio EUR	1.97 bn EUR	
Credit strength group no distress	37,113	0.168	0.109	0.0164**
Credit strength group distress	290	0.186	0.123	
Profitability group no distress	37,113	0.021	0.238	0.000***
Profitability group distress	290	-0.134	0.311	
Liquidity group no distress	37,113	0.057	0.167	0.0004***
Liquidity group distress	290	-0.006	0.261	

Notes. All calculations are based on averages of observations for individual firms between 1993 and 2007. For variable definitions see Table 7. Significance denotes the p-values of a t-test of differences in means.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

is therefore investigated in the multivariate analysis of influencing factors of financial distress.

6.3 Multivariate analysis

6.3.1 Probit regression financial distress and relationship lending

In order to investigate the determinants of financial distress a multivariate analysis is carried out. Since the dependent variable is measured as a binary variable, a probit regression is employed. The observed dependent financial distress variable is assumed to take the value one if the underlying latent financial distress variable exceeds the critical threshold defined above (the firm's distance to default is continually in the lowest 0.05 percentile for at least 10 days in a row and the absolute level of distance to default is lower than or equal to 1.5). The dependent variable is assumed to take the value 0 if the financial distress condition is not fulfilled. If the firm enters financial distress, all firm data are considered in the data sample up to the date the financial distress event occurs. Further data for the firm are not considered. However, I allow the firm to enter the sample again if the firm is still listed on the equity stock market and the first distress event is more than 750 trading days away.

The panel data structure is based on the German Credit Register reports provided on a quarterly basis. I start with a probit regression to find explanatory variables for financial distress. Due to the panel data structure, a probit regression with standard errors adjusted for firm clusters is performed (Wooldridge (2002), p. 134). Finally a random effects panel data regression model is carried out. A fixed effects panel data regression is not applied, because there are no variances in the financial distress status for most of the firms. The relationship lending variable is measured using the HHI-based criterion (regression model I-II) and using the relative relationship lending criterion (relative share for one bank is >=0.70; (model III-IV)). The results of the regression models are displayed in Table 10.

Table 10
Probit analysis of determinants of financial distress

	Probit regression model			
	I (clustered)	II (panel RE)	III (clustered)	IV (panel RE)
Explanatory variable:				
Constant	-6.15*** (0.000)	-7.01 (0.992)	-6.13*** (0.000)	-6.96 (0.991)
RL HHI	0.09 (0.241)	0.09 (0.222)		
RL relative			0.10 (0.169)	0.10 (0.166)
Borrower unit	-0.10* (0.093)	-0.10* (0.095)	-0.10* (0.076)	-0.11* (0.077)
DD industry	-0.01*** (0.000)	-0.02*** (0.000)	-0.02*** (0.000)	-0.02*** (0.000)
Profitability	-0.27*** (0.007)	-0.29***(0.000)	-0.27*** (0.007)	-0.29*** (0.000)
Liquidity	-0.07** (0.032)	-0.06***(0.001)	-0.07** (0.033)	-0.06*** (0.001)
Size	-0.02* (0.051)	-0.025* (0.064)	-0.027** (0.044)	-0.02* (0.055)
Efficiency	-0.06* (0.052)	-0.06** (0.036)	-0.06* (0.054)	-0.06** (0.038)
Interact DD RL	-0.00 (0.914)	-0.00 (0.945)	0.00 (0.874)	0.00 (0.761)
Number of observations	35,139	37,403	35,319	37,403
Pseudo R^2	0.07		0.07	
Number of cluster/ groups	1,265	1,265	1,265	1,265

Notes. The table shows a probit regression to identify determinants of financial distress. The table is based on time-series observations for individual firms between 1993 and 2007. Models I and III show the results of a probit regression with standard errors adjusted for firm clusters and model II and IV of a random effects panel data probit regression. For variable definitions see Table 7. Year dummies are included. P-values are in parentheses.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

The estimation results of all models indicate that there is no significant influence by the relationship lender on the probability of financial distress. This finding supports the equilibrium structure hypothesis that having a relationship lender is an endogenous outcome of a selection of advantages and disadvantages of having a relationship lender arrived at a bank-relationship equilibrium. Consequently, having a relationship lender has no effect on the firm's probability of financial distress.

The regression models further suggest that, as expected, belonging to a borrower unit has a negative significant influence on the probability of financial distress. If a firm belongs to a borrower unit, the probability of financial distress is lower than for firms which do not belong to a borrower unit. Further, the model indicates that the industry level of the distance to default has explanatory power. As expected, the higher the distance to default average of the industry, the lower the probability of financial distress of the single firm. Profitability has, as expected, a significant negative influence on reaching financial distress, as do liquidity and size.

In a next step a regression model is performed investigating the determinants of relationship lending (see Equation (2)). The observed dependent variable representing relationship lending is assumed to take the value 1 if the underlying latent variable HHI is higher than 0.40 and zero otherwise. Since the relationship lending status is a binary variable, a probit regression is performed. I apply panel data on a quarterly basis. A probit regression is conducted to find explanatory variables for a relationship lender. Due to the panel data structure, a probit regression with standard errors adjusted for firm clusters (model V) is performed (Wooldridge (2002), p. 134). Finally a random effects panel data regression model (model V) is applied. A fixed effects panel data regression is not applied, because there are no variances in the relationship lending status for most of the firms. The results of the regression models are displayed in Table 11.

Table 11
Probit analysis of determinants of relationship lending

	Probit regression models	
	V (clustered)	VI (panel RE)
Explanatory variable:		
Borrower unit	-0.788*** (0.000)	-0.562*** (0.000)
Average DD	-0.003*** (0.007)	-0.002*** (0.000)
Size	-0.225*** (0.000)	-0.192*** (0.000)
Leverage	0.064 (0.756)	-0.169* (0.096)
Cash strength	-0.004 (0.688)	-0.006 (0.541)
Leverage industry	-0.905*** (0.006)	-0.726*** (0.000)
Information asymmetry	-0.045 (0.878)	-0.015 (0.960)
Constant	-1.913*** (0.000)	-7.471 (0.991)
Number of observations	37,403	37,403
Pseudo R^2	0.11	
No of cluster/ groups	1,265	1,265

Notes. Probit regression of relationship lending based on time-series observations for individual firms between 1993 and 2007. Model V shows the results of a probit regression with standard errors adjusted for firm clusters and model VI of a random effects panel data probit regression. For variable definitions see Table 7. Year dummies are included. P-values are in parentheses.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

As expected, the estimation results of all models indicate that belonging to a borrower unit has a negative significant influence on the relationship lending status. If a firm belongs to a borrower unit, the probability of having a relationship lender is lower than for firms which do not belong to a borrower unit. Furthermore, the model indicates that the average of the distance to default has explanatory power. As expected, the lower the distance to default average is, the higher the probability of having a relationship lender. Size has, as expected, a significant negative influence on having a relationship lender, as does the leverage of the industry. As a robustness check the relationship lending status is measured using the relative relationship lending criterion (relative share for one bank is >=0.70). This does not lead to a change in the results.

6.3.2 Bivariate probit regression on financial distress and relationship lending

As discussed above, the separated probit regression models assume that the choice of having a relationship lender does not depend on the firm's level of distress. However, a relationship lender is as likely to influence the firm's probability of financial distress as the firm's probability of financial distress is to influence the bank relationship. It could for example be the case that especially those firms which are in need of a relationship lender that choose to have one. In this case a separated probit regression might lead to the wrong results. Consequently, a bivariate probit regression model is applied to solve the two equations simultaneously. As dependent variables I use the relationship lending status identified by using the the HHI-based criterion and the probability of financial distress using the Merton model-based financial distress criterion. Regression models with standard errors adjusted for firm clusters are applied. The results are displayed in Table 12.

The bivariate regression model confirms what the probit regression model indicates. There is no significant influence by the relationship lender on the probability of financial distress by the firm. This finding supports again the equilibrium structure hypothesis that having a relationship lender is an endogenous outcome of a selection of advantages and disadvantages of having a relationship lender arrived at a bank-relationship equilibrium. Consequently, having a relationship lender has no effect on the firm's probability of financial distress.

As expected, the regression model further suggests that the industry level of the distance to default has explanatory power. The higher the distance to default average of the industry, the lower the probability of financial distress of the single firm. As expected, the firm's profitability has a significant negative influence on reaching financial distress as does liquidity and efficiency. The more profitable the firm the higher its liquidity, and the more efficient the firm the lower is its probability of financial distress. As a robustness check the relative relationship lending criterion is applied and the Gross Domestic Product is used instead of year dummies. This does not lead to a change in the results.

In terms of the determinants of a relationship lender I find that belonging to a borrower unit has a negative significant influence on the relationship lending status. If a firm belongs to a borrower unit, the probability of having a relationship lender is lower than for firms which do not belong to a borrower unit. Furthermore, the model indicates that the average of the firm's distance to default has explanatory power. The lower the distance to default average is, the higher the probability of having a relationship lender. Size has a significant

Table 12
Bivariate probit analysis of determinants of financial distress and relationship lending

	Biprobit regression models			
	VII	VIII	IX	X
	(clustered)	(clustered)	(clustered)	(clustered)
1. Dependent variable: no RL (0)/RL (1)				
Explanatory variable:				
Borrower unit	-0.788*** (0.000)	-0.815*** (0.000)		-0.815*** (0.000)
Average DD	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.009)	0.003*** (0.000)
Size	-0.225*** (0.000)	-0.221***(0.000)	-0.161*** (0.000)	-0.221*** (0.000)
Leverage	0.065(0.247)			
Equity		0.232*** (0.000)	0.058 (0.217)	0.231* (0.060)
Cash strength	-0.004 (0.439)	-0.002 (0.529)	-0.005 (0.592)	-0.002 (0.780)
Leverage industry	-0.905*** (0.000)	-0.702*** (0.000)	-0.396 (0.144)	-0.702*** (0.009)
Information asymmetry	-0.043(0.790)	-0.040 (0.831)	-0.342 (0.501)	-0.040 (0.898)
Constant	-2.101*** (0.000)	-2.499 (0.993)	-3.852 (0.553)	-2.499* (0.063)
2. Dependent variable: no distress (0)/distress (1)				
Explanatory variable:				
RL HHI	0.101 (0.717)	0.040 (0.840)	0.2754 (0.813)	0.040 (0.879)
BU member	-0.101 (0.211)			
DD industry	-0.015*** (0.000)	-0.016*** (0.000)	-0.014*** (0.000)	-0.016*** (0.000)
Profitability	-0.279*** (0.000)		-0.275*** (0.008)	
Liquidity	-0.070*** (0.000)		-0.072** (0.037)	
Size	-0.026 (0.164)	-0.034** (0.013)	-0.011 (0.787)	-0.034** (0.035)
Efficiency	-0.064** (0.046)	-0.071** (0.014)	-0.055* (0.076)	-0.071** (0.027)
Interact RL DD	-0.000 (0.915)	-0.001 (0.785)	-0.000 (0.928)	-0.001 (0.827)
Constant	-6.385*** (0.000)	-5.490 (0.986)	-7.112*** (0.000)	-5.490*** (0.000)
Number of observations	37,403	37,403	37,403	37,403
Number of cluster	1,265	1,265	1,265	1,265

Notes. The table shows a bivariate probit regression of financial distress and relationship lending with standard errors adjusted for firm clusters. The analysis is based on time-series observations for individual firms between 1993 and 2007. For variable definitions see Table 7. Year dummies are included. P-values are in parentheses.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

negative influence on having a relationship lender, as does the leverage ratio of the industry. The significant explanatory variables show a sign as expected. As a robustness check the relationship lending status is measured using the relative relationship lending criterion (relative share for one bank is >=0.70). This does not lead to a change in the results.

7 Conclusion

A relationship lender can be characterised as having an information advantage compared to other lenders having no close relationship (arm's length banks). The relationship lender is able to renegotiate credit contracts and possesses a certain degree of negotiating power (Boot (2000) and Elsas (2005)). The relationship lender might accept a loan contract which is not profitable in the short term but leads to a profitable relationship in the long term (Boot

(2000)). Having a relationship lender might lead to different bank and firm decisions and thus a relationship lender might influence the firm's probability of financial distress.

In the literature several arguments can be found to support the hypothesis that having a relationship lender might reduce the firm's probability of financial distress. E.g. the customer can benefit through better loan terms (Petersen/ Rajan (1994) and Berger/ Udell (1995)), more easily attainable capital (Petersen (1999)), and liquidity insurance (Elsas/ Krahnen (1998)).

