Corporate Default Risk in Emerging Markets

Gonzalo Asis

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1 Introduction

Economists and policymakers are worried about the poor health of non-financial corporations around the world. McKinsey & Company reported in February 2015 annual global debt growth of 5.3% and corporate debt growth of 5.9% between 2007 and 2014. Standard & Poor's data shows global debt to earnings ratios at 12-year highs, a result of both higher debt and the effect of weak global demand and lower commodity prices on revenues. The consequences of these poor solvency conditions are starting to show. Moody's reported on March 1^{st} that global corporate defaults had reached their peak since the Global Financial Crisis (GFC). Furthermore, the rating agency forecasted a 30% year-over-year increase in speculative-grade defaults by the end of 2016.

Even though corporate fragility has expanded worldwide, emerging markets (EMs) seem to be the most compromised. The International Monetary Fund raised a flag about EM corporate leverage in its 2015 Global Financial Stability Report, which shows 4 times larger EM corporate debt levels in 2014 than in 2004. The report warns about the quality of the firms holding the debt, noting that the share of debt held by troubled firms is the highest in over a decade. Furthermore, it shows that EM corporate debt constitutes a significant part of domestic bank assets - as much as 50% or more of total loans for eight EMs.

Policymakers are monitoring debt composition, too. Avdjiev et al. (2014) specifically show that total dollar bond issuance doubled between 2010 and 2014. IMF (2015) worries about the increase in bonds as a share of total debt, since the authors argue that bonds are harder to apply macro-prudential measures to than bank loans.

Currency denomination of the debt is yet another source of concern. The sharp appreciation of the U.S. dollar has added extra pressure on NFCs with large liabilities denominated in the greenback. Avdjiev et al. (2015) document that borrowers residing in emerging markets account for over a third of global dollar credit to non-banks outside the U.S. and that dollar bond issuance doubled between 2009 and 2015. Bruno and Shin (2016) use BIS data to show that issuance of international debt securities in foreign currency by NFCs rose from \$3 billion in Q1 2001 to over \$60 billion in Q1 2015. \$51.6 billion of those \$60 billion were denominated in U.S. dollars. The shortage of accurate data on currency composition has limited the research on the drivers and consequences of high currency exposure.[1] However, the view most widely held is that foreign-currency liabilities are in fact a concern for EM NFCs – and particularly troubling for firms that do not have natural currency hedges in place (e.g. firms in non-tradable industries).[2] Harvey and Roper (1999) show that high foreign currency-denominated leverage and with low profitability were important factors spreading the East Asian Financial Crisis. Dell'Ariccia et al. (2015) corroborate the idea that foreign currency borrowing increases systemic risk and exposes lenders to the risk of default if the borrower's currency depreciates sharply.

[1] The two major issues compiling accurate data on debt currency composition are: 1. Many corporate reports present the currency composition of their liabilities in the notes of the reports and not in hard data, and 2. the use of offshore intermediaries to borrow funds makes it difficult to establish the residence of the ultimate debt-holder (a problem documented in Shin and Zhao (2013) and Avdjiev et al. (2014) among others).

[2] Kalemli-Ozcan et al. (2015) and others find that currency exposure is not as risky for companies with natural hedges.

Many also find the recent surge in offshore borrowing troublesome. Bruno and Shin (2016) show that more than 50% of NFC international debt securities since 2010 have been issued by offshore affiliates of EM NFCs. The implication of this is that large NFCs are acting as financial intermediaries, as they borrow from abroad and funnel the funds into their local economies.

This cross-border financial activity of NFCs presents several dangers in addition to the obvious foreign currency risk. First, Bruno and Shin (2016), Caballero et al. (2015), and Avdjiev et al. (2014) express concerns about NFCs using leverage for speculative activities, since it exposes them more directly to market conditions. Second, Chui et al. (2014) suggest that since larger, more creditworthy EM NFCs have access to international markets, local banks end up lending to smaller, riskier firms than they otherwise would. Bruno and Shin (2016) concur – the carry trades performed by EM NFCs help channel international funds into their local economies, expanding the supply of credit and easing funding conditions for smaller, riskier domestic borrowers. Hattori et al. (2009) argue that this is exactly what happened in Japan in the 1980s. When international markets opened to large NFCs, banks were forced to target riskier sectors for their lending (e.g. real estate), resulting in a huge financial asset bubble and ensuing 'lost decade'. Third, Avdjiev et al. (2014) suggest that offshore intermediaries play a role in evading capital controls and transmitting external macroeconomic conditions into the domestic financial system. Last, since the regulations on non-banks are not as strict as those on banks, NFCs are likely to engage in riskier lending practices than their financial counterparts.

