Bankruptcy Prediction with Financial Systemic Risk

Abstract

Financial systemic risk – defined as the risk of collapse of an entire financial system vis-à-vis any one individual financial institution – is making inroads into academic research in the aftermath of the late 2000s Global Financial Crisis. We shed light on this new concept by investigating the value of various systemic financial risk measures in the corporate failure predictions of listed nonfinancial firms. Our sample includes 225,813 firm-quarter observations covering 8,604 US firms from 2000 Q1 to 2016 Q4. We find that financial systemic risk is incrementally useful in forecasting corporate failure over and above the predictions of the traditional accounting-based and market-based factors. Our results are stronger when the firm in consideration has higher equity volatility relative to financial sector volatility, smaller size relative to the market, and more debts in current liabilities. The combined evidence suggests that systemic risk is a useful supplementary source of information in capital markets.

Keywords: Bankruptcy prediction; Systemic risk; Hazard model.

JEL classification: G33; G32; C35; G10.

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1. Introduction

Due to its obvious importance for investors, firms and policy-makers, the 2008 Global Financial Crisis (GFC) has piqued interest among academics and practitioners in bankruptcy prediction, which has arguably been one of the most important topics in subjects such as accounting, economics and finance over the past decades (e.g., Altman, 1964; Ohlson, 1980; Shumway, 2001; Campbell et al., 2008; Jones, 2017). With few exceptions, this strand of literature has relied on corporate accounting ratios (i.e., accounting-based models) and/or security market information (i.e., market-based models). These indicators are all firm-specific information, which are under the unconscious assumptions that they contain complete information about bankruptcy. However, exogenous factors that might increase the damage should be taken into account. There was unprecedented popularity of systemic risks in the financial sector (e.g., Benoit et al., 2017), which warrants research attention. We propose and confirm that systemic risk, as an exogenous factor, shows a strong and significant association with a nonfinancial firm's bankruptcy.

One of the fundamental points facing financial market regulation and supervision after the GFC is how increased systemic risk in the financial sector, particularly in banks, affects their corporate borrowers. Therefore, many papers have tried to track the impacts (e.g., Chava and Purnanandam, 2011; Chodorow-Reich, 2013). However, due to the complexity of the financial system and the limitation of perfect measures, the effects of systemic risk are particularly hard to track (Linn and Weagley, 2018). We attempt to understand the spill-over effects of financial sector systemic risk from an 'extreme event' perspective, namely bankruptcy. We focus on the association between systemic risk and the likelihood of nonfinancial firms' bankruptcy. This offers us opportunities to attempt to explain how systemic risk affects a firm's behaviour and what sorts of firms with specific characteristics will be affected the most.

Our rationale for choosing financial systemic risk as a predictor stems from extensive research of systemic risk in recent years. We were motivated by Allen et al. (2012), Chauvet et al. (2015), Giglio et al. (2016) and Acharya et al. (2017), who document that financial systemic risk can affect real economic activities and can predict future macroeconomic shocks. The channels that link systemic risk and macroeconomics include, for example, the changes in the demand side and supply side of investment activity (Allen et al. 2012) and the business cycle (Hall, 2011). More specific to our context, the financial system establishes and changes the financing and investing environment which nonfinancial firms are living in, and thus has an impact on nonfinancial firms[1]. From the perspective of managerial risk preference theory, when the financial sector is less risk-averse, systemic risk is relatively high.

On the one hand, as funding sources and costs are more uncertain, more risk-taking in the financial sector means the supply of funds will decrease to those risk-averse firms, which will then limit their growth opportunities (Allen et al., 2012). On the other hand, those risk-seeking firms tend to invest in riskier projects or tend to over-invest during a period of high systemic risk (Adachi-Sato and Vithessonthi, 2017). Both of the cases negatively impact on the health of a firm (e.g., weaker and less certain profitability (Chava and Purnanandam, 2011)), especially when a firm is vulnerable (i.e., in financial distress). Thus, the systemic risk might contain useful information about a firm's bankruptcy. Another possible way to explain it is from the perspective of asset pricing. Linn and Weagley (2018) document that the stock of US-listed nonfinancial firms reflects the effect of systemic risk in price that is incorporated by the investors after systemic events. Since the stock price is a significant predictor of firm bankruptcy, from a securities market perspective, it is not unreasonable to develop systemic risk information-contained variables as predictors of nonfinancial firm bankruptcy. Also, Giglio et al. (2016) argue that financial market distress is likely to be ahead of monetary policy, but the policy is not sufficient enough to diffuse systemically risky conditions which can finally lead to adverse macroeconomic consequences. Therefore, information about systemic risk could release information of future economic conditions that nonfinancial firms must deal with. In particular, financial sector equity volatility is much more informative about future real activity, compared with nonfinancial volatility (Giglio et al., 2016).

Specifically, we ask two questions in this study. First, is financial systemic risk information useful in forecasting corporate bankruptcy? Second, can financial systemic risk forecast

[1] See e.g. Ivashina, and Scharfstein (2010), Lemmon and Roberts (2010), Chava and Purnanandam (2011).

corporate bankruptcy over and above the predictions of the traditional accounting-based and market-based factors? With a sub-sample of 83,795 observations based on monthly observation intervals from January 2000 to January 2012, our first-stage analysis investigates the use of systemic risk measures documented in the literature on firm bankruptcy prediction. In the second-stage analysis, we construct and test our novel systemic risk variables using the full sample, which includes 225,813 firm-quarter observations of 8,604 listed firms on the US stock market from 2000 Q1 to 2016 Q4. Then we propose our AMS model that incorporates systemic risk information into conventional accounting and market variables-based models and finally evaluate it.

The first-stage results show that the systemic risk in the US financial sector is positively related to, and contains useful information about nonfinancial firms' bankruptcy risks. We also find that positive change in systemic risk is also positively related to bankruptcy, but these effects do not apply to all the measures. In the second-stage analysis, we find that our proposed variables, which contain both individual firm-level information and financial sector systemic risk information, have strong predictabilities in nonfinancial firms' bankruptcy prediction. In detail, financial sector equity volatility is particularly informative in bankruptcy prediction. Credit condition measures also show high predictive power when interacting with firm-specific characteristics. Compared to the accounting-variables-only and market variables-only models, the systemic risk variables-only model is an alternative for bankruptcy prediction. The incorporation of systemic risk information also increases prediction accuracy. Furthermore, we find that a firm, which has higher equity volatility relative to financial sector equity volatility, smaller relative size, and more debts in current liabilities, is more likely to be affected by financial market distress and adverse credit conditions, and is thus more likely to go bankrupt.

Our primary contribution in this study is to explore the possible role of systemic risk measures in corporate bankruptcy prediction and its significance. To the best of our knowledge, this paper offers a first look at the value of financial systemic risk in corporate bankruptcy prediction. In the stream of literature finding reliable predictors of firm bankruptcy, more are based on firm-specific accounting and market data (see e.g., Altman, 1964; Merton, 1974; Ohlson, 1980;

Shumway, 2001; Hillegeist et al., 2004; Campbell et al., 2008), or other firm-specific data, such as ownership structure and CEO compensation (e.g. Jones, 2017), technical efficiency (Eling, and Jia, 2018), size (e.g. Ciampi and Gordini, 2013; Gupta et al., 2018) and tail risk (Gupta and Chaudhry, 2019). Only a few have attempted, like the present paper, to examine time-variant data into prediction models, such as those by Christidis and Gregory (2010), and Tinoco and Wilson, (2013). However, their research is predominantly focused on incorporating macroeconomic variables. Apart from adding possible time-variant predictors, our findings that the incorporation of systemic risk information can improve the accuracy and prediction ability of the bankruptcy prediction models also provide support for financial systemic risk as a supplementary source of information in capital markets. Our paper may be the first paper to test exogenous factors other than the macroeconomic index in bankruptcy predicting research.

In addition, our study contributes to the strand of literature that demonstrates the importance of including industry effects in corporate bankruptcy prediction (e.g., Chava and Jarrow, 2004 and the references therein). Unlike the previous studies which highlight the different likelihood of bankruptcy for firms in different industries with otherwise identical balance sheets, to the best of our knowledge, we are the first to explore the forecasting of bankruptcy of firms in one industry (the nonfinancial industry in our sample) using the information from another industry (the financial industry). We also add discussion on the impact of financial sector shocks on nonfinancial firms (e.g., Lemmon and Robert, 2010; Chava and Purnanandam, 2011; Chodorow-Reich, 2013). Not much attention has been paid to the bankruptcy perspective; probably due to the overlooking of the role of systemic risk prior to the GFC. Yet, both economic intuition and recent literature on systemic risk suggest that the systemic risk of the financial sector should be an important predictor for nonfinancial firms' bankruptcy predictions given the systemic importance of the financial industry vis-à-vis nonfinancial industries. Nevertheless, the findings from the extant literature using a smaller dataset from one or more decades ago need updating, and call into question the possibility of new predictors in the period building up to the GFC and the post-crisis period.

This study fits into a broader strand of literature which explores effective *ex-ante* risk management and constructs an early warning system for practitioners. Our findings highlight the importance of risk management in the financial sector, and imply that financial institutions and investors/creditors should take early measures to defend themselves from risky investing situations when systemic risk rises, while firm managers should adjust firm strategies when potential bankruptcy hazards are growing due to systemic risk.

The remainder of this paper is structured as follows. Section 2 discusses the relevant background literature, Section 3 describes the data and empirical methodology, and Section 4 presents the empirical results from the logistic regressions of firm bankruptcy prediction models. A summary of discussion and evaluation are then presented in Section 5, and finally, Section 6 concludes.

2. Background Literature

Our paper relates to two strands of the literature. It draws upon studies that seek to identify the determinants of corporate bankruptcy and models to predict corporate bankruptcy with these determinants. It is also linked with studies highlighting the importance of and investigating the possible roles of systemic risk in the aftermath of the 2008 GFC.

In the literature, the real debate is on the choice of predictors for bankruptcy. Typically, the development of conventional models is based on searching the linear relations between i) accounting ratios and bankruptcy (i.e., accounting-based models); and ii) market information and bankruptcy (i.e., market-based models). Arguably, the accounting-based models lack theoretical grounding. For instance, the preparation of accounting data is affected by accounting rules in a period that might hinder a true representation of a firm's health and varies over time (Agarwal and Taffler, 2008). Also, the prediction accuracy is associated with the development of accounting-based models. Therefore, these models should be redeveloped frequently because simply updating the model coefficients does not improve the performance (Begley et al., 1996; Hillegeist et al., 2004). Previous studies also investigate the performance of market variables and confirm their performance in firm bankruptcy prediction models by employing models such as the Merton Distance to Default (DD) Model (Merton, 1974) which adopts an option-based approach. However, the DD model is not suitable for our contest given the explanatory variables' structure.