On the other hand, having a strong relationship might lead to costs for the firm. Having a relationship lender gives an information monopoly to the lender and might lead to high switching costs (Sharpe (1990), Rajan (1992)). These aspects indicate that a relationship lender could have a negative impact on the firm's probability of financial distress. A further potential negative effect might be the fact that those firms which are especially in need of a relationship lender choose to have one. For example small firms with limited access to the capital market or firms mainly invested in risky assets might choose this type of lender. Consequently, the potential endogeneity between relationship lending and the firm's probability of financial distress has to be taken into account. A bivariate probit regression using the determinants of relationship lending as a first stage equation is applied to address the endogeneity between relationship lending and the firm's probability of financial distress within this study.

The equilibrium structure argument derived in accordance to Demsetz (1983) supports the hypothesis that having a relationship lender is an endogenous outcome of a selection of advantages and disadvantages of having a relationship lender arrived at a bank-relationship equilibrium. Consequently, having a relationship lender would have no effect on the firm's probability of financial distress.

Based on the three hypotheses, this paper examines whether having a relationship lender affects the firm's probability of financial distress. For the empirical investigation German Credit Register information is applied for a time period 1993-2007 to identify the relationship lending status of a firm. Moreover, the Merton model is used to derive a criterion to identify the firm's probability of financial distress. I use probit regression models to identify determinants of financial distress and relationship lending. In addition, a bivariate probit regression model is applied to model the decision to have a relationship lender and the influencing factors on the firm's probability of financial distress simultaneously. Both models indicate that having a relationship lender does not significantly influence the firm's probability of financial distress. Thus the regression models support the equilibrium structure hypothesis.

The regression model further suggests that the industry level of the distance to default has explanatory power. The higher the distance to default average of the industry, the lower is the probability of financial distress of the single firm. This underlines the fact that a lower industry level of distance to default might indicate that the firm belongs to a more risky industry which is inclined to enter financial distress. Additionally, the firm's profitability has a significant negative influence on reaching financial distress, as do liquidity and efficiency. The more profitable the firm, the higher its liquidity and the more efficient the firm, the lower the probability of entering financial distress. This indicates that high profitability, liquidity and efficiency protect the firm from entering financial distress.

In terms of the determinants of a relationship lender I find that belonging to a borrower unit has a negative significant influence on the relationship lending status. If a firm belongs to a borrower unit, the probability of having a relationship lender is lower than for firms which do not belong to a borrower unit. This might be the case because a borrower unit relationship leads to internal credit access. Thus, bank ties might be less strong. Furthermore, the model indicates that the average of the distance to default has explanatory power. The lower the distance to default average of the firm is, the higher the probability of having a relationship lender. As Yosha (1995) observes, more profitable firms prefer bilateral financing to reduce information disclosure, thus firms with a higher distance to default might prefer bilateral lending as well. Size has a significant negative influence on having a relationship lender according to the model. This might indicate that bigger firms have better access to the capital market and are not as in need of strong bank ties as small firms are. Finally, the leverage ratio of the industry shows a significant negative sign. This might denote that the more the industry relies on bank debt, the higher is the probability of having a relationship lender.

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Appendix

A Relationship lending criterion

A.1 German Credit Register and borrower unit

To investigate whether there is a difference between the borrower unit according to the German Banking Act and the corporate group according to the German Corporate Law, I investigate and compare the definitions of the borrower unit and the corporate group. The difference in definitions indicates that using the German Banking Act-based German Credit Register information leads to an information advantage for this investigation. This is mainly based on the fact that banks are informed about the borrower units' level of debt and are able to consider this within their credit decision process. The comparison shows that differences between these two categories might occur due to differences in the definitions. The borrower unit also includes risk related firms as well as partnerships under the German Civil Code. A detailed description of the comparison can be found in Table A.1.

Table A.1
Borrower unit (KWG) versus corporate group (German AktG)

Reason for a borrower unit	Explanation	Comparison to consolidated groups
Consolidated group membership	§19 II KWG: combine group entities to a borrower unit if following requirements are met: – centralised management – majority ownership – dominating influence – take over of losses	1. In case of fully consolidated subsidiaries: conformity of borrower unit (KWG) and corporate group (AktG). But dominating influence is, according to the AktG, basically only possible from one side, however, an assignment to more than one borrower unit is possible according to the KWG 2. Joint companies: full debt attribution (borrower unit) vs. proportional consolidation (group statement) 3. Affiliated companies: full debt attribution (borrower unit) vs. recognition using the "at equity method" (group statement)
Risk unit	Combine firms to a borrower unit if reciprocal dependencies exist (e.g. financial distress affects other entities)	Economic dependencies (KWG) vs. dominating influence (AktG) as the attribution concept
Partnership under the German Civil Code	No borrower unit is formed but indebtedness is assigned to every partner	Full attribution of debt in case of proportional and full partnership liability (KWG) vs. dominating influence concept (AktG)

Notes. The table shows an overview of the reasons for a firm to join a borrower unit according to the KWG and the differences between a borrower unit and the consolidated group according to the AktG.

Beside the investigation of different definitions of the borrower unit and the corporate group, an empirical comparison is performed. A difference strengthens the fact that using the German Banking Act-based German Credit Register information leads to an information advantage for this investigation. The empirical comparison shows that differences between these two categories occur. A detailed description of the comparison can be found in Table A.2.

Table A.2
Borrower unit (BU) member versus corporate group (CG) subsidiary

Subgroup for borrower unit and corporate group comparison	**Absolute number of firms**	**Relative number of firms**
Group 1) Borrower unit name and corporate group name are equal	491	
thereof consistent with corporate group	398	81%
Group 2) Borrower unit name equals name of a private person	341	
thereof consistent with corporate group	72	21%
Group 3) Borrower unit name equals differing national group name	203	
thereof consistent with corporate group	21	10%
Group 4) Borrower unit name equals a differing international group name	107	
thereof consistent with corporate group	23	21%
Total Borrower units investigated	1,142	
thereof consistent with corporate group	514	45%

Notes. The table shows the differences of the borrower unit (BU) members versus corporate group (CG) subsidiary. The numbers are based on an analysis for a representative period of time between 1998 and 2007. The table above displays different categories of borrower unit names. I find cases in which the corporate group name equals the borrower units name at a 99% level or higher (Group (1)). 81% of these firms show identical borrower unit members (central bank data) and corporate group members (German Corporate Group Act). I also find that a matched firm is related to a borrower unit in which the name equals the name of a private person (in most cases a major shareholder or a limited partners) (Group (2)). Group (3) includes borrower units with the name of a national group that does not equal the firm's name (e.g. when the matched firm is part of a corporate group). Group (4) includes borrower units named after an international group. Group (1) shows the highest consistency of borrower unit and corporate group members.

To learn more about the German Credit Register reports used for the investigation, a detailed analysis of the German Banking Act regulations in terms of the 1.5 million EUR reports is performed. The analysis of the German Banking Act shows that not only loans are reported by German banks. Furthermore, off-balance sheet transactions such as certain derivatives and warranties are reported as well. This again underlines that using German Credit Register reports leads to an information advantage compared to using balance sheet data. A detailed overview of reported items under the German Banking Act is provided in Table A.3.

Table A.3
1.5 million EUR reports according to the German Banking Act (KWG)

Reporting trigger event	Loans of 1.5 mio EUR or more to: – a single borrower – a borrower unit
Reporting date	each 31^{st} March, 30^{th} June, 30^{th} September, 31^{st} December
Reporting scope	**Reporting Type 1 ("Satzart 1")** – sum of loans at reporting date – overall level of debt thereof: – asset items according to §19 I 2 KWG – off-balance sheet transactions thereof: derivatives according to §19 I 1 KWG (credit equivalent amount) warranties for derivatives according to §19 I 1 KWG guarantees and other warranties according to §19 I 3 No. 3-5, 7, 9, 12 leasing receivables according to §19 I 2 No. 9 KWG and receivables resulting from the monetary acquisition of monetary claims mortgages according to §14 II 3 No. 5 KWG publicly guaranteed loans according to §14 II 3 No. 4 KWG inter-bank loans according to §20 III 3 No. 2 KWG **Reporting Type 6 ("Satzart 6")** – bails/ guarantees/ warranties – syndicate quota/ syndicate management (extended by way of guarantee) **Reporting Type 7 ("Satzart 7")** – loans secured by a guarantees – syndicated loans (extended by way of guarantee)
Reporting receiver	Deutsche Bundesbank's Credit Register ("Evidenzzentrale")
Reporting unit	– domestic banks – financial services institutions according to §1 Ia 2 No. 4 (proprietary traders) – branches of enterprises domiciled abroad (§53) located in Germany unless they are covered by the European Banking Passport
Institutions included in reporting	According to §14 I 2 KWG, the subordinated domestic enterprise has to report borrowers separately for all banks domiciled abroad – all banks domiciled abroad – financial services institutions domiciled in Germany or abroad by definition of §1 1a KWG (except domestic proprietary traders) – financial enterprises domiciled in Germany or abroad by definition of §1 III KWG (except domestic factoring enterprises) – financial holding enterprises domiciled in Germany or abroad by definition of §1 IIIa KWG – ancillary banking enterprises domiciled in Germany or abroad by definition of §1 IIIc KWG belonging to the group

Notes. The table shows an overview of the German Banking Act related to the 1.5 million EUR reports.

To analyse whether a firm belongs to a certain borrower unit and never changes this unit, a borrower unit change of a firm is investigated. The empirical analysis shows that most of the firms change their borrower unit over time. The reasons are the change of a corporate group, the change of a risk unit or the change of partnerships under the German Civil Code as displayed in Table A.1. The change of a borrower unit is included in the regression analysis as an indicator for a change of the influencing equity holder.

Table A.4
Borrower unit relationship change over time

Borrower unit change	Number of firms	Percent	EBIT mean (mio EUR)	Asset mean (bn EUR)
Firms with borrower unit relationship	944			
thereof				
without change	176	19%	111	2.01
with change	768	81%		
thereof				
once	364	48%	71.0	1.62
twice	215	28%	67.8	2.64
three times	108	14%	9.0	230
four times	50	7%	4.0	360
five times	18	2%	66.0	655
six times	10	1%	2.1	124
seven times	1	0%	0.9	26
eight times	2	0%	3.0	220

Notes. The table above shows the investigation of borrower unit relationships between 1993 and 2007. Only 176 firms of the 944 firms which are included in a borrower unit do not change their borrower unit over the period. The mean of the total assets is based on pooled firm data and indicates that bigger firms show a lower frequency of changing the borrower unit.

A.2 Relationship lending criterion

To compare the derived relationship lending identification criterion based on the Herfindahl-Hirschman index (RL HHI) and the derived relative criterion (RL relative; relative loan share is equal to or higher than 70%), I investigate how many firms are identified as having a relationship lender according to both of the criteria. The investigation underlines that the HHI-based cirterion covers all firms identified by the relative criterion. Furthermore, this wider definition includes such cases as e.g. one bank holds a 45% debt share, however, 2 other banks hold the rest of the debt.

Table A.5
Estimation matrix relative relationship lending (RL relative) criterion and HHI-based criterion (RL HHI)

first quarter 1996	no RL HHI	RL HHI
no RL relative	386	64
RL relative	0	95

first quarter 2000	no RL HHI	RL HHI
no RL relative	464	105
RL relative	0	131

first quarter 2003	no RL HHI	RL HHI
no RL relative	451	107
RL relative	0	181

first quarter 2007	no RL HHI	RL HHI
no RL relative	496	88
RL relative	0	171

Notes. The estimation matrix is based on Credit Register data and shows how many firms have a HHI>0.40 and a relationship lender which holds a relative debt share of >=0.70. The tables show exemplary results of the first quarters 1996/ 2000/ 2003/ 2007.

Does relationship lending matter in financial distress?

Working Paper III

R. Elsas, I. Stein, N. Stephenson [1]

Abstract

This study examines whether having a relationship lender matters if firms are in financial distress. Due to the private information possessed by a relationship lender about firm quality, borrowers face high switching costs if they terminate the bank-borrower relationship. This in turn suggests that the relationship lender will make different distress decisions (i.e. to terminate or support the firm) compared to an arm's length lender. We test this prediction by analysing the determinants of the outcome of financial distress, controlling for relationship lending and several potential restructuring measures such as management turnover, recapitalisations, ownership change, and others. We also test whether relationship lenders are more willing to provide financial support to distressed firms, or whether receiving financial support from a relationship lender affects the likelihood of a successful restructuring. All these tests unequivocally show that relationship lending does not matter to the outcome of financial distress, while other restructuring activities, in particular ownership changes and capital infusions, systematically increase the likelihood of surviving financial distress.

