Creditor coordination effects and bankruptcy prediction

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ABSTRACT

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This study investigates the increase in forecasting accuracy of hazard rate bankruptcy prediction models with creditor coordination effects over the forecasting period 1990-2009. A firm's probability of bankruptcy is likely to be marginally affected by creditors' coordination behavior, since failure to coordinate may result in premature foreclosure, denial of refinancing, or disagreement over private restructuring. Applying findings from prior literature, I present creditor coordination effects as interactions between the ex ante likelihood of creditor coordination failure and a firm's information characteristics. The most striking finding of this study is an increase, on average, of 10% in the out-of-sample forecasting accuracy of private firm prediction models with creditor coordination effects. The contributions of this study are twofold, (1) the hazard rate model results provide evidence that creditor coordination can exert marginal effects on firms' probability of bankruptcy, and (2) the forecast accuracy results suggest that incorporating creditor coordination effects can significantly improve the forecasting accuracy of bankruptcy prediction models for private firms.

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DEDICATION

This work is first and foremost dedicated to my parents, my mother Myung Ae Yom, and my father Sung Gon Lee. They have shown me by example how to have courage to pursue what I love, no matter what other people say. This work is also dedicated to my grandparents, Young Ji Kim, Don Sook Choi, Jong Jik Lee, and Jaegeun Yom. They have been my source of inspiration and support throughout my life to shape me into what I am. I dedicate this work to my brother, Sang Who Lee, for being my only, and the most supportive and loving sibling one could ever have. Last but not the least, this work is dedicated to Ramin Mehdizadeh, who has kept me going in spite of all the ups and downs, with his incredible strength, love, courage and optimism. I am truly blessed to have him as my husband.

Section 1: Introduction

With the unprecedented expansion of credit markets[1] and surging number of defaults and bankruptcies[2] over the past decade[3], the economic significance of bankruptcy hazard rate estimation has steadily increased. In particular, as private firms have become dominant players in the U.S. credit universe in recent years (Witman and Diz, 2009), estimating the probability of bankruptcy[4] in the absence of equity market price information has become a particular challenge for investors and academics.

To assess the probability of bankruptcy more accurately in the absence of equity market price information, a prediction model must be able to capture, from financial statements and other publicly available sources, a comprehensive set of information regarding bankruptcy risk of the firm. However, as Beaver, Correia, and McNichols (2010) note, extant private firm models[5] for predicting financial distress or bankruptcy based on financial ratios are limited to financial statement information, which constitutes only part of the total mix of available information. The purpose of this study

[1] According to Securities Industry and Financial Markets Association (SIFMA), during the past decade, the total amount of outstanding debt in U.S. corporate bond market has more than doubled, from $3.4 billion in 2000 to $6.9 billion in 2009. As a percentage of the Gross Domestic Product (GDP), corporate debt increased from 33.7% in 2000 to 48.7% in 2009 (Bureau of Economic Analysis; SIFMA).

[2] Bankruptcy in this study refers to Chapter 11 and Chapter 7 bankruptcy filings.

[3] Himmelberg, et al. (2010) document that bond default rate has been the highest in the most recent recession compared to previous recessions. Table 2 in this paper also provides evidence on this trend.

[4] This study focuses on bankruptcy prediction instead of financial distress or default prediction. Since creditor coordination effects are likely to be most crucial when we analyze their role in bankruptcy due to their central role in the out-of-court restructuring, the implications of creditor coordination effects are most comprehensive in predicting bankruptcy. However, the tenor of the results remains unchanged when I expand the sample to financially distressed firms, or restrict the sample to defaults.

[5] Private (public) firm bankruptcy prediction model refers to models that predict bankruptcy without (with) equity market information, using accounting-based or information-based variables. While private firm models can be used for prediction of both private and public equity firm bankruptcies, they are the best available models for private equity firms, since public firm models can be only used for public equity firms with equity price information.

is to expand the pool of information relevant to estimating the probability of bankruptcy by shifting attention to the unique role of creditor coordination in the firm's path to financial distress and bankruptcy.

This study investigates how incorporating creditor coordination effects increases the forecasting accuracy of hazard rate bankruptcy prediction models. In this study, creditor coordination effects are defined as the effects creditors' coordination failure can have on the likelihood of a firm filing for bankruptcy. Prior research and anecdotal evidence on financial distress and creditor coordination suggest that the probability of default or bankruptcy depends not only on where the firm stands in terms of current accounting fundamentals, but also on the likelihood of creditors' coordination failure[6]. Creditors that normally play a passive role in the firm's operations can become highly influential in the firm's destiny at crucial decision-making points such as lending (Morris and Shin, 2004), refinancing (Hertzberg, Liberti and Paravisini, 2010) or private restructuring (Brunner and Krahnen, 2009). Creditors' decisions to foreclose on loans, deny refinancing, or disagree on private restructuring terms, can increase the likelihood of financial distress and bankruptcy for a firm.

Anecdotal evidence suggests that creditor coordination is a manifestation of a combination of complicated strategic decisions that reflect diverse interests. From the complex creditor coordination games that play out in the real world, the theoretical literature on creditor coordination has extracted core dimensions of coordination among creditors from which rigorous frameworks for analyzing creditor coordination behavior

[6] Morris and Shin (2004) analyze the ex ante risk of creditor coordination failure, which should be marginally priced in debt securities. Gilson, John, and Lang (1990) provide evidence on distressed firms' failure of coordination among creditors, and how this increases the likelihood that the firm fails to reach an agreement in private restructuring, leaving the firm to seek no other option but to file for bankruptcy.

have been devised. The present study employs theoretical frameworks from prior literature on creditor coordination to analyze creditor coordination behavior in terms of the interaction between specific variables, namely, the ex ante likelihood of creditor coordination failure and a firm's information characteristics.

Theory and anecdotal evidence suggest that a firm's ex ante likelihood of coordination failure is determined first and foremost by various aspects of a firm's capital structure. The composition and strategic positions of creditors and maturity structure of debt have been identified as major aspects of capital structure that constitute potential creditor coordination problems. For instance, the greater the number of creditors, the more diverse their interests, or if the firm has public debt-holders, prior studies document the greater the ex ante likelihood of coordination failure, *ceteris paribus* (e.g., Bolton and Scharfstein, 1996; Anderson and Sundaresan, 1996).

Furthermore, prior research suggests that creditor coordination problems are affected by firms' information characteristics. Three characteristics of firm-specific information have been identified by prior research as most relevant to the decisions of creditors in the strategic setting of the creditor coordination game: (1) ex ante credit quality of the firm (2) uncertainty on the firm's future fundamentals, and (3) public exposure of firm-specific information[7].

Prior studies suggest that a firm's ex ante likelihood of coordination failure is influenced by ex ante credit quality of the firm. Morris and Shin (2004), Brunner and Krahnen (2008), and Hertzberg, Liberti, and Paravisini (2010) note that conditional on

[7] Hertzberg, Liberti and Paravisini (2010), Anctil et al. (2004), and Walther (2004) studies the role information transparency plays in creditor coordination game. This study draws implications from these studies on how public exposure of firm-specific information can affect creditor coordination, as measured by creditor transparency index (CTI), which is based on how the firm's information is exposed to creditors through market transactions.

the firm's capital structure, firms with lower credit quality are likely to have more sever creditor coordination problems. This is due to the fact that when the credit quality of the firm is lower, strategic uncertainty on actions of other creditors tends to increase. Prior studies also suggest that creditor coordination problems are likely to be exacerbated when there is higher uncertainty on future fundamentals of the firm, which impose higher information uncertainty among creditors (Morris and Shin, 2004). Public exposure of firm-specific information, on the other hand, has been shown to have an ambiguous effect on creditor coordination. Greater exposure of firm-specific information to creditors can exacerbate or ameliorate creditors' coordination depending on whether it generates higher strategic uncertainty among creditors (Morris and Shin, 2004) or serves as an anchor in private restructuring negotiations[8].

Applying findings from prior literature to the hazard rate prediction model, I present creditor coordination effects as interactions between two set of factors, (1) the ex ante likelihood of creditor coordination failure measured in terms of the firm's capital structure variables (2) the firm's information characteristics, specifically, the firm's ex ante credit quality, uncertainty on future fundamentals of the firm as measured by the negative accruals, and degree of public exposure of firm-specific information to creditors, as measured by a creditor transparency index (CTI).

If creditor coordination effects provide information regarding the firm's probability of bankruptcy over and above what is suggested by current accounting fundamentals (i.e., financial ratios), coefficients of hazard rate model should be consistent with theoretical predictions, and incorporating these effects into hazard rate bankruptcy

[8] Detragiache (1994) notes that market price acts as a reference point for setting terms of distressed exchanges for creditors to agree upon, thereby ameliorating coordination problems in private debt restructuring.

prediction models should improve the accuracy of their predictions regarding the probability of bankruptcy.

I employ hazard rate models following Shumway (2001), Beaver, McNichols, and Rhie (2005), Campbell, Hilscher, and Szilagyi (2008), and Bharath and Shumway (2008) to estimate the ex ante probability of bankruptcy with creditor coordination effects. As Campbell, Hilscher, and Szilagyi (2008) and Bharath and Shumway (2008) document, simple hazard rate models using a multivariate logit framework have higher out-of-sample forecasting accuracy than other methodologies for estimating the probability of financial distress or bankruptcy.

Consequently, I use the hazard rate methodology adopted by Shumway (2001), and the models with sets of variables from Altman (1965), Ohlson (1980), Zmijewski (1984), and Bharath and Shumway (2008), as my basic private and public firm models. After fitting the models and calculating scores for each firm-year, I rank the scores and compare them with actual occurrences of bankruptcies to measure forecasting accuracy at different cut-off points for binomial outcomes.

When I fit the hazard rate model with creditor coordination effects, I find the coefficients to be statistically significant and signs to be consistent with predictions from prior research. Firms with higher ex ante likelihood of creditor coordination failure, more negative accruals, higher earnings volatility, higher analyst forecast dispersion and more public exposure in the eyes of creditors are more likely to file for bankruptcy than otherwise similar firms. In analyzing the interaction terms, I further find that firms with higher ex ante likelihood of creditor coordination failure are, if their ex ante credit quality is lower, accruals are more negative, or earnings volatility is higher, significantly more likely to file for bankruptcy than firms with a similar ex ante likelihood of creditor coordination failure. For firms with greater public exposure of firm-specific information as measured by the creditor transparency index, the results vary with the different types of ex ante creditor coordination variables, consistent with analytical predictions from prior research.

Using coefficients from hazard rate bankruptcy prediction models to calculate forecasting accuracy based on actual observations of hand-collected bankruptcy filings, I find the out-of-sample forecasting accuracy of the bankruptcy prediction models measured by the area under the Receiver Operating Characteristics curve ("ROC curve") to be higher by, on average, 10% across 20 years of rolling forecast period, when creditor coordination effects are incorporated into private firm models. The finding on private firm models is striking with regards to its magnitude of increase in forecasting accuracy[9], which is clearly economically significant. For public firm models, increase in forecast accuracy is consistently 1-2%, which is statistically significant but economically less meaningful compared to private firm models. The finding on public firm models is consistent with information contained in creditor coordination effects mostly, but not wholly, impounded into public equity prices.

I find these results consistently for different specifications of the hazard rate bankruptcy prediction models, which suggests that creditor coordination effects provide additional predictive power over and above the comprehensive sets of financial ratios, and even equity-market-based variables studied in prior research. My results are also consistent with creditor coordination effects not being subsumed by information on current accounting fundamentals or equity market prices, but rather providing a distinct set of information on the probability of bankruptcy.

To check the robustness of the finding, I perform various tests to investigate the endogeneity issues related to creditor coordination variables and their interactions with information characteristics variables. I also perform predictions based on more detailed components of accruals to explore which components are most relevant to creditor coordination effects.

Results from these additional tests on endogeneity generally corroborate interpretation of my results as effects of creditor coordination on the probability of bankruptcy, and are inconsistent with alternative explanations for the finding, such as the endogeniety of capital structure variables, agency problem arising from information asymmetry, market risk premium or other predictors of financial distress associated with creditor coordination effects.

This study makes several contributions. First, it predicts bankruptcy from the novel perspective of incorporating the role of creditor coordination in the path to financial distress that ultimately leads to bankruptcy. By incorporating creditor coordination effects derived from theory, this study adopts a broader set of variables that contain information about distress and bankruptcy risk, specifically, the risk that creditors will fail to coordinate based on firm-specific information characteristics. This study thus extends the set of information that can be used to assess distress or bankruptcy risk based on a rigorous analytical framework, and suggests that creditor coordination effects provide information on the probability of bankruptcy beyond what can be captured by accounting ratios that reflect a firm's current financial condition.

Second, the study provides evidence that incorporating creditor coordination effects into private firm bankruptcy prediction models substantially improves the accuracy of bankruptcy prediction. The degree to which forecasting accuracy is improved, for both private firm model (10%) and public firm model (1-2%) is especially striking given that the area under the ROC curve is one of the most rigorous measures of forecasting accuracy for binomial outcomes. Evidence from prior studies suggests that it is extremely difficult to consistently increase the out-of-sample forecasting accuracy of hazard rate prediction models by including additional variables. Chava and Jarrow (2004), for example, cite as one of the major contributions of their study their documentation of only a 1-2% improvement in out-of-sample forecasting accuracy, as measured by the area under the ROC curve, when industry effects are incorporated.

By incorporating variables that capture the role of creditors as active decision-makers in firms' destinies, this study demonstrates that the more comprehensive set of information as a result of incorporating creditor coordination effects is able to improve the forecasting accuracy of default or bankruptcy prediction, especially for private firm models. Therefore, this study can be most useful to academics, managers, investors, and others to predict private firm bankruptcies more accurately by incorporating creditor coordination variables into prediction models.

Lastly, this study provides evidence on the role of uncertainty on future fundamentals of the firm as measured by analyst forecast dispersion, and negative accruals in influencing creditors' decisions to coordinate, and thereby the probability of bankruptcy. Although prior bankruptcy prediction research has considered information contained in the volatility of accounting variables (Dambolena and Khoury, 1980) and equity market price (Shumway, 2001), the effect of analyst forecast dispersion, and negative accruals on creditors' coordination decisions has previously not been taken into account in distress or bankruptcy prediction. By providing evidence on the role of analyst forecast dispersion, and negative accruals in creditor coordination leading to bankruptcy outcomes, this study adds to our understanding of creditors' use of analyst forecasts and accounting information, and how information on firms' future fundamentals may affect coordination among creditors[10].

The remainder of the paper is organized as follows. In section 2, I provide a literature review and formulate hypotheses. In section 3, I present the hazard rate model and variables I use to measure creditor coordination effects. In section 4, I explain my sample selection and provide sample characteristics. Empirical results are presented in section 5, and I conduct robustness tests in Section 6. I summarize and conclude in section 7.

Section 2: Literature review and hypotheses development

I investigate the increase in forecasting accuracy of hazard rate bankruptcy prediction models by incorporating creditor coordination effects. Notably, the role of creditor coordination in determining optimal credit, default, and bankruptcy has been extensively studied in theoretical research (Diamond and Dvybvig, 1983; Bruche, 2010; Morris and Shin, 2004; Bris and Welch, 2005; Anctil et al, 2010), as well as in experimental research (Anctil et al. 2004; Cornand and Heinemann, 2010).

[10] Penman (2007) suggests that fundamental analyses can help creditors to analyze default and bankruptcy risk of the firm more effectively. Relatedly, understanding how creditors coordinate based on accounting fundamentals can expand our applications of fundamental analyses to credit analyses.

Creditor coordination has been studied in relations to the choice of capital structure (Bolton and Sharfstein, 1996; Bris and Welch, 2005), reorganization law (Gertner and Scharfstein, 1991; Mooradian, 1994), and debt pricing (Morris and Shin, 2004; Bruche, 2010), among many other topics. Relatedly, Walther (2004) notes that empirical work identifying costs and benefits of improved transparency in creditor setting is crucial in complementing theoretical and experimental works on creditor coordination.

