The Effect of Banking Relationships on the Future of Financially Distressed Firms

Claire M. Rosenfeld*
Carlson School of Management
University of Minnesota
crosenfeld@csom.umn.edu

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Abstract

Financially distressed firms, by definition, need funding to remain solvent. Repeated lending may provide banks information on the condition of a firm that is otherwise unobservable. In the case of financial distress, when the true state of the firm is difficult to discern, prior (relationship) lenders may have valuable insights. Using hand-collected data, I empirically examine U.S. publicly traded firms to determine the impact of banking relationships on the future of financially distressed firms. In my analysis, I control for firm, loan timing, industry, macroeconomic, and information attributes. I find that banking relationships have a significantly positive impact on the future success of firms, so long as the sample does not solely consist of severely distressed firms. In that case, there is no effect of lending relationships on the future performance of severely financially distressed firms. Evidence shows that the value of banking relationships is determined by proxies for information asymmetry, the competitive nature of the banking environment and the firm's prior reliance upon relationship funding. Even after controlling for endogeneity, I find strong evidence that banking relationships have a significantly positive impact on the future success of moderately financially distressed firms. Further, upon expanding the analysis to include non-financially distressed firms, I find evidence that obtaining relationship funding maintains a significantly positive impact on future firm success. These results are robust to variations on the sample definition of financial distress as well as the degree and definition of failure.

I. Introduction

A banking relationship has many forms, with its most basic form as a lender repeatedly providing credit to a firm[1]. Repeated lending may provide "soft" information on the firm's ability to repay debt, including information on management's ability to overcome adverse situations, the firm's internal control of spending, and the veracity of the firm's financial statements. Such information may be most critical when a firm is in financial distress, which is, by general definition, when a firm is unable to meet its debt obligations. A financially distressed firm exhibits the characteristic that without financial assistance, the firm is unable to remain in operation; at the same time, the firm's true financial position may be unknown to its lenders, and, possibly, the firm itself. Thus, evaluating the impact of banking relationships on the future of a financially distressed firm is especially interesting because of the presence of both the firm's need for funding and the heightened informational asymmetries between the firm and its lenders.

Particularly in the case of distress, a firm may adopt business practices aimed at appeasing its lender simply out of hope that the lender will continue to provide it with funds. In such a situation, a lender to a distressed firm might follow the pattern documented in Weinstein and Yafeh (1998), where prior lenders provided credit but inhibited the firm's ability to generate profits. On the other hand, it may be that lenders provide liquidity to the distressed firm under loan terms that exhibit preferential treatment to valued customers[2].

This study examines the effect of banking relationships on the future of financially distressed firms. I use a unique dataset of publicly traded U.S. firms created by combining information from COMPUSTAT, CRSP, DealScan, I/B/E/S, SDC, the Chicago and St. Louis Federal Reserve Banks, and the FDIC. I then perform probit regressions with controls for firm,

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[1] Throughout this paper "bank" refers to any lending institution.

[2] Elsas and Krahnen (1998) find that German Hausbanks provide liquidity insurance to their relationship borrowers through a moderate amount of financial deterioration, while Petersen (1999) provides evidence that relationship lenders make capital easier to obtain. Petersen and Rajan (1994), Berger and Udell (1995) and Santos and Winton (2005) document that lending relationships lead to better loan terms. Dahiya et al (2003) find that obtaining debtor-in-possession funding from a relationship lender leads to a quicker resolution of Chapter 11 bankruptcy proceedings.

loan timing, industry, macroeconomic and information asymmetry attributes to analyze the marginal effect that banking relationships have on the probability of a financially distressed firm's future recovery. I address the endogeneity of determining the nature of the relationship backing the distressed loan, and I determine how the effect of banking relationships changes when I expand the sample to include non-distressed firms.

I find that banking relationships—defined as lead lenders that were prior lead lenders or syndicate members—have a positive impact on the recovery of large financially distressed U.S. firms when firms obtain loans in the six months prior to distress identification. Specifically, I find that over varying degrees of distress, as measured by rank of expected default frequency, firms are more likely to recover to lower ranks of expected default frequency when borrowing from a prior lender. The exception to this finding is that when only considering the most severely distressed firms, there is no impact of the lending relationship on the firm's future success. That is, if a firm is considered financially distressed when its expected default frequency is in the 70th percentile or higher, and success is when a firm remains active and lowers its expected default frequency to the 60th percentile or lower, obtaining distressed funding from a prior lender significantly positively affects the firm's probability of success three years following the identification of distress. This result holds when financial distress (and failure) is onset at the 80th percentile of expected default frequencies, but it becomes insignificant when the distress (and failure) threshold is the 90th percentile. This finding is similar to that of Elsas and Krahnen (1998), where German Hausbanks provide liquidity insurance to distressed firms, but only through moderate distress.

The findings in this paper are robust to addressing the endogeneity inherent in determining the lending relationship. I use bivariate probit regressions to control for endogeneity, whereby I simultaneously predict future firm success given an exogenous (actual) relationship

and the nature of the lending relationship given identifying instruments[3]. In particular, I find that measures of information asymmetry, including analyst coverage, are significant predictors of whether a distressed firm will obtain funding from a relationship lender. The firm's prior reliance upon relationship funding positively predicts lending relationships, as does the degree of deposit concentration within a banking environment in most cases.

My results are also robust to the definition of financial distress. Although my main mechanism of identifying financial distress is the KMV-Merton model approximation of expected default frequencies furnished by Bharath and Shumway (2004), I also find similar results using Shumway's (2004) hazard model, which generates the expected probability of a firm filing for bankruptcy, rather than the expected probability of a firm defaulting (as in Bharath & Shumway (2004)). The significant effect of lending relationships on future firm performance persists when I identify distress by low interest coverage ratios—defined as the ratio of annual operating cash flows to interest paid. These results are shown in the Technical Appendix, which can be found at http://webpages.csom.umn.edu/finance/crosenfeld.

The modern literature on banking relationships has a foundation in James's (1987) study of bank loans, followed by Sharpe's (1990) and Rajan's (1992) work on the informational rents extracted by lenders, which establishes a set of testable theories for future empirical work. More recent empirical work analyzes German firms (Elsas and Krahnen (1998) and Elsas (2005)), Japanese firms (Weinstein and Yafeh (1998)), Belgian firms (Degryse and Ongena (2005)), Norwegian firms (Ongena and Smith (2001)), small American firms (Petersen and Rajan (1994), Berger and Udell (1995) and Petersen (1999)), and large American firms amidst formal bankruptcy proceedings[4] (Dahiya et al (2003)). Houston and James (1996 & 2001), Gonzales and

[3] Each of the simultaneously predicted models also includes the same control variables as the original probit regressions.
[4] These firms are beyond mere financial distress. They require legal protection in order to remain in operation.

James (2005), and Schenone (2005 and 2006) also study banking relationships involving large publicly traded firms.

There are several hypotheses common to papers in this literature[5]. First, there is the notion that banking relationships alleviate information asymmetry through continued contact with their customers. This reduced information asymmetry can benefit the borrower through better loan terms (Petersen and Rajan (1994), Berger and Udell (1995) and Santos and Winton (2005)), more easily accessible capital (Petersen (1999)) and improved liquidity insurance (Elsas and Krahnen (1998)). My work adopts the information asymmetry hypothesis, but unlike earlier papers, I focus on the potential influence of banking relationships on the ability of publicly traded firms in financial distress to survive over an extended period of time.

My analysis makes three distinct contributions to the empirical work on banking relationships. First, it is the first to evaluate the long-term effect of banking relationships on financially distressed firms. Such firms are unique both in their reliance on external funding, which allows them to remain in operation, and in the increased information asymmetries created by distress. Although Dahiya et al (2003) investigate the impact of relationship debtor-in-possession financing, they only evaluate firm performance within bankruptcy proceedings. Thus, their sample consists solely of firms in severe financial distress, and within that sample, they evaluate the impact of relationship funding on the probability of emergence and time to bankruptcy resolution. My work differs from theirs in that I examine firms under varying levels of distress ranging from firms experiencing no distress to firms with modest financial distress and, finally, severely financially distressed firms. Moreover, I analyze general firm performance over a three-year window of time, regardless of whether a firm enters and/or exits bankruptcy.

My second contribution is that I study publicly traded U.S. firms, which represent a broad range of large firms. There is growing evidence that relationships between banks and large firms

[5] For a review of banking relationship literature, please see Ongena and Smith (2000).

still have value despite the conventional wisdom that claims banking relationships with smaller firms are more apt to have value[6].

Finally, I address the endogeneity in banking relationships: is it that banking relationships evoke firm success or that good firms merit banking relationships? I accomplish this by implementing bivariate probit regressions to simultaneously predict lending relationships—using information asymmetry and bank market concentration measures as well as the firm's prior reliance upon relationship funding as instruments—and the effect of lending relationships on the firm's future performance.

In related work, Gilson, John and Lang (1990) find that stockholders of financially distressed firms are better off when debt is restructured privately, rather than in formal bankruptcy proceedings. Andrade and Kaplan (1998) study financially distressed firms that took part in highly leveraged transactions, finding that "[t]o the extent that they do occur, the costs of distress are highly concentrated in the period after firms become distressed, but before they enter Chapter 11" (p. 1487). Finally, Asquith, Gertner and Scharfstein (1994) find that the presence of secured bank debt in a financially distressed firm's funding mix influences creditors' willingness to restructure.

The remainder of this paper is organized as follows: Section II contains a description of the study's samples and provides variable definition and descriptive statistics. I describe the study's methodology and regression results in Section III. In Section IV I discuss endogeneity, and I conclude in Section V.

[6] Indeed, James (1987) establishes the foundation of empirical work on banking relationships by studying publicly traded firms. Houston and James (1996 & 2001) study publicly traded firms, as do Ongena and Smith (2005). Liberti (2005) provides evidence that soft information on large firms still matters in loan decisions.

II. Data

A. Sample Universe

My sample universe consists of the intersection of COMPUSTAT's North America Industrial Annual database and Loan Pricing Corporation's DealScan database, and spans from 1982 to 2005. DealScan is a loan database that details commercial loan transactions by providing, among other information, loan date, tranche amount, lender information, fee structure, loan terms, and type of loan[7]. I manually match COMPUSTAT to DealScan by company name, and when necessary, city and state of firm headquarters. I require that each firm in the sample has at least two loans listed in DealScan so that there is a basis for determining the nature of a loan's lending relationship. This results in a sample with 43,341 tranches from 30,637 loans to 5,685 distinct firms. Since lending relationships are at issue, the first loan for each firm (or 5,685 loans) is ineligible for the sample since it only provides a basis on which to determine the nature of future loan relationships. Table I lists information on loan distribution over time. The first loan observation is in 1982, but 80% of the sample loans occur after 1992[8]. Since I am evaluating firm performance over the three years following distress identification, my sample ends in 2002.

To isolate the issue of financial distress from the common financial instability of start-up firms, I require all firms to be publicly traded for at least three years. I also eliminate firms in the financial sector (SIC codes 6000-6799). I perform my analysis on two types of samples: one sample allows multiple firm observations and the other allows only one observation for each firm. When I consider only one observation for each firm, I include the first distressed observation.

B. Sample Definition

There are many ways to identify a firm as financially distressed. Gilson, John and Lang (1990) use a combination of a low cumulated stock return with news of a defaulted payment,

[7] Please see Carey, Post and Sharpe (1998) or Dichev and Skinner (2002) for a thorough database description.
[8] Results are qualitatively similar when the sample starts in 1992, as shown in the Technical Appendix at http://webpages.csom.umn.edu/finance/crosenfeld.

while Andrade and Kaplan (1998) examine firms with low interest coverage ratios. Shumway (2001) points out that these static methods incorporate less information than in a hazard model setting[9]. In this paper I use the hazard model specification developed by Bharath and Shumway (2004) to estimate the KMV-Merton model[10], which the authors summarize nicely below (p. 1):

> The KMV-Merton model applies the framework of Merton (1974), in which the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. The model recognizes that neither the underlying value of the firm nor its volatility are directly observable. Under the model's assumptions both can be inferred from the value of equity, the volatility of equity and several other observable variables by solving two nonlinear simultaneous equations. After inferring these values, the model specifies that the probability of default is the normal cumulative density function of a z-score depending on the firm's underlying value, the firm's volatility and the face value of the firm's debt.

This iterative process produces probabilities, termed expected default frequencies, that I will rank to determine financial distress. While they do not claim to have exactly the same algorithm as that of Moody's KMV to convert distances to default into expected default frequency probabilities, the ranks of their probability estimates are highly correlated with those of Moody's KMV. Not only is the Merton model widely used by academics, but it has been successfully augmented to provide adequate information on which KMV presumably profitably trades. Thus, expected default frequency by way of the KMV-Merton model is relevant as a measure of distress since it is used by academics and practitioners, alike. A nice feature of the KMV-Merton model is that it is based on probability of firm default, rather than firm extinction or bankruptcy. This focus is conceptually ideal for identifying financial distress, which also occurs without necessitating firm extinction or formal bankruptcy proceedings. This method also lacks the survivorship bias present in a method that identifies distress over an extended time frame, as in Gilson, John and Lang's (1990) cumulated stock return measure. Finally, this measure is

[9] Shumway (2001) argues that hazard models adjust for a firm's period at risk, incorporate "explanatory variables that change with time", and "they may produce more efficient out-of-sample forecasts by utilizing much more data" than static models (p. 102-103).