[1] The research for this paper was conducted while Nadine Stephenson was a visiting researcher at the Deutsche Bundesbank. We would like to thank the Deutsche Bundesbank most sincerely for its hospitality and for providing its data. This working paper represents the authors' personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank or its staff. Special thanks go to Nikolas Breitkopf for his valuable suggestions and inputs. Of course, all remaining errors are those of the authors.

1 Introduction

Relationship lending is defined as a long-term implicit contract between a bank and its debtor. Due to information production and repeated interactions with the borrower over time, the relationship lender bank accumulates private information, establishing close ties between the bank and the borrower. Such ties enable the well-known potential benefits from the lending institution suggested in the theoretical literature: inter-temporal smoothing, increased credit availability, and more efficient decisions where borrowers face financial distress (e.g. Fischer (1990), Sharpe (1990), Rajan (1992) and Petersen/ Rajan (1995)).[2]

This paper contributes to our understanding of the importance of relationship lending for corporate finance by examining whether having a relationship lender matters when firms are in financial distress. Thus, the analysis examines the one theoretical benefit of relationship lending which potentially provides the highest utility to firms, thereby studying the most important potential real-world consequence of this lending institution.[3]

Our empirical analysis is based on the sample of exchange-listed German corporations in the period 1993-2007, and it is unique for several reasons:

- We identify relationship lending by using data on firms' (bank) debt structure taken from the German Credit Register, which contains quarterly updated (regulatory) information on companies' bank lenders and their respective financing shares.
- We employ a timely criterion to identify financial distress of firms, which has a high predictive power for future financial distress measured by means of the criterion's statistical size, power, and type-I and type-II error.
- Economically, financial distress is a particularly interesting situation to investigate with respect to corporate finance issues. It is defined as occurring where a firm has a critically high probability of default, such that stakeholders start engaging in restructuring activities, which can then be observed at a high frequency. Note that financial distress typically precedes the initiation of legal bankruptcy proceedings.
- The German financial system is often viewed as the prototype of a bank-based financial system, where banks (so-called "Hausbanks") play an important role in corporate finance even for large and exchange-listed companies. Hence German data offers a unique opportunity to learn about the pros and cons of relationship lending.

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[2] Relationship lending is not the dominant type of financing, since it is, inevitably, associated with costs. One possible type of such costs are monitoring costs, in the spirit of Gale/ Hellwig (1985) and Diamond (1991). More specific with regard to relationship lending are switching cost in the sense of Sharpe (1990) and Rajan (1992). In their models, the information privilege of banks endogenously induces bargaining power, thereby giving rise to a hold-up problem.

[3] Except for the study by Hoshi/ Kashyap/ Scharfstein (1990), however, there is no other study we are aware of that examines relationship lending in this context.

Using data on debt structures of companies from the German Credit Register helps us to identify the incidence of relationship lending for a given company in an arguably more reliable manner than previous studies, because we can rely on detailed and rather timely information provided by banks for regulatory purposes. As suggested by the empirical analysis of Elsas (2005), a relationship lender will be identified using the Herfindahl-Hirschman index of a firm's bank debt structure, thereby controlling for the number of bank relationships of a firm and their respective financing shares of debt simultaneously.

There are few studies which analyse financial distress at all, and these studies all use a distress identification criterion based on financial statements data (e.g. DeAngelo/ DeAngelo (1990), Hoshi/ Kashyap/ Scharfstein (1990), Asquith/ Gertner/ Scharfstein (1994), Griffin/ Lemmon (2002)). This necessarily implies uncertainty over the timing of the distress event due to the low disclosure frequency of annual reports. In contrast thereto our distress criterion is based on a probability of default estimate based on a structural model as suggested by Merton (1974) [4] . Thus, we can rely on daily stock prices of firms as the main input, providing a daily updated creditworthiness assessment that uses the price mechanism of financial markets as the arguably most powerful mechanism to acquire and process information. As we will show below, by analysing the incidence of bankruptcy proceedings and the occurrence of restructuring activities of firms (indicated by significant recapitalisations, management turnover, ownership transfers and other measures) the distress criterion based on these "capital market ratings" has a high predictive power for financial distress with low associated errors in its distress classification.

Having identified distressed firms with and without relationship lenders, we then examine which factors determine the outcome of financial distress, i.e. differentiating between distressed firms which subsequently go into bankruptcy, or re-emerge as a financially sound and restructured firm. The emphasis of this analysis lies on the question whether the outcome of financial distress is systematically affected for a distressed firm by having a relationship lender.

To this end, we conduct three different tests. At first we analyse generally whether the outcome of distress is affected by having a relationship lender, controlling for other restructuring activities such as ownership changes, acquiring new funds, management turnover and so on. Second, we test whether relationship lenders systematically provide more funds (i.e. financial support) to distressed firms than arm's length lender. Third, we test whether receiving financial support from a relationship lender affects the likelihood of a successful restructuring. All these tests unequivocally show that relationship lending does not matter to the outcome of financial distress, while other restructuring activities, in particular ownership changes and capital infusions, systematically increase the likelihood of surviving financial distress.

[4] So far only Vassalou/ Xing (2004) apply the Merton model to identify financial distress and investigate default risk and equity returns.

The remainder of this paper is organised as follows: Section 2 discusses theoretical predictions on the role of relationship lending if firms enter financial distress, and the related empirical evidence. In Section 3, we describe our data and how we identify whether a given firm has a relationship lender. In Section 4, we suggest a new criterion to identify firms in financial distress. The section also contains the analysis of the criterion's characteristics in terms of its statistical properties for distress prediction. Section 4 includes the definition of the main variables: Corporate failure and relationship lending. In Section 5 the regression results are presented and Section 6 concludes.

2 Previous results and predictions on the role of relationship lending where borrowers are in financial distress

Following Boot (2000), Elsas (2005) and Elsas/Krahnen (1998), a relationship lender is considered to be the premier lender of a firm. Due to information production and repeated interactions over time, the relationship lender is equipped with more reliable and more timely information than any arm's length lender (e.g. Diamond (1984), Ramakrishnan/ Thakor (1984), Fama (1985), Rajan (1992)). The informational advantage of the relationship lender leads to high switching costs for the borrower (Sharpe (1990), Rajan (1992)). Economically, this has two implications. On the one hand, the firm is tied to its relationship lender, which might allow the bank to extract rents: this is the well-known "hold-up problem". On the other hand, having private information and knowing that the borrower cannot easily switch to another bank changes the intrinsic perspective of the bank into a long-term perspective.

This becomes particularly relevant if firms are in financial distress, because the bank knows that it might recoup losses due to the distress situation in later periods, where the borrower might have recovered. Thus continuation or liquidation decisions will potentially differ from other lenders of a distressed firm. It is important, though, to stress that having better information might nevertheless imply that the relationship lender should liquidate a firm - the information privilege might simply lead to the conclusion that the firm is economically distressed. From a theoretical perspective, a rationale for relationship lending based on different decisions if borrowers face financial distress thus requires that the relationship lender makes more efficient decisions. It should liquidate a company more often if the company is in economic distress (i.e. the liquidation value is higher than the continuation value), and it should continue financing more often if the company has investment projects with a positive net present value.

Measuring the efficiency of banks' continuation or liquidation decisions is notoriously difficult, because the "true" quality of a company's investments cannot be observed directly, not even in hindsight. This is for example obvious if a distressed firm is liquidated - it is impossible to observe the outcome of a hypothetical continuation of this firm.

Accordingly, empirical studies have rarely studied bank behaviour in cases where borrowers are in financial distress. Elsas/ Krahnen (1998) show that German relationship lenders tend to increase loan supply if the (internal bank) ratings of their corporate borrowers deteriorate. This analysis does not address financial distress directly, however. The study closest to ours is Hoshi/ Kashyap/ Scharfstein (1990). They find that Japanese firms with a relationship lender invest more and have higher sales growth after a certain post-distress period. However, these authors do not systematically test whether the outcome of financial distress depends on having a relationship lender. Also, their criterion used to identify financial distress is based on low-frequency, historical accounting data. Financial distress is defined as occurring if a firms' interest coverage ratio is less than or equal to one for at least two successive years. The average timing error associated with such a criterion is about 12 months, assuming an uniform distribution of distress events over time. This timing uncertainty will make it very difficult to observe strategic restructuring activities by corporate stakeholders, because one barely knows when to start observing them. Since our criterion for financial distress will be based on implied probabilities of default of companies from daily stock prices, our analysis will be based on a much more timely criterion, thereby potentially allowing us to gain new insights into the role of (informed) banks concerning firms in financial distress.

Still, the theoretical concept of relationship lending offers several empirical predictions regarding the likely impact of relationship lending where firms are in financial distress. The information privilege of a relationship lender does not imply per se that informed banks should less often liquidate firms in financial distress than an arm's length lender. The better information should have helped relationship lending banks to screen "bad" borrowers from their loan portfolios during the bank-borrower relationship. Empirically it seems likely that firms with a relationship lender for some time are selected on their quality. One might then expect that a relationship lender is more willing to support these firms if they are in financial trouble as compared to other firms where the bank does not have private information. This gives rise to the following three testable hypotheses, we will analyse in our study:

Hypothesis 1: Distressed firms which have a relationship lender are more likely to show a positive outcome after a restructuring period.

Hypothesis 2: Distressed firms which have a relationship lender are more likely to get financial support within a restructuring period.

Hypothesis 3: Distressed firms which have the financial support from a relationship lender are more likely to be successfully restructured.

3 Data and relationship lending measures

3.1 Data

Our empirical analysis comprises exchange-listed companies in Germany between January 1, 1993 and December 31, 2007. The sample includes currently operating companies as well as firms delisted due to bankruptcy or any other reason. We use share price data provided by Datastream, and data on firms' financial statements provided by Hoppenstedt.[5] Overall, we collect panel data for 1,265 firms with sufficient price and financial statement data for our analysis.

To validate the financial distress criterion suggested below, information from the Hoppenstedt database, as well as hand-collected information from a LexisNexis newspaper search, press statements made under the ad-hoc publicity requirement in Germany, and information taken from firms' websites are used. The news search for firms' restructuring activities is conducted for a time period of 500 days after a financial distress event has occurred.

To determine whether a firm has a relationship lender, information from the German Credit Register is used. The register includes quarterly reported loans of at least 1.5 million EUR, mandatorily reported by banks to the German central bank (Deutsche Bundesbank) according to § 14 of the German Banking Act (KWG). Reports to the German Credit Register need to be initiated if a single borrower or a borrower unit exceeds the 1.5 million EUR threshold. According to the German Banking Act, a borrower unit includes consolidated groups, risk units and partnerships under the German Civil Code. Hence, a borrower unit may defer from the consolidated group according to the German Stock Corporation Act (AktG).[6]

We match our sample of German-listed firms with the German Credit Register information. Primarily this needs to be based on the firm's name and registered address. The applied probabilistic record linkage procedure then considers a firm as matched if the firm's name, the city of the head office, the legal form, the commercial register number (if available) and the postal code are identical at a 98% level. Overall, we are able to match 89% of the stock market-listed firms provided by Datastream. We extract the borrower unit the firm belongs to. Firms which are a member of a borrower unit headquartered in a foreign country are excluded. As the central bank reports only include

[5] The Hoppenstedt database has a better coverage and is more reliable for German companies than financial statement information provided by Datastream. One of the reasons for this is that Hoppenstedt differentiates between accounting standards and provides different accounting schemes, in particular including information based on the German accounting standard (HGB). Since the year 2005, German-listed companies have had to draw up their financial statements according to international accounting standards.

[6] An overview of the reasons a firm is classified as a member of a borrower unit according to the KWG, and the differences between borrower units and consolidated groups according to the AktG, are displayed in Appendix A.2.

German banks reports and a foreign country-based unit has a high probability of having foreign country bank relationships we categorise that sort of borrowing unit as "not representative". Overall our matched sample includes 16.2% bankrupt firms, compared to a ratio of 12.4% within the overall Datastream sample. This indicates that we do not lose primarily bankrupt firms through our matching process.

According to the KWG a firm can either be reported as a single firm (if no further firm relationships exist) or be included into one or more borrower unit reports. To investigate whether the classification as a borrower unit (KWG) or a corporate group (AktG) constitutes a material difference, we compare the two definitions for the time period between 1993 and 2007. Based on the Amadeus database, we track subsidiaries of corporate groups and check whether the set of subsidiaries is reflected in the borrower unit definition of the German Credit Register. We define a borrower unit as "consistent" with the corporate group if the subsidiaries represent 90% of the firm's reported debt according to the German Credit Register. The two definitions turn out to be materially identical only for about 55% of all cases.