In comparison to extensive analytical research on creditor coordination problems, empirical research documenting coordination failure remains limited. Gilson, John and Lang (1990) show that in their sample of distressed firms, firms that avoid bankruptcy and privately restructure the debt are more likely to have bank debt, since it is more likely that banks are able to ameliorate the problem of coordination failure by actively engaging in a private restructuring agreement amongst debt-holders. On the other hand, Asquith, Gertner, and Scharfstein (1994) provide evidence that one of the most important determinants of disagreement among creditors in private restructuring is the existence of public debt-holders[11]. They find that having public debt dominates other possible determinants such as having bank debt as Gilson, John, and Lang (1990) suggest. More recently, Brunner and Krahnen (2009) empirically examine coordination problem of multiple creditors for German firms and find that “bank pool” serves as a mechanism to ameliorate coordination problem among creditors.

Prior research on creditor coordination suggest that firms with higher likelihood of coordination failure in lending, refinancing, or private restructuring as characterized by having public debt outstanding (Asquith, Gertner, and Scharfstein, 1994) with higher

[11] Bolton and Scharstein (1996) point out that due to the Trust Indenture Act of 1939, unanimous consents among debt-holders are required to change major terms of public debt contracts, making public debt to be subject to a much severe coordination problem than private debts.

number of debt-holders (Morris and Shin, 2004), with higher proportion of short-term debt (Morris and Shin, 2004), lower proportion of bank debt (Gilson, John, and Lang, 1990), and lower credit quality (Hertzberg, Liberti, and Paravisini, 2010) are more likely to file for bankruptcy than otherwise similar firms.

Moreover, theoretical research on creditor coordination predicts that depending on the firm's information characteristics, for the same level of ex ante likelihood of coordination failure, the probability of bankruptcy would increase further, suggesting interaction effects between ex ante likelihood of creditor coordination and the firm's information characteristics. Morris and Shin (2004) show that firms with higher likelihood of ex ante creditor coordination failure, with lower ex ante credit quality or higher uncertainty on future fundamentals, are less likely to coordinate in lending. Hertzberg, Liberti and Paravisini (2010) show that for firms with more publicly available information on their credit quality, creditors are less willing to coordinate by lending less or refusing to provide additional financing compared to firms with similar ex ante likelihood of creditor coordination. On the other hand, Anctil et al. (2004) show that the effect of transparency on creditors' coordination behavior depends on the assumptions imposed.

In sum, both theoretical and empirical findings suggest that firms with higher ex ante likelihood of coordination failure are more likely to file for bankruptcy *ceteris paribus*, and the firm's information characteristics can influence creditor coordination problems. Based on prior research, I present creditor coordination effects as interactions between two set of factors, (1) the ex ante likelihood of creditor coordination failure measured in terms of the firm's capital structure variables, and (2) firm's information characteristics relevant to creditor coordination, specifically, information that affects creditors' belief on the firm's future fundamentals as measured by the ex ante credit quality, analyst forecast dispersion, negative accruals, and degree of public exposure of firm-specific information to creditors, as measured by a creditor transparency index.

If variables representing creditor coordination effects adequately capture their relationships with the probability of financial distress or bankruptcy, I would expect to find coefficients of creditor coordination effects estimated by hazard rate models to be statistically significant, with signs of the coefficients consistent with predictions from prior research on creditor coordination. Therefore, I hypothesize the following:

H1: Coefficients of creditor coordination effects from hazard rate model estimations are significant and consistent with predictions from analytical frameworks of creditor coordination problems.

Furthermore, if creditor coordination effects provide information regarding the probability of bankruptcy over and above what is suggested by current accounting fundamentals (i.e., financial ratios), then incorporating these effects into hazard rate bankruptcy prediction models should improve the accuracy of their predictions regarding the probability of bankruptcy. Therefore, I hypothesize the following:

H2: By incorporating creditor coordination effects, both in-sample fit and out-of sample forecasting accuracies of hazard rate bankruptcy prediction models are increased significantly.

Section 3: Research Design

3.1 Hazard rate model

In order to investigate the increase in forecasting accuracy of bankruptcy prediction models by including creditor coordination effects, I employ the reduced-form econometric hazard rate model first adopted by Shumway (2001) and employed by Beaver, McNichols and Rhie (2005), Campbell, Hilscher, and Szilagyi (2008), and Bharath and Shumway (2008) to measure the ex ante probability of default and/or bankruptcy for private firms.

Bharath and Shumway (2008) find that hazard rate models outperform models based on Merton (1974)'s structural framework in terms of both in-sample-fit and out-of-sample forecasting accuracy when variables of structural model are included in the hazard rate model as explanatory variables. Duffie, Saita, and Wang (2007) also note superior performance of Beaver, McNichols and Rhie (2005) as a benchmark to compare with their hybrid corporate default prediction model. Moreover, hazard rate models can be most flexible in incorporating new set of variables without restrictions on specific functional forms or using equity market price information. Therefore, I use hazard rate models in my tests of forecasting accuracy.

As for the selection of variables, I employ four models with different sets of variables from Altman (1965), Ohlson (1980), Zmijewski (1984), Shumway (2001), and Bharath and Shumway (2008)[12]. These four models incorporate accounting-based variables that have been shown to contain a comprehensive set of information from

[12] Altman (1965) uses discriminant analysis, whereas Ohlson (1980) and Zmijewski (1984) use simple logit models. However, as Shumway (2001) and Chava and Shumway (2004) demonstrate, hazard rate prediction models with variables from Altman (1965), Ohlson (1980) and Zmijewski (1984) outperform original models in terms of both in- and out-of-sample forecasting accuracies. Hence, this study uniformly uses hazard rate models with variables from Altman (1965), Ohlson (1980), and Zmijewski (1984) to compare forecasting accuracies with different sets of variables.

financial statements on the probability of bankruptcy. The general form of the hazard model I employ is based on the following statistical relationship:

$$\text{Log}[h_j(t) / (1-h_j(t))] = \alpha(t) + BX_j(t) \qquad (1)$$

In this model, $h_j(t)$ represents the hazard, or instantaneous risk of bankruptcy, at time t for company j, conditional on survival to t; $\alpha(t)$ is the baseline hazard; B is a vector of coefficients; and $X_j(t)$ is a matrix of observations on accounting-based ratios from prior research, variables of creditor coordination effects, and other control variables. Here, the hazard ratio is defined as the likelihood odds ratio in favor of bankruptcy, and the baseline hazard rate is assumed to be a constant. The model is estimated as a discrete time logit model using maximum likelihood methods, and provides consistent estimates of the coefficients B.

3.2 Creditor coordination effects

3.2.1 Ex ante likelihood of creditor coordination

1) Public debt outstanding (PUB)

To investigate the effect of creditor coordination, I use an indicator variable, PUB, to represent whether a firm has public debt outstanding, which dramatically increases the number of creditors. Bond ownership tends to be much more diffuse than ownership of private debt, which tends to have fewer, more concentrated creditors. As noted in Bolton and Scharfstein (1996), owing to the Trust Indenture act of 1939, public debts are subject to a more severe hold-up problem. Unanimous consent being required to change the major terms of a bond contract, it is more difficult, and sometimes impossible, to restructure debt for a firm with public debt outstanding. It is consequently not surprising for bankruptcy filings to result from the failure of creditors to coordinate in restructurings when a small group of creditors holds public debt.

Public debt-holders also tend to have more diverse interests compared to private debt-holders who provide financing to the firm based on close relationships with the firm and based on private information. There are public debt-holders who are long-term investors seeking to hold debts until maturity, whereas substantial public debt-holders seek short-term profits for speculative purposes (Whitman and Diz, 2009).

The recent expansion of the credit default swap (CDS) market, which enables bond-holders to insure against default or bankruptcy linked to public debt obligations, has exacerbated creditor coordination problems in private restructurings for firms with public debt. Holding substantial amounts of CDS contracts give the CDS holders a strong incentive to hold up, even absent disagreement on restructuring terms. Firms that have public debt outstanding, and may therefore also have CDS contracts outstanding, are thus more likely to be subject to creditor coordination problems.

In sum, as Asquith, Gertner, and Scharfstein (1994) document, having public debt outstanding is likely to be one of the major determinants of creditor coordination problems. Moreover, when the investors' belief is more negative on future fundamentals of the firm, if there is higher uncertainty on the future fundamentals of the firm, or when the firm-specific information is more publicly exposed, creditor coordination problem from having public debt is likely to be exacerbated (Morris and Shin, 2004; Brunner and Krahnen, 2008, Hertzberg, Liberti, Paravisini, 2010). I therefore use PUB as one of my main measure of ex ante likelihood of creditor coordination failure, and incorporate interaction terms with information characteristics as measures of creditor coordination effects.

2) Current liabilities to total assets (CLTA)[13]

According to Morris and Shin (2004), default trigger point is pushed up when there is higher likelihood of creditor run. One of the variables they suggest to measure the likelihood of lending coordination failure is the proportion of current liabilities in the capital structure of the firm. The rationale is that higher the current liabilities subject to refinancing or foreclosure, the more vulnerable the firm is to creditor coordination problem rising from the uncertainty over actions of creditors holding current liabilities[14]. If any of the short-term creditors decide not to refinance or decide to foreclose upon their claims, this may result in collective actions of withdrawal of credit[15]. If the proportion of current liabilities in the capital structure is large enough, then such lack of coordination among creditors is likely to disrupt the firm's operation. Hence, the likelihood of lending or refinancing coordination failure is higher when there is higher impending liquidity needs as measured by the ratio of current liabilities to total assets[16].

Moreover, Morris and Shin (2004) and Hertzberg, Liberti, and Paravisini (2010) predict that lending or refinancing coordination problem arising from having higher proportion of short-term liabilities in the firm's capital structure is exacerbated when

[13] In an untabulated test, I also employ an indicator variable which represents whether the firm is refinancing its debt. Results for this alternative variable are qualitatively similar to CLTA.

[14] Firms with higher current liabilities in their capital structure are more likely

[15] Such collective actions of creditors to foreclose on their short-term debt are often referred to as creditor run.

[16] This measure can also capture the degree of sensitivity towards market-wide risk appetite. I address this issue in the robustness checks. I appreciate Hyun Song Shin for raising this point.

the firm's ex ante credit quality is lower, or when the firm-specific information is more publicly exposed. Ex ante credit quality is one of the major signals creditors' observe in making their decision to coordinate or not. If such signal is negative, this is likely to exacerbate coordination problems for firms. On the other hand, higher public exposure of firm-specific information through major trading venues increases the likelihood that any negative news will be more promptly exposed and transmitted among creditors, thereby increasing the likelihood of lending or refinancing[17] coordination failure. Therefore, I use current liabilities to total assets as a variable to capture creditor coordination problems in lending or refinancing, and incorporate interaction terms with information characteristics as measures of creditor coordination effects.

3) Long-term liabilities to total liabilities (LLTL)

Theory and anecdotal evidence suggest that when there is higher proportion of long-term creditors in the creditor group at the restructuring, they are less likely to coordinate, especially when the firm's credit quality is low. This is because for long-term creditors, the outcome of out-of-court restructuring is more uncertain compared to short-term creditors, particularly when the firm's credit quality is low, since the possibility of receiving payments in longer term is more uncertain. This effect of creditor coordination problem due to term structure of liabilities of the firm has often

[17] Exposure in the bond market serves an example of how public exposure of information through trading venues exacerbates creditor coordination problems in lending or refinancing. In practice, bond prices often serve as a benchmark for lenders to decide whether to refinance their loan. Any negative news promptly impounded into bond prices will increase the likelihood that a creditor will decide not to refinance their loan, since a creditor is likely to be concerned that other creditors to the same firm concurrently observes the negative news, and based on similar concerns, would also be reluctant to refinance their loans. Such effect of public market exposure on creditor coordination problem is likely to be relevant to any actively traded secondary markets such as equity or syndicated loan markets. I appreciate Alberto Gallo at Goldman Sachs for this point.

been noted as a significant source of disagreement among creditors, leading to bankruptcy (Gilson, John, and Lang, 1990). I therefore use long-term liabilities to total liabilities (LLTL) as a variable to capture creditor coordination problems arising from term structure differences, and incorporate interaction terms with ex ante measure of credit quality as a measure of creditor coordination effects.

3.2.2 Information characteristics

1) Credit quality of the firm (ZQ or ZQLAST)

Morris and Shin (2004) analytically show that the effect credit quality has on value of the debt is twofold. The first effect is referred to as conventional effect, which suggests that firms with weaker accounting fundamentals ex ante will have higher probability of default due to higher mean value of ex ante default. The second effect is referred to as coordination effect, which suggests that firms' coordination effect will interact with conventional effect. The equations representing these two effects are as follows:

$$\partial W/\partial y = \sqrt{\alpha}ø - \partial\psi/\partial y * \sqrt{\alpha}ø \quad (2)$$

W represents asset value of the debt, y represents ex ante mean value of distribution of underlying state of the firm, α represents precision of the distribution of the underlying state of the firm, and ø represents slope of the standard normal evaluated at a certain point. As fundamental values of the firm deteriorates (represented by decrease in $\partial W / \partial y$), not only the conventional effect drives down the price of the debt ($\sqrt{\alpha}ø$ goes down), but also since the coordination effect is stronger as deterioration becomes more serious due to the threat of creditor run, which incrementally decreases the value of the debt (the interaction of $\partial\psi/\partial y$ and $\sqrt{\alpha ø}$ further decreases $\partial W / \partial y$)[18]. Hence, according to Morris and Shin (2004), firms with lower ex ante credit quality will be more likely to have coordination problem, *ceteris paribus*.

To capture underlying state, W, or credit quality of the firm, I use Z-score using private firm version of the following model developed in Zmijiewski (1984):

$$\mathrm{Log}[h_j(t) / (1-h_j(t))] = b_0 + b_1{*}ROA_j(t) + b_2{*}TLTA_j(t) + b_3{*}CACL_j(t) \quad (3)$$

This model incorporates major accounting ratios relevant for default prediction such as profitability (ROA: Net income to total assets), leverage (LTA: total liabilities to total assets), and liquidity (CACL: current assets to current liabilities), and has been tested as one of the most robust model in capturing the probability of default. I have also tried including ETL (EBITDA to Total liabilities) as a measure of interest coverage following Beaver, McNichols, and Rhie (2005), but found that the effect of this variable is subsumed by ROA, and does not affect my results in any way. I have also performed tests using Ohlson (1980)'s O-Score, as well as the score from Shumway (2001)'s private firm model, and found similar results for all the tests I run in this paper. To control for potential non-linearity of the Z-score, I rank Z-scores and use Z-score quintiles as a measure of ex ante credit quality of the firm ("ZQ"). Also, both analytical findings and anecdotal evidence suggest that for firms with worst credit quality, creditor coordination problem will be exacerbated when the proportion of long-term debt-holders in the creditor group is higher due to term structure conflicts. Therfore, I define ZQLAST as an indicator variable which capture firms with lowest credit quality as measured by Z-score, and interact LLTL with ZQLAST to represent creditor coordination problem in restructuring arising from term structure conflicts.

[18] Since $\partial\psi/\partial y < 0$, the coordination effect reinforces the conventional effect.

2) Analyst forecast dispersion (DISP)

In the stylized model of Morris and Shin (2004), higher the ex ante precision of information on the fundamentals, lower the effect of creditor coordination. Anecdotal evidence also demonstrates that if there is higher uncertainty on fundamentals of the firm, then it is more difficult for creditors to agree on restructuring terms, ceteris paribus. Hence, both in lending and private restructuring coordination, higher uncertainty of information on fundamentals will exacerbate the effect of coordination problems on the probability of default or bankruptcy.

I use analyst forecast dispersion as the equity market-based measure of uncertainty on future fundamentals of the firm[19]. Diether, Malloy, and Scherbina (2002), Sadka and Scherbina (2007), Avramov et al. (2009), Ali et al. (2010) show higher analyst forecast dispersion to be associated with negative future stock returns explained by short-selling factors, liquidity, or distress risk. Guntay and Hackbarth (2010) find bond and equity prices to exhibit a similar pattern, firms with higher analyst forecast dispersion having lower bond returns in the following period. Ali et al. (2010) provide evidence that less corporate disclosure leads to higher analyst forecast dispersion. Taken together, these findings suggest that analyst forecast dispersion is a proxy for uncertainty in future fundamentals of the firm.