Researchers have tried to combine accounting models and market models. Following the work by Shumway (2001), a majority of later hazard models incorporate accounting and market variables in simple discrete-time logit models (e.g., Chava and Jarrow, 2004; Campbell et al., 2008). The traditional indicators previous paper uses include accounting ratios, such as profitability and liquidity, and market ratios, such as relative size and price. These studies are sound evidence that accounting ratios do not include complete information about the bankruptcy, and market indicators might complement the deficiency. Some firm-specific characteristics other than traditional indicators have been examined recently, namely ownership structure and CEO compensation (e.g., Jones, 2017), technical efficiency (Eling, and Jia, 2018), size (e.g. Ciampi and Gordini, 2013; Gupta et al., 2018) and tail risk (Gupta and Chaudhry, 2019). However, their attempts are limited to firm-level indicators and have failed to examine time-variant data into the prediction models. Some pioneering researchers have recently been trying to explore exogenous indicators of bankruptcy, but they predominantly focus on macro-level characteristics. Relevant studies include the paper by Christidis and Gregory (2010) who find that the inflation rate and the interest rate can add to the predictive power of bankruptcy. Tinoco and Wilson (2013) find that adding macroeconomic data into a credit model is incrementally useful in UK-listed firms' bankruptcy predictions. Eling and Jia (2018) also develop models that mix firm-specific data and macroeconomic data in insurance companies' failure predictions.

In the aftermath of the 2008 GFC, systemic risk has been widely used in macroeconomic forecasting. Examples can be found in Giglio et al. (2016) who empirically investigate 19 systemic risk measures and find equity volatility in the financial sector is informative for future real economic activities. Allen et al. (2012) also state that '*high levels of systemic risk in the banking sector impact the macro economy through aggregate lending activity*'. The association between volatility and real economic activities has gradually become a consensus among academics (e.g., Bloom, 2009; Schwert, 2011; Chauvet et al., 2015). Apart from volatility, credit condition also shows connections with the macro economy (e.g., Gilchrist and Zakrajsek, 2012; Schularick and Taylor, 2012). More specific to our context, the existing literature extensively explored the impact of financial system shocks on nonfinancial firms' activities. Ivashina and Scharfstein (2010) find that bank lending significantly declined during the GFC. Lemmon and Roberts (2010) find that firm financing and investment activity are negatively influenced by the adverse shock in credit supply. Chava and Purnanandam (2011) also confirm the relationship and find evidence during the Russia crisis that bank-dependent firms experienced weaker profitability. Chodorow-Reich (2013) shows that less bank lending availability reduces employment in a firm after the 2008 GFC. Adachi-Sato and Vithessonthi (2017) find evidence in the US that high systemic risk leads to overinvestments in firms. Linn and Weagley (2018) document that US-listed nonfinancial firms' stock reflects the effect of systemic risk in price that is incorporated by the investors after systemic events. All these results raise questions about how risks in the financial sector can affect the performance of a nonfinancial firm. Our paper directly addresses this question.

Although the relationship between financial sector shocks and nonfinancial firms has been widely explored, none of the above papers have examined the role of systemic risk in corporate bankruptcy prediction. This is an important task given the recently established connection between systemic risk and real economic activities, especially in the period build-up to the GFC and the post-crisis period. Our paper attempts to fill this gap.

3. Data and Methodology

3.1. Dataset

We searched the entire CRSP database for listed firms and identified firms with sufficient bankruptcy information, accounting information and market information. Finally, we obtained a sample consisting of 8,604 listed nonfinancial companies on the US stock market at any time between 2000 Q1 and 2016 Q4, which includes the 'dotcom bubble' in 2002 and the GFC in 2008. Observations are based on quarterly observation intervals, which we believe are superior to monthly intervals and yearly intervals: one month is too short for a firm to respond when the prediction shows a trend of bankruptcy and a yearly prediction might be less useful in practice than a quarterly prediction, as a firm's health condition is most likely to change the most over the course of one year.

To maximise the information captured by variables, accounting variables are constructed quarterly, while market variables, including systemic risk variables, are constructed monthly. This stems from the fact that the effects of accounting variables on bankruptcy prediction are slightly weaker as data are collected more frequently, while the consequences of market variables are stronger (Campbell et al., 2008). Many systemic risk measures should contain more information if are constructed with higher frequency data. For example, volatility plays a significant role in amplifying systemic risk and lower frequency data smooths out volatility; hence, one may expect even stronger effects of volatility in higher frequency data. This is particularly true in security market information-based prediction models (i.e., market-based models). Only listed firms recorded in the CRSP database stock file are included in the sample. Firms are identified by CRSP Permanent Number Variable Name (PERMNO code), ignoring changes in names or capital structure. Thus, the entire market history of an individual firm can be tracked according to PERMNO, which neither changes during an issue's trading history nor is reassigned after an issue ceases trading. Then, according to the Standard Industrial Classification (SIC) code, firms belonging to the Finance, Insurance and Real Estate sector are excluded from our sample. This is reasonable as we are exploring effects from the financial sector and the systemic risk to nonfinancial firms.

The definition of what constitutes firm bankruptcy can be regarded as the outcome of the analysis process. Referring to earlier discussions and recent papers, this paper quotes Agarwal and Taffler’s (2008) definition that bankruptcy is one of the following: liquidation, administration/receivership, or a valueless company. Therefore, firms that have failed are identified as those that meet the delisting codes between 450 and 490, and 550 and 587 according to the CRSP; otherwise they are defined as non-failed. Firms normally stop providing financial statements before they are legally bankrupt (Tinoco and Wilson, 2013), so for the firms that are identified as failed according to the above codes, we take their final statement as the last observation. Quarterly financial data of both financial firms and nonfinancial firms are all collected from CRSP/Compustat Merged databases provided by

WRDS. Daily and monthly market data are provided by CRSP. In addition, financial market credit condition data are taken from the Federal Reserve Bank of St. Louis[2]. Finally, covering the period between 2000 and 2016, 225,813 firm-quarter observations for a total of 8,604 nonfinancial firms are collected for our main empirical analysis.

3.2. Variables selection

3.2.1. Systemic risk measures

Regarding systemic risk measures[3], we use several popular systemic risk measures proposed in the literature (see Appendix Table A.1a.) in our first-stage analysis. In a univariate logit regression, we test 21 financial systemic risk measures. The data to construct the measures are mostly adopted from data documented in Giglio et al. (2016)[4], except for two other measures that are relevant to our study: Component Extended Shortfall (CES) from Banulescu and Dumitrescu (2015) and the WSF from López-Espinosa et al. (2012). The details can be found in Appendix 1. It is interesting to know how the systemic risk in the core of the financial sector can affect nonfinancial firms, and thus the data used in calculating measures were from the US financial institutions that rank in the top 20 in terms of market capitalisation in a given month[5].

The measures used in our analysis measure systemic risk from different angles. They are categorised into four categories, as specified in Giglio et al. (2016): institution-specific risk and liquidity, co-movement and contagion, volatility and instability, and credit condition. There are also two measures, CES and short-term Wholesale Funding (WSF), which are not covered by Giglio et al. (2016). CES is a measure of interconnectedness, while WSF is total short-term borrowings over total assets calculated quarterly, which captures liquidity risk exposure. It is converted to monthly measures by assuming it changes arithmetically between quarters. The data for calculating CES and SF are from CRSP and Datastream, respectively.

[2] Available at: https://fred.stlouisfed.org/

[3] Considering the existence of the time gap between systemic risk in the financial sector and its transporting to individual firms, we take one month/quarter lag for all systemic risk measures and our proposed systemic risk variables in predictions depending on our observation interval.

[4] We would like to thank Giglio, Kelly, and Pruitt for sharing these measures data and code, which can be downloaded from https://sethpruitt.net/research/downloads/.

[5] Note size concentration is calculated based on the top 100 financial institutions (Giglio et al., 2016), and WSF is calculated based on the top 20 banks (López-Espinosa et al., 2012).

3.2.2. Indicators in full model

This section describes the indicators used in our second-stage analysis. All the selected nonfinancial firms' accounting and market variables in our full models are winsorised at the 5% and 95% levels to reduce the effect of possible spurious outliers caused by a few extreme values. All firms in the sample have full coverage of the subsequently described variables[6].

Accounting ratios that reflect a firm's leverage, profitability and liquidity, were carefully selected. These three types of accounting ratios are standard and widely accepted measures that are employed in prediction models (e.g., Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008). Leverage reflects the long-term financial position of a firm and is a significant indicator of bankruptcy in the paper by Zmijewski (1984). More recent papers, such as those by Shumway (2001), Chava and Jarrow (2004), and Christidis and Gregory (2010), have tested it and confirmed its consistency and contribution to bankruptcy prediction models. The higher gearing a firm has, the more financial risk and therefore bankruptcy risk a firm might face. We construct the variable Total Liabilities/Total Assets (TLTA) to capture the gearing ratio, which is calculated by total liabilities over total assets. The expected sign of TLTA is positive. The profitability of a firm is suggested to be an important indicator of bankruptcy in most studies since more profitable firms would be expected to be more liquid and lowlier geared, and thus less likely to go bankrupt.

Original data, such as net income, earnings before interest and tax, retained earnings, etc., can report firms' profitability at different earning process stages. Using net income data collected from CRSP/Compustat Merged, we construct net income relative to total assets (NITA) as a predictor of a firm's bankruptcy[7]. When the net income is not able to cover the financial liabilities, the firm is more likely to go bankrupt. On the other hand, the market, as well as stakeholders, tend to negatively judge a less profitable firm, which can lead to a decrease in market value (Pindado et al., 2008). Therefore, NITA is expected to have a negative value,

[6] Appendix Table A.1b lists the details of indicators used in this study.

[7] Net Income to Market-valued Total Assets (NIMTA) is an alternative profitability measure (e.g. Campbell et al., 2008; Gupta and Chaudhry, 2019). As far as we are concerned, NIMTA is a 'half market variable, as it is constructed by dividing net income by market value of total assets. However, we construct pure accounting variables which enable us to make a comparison of the performance of different types of measures (e.g., accounting/market/systemic risk measures) in the prediction.

which is in line with the findings in the literature (e.g., Campbell et al., 2008; Tinoco and Wilson, 2013). Liquidity reflects the ability of a firm to meet its short-term commitments and the potential to generate working capital funds (Gregory and Christidis, 2010). A firm with good liquidity conditions is more capable of employing itself to pay the upcoming expenses such as interest payments and tax payments, and might be able to take measures to prevent bankruptcy until current conditions become better. Regarding long-run operation, firms may not maximise liquidity because over-liquidity will cause firms to lack productive assets. A failed firm is more likely to face liquidity problems because of inadequate cash and cash equivalents (Gupta and Chaudhry 2019). This paper employs Working Capital/Total Assets (WCTA) as a measure of a firm's liquidity, which is constructed by dividing working capital by total assets (Shumway, 2001).

Previous studies have investigated the predictive power of predictors that employ market data to predict firm bankruptcy (Campbell et al. 2008; Tinoco and Wilson, 2013). We include three market predictors in the proposed model. The first variable is RELSIZE, which considers the value of a firm's market capitalisation relative to the market capitalisation of the S&P 500. The relative size of a firm's capitalisation allows the consideration of non-firm-specific factors that affect firm bankruptcy by dividing by the S&P 500 index. The small firm market value indicates that traders are discounting equity value as a firm is approaching bankrupt (Chava and Jarrow, 2004). Therefore, there is a negative relationship between a firm's relative size and the risk of bankruptcy.

However, the changes in the relative size of a firm are also aspects that traders are looking at. These changes can be captured by EXRET, which is our second market variable. This indicator contains the information for both the relative size of the firms and changes in market returns (Campbell et al., 2008). EXRET is calculated by monthly returns of the firm deducted from the value-weighted market return (CRSP NISE/AMEX index return) measured in the most recent one-month period. A firm which has more positive relative returns is less likely to fail (Gupta and Chaudhry, 2019). Thus, EXRET has an expected positive value. The last market variable employed is PRICE. Many papers such as those by Campbell et al. (2008), Christidis and

Gregory (2010) and Tinoco and Wilson (2013) examined equity prices as an indicator of bankruptcy and confirmed that it has a positive effect on the predictive power of the model. First, the original firms' daily stock price obtained from CRSP was winsorised above $15. The NYSE and NASDAQ commonly delist stocks that are under a minimum price requirement of $1. Then these daily data were constructed into quarterly data, and then the log value of the winsorised price of the firms. PRICE indicates the equity value on the market. Thus a firm that has a high price below $15 is more likely to go bankrupt, as Campbell et al. (2008) argued. PRICE is expected to have a negative sign coefficient, i.e., price decreases the probability of bankruptcy.