Hence, the borrower unit classification within the regulatory German Credit Register leads de facto to a different classification compared to the legal definition by the German Securities Act (AktG). However, including risk-related firms within one unit appears economically reasonable. Moreover, the borrower unit classification is actually primarily based on assessments of the reporting banks and consequently considers all credit decisions of the bank when dealing with this borrower. [7]

Finally, it is worth mentioning that German Credit Register information on firms' indebtedness with banks covers more information than annual reports under the German accounting standards. For example, guarantees provided by banks as well as bank-firm off-balance-sheet transactions have to be reported as well.

The additional information provided by the German Credit Register improves our identification of relationship lenders since it better reflects the debt structures of firms as compared to an analysis only based on financial statement information. [8]

3.2 Relationship lending measures

This study defines a relationship lender as "...the premier lender of a firm, being equipped with more reliable and more timely information than any non-relationship-lending institution." (Fischer (1990), Elsas/ Krahnen (1998), Boot (2000)). The definition underlines the key aspects of the premier lender, namely

[7] A bank reporting borrower loans to the central bank receives the information whether or not the firm is already included in a borrower unit, and the amount (and type) of debt provided by other banks to this borrower unit in return.

[8] Appendix A.1 provides further details of the German Credit Register loan reporting.

information advantage and information asymmetry. These aspects should be considered in the search for an identification criterion for relationship lending.

To identify relationship lending empirically, different proxies are suggested in the literature. Petersen/ Rajan (1994), Berger/ Udell (1995) and Ongena/ Smith (2001) apply the duration of a firm-bank relationship as a criterion to identify the relationship lender. This approach is based on the idea that the longer the relationship lasts, the more valuable private information the bank will have accumulated. However, Elsas (2005) finds that the duration of a firm-bank relationship is empirically not related to banks' self-assessment as to whether they are the Hausbank of a borrower or not. Thus, duration is not applied to identify relationship lenders within this study.

The literature also suggests using the number of bank relationships a firm maintains, or the share of debt provided by a bank, as measures to identify relationship lending. Elsas (2005) finds in his empirical study that both measures are indeed systematically related to the Hausbank status of banks. We therefore employ these measures to identify relationship lending in our analysis, using the Herfindahl-Hirschman index (HHI) as a concentration index for a firm's bank debt structure. This captures the two aspects "high share of debt of one bank" and "number of bank relationships" simultaneously.

To identify a relationship lender, the HHI is applied by using the reported loan amount according to the German Credit Register provided by each single bank (FA). The index is calculated by dividing the sum of the squared reported loan amounts by the squared sum of total reported loan amounts:

$$HHI = \frac{\sum_{i=1}^{N} (FA_i)^2}{(\sum_{i=1}^{N} FA_i)^2}. \tag{1}$$

Aiming at identifying high shares of debt financing and a low number of bank relationships, we define for a robustness check a lender as a relationship lender if the bank holds more than 70% of the firm's debt. [9]

To define the HHI-related relationship lending criterion we perform further investigations on the HHI. To find out how many bank relationships firms with a higher HHI level have, we look at different HHI scores and investigate the number of bank relationships. We find that for HHI scores between 0.41 to 0.50 the number of bank relationships is three or less for 25% of the sample firms. This low number may also indicate that two or three banks hold an equal share of the firm's debt. In this case there is no asymmetry of power that leads to the advantages of a relationship lender. To find out whether asymmetry in bank

[9] To avoid the problem that fractions of debt financing might overstate the relevance of a bank as a financier, we further require that a firm's debt ratio needs to be at least 10% of total assets in order to be eligible to have a relationship lender. For example, a bank that has 90% share of a firm's total debt financing may nevertheless be unimportant as a financier, simply because the firm has only 1% of its funds coming from debt.

relationships exists at an HHI level higher than 0.40 we look at how high the debt share of the major lender is in these cases. We find that if a firm has an HHI of 0.41 or higher, the share of debt of the largest debt provider is 45% or more. Holding the major share of 45% or more provides asymmetric power to a bank. Consequently, we consider a bank as a “relationship lender” if it is the firm’s largest lender and the firm’s HHI is higher than 0.40.

Using the relationship lending criterion of an HHI>0.40 and the relative as well as a one-bank-relationship criterion, we investigate how many of our sample firms do have a relationship lender. The investigation shows that between e.g. 29% (1996) and 39% (2007) of the firms have a relationship lender according to the HHI. According to the relative criterion 17% (1996) and 24% (2007) of the firms have a relationship lender. According to the one-bank-relationship criterion 9% (1996) and 15% (2007) of the firms are identified as having a relationship lender. The number of relationship lenders increases over time, which might be related to consolidation activities in the German banking market.

A comparison of the banks identified as a relationship lender according to the three criteria underlines that the HHI identifies additional firms as relationship lenders. The above-mentioned investigation of the major borrower share for an HHI>0.40 shows the major borrower holds 45%. From our perspective, asymmetry of influencing power in this case already exists. The relative relationship lending criterion of >=0.70 and a one-bank-relationship criterion thus seems to be a too narrow definition.

As mentioned above, if a firm is not included in a borrower unit, we use the single firm data to determine whether or not this firm has a relationship lender. The investigation shows that a relationship lender occurs more often on a single firm basis. In the following step, we investigate whether for one firm the relationship lending criterion differs on a single firm basis compared to a borrower unit basis. We find that in most cases (79%) the criterion on a single firm basis and on a borrower unit basis equals. A different relationship lending status occurs more often for smaller firms. If a firm is included in a borrower unit, an alternating relationship between firms in the borrower unit exists according to the definition of the KWG. Consequently, we use the HHI on a borrower unit basis in case the firm is included in a borrower unit.

4 Identification of financial distress

4.1 Composition of the financial distress sample

To compose the sample of distressed firms, we apply the Merton model. The debt data from Hoppenstedt serve the calculation of the default threshold. In accordance with Moody’s KMV the short-term debt is considered at 100% while the long-term debt is only considered at 50% (Crosbie/ Bohn (2003)).

Fig. 1. Development of the distance to default percentile values 0.10, 0.05, 0.01 over time and the development of the German DAX

Notes. The figure on the left shows the Merton model-based distance to default development of the 0.10 (upper line), the 0.05 (middle line) and 0.01 (lower line) distance to default percentile values. The figure on the right shows the development of the German stock index (DAX) in comparison.

The FIBOR and later the EURIBOR are applied as the risk-free interest rate. The applied time to maturity T is set to $T = 1$.

To determine a financial distress criterion, different approaches of classification in terms of distance to default percentiles are compared. A matrix is set up comparing the combinations of distance to default percentiles and the number of days in a row a company stayed within this percentile. The matrix serves as a basis to investigate how many of the companies belonging to a certain percentile for a certain time period filed for bankruptcy.

To gain knowledge about the distance to default development over time different percentile values are observed. The variation of the distance to default threshold level for certain percentiles compared to the German Dax is shown in Figure 1.

Figure 1 shows that the distance to default values of different percentiles vary over time. In a situation of moderate market conditions even higher percentiles show a low distance to default. This reflects that in bad market conditions a higher number of firms are in danger of entering financial distress. In good market conditions, even the lower 0.01 percentile shows a distance to default higher than 1.5, reflecting that in good market conditions fewer firms are in danger of entering financial distress. In terms of the classification criterion this indicates that not only a relative criterion should be chosen. Thus, a threshold of an absolute distance to default value of 1.5 is included in the criterion. The matrix in Table 1 displays different combinations of distance to default percentiles and the number of days in a row a company stayed within this percentile while the distance to default of that firm was 1.5 or below. It also displays how many of these companies filed for bankruptcy.

An investigation of the criterion shows that firms may fall below the threshold more than once. To address this aspect, multiple event data of one firm are used, if the distance of a shortfall below threshold is bigger than 750 trading days. If the distance between the events is less than 750 trading days, the company is included in the distress sample only with the first event. Hence the overall number of firm cases might vary.

Table 1
Default sample according to the financial distress criterion

Percentile	Days in a row	Financially distressed & ahead of bankruptcy	Not financially distressed & bankrupt	Not financially distressed & no bankruptcy	Financially & no bankruptcy	Overall number of financial distress
0.05	22	106	57	875	253	359
	20	108	56	874	254	362
	14	108	56	863	267	375
	12	110	52	861	267	377
	10	**114** (75% of bankruptcy firms)	**49**	**860**	**268**	**382** (30% of all firms)
	9	115	48	859	269	384
	8	116	48	857	271	387
	4	116	45	854	276	392
	3	119	42	852	277	396
	1	121	42	847	285	406
0.03	22	86	78	918	204	290
	20	87	77	914	207	294
	13	93	72	914	211	304
	12	92	73	910	215	307
	10	95	70	908	220	315
	9	98	67	906	222	320
	8	100	67	906	224	324
	4	105	61	903	225	330
	3	106	60	898	227	333
	1	113	53	884	242	355
0.01	4	63	97	974	143	206
	3	63	95	971	146	209
	1	70	89	964	154	224

Notes. The migrations matrix is based on a comparison of the distance to default over time calculated using the Merton model. The above-presented criterion combines the percentile of a firm's distance to default with an absolute level lower than or equal to 1.5 as a default criterion.

Table 1 shows that 114 cases occur in which a company belongs to the 0.5 percentile for 10 days in a row, having a distance to default below 1.5 and went bankrupt after this event occurred. This covers 75% of the bankrupt firms for which data is available to calculate the distress criterion. 49 companies never belonged to the 0.5 percentile for 10 days and had a distance to default below 1.5 but went bankrupt. 860 companies never belonged to the 0.5 percentile for 10 days in a row having a distance to default below 1.5 and never went bankrupt. Finally 268 cases occurred in which a company belonged to the 0.5 percentile for 10 days in a row, having a distance to default below 1.5 and never went bankrupt. Overall 382 financial distress cases are identified. As discussed above, even if a company never filed for bankruptcy, a classification as financially distressed could be reasonable for the sample, because firms using the way of private restructuring also ought to be included in the sample. Consequently, we allow these cases to occur in the matrix.

According to the results of the calibration matrix, we define a firm as financially distressed if the firm belongs to the lowest 0.05 percentile for at least 10

Fig. 2. Development of the financial distress cases over time

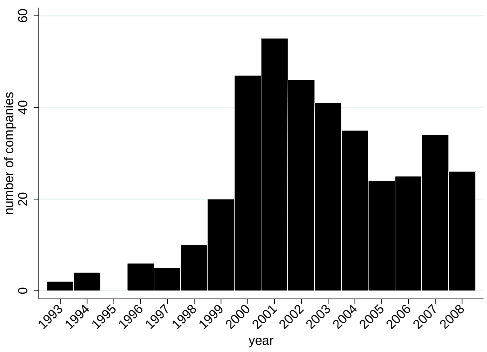
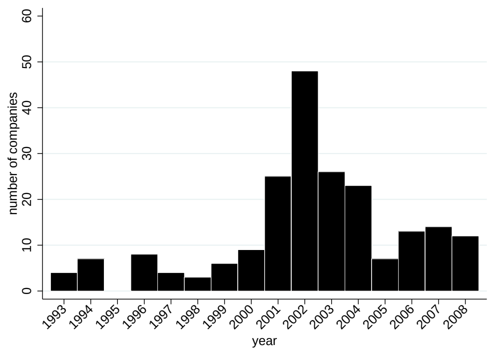


Fig. 3. Development of bankruptcy cases of sample firms over time



Notes. Figure 2 shows the point in time the financial distress cases occur in the first place. To identify financial distress the Merton model-based financial distress criterion is used. Figure 3 shows the point in time the sample firms filed for bankruptcy. The bankruptcy information is supplied by Hoppenstedt and LexisNexis as well as the firms' homepages.

days in a row and if in addition its distance to default is lower than or equal to 1.5. The combination of the relative and absolute criterion leads to a financial distress criterion which also takes into account economic up- and downturns (see Figure 2).

Figure 3 shows the number of legal bankruptcy proceedings for the sample firms over time. Compared to Figure 2, Figure 3 indicates that the financial distress situation is recognised before the firm enters a legal bankruptcy process: Whereas Figure 2 has its peak of first recognition of a financial distress situation in 2001, the peak of legal bankruptcy process occurred in 2002. Furthermore, financial distress occurs more often. This reflects the fact that companies which did not file for bankruptcy but chose private debt-restructuring as a way to overcome the financial distress are also included in the sample used in this investigation.