Other papers focus on specific financial sheet variables to identify corporate malaise. Alfaro et al. (2016) use firm-level data to show that corporate fragility is currently less severe but more widespread in EMs than during the build-up of the East Asian Financial Crisis (EAFC). The authors emphasize today's higher liquidity needs (measured by current over total liabilities), weaker solvency positions (lower interest coverage ratios), and lower return on invested capital. They show that high corporate leverage following the GFC is more widespread than in the pre-EAFC period. However, no country has debt levels as high as the troubled East Asian nations in the mid-1990s. More specifically, seven countries have debt-to-equity ratios above 1 compared with only four in pre-EAFC. But South Korea had a 2.8 ratio on average in the years leading up to the EAFC and the highest ratio post-GFC is below 1.5.

Chui et al. (2014) and Bruno and Shin (2016) also focus on firms' balance sheets, as they point out the increase in cash holdings among NFCs in EMs. Both papers argue that firms are not accumulating cash as a precautionary measure, but to engage in cross-border speculative activities (i.e. to take advantage of interest rate spreads). Hence, the traditional belief that cash increases a firm's repaying ability may not hold in this environment.

Lastly, there are concerns about the financial system's exposure to corporate fragility. Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke et al. (1999), and Mendoza (2005) show that the financial system amplifies macroeconomic shocks. This suggests that banks' exposure to corporate defaults will partially determine the extent to which a regional corporate crisis affects the global economy. Chui et al. (2014) worry that the co-existence of asset- and liability-side exposures can cause a powerful feedback effect to the financial system, amplifying the macroeconomic impact of exchange and interest rate shocks. The asset exposures they mention include loans to corporations that are subject to currency and rollover risk. By liability exposures they refer to corporate deposits, which are particularly risky if firms are acting as financial intermediaries. The authors argue that the realization of rollover and currency risks would increase the financing costs of NFCs and worsen funding conditions, consequently hurting economic growth. At the same time, local banks and other EM corporate debt holders would suffer from drops in bond prices, while banks lose capital as troubled firms withdraw their deposits.

All these concerns are exacerbated by the global monetary outlook. The IMF is one of many to point out that a potential reversal of global monetary conditions is a key risk for the emerging market corporate sector. Should interest rates go up in advanced economies, in particular in the U.S., the smaller carry on EM currencies would lower the demand for EM securities, making debts pricier to roll-over. As the U.S. dollar rises in response to the higher U.S. rates, dollar-denominated liabilities in EMs would grow in local currency terms. Powell (2014) shows similar concerns about global debt paired with other macro conditions. In particular, the report warns about the risk of asset price drops, currency depreciations, and a fall in Chinese demand for raw materials damaging the repaying ability of EM NFCs.

The purpose of this project is to explore the determinants of corporate bankruptcy risk in emerging markets – the firm variables and market data policymakers should pay attention to if concerned about widespread defaults. In addition to their particularly fragile status, a number of fundamental idiosyncrasies of EMs justify a specific approach to analyze their corporate health. First, Mendoza and Terrones (2008) find that corporate credit booms in EMs are followed by larger macroeconomic responses (such as drops in output, investment, and consumption) than in advanced economies. The authors also show that credit expansions are determined by different factors in the two regions: financial reforms and productivity gains in advanced economies and large capital inflows in EMs. Second, an extensive literature on capital flows suggests that emerging markets have higher liquidity risks than advanced economies.[3] Third, EMs have larger exposure to currency risk, since around 80% of outstanding EM bonds are denominated in a foreign currency (largely the U.S. dollar).[4] Fourth, the partial opening of international financial markets has given rise to offshore financial intermediation in EMs. As mentioned before, the large, creditworthy firms that have access to international capital borrow from abroad and funnel the funds into their local economies, in what resembles a carry trade.[5] This not only increases currency risk for the intermediaries, but it also reduces the effectiveness of capital controls and leaves domestic banks able to lend only to the smaller, riskier local firms.

The paper contributes to the existing corporate default literature in three ways. First, it determines which accounting, financial market, and macroeconomic variables are associated with corporate default in emerging markets – and compare them to those in advanced economies. Second, it improves corporate default predictability in emerging markets. The lack of studies specific to emerging markets makes it difficult to estimate corporate default risk in the region. Instead of simply adjusting the coefficients on variables borrowed from U.S.-based models, my specification includes the set of explanatory variables that maximizes predictive power for the countries in the sample. Third, the paper includes asset pricing im-

[3] See Koepke (2015) for a survey of the empirical EM capital flows literature.

[4] World Bank data.

[5] Documented by Chui et al. (2014) and Bruno and Shin (2016), among others.

plications of the model, testing whether market participants are accurately pricing default risk in EMs.