This paper also involves model comparisons with previously proposed models. Therefore, the accounting and market variables that emerged in those models are also included in the present paper. The models they proposed have been tested and have shown consistent validity across time (e.g., Gregory and Christidis, 2010). Using newly collected data within our sample period, we meticulously follow the methods they used to construct the variables required in their models (see Altman, 1968; Shumway, 2001; Campbell et al., 2008 and the description therein).

Based on our results from the first-stage analysis, we further construct four novel systemic risk measures that link systemic financial risk measures with the individual nonfinancial firm. The first novel systemic risk measure we propose is FMVOL. To construct this variable, we first calculate the standard deviation of each firm's equity stock return over the last month as the measure of a firm's equity volatility, and then we take the average of standard deviation of the top 20 largest financial institutions' equity stock return over the last month as the measure of financial sector volatility (following Giglio et al., 2016).[8] FMVOL is the ratio of firm volatility over financial sector volatility. It is proposed in order to capture relative volatility between the individual firm and the financial sector. Systemic risk cannot be diversified; thus, systemic volatility can be regarded as a benchmark of volatility. We hypothesise that, in a certain period, if a nonfinancial firm's relative equity volatility is larger than financial sector systemic volatility, the firm may face a higher level of risks than financial sector systemic risk provides,

[8] If less than 20 institutions are available, we construct volatility measures from all available institutions.

or will be more sensitive in responding to the risk. A positive sign of the FMVOL variable's estimate is therefore expected.

Our second systemic variable is RELVOL, which represents the systemic risk's effects on a firm's bankruptcy according to firm size. It is calculated by multiplying the firm's relative size by the average daily equity volatility of the top 20 largest financial institutions in the previous month. RELVOL is an interaction variable designed to examine the interaction effects of systemic risk on firm size. Shumway (2001) argues that a small market value reflects the fact that investors are discounting the value of equity, and thus, it has a negative expected sign. However, by incorporating systemic risk measure (assuming RELVOL will have a negative sign), it is expected that larger firms are less vulnerable when facing the same level of systemic financial risk than smaller firms and therefore less likely to go bankrupt.

Third, many researchers have found relationships between credit spread and the real economy (e.g., Gilchrist et al., 2009; Gilchrist and Zakrajsek, 2012). As credit spread is reflecting the credit conditions, it may contain useful information in predicting firm bankruptcy. We propose another systemic risk measure, CLDEF, which is the firm debt in current liabilities multiplied by default spread (BAA bond yield minus AAA bond yield). Default spread represents the financial market credit condition (Giglio et al., 2016), and firm debts in current liabilities represent the number of debts in short-term that a firm exposure to the systemic risk. The firms who have more debts in current liabilities take more risks when credit condition in the market is adverse (i.e., default spread is relatively large), meaning that CLDEF is assumed to have a positive sign.

Since a high leverage ratio in financial institutions is associated with the real economy (Schularick and Taylor, 2012), we construct the financial institution's average leverage ratio and then multiply it by the relative size of a firm to construct our last systemic risk measure, RELLR. Giglio et al. (2016) argue that leverage for the financial institutions captures the instability in the sector. As they did not find a robust relationship between the average leverage of the top 20 largest financial institutions and macroeconomic activities, we substitute the measure of instability with all the average leverage in the financial sector. As Schularick and

Taylor (2012) have proved the relationship between average leverage of entire financial sector with GDP, we believe, therefore, that it might be a better measure of instability and can employ it to construct the variable RELLR. Again, a larger firm is more stable in an unstable environment and a negative sign of RELLR is expected.

3.3. Summary statistics

All the data are weighted equally every firm-quarter. This means every company has the same weight of information, which implies that the distribution can be greatly affected by relatively small firms. In addition, the cross-section and time series will have effects on the selected variables' distributions.

[Insert Table 1 around here]

Table 1 summarises the properties of selected prediction variables. The leverage of failed firms is relatively high; the given mean leverage is 70.1% and the median is 78.9%. This is consistent with our expectation that a higher leverage ratio indicates that the firm is more likely to go bankrupt (Ohlson, 1980). The mean of NITA is lower than the median of NITA, showing that the distribution of profitability is negatively skewed. This reveals more unprofitable firms than profitable ones, but the gap between median and mean is not large in NITA. Comparing Panels A, B and C, it is obvious that failed firms have differences from non-failed firms. Their NITA is lower than that of non-failed firms, making a mean (median) annual loss of 6.7% (7.8%). The mean working capital over total assets is 9.1%, lower than non-failed firms, and the median is actually negative. The failed firms also have smaller relative sizes compared with non-failed firms. They also experience a very significant negative return relative to the past three months' return, having a mean of -32.9% and a median of -41.1%, whereas non-failed and entire firms have a mean value that is no less than -6.6% and a median of no less than -1.8%. The log value of the price of a failed firm is also small, being 0.388 on mean and 0.000 on the median value, which is a very low level compared with a non-failed firm. For FMVOL, failed firms have larger relative equity volatility concerning financial sector volatility. Failed firms have smaller average CLDEFs, which is as expected. Failed firms also have smaller average RELVOL and RELLR.

3.4. Baseline model specification

Over the past decades, several earlier prediction models have been introduced, such as the Z-score model proposed by Altman (1968), the O-score model proposed by Ohlson (1980), and Merton's (1974) distance to default measure. Recent studies are more based on a logistic regression model, as it is a conventionally preferred technique for modelling a firm's bankruptcy risks where the dependent variable is binary (see, Ohlson, 1980; Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008). The logit model is superior to the alternatives, such as the Cox-Hazard model, in predicting binary outcomes using interval-censored data (Bauer and Agarwal, 2014; Gupta et al., 2018). A logit model has one essential advantage. Unlike the linear regression model, a logit model does not assume a linear relationship between independent variables and the probability of bankruptcy. Instead, it describes the relationship between independent variables and log odds ratio, which has very good interpretability. When predicting an individual firm, the logit model can output a simple percentage result, which is convenient and comfortable in practice. Shumway (2001) also shows that a logit model is a 'dynamic' model, which allows for time-varying covariates and can be regarded as a hazard model. The estimation of coefficients also shows the robustness. Therefore, following Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008), we employ a logistic regression model for our empirical analysis.

The definition of bankruptcy that we adopt is the definition used by Agarwal and Taffler (2008), in which a failed firm is defined as delisted for certain reasons according to what the CRSP delisting code specifies. The sample outcome is either 0 (non-failed) or 1 (failed) in one firm-quarter, which is a binary dependent variable. The probability that bankruptcy of firm i occurs at time t is denoted by $\Pr(Y_{it} = 1|x') = \pi_{it}(x')$, where x' is a vector representing a collection of k independent variables, $x(1,it)$, $x(2,it)$… $x(k,it)$. Let $g(x')$ denote a linear regression of $x(k,it)$. It can be expressed as:

$$g(x') = \alpha + \beta_1 x(1,it) + \beta_2 x(2,it) + \cdots + \beta_k x(k,it), \qquad (1)$$

where α and β_k are unknown parameters to be estimated. The dependent variables are given by the following logistic function:

$$\pi_{it}(x') = \frac{e^{g(x')}}{1+e^{g(x')}} \ . \tag{2}$$

Then,

$$\Pr(Y_{it} = 1|x') = \pi_{it}(x'), \tag{3}$$

which also can be expressed as:

$$\Pr\left(Y_{it} = 1\middle|x(1,it), x(2,it) \ldots x(k,it)\right) = \frac{e^{g(x')}}{1+e^{g(x')}} \ . \tag{4}$$

Therefore,

$$\Pr\left(Y_{it} = 1\middle|x(1,it), x(2,it) \ldots x(k,it)\right) = \frac{1}{1+e^{-\alpha-\beta_1 x(1,it)-\beta_2 x(2,it)-\cdots-\beta_k x(k,it)}} \ . \tag{5}$$

Given that the relationship between $\pi_{it}(x')$ and x(k,it) is non-linear, an odds ratio, $\pi_{it}(x')/(1-\pi_{it}(x'))$, is applied to make the function linear and to make the coefficients interpretable. Thus, the logistic regression model is given by:

$$\ln\left(\frac{\pi_{it}(x')}{1-\pi_{it}(x')}\right) = \alpha + \beta_1 x(1,it) + \beta_2 x(2,it) + \cdots + \beta_k x(k,it) \tag{6}$$

where x(k, it) denotes the k-th independent variables of the firm i at time t.

This paper uses function (6) as the ultimate model. To estimate the variables' coefficients, we can use maximum likelihood estimation, which involves obtaining the coefficient values by maximising the agreement between the logit model and the observations. Alpha gives the log value when all the variables are zero; beta means the change of log value when the variable increases by one unit and all other variables remain constant.

4. Empirical Analysis

4.1. First-stage: systemic risk measures and bankruptcy

The first part of our empirical analysis is designed in order to do a preliminary test and to confirm our assumption that a build-up of financial sector systemic risk increases the likelihood of a nonfinancial firm going bankrupt. Systemic risk measures[9] are calculated based on the financial sector's market information; thus, higher frequency data is preferable for pursuing this problem. However, due to the limitation of date information, we are only able to do the first-stage analysis by testing a sub-sample from our whole sample, which has 83,795 firm-month observations from January 2000 to January 2012. The measures are lagged for one month as a nonfinancial firm may respond slowly to systemic risk (e.g., Linn and Weagley, 2018). In the period from January 2000 to January 2012[10], we examined the relationship between 21 systemic risk measures and nonfinancial firms' bankruptcy using a simple logit model, function (7):

$$\ln\left(\frac{\pi_{it}(x)}{1-\pi_{it}(x)}\right) = \alpha + \beta x(it) \tag{7}$$

where x(*it*) denotes the independent variables (i.e., systemic risk measures) of the firm *i* at time *t*. The majority of systemic risk measures were calculated by Giglio et al. (2016) and we use a similar collection to the one that Giglio et al. (2016) use, where systemic risk measures are categorised into institution-specific risk and liquidity, co-movement and contagion, volatility and instability, credit condition and others not covered by Giglio et al. (2016). Additionally, we also wonder whether shocks in the financial sector can indicate bankruptcy in a nonfinancial firm. We measure shocks by simply taking the difference of systemic risk level between the previous month and the current month (Delta). Larger positive shocks are assumed to be associated with firm-level bankruptcy probability, and *vice versa*.

[Insert Table 2 around here]

Column Var in Table 2 illustrates the coefficients of systemic risk measures as a univariate independent variable after logistic regression. Systemic risk measures in each category show a significant association with firm bankruptcy, except for DCI, intl. spill-over, book lvg, and TED spr. All the significant measures have a positive sign, with only WFS showing a negative sign. As known in general, a larger asset-liability maturities mismatch makes financial institutions

[9] See Appendix Table A.1a for the systemic risk measures in detail.