To further validate the criterion we investigate how many of the 382 identified distress firms filed for bankruptcy within a time period of 10 trading days before and 500 days (about 375 trading days) after the financial distress event. 95 of the financially distressed firms filed for bankruptcy (75% of the overall bankruptcy firms for which data is available) within this period around financial distress identification. We use LexisNexis to find out more about the remaining firms. As restructuring may be an indicator for a financial distress situation, we search for the word "restructuring" in combination with the company name. We analyse a time period of 500 days after the financial distress event has occurred. We find that an additional 113 firms (in addition to the 95 firms which filed for bankruptcy) report restructuring measures within that time period.

Six of the remaining firms reported an agreement of liquidation at their annual general meeting, five firms mention a sale of a business segment and an additional three firms were reported as "dead" by Datastream within a

Fig. 4. Distance to legal insolvency in relation to financial distress event

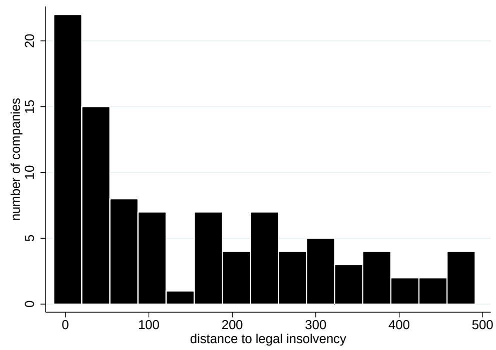
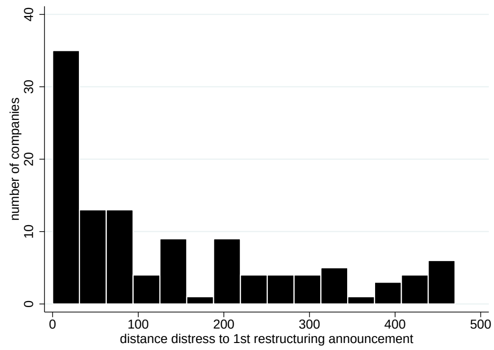


Fig. 5. Distance to 1st restructuring announcement after financial distress event



Notes. Figure 4 shows the time range between the point in time the financial distress event occured and the event of legal bankruptcy. The financial distress event is identified using the Merton model-based combined criterion. Legal bankruptcy is identified using Hoppenstedt, LexisNexis and the firms' homepages. Figure 5 shows the time range between the point in time the financial distress event is recognised and a restructuring event is reported in LexisNexis.

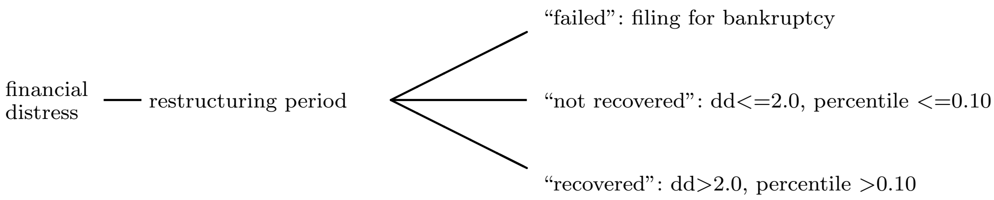
time period of 500 trading days after the distress event. Another 18 (5%) firms filed for bankruptcy after a period of more than 500 trading days. 17 of the remaining firms are reported as "dead" by Datastream after a time period of 500 days post-financial distress.

The distances between the legal bankruptcy filing and the first announcement of restructuring after the financial distress event of the firms are displayed in Figures 4 and 5. The figures indicate that the bankruptcy and restructuring information occur close to the financial distress identification date. We consider the applied distress criterion (stay within the 0.05 percentile for at least 10 days in a row with a distance to default of 1.5 or below) to be a reliable criterion for the following investigation. As a consequence 382 firms are identified as financially distressed. 42 firms which are already in a legal bankruptcy process within the entire distress period (starting more than 10 days before the distress event) are excluded, as those firms face a special legal situation. This leads to a sample of 340 financially distressed firms.

4.2 Corporate failure definition

To evaluate the influence of a relationship lender in terms of the restructuring outcome, a period of time needs to be determined after which the restructuring outcome should be evaluated. To investigate how long it takes a firm to change its financial status on average, we examine how long it takes a firm on average to get out of the 0.05 percentile in terms of a distance to default ranking. The investigation shows that 95% of the firms left the 0.05 percentile after a maximum of 375 trading days in a row within the percentile. Consequently, we choose to investigate the firm performance after 375 trading days after the event of financial distress has occurred. For our ordered probit regression

Fig. 6. Development after financial distress recognition



Notes. The figure shows the three outcome stages 375 trading days after the financial distress event is recognized. We define a firm as “failed”, if the firm files for bankruptcy within this period. We define a firm as “not recovered” if the distance to default (dd) is lower than or equal to 2.0 and the firm belongs to the 0.10 percentile in terms of a distance to default ranking at least during the period 365-375 days after the event occurred. We define a firm as “recovered” if the distance to default is higher than 2.0 and the firm belongs to higher distance to default percentile than the 0.10 percentile 375 trading days after the financial distress event.

model we define a firm as “failed” if the firm filed for bankruptcy within the time period of 375 trading days after the financial distress is recognised. We define a firm as “not recovered” if the firm is within the 0.10 percentile or lower in terms of its distance to default and its distance to default is lower than or equal to 2.0 at least within a time period of 365-375 trading days after the financial distress is recognised. We define a firm as “recovered” if the distance to default is higher than 2.0 and the firm is within a percentile higher than the 0.10 percentile. Firms which are delisted, which have been taken over or for which no financial reporting is provided are taken into account with the last calculated value before one of those events occurs.

Using the definitions displayed above, 95 firms are considered as “failed” because they filed for bankruptcy within the 375 trading days after the financial distress event. A further four firms are considered as failed as they are liquidated based on a liquidation agreement according to LexisNexis. 146 firms are considered as “not recovered” because they show a not sufficient distance to default at the end of the investigated time period. 95 firms are classified as “recovered” as they increased their distance to default and left the 0.10 percentile in terms of the distance to default. As mentioned above, 42 firms filed for bankruptcy more than 10 days before they entered the financial distress sample and are excluded from the sample. Three firms are excluded because their distress period ends in 2010. For our probit regression, all firms showing a sufficient distance to default and distance to default percentile at the end of the investigated time period are considered as recovered (95 firms) and the rest are considered as “not recovered”.

4.3 Univariate results on financial distress and relationship lending

Regarding our distress sample of 340 firms we could identify 295 firms with available German Credit Register information. We find, that 89 firms filed for bankruptcy within the following 375 trading days, 119 firms are still not recovered in terms of the distance to default and 87 firms are identified as recovered. We further investigate which of these financially distressed firms do have a relationship lender. A detailed description can be found in Table 2.

Table 2
Distressed firms and relationship lending criterion status quo after 375 trading days:

	Overall	**thereof:**		
	firms	failed	not recovered	recovered
Distressed firms with central bank data	295	89	119	87
thereof				
firms with HHI criterion based relationship lender (1) or without (0) in the quarter before financial distress:				
0	205	55	86	64
1	90	34	33	23
firms with HHI criterion based relationship lender (1) or without (0) after 375 trading days or last reported period after financial distress:				
0	205	49	90	66
1	90	40	29	21
firms with relative criterion based relationship lender (1) or without (0) in the quarter before financial distress:				
0	233	66	96	71
1	62	23	23	16
firms with relative criterion based relationship lender (1) or without (0) after 375 trading days or last reported period after financial distress:				
0	230	61	96	73
1	65	28	23	14

Notes. The table above shows the investigation of the outcome categories “failed”, “not recovered” and “recovered” and the relationship lending status of the firms. The table displays whether or not a firm has a relationship lender according to the HHI-based and the relative criterion in the quarter before the firm enters financial distress and 375 trading days after the financial distress event occured.

5 Determinants of the distress outcome

5.1 Relationship lending and restructuring outcome

To determine the effect a relationship lender has on the restructuring outcome ($P(recovered)$, Hypothesis (1)), we use the following basic regression model:

$$
\begin{aligned}
P(recovered)_i = \beta_0 + \beta_1\ RL_i + \beta_2\ ownership\ change_i + \beta_3\ size_i \\
+ \beta_4\ dd_i + \beta_5\ delta\ leverage_i + \beta_6\ management\ change_i \\
+ \beta_7\ analyst\ coverage_i + \beta_8\ industry_i + u_i
\end{aligned} \tag{2}
$$

The subscripts refer to the firm's relationship lending status (RL_i), a change of the borrower unit status ($ownership\ change_i$), size ($size_i$), the distance to default level at the end of the quarter before the financial distress event (dd_i), change in debt for the period between the distress event and 375 trading days ($delta\ leverage_i$), change in management ($management\ change_i$), analyst coverage ($analyst\ coverage_i$), industry ($industry_i$) and the error term (u_i).

To measure the relationship lending status at the end of the quarter before the firm enters financial distress, we use the HHI criterion as a dummy variable (1 if the HHI is >0.40 and 0 otherwise) and alternatively the HHI itself as well as the relative criterion as a dummy variable (1 if the share of largest lender is higher than or equal to 0.70 and 0 otherwise). We further consider a firm as "having no relationship lender" in case the firm's debt ratio is below 0.1.

For a further investigation we also include the variable of a change of the relationship lender in one of our regression models. We measure a change by comparing the end of the quarter before the financial distress event occurred and after 375 trading days. The variable is defined for both the HHI and the relative criterion. A bank is considered as a relationship lender if it holds the largest share of debt while the firm's HHI is higher than 0.40 (or if the bank provides 0.70 or more of the firm's debt for the relative criterion). We consider a firm as "having no relationship lender" in case the firms debt ratio is below 0.1. Beside considering a change in the relationship lender we also classify the change of "having a relationship lender" and "not having a relationship lender" as a "change". An overview of changes of the relationship lender can be found in Appendix B.1. The Appendix shows that according to the HHI criterion 69 of the distressed firms changed their relationship lender.

To control for factors that might influence the firm's restructuring outcome we use workout measures and firm characteristic variables. To control for workout measures we use the change in the firm's debt for the period between the distress event and 375 trading days afterwards. To measure the change in debt we use the central bank's overall debt data for the borrower unit or if not existent for the single firm. As an increase in debt potentially allows workout investments, we expect a positive influence of a debt increase in terms of the probability of recovery.

To control for changes in management we use hand-collected data from LexisNexis in a first step. We count every board member change of each firm reported in the news database within a period of 375 trading days after the financial distress event. To validate the numbers, we compare the names of the board members provided in the Amadeus database. For most firms the changes in management reported in LexisNexis could be confirmed. In case of a different outcome, we check for further evidence on the internet and call a report "confirmed" if further reports from different newsagents occur. 141 of the financially distressed firms show a change in management. Further details about the changes in management for the distressed firms are provided in Appendix B.1. A change in management is included as a dummy variable in our regression model. As a change in management might be able to lead to an improved business strategy, we expect to find a positive influence of this variable on the probability of recovery.

To measure an ownership change we use the central bank information on the firms' borrower unit. We measure a change in borrower units by comparing the borrower unit at the end of the quarter before the financial distress event occurred and after 375 trading days. We also consider being a member of a borrower unit and not being a member as a "change". 47 of the 295 firms experienced a borrower unit change according to the German Credit Register. An overview of changes in the ownership and distress period outcome is provided in Appendix B.1. As a change of the borrower unit might lead to a change in the firm's strategy or further capital access, we expect to find a positive sign for this variable in terms of the probability of recovery.

To control for further firm characteristics, we use the firm's distance to default at the end of the previous quarter before the firm enters the financial distress state according to our criterion. It is expect that a firm with a lower distance to default has a lower probability of recovery. We include firm size as a variable which controls for the firm's level of public perception as well as for the ability of the firm to survive in the long run. Firm size is measured using the logarithm of the firm's total assets according to its balance sheet. We expect that bigger firms will show a higher probability of recovery.

Analyst coverage is used as a regressor to control for the amount of information available on the firm. We expect a positive effect of analyst coverage on the firm's probability of recovery as the distress situation becomes a public issue if several analysts cover that firm. To measure analyst coverage we use the number of analysts covering the firm according to the IBES database of Thomson One Banker. We use the last figure reported before the firm enters our financial distress sample. It has to be mentioned, however, that the distressed firms in general are not very well covered.

We further use SIC code categories to control for industries. In our regression model we control for the mining and construction (SIC code first digit is "1") and manufacturing industry (SIC code first digit is "2" and "3") as those sectors tend to have a high ratio of tangible assets. As a high ratio of tangible assets leads to a lower ratio of liquid assets, a negative sign for this variable is expected. We finally use year dummies to control for macroeconomic influences.