I define DISP as the quintile value of analyst forecast dispersion after ranking it in ascending order, and use its interaction term with ex ante measures of creditor coordination failure to represent coordination effects.

[19] DISP is not available for private firms, and firms that are not covered by more than two analysts. Therefore, I complement DISP with accounting-based measures of uncertainty on future fundamentals of the firm.

3) Negative accruals (NACCQ)

Prior research suggests that the magnitude of accruals provide information about future earnings and cash flows of the firm. Sloan (1996) and Richardson et al. (2005) find that for firms with more extreme accruals, earnings are less persistent. Richardson et al. (2005) relate earnings persistence to the concept of accrual reliability, and suggest that firms with higher proportion of less reliable accruals in their earnings have lower earnings persistence. Focusing more on accruals with negative values, Dechow and Ge (2006) provide evidence that results of lower persistence for extreme accruals is driven by firms with negative accruals. Melumad and Nissim (2008) suggest that different components of accruals can help us better understand distress risk of the firm.

I use the quintile values of accruals ranked in the descending order, with more negative values ("negative accruals") having higher NACCQ, to capture uncertainty on future fundamentals of the firm perceived by creditors[20]. More extreme values of accruals, whether positive or negative, are likely to increase uncertainty with respect to future earnings and cash flows due to lower earnings persistence associated with accruals. However, negative accruals, in the eyes of creditors, increase uncertainty to a greater extent, since negative accruals represent current losses that will be realized as

[20] While Sloan (1996), Richardson et al. (2005), and Bhojraj and Swaminathan (2009), among many others show that investors do not seem to fully impound differential persistence of accruals and cash flows (known as accrual anomaly) in equity and bond prices, Dechow, Richardson and Sloan (2008) provide evidence that accrual anomaly is more likely to be a capturing mispricing of diminishing returns to new investments, rather than investors' mispricing on differential persistence. Also, Lev and Nissim (2006) suggest that institutional investors understand implications in accruals. Since credit investors are mostly institutional investors, it is reasonable to assume that creditors are aware that accrual component of earnings is less persistent than cash flow component of earnings, hence, is more uncertain, less reliable, and associated with higher uncertainty on future fundamentals of the firm. However, to the extent that the such implication is not fully recognized by investors, negative accruals may not be able to fully capture the uncertainty on future fundamentals of the firm perceived by creditors in their decision to coordinate.

negative cash flows in the future. Given creditors' asymmetric loss functions – creditors care more about the downside risk of the firm - the more negative accruals a firm has, the more uncertainty the firm has in the eyes of creditors with regards to negative future cash flow implications[21].

This paper uses Sloan (1996)'s definition of accruals to measure operating accruals[22]. While I use balance sheet approach to measure accruals in my main test since cash flow information is missing for substantial number of firms in my sample, I find very similar results when cash flow approach is used following Hribar and Collins (2002). To control for potential non-linearity, I rank accruals in descending order, allocate firm years based on operating accruals, and use quintile values for hazard model tests. Therefore, in my definition of negative accruals (NACCQ), most negative accrual firm-years are in the highest quintile, which represent highest degree of uncertainty with respect to negative future cash flow implications.

4) Public exposure of information (CTI)

Hertzberg, Liberti and Paravisini (2010) show that when information on credit quality of the firm becomes publicly available, therefore, is more transparent, this alone can magnify coordination problem to the extent that creditors are likely to be subject to higher uncertainty over actions of other creditors when public information is observable by other creditors. As Morris and Shin (2004) point out, the notion of transparency is multi-faceted. In this paper, I focus on one narrow aspect of transparency, that is to say,

[21] Ozel (2010) provides evidence that private debt-holders consider working capital accruals to be informative.

[22] I also employ total accruals following Richardson et al. (2005) and Bhojraj and Swaminathan (2009) to measure negative accruals. Results are unaffected by employing alternative definition of accruals.

transparency which can affect creditor coordination through public exposure of firm-related information through active secondary trading markets[23].

I construct a creditor transparency index (CTI) to capture firms' degree of transparency or public exposure of information in the eyes of creditors when they make decision to coordinate or not. CTI increases when the firm has more actively traded secondary market for public debt, credit default swaps (CDS), or syndicated loan securities. Hence, CTI is highest for firms with actively traded public equity, public debt, and syndicated loans, and is the lowest for firms without actively traded securities. To adjust for the degree of exposure of information across different secondary trading markets, CTI is calculated as the following[24]:

CTI = Median trading volume of public debt securities + Median trading volume of public equity securities + Median trading volume of syndicated loan securities

I rank CTI in the ascending order, and use the quintile values of CTI to adjust for any non-linearity issues in my tests as a measure of public exposure of firm-specific information.

3.2.3 Other control variables correlated with creditor coordination variables

[23] Bushman, Smith, and Wittenberg-Moerman (2010) document transmission of private information through syndicated loan trading venues.

[24] I assume that firm-specific information is most actively exposed to creditors through trading in three major trading venues: public debt, public equity, and syndicated loan markets. Also, I assume that the degree of market exposure is proportional to the number of trades. Since this measure is likely to be associated with the market liquidity of the firm from various trading venues, I control for various measures of market liquidity in my hazard model tests to ensure the adequacy of this measure. As an alternative way to measure CTI, I also use simple indicator variable of 1 to represent the firm's presence in each of the three trading venues and define CTI as the sum of indicator variables. I find that results are robust to different measurement of CTI.

To ensure that my findings are not capturing other capital structure or firm characteristics associated with distress or bankruptcy risk of the firm which are unrelated to creditor coordination effects, and to minimize any bias from omitted variables, I control for other variables used in the prior literature that may be correlated with my empirical measures of creditor coordination effects.

1) Availability of funds from the external capital market

Firms with more funds available from the external capital market such as public equity, debt, or syndicated loan markets are likely to be able to tab external capital markets more easily than firms without outside funds. To control for the availability of funds from the external capital market, I include log of book value of total liabilities (FD) and the log of book value of total assets (ASSETS). Including ASSETS also controls for the effect of firm size. My measure of ex ante likelihood of coordination failure, PUB, because it represents a company's presence in the public bond market rather than the coordination effect of having public creditors per se in creditor coordination, may capture a firm's ability to tap the external capital market. To the extent that firms with public debt have greater external liquidity, being more likely to be able to borrow from the external capital market and, hence, less likely to default, *ceteris paribus*, having this variable would bias against finding the effect of creditor coordination.

2) Capital structure

Following Gilson, John, and Lang (1990) and Brunner and Krahnen (2008), and as suggested in the theoretical literature, I also run tests to control for the existence of senior or secured debt in the capital structure as well as proportion of bank debt, number of debt contracts outstanding, and ex ante recovery rates measured by market value of the firm over replacement value if equity market information is available. Including these capital structure variables does not affect my results, most likely because much of the effect associated with creditor coordination is dominated by the main variable of creditor coordination, PUB, which is consistent with the findings of Asquith, Gertner, and Scharfstein (1994). Hence, I present my main results without these capital structure variables.

3) Covenants

I include dummy variables representing the existence of various covenants in tests run for a subset of my sample for which covenant information is available from Mergent FISD. Rauh and Sufi (2008) show that firms are more likely to include tighter covenants and capital structure restrictions when a firm's credit quality is low and there is higher risk of default ex ante. In a similar vein, it is possible that creditors may include certain covenants to prevent anticipated creditor coordination problems. I include covenant dummies to control for a potential ex ante contracting effect. My results being unaffected by the inclusion of covenant dummies, and because covenant information is available for only about 10% of my sample, I present my main results without covenant fixed effects.

4) Investment and growth

Because including capital structure variables may capture the agency problem associated with overinvestment and ex ante contracting efforts to prevent such concerns, as suggested in Nini, Smith, and Sufi (2009) and Lyandres and Zhadanov (2007), I control for capital expenditure (CPX). To distinguish creditor coordination effects from confounding effects of underlying investment or growth associated with a higher proportion of current liabilities in the capital structure or having public debt, I control for the CPX.

5) Information asymmetry, information uncertainty, and other financial reporting quality variables

To control for the effect of information asymmetry, I run various tests including bid-ask spread for bonds. To control for information uncertainty, I include firm age, bond return volatility, and average daily turnover for bonds following Jiang, Lee, and Zhang (2005) whenever information is available. I also control for financial reporting quality measure following Francis et al.'s (2005) to control for confounding effects of financial reporting quality. Inasmuch as they were unaffected when they are included in hazard rate models, I present my main results without these variables.

6) Earnings volatility (EVOLQ)

For an alternative accounting-based measure of uncertainty on future fundamentals of the firm, I use earnings volatility measured over five years of previous annual earnings following Dichev and Tang (2009). Dichev and Tang (2009) note that while managers believe volatile earnings tend to be less persistent (Graham et al. 2005), equity market and equity analysts fail to fully reflect the implication of earnings volatility with respect to persistence of earnings. However, even without being fully aware of the relationship between ex ante earnings volatility and persistence of earnings, as investors update their beliefs based on their observations of historical patterns of earnings, volatility of earnings serves as an appropriate empirical measure of ex ante precision of earnings. As Dichev and Tang (2009) suggest, historical earnings volatility is likely to contain information about uncertainty on future fundamentals of the firm beyond those contained in negative accruals. Therefore, I incorporate the quintile value of the interactions of earnings volatility (EVOLQ) with ex ante measures of creditor coordination failure to represent creditor coordination effects. However, I find that effects of EVOLQ in all of the tests are subsumed by NACCQ and other variables. Therefore, I exclude EVOLQ in presenting my main results.

7) Other control variables associated with the availability of public information

To prevent the availability of other information from driving my results, I control for sources of information from debt and equity markets that may be associated with variables that capture creditor coordination effects including whether the firm is rated by any of the three ratings agencies (S&P, Moody’s, and Fitch), and the firm’s book value of assets normalized by inflation rate, larger firms being more likely to have more public information available. Finding the effects of these other variables to be subsumed by my main variables of creditor coordination, I exclude them from the presentation of my main results.

Section 4: Sample selection and sample characteristics

4.1 Bankruptcy dataset

The sample of bankruptcies in this paper is hand-collected and compiled from a number of sources including SDC Platinum restructuring database, the 2009 Compustat Annual Industrials file, the CRSP Monthly Stock file, the website Bankruptcy.com, and the list of bankruptcy filings generously provided by Lynn Lopucki[25]. The full sample of bankruptcies from 1980 to 2009 is 3,120 firms, but more than 30% are private firms (both debt and equity) for about two thirds of which financial information is not publicly available. Restricting my sample to COMPUSTAT firms and excluding firms in financial industries (SIC code 6000-6800) yields a sample of 2,518 bankruptcies. My final sample of 1,479 bankruptcies reflects the constraint of data required for hazard model analysis. The bankrupt year is defined as the calendar year in which a firm files for bankruptcy. Following Chava and Jarrow (2004), all COMPUSTAT firms that did not file for bankruptcy and are not in financial industries are included in the sample as non-bankrupt firms.

(Insert Table1 here)

Table 1 shows the breakdown of bankrupt and non-bankrupt firms by industry using the broad industry classification employed by Chava and Jarrow (2004). The greatest number of observation of bankrupt and non-bankrupt firm years are in manufacturing, followed by service industries and retail trade. Finance, insurance, and real estate bankruptcies represent a smaller proportion of my initial sample, but are excluded from my final analyses due to the composition of their financial statements and default risk

[25] I am very much grateful to Lynn Lopucki for providing me with the bankruptcy dataset.

characteristics, as noted in prior literature on bankruptcy prediction (Chava and Jarrow, 2004). A bar chart showing the percentage of bankruptcies by industry is presented in Figure 1. The number of bankruptcies for each industry is comparable to other bankruptcy studies.

(Insert Table 2 here)

Table 2 shows the breakdown of bankrupt and non-bankrupt firms by calendar year. The frequency of bankrupt firms reflects the number of bankruptcies, and the frequency of non-bankrupt firms reflects the number of firm-years provided by the non-bankrupt firms. A bankrupt firm appears in the count only once, in the year in which its bankruptcy is declared. The ratio of bankrupt to non-bankrupt firms in a given year is hence an approximation of the relative frequency of bankruptcy. Overall, the ratio is less than 1%. Three peaks in the bankruptcy rate—in 1991, 2000-2001, and 2008 the ratio exceeded 1%—reflect three troughs in credit cycles over the past 30 years. My final sample is consistent with general characteristics of bankruptcy samples of public firms as documented in Chava and Jarrow (2004), Bharath and Shumway (2008), and Campbell, Hilscher, and Szilagyi (2008).

The significant proportion of bankruptcies from the credit turmoil in the late 2000s in my final sample provides a new perspective on the most recent credit cycle. Approximately 11% of the bankruptcies in my sample are from the 2007-2009 period, which has been little studied to date. Compared to the 2001 recession that followed the Internet boom and bust, the recent credit turmoil has produced fewer bankruptcies than expected relative to its impact on credit markets and the economy overall. Himmelberg et al. (2010) observe that the high yield default rate has been highest in the most recent recession compared to previous recessions. But limited debtor-in-possession (DIP) financing has favored distressed exchange over bankruptcy. Thus, default probabilities have, in fact, been much higher but bankruptcies less frequent due to the illiquidity of the credit market during the turmoil.

(Insert Table 3 here)

Table 3 describes the composition of my sample in terms of public-private equity and debt status. In my sample, private equity firms are more likely than public equity firms to go bankrupt, but public debt firms more than twice as likely as firms without public debt to go bankrupt. Public status in either equity or debt tending to be associated with firm size and greater use of external capital, this simple classification provides an initial perspective on the public-private status of equity and debt firms, but its relationship to the probability of bankruptcy should be interpreted with caution.

(Insert Figure 3 here)

Figure 3 describes the composition of the public-private status of the sample in terms of equity and debt. Most of the sample is public-equity, private-debt firms. Firms with public debt represent a relatively smaller proportion of 11.1%.

4.2 Univariate sample characteristics

My final sample of non-bankrupt firms is from the COMPUSTAT annual database, from which I also obtain accounting information for bankrupt and non-bankrupt firms. I use SDC Platinum and Moody's Mergent FISD database for public debt and syndicated loan offering information, and Bloomberg for CDS trading volume information. I obtain covenants and ratings information from Moody's Mergent FISD database.

Independent variables are lagged to ensure that the data are observable prior to the declaration of bankruptcy. Because all sample firms file annual financial statements with the SEC (i.e., 10-Ks), following Beaver, McNichols, and Rhie (2005), financial statements are assumed to be available by the end of the third month after a firm's fiscal year-end. Although quarterly statements may already have been filed several months prior to this time, for a firm that declares bankruptcy within three months of its fiscal year-end, it is assumed that the most recent year's financial statements are not available and the prior fiscal year is defined as the year before bankruptcy. Because it does not incorporate information in quarterly financial statements, this rule is likely to be a conservative one that may understate the predictive power of financial statement data, as noted in Beaver, McNichols, and Rhie (2005).

(Insert Table 4 here)

Table 4 reports the summary statistics for each of the explanatory variables used in my main tests. The main explanatory variables are accounting ratios and creditor coordination variables. For my main model, I use ROA, LTA, and CACL to capture the credit quality of a firm as measured by accounting ratios. ROA is return on total assets, which is measured as net income divided by total assets. LTA is total liabilities divided by total assets, a measure of leverage. CACL, calculated as current assets to current liabilities, is a measure of firm liquidity. I use the Z-score, based on Zmijewski (1984), as a measure of ex-ante credit quality. I found, using Ohlson's (1980) O-score, Shumway's (2001) score, and Beaver, McNichols, and Rhie's (2005) score, that different models produced similar results and that a linear combination of three variables in my test following Zmijewski (1984) captures most of the explanatory power of the financial statement variables used in other models. This result is not surprising because financial ratios are highly correlated.

The three accounting ratios capture three key elements of a firm's financial strength. ROA is a measure of the profitability of assets. Profitability is expected to be a critical element, prior research having shown capital markets to be concerned about a firm's ability to repay its debts, and profitability being a key indicator of ability to pay. LTA, the second element, is a measure of the debt to be repaid relative to the total assets available as a source for repaying the debt. The third element, CACL, is a measure of short-term liquidity, which is also a crucial measure of a firm's financial condition.