[10] The sample exceptions are January 2000 to January 2010 for the measurement of GZ and January 2000 to September 2010 for intl. spillover (See Giglio et al., 2016 for more details).

more vulnerable to liquidity risk. WSF, an alternative measure that relates to liquidity risk as well, should be expected to have a positive sign. The negative sign on WSF is therefore contrary to our expectation. We find evidence to explain this in the literature that US banks behave differently to others regarding short-term wholesale funding (López-Espinosa et al., 2012). Furthermore, we believe this abnormal sign can be explained by the research conducted by Dewally and Shao (2014). In their research, they find that wholesale funding has been gradually increasing since before 2007–2009, and dropped significantly during the financial crisis. This trend is opposite to the probability of firm bankruptcy. Theoretically, they argue that liquidity shocks in wholesale sale funding markets lead to contraction of bank credit, and consequently do harm to their borrowers. Therefore, it is a sign of liquidity risk shocks when banks dramatically decrease the use of short-term wholesale funding meaning that firms are more likely to go bankrupt due to the reduced credit supply. Column Delta in Table 2 shows that some of the deltas of financial systemic risk are positively related to bankruptcy, but are not as strong as the original systemic measures. This implies that the change in systemic risk does not show constant or better predictability than the systemic risk measures themselves. In particular, the volatility measure, which has been widely used as a reliable measure of systemic risk (e.g., Linn and Weagley, 2018), shows a positive and significant association with firm bankruptcy in our sample.

The results support the view, such as that stated by Giglio et al. (2016), that '*financial sector equity volatility is the most useful individual predictors in macroeconomic downturns*', while in our context, it is one of the most useful individual predictors of nonfinancial firm bankruptcy. Many studies have been studying the relationship between volatility and macroeconomic activities and have shown their deep ties. Chauvet et al. (2015) also reached similar conclusions. This suggests that our hypothesis, as well as results, are supported by the literature. It also supports us in constructing our novel variables from a theoretical background.

Although most of the systemic risk measures tested in this paper are significantly positive when related to bankruptcy, we will not combine all the existing measures into one when we construct our novel systemic risk variables. Instead, in the next section, we will only use measures that provide information about volatility, instability and credit conditions, because measures in these categories show relatively significant and reasonable predictability in macroeconomic downturns (Giglio et al., 2016), and thus might be better used for bankruptcy predictions. These categories are financial sector volatility (volatility measure), financial institutions average leverage ratio (instability measure) and default spread (credit condition measure).

4.2. Second-stage: the use of systemic risk information in prediction

In the second-stage analysis, we construct our models based on the results in the first-stage analysis. We test each model in this section using the full sample, which consists of 8,604 listed nonfinancial companies on the US stock market at any time between 2000 Q1 and 2016 Q4.

4.2.1. Incorporating systemic risk information into previous studies

This paper estimates the models developed by Shumway (2001) and Campbell et al. (2008) and tests their performance when incorporating proposed the systemic risk measures of FMVOL, RELVOL, CLDEF, and RELLR. The aim is to test the validity of the previously proposed models' performance under the current dataset and to test the contribution and limitation of our systemic risk measures to their models[11]. Note that we excluded SIGMA when incorporating the systemic risk variables as they could also be alternative measures. Table 3 presents the estimated coefficients of the three models with the current dataset as well as when adding systemic risk measures.

[Insert Table 3 around here]

First, when compared with the previous studies' own estimation, it can be seen that all the variables' coefficients estimated using our full sample have the same sign. However, the absolute values of previous and current results that the same model gives are quite different. This suggests that, although there are various estimates of the probability of bankruptcy, the models still produce similar estimates of the relative bankruptcy risk of the firm in different periods. Recent studies have shown the same conclusion (e.g., Agarwal and Taffler, 2008;

[11] The Internet Appendix reports the correlation matrix of variables used by Shumway (2001) and Campbell et al. (2008) and our novel systemic risk measures.

Gregory et al., 2010). In addition, it can be concluded that the predictors that previous models have employed are consistent across time, models, markets and the observation period (yearly, quarterly or monthly).

A notable exception in Panel C is that the coefficient of RELSIZE that Campbell et al. (2008, p. 2,910) estimated has a positive sign, but is negative in the current paper. Campbell et al. (2008) argue that the inclusion of price per share results in an ad hoc correction to the negative effect of price. However, in this paper, once price per share is included there is no opposite sign on RELSIZE. The correlation coefficient between RELSIZE and PRICE is 0.73, which shows that there might be a strong relationship between them. However, it is a positive correlation. We argue that the previous articles used original calculated ratios and data, whereas this paper, uses the winsorised data. Winsorised data can limit the effect of undesirable outliers such as extreme values in the dataset. If more data were included, the effects of market impacts would become stronger and the effects of accounting impacts would become slightly weaker, yet there is a slightly different effect (Campbell et al., 2008). The cause of the differences between the present estimates; results and the previous results from the literature might be because of the impacts of the winsorised data. However, it can be concluded that the accounting and market data that the present paper employs are powerful, and that the relative risk of a firm that these predictors indicate is consistent with the previous studies.

[Insert Figure 1 around here]

The present paper also investigates the effects of incorporating our proposed systemic risk measures into previously proposed models. The model proposed by Shumway (2001) and Campbell et al. (2008) are the representatives of classic accounting-only models and market-accounting-based models, respectively. Table 3 (Panels A, B and C) suggests that the systemic risk measures that are simply incorporated into previous models show statistically significant and expected coefficient signs. It reveals that the systemic risk measures we propose have information about firm bankruptcy. SIGMA is excluded when we incorporate systemic risk variables because we argue that there might be potential multicollinearity between market variables and systemic risk measures, as well as potential information overlapping. In order to link systemic risk measures and individual firms together, our proposed variables contain both systemic risk information and firm characteristics. The incorporation of systemic risk measures is useful in bankruptcy prediction. Evidence can also be seen in Figure 1, where the significant increase in areas under ROC (AUC) when systemic risk measures are included confirms the finding. This suggests that the use of systemic risk information enhances the ability of the previously proposed prediction models, particularly when combined with a pure accounting model (Shumway, 2001), which shows the greatest improvement.

4.2.2. The Accounting, Market and Systemic Risk (AMS) model

Given the results discussed, we propose an AMS model to predict nonfinancial firm bankruptcy, which combines accounting-information-based variables, market information-based variables and financial sector systemic risk measures together. We maximise the utility of systemic risk in individual firm bankruptcy predictions and expect the AMS model to have better predictability than the accounting market only models in US firm bankruptcy predictions. The other models, Model A to Model F, are comparison models. Model A is an accounting-variables-only model; Model B is a market variables-only model; Model C is a systemic risk measures only model; Model D is an accounting and systemic risk measures model; Model E is a market and systemic risk measures model; and Model F is an accounting variables and market variables model. Table 4 illustrates the results from seven logit regressions of the firm bankruptcy indicators on the predictor variables.

[Insert Table 4 around here]

In Table 4, all the estimated coefficients of variables in seven models are significant at the 1% significance level and with the expected sign. It can be concluded that all the models' estimations are efficient predictors of the probability of firm bankruptcy. The estimates of predictors from each model are quite different; for example, WCTA is estimated to be -2.5658 from Model A, whereas it is -0.9030 from the AMS model. This suggests that the absolute risks of firms differ widely across the models, although the relative risk is quite consistent. The AMS model can be regarded as a simple combination of Model A, Model B and Model C. All the variables that are incorporated in the AMS model are statistically significant at the 1% level, suggesting that the selected variables are informative and statistically useful indicators between the models. The inclusion of systemic risk measures changes the coefficients of the common variables to a slight degree. However, the sign of common variables' coefficients is consistent among models. In the AMS model, RELSIZE, RELVOL and RELLR all have negative signs. It suggests that, apart from the fact that relative size has a negative relationship with bankruptcy, the interaction of relative size and systemic risk measures intensifies the relationship. It also means that a larger firm can better defend against systemic volatility and instability than a smaller one.

One argument is that larger firms tend to show risk-averse management, while smaller firms tend to be managed more by people who love taking risks, and thus always face the problem of overinvestment. During a period of high systemic risk, larger firms are more likely to benefit from 'underinvesting'. This implies that firm size weakens the positive effects of systemic risk on bankruptcy. The signs of estimated coefficients of FMVOL and CLDEF are as we expected. The negative sign of FMVOL suggests that if a firm has higher equity volatility than financial sector equity volatility, its probability of bankruptcy will increase. One explanation is that the firm is facing more risk than the systemic risk would otherwise indicate. For CLDEF, the explanation is that debts in current liabilities make a firm more vulnerable when systemic risk arises. We would argue that adverse credit conditions in the financial market increase the probability of a firm going bankrupt as the cost of debts increases, especially when the debts are with a floating rate. Although the statistics of both Pseudo R-square and LR Chi-square tests increased after incorporating the macroeconomic variable, the results are still not robust and trustworthy enough to conclude that our hypothesis is correct. In later sections, further discussion will be made to conclude.

4.2.3. Long-horizon prediction

In practice, risk managers are required to use the data available at the time of the analysis. However, a firm's bankruptcy date is not known, and data for predictions are not updated daily. Furthermore, shorter period prediction does not give time for related institutions or individuals to react to the trend towards bankruptcy. Previous studies have found that the accuracy of bankruptcy prediction models generally experiences a decline with the earlier horizon (Campbell et al., 2008). It is interesting to whether our models' prediction is still accurate with longer horizons. Accordingly, this paper estimates firm bankruptcy in *n* quarters prior to the observation of a firm going bankrupt[12].

[Insert Table 5 around here]

Table 5 illustrates the results in a two-quarter prediction. Compared to Table 4, the coefficients and significance fit statistics decline as predicting horizon prolonged[13]. In detail, all the variables remain statistically significant at the 1% level. This indicates that our models retain predictability in long-term predictions. The liquidity variable, WCTA, has a coefficient that decays slowly with the horizon, suggesting that the liquidity of a firm is a constant indicator during the two quarters. The coefficient of profitability, NITA, shows an increase as predicting horizon prolonged, indicating that profitability is more important in longer period predictions. The coefficients of TLTA show relatively faster declines with the horizon. The same declining trend and rate also can be seen on EXRET, PRICE, FMVOL and CLDEF, suggesting these variables are primarily shorter-term indicators of firm bankruptcy. One point to be noticed is that RELSIZE's coefficient shows a dramatic decline, with significance down to 5% level, which suggests a relative firm size is not as important as other variables in long-term predictions. Surprisingly, relatively to predictions in *t*, RELVOL and RELLR's coefficients see an increase in t-1 and t-2, respectively[14]. This suggests that, compared with other predictors, although firm relative size loses predictability in the longer term, it plays a relatively more significant role in a longer prediction when related to systemic risk. Overall, variables within models become less important as the prediction horizon becomes longer. In Table 5, the number of observations sees a downward trend with the horizon. It is caused by declining observations at the two sides of the dataset that are driven by an increasing horizon. A failed firm in first *n* quarter cannot be related to the condition of the firm *n* quarters previously. The most recent period of the failed firm cannot be used to predict bankruptcy. However, the trend is in line

[12] See Appendix 2.
[13] Note we do not report the results of one-quarter prediction here since they can see the same trends as two-quarter predition shows. However, they are presented in the Internet Appendix.
[14] We do not report results of one-quarter prediction here.

with previous evidence (Campbell et al., 2008).