The rest of the paper is organized as follows. Section 2 explores the literature on the determinants of corporate default, focusing on the ability different models to accurately predict bankruptcy. It follows its progression from correlations between individual accounting ratios and bankruptcy to hazard models that include accounting, market, and macroeconomic data to estimate firms' likelihood of default. Section 3 presents the data I plan on using for the analysis. Section 4 explains the model and variable selection methodology. Section 5 discusses the intended asset pricing analysis. Section 6 concludes.

2 Determinants of Corporate Default

Debt levels have received the bulk of the scrutiny in the analysis of corporate health and prediction of corporate default. However, several studies have shown the importance of other variables in forecasting default. Edward Altman developed the most influential measure of corporate default risk in 1968, the Z-score.[6] Before his work, the literature on corporate bankruptcy predictors was developed almost exclusively using univariate methods, i.e. focusing on just one ratio at a time to estimate the probability of corporate failure.[7] Altman hypothesized that using multiple variables simultaneously would improve the accuracy of previous studies. From a starting list of 22 accounting ratios used in prior research, Altman found a set of five ratios and coefficients that best predicted bankruptcy for his 66 U.S. manufacturing firms (33 bankrupt) and 20 years of data. The measure that results from combining them is known as Altman's Z-Score, and it decreases in the probability of bankruptcy:

$$Z = .012X1 + .014X2 + .033X3 + .006X4 + .999X5$$

where $X1$ = working capital to total assets, $X2$ = retained earnings to total assets, $X3$ = EBIT to total assets, $X4$ = market value of equity to book value of total liabilities, and $X5$ = sales to total assets.

The estimation method Altman uses is Multiple Discriminant Analysis (MDA). The reason for using MDA is that the estimation aims to derive a linear combination of the independent variables that best discriminates between the dependent variable's categories. Since the dependent variable categories Altman uses are "bankrupt" and "non-bankrupt", the resulting set of characteristics and coefficients can be used to measure the probability of bankruptcy. When tested in sample using data one year prior to bankruptcy, his model classifies correctly 31 bankrupt and 32 non-bankrupt firms out of the 33 of each. But when trying to predict bankruptcy with data two years in advance, the model predicts only 23 bankrupt and 31 non-bankrupt accurately. The model showed very little predictive power using data from more than two years before failure. Taking it out of sample, 96% of bankrupt and 79% of non-bankrupt firms are correctly classified one year prior to bankruptcy. The

[6]See Altman (1968).

[7]Beaver (1966) was the first to use multiple accounting ratios to predict bankruptcy, but he simply investigated if specific ratios were good predictors of failure by comparing them in bankrupt and non-bankrupt firms.

lower performance in classifying non-bankrupt firms led Altman to create a "gray area" in the Z-Score range (between 1.81 and 2.99) in which a firm's fate is "uncertain".

Houghton and Woodliff (1987) perform a similar analysis to Altman (1968), using Discriminant Analysis on a set of 12 bankrupt and 36 non-bankrupt firms. While looking for determinants of corporate success, they find another determinant of corporate failure overlooked by Altman: low dividends to earnings.

Both papers mentioned so far perform their analysis on small sample sizes. Ohlson (1980) aimed for more robust conclusions using a dataset of 105 bankrupt and 2,058 non-bankrupt firms. More importantly, the author used a likelihood estimation of a conditional logit model instead of the hitherto more common Multivariate Discriminant Analysis. He defended his choice by pointing out the following problems with MDA: (1) it assumes equal variance-covariance matrices for both default and non-default groups of firms, (2) the estimation output is an ordinal ranking with little economic interpretation, and (3) bankrupt and non-bankrupt firms in the studies are matched based on some arbitrary characteristics (e.g. size, industry), instead of incorporating those characteristics into the model as predictors of default. By estimating a conditional logit model, Ohlson avoids any assumptions about the distributions of predictors or the prior probabilities of bankruptcy. He argues that the estimation problem can be reduced to the following question: "given that a firm belongs to some pre-specified population, what is the probability that the firm fails within some pre-specified time period?"

The results from Ohlson's estimation show that corporate default is associated with small firm size, low net income to total assets, high total liabilities to total assets, and low working capital to total assets. However, when testing his predictive model, the author found that it is unable to match the predictive power of Altman's (1968)—85% prediction rate in-sample compared to Altman's 95% for bankrupt firms. To this he attributes differences in the data collection process (sample size, time period, and Altman classifying bankruptcy based on the less periodical Moody's Manual than Ohlson's data from firms' 10-K reports) but admits that such differences cannot explain the entire resulting variance.[8] Finally, Ohlson calls for independent testing of different models and suggests that incorporating price data to the model would increase its predictive power.