My second set of variables consists of control variables for creditor coordination effects. CPX is obtained as capital expenditure over total assets. ASSETS is the log of the book value of a firm's assets. I do not deflate ASSETS with GDP price index, as in Ohlson (1980), because in my tests this variable represents the amount of external capital obtained by a firm, or amount of information available on the firm. Deflating by GDP price index does not affect my results. I also use FD as the log of total book value of liabilities on the balance sheet to control for total debt financing outstanding. Because, used together, my variables of creditor coordination and probability of bankruptcy may be associated with CPX, ASSETS, and FD, I control for these variables to disentangle the association of creditor coordination variables with probability of bankruptcy. I also include Log (market value of equity) (log(MVE)) and book-to-market ratio (B/M) for public equity firms to control for the effect of growth and investment on the probability of bankruptcy.

For creditor coordination variables, I employ as my measure of the potential restructuring coordination problem PUB, an indicator variable that represents firms that have public debt outstanding. Following Morris and Shin (2004), Hertzberg, Liberti, and Paravisini (2010), and Brunner and Krahnen (2008), I control for lending coordination variables and interaction effects. CLTA, a measure of the potential lending coordination problem that also represents a firm's imminent liquidity needs, is obtained as current liabilities minus cash and cash equivalents, minus available revolving credit facility, over total assets. ZQ represent ex ante credit quality of the firm measured by quintile values of Zmijewski (1984)'s Z-score ranked in the ascending order. Following Hertzberg, Liberti, and Paravisini (2010), I use CTI (Creditor Transparency Index) to represent the degree of exposure of firm-specific information from secondary trading venues. The CTI variable hence captures the degree of transparency afforded to creditors through secondary trading markets. LLTL, the ratio of long-term liabilities to total liabilities, is used to capture the term structure conflicts. Following Hertzberg, Liberti, and Paravisini (2010), ZQLAST is included as an interaction effect of low credit quality that is set to 1 when a firm's Z-score is in the highest quintile and its credit quality, hence, is the lowest. DISP, and NACCQ represent uncertainty on future fundamentals of the firm. DISP represents quintiles of analyst earnings forecast dispersion. Following Diether, Malloy, and Scherbina (2002), analyst earnings forecast is measured as the standard deviation of the 1-year ahead equity analyst forecast over the median forecast. NACCQ represents quintile values of negative operating accruals ranked in descending order.

Table 4 provides summary statistics including the mean, median, and standard deviation values of the individual variables for the bankrupt and non-bankrupt firms in each of the four years prior to bankruptcy. The financial ratios of the bankrupt firms exhibit mean and median differences for as much as four years prior to bankruptcy, and the deterioration of the ratios becomes progressive as the year of bankruptcy approaches. These results are similar in spirit to those reported by Beaver (1966) and in subsequent research. This descriptive statistic can provide some preliminary indication of the behavior of the variables prior to bankruptcy. Following Shumway (2001), I mitigate the effects of outliers on the estimates of the hazard model parameters by winsorizing all observations at the 1% level and 99% level, respectively. As a result, the minimum and maximum values for each of the four years before bankruptcy and for the non-bankrupt firm distribution are identical, as reported in Table 4. This trend not being apparent in PUB, CTI, and some other variables, their association with the probability of bankruptcy should be explored in multivariate hazard model tests.

This trend not being apparent in PUB, CTI, and some other variables, their association with the probability of bankruptcy should be explored in multivariate hazard model tests. Figures 4-21 present similar information graphically by plotting empirical cumulative distribution functions (CDF).

(Insert Figures 4-21 here)

Each figure reports the cumulative distribution function (CDF) for bankrupt and non-bankrupt firms. As noted in Beaver, McNichols, and Rhie (2005), the CDF is informative over the entire distribution of each variable. The figures show the CDFs of the major accounting variables ROA, LTA, and CACL, as well as the equity market variables RSIZ, EXRET, LSIGMA for bankrupt firms, to be distinct from those for non-bankrupt firms. DISP and ACCQ, also follow this pattern, suggesting that uncertainty on future cash flows or negative prospects on the firm reflected in accruals is higher for bankrupt firms. The CDF of ZQ (Zmijewski's score quintile) demonstrates that Zmijewski's model is also able to capture the probability of bankruptcy, 90% of the bankrupt firms being classified in the highest Z-score quintile. Taken together, these findings are consistent with CDF plots in Beaver, McNichols, and Rhie (2005), and reflect differences in the distribution of fundamentals when firms approach bankruptcy.

Measures of creditor coordination, investment, and other control variables do not exhibit consistent patterns as firms approach bankruptcy. Bankrupt firms tend to have lower capital expenditures, more assets, a higher BV of debt, and higher current liabilities in capital structure than non-bankrupt firms. Bankrupt firms also tend to have higher DISP and NACCQ, and be more likely to have public debt, than non-bankrupt firms. B/M ratio, LLTL, and log (MVE) also do not exhibit significant patterns in CDF plots. Although these findings provide preliminary implications of the association of DISP, NACCQ, and creditor coordination with ex post bankruptcy outcomes, multivariate hazard model analyses are required to draw meaningful conclusions about each variable's incremental effect.

4.3 Correlation table

Before initiating multivariate analyses, I examine correlations among major variables in hazard models. Table 5 presents Spearman's correlation coefficients on the upper diagonal and Pearson's correlation coefficients on the lower diagonal.

(Insert Table 5 here)

Major accounting and market variables are correlated in expected ways. ROA is positively associated with RSIZ and EXRET and negatively associated with LSIGMA. ROA is also positively associated with CPX, ASSETS, FD, and Log (MVE). Leverage (LTA) is negatively associated with CACL, but positively associated with ASSETS and ratios of liabilities such as CLTA and LLTL, highly leveraged firms being more likely to have higher proportions of current liabilities subject to creditor coordination in the capital structure and more long-term debt.

My main measure of ex ante coordination failure, PUB, is positively associated with LTA, ASSETS, FD, and CTI. Firms with significant assets are more likely to be able to tap the public debt capital market, and their book value of assets and liabilities consequently likely to be high. Also, most firms with public debt are likely to have public equity and syndicated loans traded, and hence, has higher exposure of firm-specific information.

The measure of lending coordination (Morris and Shin, 2004), CLTA, is positively associated with LTA and ZQ and negatively associated with CACL, CTI, and LLTL. Firms subject to higher creditor coordination problems in lending are also likely to be less liquid, less transparent, and have fewer total liabilities in their debt structure (Morris and Shin, 2004).

Variables relevant to creditor coordination effects exhibit predicted associations. Firms with higher DISP, and NACCQ tending to have lower ROA and CACL, and higher ex ante default risk as measured by ZQ (Zmijewski, 1984's score). In sum, the correlation coefficients suggest that variables in the hazard models tend to be highly correlated, and DISP, NACCQ, CTI, and other variables related to creditor coordination to be correlated with other accounting variables. Hence, their net effect on bankruptcy outcomes can only be investigated in a multivariate framework with appropriate controls.

Section 5: Empirical Results

5.1 Hazard model estimation results

Table 6 reports the results of my hazard model estimation, following Shumway (2001), for 1-year forecasting horizons. Campbell, Hilscher, and Szilagyi (2008) show that the reduced-form econometric approach of the hazard model results in superior in-sample fit and out-of-sample accuracy relative to other default and bankruptcy prediction models such as that of Vassalou and Xing (2004). Duffie, Saita, and Wang (2007), comparing their results with those of Beaver, McNichols, and Rhie’s (2005) hazard rate model, find their in-sample fit and out-of-sample accuracy comparable to that of Beaver, McNichols, and Rhie (2005), confirming the superior predictability of the reduced form model compared to structural models. Bharath and Shumway (2008) also show that the more flexible form of estimation enabled by the reduced econometric form of the hazard model affords predictability over and above that of other default and/or bankruptcy prediction models to date.

Based on these findings, I use the hazard model to estimate the role of analyst forecast dispersion and accruals in bankruptcy. As Beaver, McNichols, and Rhie (2005) note, due to the high level of correlation among variables used to predict bankruptcy, to prevent spurious correlation bias from including too many variables and ensure optimal fit, my main results employ accounting variables following the most rigorous model used by Zmijewski (1984). Using variables from Altman (1968), Ohlson (1980), and Bharath and Shumway (2008) yield similar results for creditor coordination variables. This confirms that my results are robust to the models employed, and that the effects of my variables are not subsumed by other predictors of default or bankruptcy from the prior literature. To control for year- and industry-specific effects, I also include year and industry fixed effects in the hazard rate estimation.

I provide my results separately for the private and public firm models. I show my findings to be robust to the inclusion of equity market variables, and that there is more to be gained from using analyst forecast dispersion, accruals, creditor coordination, and other control variables to significantly increase in-sample fit and out-of-sample forecasting accuracy when both private and public firm models are estimated. Table 6 reports the estimated coefficients for the hazard model under the private firm specification. Table 6 reports the estimated coefficients for the hazard model under the private firm specification.

(Insert Table 6 here)

Consistent with Zmijewski (1984), all accounting variables are significant. Most importantly, interaction effects of coordination variables are significant in all three models, indicating that creditor coordination variables have additional explanatory power over and above other variables. Firms with higher analyst forecast dispersion or more negative accruals are more likely to file for bankruptcy after controlling for other predictors of bankruptcy. Taken together, my results suggest that creditor coordination effects provide information on future bankruptcy outcomes over and above that provided by other predictors of bankruptcy.

In Model 3, a major variable that represents ex ante likelihood of creditor coordination failure, PUB, is positively associated with the probability of bankruptcy for firms with higher DISP or higher NACCQ, as measured by interaction terms of PUB with DISP and NACCQ. These results are consistent with negative accruals and earnings volatility containing information that affects creditors' coordination, and, hence, the probability of bankruptcy, to a greater extent for firms with public debt.

Another variable of creditor coordination, CLTA, is positively associated with the probability of bankruptcy for firms with higher CTI and worse credit quality, as measured by interaction terms with CTI and ZQ. CLTA is, however, negatively associated with the probability of bankruptcy for other firms, consistent with greater transparency and worse credit quality aggravating lending coordination and increasing the probability of bankruptcy. These results are consistent with Morris and Shin (2004). But the interaction term of PUB and CTI is negatively and significantly associated with the probability of bankruptcy, consistent with transparency ameliorating the creditor coordination problem in restructuring, as shown in Hertzberg, Liberti, and Paravisini (2010). That the interaction term of LLTL and ZQLAST is also significant suggests that firms with low credit quality and a higher proportion of long-term creditors within a creditor group have a higher probability of bankruptcy. These results are also consistent with creditor coordination problems arising from term structure differences, as documented in Gilson, John, and Lang (1990).

Model 4 and Model 5 represent public firm models in which equity market variables are included. That DISP, and NACCQ are not significant in Model 4 suggests that equity market prices impound information regarding DISP and NACCQ as predictors of bankruptcy outcome. But the interaction effects of DISP, and NACCQ with PUB remain statistically significant in both models. The interaction effect is stronger for DISP than NACCQ, but both effects are significant at the 5% level, and each interaction term has distinctive effects, as shown in Model 3. This suggests that the effect of analyst forecast dispersion, negative accruals, and earnings volatility is much stronger for firms with public debts, and not fully impounded into equity market prices for firms subject to more severe creditor coordination problems.

Overall, the results of the hazard model tests are consistent with creditor coordination effects providing incremental information on future bankruptcy outcomes.

5.2 In-sample forecasting accuracy

My main framework of bankruptcy prediction, based on Zmijewski (1984) and Shumway (2001), compares the in-sample fit of the model with and without creditor coordination effects across different model specifications. I estimate the hazard models using variables based on Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001). The chi-square statistics presented in Table 7 and Table 8 demonstrate that incorporating creditor coordination effects significantly improves in-sample fit as shown by the P-values of comparison across the models.

(Insert Table 7 and Table 8 here)

For both private firm models (Table 7) and public firm models (Table 8), in-sample fit is improved significantly not only relative to the original model (Model 1) and model with additional variables (Model 2 or Model 3), but also compared to the appended model without interaction terms (Model 2) and final model with interaction terms (Model 3). That creditor coordination variables improve in-sample fit suggests that these additional variables representing creditor coordination effects are economically significant predictors of bankruptcy. Including interaction terms with the creditor coordination effects further improves in-sample fit, consistent with creditor coordination effects significantly affecting creditor coordination, and, in turn, the probability of bankruptcy.

5.3 Out-of-sample forecasting accuracy

I first report comparisons of out-of-sample forecasting accuracy for 2005-2009 using the hazard model estimated with observations from the earlier period, 1980-2004, and classification tables that follow Chava and Jarrow (2004) and Beaver, McNichols, and Rhie (2005). The probabilities of bankruptcy are calculated for each year based on the hazard model estimation, and the companies are grouped into deciles according to these probabilities. The number of bankruptcies in each decile for each year are aggregated over 2005-2009 and reported in Table 9 and Table 10.

(Insert Table 9 and Table 10 here)

I investigate whether creditor coordination effects are economically meaningful in the sense that it can improve the forecasting accuracy of bankruptcy prediction models, and whether significant in-sample results are driven by over-fit due to spurious correlations, by estimating the out-of-sample accuracy of the hazard models with and without creditor coordination variables, using different model specifications suggested by the prior literature on bankruptcy prediction. I estimate the hazard models using variables from Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2004). For all of these models, improvement in out-of-sample forecasting accuracy is apparent from the results, higher proportions of bankrupt firms being reported in the first and second probability deciles.

Figures 22 to 29 illustrate graphically the out-of-sample forecasting accuracy for year-by-year bankruptcy predictions based on up-to-date historical data. The area under the ROC curve is presented, following Chava and Jarrow (2004), as a measure of comprehensive out-of-sample forecasting accuracy.

(Insert Figures 22 to 29 here)

I first estimate a model with data from 1980 up to the prior year of estimation, then use this model to predict bankruptcy outcomes for the year of estimation. Hence, bankruptcy probabilities are calculated for each year for each firm, and an ROC curve constructed from predicted probabilities and the status of each firm in each year. The area under the ROC curve is computed as a measure of the model's forecasting accuracy. This procedure is repeated for every year up to 2009.

As noted in Chava and Jarrow (2004), the area under the power, or ROC (Receiver Operating Characteristic), curve is a widely used measure of the out-of-sample accuracy of forecasting models (Sobehart, Keenan, and Stein, 2000). For comparison across models, the area under the ROC curve is measured relative to the area of the unit square. A value of 0.5 indicates a random model with no predictive ability, whereas a value of 1.0 perfect discrimination. Chava and Jarrow (2004) report the mean area under the ROC curve to be 0.9101 for their model with industry effects, and 0.9113 for Shumway's (2001) public firm model. For the private firm model, the mean area under ROC curve is much lower, at 0.7646 for Chava and Jarrow's (2004), and 0.7513 for Shumway's (2001), model. As Chava and Jarrow (2004) demonstrate, to increase the area under the ROC, the variables included should not only be highly significant, but also have incremental effects not subsumed by other variables in the model.

I find for both the private and public firm models that including creditor coordination effects and control variables significantly improves the forecasting accuracy of bankruptcy prediction, as measured by the area under the ROC curve, compared to models without these variables.

The mean area under the ROC curve increased from 0.681 to 0.837 using Altman's (1968) variables, and from 0.790 to 0.861 using Ohlson's (1980) variables. Of the four models, Shumway's (2001) original model seems to have the best out-of-sample accuracy, with a mean area under the ROC curve of 0.803, which is improved by including my variables to 0.841. Using my main model of estimation based on Zmijewski's (1984) variables, I find that forecasting accuracy increases from 0.733 to 0.848. Performing, in an untabulated test, a stepwise regression with all candidate accounting ratios from the prior literature used together in the hazard model, I find a significant improvement in forecasting accuracy. I therefore conclude that my findings are unaffected by other explanatory variables that can be included in bankruptcy prediction models.

That improvement in out-of-sample forecasting accuracy is sizeable for private firm models across all model specifications, as presented in Figures 22 to 25, suggests that including the additional variables proposed in this paper, especially for private equity firms without timely equity market information, improves the forecasting accuracy of these models substantially. Given that private equity firms represent more than half of the high-yield corporate bond market, this finding is likely to be useful to academics, practitioners, and investors interested in estimating the probability of bankruptcy more accurately for private equity firms.