[10] This model is an application of Merton's 1974 model that was developed by KMV. I continue Bharath and Shumway's terminology.

generated on data that is available quarterly, which inherently produces a larger sample on which to test hypotheses.

Bharath and Shumway (2004) provide SAS code to define their estimates of the KMV-Merton model expected default frequency. Their method has five steps. First, they estimate equity volatility from historical stock returns. Second, they adopt the book value of firm's total liabilities to measure the face value of the firm's debt, and they adopt a one-year time horizon. Third, they collect risk-free rates and the market equity of the firm. Fourth, they iteratively simultaneously solve two equations [the Black-Scholes-Merton option valuation equation and equity volatility = (firm value/equity value)*N(d_1)*volatility of firm value, where N( ) is the cumulative standard normal distribution and d_1 is as defined in the Black-Scholes-Merton sense] for two unknowns—total firm value and volatility of firm value. Finally, they calculate the distance to default as: $DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}$, where μ is an estimate of the expected annual return of the firm's assets, and V denotes firm value. The corresponding implied probability of default, called the expected default frequency, is the cumulative standard normal probability of the negative of the distance to default.

I begin extracting my sample of distressed firms from all firms in my sample universe of COMPUSTAT intersected with DealScan by feeding two files into Bharath and Shumway's code. I first create a dataset from COMPUSTAT's quarterly database consisting of current liabilities and total debt, winsorized at the 1st and 99th percentile. I combine this sample with data on the annual risk-free rate of return, obtained from the Federal Reserve Bank of St. Louis. I also provide a second dataset from CRSP's daily stock file with firm identifiers, current shares outstanding and their prices. I then use the SAS code, as provided in Bharath and Shumway (2004), to generate expected default frequencies (hereafter referred to as edfs) for each quarter for each sample firm.

As noted in their paper, the algorithm that converts distances to default into expected default frequencies may not be correct, but it will produce the correct ranking of edfs. I then rank these edfs into ten deciles, zero through nine, with each increase in decile rank denoting the increase in probability of defaulting. Since the algorithm that converts distances to default into probabilities—or expected default frequencies—is uncertain, there is little intuition behind the firm's rank other than capturing the firm's distance to default compared to all other firm-year distances to default. That is, a seven merely denotes that the firm is in the 70th percentile of ranked expected default frequencies[11]. Thus, for a thorough analysis, I vary the rank identifying financially distressed firms from seven through nine. Table II shows the ranking of predicted expected default frequencies when the normal distribution is used to convert distances to default into edfs. Under the normal distribution, the edfs in rank 7 range from 2.21% to 26.21%, which means that the firm with an edf ranked 7 has a probability of defaulting over the next year between 2.21% and 26.61%. Rank 8 edfs range from 26.61% to 91.67%, while rank 9 edfs range between 91.67% and 100%. Thus, under the normal probability distribution, it is very likely that a firm with an edf ranked 9 will default within one year.

Finally, I narrow this sample by requiring all firms to have a loan activated in the six months prior to distress identification. This restriction allows the distressed firm's management to act in anticipation of the upcoming distress diagnosis while it requires the bank to grant a loan before distress is assessed, and it reduces lender selection bias. I analyze varying degrees of distress, with the most modest distress occurring with an edf ranked 7, with increased distress severity realized in ranks 8 and 9.

The samples are created to test the impact of obtaining a relationship or non-relationship loan. Thus, the samples are conditioned upon distressed firms obtaining a bank loan. Any

[11] Similarly, 8 denotes being in the 80th percentile of ranked expected default frequencies, and 9 denotes being in the 90th percentile of ranked expected default frequencies.

selection bias due to firms successfully acquiring bank debt is inherent in the sample, and is difficult to mitigate, especially when addressing the endogeneity of banking relationships.

C. Failure Definition

I evaluate firm performance over the three years following the identification of the firm as distressed. I define firm recovery as not "failing", and I denote it with an indicator variable. I identify a firm as failing if it meets one of three criteria. First, a firm may fail by permanently delisting for reason other than going private or merging. Second, a firm can fail for halting financial reporting for reason other than going private or merging. Third, a firm can fail by meeting or exceeding the original distress measure three years following the identification of distress. As with distress identification, I vary the rank of future edfs between 7 and 9 to capture various acceptable levels of firm recovery. I denote merging and going private with separate indicator variables, as these are distinct events from continuing operations as the same entity or failing to continue such operations[12].

D. Relationship Definition

The loan that is closest to the identification of distress and that falls within six months prior to the identification of distress is termed the distressed loan. I follow Schenone (2004) and Bharath et al. (forthcoming) by denoting a lending relationship with an indicator variable[13]. I determine whether each tranche within a loan deal is a relationship tranche and then evaluate the entire loan to determine whether the whole loan is a relationship loan. The distressed tranche is considered a relationship tranche if any lead lender has ever participated in a prior loan. I then take the maximum relationship indicator across all tranches within a loan deal to arrive at the loan

[12] In the Technical Appendix, which can be found at http://webpages.csom.umn.edu/finance/crosenfeld, I provide results where I incorporate performance of firms that merge and go private into the failure measure.
[13] While an indicator variable is only one of the various measures used by Bharath et al. (forthcoming) to determine the nature of a lending relationship, their other methods generate similar results. Thus, they seemingly all capture similar information. Santos and Winton (2005) also measure lending relationships with an indicator variable. Their two measures, which differ by including prior syndicate members as potential relationship lenders, yield the same results, implying that both measures capture the same information. Bharath et al. limit the lending history to the five prior years, while Santos and Winton limit their lending history to the three prior years.

relationship[14]. Relationships are tracked through bank mergers and acquisitions, as in Ljungvist et al. (2006). As in Bharath et al. (forthcoming), I consider any bank that DealScan does not explicitly name a participant in DealScan to be a lead lender.

E. Sample Details

I analyze two datasets in this paper with two key distinctions. The first distinction is the number of observations per firm: the first sample includes only the first firm observation that meets the sample criteria, while the second sample allows multiple firm observations. When working with datasets including multiple observations per firm, I require that firm observations are at least three years apart to ensure that I am not sampling overlapping distress observations. The second difference in datasets is the nature of the distress. The first dataset only considers distressed firms, while the second dataset expands to allow non-distressed firms into the sample[15].

Within the financially distressed dataset, I consider various levels of distress. There are three sub-samples within this dataset differing only by the severity of distress. The first includes moderately distressed firms, which experience edfs ranked 7, 8, or 9. The second sample of distressed firms consists of firms with edfs ranked 8 or 9. The final sample of distressed firms is that of severely distressed firms, which experience an edf ranked 9. The second dataset allows firm observations with any rank 0 to 9. Throughout the remainder of this paper, I refer to the first dataset as the distressed dataset and the second dataset as the expanded sample. Within both datasets I also vary the definition of failure.

Failure identification matches distress identification, so whatever is the sample minimum distress rank: 7, 8 or 9, the same value sets the threshold for determining future failure or recovery. For example, consider a sample where a firm with an edf ranked 7 or higher is

[14] The vast majority of deals with multiple tranches have the same lending relationship across all tranches.
[15] As shown in the Technical Appendix, at http://webpages.csom.umn.edu/finance/crosenfeld, I also analyze the distressed firm dataset with multiple observations. All relationship attributes are qualitatively consistent with those reported for the single-firm observation samples. Similarly, I analyze the expanded dataset allowing only one observation per firm. Nearly all relationship attributes are also qualitatively similar to those from the samples including multiple firm observations.

considered distressed. If that firm still exists as its own entity three years following its identification as distressed and it experiences an edf ranked 6 at the end of that time, it is deemed a success. However, if that same firm experiences a future edf ranked 8, it is deemed a failure by distress. That firm would also be considered a failure due to prolonged distress if it experienced a future edf ranked either 7 or 9 since the firm still fails to recover from the sample definition of distress. On the other hand, if the firm merges or goes private in that time period, it is removed from the sample. Further, if that firm delists for reason other than going private or merging, it is deemed a failure due to delisting.

Table III shows the number of observations in each sample by fiscal year of identification. Panel A shows results for distressed firms, while Panel B shows results for the expanded sample. In general, in proportion to yearly observations, relationship loans increase as severity of distress increases, as shown in Panel A. Panel A also lists increased distressed observations around 1990 and again in 2000. This pattern holds across distressed sub-samples. Proportionally more firms go on to fail when their distress is identified in 1988-1989 and 1996-1999. The most firms fail by delisting when their distress is identified between 1996 and 2000. The expanded sample, which includes non-financially distressed firms in addition to financially distressed firms, shows heightened failure during those same time periods. Notice that in Panel B, the only thing that changes across sub-samples is the proportion of firms that fail by distress (and, therefore, total failure, too), which is the only characteristic that varies across the sub-samples.

F. Control Variables

I control for five categories of characteristics that either affect the future outcome of the firm or the likelihood of the firm to obtain relationship funding. These five categories include firm attributes, loan timing, industry, macroeconomic and information asymmetry attributes. Table IV provides summary statistics on each sample's control variables.

Firm Controls

I control for firm traits that may impact the future of the firm by including determinants of firm performance at the end of the fiscal year in which the firm is identified as distressed. These attributes include firm age, the proportion of the firm funded by debt (debt to market value of assets), operating profit margin, net sales as a percentage of assets, size of the firm, and interest coverage ratio.

Including firm age as a regressor controls for the amount information available on the firm as well as for the ability of the firm to survive shocks. I measure age as the time in years between the date that it became public and the distress identification date[16]. I anticipate a positive marginal effect of age on future firm performance.

To control for the firm's debt, I use the ratio of total debt to market value of assets, as in Frank and Goyal (2004). Particularly with distressed firms, it is important to control for the market's valuation of the firm rather than book value since liquidation is of heightened interest to stakeholders. Referencing COMPUSTAT annual data items, total debt is the sum of debt in current liabilities (data34) and long-term debt (data9). The market value of assets is the sum of total debt, market value of equity (data199*data54), and preferred stock liquidating value (data10), less deferred taxes (data35). Among distressed firms, the median leverage ratio ranges from .50 when the distress rank is 7 to .70 when the distress rank is 9. This shows that rank of expected default frequency captures the increased risk of default that stems from increased leveraging. Especially considering such high median leverage ratios, I anticipate that a marginal increase in leverage will result in a negative impact on future firm success.

Operating profit margin gives the ability of the firm to manage its operating expenses in order to retain its operational revenues. I also control for the firm's ability to produce revenues from its assets. I predict a positive effect of profit margin and ratio of sales to assets on future

[16] Since the value of an additional year falls as the firm ages, I also consider the natural logarithm of age, which produces qualitatively similar results. These results are shown in the Technical Appendix.

firm performance. Table IV shows that the median operating profit margin for each of the distressed firm samples, as well as the expanded samples, is positive. Thus, our financially distressed firms are not necessarily unprofitable, but are still in danger of financial crisis.

To control for how much collateral is available for loan security, I include the proportion of the firm's assets that are fixed. The ability to pledge security should positively impact future firm performance.

I capture firm size with the amount of firm assets in billions. As reported in the Technical Appendix, I also use sales and number of employees to control for firm size. All measures yield qualitatively similar results. Since bigger firms are thought of as being better able to endure rough financial times than smaller firms, I predict a positive impact of assets on the probability of future firm success.

The final firm control is a modified interest coverage ratio: the ratio of net operating cash flows (including interest paid) to interest paid. According to Dichev and Skinner (2002), the interest coverage ratio is the second-most prevalent accounting-based loan covenant referenced in DealScan, so it is a measure that lenders care about. Further, it captures the firm's capacity to make debt payments, which depicts the degree of the firm's financial distress. Thus, as the modified interest coverage ratio decreases, I expect that the probability of future firm success decreases. Table IV shows the incredible variation of this measure in all of the sub-samples in both datasets. When considering the most moderately distressed sub-sample (edfs ranked 7 and higher), we see a winsorized variation of -48 to 50, so these firms vary considerably in terms of bringing the necessary cash into the firm to cover their interest payments.

To alleviate any errors in reporting as well as to minimize the effect of outliers, each of the above variables, with the exception of firm age, has been winsorized at the 1st and 99th percentile. Firm age is not prone to the extreme observations common to the other controls.

Timing Control

I control for the timing of the loan by including the number of days between the date the loan became active and the date of distress identification. It could be that a firm that is more proactive in seeking financial assistance will have better future performance. It could also be that the further the bank issues the loan prior to distress identification, the less predictive capabilities the bank has in foreseeing the upcoming distress. Table IV lists that firms with edfs ranked 7 and higher have a median timing difference of 55 days, while firms with edfs ranked 9 have a median loan lead time of 62 days. Looking at the sample including all firms, including multiple firm observations, the median loan lead time is 47 days. This is evidence that more severely distressed firms obtain funding earlier than moderately or non-financially distressed firms.

Industry Controls

I control for major SIC classified industries through indicator variables. Due to multi-collinearity in regressions, I am only able to control for four major industries in regression analysis: manufacturing, wholesale, retail, and services. I control for the rest of the industries through omission of an "other" industry category accounting for these omitted industries: agriculture, mining, public sector, construction and transportation. Manufacturing comprises nearly half the sample, so differentiating it is important. Transportation is the next largest proportion of the sample, but its indicator is one source of multicollinearity. The next three largest industries are retail, wholesale, and services. The remaining industries either did not have enough firms in each category to justify their own indicator or are the source of multicollinearity. According to the summary statistics in both panels of Table IV, the proportion of firms in each industry is fairly constant across all samples and between both datasets.