As we have no panel data structure and our independent variable is measured as "failure" or "no failure", we start by performing a probit regression (see Table 3) using the HHI to create a dummy variable (HHI>0.40, model Ia/ IIa/ IIIa/ IVa/ IVb). Further, we use the HHI score itself (HHI-score, model

Ib/ IIb/ IIIb) as well as the relative criterion (relative loan share >=0.70, model Ic/ IIc/ IIIc) as an independent variable. Each criterion is measured at the end of the last quarter before the financial distress event.

As a robustness check we also measure the relationship lending criterion one year before the firm entered financial distress (model IV a-d). We call models I-III our basic regression models. We apply year dummies to control for macroeconomical effects and perform a Wald test to investigate whether or not year dummies are significant and hence should be included. The Wald test leads to the result that year dummies can be excluded.

The regression models indicate that there is no significant effect of a relationship lender on the probability of recovery. We could thus not confirm Hypothesis (1). As we expected, an increase in the borrowers debt has a positive significant influence in all regression models, however, the coefficient is very small. The distance to default in the pre-financial distress period has a significant positive influence on the restructuring outcome in all models. As expected, the higher the distance to default at the end of the quarter before entering the distress sample, the higher the probability of a successful restructuring outcome. Furthermore, as expected ownership change shows a positive significant influence on the restructuring outcome. Against what we expected, analyst coverage has a negative significant influence according to our regression outcome. Some of the regression models also show that size matters in times of financial distress. As expected, the bigger the firm the higher the probability of a successful debt restructuring. A change in management as well as the industries with a high tangible assets ratio do not influence the outcome according to our sample data.

In a next step, we perform an ordered probit regression. The results can be found in Appendix C.1. The dependent variable differentiates between three above explained stages: the firm "failed" (0), the firm shows "no recovery" (1), the firm shows a "recovery" (2). The model indicates again that relationship lending has no significant influence on the restructuring outcome. As expected, an increase in the borrower's debt has a positive significant influence in all regression models, but with a very small coefficient. The distance to default at the end of the quarter before financial distress is recognized has again a significant positive influence on the restructuring outcome in all models. As with the probit regression model, the ordered probit regression model indicates that size matters in times of financial distress, as size has a significant positive influence.

As most of the firms in our overall sample never enter financial distress, the problem of a selection bias might occur. Consequently we perform a two-step probit and an ordered probit regression. We add an explicit selection equation to our model to test and correct for a sample selection bias. A first-stage-regression including 974 firms of our overall sample is performed.

Table 3

Hypothesis (1): Probit regressions predicting workout outcome

	Distress sample										
	Basic regression model									RL previous year model	
Dependent variable:											
No recovery (0)/ recovery (1)											
Independent variable:	Ia	Ib	Ic	IIa	IIb	IIc	IIIa	IIIb	IIIc	IVa	IVb
Relationship lending criterion											
HHI dummy	-0.095			-0.102			-0.152			0.115	0.104
	(0.604)			(0.580)			(0.396)			(0.543)	(0.582)
HHI-score		-0.155			-0.162			-0.232			
		(0.518)			(0.498)			(0.324)			
RL relative dummy			0.086			0.074			0.000		
			(0.675)			(0.718)			(0.997)		
Workout measures											
Delta leverage	0.0001***	0.0001***	0.0001***	0.0001**	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.008)	(0.008)	(0.007)	(0.019)	(0.009)	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)
Ownership change	0.437**	0.438**	0.431*	0.441**	0.442**	0.436**	0.475**	0.476**	0.470**	0.433*	0.438**
	(0.047)	(0.047)	(0.052)	(0.044)	(0.044)	(0.048)	(0.026)	(0.026)	(0.029)	(0.051)	(0.047)
Management change	-0.103	-0.098	-0.093	-0.105	-0.099	-0.095				-0.106	-0.107
	(0.558)	(0.579)	(0.599)	(0.551)	(0.574)	(0.590)				(0.551)	(0.547)
Firm characteristics											
Distance to default	0.358***	0.355***	0.360***	0.364***	0.360***	0.366***	0.386***	0.380***	0.386***	0.356***	0.363***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.077	0.077	0.084*	0.080*	0.080*	0.087*	0.037	0.038	0.043	0.097*	0.099*
	(0.112)	(0.108)	(0.082)	(0.093)	(0.088)	(0.064)	(0.376)	(0.358)	(0.315)	(0.077)	(0.067)
Analyst coverage	-0.327*	-0.326*	-0.357**	-0.333*	-0,332*	-0.363**				-0.352**	-0.359**
	(0.074)	(0.073)	(0.050)	(0.066)	(0.065)	(0.044)				(0.049)	(0.043)
Mining & construction	0.067	0.062	0.112							0.130	
	(0.885)	(0.894)	(0.810)							(0.781)	
Manufacturing	0.076	0.076	0.089							0.091	
	(0.677)	(0.677)	(0.627)							(0.620)	
Constant	-2.082**	-2.062**	-2.250***	-2.110**	-2.089**	-2.283***	-1.534**	-1.518**	-1.672**	-2.526**	-2.537**
	(0.013)	(0.013)	(0.007)	(0.011)	(0.011)	(0.006)	(0.049)	(0.049)	(0.032)	(0.011)	(0.011)
Number of observations	295	295	295	295	295	295	295	295	295	295	295
Pseudo R^2	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.09	0.08	0.10	0.10

Notes. P-values are in parenthesis: * Significance at the 10% level, ** Significance at the 5% level, *** Significance at the 1% level.

The 974 firms include all 295 distressed sample firms and include additional firm data of non-distressed firms measured at the same point in time that the financial distress occurred. The dependent variable in the first stage regression is a dummy variable indicating "distress" (1) or "no distress" (0) ($P(distress/no\ distress)_i$). The independent variables used for the model are a relationship lending variable (RL_i), measured by using the HHI and the relative criterion. Further we use the moving average of the distance to default ($average\ dd_i$), measured for the last 90 days, the firm size ($size_i$), measured using the logarithm of total assets, the return on assets ($profitability_i$), measured as EBIT divided by total assets and a liquidity ratio ($liquidity_i$), measured as current assets/ current liabilities:

$$\begin{aligned} P(distress/no\ distress)_i = \beta_0 + \beta_1\ RL_i + \beta_2\ average\ dd_i + \beta_3\ size_i \\ + \beta_4\ profitability_i + \beta_5\ liquidity_i + u_i \end{aligned} \tag{3}$$

After performing the first step regression model, we use the Heckman model to calculate the inverse Mills' ratio. Using the inverse Mills' ratio ($Mills\ ratio_i$) we again perform the probit and ordered probit regressions described above:

$$\begin{aligned} P(recovered)_i = \beta_0 + \beta_1\ RL_i + \beta_2\ ownership\ change_i + \beta_3\ size_i \\ + \beta_4\ dd_i + \beta_5\ delta\ leverage_i + \beta_6\ management\ change_i \\ + \beta_7\ analyst\ coverage_i + \beta_8\ industry_i + \beta_9\ Mills\ ratio_i + u_i \end{aligned} \tag{4}$$

The coefficient of the inverse Mills' ratio shows in all regression models a very small t-statistic. Thus there is no evidence of a sample selection problem. Further, including the inverse Mills' ratio leads to the same results for most of the models as the probit and ordered probit regressions above: A relationship lender does not affect the probability of recovery. This model likewise does not confirm Hypothesis (1). Again the distance to default of the firm in the quarter before entering the distress sample has a significant influence. Moreover, an ownership change has a significant and positive influence in the probit regression model, as does an increase in the firm's debt ratio. For the detailed results see Appendix C.2.

5.2 Relationship lending and financial support in times of financial distress

We proceed to investigate the hypothesis that firms which have a relationship lender are more likely to get financial support within a restructuring period (Hypothesis (2)). To this end we perform a probit regression model using financial support ($P(financial\ support)$) as a dependent variable and a relationship lender variable as an independent variable (RL_i). Financial support is measured as an increase in debt according to the German Credit Register reports during the restructuring period. Within this model, financial support does not necessarily come from the relationship lender itself. Even an increase of debt from a smaller lender is considered as an increase. The relationship lender variable is measured by using the HHI.

We control for the level of distance to default (dd_i) at the end of the quarter before the firm enters the financial distress state. We expect that a firm with a lower distance to default has a lower probability of financial support. Firms facing enormous liquidity problems for example might be categorised as too risky for workout investments provided by banks.

We control for firm size ($size_i$), analyst coverage ($analyst\ coverage_i$), and whether the firm belongs to a borrower unit ($group\ member_i$). We expect that bigger firms and firms with a high analyst coverage have a higher probability of receiving financial support due to their degree of popularity. Firms that belong to a borrower unit might also have a higher probability of receiving financial support. Potential guarantees provided by parent companies or subsidiaries or unit internal cash flow distributions might improve the firm's attractiveness in terms of workout investments.

We further control for asset intensive industries ($asset\ intensive\ industry_i$), profitability ($profitability_i$, measured as EBIT divided by total assets) as well as retained earnings ratio ($retained\ earnings\ ratio_i$, measured as retained earnings divided by total assets). A dummy variable for asset intensive industries indicates if a firm belongs to the mining and construction or manufacturing sectors. More assets-intensive industries are more dependent on further financial support, as their liquidity is tied up. The need of liquidity might lead to higher support. However, as the capital of those firms is tied up, it could also be the case that banks classify those firms as more risky. In this case, the variable assets intensive industry would show a negative sign in terms of the probability of financial support. Higher profitability and higher equity capital might increase the willingness of banks to provide financial support. We thus expect that the higher the profitability and the retained earnings ratio, the higher the probability of financial support.

The applied regression equation is displayed below:

$$\begin{aligned} P(financial\ support)_i = \beta_0 + \beta_1\ RL_i + \beta_2\ DD_i + \beta_3\ size_i \\ + \beta_4\ analyst\ coverage_i + \beta_5\ group\ member_i + \beta_6\ profitability_i \\ + \beta_7\ retained\ earnings\ ratio_i + \beta_8\ asset\ intensive\ industry_i + u_i \end{aligned} \tag{5}$$

We include year dummies, but performed a Wald test which leads to the result that the year dummies can be excluded. The results of the regression models can be found in Table 4.

The results show that having a relationship lender positively influences financial support in terms of financial distress. Thus Hypothesis (2) can not be rejected according to our sample and model. As expected, size and belonging to a borrower unit do have a positive sign and significantly influence the probability of financial support.

Table 4
Hypothesis (2): Probit regressions predicting financial support

	Distress sample				
	Basic regression model				
Dependent variable: no financial support (0) / financial support (1)					
Independent variable:	I	II	III	IV	V
Relationship lending criterion					
HHI dummy	0.460**	0.446**	0.463**	0.489**	0.476**
	(0.019)	(0.023)	(0.018)	(0.014)	(0.017)
Firm characteristics					
Distance to default	0.016*	0.171*	0.162*	0.141	0.153
	(0.094)	(0.075)	(0.090)	(0.142)	(0.114)
Size	0.123**	0.125**	0.121**	0.101	0.104*
	(0.038)	(0.033)	(0.039)	(0.103)	(0.095)
Analyst coverage	0.095	0.088	0.098	0.138	0.133
	(0.616)	(0.645)	(0.607)	(0.470)	(0.489)
Group member	1.084***	1.089***	1.084***	1.080***	1.085***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Profitability			0.057	0.463	0.492
			(0.874)	(0.312)	(0.284)
Retained earnings ratio				0.011	0.009
				(0.976)	(0.980)
Asset intensive industry		-0.136			0.157
		(0.469)			(0.402)
Constant	-4.282***	-4.311***	-4.279***	-3.880***	-3.884***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Number of observations	295	295	295	295	295
Pseudo R^2	0.12	0.12	0.12	0.12	0.12

Notes. Hypothesis (2): Probit regressions predicting financial support. P-values are in parenthesis.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

An investigation of the lending banks shows that the relationship lender is not necessarily the entity who increases the debt position during the restructuring period. To investigate Hypothesis (3): Firms which have the financial support of a relationship lender within a restructuring period are more likely to be successfully restructured, we perform a probit and ordered probit regression using again recovery ($P(recovered)_i$) as a dependent variable and the loan support of the relationship lender ($RL\ financial\ support$) as an independent variable:

$$\begin{aligned} P(recovered)_i &= \beta_0 + \beta_1\ RL\ financial\ support_i \\ + \beta_2\ ownership\ change_i &+ \beta_3\ size_i + \beta_4\ DD_i + \beta_5\ delta\ leverage_i \\ + \beta_6\ management\ change_i &+ \beta_7\ analyst\ coverage_i + \beta_8\ industry_i + u_i \end{aligned} \tag{6}$$

We control for workout measures comprising a change in debt for the period between the distress event and 375 trading days later ($delta\ leverage_i$), a change of the borrower unit ($ownership\ change_i$) and a change in management ($management\ change_i$). It is expected that an increase in debt has a positive influence on the probability of recovery, as further debt allows workout investments. A change in the borrower unit as well as a change in management is expected to have a positive influence as this might lead to a change in the firm's strategy.