Improvement in forecasting accuracy as measured by the area under the ROC curve, albeit less striking, is nevertheless significant and consistent across different model specifications for public firm models, as presented in Figures 26 to 29. Forecasting accuracy increases from 0.852 to 0.875 for the model with Altman's (1968) variables, from 0.866 to 0.883 for Shumway's (2001) model, from 0.873 to 0.890 for Bharath and Shumway's (2008) specification, and from 0.868 to 0.885 for the main hazard rate model specification in this paper. Taken together, these findings suggest that adding the variables used in my analyses to capture the role of analyst forecast dispersion, accruals, and creditor coordination in bankruptcy outcomes can help academics, managers, investors, and regulators more accurately predict bankruptcies.

Section 6: Robustness checks

6.1 Controls for capital structure, information asymmetry, and market-wide risk premium

As mentioned earlier, I perform my main tests using the hazard model, controlling for the existence of senior and secured debt as well as the proportion of bank debt, and number of debt contracts outstanding. I also include covenant dummies and rating information as controls for capital structure, ex ante contracting incentives, information environment, and measures of information asymmetry such as bid-ask spreads. Finally, I include measures of market-wide risk premium such as VIX index and NBER. I include the VIX index quintile (VIX) to control for potential market volatility which can serve as a proxy for market-wide risk premium. I also include NBER, an indicator variable set to 1 for recessions and 0 for other periods according to the National Bureau of Economic Research (NBER), since during recessions, investors are more risk averse in lending or refinancing, which can be associated with my ex ante measures of creditor coordination such as PUB and CLTA. This is because for firms that are subject to higher likelihood of ex ante creditor coordination failure such as public debt firms or firms with higher proportion of short-term debt in the capital structure,

Data availability constrained these tests to a subset of only about 10-20% of the final full sample. Nonetheless, I find that including these variables in a smaller sample does not affect the overall tenor of my results. Therefore, I conclude that to the extent that the variables I incorporate capture capital structure characteristics, information asymmetry, or market risk premium which can be correlated with my measures of creditor coordination effects, variables representing creditor coordination effects are unaffected by these control variables, consistent with theoretical predictions.

6.2 Two-stage Heckman correction test for endogeneity

Bharath, Sunder, and Sunder (2008) present evidence consistent with accounting quality affecting firms' choices of debt capital markets. They show firms that issue public debt to have superior accounting quality relative to firms with only private debt. Following prior literature (Katz, 2009; Balachandran, Kogut, and Harnal, 2010), I use the Heckman (1979) two-stage approach to control for any endogeneity that might result from selecting public debt. In the first stage, I estimate a probit selection model using size (total assets and sales), leverage (LTA), profitability (ROA), and current assets to current liabilities (CACL) as my predictor variables, which Denis and Mihov (2002) show to be relevant to the choice of public debt. All of these variables are significant at the 1% level. I then use the estimates of this PROBIT model to compose the inverse Mills ratio for each sample firm, which I include in the second stage, allowing its coefficient to vary between firms with and without private debt, as a control in the hazard rate estimation models. I also perform similar tests for the proportion of short-term debt in the capital structure based on Denis and Mihov (2002).

My results, after controlling for the endogeneity, remaining qualitatively unaltered, I rely on the main results of the hazard models after controlling for the main selection variables ROA, LTA, and CACL, which coincide with the accounting variables included in my main model.

6.3 Analyses with detailed accrual components

I also conduct my hazard rate model analyses with more detailed accrual components. I use total accruals to calculate negative accruals (NACCQ), and decompose these accruals into three components: operating, investing, and financing. Consistent with accruals with higher reliability having less persistence, hence higher uncertainty on future fundamentals, I find that only the operating component of total accruals are significant in the hazard rate test. This is also consistent with Ozel (2010). Ozel (2010) provides evidence that private debt-holders consider working capital accruals to be most informative. Hence, results on NACCQ and its specific components are consistent with adopting NACCQ as a measure of uncertainty on future fundamentals of the firm.

Section 7: Summary and conclusions

In this paper, I provide evidence on the significant role played by creditor coordination effects in bankruptcy prediction. Using a hand-collected sample of bankruptcy filings for the period 1980-2009, I find creditor coordination effects to be significant incremental predictors of bankruptcy. After controlling for other predictors of bankruptcy suggested in the prior literature, I find firms with higher ex ante likelihood of creditor coordination failure interacted by information characteristics to be more likely than otherwise similar firms to file for bankruptcy. Consequently, I document a significant increase in out-of-sample forecast accuracy across 20 years of forecasting period, consistently for different model specifications, after including creditor coordination effects. Taken together, results suggest that creditor coordination effects provide marginal information on the firm’s probability of bankruptcy, and we can predict bankruptcy more accurately for private firms by including creditor coordination effects into hazard rate bankruptcy prediction models.

Possible extensions of this study include exploring other variables that capture uncertainty on future fundamentals or management expectations of future outcomes based on information characteristics or accounting ratios, which can help us predict bankruptcies more accurately with creditor coordination effects. Also, investigating other information relevant to creditors' in coordinating among themselves could shed further light on the dynamics of creditors' use of information and the association of that information with bankruptcy outcomes.

Table 1: Bankrupt and non-bankrupt firms by industry

This table presents bankrupt and non-bankrupt firms by industry following broader classification in Chava and Jarrow (2004) based on SIC Codes. All industries are represented except for financial industries.

Industry classification	SIC Code	Industry name	Number of Firms			% of bankruptcies
			Bankrupt	Non-Bankrupt	Total	
1	<1000	Agriculture, forestry and fisheries	2	1,241	1,243	0.16%
2	1000 to less than 1500	Mineral	88	21,541	21,629	0.41%
3	1500 to less than 1800	Construction	37	3,561	3,598	1.03%
4	2000 to less than 4000	Manufacturing	592	129,882	130,474	0.45%
5	4000 to less than 5000	Transportation, communications, and utilities	200	29,962	30,162	0.66%
6	5000 to less than 5200	Wholesale trade	58	12,021	12,079	0.48%
7	5200 to less than 6000	Retail trade	222	19,259	19,481	1.14%
8	7000 to less than 8900	Service	280	39,987	40,267	0.70%
		Total	**1,479**	**257,454**	**258,933**	**0.57%**

Table 2: Bankrupt and non-bankrupt firms by year

This table presents distribution of bankrupt vs. non-bankrupt firms over the sample period of 1980 to 2009. Bankrupt year is defined as the calendar year in which the firm filed for bankruptcy.

Year	Non-bankrupt	Bankrupt	Total	% of bankrupt firms
1980	5,071	6	5,077	0.12%
1981	4,834	9	4,843	0.19%
1982	4,889	12	4,901	0.24%
1983	4,978	4	4,982	0.08%
1984	5,323	14	5,337	0.26%
1985	5,377	21	5,398	0.39%
1986	5,651	18	5,669	0.32%
1987	6,030	20	6,050	0.33%
1988	6,166	32	6,198	0.52%
1989	6,080	35	6,115	0.57%
1990	5,929	55	5,984	0.92%
1991	5,917	67	5,984	1.12%
1992	5,979	43	6,022	0.71%
1993	6,187	39	6,226	0.63%
1994	6,601	32	6,633	0.48%
1995	6,984	29	7,013	0.41%
1996	7,421	35	7,456	0.47%
1997	8,230	52	8,282	0.63%
1998	8,191	71	8,262	0.86%
1999	7,922	81	8,003	1.01%
2000	8,238	141	8,379	1.68%
2001	8,056	182	8,238	2.21%
2002	7,728	137	7,865	1.74%
2003	7,409	89	7,498	1.19%
2004	7,283	38	7,321	0.52%
2005	7,150	37	7,187	0.51%
2006	6,951	31	6,982	0.44%
2007	6,834	43	6,877	0.63%
2008	6,535	81	6,616	1.22%
2009	4,911	43	4,954	0.87%
Total	**194,855**	**1,479**	**196,352**	**0.76%**

Table 3: Bankrupt and non-bankrupt firms by private-public status

This table presents composition of bankrupt vs. non-bankrupt firms over the sample period of 1980 to 2009 by having public equity and public debt outstanding.

Panel A: Equity

	Non-bankrupt	Bankrupt	% of bankrupt firms
Private	79,760	527	0.7%
Public	181,458	970	0.5%

Panel B: Debt

	Non-bankrupt	Bankrupt	% of bankrupt firms
Private	232,358	1,159	0.5%
Public	28,860	338	1.2%

Table 4: Descriptive statistics for bankrupt and non-bankrupt firms by years before bankruptcy

This table presents the descriptive statistics for the variables used in the analyses of bankrupt and non-bankrupt firms. Definitions of the variables are provided in the Appendix. All variables are winsorized at 1% and 99%, following Shumway (2001).

Panel A: 1 year before bankruptcy

(N = 1,479)	Min.	1Q	Median	Mean	3Q	Max.	SD
ROA	-1.98	-0.16	0.00	-0.13	0.07	0.48	0.39
LTA	0.06	0.68	0.87	1.03	1.13	4.99	0.73
CACL	0.04	0.51	1.00	1.27	1.60	14.87	1.25
RSIZ	-15.06	-13.80	-12.80	-12.63	-11.63	-5.74	1.58
EXRET	-0.84	-0.80	-0.63	-0.50	-0.37	2.19	0.45
LSIGMA	0.04	0.14	0.19	0.22	0.28	0.46	0.11
CPX	0.00	0.02	0.04	0.08	0.08	0.53	0.11
ASSETS	0.00	0.85	3.34	19.06	11.57	119.3	72.9
FD	0.00	0.66	3.01	18.11	10.64	231.2	80.6
LOGMVE	7.04	9.05	10.04	10.18	11.07	16.71	1.58
B/M	-0.29	0.08	0.76	1.57	1.77	28.76	3.01
CLTA	0.05	0.24	0.43	0.63	0.78	4.99	0.69
CTI	1.00	1.00	1.00	1.93	2.14	2.66	0.69
ZQ	1.00	5.00	5.00	4.67	5.00	5.00	0.76
PUB	0.00	0.00	0.00	0.23	0.00	1.00	0.42
NACCQ	1.00	5.00	8.00	7.04	10.00	10.00	2.99
DISP	1.00	2.00	3.00	3.21	4.00	5.00	1.32
LLTL	0.00	0.09	0.39	0.40	0.68	0.93	0.31

Panel B: 2 years before bankruptcy

(N = 1,485)	Min.	1Q	Median	Mean	3Q	Max.	SD
ROA	-1.98	-0.11	0.04	-0.08	0.11	0.48	0.37
LTA	0.02	0.56	0.74	0.84	0.93	4.99	0.64
CACL	0.04	0.88	1.42	1.90	2.19	27.51	2.02
RSIZ	-15.06	-13.12	-12.05	-11.95	-10.86	-5.83	1.61
EXRET	-0.84	-0.64	-0.43	-0.26	-0.09	2.19	0.58
LSIGMA	0.05	0.12	0.16	0.19	0.23	0.46	0.10
CPX	0.00	0.02	0.04	0.09	0.10	0.53	0.11
ASSETS	0.00	0.91	3.30	19.12	11.91	119.3	69.32
FD	0.00	0.53	2.34	15.23	9.36	147.8	59.53
LOGMVE	7.04	9.76	10.77	10.90	11.91	16.71	1.66
B/M	-0.29	0.22	0.65	1.20	1.37	28.76	2.16
CLTA	0.02	0.18	0.29	0.43	0.48	4.99	0.55
CTI	1.00	1.00	1.00	2.01	2.13	2.66	0.65
ZQ	1.00	4.00	5.00	4.32	5.00	5.00	1.04
PUB	0.00	0.00	0.00	0.22	0.00	1.00	0.41
NACCQ	1.00	3.00	7.00	6.11	9.00	10.00	3.13
DISP	1.00	2.00	3.00	3.07	4.00	5.00	1.39
LLTL	0.00	0.19	0.50	0.47	0.73	0.93	0.29

Table 4: Descriptive statistics for bankrupt and non-bankrupt firms by years before bankruptcy

This table presents the descriptive statistics for the variables used in the analyses of bankrupt and non-bankrupt firms. Definitions of the variables are provided in the Appendix. All variables are winsorized at 1% and 99%, following Shumway (2001).

Panel C: 3 years before bankruptcy

(N = 1,452)	Min.	1Q	Median	Mean	3Q	Max.	SD
ROA	-1.98	-0.07	0.07	-0.05	0.13	0.48	0.39
LTA	0.02	0.49	0.68	0.76	0.86	4.99	0.61
CACL	0.04	1.02	1.57	2.21	2.40	27.51	2.70
RSIZ	-15.06	-12.71	-11.70	-11.61	-10.56	-5.41	1.58
EXRET	-0.84	-0.51	-0.27	-0.11	0.11	2.19	0.62
LSIGMA	0.02	0.11	0.15	0.17	0.21	0.46	0.09
CPX	0.00	0.02	0.04	0.08	0.10	0.53	0.11
ASSETS	0.00	0.88	3.36	18.08	12.03	119.3	66.90
FD	0.11	0.46	2.11	13.95	8.87	122.1	54.93
LOGMVE	7.04	10.04	11.04	11.16	12.20	16.71	1.63
B/M	-0.29	0.24	0.59	0.97	1.15	28.76	1.74
CLTA	0.02	0.17	0.27	0.39	0.42	4.99	0.56
CTI	1.00	1.00	1.00	1.01	2.10	3.00	0.64
ZQ	1.00	3.00	4.00	4.03	5.00	5.00	1.17
PUB	0.00	0.00	0.00	0.22	0.00	1.00	0.42
NACCQ	1.00	3.00	6.00	5.75	9.00	10.00	3.18
DISP	1.00	2.00	3.00	3.09	4.00	5.00	1.42
LLTL	0.00	0.18	0.51	0.47	0.73	0.93	0.30

Panel D: 4 years before bankruptcy

(N = 1,404)	Min.	1Q	Median	Mean	3Q	Max.	SD
ROA	-1.98	-0.06	0.08	-0.04	0.14	0.48	0.40
LTA	0.03	0.47	0.65	0.73	0.83	4.99	0.62
CACL	0.04	1.07	1.64	2.38	2.53	27.51	3.04
RSIZ	-15.06	-12.56	-11.50	-11.45	-10.40	-5.35	1.60
EXRET	-0.84	-0.47	-0.24	-0.09	0.11	2.19	0.59
LSIGMA	0.02	0.10	0.14	0.16	0.20	0.46	0.09
CPX	0.00	0.02	0.05	0.09	0.09	0.53	0.11
ASSETS	0.00	0.81	3.33	16.85	11.28	119.3	61.83
FD	0.00	0.36	1.89	12.58	7.97	115.4	48.73
LOGMVE	7.04	10.02	11.11	11.19	12.26	16.44	1.63
B/M	-0.29	0.25	0.56	0.86	1.04	28.76	1.57
CLTA	0.02	0.17	0.26	0.36	0.41	4.99	0.50
CTI	1.00	1.00	1.00	1.98	2.01	3.00	0.62
ZQ	1.00	3.00	4.00	3.86	5.00	5.00	1.24
PUB	0.00	0.00	0.00	0.19	0.00	1.00	0.40
NACCQ	1.00	3.00	6.00	5.60	9.00	10.00	3.12
DISP	1.00	2.00	3.00	3.10	4.00	5.00	1.40
LLTL	0.00	0.19	0.50	0.46	0.72	0.93	0.29

Table 4: Descriptive statistics for bankrupt and non-bankrupt firms by years before bankruptcy

This table presents the descriptive statistics for the variables used in the analyses of bankrupt and non-bankrupt firms. Definitions of the variables are provided in the Appendix. All variables are winsorized at 1% and 99%, following Shumway (2001).