Zmijewski (1984) challenges the methods used by Altman, Ohlson, and others. The author points out that the assumptions made in previous models of corporate failure risk (e.g. random sampling, conditioning on complete data) are not appropriate given the sampling process. Specifically, by using datasets containing a much larger percentage of bankrupt firms than that of the entire population, standard estimation techniques yield biased parameter and probability estimates. Zmijewski's solution is to estimate a probit model using the weighted exogenous sample maximum likelihood (WESML) technique. This method differs from a standard maximum likelihood estimation in that it weighs the log-likelihood function by the ratio of the population frequency rate to the sample frequency rate of the bankrupt and non-bankrupt groups. Zmijewski's estimation of the unweighted probit with and without the WESML adjustment yield the following results. First, there exists a sample bias when using an unweighted probit but not when adjusting for sample and population differences.

[8] Predictive ability seems to vary by time period, as Begley, Ming, and Watts (1996) show that Ohlson's model outperforms Altman's in the 1980's.

Second, the bias diminishes as the sample percentage of bankrupt firms approaches the population percentage.

The purpose of Zmijewski (1984) is not to develop a premier prediction model, but to shed light on the estimation errors made in the literature and suggest an alternative approach. However, the coefficients from the estimation of his model are informative given that he uses the three most common determinants in the literature – net income to total assets, total debt to total assets, and current assets to current liabilities. His dataset contains all non-financial firms listed in the NYSE or AMEX between 1972 and 1978 – a population that includes 81 bankruptcies and a range of 2,082-2,241 firms per year. As expected, higher leverage and lower return on assets are associated with a higher probability of default, while the relationship between liquidity and default risk is not statistically significant.

Most models up to this point were static in the sense that they ignored a firm's behavior over time when estimating its probability of bankruptcy. Shumway (2001) points out that in order to use a static model effectively researchers must have a very long time-span of data. They must also choose arbitrarily how long ahead of bankruptcy to observe the firms' characteristics—adding selection bias to the process. Shumway instead calls for using dynamic forecasting models, though he was not the first to make this suggestion. Queen and Roll (1987) use only market data (price, average return, volatility of return, beta and market capitalization) in multiple logistic regressions and find that low firm size, low returns, and high return volatility are significant predictors of corporate default one year in advance. Only firm size remains significant at longer horizons. The dynamism is introduced by calculating mortality rates through time and observing their correlation with explanatory variables. For instance, the authors order firms in ten groups based on size and tally how many firms from each decile go bankrupt in each of the 23 years analyzed. They find a strong negative relationship between size and mortality rates: the number of firms that go bankrupt through time is highest in the smallest decile and lowest in the largest decile.

Shumway's (2001) main contribution was estimating a hazard model, which enabled him to "use all available information to determine each firm's bankruptcy risk at each point in time". This improves the static logit model in that it includes all firm-years as observations instead of only one firm-year for each firm. Specifically, the author uses a dataset of non-financial firms that began trading between 1962 and 1992 on either NYSE or AMEX. The resulting dataset contains 300 bankruptcies among 3,182 firms and 39,745 firm-years. The dependent variable is set to 1 when the firm goes bankrupt and to 0 otherwise. Firms that leave the healthy group for reasons other than bankruptcy (e.g. merger or delisting) are ignored.

There are several advantages to using a hazard model. First, it allows the researcher to control for "period at risk"—the fact that some firms fail after being at risk for many years and others go from healthy to bankrupt much faster. Second, a hazard model allows explanatory variables to change with time, providing a picture of a firm's changing health. Third, by including each firm-year as a separate observation, the amount of data used for estimation is much larger (ten times larger if we have ten years of data) than in static models. While Altman (1968) and Ohlson (1980)'s methods use only the most recent data to explain bankruptcy, Shumway's hazard model takes into account all available data since the firm went public.

The hazard model was developed to deal with duration data—in Shumway's case, the amount of time a firm stays healthy. Its main tenet is that it uses conditional probabilities: the probability that a firm remains healthy t years given that it has been healthy t-1 years. This conditional probability is known as a hazard function for the random variable "years healthy", and the probability of surviving up to time t is called the survivor function. When estimating a hazard model through maximum likelihood, the hazard function takes the place of the CDF and the survivor function of (1-CDF). Shumway proves that estimating the probability of bankruptcy in a static setting introduces biases and overestimates the impact of the predictor variables, while the estimate of a discrete-time hazard model is never biased and consistent in some cases. This is because the static model does not take into account that a firm could have had unfavorable indicators several periods before going into bankruptcy.