We control for general firm characteristics namely the distance to default level at the end of the quarter before the financial distress event (dd_i), size ($size_i$), and analyst coverage ($analyst\ coverage_i$) as well as for assets intensive industries as mining and construction and manufacturing ($industry_i$). We expect that the higher the distance to default when entering financial distress, the higher the probability of financial recovery. As bigger firms and firms with a high analyst coverage face higher public awareness, they might have a higher probability of receiving financial support. Size might further serve as an indicator for the firm's ability to survive during different market conditions. Consequently we expect a positive sign for size and analyst coverage in terms of the probability of recovery.

The variable relationship lender support ($RL\ financial\ support_i$) is measured as a dummy variable using the HHI to identify the relationship lender. To determine if the relationship lender increases its debt position, we use the German Credit Register information. An observation is considered as an increase if the relationship lender expands its debt position according to the German Credit Register within a 375 trading day period after the distress event. We run a probit and an ordered probit regression. For both we run a Wald test to investigate whether year dummies should be included. We find that year dummies need to be considered in the ordered probit regression model. The regression results can be found in Table 5.

The results indicate that the financial support of a relationship lender does not significantly influence the distress outcome. We could thus not confirm Hypothesis (3). The level of distance to default and size positively and significantly influence the outcome as expected. An increase in debt influences the outcome, however, the coefficient is again very low. Ownership change has a significant positive influence within the probit regression and analyst coverage has a significant negative influence in all regression models as expected.

As a robustness check to test Hypothesis (3), we use long-term survival ($P(long\ term\ survival)_i$) as a dependent variable and the increase of loans by the relationship lender ($RL\ financial\ support_i$) during the restructuring period as an independent variable. Thus, we investigate whether or not firms which get financial support of a relationship lender within a restructuring period, are more likely to show a long-term survival.

$$\begin{aligned} P(long\ term\ survival)_i = \beta_0 + \beta_1\ RL\ financial\ support_i \\ + \beta_2\ ownership\ change_i + \beta_3\ size_i + \beta_4\ dd_i \\ + \beta_5\ delta\ leverage_i + \beta_6\ management\ change_i \\ + \beta_7\ analyst\ coverage_i + \beta_8\ industry_i + u_i \end{aligned} \tag{7}$$

Table 5
Hypothesis (3): Probit and ordered probit regressions predicting workout outcome using HHI support

	Distress sample			
	Probit regression model		Ordered probit regression model	
Independent variable:	I	II	III	IV
Relationship lending criterion				
RL's financial support	-0.053	-0.041	0.011	0.007
	(0.891)	(0.916)	(0.973)	(0.981)
Workout measures				
Delta leverage	0.0001***	0.0001***	0.0001*	0.0001*
	(0.008)	(0.007)	(0.057)	(0.056)
Ownership change	0.435**	0.431*	0.291	0.293
	(0.048)	(0.051)	(0.193)	(0.189)
Management change	-0.098	-0.096	-0.228	-0.228
	(0.578)	(0.585)	(0.122)	(0.123)
Firm characteristics				
Distance to default	0.362***	0.356***	0.679***	0.681***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.084*	0.081*	0.096**	0.097**
	(0.072)	(0.091)	(0.025)	(0.024)
Analyst coverage	-0.350*	-0.343*	-0.264*	-0.268*
	(0.051)	(0.057)	(0.085)	(0.083)
Mining & construction		0.093		-0.033
		(0.841)		(0.944)
Manufacturing		0.081		-0.033
		(0.659)		(0.837)
Constant	-2.211***	-2.174***		
	(0.006)	(0.008)		
Cut1			1.674	1.683
Cut2			2.929	2.938
Number of observations	295	295	295	295
Pseudo R^2	0.10	0.10	0.12	0.12

Notes. Hypothesis (3): Probit and ordered probit regressions predicting workout outcome using HHI support. Year dummies are included. P-values are in parenthesis.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

Long-term survival is measured as a dummy variable within the probit regression model. The variable for long-term survival is measured 175 trading days after the restructuring period of 375 trading days ended. The value is 0 if the firm went bankrupt (92 firms), is reported as dead according to Datastream (additional 5 firms) or if its distance to default is lower than or equal to 2 or the firm belongs to the 0.05 percentile in terms of its distance to default. The value is 1 if the firm did not file for bankruptcy, is not reported as dead and its distance to default is higher than 2 and the firm belongs to a higher percentile than the 0.05 percentile according to its distance to default (122 firms).

For the ordered probit regression we measure the status of long-term survival as follows. If the firm filed for bankruptcy or is reported as dead, the variable value is 0 (97 firms). If the distance to default is below 2 or the firm belongs to the 0.05 percentile in terms of its distance to default (76 firms), the variable value is 1. If the distance to default is higher than 2 and the firm belongs according to its distance to default to a higher percentile than the 0.05 percentile (122 firms), the variable value is 2.

We further control for workout measures during the restructuring period: a change in debt for the period between the distress event and 375 trading days ($delta\ leverage_i$), a change of the borrower unit status ($ownership\ change_i$), and a change in management ($management\ change_i$). As a change in debt allows workout investments, and a borrower unit change as well as a management change might have led to a change in the firm's strategy, we expect a positive sign for these variables.

We control for general firm characteristics such as the distance to default level at the end of the quarter before the financial distress event (dd_i), size ($size_i$), analyst coverage ($analyst\ coverage_i$) as well as for specific industries ($industry_i$). Firms with a high distance to default face a "mild" form of financial distress and we expect a higher probability of long-term survival for those firms. The bigger the firm and the higher the analyst coverage, the higher the public awareness of the firm might be. For this reason we expect a positive influence for these variables on long-term survival.

The variable relationship lender support ($RL\ financial\ support_i$) is measured as a dummy variable. To identify the relationship lender we use the HHI. To determine if the relationship lender increases its debt position, we use the German Credit Register information and consider an observation as an increase if the relationship lender expands its debt position according to the German Credit Register within the restructuring period of 375 trading days after the distress event.

We run a probit and an ordered probit regression. For both we run a Wald test to investigate whether year dummies should be included. We find that year dummies need to be considered in both regression types. The regression results can be found in Table 6. The results indicate that a relationship lender's financial support does not significantly influence the long-term outcome. As expected, the level of distance to default positively and significantly influences the outcome. An increase in debt influences the outcome, however, the coefficient is quite low. Contrary to our intuition, a change in management during the restructuring period negatively influences the outcome.

Table 6
Hypothesis (3): Robustness check probit and ordered probit regressions predicting long-term survival

	Distress sample			
	Probit regression model		Ordered probit regression model	
Independent variable:	Ia	Ib	IIa	IIb
Relationship lending criterion				
RL's financial support	0.080	0.098	-0.156	-0.137
	(0.821)	(0.785)	(0.667)	(0.707)
Workout measures				
Delta leverage	0.0001*	0.0001*	0.0001*	0.0001
	(0.081)	(0.071)	(0.083)	(0.112)
Ownership change	0.338	0.324	0.172	0.160
	(0.133)	(0.150)	(0.442)	(0.479)
Management change	-0.339**	-0.338**	-0.335**	-0.333**
	(0.046)	(0.046)	(0.024)	(0.025)
Firm characteristics				
Distance to default	0.526***	0.516***	0.668***	0.660***
	(0.001)	(0.001)	(0.000)	(0.000)
Size	0.086	0.080	0.068	0.063
	(0.104)	(0.132)	(0.164)	(0.198)
Analyst coverage	-0.247	-0.228	-0.170	-0.153
	(0.175)	(0.201)	(0.294)	(0.339)
Mining & construction	-0.224		-0.209	
	(0.711)		(0.713)	
Manufacturing	-0.179		0.159	
	(0.340)		(0.314)	
Constant	-2.243**	-2.184**		
	(0.019)	(0.024)		
Cut1			1.167	1.124
Cut2			1.948	1.904
Number of observations	295	295	295	295
Pseudo R^2	0.13	0.13	0.11	0.11

Notes. Hypothesis (3): Robustness check probit and ordered probit regressions predicting long-term survival. Year dummies are included. P-values are in parenthesis.

* Significance at the 10% level.

** Significance at the 5% level.

*** Significance at the 1% level.

6 Conclusion

As discussed in this paper, arm's length and relationship lender-based firm-bank relations differ in the respect that relationship banks face an information advantage as well as a considerably expanded possibilities for influence. To find out more about bank-firm relationships, this study investigates the effect of a relationship lender on the restructuring outcome of a financially distressed firm.

We use loan data from the German central bank for our sample consisting of German listed firms. To determine whether or not a firm is in financial distress, we use a Merton model-based identification criterion. Our distress sample finally consists of 295 stock market-listed firms. To analyse whether a relationship lender has an influence on the outcome of a financial distress period, we investigate the following hypotheses: Hypothesis (1) investigates whether firms which have a relationship lender when entering a financial distress are more likely to show a positive outcome after a restructuring period.

Hypothesis (2) examines the question whether distressed firms which have a relationship lender are more likely to get financial support within a restructuring period. Hypothesis (3) deals with the question whether distressed firms which have the financial support from a relationship lender are more likely to be successfully restructured.

To test the hypotheses we perform different probit regression and ordered probit regression analyses. To control for factors that might influence the firm's restructuring outcome we use workout measures and firm characteristic variables. To control for workout measures we use the change in the firm's debt for the period between the distress event and 375 trading days afterwards. To measure the change in debt we use the central bank's overall debt data for the borrower unit or, if not existent, for the single firm. We control for ownership change and use the central bank information of the firm's borrower unit and the change of borrower unit. To control for changes in management we use the Amadeus database and hand-collected data from LexisNexis.

To control for further firm characteristics, we use the firm's distance to default according to the Merton model at the end of the previous quarter before the firm enters the financial distress state. We include firm size as a variable which controls for the firm's level of public perception as well as for the ability of the firm to survive during different market conditions. Analyst coverage is used as an indicator for publicly available information about the firm. We further use SIC code categories to control for industries. In our regression model we control for the mining and construction and manufacturing industry as those sectors tend to have a high ratio of tangible assets. We finally use year dummies to control for macroeconomic influences.

The performed regression models do not indicate that firms which have a relationship lender when entering a financial distress situation are more likely to show a positive outcome after a restructuring period (Hypothesis (1)). However, the models indicate that firms which have a relationship lender are more likely to get financial support within a restructuring period (Hypothesis (2)). The regression models further indicate that the financial support of a relationship lender itself within a restructuring period does not lead to a positive outcome after the restructuring period (Hypothesis (3)). The models also do not indicate that a relationship lenders' financial support significantly influences long-term survival of the affected firm.

As expected, in the regression models the level of distance to default of the firm in the quarter before entering the distress sample has a significant influence. The higher the distance to default is at the end of the quarter before entering financial distress, the higher is the probability of recovery (Hypotheses (1) and (3)), the higher the probability of financial support (Hypothesis (2)) and the higher the probability of long-term survival. Finally the performed regression models indicate that an increase in the firm's debt ratio has a positive significant effect on the outcome of a restructuring period. However the coefficient is very low.

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Appendix

A Relationship lending criterion

To learn more about the German Credit Register reports used for the investigation, a detailed investigation of the German Banking Act regulations in terms of the 1.5 million EUR reports is performed. The analysis of the banking act shows that it is not only loans that are reported by German banks; off-balance-sheet transactions such as certain derivatives and warranties are reported as well. This again underlines that using German Credit Register reports leads to an information advantage compared to using balance sheet data. A detailed overview of reported items under the German Banking Act is provided in Table A.1.