Macroeconomic Control

I control for macroeconomic influences by including the Chicago Fed National Activity Indicator (CFNAI) as of the month the loan was activated. The CFNAI is an assessment of current economic activity that is wholly determinable at the time of assessment, unlike the

National Bureau of Economic Research's (NBER) lagged indicators of expansion and contraction cycles. I expect a positive correlation between economic activity and future firm success. Panel A of Table IV shows that the median and mean CFNAI are negative, which means that at the time of distressed loan issuance, the economy was often growing at a rate below its trend.

G. Additional Summary Statistics

Loan Attributes

The last section in table IV lists two different loan attributes each determined two ways. Since both the number of lenders and loan maturity are determined at the same time as the nature of the lending relationship, I omit these traits from regressions to maintain econometric integrity. Their statistics are still descriptive, though.

If a large loan comes from twenty lenders rather than one lender, the liability assumed by each of those twenty lenders is considerably less than that assumed by the single lender. Under this logic, it is possible that a firm of poor financial quality may be able to obtain a loan from many lenders rather than a single lender. Denis and Mullineaux (1999) find evidence that the better the quality of information about the borrower is, or the more "saleable" the debt contract is, the more likely it is to be syndicated. I determine the average number of lenders for each loan by taking the average number of lenders across all tranches within each loan. I arrive at the weighted average by using the monetary tranche value in proportion to the total loan value as weights. In Panel A of Table IV, it is evident that the median number of lenders remains the same as severity of distress increases, although the mean increases slightly. Further, the mean average number of lenders computed in either manner is higher in the expanded sample than in the distressed sub-samples.

I also calculate the simple and weighted averages of maturity for each loan. The median maturity is 1096 days across all sub-samples, which is three years. This reinforces the applicability of my three-year timeline for evaluating long-term performance. If three years is the most common loan maturity, then banks have an interest in survivability of firms over the three

years following their loan issuance. It appears, from Table IV, that the mean and median are quite consistent over all samples and between the two datasets.

III. Results

A. Methodology

I use the following probit model to determine the effect that each of the above defined variables has on the future of financially distressed firms:

$$\Pr(\text{Success}) = \alpha + \beta_{rship}X_{rship} + \beta_{firm}X_{firm} + \beta_{timing}X_{timing} + \beta_{industry}X_{industry} + \beta_{econ}X_{econ}$$

where the subscripts refer to relationship, firm, loan timing, industry, and macroeconomic attributes, respectively. Results from probit regressions on an indicator of future firm success are listed in Tables V and VI, where output from the single-firm observation samples are in Table V and multiple firm observation samples are in Table VI. Each of the five specifications builds on the previous, more basic regression, by adding controls that capture different attributes. The figures adjacent to the control variable are marginal effects, and their p-values are below. All regressions are performed with robust errors.

B. Results

Distressed Firm Observations

A cursory look at Table V shows that the importance of the banking relationship backing the distressed loan is inconsistent across degrees of distress. In the case of moderate distress, when firms with edfs ranked 7 and higher are considered distressed (Columns I-V), banking relationships have a significantly positive impact on the distressed firm's future performance. The only significance of banking relationships in firms with increased distress (Columns VI-X) is controlled away with firm attributes. There is no significant effect of lending relationships on the future of the most severely distressed firms (rank 9, Columns XI-XV)

Leverage has the most significant impact on future firm success of all the control variables, as it deters future firm success, no matter the degree of distress. Similarly, downturns in the economy are significantly detrimental to future firm success to firms across all magnitudes

of distress. In all sub-samples, age has a significantly positive impact on future firm performance. The proportion of total assets that are fixed is a proponent of future firm success for samples that include less severely distressed firms (Columns I-X). In the same specifications), increases in firm size increase the probability of future firm success. Interest coverage and loan timing have an insignificant role in predicting future firm performance, as do industry controls.

At first glance, this outcome is consistent with lending relationships benefiting moderately distressed firms, but not severely distressed firms. As shown in the Technical Appendix, the same samples including multiple observations per firm[17] are qualitatively similar in regard to the significance of lending relationships existing only when allowing firms under moderate distress into the sample. This is consistent with Elsas and Krahnen's (1998) findings that German Hausbanks provide liquidity insurance to firms, but only through moderate distress.

Expanded Sample Observations

Moving to Table VI, where multiple firm observations from non-distressed firms are included in the sample, lending relationships have a significantly positive impact on future firm success across all failure definitions. The negative effects of both leverage and the economy persist and have larger magnitudes than the impact of lending relationships. Other consistencies between datasets include the positive impact of firm age across all levels of failure, although this effect is lower in magnitude than that of lending relationships. In addition, operating profit margin has a significantly positive impact on future firm performance, as does the proportion of total assets that are fixed. Finally, the interest coverage ratio has a significantly positive impact on future firm performance, but only when considering a lower failure threshold.

These findings again suggest the significance of the impact of lending relationships on future firm performance, only in this expanded sample, it is not just distressed firms that realize

[17] The samples referenced here are the same as shown in Table V, except that they allow multiple distressed firm observations into the sample so long as the observations are at least three years apart. These regressions control for clustered errors within firm observations.

such benefits. Rather, it is non-distressed and distressed firms, alike, that markedly benefit from relationship lending.

IV. Endogeneity

A. Methodology

The results from my analysis thus far indicate that when they obtain funding from a relationship lender, firms are more likely to recover from distress. An important issue to address is whether it is banking relationships that help firms perform better or that better firms obtain relationship funding. To further investigate this matter, I perform bivariate probit regressions where there are two equations simultaneously estimated: the first equation predicts future performance given an exogenous (actual) relationship indicator and the remaining previous controls while the second equation predicts the nature of the banking relationship using the same controls as the first equation as well as an instrument to identify the relationship. One of the test statistics of interest in this analysis is rho, which is the correlation coefficient between the residuals from the two simultaneous probit estimations. When rho is significantly different from zero, it is prudent to use this simultaneous estimation. When rho is insignificant, random shocks to the second equation, which predicts lending relationship, have no effect on the simultaneously predicted future firm success, so lending relationships are considered exogenous.

B. Instruments

Literature provides a number of potential instruments to predict banking relationships including measures of information asymmetry and banking market concentration. When Sharpe (1990) brought new life to the relationship banking literature, it was through the notion that banking relationships extract value from the information provided through continued interaction with their customers. Ever since, this notion of informational value has been a key element in the banking relationship literature. Thus, information asymmetry is a natural instrument for predicting banking relationships. It is sufficient as an instrument since it is theoretically

correlated with banking relationships while it maintains theoretical independence from the firm's future success.

To explicitly capture information asymmetry, I use an indicator to denote analyst coverage. Using I/B/E/S's summary history database, I determine which of the sample firms analysts cover by estimating quarterly earnings over the fiscal year prior to the identification of distress. To eliminate any extraneous analyst coverage, I only include estimates given through the end of each fiscal quarter. In results shown in the Technical Appendix, I have also controlled for information asymmetry using the natural logarithm of one plus the average number of analyst estimates over the four quarters prior to the identification of each firm as distressed, which yields qualitatively similar results[18]. I anticipate that increases in information asymmetry measured by analyst coverage will have a positive impact on firms obtaining relationship-backed distressed funding. To control for the influence that the proportion of debt funding has on analyst coverage, I also include an interaction of the leverage ratio (winsorized at the 1st and 99th percentile) and the analyst coverage indicator.

Next, I use bank market concentration as an instrument for lending relationships. Literature finds theoretically (Petersen and Rajan (1995), Boot and Thakor (2000), and Hauswald and Marquez (2000)) as well as empirically (Petersen and Rajan (1995)) that the degree of bank market concentration affects lending policies, including banks' reliance upon relationship loans. Specifically, Petersen and Rajan (1995) suggest that increased concentration in banking markets leads to relationship lending. In contrast, Boot and Thakor (2000) and Hauswald and Marquez (2000) find that as competition in the lending market increases, so does the lender's reliance upon relationship funding, thereby implying that increased competition drives banking relationships.

[18] A large proportion of the sample firms lacks analyst coverage over the four quarters leading up to distress identification, so it is illogical to use Gomes and Philips's (2005) exact measure, which is the standard deviation of earnings surprises over the same time period. Rather, I use natural logarithm to emphasize the difference between zero and very few analysts providing quarterly estimates while minimizing the distinction among observations with many analysts providing estimates.

Again, the level of bank market concentration is theoretically tied to the development of banking relationships while it remains independent of the firm's future success.

To measure the bank market concentration, I use the Herfindahl-Hirschman Index of concentration of deposits (winsorized at the 1st and 99th percentile, and divided by 100) as a proxy for the availability of credit in the metropolitan statistical area surrounding the financially distressed firm's headquarters. As in Petersen and Rajan (1995), it is assumed that wherever deposits are competitively held, so, too, are loans. Petersen and Rajan (1995) contend that concentrated, rather than competitive, banking areas are conducive to relationship lending, while Elsas (2005) finds that there is a non-monotonic association between bank concentration and banking relationships. In particular, "for low and intermediate values of concentration in local debt markets..., we find that the likelihood of observing a Hausbank relationship decreases with increasing concentration" (Elsas (2005) p. 50). Further, Elsas finds that for high levels of concentration, the Hausbank likelihood increases as bank market competition increases. It is unclear if either of the above patterns will hold in this paper since the samples underlying both of the above papers are so different from the samples used in this paper.

Another instrument I use to identify the distressed lending relationship is a lagged relationship indicator, which is the relationship indicator from the most recent loan prior to the distressed loan. While this variable captures the firm's recent reliance upon relationship lenders as a source of debt funding, it does not capture the firm's reliance upon a specific lender, namely, the distressed lender, as a source of funds. I anticipate that a firm with a history of borrowing from a relationship lender will be more likely to find distressed funding from a prior lender.

C. Results

Output from bivariate regressions can be found in Tables VII and VIII. Each table spans two pages, one for each simultaneously estimated equation. Coefficients are listed next to the variable name, and their p-values are listed below. As referenced above in the methodology section, key statistics from bivariate probit are rho and its p-value.

Distressed Firm Observations

Analyst coverage, even when controlling for its interaction with leverage, is a significantly positive predictor of distressed lending relationships for sub-samples that include less severely distressed firms (Columns III, IV, VII, and VIII). Thus, as information asymmetry decreases, the probability of obtaining distressed funding from a relationship lender increases. This is contrary to the popular hypothesis that lending relationships derive value from informational advantages, since this finding suggests that lending relationships are more prevalent when external sources of information are available. This effect becomes insignificant in the sample consisting of the most severely distressed firms (Columns XI-XII), when the leverage interaction term eliminates the significance of analyst coverage.

Bank market concentration is a significant predictor of distressed lending relationships, but only for sub-samples including firms that are not severely distressed (Columns I and V). This implies that as bank market concentration increases, so does the probability of obtaining relationship funding. However, bank market concentration has no significant effect on the most severely distressed sub-sample's (Column IX) probability of obtaining a relationships loan.

The lagged relationship indicator is a significantly positive predictor of distressed lending relationships across all sub-samples (Columns II, VI, and X). Thus, a firm that obtained its most recent loan from a prior lender is more likely to receive its distressed funding from a prior lender. This finding does not reflect whether the distressed relationship is a continuation of a relationship from the most recent prior loan, but rather whether a firm consistently obtains funding from any prior lender.

Each model in the two sub-samples of firms that include more moderately distressed firms (Columns I-VIII) generates a significantly positive instrument and a significant rho. Therefore, it is appropriate to simultaneously estimate the two equations in these specifications, and when I do so, it results in a significantly positive effect of the relationship indicator on future firm performance. Thus, even after controlling for endogeneity, obtaining distressed funding

from a relationship lender significantly increases the probability of future firm success for sub-samples including both moderately and severely financially distressed firms.

When only considering severely distressed firms (Columns IX-XII), only models X and XI have significant instruments. In Column X, rho is insignificant, which means that there is no evidence of endogeneity, so the simple probit model is adequate. However, in Column XI, rho is significant, and the coefficient on lending relationships is significantly negative. Once the interaction of leverage and analyst coverage is introduced, there is no significant identifying instrument, so I disregard model XII[19]. Bank market concentration is an insignificant instrument.

These findings are largely consistent with our story from before: lending relationships positively affect the future of financially distressed firms, but only when we allow firms experiencing moderate distress into the sample. As shown in the Technical Appendix, there is still strong evidence that after controlling for endogeneity, lending relationships have a positive effect on future firm performance when we allow multiple observations for each distressed firm into the sample[20].

Expanded Sample Observations

Table VIII, which displays results from samples composed of multiple observations from financially distressed and non-financially distressed firms, reiterates most of these findings. First, analyst coverage is a significantly positive determinant of lending relationships, and these lending relationships now include those with financially distressed and non-distressed firms. Using analyst coverage as an instrument, even when controlling for its interaction with leverage, gives evidence of the endogeneity of lending relationships; that is, rho is significant (Columns III, IV,

[19] As listed in the Technical Appendix, when I use the natural logarithm of the average number of analysts providing quarterly earnings estimates in place of the analyst coverage indicator, both the analyst coverage instrument and interaction of analyst coverage with leverage are significantly positive determinants of lending relationships. However, rho is insignificant in these models. Thus, the result of a negative impact of lending relationships on future firm performance in not robust.