Another contribution of Shumway (2001) was adding equity market variables to the set of scaled accounting measures used in the earlier literature. After estimating the model, the forecasting part of the exercise involves using the estimated coefficients to order firms from most to least likely to fail. His results are encouraging: out of sample, the model classifies 75% of bankrupt firms in the highest bankruptcy decile, and it only classifies 3.5% percent of bankrupt firms below the bankruptcy probability median. After testing his model using both existing and novel specifications (including Altman's (1968) with and without market-driven variables), the author concludes that bankruptcy forecasts are more accurate when adding equity market variables to models. The set of variables that performed best in his testing comprises market size, past stock returns, idiosyncratic standard deviation of stock returns, net income to total assets, and total liabilities to total assets.

Chava and Jarrow (2004) use an expanded bankruptcy dataset and improve the observation intervals to monthly frequency. This dataset of U.S. firms listed in both Compustat and CRSP contains 1,461 bankruptcies between 1962 and 1999, compared to no more than 300 bankruptcies for most other previous studies. The authors show that using monthly data improves the predictive power of their model.

The improved sample also allows the authors to investigate the role of industry effects in bankruptcy prediction. Opler and Titman (1994) show that "the adverse consequences of leverage are more pronounced in concentrated industries", suggesting that the industry a firm belongs to influences its bankruptcy risk. Recent data corroborates this claim. Some of the largest and most leveraged NFCs in EMs today are energy producers. The drop in commodity prices has weakened their cash receipts, further hurting their solvency. According to Moody's, The Metals & Mining sector had the highest default rate in 2015 at 6.5%, followed by the Oil & Gas sector at 6.3%.

To explore the extent to which industry effects influence the probability of default, Chava and Jarrow (2004) include intercept and slope dummy variables for the industry groups in their models, which is equivalent to running one hazard model for each industry group. The four industry groups are based on regulatory environments and asset structures: (1) finance, insurance, and real estate; (2) transportation, communication, and utilities; (3) manufacturing and mineral; and (4) miscellaneous (all other industries). One model is run with only the accounting variables in Zmijewski (1984) and another adds the market variables used in Shumway (2001).[9] The latter yields better prediction results. In the estimation that

[9]Zmijewski's variables: net income to total assets (NI/TA), total liabilities to total assets (TL/TA), and

excludes the financial industry group, the industry coefficients are almost all statistically significant, and the whole set of industry variables is statistically significant using a chi-squared test – indicating the existence of an industry effect.

The intercept coefficients indicate that the probability of default is largest for Industry 4 (miscellaneous), followed by Industry 3 (manufacturing and minerals). Firms in Industry 2 (transportation, communication, and utilities) are the least likely to fail. The slope coefficients (interactions of industry dummies with accounting variables) show that industries 2 and 3 are less sensitive to low net income to total assets and more sensitive to high leverage than Industry 4.

Considering industry effects also yields better results in the prediction of bankruptcy, though not by a large margin. When using only accounting variables, adding industry effects improves the percentage of correctly identified bankrupt firms in the top two deciles from 60% to 60.8%. It also reduces the percentage of incorrectly identified (placed in the bottom 5 deciles) bankrupt firms from 17.6% to 15.2%.

One more contribution Chava and Jarrow (2004) make is to validate Shumway's hazard model by showing that it outperforms Altman's (1968) and Zmijewski's (1984). 86.4% of the firms Shumway's model places in the two deciles most likely to fail are indeed firms that go bankrupt. This is compared to the 77.6% and 43.2% identified by Altman's and Zmijewski's models, respectively.

Campbell et al. (2008) build on the work of Shumway (2001). Their paper uses 1963-2003 US data (1.7 million firm-months) to show that firms are more likely to enter distress if they have higher leverage, lower profitability, lower market capitalization, lower past stock returns, more volatile past stock returns, lower cash holdings, higher market-book ratios, and lower prices per share.[10] The authors reach this conclusion by estimating a hazard model of an indicator of financial distress on accounting and equity market variables. They use Shumway's (2001) specification as base and make modifications that improve the model's predictive power. First, they divide net income and leverage (both explanatory variables) by market value of assets instead of book value. Second, they add corporate cash holdings, Tobin's Q, and price per share to the set of explanatory variables. Third, the authors study default forecasts at different horizons, finding market capitalization, market-book ratio, and equity volatility the most consistently predictive characteristics of corporate distress.

To study the response of failure risk to changes in different variables, the authors shock each variable individually by one standard deviation and measure the consequent response of the probability of failure. They find that changes in leverage, volatility, share price, and profitability are the most important for failure risk; the one-standard deviation shocks change the probability of failure by 156%, 64%, -56%, and -44% respectively. Though impressed by the performance of the structural approach used by Crosbie and Bohn (2003) and others, Campbell et al. (2008) conclude that using a reduced-form econometric approach that includes other variables and allows leverage and volatility to enter with free coefficients is preferred. Bharath and Shumway (2004) also find that "distance to default" based on the work of Merton (1974) does not add much explanatory power to the model, supporting the

current assets to current liabilities (CA/CL). Shumway 's variables (NI/TA), (TL/TA), relative size (RSIZ), excess return (EXRET), and the stock's volatility (SIGMA).