5. Model Evaluation

In this section, the seven firm bankruptcy prediction models are tested to evaluate the models' performance. The present paper first discusses the marginal effects of each variable in the AMS model and then presents the results of seven models of predictive power measures. Finally, a further robustness check is provided to test the goodness-of-fit of the proposed model.

5.1. Marginal effects

The coefficients of predictors in the binary model are hard to interpret directly. Although logistic regression models' estimates can be explained by using their odds ratios, the information from the odds ratio is 'static'. The odds ratio cannot adequately describe the changing effects that variables have on binary outcomes. Previous studies have mostly focused on the overall predictability and the interpretation of each variable merely relies on the coefficient sign, while we also provide marginal effect analysis.

[Insert Table 6 and Figure 2 around here]

Table 6 presents the impacts of predictors on dependent variables. The sign of each variable is by logit regression estimates in terms of relative changes in direction, which confirm previous conclusions. In Model A, Model D, Model E and the AMS model, NITA has the largest marginal impact in absolute terms. However, we are more interested in the marginal effects of systemic risk measures. When comparing FMVOL, RELVOL, CLDEF and RELLR in each model that includes these four variables, RELLR has the smallest importance *ceteris paribus*; this is because the variable has a higher level of magnitude than other variables. Figure 2 shows the predictive margins at different values of each predictive variable in which other variables are constant. The upside or downside slope of the variables again confirms the positive or negative relationship between variables and bankruptcy. For example, the downside slope of RELVOL indicates it is negatively associated with firm bankruptcy. Interestingly, the slopes of our systemic risk measures are even steeper than conventional accounting and market variables such as WCTA and EXRET. It can be concluded that systemic risk measures have an even greater impact on bankruptcy prediction than marginal effects suggest. However, the magnitude of each variable is not the same which can explain the phenomenon. The marginal effects of each variable in the AMS model are presented in the Internet Appendix, which confirms the relatively weak effect of RELLR.

5.2. Model predictive power

The measures of predictive power test how well a model can predict the dependent variable based on independent variables (Allison, 2014). The area under Receiver Operating Characteristics (ROC) curve, Rank-order correlations coefficients and R-square measures are often used. Table 7 includes the model predictive power statistics for the seven models. Panels A and B show measures for the seven models in *t* and *t-2*, respectively. The area under the ROC curve method is employed in the present paper to evaluate the model's performance. The ROC curve is a widely used tool in the field of signal detection theory, psychology, and particularly in medicine (Engelmann et al., 2003). Researchers found that it is also a well-established tool to validate bankruptcy prediction models (e.g., Vassalou and Xing, 2004; Agarwal and Taffler, 2008; Bauer and Agarwal 2013). AUC is the value of the area under the ROC curve[15], which is a primarily used measure in the logistic regression predictive ability tests. It is shows that the AMS model has the most powerful predictability. The coefficients' significant level shows a decline when the prediction horizons grow, and the predictive power of each model experiences a decline in the meantime. However, our AMS model still shows a relatively prominent level of predictive power as the AUC is over 0.90 even in t-2 period prediction. This paper uses the Gini rank coefficient as a rank-order correlations measure. Engelmann et al. (2003) also argued that AUC contains similar information to the Gini rank coefficient and it is a transformed format of the area under the ROC curve, which is (AUC-0.50)*2. This method is unbiased and robust, and is employed in the present paper to evaluate models. Our pseudo R-square includes several widely accepted measures. Cox and Snell's R-square is a measure based on the log-likelihood of the model. Nagelkerke's R-square and Efron's R-square are refined versions of Cox and Snell's R-square. These measures have a similar interpretation to

[15] AUC is between 0 and 1, which captures the relationship between the type I and type II errors. See the Internet Appendix for detail.

linear regression as they measure the significance of models[16]. The models' Chi-square tests are also presented, where the degrees of freedom for each model are 3 for Models A and B, 4 for Model C, 7 for Models D and E, 6 for Model F, and 10 for the AMS model.

[Insert Table 7 around here]

The measures of the seven models are agreed in the relative predictive power of each model, which enable us to conclude the following. Comparing Model A, Model B and Model C in period t prediction (Panel A), the predictability rank, from low to high, is Model A, Model C and Model B, which suggests that, in our models, market variables include more information than systemic variables in bankruptcy prediction, and accounting variables have the least information. The findings are consistent with the results in Table 2: that a systemic risk measure only model only can predict firm bankruptcy. Furthermore, Model C performed better than Shumway's (2001) accounting-only model according to the predictive power tests. The statistical differences between Model A and Model D suggest that simply incorporating systemic risk measures into the accounting variables model can improve its performance. The same improvement can be seen from Model B to Model E as well as from Model F to the AMS model. Again, the same improvements were also noted in the longer horizon predictions (e.g. in *t-2*). Even with the same dataset, the AMS model performed better than the previous models proposed by Shumway (2001) and Campbell et al. (2008), given that the AUC of the AMS model dominates other's models. If compared vertically, each model shows a decline in predictability as horizons prolong, which was also shown in the work of Campbell et al. (2008). In each panel, the proposed AMS model performs better in terms of the predictive ability which dominates the other models. The findings indicate that the incorporation of proposed systemic risk measures in a bankruptcy prediction model can increase the model's predictive accuracy. The AMS model is therefore a powerful tool for predicting bankruptcy of US firms.

5.3. Goodness-of-fit tests

Predictive power measures only are not informative enough to be used to accept a model,

[16] See Cox and Snell (1989), Nagelkerke (1991) and Efron (1978).

although they are often used (Long and Freese, 2014). A scalar measure of goodness-of-fit can be useful when comparing models as they answer the question as to whether the model is consistent with the data. Conventional goodness-of-fit tests for logistic regression models are clustering in Deviance and Pearson's Chi-squared tests, but their drawbacks drive us to reject them. Deviance and Pearson's Chi-squared tests are used when cases can be aggregated as profiles, and they perform well '*when the expected number of both events and non-events for each profile is at least 5*', as Allison (2014) states. However, he argues that aggregation is often impossible when predictors are not categorised. The AMS model contains ten continuous predictors which cannot meet the requirements of Deviance and Pearson's Chi-squared tests. Furthermore, he is also concerned that these tests are not particularly powerful. Therefore, this paper employs Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Standardised Pearson[17] as goodness-of-fit tests which do not need to group cases into profiles. Both AIC and BIC are information measures, and the Standardised Pearson test is recommended by Allison (2014). For all the goodness-of-fit tests used in this paper, the smaller the statistics are, the better a model performs. Table 7 also illustrates the statistics of models in period *t* and *t-2* predictions. Consistent with the predictive power tests, the results further confirm the utility of systemic risk information and the superiority of the AMS model in goodness-of-fit terms, as well as the declining trend in long-horizon prediction.

[Insert Table 8 around here]

We also checked the robustness of AMS model as measured by the Hosmer-Lemeshow (1980) statistic. It is another approach which is often used as an additional tool to check the goodness-of-fit. The Hosmer-Lemeshow test is a decile approach that its estimation tests the bankruptcy prediction ability of a model, from which actual probabilities of bankruptcy could be inferred (once the coefficients of the logit model are estimated). Table 8 presents the results of the Hosmer-Lemeshow test, which suggests that the observed and expected number of the failed firms in each decile are close and are statistically accepted at a significant level.

[17] Note that we use the version suggested by Osius and Rojek (1992).

Overall, 91.39% of the bankrupt firms were predicted correctly by our AMS model. In the highest probability deciles, 89.52% of the bankrupt firms were predicted correctly, while in the lowest five deciles of probability (decile 1–5), only 0.11% of the firms were reported as a misclassification. Note that the p-value Hosmer-Lemeshow measures in Table 8 respectively is below 0.05, which suggests a rejection of the AMS model. However, this can be ignored as Allison (2014) argues that it may be impossible to find a model with an acceptable p-value when the sample size is so large (the sample size of the present paper is 225,813 observations). To recap, the facts discussed above indicate that the models have a very high level of goodness-of-fit and further confirm the reliability of the AMS model.

5.4. Prediction with monthly and yearly observation intervals

Market variables, including systemic risk measures, contain more information in higher frequency data. Market-based models benefit more in prediction using higher frequency data than using lower frequency data (e.g., Merton, 1974). Systemic risk measures are mostly constructed based on market information, and thus stronger effects are expected in higher frequency data. For example, lower frequency data smooths out volatility which might omit important information. Therefore, to maximise the use of systemic risk variables in bankruptcy prediction, we test our models based on a monthly observation interval with variables constructed with monthly data[18]. For robustness concerns, we also provide a test using yearly observation intervals[19]. Our AMS model performs well in both sub-tests, except for the variable RELLR, which became insignificant in the monthly sample test. We argue that RELLR is constructed based on the accounting ratio in the financial sector; thus it is acceptable for it to become insignificant in higher frequency data based predictions.

6. Concluding Remarks

Financial systemic risk is taking root in both academia and practitioners in the aftermath of the GFC. We have contributed to the understanding of this recent and increasingly popular concept by investigating the value of financial systemic risk measures in predicting the bankruptcy rates

[18] In the Internet Appendix, we illustrate the coefficients of predictors with 83,795 monthly observations, which cover the period from January 2000 to January 2012.

[19] See also in the Internet Appendix. There are 44,536 firm-year observations from 2000 to 2016 in yearly predictions.

of nonfinancial firms. Our sample is arguably the most representative, comprehensive and updated sample in the current extant literature, which includes 225,813 firm-quarter observations of 8,604 listed firms on the US stock market from 2000 Q1 to 2016 Q4.

Motivated by the very significant and robustly positive relationship between one-quarter lagged financial sector equity volatility (and to a less extent, the other financial systemic risk measures) and the contemporaneous bankruptcy rate of nonfinancial firms, we carefully incorporated additional explanatory variables with sensible economic/financial motivations to the prevalent bankruptcy prediction models. We have found several new model specifications that have higher explanatory power than the extant state-of-the-art model specifications proposed by Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008); and hence, their seminal earlier counterparts such as Altman (1968) and Ohlson (1980). We find substantial accuracy benefits from combining financial systemic risk measures and an individual firm's characteristics as predictors. These benefits are incremental and significant, even when we relax our restrictions on contemporaneous forecasts and turn to prediction within longer horizons of one or two quarters. The performance of all the models under our scrutiny deteriorated, but our proposed model still shows superior predictability of firm bankruptcy relative to the conventional accounting and market-based models, whether in a one-quarter-ahead prediction or a two-quarter-ahead prediction. Finally, our proposed model outperformed the extant models in several forms of model evaluations, such as marginal effects and model predictive power, as well as many goodness-of-fit tests. Overall, we conclude that financial sector systemic risk is incrementally useful in predicting the bankruptcy of nonfinancial firms. We have called our newly proposed methodology the Accounting, Market and Systemic Risk (AMS) model, since it includes accounting ratios and market variables as well as systemic risk measures.

Practitioners could employ our models to predict the potential bankruptcy risk of a firm in advance and to take timely measures to prevent or reduce unexpected loss in the future. To achieve this goal, several findings may be taken into account. First, we find that relatively large firms are more likely to survive during higher systemic volatility and unstable financial conditions than smaller ones. Second, when firms have higher equity volatility than financial sector equity volatility, the probability of bankruptcy will increase. Finally, an adverse credit condition in the financial market increases the probability of bankruptcy as the cost of debts increases (especially the floating-rate debts).