[20] Analyst coverage and its interaction term with leverage is a significant predictor of lending relationships in the most severely distressed firm sub-sample. Moreover, these models generate a significant rho and a significantly negative relationship coefficient. The significance of analyst coverage persists when financial distress is identified with low interest coverage ratios, but not when identifying distress with Shumway's model. In the case of low interest coverage ratios, analyst coverage models generate an insignificant rho.

VII, and VIII). As information asymmetry decreases, the probability of obtaining a relationship loan increases. Using bivariate probit analysis and implementing analyst coverage as an instrument, I find that in sub-samples not solely containing severely distressed firms, lending relationships positively affect future firm performance. In models XI and XII, when rho is insignificant, I reject the hypothesis of endogenous lending relationships and refer to Table VI, Column XV to find that lending relationships have a (weak) significantly positive effect on future firm performance.

I also find that across all levels of failure, there is a positive influence of the lagged relationship indicator on predicting the relationship indicator. In models II and VI, this results in a significant rho and a significantly positive coefficient on the relationship indicator. In model X, where firms fail in only the most severe circumstances, rho is insignificant. Thus, there is no evidence of endogenous lending relationships, and I again refer to Table VI column XV to find a significantly positive effect of lending relationships on future firm success.

Similarly, bank market concentration is a significantly positive determinant of lending relationships across all degrees of failure. Across all sub-samples, rho is significant. In models I and V, for sub-samples including more moderately distressed firms, the coefficient on the relationship indicator is significantly positive. In model IX, the coefficient on lending relationships is significantly *negative*. As shown in the Technical Appendix, changes in control variables can alter the significance of both rho and the relationship indicator coefficient within this sub-sample[21]. Thus, the result of a negative impact of lending relationships on future firm performance is not robust in the case of surviving very severe distress.

In fact, when analyzing the same expanded sub-sample when the failure threshold rank is 9, substituting the natural logarithm of one plus the average number of analysts providing

[21] For instance, when using the natural logarithm of age, rather than age itself, the result persists. However, rho becomes insignificant when substituting employees or sales for assets to control for firm size. When evaluating the sub-sample beginning in 1992, rather than 1984, bank market concentration is an insignificant predictor of lending relationships. The same holds true when I include only the first observation for each firm, rather than multiple observations for each firm.

quarterly earnings estimates as an instrument for the analyst coverage indicator, the instrument is significantly positive, even when controlling for its interaction with leverage[22]. Both models—with and without the interaction term—generate significant rhos and significantly relationship coefficients. Further, when referring to comparable sub-samples from alternative methods of identifying financial distress, all of the original instruments, (i.e. bank market concentration, lagged relationship indicator, analyst indicator, and the interaction of analyst indicator with leverage) are significantly positive (except the interaction term), generate a significant rho, and a significantly positive coefficient on the banking relationship indicator. Thus, there is adequate evidence that lending relationships have a positive impact on firms avoiding severe future distress.

In sum, from Table VII, I have found that distressed lending relationships positively impact future performance of distressed firms, so long as the sample includes firms that are moderately distressed. From Table VIII, I have found that lending relationships positively impact future performance, even when considering various degrees of failure. These results are not inconsistent with the bank imposition of a cutoff, beyond which the costs of maintaining a lending relationship with a borrower exceed their benefits. Thus, severely distressed firms may not receive significant benefits from a relationship loan because the cost of the relationship does not exceed its benefits.

VI. Conclusion

This study has empirically examined the effect that banking relationships have on the future of publicly traded, financially distressed U.S. firms. I have demonstrated that banking relationships add value to both financially distressed and non-financially distressed firms by statistically increasing the probability of future firm success when firms obtain relationship, rather than non-relationship, loans in the six months prior to distress identification, so long as the sample does not solely consist of severely financially distressed firms. In that case, there is no

[22] These results are available in the Technical Appendix.

effect of lending relationships on the future performance of such firms. Further, I find that even after controlling for the endogeneity of determining the nature of the banking relationships backing loans, there is evidence that banking relationships provide a significantly positive impact on the future success of firms, so long as the sample does not solely consist of severely financially distressed firms. Specifically, I find that firms with reduced information asymmetry resulting from analyst coverage are more likely to obtain funding from relationship lenders. In some cases, firms that have headquarters in more concentrated bank markets or that have issued or been rated for public debt are more likely to obtain relationship funding.

This study is also significant in that it studies the long-term, rather than transaction-oriented, effects of maintaining banking relationships. Further, I have contributed to the banking relationship literature by arriving at this result by addressing its inherent endogeneity issues.

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Table I
Loan Statistics

This table contains the annual breakdown of loans to firms in the intersection of DealScan and COMPUSTAT/CRSP. The minimum, maximum, mean and median number of tranches per firm deal is listed below by calendar year. Deals are comprised of one or more tranches. The total number of tranches, deals, and number of firms to which the loans are granted are listed below by year. For example, in 1997, 2138 different firms were granted 2855 different deals comprised of 3953 tranches.

LOAN STATISTICS

Calendar	Tranches per Firm Deal						
Year	Min	Max	Mean	Median	Tranches	Deals	Firms
1982	1	2	1.33	1	4	3	3
1984	1	1	1	1	7	7	7
1985	1	4	1.38	1	18	13	12
1986	1	4	1.32	1	91	69	63
1987	1	8	1.42	1	651	457	381
1988	1	28	1.57	1	1488	945	718
1989	1	12	1.53	1	1546	1008	786
1990	1	9	1.43	1	1445	1010	820
1991	1	6	1.39	1	1495	1075	870
1992	1	9	1.37	1	1931	1408	1147
1993	1	10	1.38	1	2336	1691	1342
1994	1	7	1.37	1	2624	1922	1540
1995	1	7	1.36	1	2595	1907	1568
1996	1	8	1.38	1	3381	2450	1940
1997	1	8	1.38	1	3953	2855	2138
1998	1	8	1.45	1	3270	2254	1771
1999	1	7	1.48	1	2923	1971	1593
2000	1	9	1.47	1	2754	1871	1539
2001	1	7	1.42	1	2281	1612	1374
2002	1	9	1.38	1	2129	1543	1322
2003	1	6	1.36	1	1918	1412	1219
2004	1	5	1.4	1	2066	1472	1259
2005	1	7	1.44	1	1917	1335	1124
2006	1	4	1.48	1	518	351	341
Total	1	28	1.41	1	43341	30641	5685

Table II
Expected Default Frequency Summary Statistics

Below are the number, minimum, maximum, standard deviation, mean, and median expected default frequency by rank. The expected default frequencies (edf) are calculated using the SAS code provided by Bharath and Shumway (2004) to emulate the edfs predicted by the KMV-Merton model. They are calculated quarterly for each firm, and predict default in the year following the quarter's end. Although the algorithm chosen for converting the predicted distances to default into probabilities of default may not be correctly specified, the edf rank is maintained by this transformation. Thus, the edfs may not be completely accurate, but their rank is.

EXPECTED DEFAULT FREQUENCY SUMMARY STATISTICS

Rank	N	Min	Max	Std Dev	Mean	Median
0	14665	0.00E+00	7.84E-33	7.72E-34	1.51E-34	2.59E-50
1	14665	7.87E-33	2.57E-19	3.90E-20	1.29E-20	1.68E-24
2	14665	2.57E-19	6.05E-13	1.16E-13	5.32E-14	1.15E-15
3	14666	6.06E-13	6.38E-09	1.41E-09	8.03E-10	9.88E-11
4	14665	6.38E-09	4.69E-06	1.13E-06	7.98E-07	2.32E-07
5	14665	4.69E-06	5.86E-04	1.51E-04	1.33E-04	6.32E-05
6	14666	0.0006	0.0220	0.0059	0.0065	0.0042
7	14665	0.0221	0.2661	0.0696	0.1075	0.0900
8	14665	0.2661	0.9167	0.1984	0.5925	0.5921
9	14665	0.9167	1.0000	0.0201	0.9890	0.9998

Table III
Observations by Fiscal Year

Below is a table that lists observations and firm failure by fiscal year of the identification of firm distress. Obs is the number of observations identified in each fiscal year. Percentages are determined in proportion to Obs. Relationship is the percentage of observations that obtain funding from a prior lender. There are three samples from each of two datasets. Panel A lists observations from the first dataset, which includes one observation per firm, and it includes three samples of distressed firms. The first sample allows firms with an edf of 7 or higher (out of a sample ranked 0 through 9), and identifies future failure from distress as a firm experiencing a future edf of 7 or higher. The remaining samples within this dataset are similar, but have a minimum sample rank of 8 and 9, respectively, with the same minimum rank identifying future failure from distress. The second dataset, shown in Panel B, includes multiple observations per firm. Each of the three datasets within the second sample includes every firm in the sample universe with a relevant loan. The difference among the expanded dataset sub-samples is the threshold determining future failure, which can be 7, 8, or 9. Failure is the maximum of failing from distress and failing by being permanently delisted by an exchange for reason other than going private or merging.

OBSERVATIONS BY FISCAL YEAR

Panel A: Distressed Firms

	Sample Minimum Rank: 7 Failure Minimum Rank: 7					Sample Minimum Rank: 8 Failure Minimum Rank: 8					Sample Minimum Rank: 9 Failure Minimum Rank: 9				
			Fail					Fail					Fail		
Fiscal Year	Obs	Relationship	Total	Delist	Distress	Obs	Relationship	Total	Delist	Distress	Obs	Relationship	Total	Delist	Distress
1984	2	0.00%	50.00%	0.00%	50.00%	2	0.00%	0.00%	0.00%	0.00%	1	0.00%	0.00%	0.00%	0.00%
1986	2	0.00%	100.00%	0.00%	100.00%	1	0.00%	100.00%	0.00%	100.00%	1	0.00%	100.00%	0.00%	100.00%
1987	43	4.65%	65.12%	2.33%	62.79%	29	3.45%	55.17%	0.00%	55.17%	14	0.00%	50.00%	0.00%	50.00%
1988	78	6.41%	64.10%	2.56%	61.54%	59	5.08%	52.54%	3.39%	49.15%	29	3.45%	31.03%	0.00%	31.03%
1989	100	23.00%	74.00%	3.00%	72.00%	83	21.69%	59.04%	3.61%	56.63%	34	32.35%	44.12%	2.94%	44.12%
1990	146	32.88%	37.67%	1.37%	36.99%	122	37.70%	31.15%	1.64%	30.33%	82	36.59%	23.17%	2.44%	21.95%
1991	96	38.54%	41.67%	1.04%	40.63%	65	38.46%	33.85%	1.54%	32.31%	45	33.33%	33.33%	4.44%	31.11%
1992	87	39.08%	47.13%	0.00%	47.13%	58	53.45%	37.93%	0.00%	37.93%	36	52.78%	33.33%	0.00%	33.33%
1993	73	41.10%	47.95%	4.11%	43.84%	44	54.55%	50.00%	4.55%	45.45%	17	47.06%	35.29%	5.88%	29.41%
1994	71	40.85%	42.25%	0.00%	42.25%	49	44.90%	40.82%	0.00%	40.82%	22	54.55%	18.18%	0.00%	18.18%
1995	59	54.24%	25.42%	1.69%	23.73%	37	54.05%	29.73%	2.70%	27.03%	23	60.87%	34.78%	0.00%	34.78%
1996	113	49.56%	56.64%	11.50%	47.79%	76	46.05%	56.58%	17.11%	43.42%	33	54.55%	45.45%	18.18%	33.33%
1997	101	59.41%	70.30%	9.90%	65.35%	67	52.24%	47.76%	13.43%	40.30%	32	50.00%	56.25%	15.63%	43.75%
1998	145	61.38%	71.03%	9.66%	63.45%	107	60.75%	65.42%	11.21%	57.94%	50	76.00%	52.00%	8.00%	46.00%
1999	178	71.35%	55.62%	10.11%	50.56%	142	69.01%	44.37%	12.68%	38.73%	73	75.34%	54.79%	20.55%	47.95%
2000	186	68.28%	40.32%	8.60%	34.41%	175	73.71%	36.00%	9.71%	29.71%	99	75.76%	43.43%	14.14%	33.33%
2001	172	66.28%	30.23%	6.40%	26.16%	144	69.44%	27.08%	7.64%	22.22%	90	73.33%	27.78%	8.89%	22.22%
2002	98	68.37%	23.47%	5.10%	19.39%	85	65.88%	25.88%	5.88%	21.18%	58	68.97%	25.86%	8.62%	17.24%
Total	1750	50.29%	50.29%	50.29%	50.29%	1345	52.64%	41.93%	7.14%	37.32%	739	56.56%	37.62%	8.53%	32.34%

Table III Observations by Fiscal Year (continued)