[10]The authors define distress as either filing for bankruptcy, getting delisted, or receiving a D rating.

use of reduced-form models to estimate probability of default.

Finally, Campbell et al. (2008) study the asset pricing implications of their results using their fitted probability of failure as a measure of financial distress. Their main finding is that stocks of distressed companies experience abnormally low returns.

The literature up to this point includes several different specifications. Wu et al. (2010) perform a comprehensive evaluation of the performance of the different models (MDA, probit, standard logit, and hazard) using different data (accounting variables, market data, and firm characteristics like size and corporate diversification). They find that the predictive power of models varies through time, suggesting that each is capturing a different aspect of corporate fragility. Their two main results are that a model that integrates all three types of variables outperforms all others in forecasting ability, and that the hazard model chosen by Shumway (2001) outperforms its methodological counterparts. To reach the first conclusion, the authors compare the performance of a hazard model containing as explanatory variables the sets of variables used by Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001). To show that the hazard model beats MDA, probit, and standard logit, they use an updated dataset to re-estimate each of the models using the same econometric specification as the original authors.

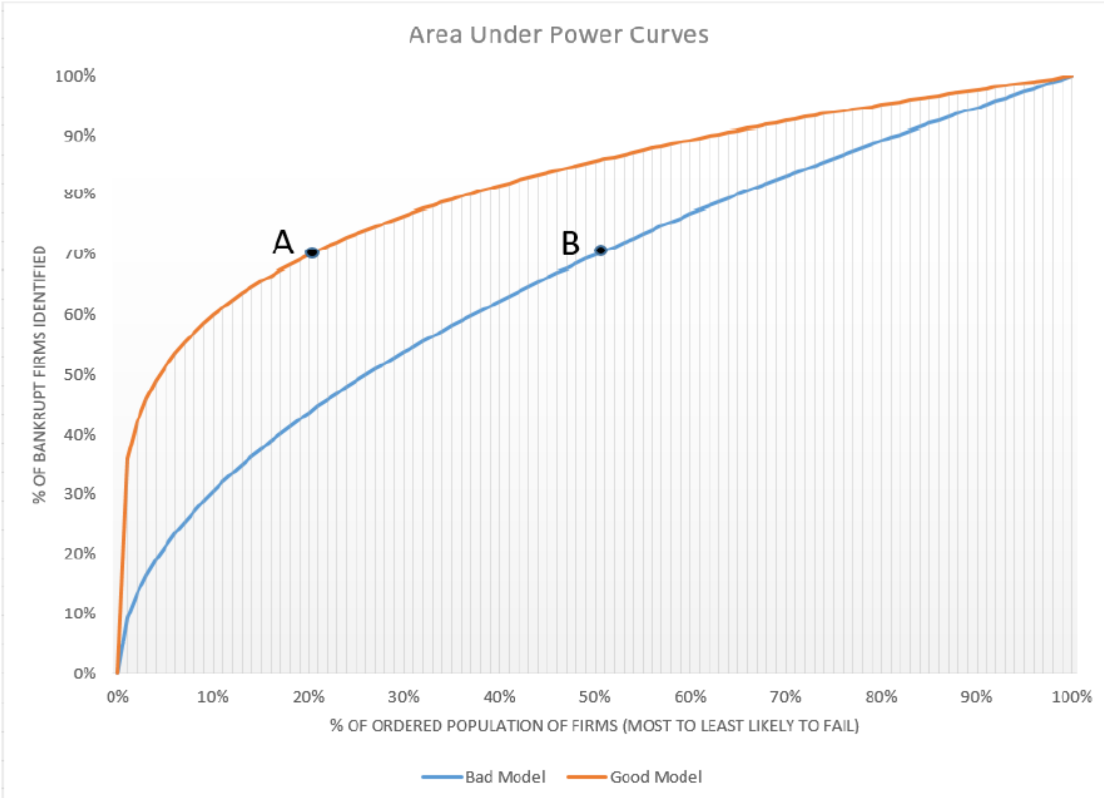
Wu et al. (2010) also develop their own set of variables to test alongside the existing models. These variables are mostly borrowed from the literature, though with some additions and modifications. These are: EBIT to total assets, change in net income (Profitability); working capital to total assets (Liquidity); total liabilities to market value of total assets (Leverage); share price (Size); and lagged excess returns, lagged return volatility, and a measure of corporate diversification (Firm characteristics).