There are several caveats to our study. Ideally, we should build our systemic risk measures on economic theory to capture the causality from one industry to another. In the absence of such a generally accepted theory, we selectively combined some financial systemic risk measures with sensible economic/financial motivation and individual firm's characteristics as predictors. Some systemic risk measures suffer from data availability constraints, and we are no longer able to update these, since they were constructed using proprietary sources that have stopped making their data available (e.g., the credit spread measure proposed by Gilchrist and Zakrajsek (2012)). There might be more and better systemic risk measures in existence, and even our proposed systemic risk measures might be used in a better way. We have followed the mainstream literature and have focused on the financial sector, but we do not exclude the possibility that some other sector(s) may be as systemically important, or more important, than the financial sector, which suggests a fruitful avenue for future research.

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TABLES AND FIGURES

Table 1. Summary statistics

This table includes the following variables (see details in data description section): TLTA (total liabilities/total assets), NITA (net income/total assets), WCTA (working capital/total assets), RELSIZE (log[firm market capitalisation to market capitalisation of S&P 500 index]), EXRET (return on the firm-value-weighted CRSP NYSE and AMEX index), PRICE (log value of price per share winsorised above $15), FMVOL (firm equity volatility/average equity volatility of 20 largest financial institution), RELVOL (relative size*average equity volatility of 20 largest financial institution), CLDEF (debt in current liabilities in hundred $*default spread) and RELLR (relative size*financial institution average market leverage ratio). Panels A, B and C show summary statistics for all firm-quarter observations, non-failed firm-quarter observations and failed firm-quarter observations, respectively. There are 225,813 observations, of which 1,690 failed, while the remaining 224,123 did not fail.

	TLTA	NITA	WCTA	RELSIZE	EXRET	PRICE	FMVOL	RELVOL	CLDEF	RELLR
Panel A: Total Data Set (Observations: 225,813)										
Mean	0.481	-0.006	0.257	-10.181	-0.064	2.067	2.089	-0.181	0.789	-92.754
Median	0.476	0.007	0.224	-10.186	-0.019	2.625	1.794	-0.151	0.025	-90.89
Std. Dev.	0.231	0.043	0.232	2.001	0.243	0.862	1.138	0.088	1.914	24.685
Min	0.114	-0.121	-0.086	-13.541	-0.657	0.000	0.678	-0.367	0.000	-155.699
Max	0.938	0.045	0.716	-6.568	0.279	2.708	5.093	-0.085	7.638	-55.411
Panel B: Non-Failed Firm Group (Observations: 224,123)										
Mean	0.479	-0.005	0.258	-10.16	-0.062	2.080	2.075	-0.180	0.789	-92.502
Median	0.475	0.008	0.226	-10.167	-0.018	2.638	1.786	-0.150	0.025	-90.674
Std. Dev.	0.230	0.043	0.231	1.992	0.241	0.850	1.126	0.087	1.914	24.522
Panel C: Failed Group Firm (Observations: 1,690)										
Mean	0.701	-0.067	0.091	-12.889	-0.329	0.388	3.929	-0.267	0.799	-126.182
Median	0.789	-0.078	-0.031	-13.541	-0.411	0.000	4.282	-0.277	0.039	-129.943
Std. Dev.	0.265	0.054	0.233	1.157	0.343	0.679	1.248	0.087	1.899	23.338

Table 2. Systematic risk measures and bankruptcy

This table presents the bankruptcy forecast results with the 21 systemic risk measures, all of which are extracted directly from the work of Giglio et al. (2016)[a], except for CES (Banulescu and Dumitrescu, 2015) and WSF (López-Espinosa et al., (2012). The dependent variable is whether or not a US nonfinancial firm went bankrupt. The sample consists of 83,795 firm-month observations covering the period from Jan 2000 to Jan 2012, except for the GZ measurement (Jan 2000 to Jan 2010) and the intl. spill-over measure (Jan 2000 to Sep 2010). WFS is calculated quarterly and converted to monthly observations by assuming that it changes arithmetically between quarters. All the measures lagged for a month in the forecast. Colum Var reports the coefficient of variable in the univariate estimation and Column Delta reports the coefficient of change of systemic risk with respect to previous month. * denotes p-value that p<0.10; ** denotes p-value that p<0.05; *** denotes that p-value p<0.01.

Category	Variable	Column Var	z	Column Delta	z
Institution-specific risk & Liquidity	CoVaR	13.870***	(4.64)	49.930**	(3.06)
	Δ CoVaR	15.860**	(2.74)	86.150**	(3.15)
	MES	6.148**	(3.15)	42.340***	(3.32)
	SRISK	10.670*	(2.14)	-1.631	(-0.14)
	AIM	43.840**	(5.09)	-10.400	(-0.94)
Comovement & Contagion	Absorption	2.351***	(3.89)	3.337	(1.54)
	Δ Absorption	1.744**	(2.80)	0.969	(1.71)
	DCI	-0.405	(-0.75)	-1.307	(-0.79)
	Intl. spillover	-0.001	(-0.27)	0.048***	(3.75)
Volatility & Instability	Volatility	14.610***	(5.64)	-5.366	(3.09)
	CatFin	5.614***	(5.76)	4.503*	(2.00)
	Turbulence	0.003**	(2.71)	-0.002**	(-2.63)
	Book lvg.	-1.796	(-0.40)	-24.640	(-1.00)
	Mkt lvg.	0.019*	(1.98)	0.111**	(2.75)
	Size conc	0.203*	(2.01)	-0.372	(-0.62)
Credit condition	TED spr.	0.001	(0.95)	-0.004*	(-2.32)
	Term spr.	0.071*	(2.28)	-0.302*	(-2.30)
	Default spr.	0.277***	(4.06)	0.387	(1.35)
	GZ	0.192***	(7.29)	0.162*	(1.02)
Measures not covered in Giglio et al. (2016)	CES	22.170***	(4.30)	118.4455***	(3.19)
	WSF	-6.657***	(-3.69)	-31.25*	(-2.47)

[a] *Source: Giglio et al. (2016) pp.460, 463*

Table 3. Incorporating systemic risk variables into previous studies

Panels A, B and C present the estimated coefficients from three previously proposed models using the current dataset and coefficient results from previous studies (Sources from: (i) Table 2 (Shumway, 2001, p. 117), (ii) Model 1, Table 3, (Campbell et al., 2008, p. 2,910), and (iii) Model 2, Table 3 (ibid.)). The variables are winsorised at the 5% and 95% levels. $^{+}$ denotes at 0.01 significance level.

Panel A:

Variables	WCTA	RETA	EBITTA	METL	STA	FMVOL	RELVOL	CLDEF	RELLR	Constant
Shumway (2001)	-2.9349^{+}	-0.4980^{+}	-19.2328^{+}	-0.1900^{+}	0.9255^{+}					-4.7292^{+}
+ Systemic risk	-2.1677^{+}	-0.1535^{+}	-8.8930^{+}	-0.0717^{+}	0.0550	0.7174^{+}	-6.5145^{+}	0.2926^{+}	-0.0249^{+}	-11.0698^{+}

Panel B:

Variables	NITA	TLTA	EXRET	SIGMA	RELSIZE	FMVOL	RELVOL	CLDEF	RELLR	Constant
Campbell et al. (2008) Model 1	-6.237^{+}	2.9868^{+}	-1.1614^{+}	36.5076^{+}	-0.6841^{+}					-17.0680^{+}
+ Systemic risk [a]	-6.7309^{+}	2.5931^{+}	-1.1214^{+}		-0.5351^{+}	0.5676^{+}	-5.1330^{+}	0.3222^{+}	-0.0125^{+}	-17.5975^{+}

Panel C:

Variables	NIMTA	TLMTA	EXRET	RELSIZE	SIGMA	CASHMTA	MB	PRICE	FMVOL	RELVOL	CLDEF	RELLR	Constant
Campbell et al. (2008) Model 2	-13.2646^{+}	2.0152^{+}	-0.8844^{+}	-0.4079^{+}	27.2859^{+}	-2.0971^{+}	0.1044^{+}	-0.6947^{+}					-11.9273^{+}
+ Systemic risk [b]	-12.6601^{+}	1.6715^{+}	-0.9130^{+}	-0.2518^{+}		-1.8449^{+}	0.1077^{+}	-0.6354^{+}	0.4710^{+}	-4.0678^{+}	0.2401^{+}	-0.0147^{+}	-12.6700^{+}

[a, b] *SIGMA excluded when incorporated systemic risk variables.*

Table 4. Logit regression results

This table reports the estimated coefficient results from seven logit regressons of bankruptcy prediction models. The absolute z statistics values are also reported under each coefficient. Model A is an accounting-variables-only model; Model B is a market variables-only model; Model C is a systemic risk variables-only model; Model D is an accounting and systemic risk variables model; Model E is a market and systemic risk variables model; Model F is an accounting variables and market variables model; while the AMS model is our proposed model that combines three sets of variables. The total number of observations is 225,813. All variables are winsorised at the 5% and 95% level. $^+$ denotes at 0.01 significance level.

Variable	Model A	Model B	Model C	Model D	Model E	Model F	AMS model
TLTA	2.1980$^+$			2.2057$^+$		2.1830$^+$	1.9869$^+$
	(17.29)			(16.41)		(16.95)	(14.79)
NITA	-21.2104$^+$			-8.9166$^+$		-6.4327$^+$	-5.5015$^+$
	(-47.82)			(-17.22)		(-12.55)	(-10.33)
WCTA	-2.5658$^+$			-1.1186$^+$		-1.5061$^+$	-0.9030$^+$
	(-17.92)			(-7.49)		(-10.46)	(-6.06)
RELSIZE		-0.4144$^+$			-0.2456$^+$	-0.4748$^+$	-0.2810$^+$
		(-12.57)			(-6.25)	(-14.37)	(-7.08)
EXRET		-1.4466$^+$			-0.9214$^+$	-1.0294$^+$	-0.6745$^+$
		(-27.68)			(-16.28)	(-18.80)	(-11.56)
PRICE		-1.4597$^+$			-1.1823$^+$	-1.1089$^+$	-0.9728$^+$
		(-17.73)			(-14.99)	(-13.37)	(-12.03)
FMVOL			0.9547$^+$	0.7145$^+$	0.5810$^+$		0.4637$^+$
			(43.45)	(29.94)	(22.33)		(17.12)
RELVOL			-8.1672$^+$	-6.6238$^+$	-4.8009$^+$		-4.2377$^+$
			(-23.95)	(-18.51)	(-12.98)		(-11.19)
CLDEF			0.3767$^+$	0.2478$^+$	0.3771$^+$		0.2687$^+$
			(25.30)	(15.29)	(22.36)		(15.00)
RELLR			-0.0280$^+$	-0.0268$^+$	-0.0129$^+$		-0.0131$^+$
			(-18.52)	(-17.58)	(-7.57)		(-7.71)
Constant	-6.4208$^+$	-8.4513$^+$	-12.8847$^+$	-12.9693$^+$	-11.4817$^+$	-10.7258$^+$	-12.7582$^+$
	(-65.84)	(-19.22)	(-78.70)	(-65.16)	(-24.58)	(-23.31)	(-26.19)
Pseudo R^2	0.200	0.283	0.289	0.344	0.343	0.342	0.377
LR Chi^2	3977.66	5634.05	5763.73	6858.33	6820.99	6809.68	7498.91

Table 5. Two quarters ahead forecast

This table reports the estimated two-quarters ahead forecast results from logit regressions of the bankruptcy prediction model. Using data from two-quarters prior to the observation of firm bankruptcy (t-2), the models are examined in order to confirm their prediction ability. The total number of observations is 208,950. All variables are winsorised at 5% and 95% level. $^{+}$ denotes at 0.01 significance level.