Panel E: Non-bankrupt years

(N = 258,011)	Min.	1Q	Median	Mean	3Q	Max.	SD
ROA	-1.98	0.03	0.12	0.05	0.19	0.48	0.33
LTA	0.02	0.32	0.50	0.58	0.66	4.99	0.59
CACL	0.04	1.21	1.92	2.78	3.01	27.51	3.46
RSIZ	-15.06	-12.15	-10.77	-10.64	-9.23	-5.35	2.10
EXRET	-0.84	-0.29	-0.05	0.02	0.20	2.19	0.51
LSIGMA	0.02	0.07	0.10	0.12	0.16	0.46	0.08
CPX	0.00	0.02	0.05	0.08	0.10	0.53	0.09
ASSETS	0.00	0.51	2.42	34.41	12.85	119.3	123.82
FD	0.00	0.19	1.03	20.86	6.82	129.6	79.66
LOGMVE	7.04	9.74	11.17	11.33	12.80	16.71	2.13
B/M	-0.29	0.33	0.62	1.26	1.12	28.76	3.29
CLTA	0.00	0.15	0.23	0.33	0.35	4.99	0.52
CTI	1.00	1.00	1.00	1.83	2.00	3.00	0.61
ZQ	1.00	2.00	3.00	2.97	4.00	5.00	1.41
PUB	0.00	0.00	0.00	0.11	0.00	1.00	0.31
NACCQ	1.00	3.00	5.00	5.48	8.00	10.00	2.86
DISP	1.00	2.00	3.00	3.00	4.00	5.00	1.42
LLTL	0.00	0.14	0.41	0.40	0.63	0.93	0.28

Panel F: Full sample of bankrupt and non-bankrupt firm years

(N=262,715)	Min.	1Q	Median	Mean	3Q	Max.	SD
ROA	-1.98	0.03	0.12	0.04	0.19	0.48	0.34
LTA	0.02	0.33	0.51	0.59	0.67	4.99	0.59
CACL	0.04	1.20	1.90	2.76	2.99	27.51	3.44
RSIZ	-15.06	-12.19	-10.81	-10.67	-9.27	-5.35	2.10
EXRET	-0.84	-0.30	-0.05	0.01	0.20	2.19	0.52
LSIGMA	0.02	0.07	0.10	0.13	0.16	0.46	0.08
CPX	0.00	0.02	0.05	0.08	0.10	0.53	0.09
ASSETS	0.00	0.52	2.44	33.91	12.80	11.93	122.53
FD	0.00	0.20	1.06	20.67	6.92	23.12	79.15
LOGMVE	7.04	9.74	11.16	11.31	12.77	16.71	2.12
B/M	-0.29	0.33	0.62	1.26	1.12	28.76	3.26
CLTA	0.00	0.15	0.23	0.34	0.36	4.99	0.52
CTI	1.00	1.00	1.00	1.83	2.00	3.00	0.62
ZQ	1.00	2.00	3.00	3.00	4.00	5.00	1.41
PUB	0.00	0.00	0.00	0.11	0.00	1.00	0.31
NACCQ	1.00	3.00	6.00	5.50	8.00	10.00	2.87
DISP	1.00	2.00	3.00	3.00	4.00	5.00	1.42
LLTL	0.00	0.14	0.41	0.40	0.64	0.93	0.28

Table 5: Correlation table

This table presents correlation coefficients of major variables in hazard rate model. The upper diagonal represents Spearman's correlation coefficients, whereas lower diagonal represents Pearson's correlation coefficients. Following Shumway (2001), all variables are winsorized at 1% and 99% level. Description of variables is provided in Appendix.

	ROA	LTA	CACL	RSIZ	EXRET	LSIGMA	CPX	ASSETS	FD
ROA	1	-0.06	0.03	0.45	0.31	-0.37	0.34	0.33	0.30
LTA	-0.49	1	-0.66	0.03	-0.04	-0.03	0.04	0.24	0.46
CACL	-0.04	-0.31	1	-0.03	0.04	0.04	-0.18	-0.19	-0.35
RSIZ	0.24	-0.02	-0.09	1	0.31	-0.51	0.27	0.80	0.74
EXRET	0.12	-0.03	0.00	0.20	1	-0.09	0.03	0.15	0.13
LSIGMA	-0.26	0.03	0.06	-0.50	0.10	1	-0.15	-0.51	-0.48
CPX	0.08	-0.06	-0.09	0.09	-0.01	-0.04	1	0.18	0.19
ASSETS	0.09	0.00	-0.10	0.43	0.01	-0.22	-0.01	1	0.96
FD	0.08	0.03	-0.10	0.39	0.01	-0.20	-0.01	0.96	1
LOGMVE	0.16	-0.01	-0.05	0.83	0.18	-0.35	0.04	0.47	0.43
B/M	0.02	0.01	-0.05	-0.16	-0.07	-0.05	-0.04	0.33	0.31
CLTA	-0.53	0.87	-0.23	-0.08	-0.02	0.08	-0.10	-0.05	-0.04
CTI	0.19	-0.16	-0.03	0.15	0.01	-0.09	-0.01	0.22	0.22
ZQ	-0.44	0.52	-0.34	-0.19	-0.13	0.21	-0.08	0.05	0.10
PUB	0.10	0.04	-0.11	0.25	0.01	-0.15	-0.01	0.30	0.31
NACCQ	-0.16	0.16	-0.16	-0.06	-0.06	0.09	0.10	0.04	0.04
DISP	-0.11	0.07	-0.01	-0.27	-0.04	0.13	-0.02	-0.11	-0.10
LLTL	0.21	0.07	-0.14	0.25	0.00	-0.22	0.16	0.17	0.17

	LOGMVE	B/M	CLTA	CTI	ZQ	PUB	NACCQ	DISP	LLTL
ROA	0.32	-0.10	-0.05	0.11	-0.48	0.09	-0.17	-0.19	0.12
LTA	-0.02	-0.03	0.49	0.23	0.82	0.24	0.12	0.04	0.46
CACL	-0.03	0.01	-0.50	-0.19	-0.53	-0.18	-0.27	-0.03	-0.17
RSIZ	0.85	-0.21	-0.17	0.26	-0.18	0.28	-0.08	-0.36	0.28
EXRET	0.26	-0.23	-0.03	0.04	-0.17	0.04	-0.07	-0.07	0.04
LSIGMA	-0.40	-0.14	0.13	-0.16	0.16	-0.19	0.07	0.17	-0.25
CPX	0.17	-0.05	-0.11	0.03	-0.11	0.04	0.06	-0.08	0.23
ASSETS	0.80	0.13	-0.11	0.44	0.02	0.41	0.01	-0.35	0.42
FD	0.72	0.12	0.04	0.45	0.21	0.43	0.04	-0.31	0.51
LOGMVE	1	-0.33	-0.21	0.43	-0.15	0.38	-0.02	-0.46	0.24
B/M	-0.14	1	-0.06	-0.07	-0.03	-0.05	0.03	0.17	0.11
CLTA	-0.08	0.00	1	-0.04	0.41	-0.05	0.03	0.10	-0.41
CTI	0.27	0.04	-0.20	1	0.13	0.84	0.06	-0.34	0.28
ZQ	-0.12	0.04	0.34	-0.05	1	0.15	0.17	0.11	0.31
PUB	0.42	0.07	-0.07	0.63	0.13	1	0.06	-0.29	0.28
NACCQ	0.00	0.04	0.13	-0.02	0.18	0.05	1	0.02	0.07
DISP	-0.44	0.04	0.08	-0.32	0.10	-0.24	0.02	1	-0.08
LLTL	0.22	0.04	-0.30	0.17	0.25	0.26	0.06	-0.06	1

Table 6: Hazard model estimation results

This table presents hazard model estimation results for probability 1-year prior to bankruptcy. Hazard rate model is estimated following Shumway (2001). Description of variables is provided in Appendix.
*P-values reported below coefficients: ***: significant at 1%; **: significant at 5%; *: significant at 10%*

	Private firm model						Public firm model			
Variables	Model1		Model2		Model3		Model4		Model 5	
ROA	-0.341		-0.911		-0.523		-0.611		-0.518	
	0.000	***	0.000	***	0.000	***	0.000	***	0.000	***
LTA	0.281		0.603		0.073		0.387		0.218	
	0.001	***	0.016	*	0.433		0.008	***	0.153	
CACL	-0.184		-0.126		-0.217		-0.139		-0.171	
	0.000	***	0.017	*	0.000	***	0.000	***	0.000	***
ASSETS	0.000		0.000		0.000		0.000		0.000	
	0.000	***	0.004	**	0.000	***	0.001	***	0.015	**
CPX	1.062		3.695		0.959		1.461		1.376	
	0.000	***	0.000	***	0.001	***	0.000	***	0.000	***
FD	0.000		0.000		0.000		0.000		0.000	
	0.000	***	0.028	*	0.000	***	0.009	**	0.069	.
ZQ	1.202		1.051		0.586		0.860		0.503	
	0.000	***	0.000	***	0.000	***	0.000	***	0.000	***
CLTA	-0.321		-0.294		-8.272		0.140		-5.022	
	0.001	***	0.430		0.000	***	0.465		0.028	**
PUB	0.035		0.320		0.345		-0.260		0.802	
	0.742		0.238		0.250		0.456		0.425	
LLTL	-1.010		-1.624		-1.708		-0.120		-0.506	
	0.000	***	0.000	***	0.000	***	0.604		0.167	
NACCQ	0.058				0.038		0.015		-0.002	
	0.000	***			0.000	***	0.256		0.888	
CTI	0.439		0.341		0.260		0.832		0.000	
	0.000	***	0.002	**	0.001	***	0.007	***	0.000	***
ZQLAST					-0.212				-0.506	
					0.369				0.981	
RSIZ							-0.225		-0.203	
							0.278		0.332	
EXRET							-1.942		-1.884	
							0.000	***	0.000	***
LSIGMA							2.934		2.817	
							0.000	***	0.000	***
LOGMVE							0.151		0.131	
							0.456		0.522	
B/M							0.022		0.020	
							0.031	**	0.061	.
DISP			0.245		0.103		0.033		-0.031	
			0.000	***	0.000	***	0.248		0.336	
CLTA * CTI					0.625				0.893	
					0.000	***			0.001	***
CLTA*ZQ					1.617				0.878	
					0.000	***			0.052	.
PUB*NACCQ					0.097				0.091	
					0.001	***			0.010	**
PUB*DISP					0.137				0.259	
					0.000	***			0.000	***
PUB*CTI					-0.561				-1.507	
					0.000	***			0.002	***
LLTL*ZQLAST					1.420				0.803	
					0.000	***			0.035	**
Industry fix. eff.	Yes		Yes		Yes		Yes		Yes	
Year fix. eff.	Yes		Yes		Yes		Yes		Yes	

Table 7: Private firm models: Comparisons of in-sample fit

Private firm models are estimated with hazard model following Shumway (2001) using variables from respective model. The P-value of chi-square statistics are reported to estimate increase in in-sample fit of the model. The sample contains variables from the final sample of bankrupt and non-bankrupt firms spanning 1980 to 2009. Observations used for each model is subject to availability of variables. Following Shumway (2001), all variables are winsorized at 1% and 99% level.

Panel A: Altman (1968)

Model 1: Y ~ (WCTA + RETA + EBTA + SLTA)
Model 2: Y ~ (WCTA + RETA + EBTA + SLTA) + (ASSETS + CPX + F2) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI)
Model 3: Y ~ (WCTA + RETA + EBTA + SLTA) + (ASSETS + CPX + F2) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Panel B: Ohlson (1980)

Model 1: Y ~ (SIZE + INTWO + OENEG + CHIN + FUTL)
Model 2: Y ~ (SIZE + INTWO + OENEG + CHIN + FUTL) + (ASSETS + CPX + F2) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI)
Model 3: Y ~ (SIZE + INTWO + OENEG + CHIN + FUTL) + (ASSETS + CPX + F2) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Panel C: Shumway (2001)

Model 1: Y ~ (NITA + LTA)
Model 2: Y ~ (NITA + LTA) + (ASSETS + CPX + F2) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI)
Model 3: Y ~ (NITA + LTA) + (ASSETS + CPX + F2) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Panel D: Main model in this paper

Model 1: Y ~ (NITA + LTA + CACL)
Model 2: Y ~ (NITA + LTA + CACL) + (ASSETS + CPX + F2) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI)
Model 3: Y ~ (NITA + LTA + CACL) + (ASSETS + CPX + F2) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Table 8: Public firm models: Comparisons of in-sample fit

Public firm models are estimated with hazard model following Shumway (2001) using variables from respective model. The P-value of chi-square statistics are reported to estimate increase in in-sample fit of the model. The sample contains variables from the final sample of bankrupt and non-bankrupt firms spanning 1980 to 2009. Observations used for each model is subject to availability of variables. Following Shumway (2001), all variables are winsorized at 1% and 99% level.

Panel A: Altman (1968)

Model 1: Y ~ (WCTA + RETA + EBTA + SLTA + LNAGE + METL)
Model 2: Y ~ (WCTA + RETA + EBTA + SLTA + LNAGE + METL) + (ASSETS + CPX +FD) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI + DISP)
Model 3: Y ~ (WCTA + RETA + EBTA + SLTA + LNAGE + METL) + (ASSETS + CPX + FD) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * DISP + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Panel B: Shumway (2001)

Model 1: Y ~ (NITA + LTA + RSIZ + EXRET + LSIGMA)
Model 2: Y ~ (NITA + LTA + RSIZ + EXRET + LSIGMA) + (ASSETS + CPX + FD) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI + DISP)
Model 3: Y ~ (NITA + LTA + RSIZ + EXRET + LSIGMA) + (ASSETS + CPX + FD) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * DISP + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Panel C: Bharath and Shumway (2008)

Model 1: Y ~ (NITA + RSIZ + EXRET + LSIGMA + F + LOGMVE)
Model 2: Y ~ (NITA + RSIZ + EXRET + LSIGMA + F + LOGMVE) + (ASSETS + CPX + FD) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI + DISP)
Model 3: Y ~ (NITA + RSIZ + EXRET + LSIGMA + F + LOGMVE) + (ASSETS + CPX + FD) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * DISP + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Panel D: Main model in this paper

Model 1: Y ~ (ROA + LTA + CACL + RSIZ + EXRET + LSIGMA + LOGMVE + B/M)
Model 2: Y ~ (ROA + LTA + CACL + RSIZ + EXRET + LSIGMA + LOGMVE + B/M) + (ASSETS + CPX + FD) + (ZQ + CLTA + PUB + LLTL + NACCQ + CTI + DISP)
Model 3: Y ~ (ROA + LTA + CACL + RSIZ + EXRET + LSIGMA + LOGMVE + B/M) + (ASSETS + CPX + FD) + (CLTA * CTI + CLTA * ZQ) + (PUB * NACCQ + PUB * DISP + PUB * CTI + LLTL * ZQLAST)

Chi-square P-value of residual deviance		
Model2	<0.001	***
Model3	<0.001	***

Table 9: Private firm models: Forecasting accuracy comparison table

This table presents forecasting accuracy of private firm bankruptcy prediction models estimated with data from 1980-2004. Yearly observation intervals is used to forecast bankruptcy probabilities for 2005 to 2009. Each year, the probabilities are calculated and then the companies are grouped into deciles based on the probability of bankruptcy. The number of bankruptcies in each decile for each year are aggregated over 2005 to 2009 and reported in the below panels.