Panel B: Expanded Sample															
	Sample Minimum Rank: 0 Failure Minimum Rank: 7					Sample Minimum Rank: 0 Failure Minimum Rank: 8					Sample Minimum Rank: 0 Failure Minimum Rank: 9				
Fiscal			Fail					Fail					Fail		
Year	Obs	Relationship	Total	Delist	Distress	Obs	Relationship	Total	Delist	Distress	Obs	Relationship	Total	Delist	Distress
1984	6	0.00%	16.67%	0.00%	16.67%	6	0.00%	0.00%	0.00%	0.00%	6	0.00%	0.00%	0.00%	0.00%
1985	9	0.00%	0.00%	0.00%	0.00%	9	0.00%	0.00%	0.00%	0.00%	9	0.00%	0.00%	0.00%	0.00%
1986	16	0.00%	31.25%	0.00%	31.25%	16	0.00%	12.50%	0.00%	12.50%	16	0.00%	6.25%	0.00%	6.25%
1987	112	2.68%	44.64%	1.79%	43.75%	112	2.68%	35.71%	1.79%	34.82%	112	2.68%	24.11%	1.79%	23.21%
1988	194	2.06%	45.36%	1.03%	44.33%	194	2.06%	28.87%	1.03%	27.84%	194	2.06%	18.56%	1.03%	17.53%
1989	212	9.91%	41.98%	1.89%	40.57%	212	9.91%	29.72%	1.89%	28.30%	212	9.91%	16.04%	1.89%	14.62%
1990	234	28.21%	29.06%	0.43%	28.63%	234	28.21%	18.38%	0.43%	17.95%	234	28.21%	10.68%	0.43%	10.26%
1991	235	37.02%	25.11%	0.00%	25.11%	235	37.02%	17.87%	0.00%	17.87%	235	37.02%	8.94%	0.00%	8.94%
1992	298	41.95%	29.87%	0.67%	29.53%	298	41.95%	19.46%	0.67%	19.13%	298	41.95%	8.39%	0.67%	8.05%
1993	293	47.44%	24.57%	1.02%	23.55%	293	47.44%	18.43%	1.02%	17.41%	293	47.44%	9.22%	1.02%	8.19%
1994	345	53.91%	22.90%	0.00%	22.90%	345	53.91%	15.65%	0.00%	15.65%	345	53.91%	4.93%	0.00%	4.93%
1995	356	58.43%	23.03%	0.84%	22.19%	356	58.43%	15.17%	0.84%	14.33%	356	58.43%	9.83%	0.84%	8.99%
1996	466	58.80%	39.27%	3.86%	36.05%	466	58.80%	27.25%	3.86%	24.03%	466	58.80%	14.59%	3.86%	11.37%
1997	492	63.82%	43.09%	2.85%	41.87%	492	63.82%	31.50%	2.85%	30.28%	492	63.82%	18.29%	2.85%	16.67%
1998	379	64.91%	45.65%	5.80%	41.42%	379	64.91%	34.83%	5.80%	30.61%	379	64.91%	21.90%	5.80%	17.68%
1999	393	70.23%	34.10%	4.83%	32.06%	393	70.23%	24.43%	4.83%	22.39%	393	70.23%	15.78%	4.83%	13.49%
2000	414	76.33%	27.54%	3.14%	25.60%	414	76.33%	20.29%	3.14%	18.36%	414	76.33%	13.53%	3.14%	11.59%
2001	416	71.63%	20.43%	3.13%	18.75%	416	71.63%	13.70%	3.13%	12.02%	416	71.63%	7.93%	3.13%	6.01%
2002	414	74.64%	14.98%	2.17%	13.77%	414	74.64%	10.39%	2.17%	9.18%	414	74.64%	6.76%	2.17%	5.07%
Total	5284	54.35%	31.13%	2.37%	29.64%	5284	54.35%	21.95%	2.37%	20.46%	5284	54.35%	12.64%	2.37%	11.03%

Table IV
Descriptive Statistics

Below are descriptive statistics for two datasets based on the expected default frequencies (edf) generated by Bharath and Shumway's 2004 KMV-Merton model SAS code. Panel A shows the first dataset, which includes only one observation per distressed firm. There are three samples within this dataset, which vary by the degree of distress experienced by the firm. The first sample consists of firms experiencing an edf of rank 7 or higher (on a scale from 0 to 9). Future failure by distress is determined by the firm experiencing an edf ranked 7 or higher. Similarly, the second and third samples consist of firms experiencing an edf of rank 8 and higher or 9, respectively, with future failure thresholds at the same rank. Panel B shows the expanded second dataset, which includes multiple firm observations from edfs of all rank. There are three samples within the second dataset, and each of them contains all sample universe firms that have relevant loans. The distinguishing attribute among these samples is the minimum distress threshold for failure, which is 7, 8, or 9, respectively. The only characteristic that varies among the samples within the second dataset is failure by delisting. The summary statistics include the number of observations, their sum, minimum, maximum, median, mean, and standard deviation. Fail is an indicator variable that is the maximum of Fail by Distress and Fail by Delisting. A firm fails by delisting if the firm is permanently delisted for reasons other than merging or going private in the three years following the identification of distress. Fail Revised is an indicator that captures whether a firm fails by delisting, prolonged distress or by its last observed edf prior to merging or failing. Merge is determined in the same fashion as Private. Merge Fail denotes whether the last observed edf prior to the firm's merge exceeds the sub-sample's failure threshold. Private equals one (and zero otherwise) if the firm permanently delists according to COMPUSTAT or CRSP for reason of going private. Private fail denotes whether the last observed edf prior to the firm going private exceeds the sub-sample's failure threshold. Expected default frequency is the initial edf that identified the firm as distressed. Relationship Indicator equals one if the lead lender was any prior lender, and zero otherwise. Firm age is the number of years between the year of distress identification and the year the firm began public trading. All remaining firm attributes have been winsorized at the 1st and 99th percentile. Leverage (Frank and Goyal (2004)) is total debt (data9 + data34) divided by the market value of assets, which is the sum of total debt, market value of equity (data199*data54), and preferred stock liquidating value (data10), less deferred taxes (data35). Operating profit margin is operating profit divided by net sales. Fixed/Total Assets is the ratio of fixed assets to total assets. Sales/Assets is the ratio of net sales to total assets. Assets is the total assets in billions of dollars, while Sales is the net sales in millions of dollars. Employees is the number of firm employees, and operating cash/Interest Paid is the ratio of Net Operating Cash Flows to Net Interest Paid. Loan Date-Distress Date is the number of days between the Deal Active Date listed on the loan and the day of distress identification (quarter end). Industry is denoted by indicator according to major SIC divisions. The Chicago Fed National Activity Indicator is matched by month and year to distress identification. The Herfindahl-Hirschman market concentration index (HHI) is winsorized at the 1st and 99th percentile, and is shown in hundreds. It denotes the FDIC's bank deposit concentration for the firm headquarters' metropolitan statistical area matched by year. HHI less than 10 is a competitive market, HHI between 10 and 18 is moderately concentrated, while HHI over 18 is concentrated. The public debt indicator denotes whether the firm has ever issued public debt prior to the identification of distress. Average number of Analyst Estimates is the average number of distinct analysts providing quarterly earnings estimates over the four quarters prior to the distress identification. Analyst Indicator equals one if Average Number of Analyst Estimates is greater than zero. The number of lenders is averaged over the number of tranches in the loan as well as being weighted by tranche monetary value in proportion to total loan value. Likewise for average maturity and weighted average maturity.

PANEL A

DESCRIPTIVE STATISTICS: DISTRESSED FIRMS

	Sample Minimum Rank: 7 Failure Minimum Rank: 7							Sample Minimum Rank: 8 Failure Minimum Rank: 8							Sample Minimum Rank: 9 Failure Minimum Rank: 9						
Variable	N	Sum	Min	Max	Median	Mean	Std. Dev	N	Sum	Min	Max	Median	Mean	Std. Dev	N	Sum	Min	Max	Median	Mean	Std. Dev
Fail	1750	858	0	1	0	0.4903	0.5000	1345	564	0	1	0	0.4193	0.4936	739	278	0	1	0	0.3762	0.4848
Fail Revised	1836	905	0	1	0	0.4929	0.5001	1397	592	0	1	0	0.4238	0.4943	763	293	0	1	0	0.3840	0.4867
Fail by Distress	1750	790	0	1	0	0.4514	0.4978	1345	502	0	1	0	0.3732	0.4838	739	239	0	1	0	0.3234	0.4681
Fail by Delisting	1750	100	0	1	0	0.0571	0.2322	1345	96	0	1	0	0.0714	0.2575	739	63	0	1	0	0.0853	0.2794
Merge	1834	84	0	1	0	0.0458	0.2091	1395	50	0	1	0	0.0358	0.1860	761	22	0	1	0	0.0289	0.1677
Merge Fail	1836	45	0	1	0	0.0245	0.1547	1397	26	0	1	0	0.0186	0.1352	763	13	0	1	0	0.0170	0.1295
Private	1752	2	0	1	0	0.0011	0.0338	1347	2	0	1	0	0.0015	0.0385	741	2	0	1	0	0.0027	0.0519
Private Fail	1836	2	0	1	0	0.0011	0.0330	1397	2	0	1	0	0.0014	0.0378	763	2	0	1	0	0.0026	0.0512
Expected Default Frequency	1836		0.0219	1	0.3199	0.4374	0.3690	1397		0.2664	1	0.7464	0.7108	0.2540	763		0.9191	1	0.9955	0.9833	0.0228
Relationship Indicator	1827	880	0	1	0	0.4817	0.4998	1390	708	0	1	1	0.5094	0.5001	758	418	0	1	1	0.5515	0.4977
Firm																					
Age	1836		3	76	8	14.4956	15.1371	1397		3	76	8	14.9084	15.3020	763		3	77	8	15.0800	15.4620
Leverage	1787		0.0244	0.9652	0.4954	0.4876	0.2215	1359		0.0291	0.9968	0.5710	0.5506	0.2221	734		0.0803	1.0442	0.6956	0.6720	0.1960
Operating Profit Margin	1792		-1.1643	0.5884	0.0851	0.0822	0.1962	1362		-1.1703	0.5980	0.0782	0.0764	0.2028	736		-0.7083	0.6129	0.0690	0.0755	0.1599
Fixed Assets/Total Assets	1797		0.0145	0.9094	0.2984	0.3525	0.2401	1366		0.0126	0.9096	0.3139	0.3581	0.2422	737		0.0084	0.8819	0.3151	0.3603	0.2400
Net Sales/Total Assets	1796		0.1235	4.4011	1.1054	1.2571	0.8149	1366		0.1183	4.6898	1.0998	1.2683	0.8548	737		0.1362	4.9401	1.1038	1.2815	0.8824
Employees	1775		0.0240	137	1.7600	8.0685	19.7534	1346		0.0210	137	1.7760	8.8345	21.4950	728		0.0300	126	2.1000	8.9858	20.9083
Sales	1796		5.6550	25530	260.340	1392.40	3618.64	1366		5.8330	33554	259.92	1672.93	4641.42	737		10.5990	37580	313.80	1930.94	5423.33
Assets	1801		0.0081	36.7360	0.2515	1.7855	5.1052	1369		0.0094	42.3430	0.2515	2.0765	6.0070	739		0.0114	48.7920	0.2813	2.5642	7.4343
Operating Cash/Interest Paid	1715		-47.66	49.66	2.6536	3.0506	9.9382	1312		-46.311	47.66	2.3613	2.4919	8.8736	704		-26.48	21.63	2.0413	1.9436	5.0259
Timing																					
Distess Date - Loan Date	1836		-182	0	-55	-62.37	48.55	1397		-182	0	-58	-65.11	49.62	763		-182	0	-62	-68.96	48.98
Industry																					
Agriculture Indicator	1836	4	0	1	0	0.0022	0.0466	1397	3	0	1	0	0.0021	0.0463	763	1	0	1	0	0.0013	0.0362
Mining Indicator	1836	95	0	1	0	0.0517	0.2216	1397	69	0	1	0	0.0494	0.2168	763	34	0	1	0	0.0446	0.2065
Manufacturing Indicator	1836	869	0	1	0	0.4733	0.4994	1397	645	0	1	0	0.4617	0.4987	763	349	0	1	0	0.4574	0.4985
Financial Indicator	1836	0	0	0	0	0.0000	0.0000	1397	0	0	0	0	0.0000	0.0000	763	0	0	0	0	0.0000	0.0000
Wholesale Indicator	1836	117	0	1	0	0.0637	0.2443	1397	92	0	1	0	0.0659	0.2481	763	54	0	1	0	0.0708	0.2566
Retail Indicator	1836	193	0	1	0	0.1051	0.3068	1397	152	0	1	0	0.1088	0.3115	763	88	0	1	0	0.1153	0.3196
Services Indicator	1836	275	0	1	0	0.1498	0.3570	1397	205	0	1	0	0.1467	0.3540	763	105	0	1	0	0.1376	0.3447
Public Sector Indicator	1836	5	0	1	0	0.0027	0.0521	1397	5	0	1	0	0.0036	0.0597	763	3	0	1	0	0.0039	0.0626
Construction Indicator	1836	31	0	1	0	0.0169	0.1289	1397	24	0	1	0	0.0172	0.1300	763	13	0	1	0	0.0170	0.1295
Transportation Indicator	1836	247	0	1	0	0.1345	0.3413	1397	202	0	1	0	0.1446	0.3518	763	116	0	1	0	0.1520	0.3593
Macroeconomy																					
Chicago Fed Nat'l Activity Indicator	1836		-2.22	1.51	-0.14	-0.2104	0.6948	1397		-2.22	1.51	-0.18	-0.2426	0.6989	763		-2.22	1.51	-0.25	-0.3264	0.7096
Instruments																					
Herfindahl-Hirschman Index	1759		2.24	27.73	9.50	10.2550	4.9697	1332		2.24	27.76	9.52	10.2519	4.8931	733		2.24	27.91	9.57	10.2074	4.8635
Competitive Market Indicator	1836	1100	0	1	1	0.5991	0.4902	1397	839	0	1	1	0.6006	0.4900	763	459	0	1	1	0.6016	0.4899
Mod. Concentrated Market Indicator	1836	608	0	1	0	0.3312	0.4708	1397	470	0	1	0	0.3364	0.4727	763	257	0	1	0	0.3368	0.4729
Concentrated Market Indicator	1836	128	0	1	0	0.0697	0.2547	1397	88	0	1	0	0.0630	0.2430	763	47	0	1	0	0.0616	0.2406
Public Debt Indicator	1836	447	0	1	0	0.2435	0.4293	1397	364	0	1	0	0.2606	0.4391	763	223	0	1	0	0.2923	0.4551
Average Number Analyst Estimates	1836		0	33	1	2.6860	4.1971	1397		0	33	1	2.5981	4.2336	763		0	33	1	2.2916	3.8637
Analyst Indicator	1836	1106	0	1	1	0.6024	0.4895	1397	822	0	1	1	0.5884	0.4923	763	446	0	1	1	0.5845	0.4931
Loan Attributes																					
Average Number Lenders	1836		0.6667	59	2	4.6536	6.6396	1397		0.6667	81	2	4.7207	6.9795	763		0.6667	81	2	4.7777	6.7715
Weighted Average Number Lenders	1835		0.9118	67	2	4.7014	6.7712	1396		0.9118	81	2	4.7853	7.1506	763		0.9118	81	2	4.8561	6.8908
Average Maturity (days)	1683		33	9131	1096	1296.01	960.04	1284		15	9131	1096	1257.13	920.37	701		42	7298	1096	1287.63	952.28
Weighted Average Maturity (days)	1683		33	9131	1096	1295.20	969.58	1284		15	9131	1096	1257.83	930.83	701		42	7298	1096	1285.85	970.94