Variable	Model A	Model B	Model C	Model D	Model E	Model F	AMS model
TLTA	1.6660^{+}			1.9808^{+}		1.8978^{+}	1.9039^{+}
	(13.19)			(15.12)		(14.77)	(14.53)
NITA	-19.6178^{+}			-9.6750^{+}		-7.7449^{+}	-6.8412^{+}
	(-43.27)			(-18.59)		(-14.59)	(-12.61)
WCTA	-1.7160^{+}			-1.0073^{+}		-1.1101^{+}	-0.8395^{+}
	(-12.52)			(-7.13)		(-8.05)	(-5.95)
RELSIZE		-0.2921^{+}			-0.0532	-0.3852^{+}	-0.1096^{+}
		(-10.61)			(-1.49)	(-13.81)	(-3.04)
EXRET		-1.0379^{+}			-0.7420^{+}	-0.6730^{+}	-0.4917^{+}
		(-23.22)			(-15.11)	(-14.12)	(-9.62)
PRICE		-1.1930^{+}			-1.0419^{+}	-0.9491^{+}	-0.8855^{+}
		(-13.73)			(-12.64)	(-10.92)	(-10.55)
FMVOL			0.7227^{+}	0.5074^{+}	0.4368^{+}		0.3326^{+}
			(33.68)	(21.62)	(16.91)		(12.34)
RELVOL			-7.0986^{+}	-5.6374^{+}	-4.2457^{+}		-3.6980^{+}
			(-20.79)	(-15.92)	(-11.49)		(-9.82)
CLDEF			0.1893^{+}	0.0754^{+}	0.1889^{+}		0.0924^{+}
			(9.20)	(3.34)	(8.52)		(3.85)
RELLR			-0.0234^{+}	-0.0240^{+}	-0.0147^{+}		-0.0158^{+}
			(-15.74)	(-16.04)	(-8.36)		(-8.93)
Constant	-6.0007^{+}	-6.9607^{+}	-10.9863^{+}	-11.2203^{+}	-8.4041^{+}	-9.4927^{+}	-10.0701^{+}
	(-63.50)	(-18.88)	(-72.25)	(-59.93)	(-20.78)	(-24.05)	(-23.69)
Pseudo R^2	0.133	0.190	0.184	0.236	0.219	0.236	0.255
LR Chi^2	2397.09	3413.32	3304.48	4243.63	3948.54	4245.03	4595.75

Table 6. Marginal effects of predictors in models

This table reports the marginal effects (%) for our seven models. This measure is designed to examine the expected changes in outcomes in response to marginal changes in predictor variables. Marginal effects are computed while keeping all other variables constant. $^{+}$ denotes at 0.01 significance level.

Variable	Model A	Model B	Model C	Model D	Model E	Model F	AMS model
TLTA	1.5524^{+}			1.4176^{+}		1.4589^{+}	1.2678^{+}
NITA	-14.9810^{+}			-5.7307^{+}		-4.2987^{+}	-3.5104^{+}
WCTA	-1.8122^{+}			-0.7190^{+}		-1.0065^{+}	-0.5762^{+}
RELSIZE		-0.2910^{+}			-0.1622^{+}	-0.3173^{+}	-0.1793^{+}
EXRET		-1.0250^{+}			-0.7806^{+}	-0.7410^{+}	-0.6208^{+}
PRICE		-1.0159^{+}			-0.6083^{+}	-0.6879^{+}	-0.4304^{+}
FMVOL			0.6426^{+}	0.4592^{+}	0.3836^{+}		0.2959^{+}
RELVOL			-5.4971^{+}	-4.2571^{+}	-3.1699^{+}		-2.7041^{+}
CLDEF			0.2535^{+}	0.1593^{+}	0.2490^{+}		0.1715^{+}
RELLR			-0.0188^{+}	-0.0173^{+}	-0.0085^{+}		-0.0084^{+}

Table 7. Model predictive power statistics and goodness-of-fit tests

This table reports model predictive power statistics and the results from the model goodness-of-fit tests. Panels A and B show the information for the seven models in *t* and *t-2* respectively. The model predictive power measures are the area under ROC (AUC), the Gini rank coefficient, Cox-Snell's R^2, Nagelkerke's R^2 and Efron's R^2. The models' Chi-squared tests are also presented, where the degrees of freedom for each model are 3 for Models A and B, 4 for Model C, 7 for Models D and E, 6 for Model F, and 10 for the AMS model. The model goodness-of-fit tests include the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Standardised Pearson. The relatively small values of the tests indicate a better goodness-of-fit of the model.

Variable	Model A	Model B	Model C	Model D	Model E	Model F	AMS model
Panel A: performance in *t*.							
AUC	0.8483	0.9216	0.9180	0.9284	0.9378	0.9328	0.9420
Gini rank coefficient	0.6966	0.8432	0.836	0.8568	0.8756	0.8656	0.884
Cox-Snell's R^2	0.017	0.025	0.025	0.030	0.030	0.030	0.033
Nagelkerke's R^2	0.207	0.292	0.299	0.354	0.353	0.352	0.387
Efron's R^2	0.054	0.064	0.083	0.123	0.113	0.116	0.146
LR Chi^2 (3, 3, 4, 7, 7, 6, 10)	3977.66	5634.05	5763.73	6858.33	6820.99	6809.68	7498.91
(*p*-value)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
AIC	15942.686	14286.294	14158.615	13070.022	13107.360	13116.671	12435.437
BIC	-3940.680	-5597.072	-5714.423	-6772.034	-6734.696	-6735.713	-7375.637
Standardised Pearson	33314.04	30452.41	31548.88	25196.11	26758.36	25146.37	22926.31
Panel B: performance in *t – 2*.							
AUC	0.8192	0.8751	0.8738	0.8983	0.8949	0.899	0.9093
Gini rank coefficient	0.6384	0.7502	0.7476	0.7966	0.7898	0.798	0.8186
Cox-Snell's R^2	0.011	0.016	0.015	0.020	0.019	0.020	0.022
Nagelkerke's R^2	0.138	0.196	0.190	0.244	0.227	0.244	0.263
Efron's R^2	0.021	0.029	0.027	0.044	0.037	0.046	0.051
LR Chi^2 (3, 3, 4, 7, 7, 6, 10)	2397.09	3413.32	3304.48	4243.63	3948.54	4245.03	4595.75
(*p*-value)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
AIC	15616.750	14600.517	14711.353	13778.206	14073.292	13774.810	13432.085
BIC	-2360.337	-3376.571	-3255.485	-4157.882	-3862.795	-4171.528	-4473.254
Standardised Pearson	39077.90	36746.05	40682.39	35622.82	36329.20	34672.09	32452.76

Table 8. Hosmer-Lemeshow statistic for the AMS Model

This table presents the results from Hosmer-Lemeshow statistic investigating the goodness-of-fit of the AMS model. The probabilities are calculated for each quarter and the firms are then grouped into deciles based on the bankruptcy probabilities. The number of bankruptcy firms in each decile for each quarter is aggregated over 2000 Q1 to 2016 Q4 and reported in the table. 'Obs' shows the actual observed number of failed firms, while 'Exp' shows the expected number of failed firms that have been predicted within each probability decile for the proposed model. '%' indicates the frequency within the specified decile as a percentage of the total number of observations, while the last column, 'Total', presents the number of firm-quarters of each decile. Group 1 represents firms with low predicted bankruptcy probabilities and Group 10 represents firms with high predicted bankruptcy probabilities.

Group	Prob	Obs	%	Exp	%	Total
1	0.01%	5	0.30	1.1	0.07	22582
2	0.01%	6	0.36	2.3	0.14	22581
3	0.02%	2	0.12	3.6	0.21	22581
4	0.03%	12	0.71	5.4	0.32	22582
5	0.04%	16	0.95	8	0.47	22581
6	0.07%	10	0.59	12.6	0.75	22581
7	0.14%	30	1.78	22.5	1.33	22582
8	0.34%	63	3.73	49.1	2.91	22581
9	1.21%	110	6.51	148	8.76	22581
10	89.52%	1436	84.97	1437.4	85.05	22581
Total	91.39%	1690	100.00	1690	100.00	225813

Number of observations = 225,813

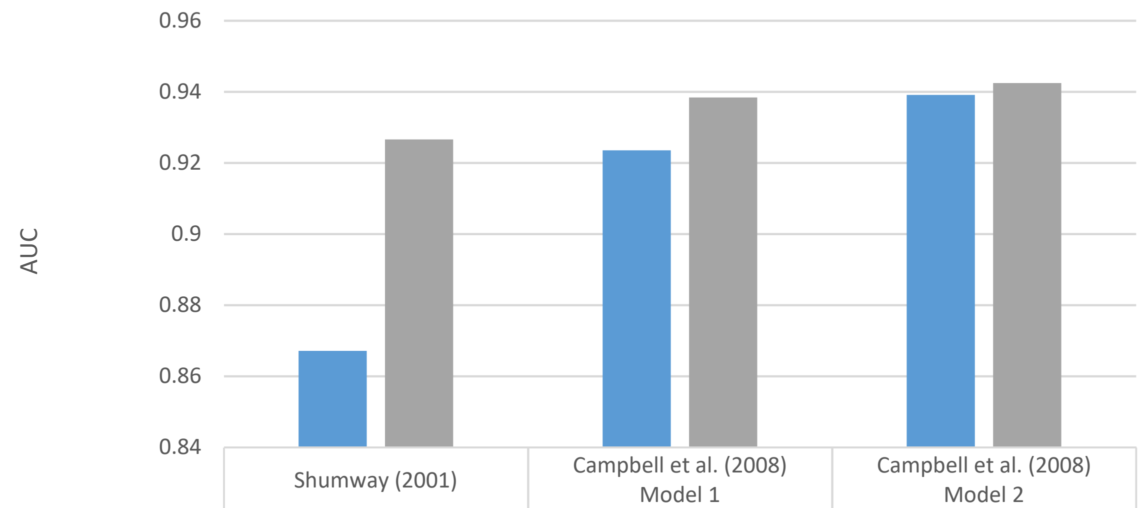
Hosmer-Lemeshow $Chi^2(8) = 53.32$

Prob > $Chi^2 = 0.0000$

Number of groups = 10

Figure 1. Incorporating Systemic Risk Information into Models in Previous Studies