Panel A: Altman (1968)

Decile	Model 1	Model 2	Model 3
1	**29.7%**	**43.2%**	**48.6%**
2	**41.4%**	**71.6%**	**75.2%**
3	52.3%	82.9%	85.1%
4	59.9%	91.0%	92.3%
5	69.4%	95.5%	95.5%
6	78.4%	97.3%	97.3%
7	82.9%	98.2%	98.2%
8	87.8%	99.1%	99.1%
9	91.9%	99.1%	99.1%
10	100.0%	100.0%	100.0%

Panel B: Ohlson (1980)

Decile	Model 1	Model 2	Model 3
1	**46.7%**	**57.3%**	**59.0%**
2	**59.9%**	**79.3%**	**80.2%**
3	71.4%	87.2%	85.9%
4	82.8%	92.1%	92.5%
5	91.2%	96.5%	96.0%
6	92.5%	96.9%	96.9%
7	93.8%	98.2%	98.2%
8	94.3%	98.7%	98.2%
9	98.7%	99.1%	99.1%
10	100.0%	100.0%	100.0%

Panel C: Shumway (2001)

Decile	Model 1	Model 2	Model 3
1	**29.5%**	**41.4%**	**47.6%**
2	**66.5%**	**74.0%**	**76.7%**
3	85.5%	88.1%	89.4%
4	93.4%	93.0%	93.8%
5	96.5%	96.5%	96.0%
6	96.5%	96.9%	97.4%
7	97.8%	98.2%	98.2%
8	98.2%	99.1%	99.1%
9	99.1%	99.1%	99.1%
10	100.0%	100.0%	100.0%

Panel D: Main hazard model

Decile	Model 1	Model 2	Model 3
1	**31.7%**	**44.9%**	**48.0%**
2	**49.8%**	**78.4%**	**80.6%**
3	62.1%	88.5%	88.5%
4	74.4%	94.3%	95.2%
5	80.6%	96.0%	96.5%
6	87.7%	97.4%	97.4%
7	95.2%	98.7%	97.8%
8	96.9%	98.7%	98.7%
9	98.2%	99.1%	99.1%
10	100.0%	100.0%	100.0%

Model specifications: Table 9

Model 1: Default model without creditor coordination effects

Model 2: Default model appended by creditor coordination effects without interaction terms

Model 3: Default model appended by creditor coordination effects with interaction terms

Table 10: Public firm models: Forecasting accuracy comparison table

This table presents forecasting accuracy of public firm bankruptcy prediction models estimated with data from 1980-2004. Yearly observation intervals is used to forecast bankruptcy probabilities for 2005 to 2009. Each year, the probabilities are calculated and then the companies are grouped into deciles based on the probability of bankruptcy. The number of bankruptcies in each decile for each year are aggregated over 2005 to 2009 and reported in the below panel.

Panel A: Altman (1968)

Decile	Model 1	Model 2	Model 3
1	**61.7**	**62.5**	**63.1**
2	**80.5**	**81.1**	**82.4**
3	85.9	86.7	86.9
4	88.3	92.2	92.2
5	90.6	96.9	98.4
6	92.2	98.4	99.2
7	95.3	99.2	99.2
8	96.9	99.2	100.0
9	99.2	100.0	100.0
10	100.0	100.0	100.0

Panel B: Shumway (2001)

Decile	Model 1	Model 2	Model 3
1	**71.7**	**72.4**	**74.5**
2	**87.4**	**89.0**	**89.5**
3	92.1	92.1	92.9
4	95.3	96.1	96.1
5	96.1	97.6	98.4
6	96.1	99.2	99.2
7	99.2	99.2	99.2
8	100.0	100.0	100.0
9	100.0	100.0	100.0
10			

Panel C: Bharath and Shumway (2008)

Decile	Model 1	Model 2	Model 3
1	**78.0**	**79.4**	**79.4**
2	**89.0**	**90.1**	**91.4**
3	93.7	93.7	93.7
4	95.3	97.6	97.6
5	98.4	98.4	98.4
6	98.4	99.2	99.2
7	99.2	99.2	99.2
8	100.0	100.0	100.0
9	100.0	100.0	100.0
10	100.0	100.0	100.0

Panel D: Main hazard model

Decile	Model 1	Model 2	Model 3
1	**71.9**	**73.4**	**78.6**
2	**88.3**	**89.1**	**90.2**
3	91.4	92.7	92.7
4	93.0	93.8	95.1
5	95.3	97.4	98.3
6	96.9	99.4	99.4
7	98.4	99.4	99.4
8	98.4	100.0	100.0
9	98.4	100.0	100.0
10	99.2	100.0	100.0

Model specifications: Table 10

Model 1: Default model without creditor coordination effects
Model 2: Default model appended by creditor coordination effects without interaction terms
Model 3: Default model appended by creditor coordination effects with interaction terms

Figure 1: Bankruptcy rate by industry

This chart plots percentage of bankrupt firms in my final sample by industry following broader industry classification in Chava and Jarrow (2004) based on SIC Codes. All industries are represented except for financial industries. Industry classification detail is provided in Table 1.

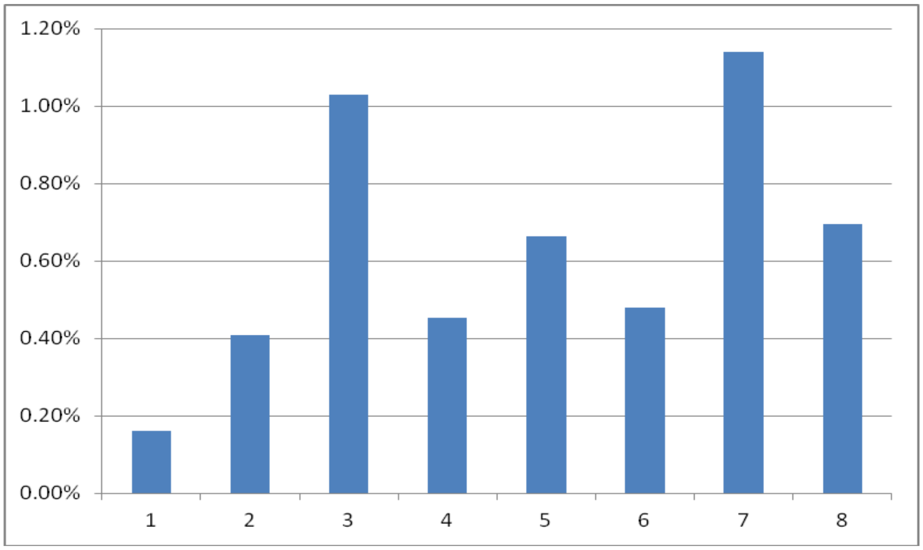


Figure 2: Bankruptcy rate by year

This chart plots percentage of bankrupt firms based on final sample in this paper by calendar year based on Table 2. The sample period is 1980 to 2009.

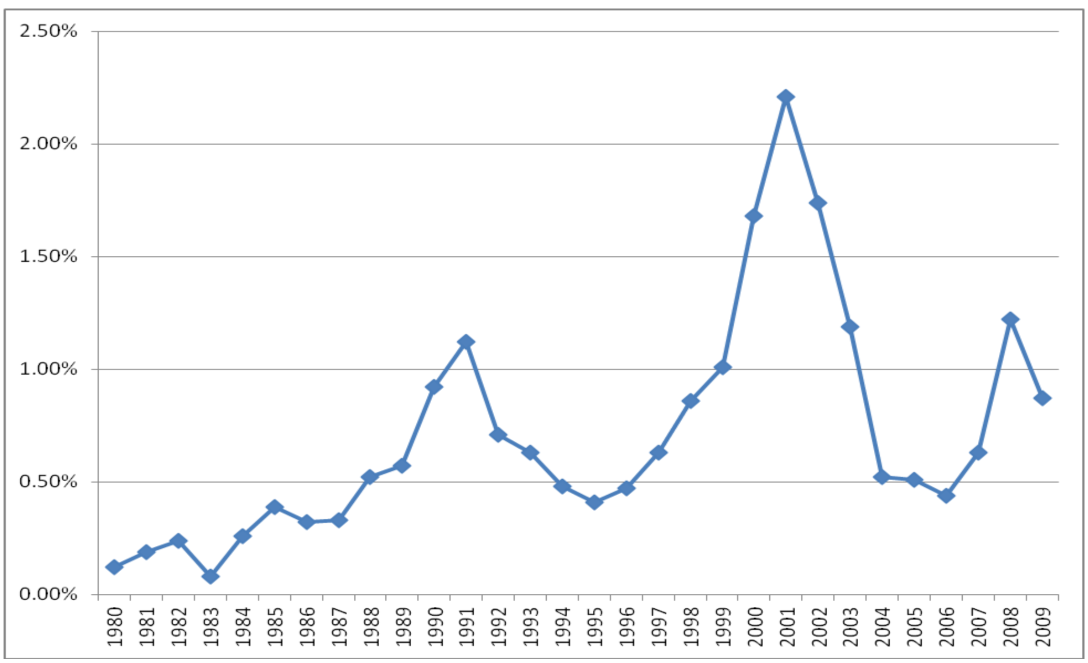
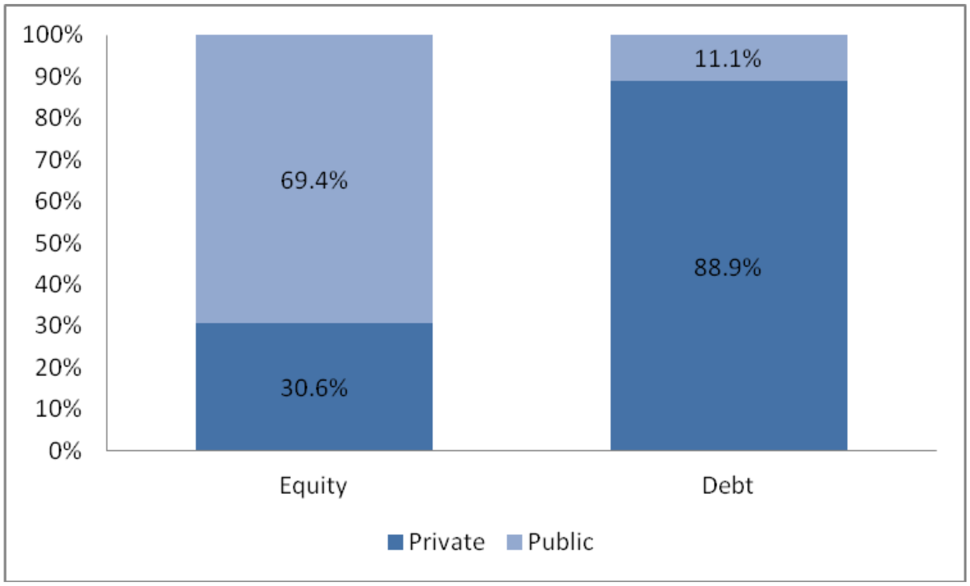


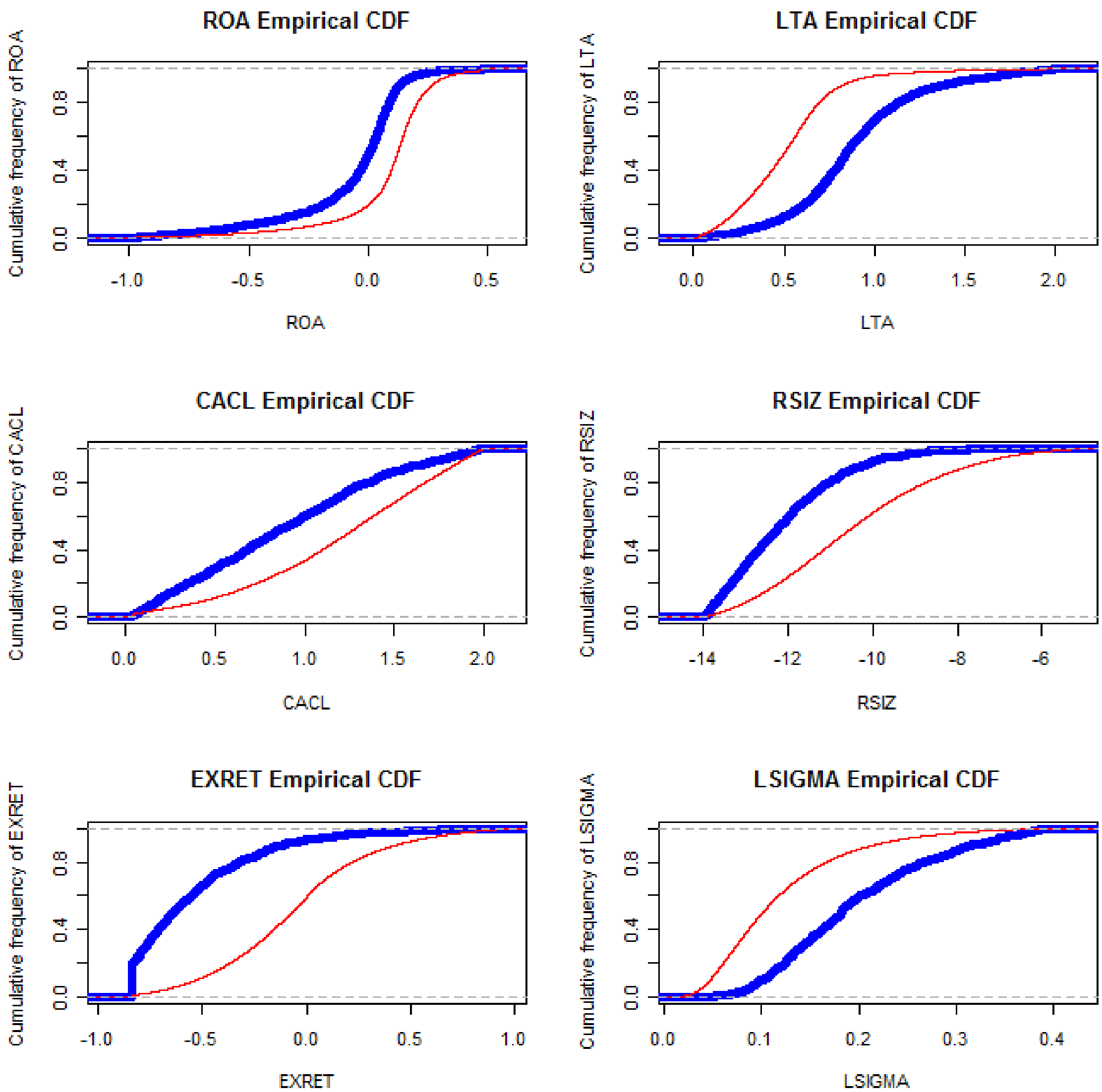
Figure 3: Final sample composition: Private vs. public in equity and debt

This chart plots percentage of firms in my sample that are private vs. public in equity and debt. Percentage of respective group is also reported in bar charts.



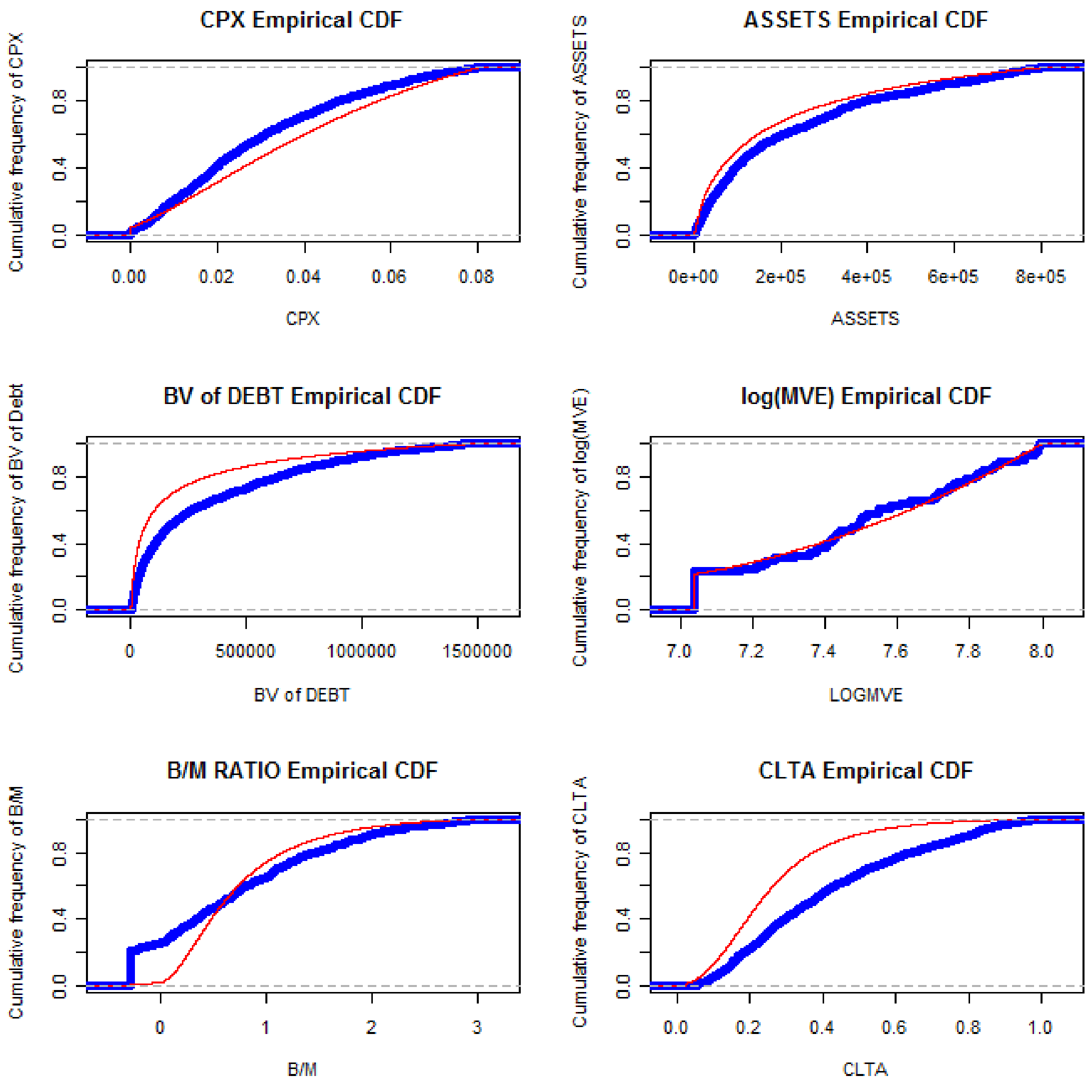
Figures 4-9: Empirical cumulative distribution function (CDF) plots for key variables

Figures 4 to 9 present cumulative distribution functions of respective variables used in my analyses. The distribution of each variable for the bankrupt year is represented as the thick line. Thin line represents the distribution of each variable for non-bankrupt years. All variables are winsorized at 1% and 99% following Shumway (2001). Definitions of the variables are provided in the Appendix.