Table A.1
1.5 million EUR reports according to the German Banking Act (KWG)

Reporting trigger event	Loans of 1.5 mio EUR or more to: – a single borrower – a borrower unit
Reporting date	each 31^{st} March, 30^{th} June, 30^{th} September, 31^{st} December
Reporting scope	**Reporting Type 1 (“Satzart 1”)** – sum of loans at reporting date – overall level of debt thereof: – asset items according to §19 I 2 KWG – off-balance sheet transactions thereof: derivatives according to §19 I 1 KWG (credit equivalent amount) warranties for derivatives according to §19 I 1 KWG guarantees and other warranties according to §19 I 3 No. 3-5, 7, 9, 12 leasing receivables according to §19 I 2 No. 9 KWG and receivables resulting from the monetary acquisition of monetary claims mortgages according to §14 II 3 No. 5 KWG publicly guaranteed loans according to §14 II 3 No. 4 KWG inter-bank loans according to §20 III 3 No. 2 KWG **Reporting Type 6 (“Satzart 6”)** – bails/ guarantees/ warranties – syndicate quota/ syndicate management (extended by way of guarantee) **Reporting Type 7 (“Satzart 7”)** – loans secured by a guarantees – syndicated loans (extended by way of guarantee)
Reporting receiver	Deutsche Bundesbank’s Credit Register (“Evidenzzentrale”)
Reporting unit	– domestic banks – financial services institutions according to §1 Ia 2 No. 4 (proprietary traders) – branches of enterprises domiciled abroad (§53) located in Germany unless they are covered by the European Banking Passport
Institutions included in reporting	According to §14 I 2 KWG, the subordinated domestic enterprise has to report borrowers separately for all banks domiciled abroad – all banks domiciled abroad – financial services institutions domiciled in Germany or abroad by definition of §1 1a KWG (except domestic proprietary traders) – financial enterprises domiciled in Germany or abroad by definition of §1 III KWG (except domestic factoring enterprises) – financial holding enterprises domiciled in Germany or abroad by definition of §1 IIIa KWG – ancillary banking enterprises domiciled in Germany or abroad by definition of §1 IIIc KWG belonging to the group

Notes. The table shows an overview of the German Banking Act related to the 1.5 million EUR reports.

To investigate whether or not there is a difference between the borrower unit according to the German Banking Act and the corporate group according to German Corporate Law, we investigate and compare the definitions of the borrower unit and the corporate group. The difference in definitions indicates that using the German Banking Act-based German Credit Register information leads to an information advantage for this investigation. This is mainly based on the fact that banks are informed about the borrower units’ amount of debt and are able to consider this within their credit decision process. The comparison shows that differences between these two categories might occur due to differences in definitions. The borrower unit also includes risk-related firms as well as partnerships under the German Civil Code.

Table A.2
Borrower unit (KWG) versus corporate group (German AktG)

Reason for a borrower unit	**Explanation**	**Comparison to consolidated groups**
Consolidated group membership	§19 II KWG: combine group entities to a borrower unit if following requirements are met: – centralised management – majority ownership – dominating influence – take over of losses	1. In case of fully consolidated subsidiaries: conformity of borrower unit (KWG) and corporate group (AktG). But dominating influence is, according to the AktG, basically only possible from one side, however, an assignment to more than one borrower unit is possible according to the KWG 2. Joint companies: full debt attribution (borrower unit) vs. proportional consolidation (group statement) 3. Affiliated companies: full debt attribution (borrower unit) vs. recognition using the "at equity method" (group statement)
Risk unit	Combine firms to a borrower unit if reciprocal dependencies exist (e.g. financial distress affects other entities)	Economic dependencies (KWG) vs. dominating influence (AktG) as the attribution concept
Partnership under the German Civil Code	No borrower unit is formed but indebtedness is assigned to every partner	Full attribution of debt in case of proportional and full partnership liability (KWG) vs. dominating influence concept (AktG)

Notes. The table shows an overview of the reasons for a firm to join a borrower unit according to the KWG and the differences between a borrower unit and the consolidated group according to the AktG.

B Other control variables

To control for changes in management we use hand-collected data from LexisNexis in a first step. We consider every change in each firm's board reported in the news database within a period of 375 trading days after the financial distress event. To validate the numbers, we use the Amadeus database and download the names of the board members. We compare the board members' names close to the distress event and close the end of the 375 trading day period. For most firms the changes in management could be confirmed. In case of a different outcome, we look for further evidence in LexisNexis and call a report "confirmed" if a report is provided by different news agents. 141 of the financially distressed firms show a change in management. To measure analyst coverage we use the number of analysts covering the firm according to the IBES database of Thomson One Banker. We used the last figure reported before the firm enters our distress sample. We find that the distressed firms in general are not very well covered. The table above shows that 168 of the firms are not covered by any analyst. 45 of the non-covered firms went bankrupt within a time period of 375 trading days after the financial distress event occurred. 64 of the firms are categorised as "not recovered" within that period and 59 could be categorised as "recovered".

Table B.1
Descriptives of the distress sample within 375 trading days after the financial distress event

	Overall firms	**thereof:** failed	not recovered	recovered
Distress firms with central bank data	295	89	119	87
thereof firms with				
change of relationship lender according to the HHI criterion:				
0	226	63	96	67
1	69	26	23	20
change of relationship lender according to the relative criterion:				
0	202	53	86	63
1	93	36	33	24
change in ownership:				
0	248	77	104	67
1	47	12	15	20
change in management:				
0	154	42	64	48
1	141	47	55	39
analyst coverage before entering financial distress:				
0	168	45	64	59
1	127	44	55	28

Notes. The table above shows the investigation regarding the outcome categories "failed", "not recovered" and "recovered" and the specification of explanatory variable. For example 226 firms change their relationship lending status according to the HHI criterion. 248 firms show an ownership change within the restructuring period and 154 firms show a change in management. 168 firms are covered at least by one analyst in the quarter before entering financial distress. 45 of the firms covered by an analyst are categorised as failed.

C Regression analysis

In addition to the probit regression, we perform an ordered probit regression to validate Hypothesis (1). The results can be found in Table C.1. The dependent variable differentiates between the three stages explained above: the firm filed for bankruptcy (0), the firm shows no successful recovery (1), the firm shows a successful recovery (2).

As most of the firms in our overall sample never enter financial distress, the problem of a selection bias might occur. Consequently we perform a two-step probit and ordered probit regression as a further robustness check. We add an explicit selection equation to our model of interest to test and correct for a sample selection bias. A first-stage-regression including 974 firms of our overall sample is performed. The 974 firms include all 295 distressed firms and include additional firm data of non-distressed firms measured at the same point in time as the financial distress occurred. The dependent variable in the first stage regression is a dummy variable indicating "distress" (1) or "no distress" (0). The independent variables used for the model are a relationship lending variable (RL_i) again measured using the HHI and the relative criterion. Further we use the moving average of the distance to default ($average\ dd_i$) measured over the last 90 days, the firm size ($size_i$) measured using the logarithm of total assets, the return on assets (EBIT divided by total assets, $profitability_i$) and a liquidity ratio (current assets divided current liabilities, $liquidity_i$). The results are displayed in Table C.2.

Table C.1

Hypothesis (1): Ordered probit regression predicting workout outcome

	Distress sample										
	Basic ordered regression model									RL previous year model	
Dependent variable: Failed (0)/ no recovery (1)/ recovery (2)											
Independent variable:	Va	Vb	Vc	VIa	VIb	VIc	VIIa	VIIb	VIIc	VIIIa	VIIIb
Relationship lending criterion											
HHI dummy	-0.196			-0.169			-0.209			0.183	0.180
	(0.293)			(0.283)			(0.159)			(0.264)	(0.272)
HHI-score		-0.246			-0.246			-0.299			
		(0.228)			(0.226)			(0.123)			
RL relative dummy			0.028			0.027			0.027		
			(0.878)			(0.880)			(0.873)		
Workout measures											
Delta leverage	0.0001***	0.0001***	0.0001**	0.0001***	0.0001***	0.0001**	0.0001***	0.0001***	0.0001***	0.0001**	0.0001**
	(0.007)	(0.007)	(0.013)	(0.007)	(0.007)	(0.011)	(0.000)	(0.001)	(0.001)	(0.023)	(0.019)
Ownership change	0.281	0.283	0.272	0.281	0.282	0.273	0.312	0.313	0.304	0.275	0.276
	(0.177)	(0.177)	(0.192)	(0.179)	(0.179)	(0.193)	(0.129)	(0.130)	(0.140)	(0.190)	(0.189)
Management change	-0.198	-0.194	-0.187	-0.198	-0.194	-0.188				-0.204	-0.205
	(0.176)	(0.186)	(0.201)	(0.177)	(0.187)	(0.201)				(0.167)	(0.166)
Firm characteristics											
Distance to default	0.543***	0.535***	0.543***	0.541***	0.533***	0.542***	0.552***	0.543***	0.554***	0.543***	0.543***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.082**	0.083**	0.090**	0.081**	0.082**	0.090**	0.042	0.044	0.048	0.116**	0.116**
	(0.038)	(0.033)	(0.022)	(0.038)	(0.033)	(0.020)	(0.201)	(0.179)	(0.145)	(0.013)	(0.013)
Analyst coverage	-0.206	-0.208	-0.248	-0.203	-0,205	-0.246				-0.262*	-0.260*
	(0.184)	(0.174)	(0.107)	(0.190)	(0.179)	(0.110)				(0.077)	(0.078)
Mining & construction	0.008	0.002	0.061							0.106	
	(0.986)	(0.997)	(0.889)							(0.807)	
Manufacturing	0.028	-0.028	0.021							-0.011	
	(0.858)	(0.860)	(0.895)							(0.946)	
Cut1	1.031	1.024	1.229	1.025	1.017	1.236	0.517	0.513	0.687	1.780	1.788
Cut2	2.239	2.234	2.434	2.234	2.227	2.440	1.714	1.711	1.878	3.987	2.995
Number of observations	295	295	295	295	295	295	295	295	295	295	295
Pseudo R^2	0.10	0.10	0.09	0.10	0.10	0.09	0.09	0.09	0.09	0.10	0.10

Notes. P-values are in parenthesis: * Significance at the 10% level, ** Significance at the 5% level, *** Significance at the 1% level.

Table C.2

Hypothesis (1): Two-step probit and ordered probit regressions

	Distress sample									
	Two-step probit regression model						Two-step ordered probit regression model			
Independent variable:	IXa	IXb	IXc	Xa	Xb	Xc	XIa	XIb	XIIa	XIIb
Relationship lending criterion										
HHI dummy	-0.228			-0.231			-0.316*		-0.284*	
	(0.235)			(0.228)			(0.060)		(0.080)	
HHI-score		-0.377			-0.379					
		(0.160)			(0.157)					
RL relative dummy			0.022			0.033		0.051		0.050
			(0.917)			(0.877)		(0.784)		(0.789)
Workout measures										
Delta leverage	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
Ownership change	0.535**	0.496**	0.495**	0.537**	0.498**	0.496**	0.320	0.309	0.343	0.309
	(0.019)	(0.028)	(0.030)	(0.018)	(0.026)	(0.028)	(0.130)	(0.144)	(0.136)	(0.144)
Management change	-0.032	-0.042	-0.033	-0.033	-0.042	-0.036	-0.155	-0.144	-0.151	-0.144
	(0.860)	(0.817)	(0.853)	(0.853)	(0.814)	(0.841)	(0.292)	(0.325)	(0.307)	(0.328)
Firm characteristics										
Distance to default	0.324***	0.332***	0.334***	0.331***	0.339***	0.342***	0.517***	0.519***	0.513***	0.518***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.094	-0.055	-0.064	-0.089	0.050	-0.058	-0.059	0.042	-0.069	-0.043
	(0.198)	(0.490)	(0.396)	(0.215)	(0.521)	(0.435)	(0.356)	(0.506)	(0.255)	(0.497)
Analyst coverage	-0.192	-0.214	-0.240	-0.201	-0,223	-0.249	-0.103	-0.149	-0.079	-0.148
	(0.312)	(0.253)	(0.201)	(0.286)	(0.230)	(0.182)	(0.513)	(0.345)	(0.617)	(0.348)
Mining & construction	-0.003	-0.017	-0.040				-0.080	-0.020		
	(0.995)	(0.976)	(0.943)				(0.872)	(0.967)		
Manufacturing	0.101	0.096	0.109				-0.018	0.011		
	(0.587)	(0.605)	(0.558)				(0.907)	(0.944)		
Inverse Mills' ratio	0.228***	0.173*	0.204**	0.225***	0.171*	0.201**	0.195***	0.190***	0.202*	0.190***
	(0.003)	(0.068)	(0.015)	(0.003)	(0.070)	(0.017)	(0.003)	(0.005)	(0.088)	(0.005)
Constant	-0.306	-0.196	-0.248	-0.258	-0.243	-0.305				
	(0.787)	(0.873)	(0.828)	(0.818)	(0.841)	(0.788)				
Cut1							-0.943	-0.573	-1.103	-0.972
Cut2							0.294	0.658	-0.143	1.289
Number of observations	295	295	295	295	295	295	295	295	295	295
Pseudo R^2	0.14	0.13	0.13	0.14	0.13	0.13	0.12	0.11	0.12	0.11

Notes. P-values are in parenthesis: * Significance at the 10% level, ** Significance at the 5% level, *** Significance at the 1% level.