Table IV (continued)

PANEL B, Part I
DESCRIPTIVE STATISTICS: EXPANDED SAMPLE

Sample Minimum Rank: 0
Failure Minimum Rank: 7-9

Variable	N	Sum	Min	Max	Median	Mean	Std. Dev
Firms	2950						
Failure Minimum Rank: 7							
Fail	5284	668	0	1	0	0.1264	0.3324
Fail Revised	5471	687	0	1	0	0.1256	0.3314
Fail by Distress	5284	583	0	1	0	0.1103	0.3133
Fail by Delisting	5284	125	0	1	0	0.0237	0.1520
Merge	5469	185	0	1	0	0.0338	0.1808
Merge Fail	5471	17	0	1	0	0.0031	0.0557
Private	5286	2	0	1	0	0.0004	0.0194
Private Fail	5471	2	0	1	0	0.0004	0.0191
Failure Minimum Rank: 8							
Fail	5284	1160	0	1	0	0.2195	0.4140
Fail Revised	5471	1200	0	1	0	0.2193	0.4138
Fail by Distress	5284	1081	0	1	0	0.2046	0.4034
Fail by Delisting	5284	125	0	1	0	0.0237	0.1520
Merge	5469	185	0	1	0	0.0338	0.1808
Merge Fail	5471	38	0	1	0	0.0069	0.0831
Private	5286	2	0	1	0	0.0004	0.0194
Private Fail	5471	2	0	1	0	0.0004	0.0191
Failure Minimum Rank: 9							
Fail	5284	1645	0	1	0	0.3113	0.4631
Fail Revised	5471	1706	0	1	0	0.3118	0.4633
Fail by Distress	5284	1566	0	1	0	0.2964	0.4567
Fail by Delisting	5284	125	0	1	0	0.0237	0.1520
Merge	5469	185	0	1	0	0.0338	0.1808
Merge Fail	5471	59	0	1	0	0.0108	0.1033
Private	5286	2	0	1	0	0.0004	0.0194
Private Fail	5471	2	0	1	0	0.0004	0.0191

Table IV (continued)

PANEL B, Part II
DESCRIPTIVE STATISTICS: EXPANDED SAMPLE

Sample Minimum Rank: 0
Failure Minimum Rank: 7-9

Variable	N	Sum	Min	Max	Median	Mean	Std. Dev
Common Traits							
Expected Default Frequency	5471		0	1	0	0.1747	0.3319
Relationship Indicator	5454	2872	0	1	1	0.5266	0.4993
Firm							
Age	5471		3	77	13	18.8887	17.3233
Leverage	5363		0.0010	0.9377	0.3041	0.3395	0.2367
Operating Profit Margin	5362		-0.4027	0.6391	0.1167	0.1342	0.1432
Fixed Assets/Total Assets	5381		0.0258	0.9094	0.3101	0.3652	0.2399
Net Sales/Total Assets	5384		0.1558	4.0493	1.1076	1.2441	0.7717
Employees	5312		0.0330	170.60	2.6720	11.2428	24.6632
Sales	5384		9.3270	37580	432.1050	2135.49	5109.89
Assets	5390		0.0114	39.1530	0.3937	2.3641	5.6307
Operating Cash/Interest Paid	5114		-25	145	4.2522	9.4886	23.1832
Timing							
Distess Date - Loan Date	5471		-182	0	-47	-51.6012	40.9003
Industry							
Agriculture Indicator	5471	14	0	1	0	0.0026	0.0505
Mining Indicator	5471	315	0	1	0	0.0576	0.2330
Manufacturing Indicator	5471	2714	0	1	0	0.4961	0.5000
Financial Indicator	5471	0	0	0	0	0.0000	0.0000
Wholesale Indicator	5471	314	0	1	0	0.0574	0.2326
Retail Indicator	5471	524	0	1	0	0.0958	0.2943
Services Indicator	5471	734	0	1	0	0.1342	0.3409
Public Sector Indicator	5471	16	0	1	0	0.0029	0.0540
Construction Indicator	5471	77	0	1	0	0.0141	0.1178
Transportation Indicator	5471	763	0	1	0	0.1395	0.3465
Macroeconomy							
Chicago Fed Nat'l Activity Indicator	5471		-2.2200	1.5100	0.0100	-0.1073	0.6396
Instruments							
Herfindahl-Hirschman Index	5267		2.2400	26.9900	9.5800	10.1882	4.8552
Competitive Market Indicator	5471	3192	0	1	1	0.5834	0.4930
Mod. Concentrated Market Indicator	5471	1941	0	1	0	0.3548	0.4785
Concentrated Market Indicator	5471	333	0	1	0	0.0609	0.2391
Public Debt Indicator	5471	1701	0	1	0	0.3109	0.4629
Average Number Analyst Estimates	5471		0	33	1	3.5937	4.8837
Analyst Indicator	5471	3604	0	1	1	0.6587	0.4742
Loan Attributes							
Average Number Lenders	5470		1	85	2	5.1892	7.1571
Weighted Average Number Lenders	5468		1	85	2	5.2384	7.2486
Average Maturity (days)	4919		0	14610	1096	1344.71	996.22
Weighted Average Maturity (days)	4919		0	14610	1096	1348.20	1002.82

Table V
Probit Regressions: Distressed Firms

Below is the output from probit regressions predicting future firm success. Marginal effects are adjacent to the independent variables, while their p-values are below. Marginal effects performed on indicator variables reflect the change in probability of future firm success when moving from 0 to 1. All other marginal effects are for infinitesimal changes from the mean. All errors are robust. Success is an indicator variable denoting not failing. Relationship is measured with an indicator variable denoting that any lead lender was a prior lender to the firm. Firm age is measured in years as the difference between distress identification and the firm's initial public trading day. Leverage is the total value of debt to the market value of assets (as in Frank and Goyal (2004)). Assets are measured in billions. The distress date is the end of the quarter that the firm is identified as distressed, and the loan date is the day the loan deal becomes active. This difference is measured in days. Industry controls are indicators for each of the following SIC classified industries: manufacturing, retail, wholesale, and services. CFNAI is the Chicago Fed National Activity Indicator matched by month and year to the distress date. The samples are from a dataset including one observation per firm. The three sets of regressions differ by their sample criteria. Regressions I-V are from a sample where edfs ranked 7, 8 and 9 are considered financially distressed. These ranks also denote future failure by distress. Regressions VI-X are from a sample where edfs ranked 8 and 9 are considered financially distressed. These are the ranks that determine future firm failure by distress. Regressions XI-XV are from a sample where only edfs with a rank of 9 are considered financially distressed, and only the firms with a future ranking of 9 are deemed failures by distress. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

PROBIT REGRESSIONS: PREDICTING FUTURE FIRM SUCCESS

Distressed Firms

	Sample Minimum Rank: 7 Failure Minimum Rank: 7					Sample Minimum Rank: 8 Failure Minimum Rank: 8					Sample Minimum Rank: 9 Failure Minimum Rank: 9				
Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV
Relationship Indicator	0.1030***	0.0819***	0.0819***	0.0817***	0.0763***	0.0474*	0.0456	0.0453	0.0462	0.0418	0.0101	-0.0183	-0.0192	-0.0172	-0.0205
	0.0000	0.0020	0.0020	0.0020	0.0040	0.0790	0.1200	0.1230	0.1160	0.1580	0.7780	0.6460	0.6290	0.6680	0.6100
Firm															
Age		0.0045***	0.0045***	0.0046***	0.0046***		0.0052***	0.0052***	0.0055***	0.0057***		0.0027*	0.0027*	0.0027*	0.0028*
		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000		0.0810	0.0770	0.0820	0.0770
Leverage		-0.7286***	-0.7277***	-0.7294***	-0.7403***		-0.6422***	-0.6385***	-0.6321***	-0.6441***		-0.7169***	-0.7102***	-0.7119***	-0.7119***
		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000
Operating Profit Margin		0.1719**	0.1716**	0.1696**	0.2060**		0.0757	0.0747	0.0672	0.0989		0.1218	0.1244	0.1261	0.1624
		0.0310	0.0320	0.0330	0.0120		0.3550	0.3610	0.4100	0.2320		0.3780	0.3670	0.3620	0.2570
Fixed Assets/Total Assets		0.1852***	0.1852***	0.1823***	0.1960***		0.1588**	0.1585**	0.1635**	0.1654**		-0.0747	-0.0752	-0.0999	-0.1046
		0.0020	0.0020	0.0060	0.0030		0.0170	0.0170	0.0240	0.0220		0.3780	0.3750	0.2870	0.2760
Net Sales/Total Assets		-0.0117	-0.0116	-0.0164	-0.0198		0.0010	0.0012	-0.0025	-0.0059		-0.0377	-0.0377	-0.0283	-0.0302
		0.4950	0.4980	0.3930	0.3110		0.9540	0.9480	0.9040	0.7760		0.1090	0.1100	0.2970	0.2800
Assets		-0.0037**	-0.0037**	-0.0038**	-0.0047***		-0.0056*	-0.0056**	-0.0057*	-0.0068**		0.0008	0.0007	0.0003	-0.0006
		0.0140	0.0140	0.0130	0.0020		0.0530	0.0500	0.0510	0.0200		0.8490	0.8680	0.9380	0.8880
Operating Cash/Interest Paid		0.0024	0.0024	0.0025	0.0017		0.0029	0.0029	0.0031	0.0024		0.0050	0.0049	0.0047	0.0037
		0.1080	0.1070	0.1030	0.2610		0.1320	0.1270	0.1020	0.2060		0.2670	0.2770	0.3120	0.4260
Timing															
Distess Date - Loan Date			0.0000	0.0000	-0.0001			-0.0002	-0.0002	-0.0002			-0.0002	-0.0002	-0.0003
			0.9130	0.9160	0.7520			0.6040	0.5740	0.4870			0.5690	0.5540	0.4490
Industry															
Manufacturing				-0.0086	-0.0080				0.0040	-0.0065				-0.0314	-0.0414
				0.8270	0.8390				0.9240	0.8790				0.5890	0.4820
Retail				0.0197	0.0221				0.0336	0.0327				-0.0467	-0.0468
				0.7140	0.6810				0.5620	0.5710				0.5650	0.5640
Wholesale				0.0266	0.0362				0.0294	0.0331				-0.0849	-0.0817
				0.6970	0.5930				0.6880	0.6470				0.3920	0.4080
Services				0.0240	0.0231				0.0790	0.0708				-0.0400	-0.0612
				0.6170	0.6320				0.1150	0.1640				0.5890	0.4210
Macroeconomy															
CFNAI					-0.1085***					-0.0921***					-0.1065***
					0.0000					0.0000					0.0000
Number of Observations	1741	1622	1622	1622	1622	1338	1249	1249	1249	1249	734	673	673	673	673
Number of Firms	1741	1622	1622	1622	1622	1338	1249	1249	1249	1249	734	673	673	673	673
Pseudo R-Squared	0.0076	0.0883	0.0883	0.0888	0.1031	0.0017	0.0742	0.0744	0.0765	0.0875	0.0001	0.0715	0.0718	0.0728	0.0895
Wald-Chi-Squared	18.3900	188.4000	188.4100	189.0100	221.5300	3.0800	118.3900	118.8200	120.9200	140.9500	0.0800	49.5700	50.3200	52.9400	70.2300
Wald p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0791	0.0000	0.0000	0.0000	0.0000	0.7783	0.0000	0.0000	0.0000	0.0000