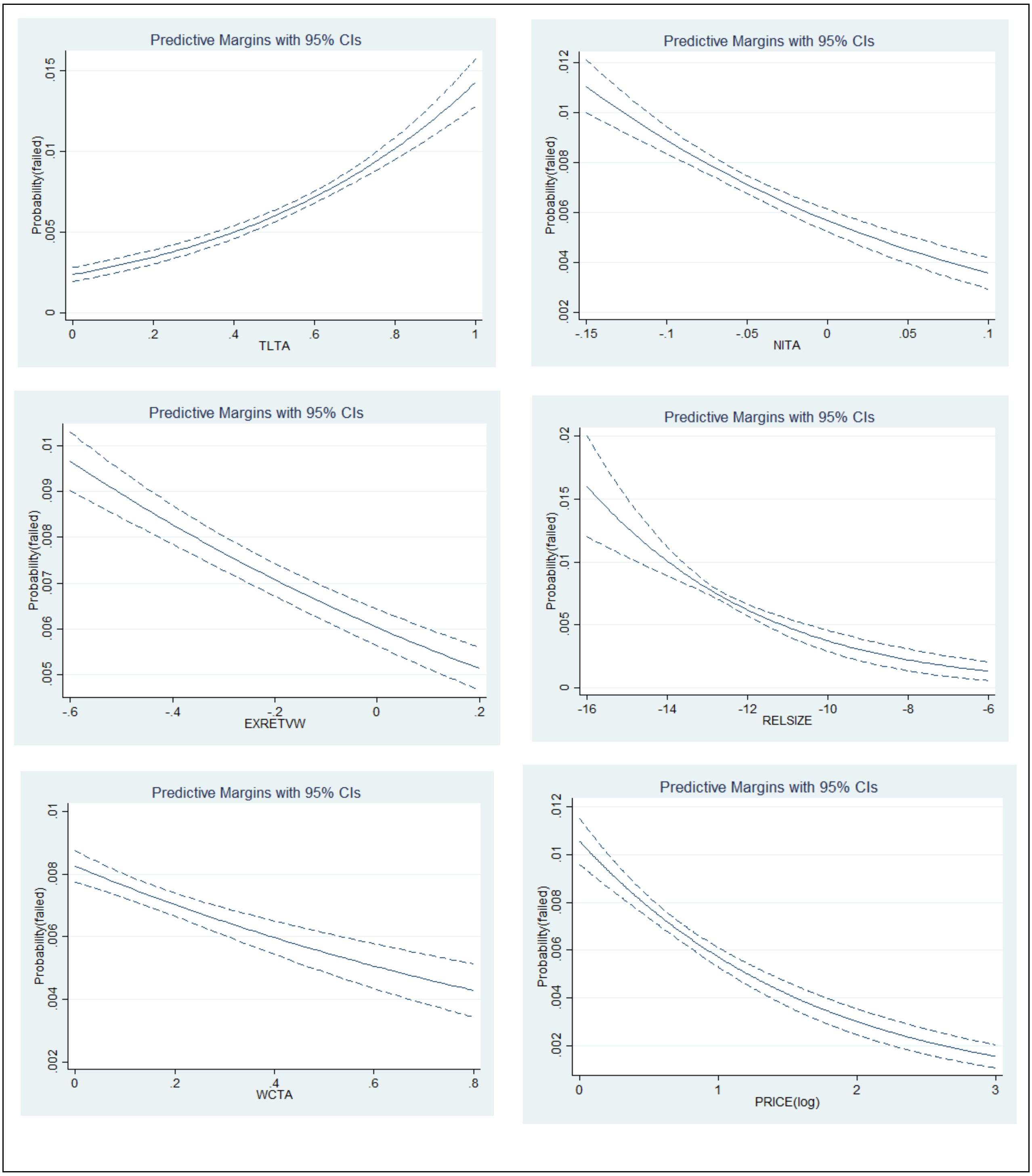
This figure plots the area under ROC (AUC) of previous models proposed by Shumway (2001) and Campbell et al. (2008), as well as the AUC of models when incorporating systemic risk measures into their original models.

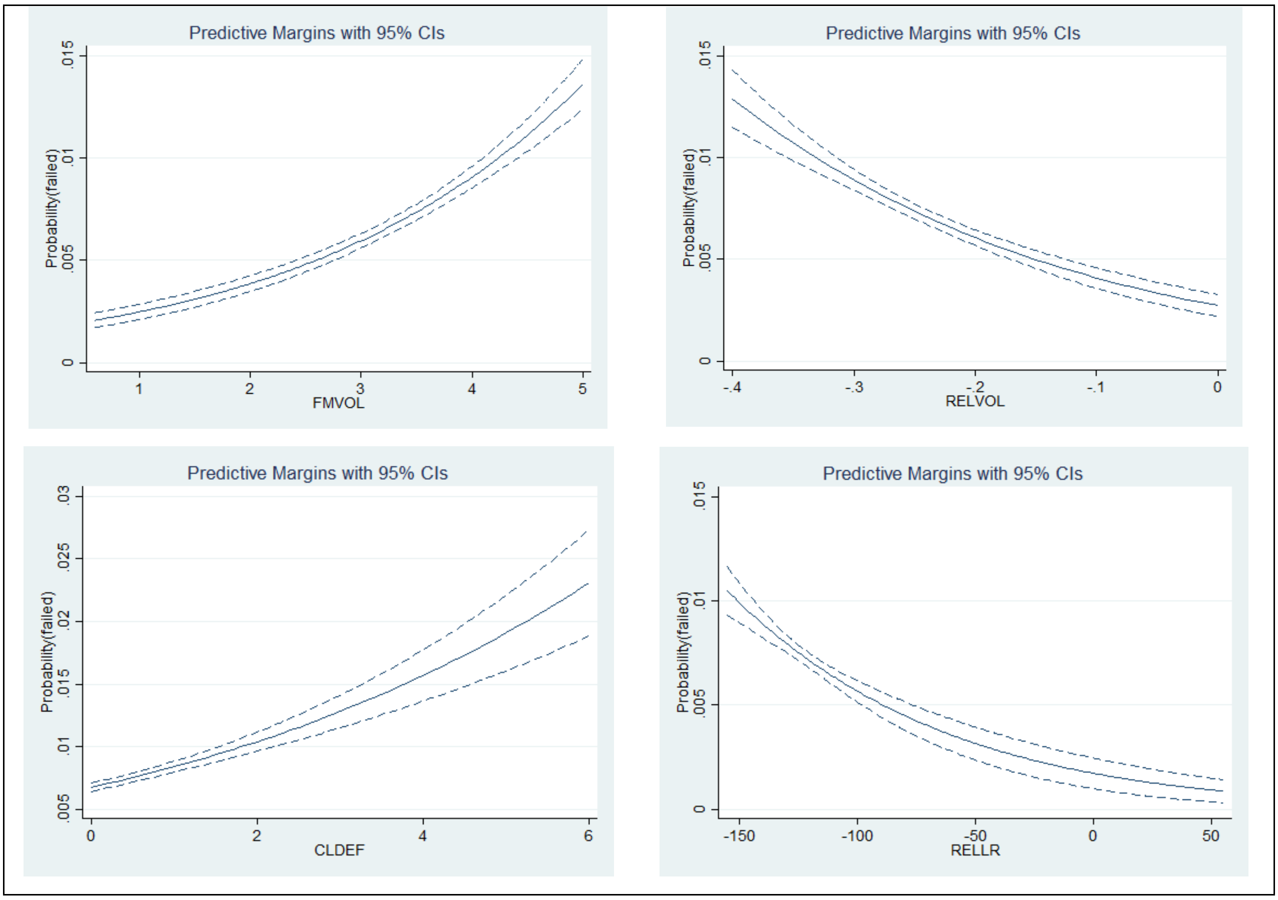


	Shumway (2001)	Campbell et al. (2008) Model 1	Campbell et al. (2008) Model 2
Original	0.8671	0.9235	0.9391
With Systemic Risk measures	0.9266	0.9384	0.9424

Figure 2. Changes in Predicted Probabilities

This figure plots the vectors reflecting changes in the probability of a firm failing. The computation was made considering all variables included in our AMS model in t. Similar shapes are shown in the prediction period of t-1 and t-2, so we do not present them here.




Predictive Margins with 95% CIs
Probability(failed)
0
.005
.01
.015
1
2
3
4
5
FMVOL
Predictive Margins with 95% CIs
Probability(failed)
0
.005
.01
.015
-.4
-.3
-.2
-.1
0
RELVOL
Predictive Margins with 95% CIs
Probability(failed)
.005
.01
.015
.02
.025
.03
0
2
4
6
CLDEF
Predictive Margins with 95% CIs
Probability(failed)
0
.005
.01
.015
-150
-100
-50
0
50
RELLR

APPENDICES

Appendix 1. List of variables

Table A.1a. List of Systemic Risk Measures

This table lists the set of systemic risk measures.

Category	Variable	Description
Institution-specific risk & Liquidity	CoVaR	Measuring individual financial company's contribution, from Adrian and Brunnermeier (2011).
	Δ CoVaR	-
	MES	Marginal Expected Shortfalls, from Acharya et al. (2017).
	SRISK	Systemic Risk, from Brownlees and Engle's (2016).
	AIM	Illiquidity measure, from Aimhud (2002).
Comovement & contagion	Absorption	Fraction of the financial system variance explained by the first 3 principal components, from Kritzman et al. (2011).
	Δ Absorption	-
	DCI	Dynamic Causality Index, from Billio et al. (2012).
	Intl. spillover	International Spillover, from Diebold and Yilmaz (2009).
Volatility & Instability	Volatility	Average equity volatility of 20 largest financial institutions.
	CatFin	A VaR measure, from Allen et al. (2012).
	Turbulence	Recent covariance relative to a longer-term covariance estimate, from Kritzman and Li (2010).
	Book lvg.	Average book leverage for 20 largest financial institutions.
	Mkt lvg.	Average market leverage for 20 largest financial institutions.
	Size conc	Size concentration in financial industry.
Credit condition	TED spr.	LIBOR minus the T-bill rate.
	Term spr.	The slope of the Treasury yield curve.
	Default spr.	BAA bond yield minus AAA bond yield.
	GZ	Credit spread measure, from Gilchrist and Zakrajsek (2012).
Measures not covered in Giglio et al. (2016)	CES	Component Expected Shortfalls, from Banulescu and Dumitrescu (2015).
	WSF	Whole Sale Funding, from López-Espinosa et al. (2012).

Table A.1b. List of Indicators of Bankruptcy

This table lists the set of indicators along with their respective definition that we use for the empirical analysis. Variables used in the work of Shumway (2001) and Campbell et al. (2008) are also included in this list.

Category	Variable	Definition
Accounting	WCTA	Working Capital/Total Assets
	RETA	Retained Earnings/Total Assets
	EBITTA	Earnings before Interests and Taxes/ Total Assets
	METL	Market Equity/Total Liabilities
	STA	Sales/Total Assets
	NITA	Net Income/Total Assets
	NIMTA	Net Income/Market Value of Total Assets
	TLTA	Total Liabilities/Total Assets
	TLMTA	Total Liabilities/Market Value of Total Assets
	CASHMTA	Cash and Short-term Investments/Market Value of Total Assets
Market	EXRET	Monthly Returns on Firm minus Value-weighted Market Returns
	SIGMA	Standard Deviation of Firm's Daily Equity Return over Last 3 Month
	RELSIZE	Log [Firm Market Capitalisation/Market Capitalisation of S&P 500]
	MB	Market Value/Book Value
	PRICE	Log [Price per Share Winsorised above $15]
Systemic Risk	FMVOL	SIGMA/Average Standard Deviation of 20 Largest Financial Institutions Equity Returns over Last 3 Month
	RELVOL	RELSIZE*Average Standard Deviation of 20 Largest Financial Institutions Equity Returns over Last Month
	CLDEF	Firm Debts in Current Liabilities*Default Spread over Last Month
	RELLR	RELSIZE*Average Market Leverage Ratio of Financial Institutions over Last Month

Appendix 2. Probability of bankruptcy in the quarter n

The likelihood of bankruptcy in the quarter n is assumed to be conditionally survival in the quarter n-1. This is given by (Campbell et al., 2008, page 2912 equation [4]):

$$\Pr\left(Y_{i(t+n)} = 1 \middle| Y_{i(t+n-1)} = 0\right) = \frac{1}{1+e^{-\alpha-\beta_1 x(1,it)-\beta_2 x(2,it)-\cdots-\beta_k x(k,it)}} \; .$$