Throughout the paper, the authors rely on Pseudo-R^2 and the Receiver Operating Characteristics (ROC) score – also used by Chava and Jarrow (2004) – as a measures of a model's ability to discriminate between bankrupt and non-bankrupt firms. The ROC score, also known as "area under the power", is computed using the cumulative fraction of defaults as a function of the ordered population of firms (from most to least likely to fail as predicted by the model). Figure 1 shows an example. Point A on the plot tells us that the 20% of firms that a particular model identifies as most likely to default include 70% of the firms that end up going bankrupt. On the other hand, point B signals that not until the fifth decile of firms (ordered from most to least likely to default) does the model identify 70% of bankrupt companies. The ROC is the area under the curve, and a larger area indicates that the model is correctly predicting more bankrupt firms as being likely to fail. The score ranges between 0.5, indicating no discriminatory power, and 1, implying perfect identification of bankrupt and healthy firms. Hence, the higher the score, the higher the model's predictive ability.[11] Wu et al.'s (2010) comprehensive model has a ROC score of 0.93, compared to 0.86, 0.89, 0.85, and 0.91 for Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001) respectively.

Giesecke et al. (2011) deviate from the established literature when they focus on predicting waves of defaults instead of failure of individual firms. They use a regime switching model on 150 years of U.S. data to examine to what extent corporate default crises can be forecast by financial and macroeconomic variables. They find that lower stock returns,

[11] Source for ROC score: Sobehart and Keenan (2001).

Figure 1: Receiver Operating Characteristics



higher stock return volatility, and lower GDP growth are strong predictors of higher default rates. They also arrive to the surprising conclusion that credit spreads are not as good at predicting corporate defaults.

All the research mentioned so far uses only U.S. data. I wrote in the introduction about the idiosyncrasies of EMs and the need to tailor research accordingly when using EM data. There is therefore value in studying the determinants of corporate default specifically in EMs. Any data limitations that prevented this from being done in the past no longer hold. My work aims to answer two main research questions. Do models developed for predicting corporate failure in the U.S. apply for predicting bankruptcy in EMs? If not, what other variables influence EM firms' probability of default? The next subsection presents the few research studies that use non-U.S. data, with the following purpose. First, to show that no bankruptcy prediction work has been done on a comprehensive dataset of EMs using a hazard model like in Campbell et al. (2008). And second, to consider their explanatory variables of choice as potential determinants of corporate default in EMs.

2.1 Bankruptcy Prediction Outside the United States

Pomerleano (1998) uses accounting ratios to study the build-up of the East Asian Crisis, finding excess leverage and poor capital performance in the years leading up to the crash. The author uses the following measures to study corporate health: leverage, debt sustainability, liquidity, profitability, tangible fixed assets growth and their financing, corporate vitality

(Tobin's Q), and financial fragility (Altman's Z-score). His data shows a dramatic increase of fixed assets financed largely by debt, as well as levels of short term debt much higher than in developed economies. He also finds a big drop in capital performance in the time period analyzed, in addition to much higher returns on equity and book-to-market ratios in Asia than in developed countries. The author concludes that there was an overuse of the banking sector and economy-wide over-leverage in Eastern Asia, which partnered with large foreign capital inflows to create very fragile financial conditions.

To adjust his Z-Score to the different environment in EMs – and instruct on its applicability – Altman (2005) introduces the Z" model and corresponding Emerging Market Scoring system.[12] The paper provides steps on how to adjust his credit rating model to each country using Mexico as a guide. These steps include reducing the score if the company is overly vulnerable to currency risk, belongs to a risky industry, or is not in a dominant position in such industry. The step to adjust for currency depreciation consists of downgrading the U.S. equivalent of the firm's bond between one notch (e.g. BB+ to BB) and one full class (e.g. BB+ to B+) depending on the level of vulnerability. This vulnerability is in turn assessed based on the level of foreign-currency debt relative to revenue and the level of foreign-currency interest expenses relative to profits. The resulting Z"-Score has different coefficients than the original Z-Score but the same predictors:

$$Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25$$

Kordlar and Nikbakht (2011) apply a slight variation of Shumway's (2001) model to the Tehran Stock Exchange. Their choice of variables outperforms Shumway's, but they are all borrowed from other studies. There is no effort from the part of the authors to adapt the variable set to the idiosyncrasies of EMs.

Xu and Zhang (2009), on the other hand, modify their variable set to match the characteristics of their target market – Japan. Adding a measure of dependence on banks and business groups (known as Keiretsu) improves the predictive power of their model, which the authors test on 3,510 listed firms (76 bankrupt) between 1992 and 2005. But they also show that the established models for prediction of U.S. bankruptcy can be safely applied to Japanese firms, since their resulting coefficients on the variables have the same sign and statistical significance as when applied to U.S. data.