Table VI
Probit Regressions: Expanded Sample

Below is the output from probit regressions predicting future firm success. Marginal effects are adjacent to the independent variables, while their p-values are below. Marginal effects performed on indicator variables reflect the change in probability of future firm success when moving from 0 to 1. All other marginal effects are for infinitesimal changes from the mean. All errors are robust and clustered by firm. Success is an indicator variable denoting not failing. Relationship is measured with an indicator variable denoting that any lead lender was a prior lender to the firm. Firm age is measured in years as the difference between distress identification and the firm's initial public trading day. Leverage is the total value of debt to the market value of assets (as in Frank and Goyal (2004)). Assets are measured in billions. The distress date is the end of the quarter that the firm is identified as distressed, and the loan date is the day the loan deal becomes active. This difference is measured in days. Industry controls are indicators for each of the following SIC classified industries: manufacturing, retail, wholesale, and services. CFNAI is the Chicago Fed National Activity Indicator matched by month and year to the distress date. The samples are from a dataset including multiple observations per firm. Each sample includes all of the sample universe firms that have relevant loans. The distinguishing attribute among the samples is the distress threshold. Regressions I-V are from a sample where future firm failure by distress is determined by experiencing an edf ranked 7, 8 and 9. Regressions VI-X are from a sample where future edfs ranked 8 and 9 merit failure by distress. Regressions XI-XV are from a sample where firms with future edfs ranked 9 are considered failures from distress. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

PROBIT REGRESSIONS: PREDICTING FUTURE FIRM SUCCESS

Expanded Sample

	Sample Minimum Rank: 0 Failure Minimum Rank: 7					Sample Minimum Rank: 0 Failure Minimum Rank: 8					Sample Minimum Rank: 0 Failure Minimum Rank: 9				
Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV
Relationship Indicator	0.0630***	0.0490***	0.0493***	0.0503***	0.0477***	0.0466***	0.0349***	0.0351***	0.0359***	0.0334***	0.0239***	0.0140*	0.0150*	0.0153*	0.0135*
	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0030	0.0030	0.0020	0.0040	0.0100	0.0910	0.0710	0.0650	0.0990
Firm															
Age		0.0038***	0.0038***	0.0038***	0.0039***		0.0031***	0.0031***	0.0032***	0.0032***		0.0023***	0.0023***	0.0023***	0.0023***
		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000
Leverage		-0.6913***	-0.6915***	-0.6900***	-0.7117***		-0.5663***	-0.5665***	-0.5673***	-0.5806***		-0.3616***	-0.3622***	-0.3617***	-0.3656***
		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000
Operating Profit Margin		0.3938***	0.3938***	0.3869***	0.4056***		0.2566***	0.2565***	0.2468***	0.2606***		0.1263***	0.1255***	0.1236***	0.1293***
		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000
Fixed Assets/Total Assets		0.1339***	0.1338***	0.1338***	0.1448***		0.1250***	0.1250***	0.1252***	0.1312***		0.0531***	0.0531***	0.0538**	0.0565***
		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000		0.0060	0.0060	0.0140	0.0090
Net Sales/Total Assets		-0.0007	-0.0008	0.0062	0.0060		0.0012	0.0012	0.0044	0.0039		0.0022	0.0022	0.0043	0.0037
		0.9390	0.9380	0.5680	0.5830		0.8830	0.8840	0.6240	0.6590		0.6860	0.6910	0.5030	0.5640
Assets		-0.0008	-0.0007	-0.0007	-0.0012		-0.0007	-0.0007	-0.0007	-0.0011		-0.0004	-0.0003	-0.0003	-0.0005
		0.6600	0.6650	0.6730	0.4770		0.6430	0.6490	0.6260	0.4420		0.4970	0.5390	0.5410	0.3390
Operating Cash/Interest Paid		0.0012***	0.0012***	0.0013***	0.0012***		0.0007*	0.0007*	0.0007*	0.0006		0.0003	0.0003	0.0003	0.0003
		0.0040	0.0040	0.0040	0.0060		0.0830	0.0820	0.0780	0.1140		0.2930	0.2940	0.2910	0.3420
Timing															
Distess Date - Loan Date			0.0000	0.0000	0.0000			0.0000	0.0000	0.0000			0.0002*	0.0002	0.0001
			0.8040	0.8400	0.9110			0.8000	0.8320	0.9150			0.1000	0.1030	0.1290
Industry															
Manufacturing				-0.0104	-0.0084				-0.0138	-0.0124				-0.0026	-0.0018
				0.6340	0.7000				0.4450	0.4940				0.8410	0.8850
Retail				-0.0370	-0.0403				-0.0250	-0.0266				-0.0127	-0.0129
				0.2650	0.2260				0.3690	0.3370				0.5110	0.4990
Wholesale				-0.0330	-0.0229				-0.0085	-0.0011				-0.0074	-0.0033
				0.3910	0.5440				0.7810	0.9700				0.7410	0.8770
Services				0.0112	0.0101				0.0188	0.0181				0.0033	0.0027
				0.6810	0.7130				0.3810	0.4020				0.8270	0.8600
Macroeconomy															
CFNAI					-0.0798***					-0.0591***					-0.0334***
					0.0000					0.0000					0.0000
Number of Observations	5267	4906	4906	4906	4906	5267	4906	4906	4906	4906	5267	4906	4906	4906	4906
Number of Firms	2758	2650	2650	2650	2650	2758	2650	2650	2650	2650	2758	2650	2650	2650	2650
Pseudo R-Squared	0.0037	0.1426	0.1426	0.1432	0.1521	0.0030	0.1522	0.1522	0.1531	0.1612	0.0017	0.1798	0.1806	0.1808	0.1883
Wald-Chi-Squared	23.7800	704.5200	704.6000	710.2200	752.3700	16.7100	680.0500	680.3200	685.6800	718.8300	6.5400	515.8800	518.5500	520.3900	526.2500
Wald p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0105	0.0000	0.0000	0.0000	0.0000

Table VII
Bivariate Probit Regressions: Distressed Firms

Below is the output from bivariate probit regressions. There are two simultaneous probit stages: the first predicts future firm success with an exogenous relationship indicator and the second predicts the relationship indicator with the same controls in addition to an identifying instrument. Coefficients are adjacent to the independent variables, while their p-values are below. All errors are robust. Success is an indicator variable denoting not failing. Relationship is measured with an indicator variable denoting that any lead lender was a prior lender to the firm. Firm age is measured in years as the difference between distress identification and the firm's initial public trading day. Leverage is the total value of debt to the market value of assets (as in Frank and Goyal (2004)). Employees are measured in thousands. The distress date is the end of the quarter that the firm is identified as distressed, and the loan date is the day the loan deal becomes active. This difference is measured in days. Industry controls are indicators for each of the following SIC classified industries: manufacturing, retail, wholesale, and services. CFNAI is the Chicago Fed National Activity Indicator matched by month and year to the distress date. HHI market concentration is the Herfindahl-Hirschman Index of bank deposit concentration in the metropolitan statistical area surrounding the firm headquarters divided by 100. Lagged Relationship Indicator is the relationship indicator from the most recent loan prior to the distressed loan. Analyst Indicator is whether the firm has analysts providing quarterly earnings estimates over the four quarters prior to the distress identification. The samples are from a dataset including one observation per firm. The three sets of regressions differ by their sample criteria. Regressions I-V are from a sample where edfs ranked 7, 8 and 9 are considered financially distressed. These ranks also denote future failure by distress. Regressions VI-X are from a sample where edfs ranked 8 and 9 are considered financially distressed. These are the ranks that determine future firm failure by distress. Regressions XI-XV are from a sample where only edfs with a rank of 9 are considered financially distressed, and only the firms with a future ranking of 9 are deemed failures by distress. Rho is the correlation coefficient of the residuals from each of the two probit estimations. When rho is significantly different from zero, the equations should be estimated simultaneously. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

BIVARIATE PROBIT: DISTRESSED FIRMS

Simultaneous Bivariate Probit: Predicting Future Firm Success

	Sample Minimum Rank: 7 Failure Minimum Rank: 7				Sample Minimum Rank: 8 Failure Minimum Rank: 8				Sample Minimum Rank: 9 Failure Minimum Rank: 9			
Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	0.0208	0.1811	0.0863	0.0708	0.2390	0.4644*	0.1896	0.1759	1.7647***	1.5315***	1.9288***	1.9286***
	0.9280	0.4340	0.6650	0.7250	0.3450	0.0720	0.3840	0.4210	0.0000	0.0010	0.0000	0.0000
Relationship Indicator	0.9584***	0.7889***	0.9215***	0.9516***	0.8661***	0.6858***	1.0401***	1.0664***	-1.4512***	0.1308	-1.3363***	-1.3365***
	0.0010	0.0000	0.0000	0.0000	0.0040	0.0010	0.0000	0.0000	0.0000	0.7700	0.0000	0.0000
Firm												
Age	0.0110***	0.0089***	0.0112***	0.0111***	0.0135***	0.0124***	0.0126***	0.0125***	0.0065*	0.0074	0.0057	0.0057
	0.0000	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0740	0.1060	0.1560	0.1570
Leverage	-1.6013***	-1.7054***	-1.6351***	-1.6205***	-1.5329***	-1.5715***	-1.4638***	-1.4522***	-1.2912***	-1.8725***	-1.5121***	-1.5118***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Operating Profit Margin	0.3292	0.2474	0.2900	0.2793	0.0923	0.1212	0.0087	-0.0005	0.3661	0.3636	0.4076	0.4076
	0.1540	0.3610	0.1780	0.1970	0.6920	0.6570	0.9680	0.9980	0.2870	0.4220	0.2600	0.2600
Fixed Assets/Total Assets	0.5011***	0.4769**	0.4444***	0.4393***	0.4102**	0.3010	0.3237*	0.3181*	-0.0511	-0.3307	-0.0834	-0.0833
	0.0030	0.0130	0.0070	0.0070	0.0310	0.1600	0.0740	0.0790	0.8250	0.2620	0.7480	0.7490
Net Sales/Total Sales	-0.0208	-0.0673	-0.0295	-0.0287	-0.0003	-0.0671	-0.0031	-0.0027	-0.1568**	-0.0641	-0.1445**	-0.1445**
	0.6740	0.2400	0.5420	0.5530	0.9960	0.2640	0.9540	0.9600	0.0270	0.4410	0.0460	0.0460
Assets	-0.0290***	-0.0209**	-0.0276***	-0.0281***	-0.0287***	-0.0249***	-0.0302***	-0.0305***	0.0255*	0.0038	0.0210	0.0210
	0.0010	0.0110	0.0010	0.0010	0.0000	0.0020	0.0000	0.0000	0.0560	0.7600	0.1510	0.1530
Operating Cash/Interest Paid	0.0040	0.0043	0.0040	0.0039	0.0055	0.0066	0.0053	0.0053	0.0183*	0.0171	0.0185	0.0185
	0.2830	0.3450	0.2790	0.2800	0.2540	0.2630	0.2510	0.2500	0.0780	0.2720	0.1060	0.1060
Timing												
Distess Date - Loan Date	-0.0001	0.0001	-0.0001	-0.0001	-0.0005	-0.0001	-0.0003	-0.0003	-0.0008	-0.0007	-0.0010	-0.0010
	0.8830	0.8550	0.8540	0.8590	0.5150	0.8710	0.7010	0.7100	0.3610	0.5710	0.2720	0.2720
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomy												
CFNAI	-0.2016***	-0.2622***	-0.2194***	-0.2167***	-0.1898***	-0.2365***	-0.1817***	-0.1790***	-0.1894***	-0.3229***	-0.2366***	-0.2366***
	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0010	0.0010	0.0040	0.0000	0.0010	0.0010