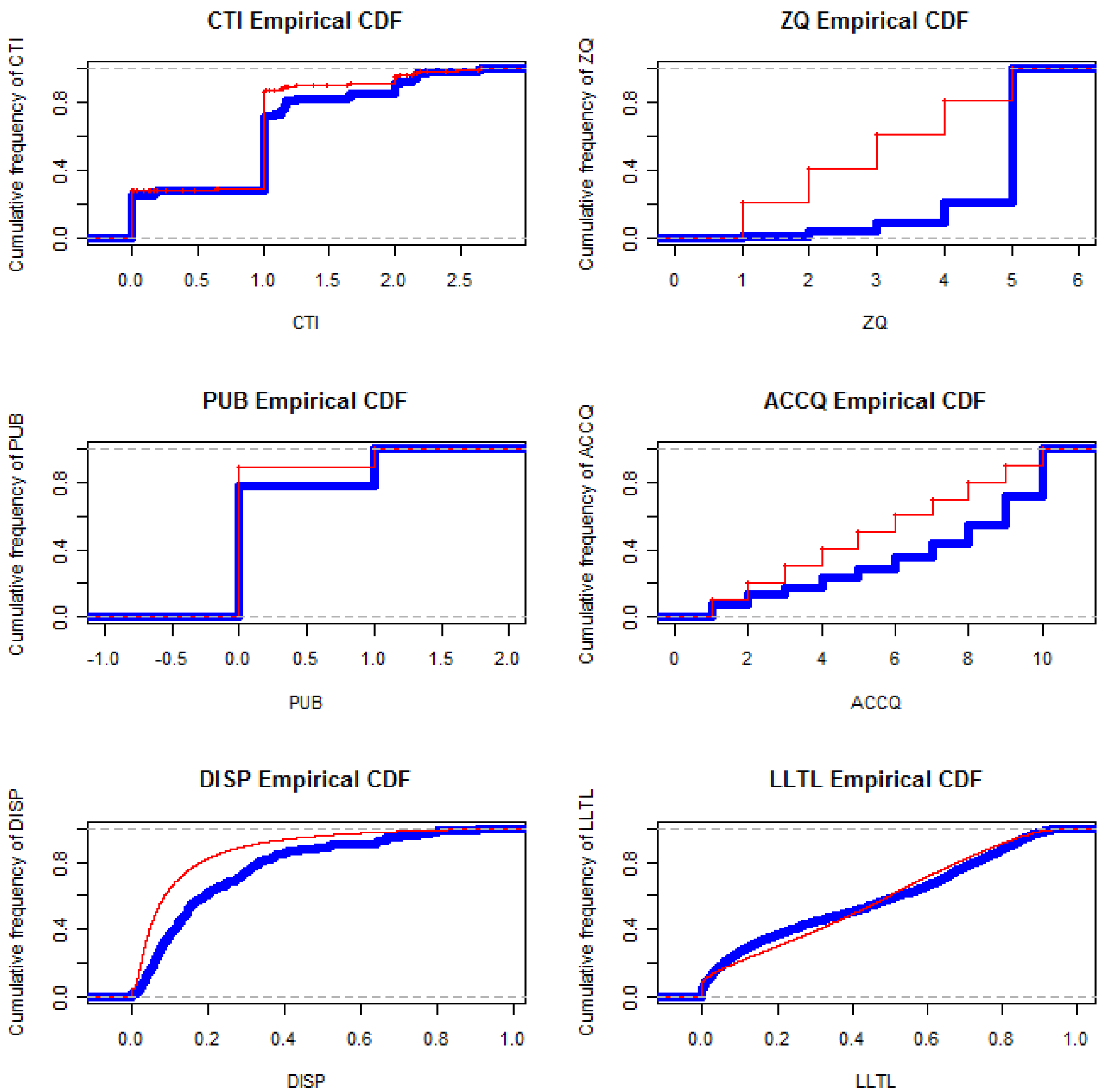
Figures 10-15: Empirical cumulative distribution function (CDF) plots for key variables

Figures 10 to 15 present cumulative distribution functions of respective variables used in my analyses. The distribution of each variable for the bankrupt year is represented as the thick line. Thin line represents the distribution of each variable for non-bankrupt years. All variables are winsorized at 1% and 99% following Shumway (2001). Definitions of the variables are provided in the Appendix.



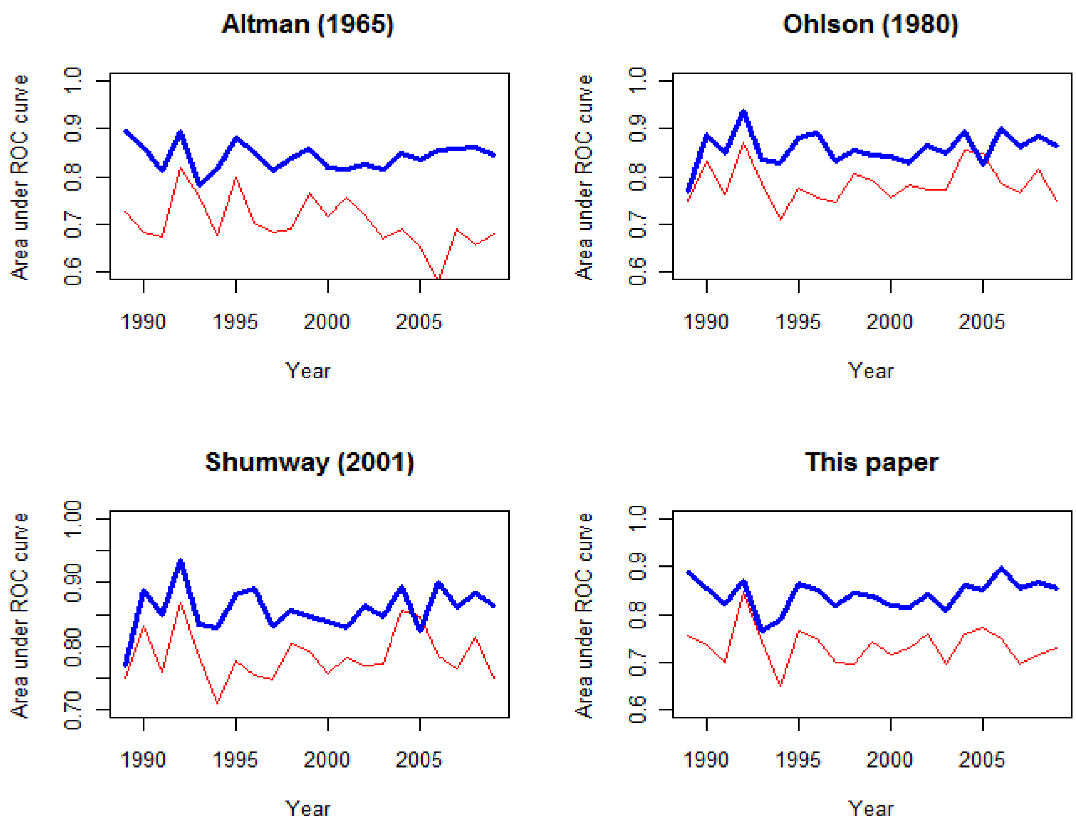
Figures 16-21: Empirical cumulative distribution function (CDF) plots for key variables

Figures 16 to 21 present cumulative distribution functions of respective variables used in my analyses. The distribution of each variable for the bankrupt year is represented as the thick line. Thin line represents the distribution of each variable for non-bankrupt years. All variables are winsorized at 1% and 99% following Shumway (2001). Definitions of the variables are provided in the Appendix.



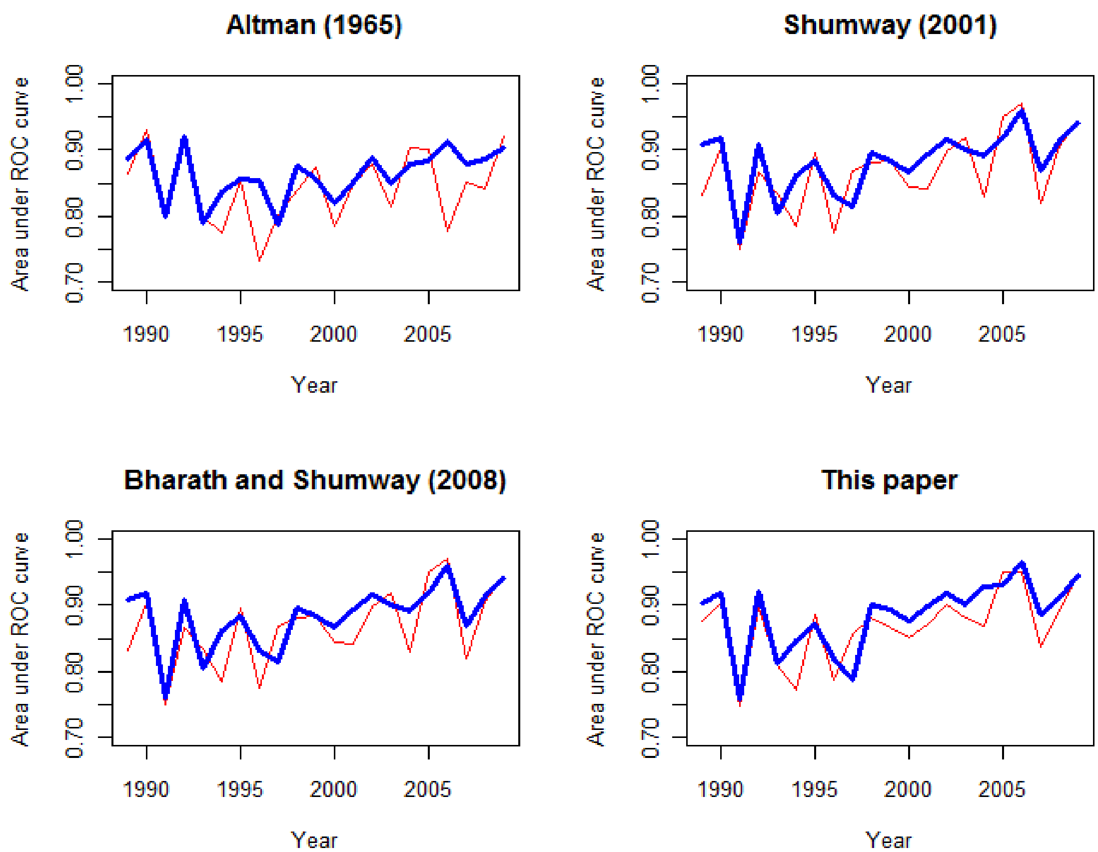
Figures 22-25: Private firm models: Comparison of forecasting accuracy - area under ROC curve

These plots present forecasting accuracy measured by area under ROC (Receiver Operating Characteristic) curve estimated based on variables from four different bankruptcy prediction models. The area under ROC curve is a widely used measure of the out-of-sample accuracy of forecasting models (Sobehart, Keenan, and Stein, 2000). A value of 0.5 indicates a random model with no predictive ability, whereas a value of 1.0 perfect discrimination. Thin line represents models (Model 1) estimated based on original variables without analyst forecast dispersion, accruals, or creditor coordination variables. Thick line represents models (Model 3) based on original variables with analyst forecast dispersion, accruals, creditor coordination variables, and interaction terms. (Model specifications in Table 7)



Figures 26-29: Public firm models: Comparison of forecasting accuracy - area under ROC curve

These plots present forecasting accuracy measured by area under ROC (Receiver Operating Characteristic) curve estimated based on variables from four different bankruptcy prediction models. The area under ROC curve is a widely used measure of the out-of-sample accuracy of forecasting models (Sobehart, Keenan, and Stein, 2000). A value of 0.5 indicates a random model with no predictive ability, whereas a value of 1.0 perfect discrimination. Thin line represents models (Model 1) estimated based on original variables without analyst forecast dispersion, accruals, or creditor coordination variables. Thick line represents models (Model 3) based on original variables with analyst forecast dispersion, accruals, creditor coordination variables, and interaction terms. (Model specifications in Table 8)



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Appendix: Definition of variables

Variables	Definitions
ROA / NITA	Net income / Total assets
TLTA / LTA	Total liabilities / Total assets
CACL	Current assets / Current liabilities
RSIZ	Log (firm's market capitalization / Total market cap of NYSE, AMEX and NASDAQ)
EXRET	Excess annual return over the value-weighted NYSE, AMEX and NASDAQ return
LSIGMA	Standard deviation (residual return from a regression of twelve monthly returns of the firm on monthly returns of the market index)
CPX	Capital expenditure / Total assets
ASSETS	Log (total assets (book value))
FD	Log (total liabilities (book value))
LOGMVE	Log (Market value of equity)
B/M	Book value of equity / Market value of equity
CLTA	(Current liabilities-Cash or cash equivalents-Available revolving credit facility) / Total assets
CTI	Quintile of Creditor Transparency Index (CTI), calculated as: CTI = Median annual trading volume of public equity securities + Median annual trading volume of public debt securities + Maximum annual trading volume of syndicated loan securities [Alternative] CTI = 1 (public debt outstanding)+1(public equity outstanding)+α*1(syndicated loan outstanding, where α is a relative transparency of syndicated loan market measured by relative trading volume with trading volume of 2000 as 1). For 2000-2009, α is 1. (1: indicator variable)
ZQ	Quintile of Z-score measured according to private firm model of Zmijewski (1984)
ZQLAST	Indicator variable of 1 if Z-score quintile is the highest, representing lowest credit quality measured by Z-score based on Zmijewski (1984)'s private firm model
PUB	Indicator variable of 1 if public debt is outstanding, and 0 otherwise
NACCQ	Decile of accounting quality measured as higher decile representing lower operating accruals (or more negative operating accruals) as measured in Sloan (1996)
DISP	Standard deviation (equity analyst 1-year earnings forecast) / Median (equity analyst 1-year earnings forecast)
LLTL	Long term liabilities / Total liabilities
WCTA	Working capital / Total assets

RETA	Retained earnings / Total assets
EBTA	Earnings before interest and taxes / Total assets
SLTA	Sales / Total assets
SIZE	Log (Total assets / GNP price index)
INTWO	Indicator variable of 1 if net income was negative for the last two years, 0 otherwise
OENEG	Indicator variable of 1 if total liabilities exceeds total assets, zero otherwise
CHIN	$(Ni_t – Ni_{t-1}) / (\|Ni_t\| + \|Ni_{t-1}\|)$, where NI is net income
FUTL	Funds provided by operations divided by total liabilities as measured in Begley, Ming and Watts (1996)
F	Face value of debt as measured in Bharath and Shumway (2008)
LNAGE	Log (equity trading age of the firm)
METL	Market value of equity / Total liabilities