Simultaneous Bivariate Probit: Predicting Relationship Indicator												
	Sample Minimum Rank: 7 Failure Minimum Rank: 7				Sample Minimum Rank: 8 Failure Minimum Rank: 8				Sample Minimum Rank: 9 Failure Minimum Rank: 9			
Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	-0.3995**	-0.2488	-0.5571***	-0.6165***	-0.5004**	-0.1594	-0.5372***	-0.6032***	0.0404	0.4996	-0.1255	-0.3350
	0.0230	0.2250	0.0010	0.0020	0.0140	0.4880	0.0060	0.0080	0.8900	0.1600	0.6890	0.3340
Firm												
Age	-0.0007	0.0041	-0.0014	-0.0014	0.0012	0.0003	0.0004	0.0003	0.0002	-0.0073	0.0003	0.0003
	0.8040	0.2590	0.6060	0.6010	0.7150	0.9420	0.9060	0.9200	0.9530	0.1320	0.9470	0.9470
Leverage	-0.2617	-0.1223	-0.1967	-0.0834	-0.0547	-0.0896	0.0077	0.1229	-0.2179	-0.5716*	-0.0820	-0.0849
	0.1090	0.5360	0.2260	0.7340	0.7650	0.6670	0.9660	0.6400	0.4310	0.0920	0.7720	0.8270
Operating Profit Margin	0.5998***	0.6581**	0.5860***	0.5886***	0.5833**	0.8058***	0.6036***	0.6043***	0.0728	0.4478	0.0425	0.0425
	0.0060	0.0160	0.0070	0.0070	0.0130	0.0080	0.0090	0.0090	0.8490	0.3380	0.9110	0.9110
Fixed Assets/Total Assets	0.0190	0.0527	0.0281	0.0343	-0.0008	0.0334	0.0024	0.0102	0.0826	0.1853	0.0659	0.0658
	0.9080	0.7920	0.8630	0.8340	0.9970	0.8820	0.9900	0.9560	0.7430	0.5460	0.7930	0.7930
Net Sales/Total Sales	-0.0480	0.0760	-0.0411	-0.0396	-0.0449	0.0245	-0.0367	-0.0351	-0.1721**	-0.1743**	-0.1757**	-0.1757**
	0.3400	0.2050	0.4090	0.4280	0.4130	0.6970	0.5010	0.5210	0.0270	0.0470	0.0240	0.0240
Assets	0.0789***	0.1052***	0.0738***	0.0736***	0.0663***	0.0926***	0.0622***	0.0621***	0.0588***	0.0785**	0.0590***	0.0590***
	0.0000	0.0030	0.0000	0.0000	0.0030	0.0040	0.0020	0.0020	0.0000	0.0170	0.0010	0.0010
Operating Cash/Interest Paid	-0.0004	-0.0104**	-0.0013	-0.0014	0.0003	-0.0095	-0.0004	-0.0005	0.0203*	0.0169	0.0190*	0.0190*
	0.9080	0.0320	0.7250	0.7120	0.9430	0.1390	0.9250	0.9160	0.0540	0.2530	0.1000	0.1000
Timing												
Distess Date - Loan Date	-0.0002	0.0003	-0.0002	-0.0002	-0.0004	0.0006	-0.0004	-0.0004	-0.0009	0.0016	-0.0006	-0.0006
	0.7230	0.6960	0.8250	0.8140	0.5790	0.5360	0.5590	0.5770	0.3760	0.2060	0.5190	0.5190
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economy												
CFNAI	-0.0863*	-0.1155*	-0.0829*	-0.0806*	-0.0532	-0.1174*	-0.0662	-0.0633	0.0098	-0.0913	-0.0056	-0.0056
	0.0690	0.0540	0.0760	0.0860	0.3200	0.0800	0.2050	0.2270	0.8900	0.3350	0.9410	0.9410
Instruments												
HHI Market Concentration	0.0194***				0.0246***				0.0094			
	0.0020				0.0010				0.1690			
Lagged Relationship Indicator		0.8262***				0.8773***				0.9144***		
		0.0000				0.0000				0.0000		
Analyst Indicator			0.5971***	0.6890***			0.4929***	0.6014***			0.3825***	0.3790
			0.0000	0.0000			0.0000	0.0020			0.0020	0.2700
Analyst Indicator * Leverage				-0.1929				-0.2005				0.0050
				0.5300				0.5410				0.9910
Number of Observations	1550	1162	1622	1622	1187	941	1249	1249	646	542	673	673
Number of Firms	1550	1162	1622	1622	1187	941	1249	1249	646	542	673	673
Wald Chi-Squared	346.9300	355.9200	475.9200	491.6600	235.0100	264.6200	378.1100	391.3700	.	157.9400	295.9700	296.7800
Wald p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	.	0.0000	0.0000	0.0000
Rho Chi-Squared	4.3241	8.4305	9.3430	9.0311	3.9784	8.4973	13.9619	13.4842	21.1503	0.0317	3.0072	2.92644
Rho p-Value	0.0376	0.0037	0.0022	0.0027	0.0461	0.0036	0.0002	0.0002	0.0000	0.8588	0.0829	0.0871

Table VIII
Bivariate Probit Regressions: Expanded Sample

Below is the output from bivariate probit regressions. There are two simultaneous probit stages: the first predicts future firm success with an exogenous relationship indicator and the second predicts the relationship indicator with the same controls in addition to an identifying instrument. Coefficients are adjacent to the independent variables, while their p-values are below. All errors are robust and clustered by firm. Success is an indicator variable denoting not failing. Relationship is measured with an indicator variable denoting that any lead lender was a prior lender to the firm. Firm age is measured in years as the difference between distress identification and the firm's initial public trading day. Leverage is the total value of debt to the market value of assets (as in Frank and Goyal (2004)). Assets are measured in billions. The distress date is the end of the quarter that the firm is identified as distressed, and the loan date is the day the loan deal becomes active. This difference is measured in days. Industry controls are indicators for each of the following SIC classified industries: manufacturing, retail, wholesale, and services. CFNAI is the Chicago Fed National Activity Indicator matched by month and year to the distress date. HHI market concentration is the Herfindahl-Hirschman Index of bank deposit concentration in the metropolitan statistical area surrounding the firm headquarters divided by 100. Lagged Relationship Indicator is the relationship indicator from the most recent loan prior to the distressed loan. Analyst Indicator is whether the firm has analysts providing quarterly earnings estimates over the four quarters prior to the distress identification. The samples are from a dataset including multiple observations per firm. Each sample includes all of the sample universe firms that have relevant loans. The distinguishing attribute among the samples is the distress threshold. Regressions I-V are from a sample where future firm failure by distress is determined by experiencing an edf ranked 7, 8 and 9. Regressions VI-X are from a sample where future edfs ranked 8 and 9 merit failure by distress. Regressions XI-XV are from a sample where firms with future edfs ranked 9 are considered failures from distress. Rho is the correlation coefficient of the residuals from each of the two probit estimations. When rho is significantly different from zero, the equations should be estimated simultaneously. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

BIVARIATE PROBIT: EXPANDED SAMPLE												
Simultaneous Bivariate Probit: Predicting Future Firm Success												
	Sample Minimum Rank: 0				Sample Minimum Rank: 0				Sample Minimum Rank: 0			
	Failure Minimum Rank: 7				Failure Minimum Rank: 8				Failure Minimum Rank: 9			
Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	0.1860	0.4023***	0.2628**	0.2485**	0.5892***	0.8098***	0.6590***	0.6385***	1.6790***	1.4438***	1.5371***	1.5140***
	0.1510	0.0070	0.0200	0.0270	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Relationship Indicator	1.1551***	0.6443***	1.0782***	1.1096***	1.0315***	0.5649***	0.9785***	1.0182***	-1.0267***	0.2769	0.2972	0.3538
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.1460	0.1860	0.1640
Firm												
Age	0.0086***	0.0093***	0.0092***	0.0090***	0.0102***	0.0099***	0.0103***	0.0102***	0.0146***	0.0142***	0.0144***	0.0142***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Leverage	-1.8932***	-1.9999***	-1.9505***	-1.9365***	-2.0267***	-2.1279***	-2.0961***	-2.0819***	-1.8858***	-2.3174***	-2.4024***	-2.4002***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Operating Profit Margin	0.5242**	0.8281***	0.5350***	0.5053***	0.4019	0.8302***	0.4244**	0.3914*	1.3240***	0.7083**	0.7237***	0.6884***
	0.0210	0.0010	0.0060	0.0100	0.1050	0.0010	0.0360	0.0540	0.0000	0.0110	0.0040	0.0090
Fixed Assets/Total Assets	0.4803***	0.3852***	0.4479***	0.4454***	0.5440***	0.3854***	0.5156***	0.5127***	0.2299*	0.3318**	0.3822***	0.3847***
	0.0000	0.0030	0.0000	0.0000	0.0000	0.0060	0.0000	0.0000	0.0940	0.0420	0.0070	0.0070
Net Sales/Total Sales	0.0271	-0.0087	0.0191	0.0191	0.0208	-0.0278	0.0161	0.0159	0.0033	-0.0026	0.0256	0.0259
	0.3640	0.8170	0.5210	0.5190	0.5130	0.4940	0.6110	0.6120	0.9330	0.9560	0.5370	0.5310
Assets	-0.0156***	-0.0084	-0.0143***	-0.0146***	-0.0150***	-0.0080	-0.0138***	-0.0141***	0.0069	-0.0019	-0.0043	-0.0045
	0.0020	0.1260	0.0030	0.0030	0.0070	0.1890	0.0100	0.0080	0.3370	0.5950	0.1610	0.1370
Operating Cash/Interest Paid	0.0029**	0.0071***	0.0031***	0.0031***	0.0022	0.0044**	0.0022	0.0021	0.0023	0.0072**	0.0020	0.0020
	0.0120	0.0000	0.0060	0.0060	0.1090	0.0130	0.1030	0.1020	0.2360	0.0310	0.3380	0.3360
Timing												
Distess Date - Loan Date	0.0012**	0.0002	0.0010**	0.0010**	0.0011**	0.0001	0.0009*	0.0009*	-0.0003	0.0009	0.0012*	0.0012*
	0.0200	0.7430	0.0490	0.0410	0.0440	0.8080	0.0980	0.0840	0.7220	0.2250	0.0820	0.0720
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomy												
CFNAI	-0.1795***	-0.1987***	-0.1888***	-0.1862***	-0.1796***	-0.1905***	-0.1879***	-0.1852***	-0.2053***	-0.2037***	-0.2133***	-0.2115***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Simultaneous Bivariate Probit: Predicting Relationship Indicator												
	Sample Minimum Rank: 0 Failure Minimum Rank: 7				Sample Minimum Rank: 0 Failure Minimum Rank: 8				Sample Minimum Rank: 0 Failure Minimum Rank: 9			
Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	-0.5889***	-0.3047**	-0.7884***	-0.8408***	-0.5820***	-0.3009**	-0.7889***	-0.8392***	-0.5456***	-0.3040**	-0.7839***	-0.8142***
	0.0000	0.0110	0.0000	0.0000	0.0000	0.0120	0.0000	0.0000	0.0000	0.0110	0.0000	0.0000
Firm												
Age	0.0027**	0.0038**	0.0026**	0.0026**	0.0027**	0.0038**	0.0026**	0.0026**	0.0036***	0.0040**	0.0037***	0.0036***
	0.0390	0.0210	0.0410	0.0450	0.0390	0.0200	0.0410	0.0450	0.0100	0.0140	0.0070	0.0080
Leverage	0.1708*	-0.0930	0.3071***	0.4548***	0.1664*	-0.0945	0.3052***	0.4455***	0.1764**	-0.0938	0.3128***	0.3959***
	0.0540	0.4110	0.0010	0.0010	0.0610	0.4010	0.0010	0.0010	0.0460	0.4050	0.0000	0.0060
Operating Profit Margin	1.4832***	1.2543***	1.3821***	1.3660***	1.4851***	1.2548***	1.3869***	1.3729***	1.4809***	1.2395***	1.3825***	1.3747***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Fixed Assets/Total Assets	-0.2332**	0.0246	-0.2496**	-0.2447**	-0.2341**	0.0230	-0.2480**	-0.2440**	-0.2386**	0.0356	-0.2431**	-0.2405**
	0.0250	0.8470	0.0140	0.0170	0.0250	0.8570	0.0150	0.0170	0.0240	0.7810	0.0180	0.0190
Net Sales/Total Sales	-0.0113	0.0488	0.0018	0.0012	-0.0113	0.0484	0.0017	0.0014	-0.0210	0.0485	-0.0053	-0.0056
	0.7190	0.2240	0.9540	0.9680	0.7210	0.2270	0.9560	0.9650	0.5040	0.2250	0.8650	0.8570
Assets	0.0442***	0.0351***	0.0403***	0.0405***	0.0434***	0.0342***	0.0396***	0.0399***	0.0322***	0.0319***	0.0290***	0.0291***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Operating Cash/Interest Paid	-0.0002	-0.0012	-0.0010	-0.0011	-0.0002	-0.0012	-0.0009	-0.0010	-0.0001	-0.0012	-0.0009	-0.0009
	0.7940	0.2880	0.2580	0.2090	0.8470	0.2960	0.2910	0.2420	0.8760	0.2960	0.3170	0.2870
Timing												
Distess Date - Loan Date	-0.0028***	-0.0011*	-0.0026***	-0.0026***	-0.0028***	-0.0011*	-0.0026***	-0.0026***	-0.0028***	-0.0011*	-0.0026***	-0.0026***
	0.0000	0.0560	0.0000	0.0000	0.0000	0.0550	0.0000	0.0000	0.0000	0.0530	0.0000	0.0000
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomy												
CFNAI	-0.0501*	-0.1023***	-0.0434	-0.0425	-0.0514*	-0.1036***	-0.0440	-0.0432	-0.0518*	-0.1038***	-0.0431	-0.0426
	0.0800	0.0060	0.1260	0.1350	0.0740	0.0060	0.1230	0.1300	0.0700	0.0060	0.1320	0.1370
Instruments												
HHI Market Concentration	0.0106***				0.0104***				0.0091**			
	0.0030				0.0050				0.0160			
Lagged Relationship Indicator		0.8342***				0.8359***				0.8389***		
		0.0000				0.0000				0.0000		
Analyst Indicator			0.5021***	0.5892***			0.5051***	0.5882***			0.5162***	0.5664***
			0.0000	0.0000			0.0000	0.0000			0.0000	0.0000
Analyst Indicator * Leverage				-0.2493				-0.2359				-0.1395
				0.1180				0.1500				0.4560
Number of Observations	4724	3612	4906	4906	4724	3612	4906	4906	4724	3612	4906	4906
Number of Firms	2546	2182	2650	2650	2546	2182	2650	2650	2546	2182	2650	2650
Wald Chi-Squared	1543.1100	1156.1800	1759.9600	1819.3900	1288.4200	1095.6400	1558.7800	1609.6200	996.5800	900.4000	950.0300	961.7200
Wald p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rho Chi-Squared	18.5794	11.4068	38.4459	39.8316	10.8524	6.4968	30.3867	31.9410	6.2051	0.2429	0.8710	1.0844
Rho p-Value	0.0000	0.0007	0.0000	0.0000	0.0010	0.0108	0.0000	0.0000	0.0127	0.6221	0.3507	0.2977