Agarwal and Bauer (2013) test the predictive power of several models on a set of NFCs listed in the London Stock Exchange between 1979 and 2009. The authors find that the hazard model in Shumway (2001) and Campbell et al. (2008) has a higher ROC score than the traditional accounting-based approaches and the structural models I mention in the next section (0.90 versus 0.84 and 0.87 respectively).

Hernandez Tinoco et al. (2013) use a dataset of 23,218 firm-year observations of companies listed in the United Kingdom between 1980 and 2011. Notably, they add macroeconomic variables to the standard hazard bankruptcy prediction model. The variables they include in their model are: equity price, lagged cumulative security residual return, market capitalization relative to FTSE All Share Index, and market capitalization to total debt (market variables); inflation and short term interest rate (macroeconomic variables); and EBIT to

[12] More information on the specifics of the Z" model derivation can be found in Altman (2005).

total liabilities, total liabilities to total assets, working capital to daily operating expenses, and interest coverage (accounting variables).

The authors find that the model which includes all variables has higher explanatory power than models that include combinations of one or two types of variables (i.e. accounting and macro, market and macro, market only, or accounting only). It also achieves a higher ROC score when used to predict default. The following are the one-year determinants of corporate distress they find: low EBIT to total liabilities, high total liabilities to total assets, low working capital to daily operating expenses, low interest coverage, high inflation, high interest rates, low equity price, low residual returns, low relative market capitalization, and low market capitalization to total debt. When expanding the prediction horizon to two years, the signs of the coefficients remain the same and only relative market capitalization and total liabilities to total assets lose statistical significance.

Two other notable conclusions from their study are related to the effect of the macroeconomic variables to firm default. First, the size of the inflation and interest rate coefficients is small relative to those of the accounting and market variables. This indicates that they have a smaller effect on firms' likelihood of failure. Second, the addition of macroeconomic variables results in a tiny improvement in the model's predictive power with a one-year horizon. Their contribution even turns negative when predicting two years in advance – the ROC score decreases when adding macroeconomic variables to the accounting-only model.

Lastly, Hernandez Tinoco et al. (2013) introduce marginal effects as yet one more tool to analyze the effect of an independent variable on firm health. They argue that the methods used in the literature don't allow for direct interpretation of the relationship between the predictor variables and the binary outcome. Marginal effects, which are the partial derivative of the event probability with respect to a particular explanatory variable, can fill this gap.[13]

3 Data

The data I hope to use for this study is from the Risk Management Institute at the National University of Singapore. The dataset contains detailed bankruptcy, accounting, and market data for over 60,000 exchange-listed firms in 119 countries between 1990 and 2016. Out of the 119 countries, 78 of them have public exchanges to which RMI has data access. For the remaining countries, the dataset includes companies domiciled in the economy but listed in a foreign exchange. The following are the countries included in the dataset:

[13] As mentioned previously, Campbell et al. (2008) perform a similar analysis by shocking each variable individually and observing the impact on the probability of default.

Region	Economy
Asia Pacific (Developed) (7)	Australia, Hong Kong, Japan, New Zealand, Singapore, South Korea, Taiwan.
Asia Pacific (Emerging) (15)	Bangladesh, Cambodia, China, India, Indonesia, Kazakhstan, Macau, Malaysia, Mongolia, Pakistan, Papua New Guinea, Philippines, Sri Lanka, Thailand, Vietnam.
North America (4)	Bermuda, Canada, Greenland, United States.
Western Europe (28)	Austria, Belgium, Cyprus, Denmark, Faeroe Islands, Finland, France, Germany, Gibraltar, Greece, Guernsey, Iceland, Ireland, Italy, Isle of Man, Jersey, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, Reunion, Spain, Sweden, Switzerland, United Kingdom.
Eastern Europe (19)	Azerbaijan, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Montenegro, Poland, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Turkey, Ukraine.
Latin America and Caribbean (18)	Argentina, Bahamas, Belize, Brazil, British Virgin Islands, Cayman Islands, Chile, Colombia, Curacao, Dominican Republic, Falkland Islands, Jamaica, Mexico, Peru, Panama, Puerto Rico, U.S. Virgin Islands, Venezuela.
Middle East and Africa (28)	Angola, Bahrain, Cameroon, Egypt, Gabon, Ghana, Iraq, Israel, Jordan, Kuwait, Madagascar, Mauritius, Morocco, Mozambique, Namibia, Nigeria, Niger Republic, Oman, Qatar, Saudi Arabia, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Tunisia, United Arab Emirates, Zambia.

The countries I will include in my analysis are those classified as Emerging Markets by MSCI at any point during my sample period (1990-2016): Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Jordan, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, United Arab Emirates, Vietnam. For comparison purposes, I will also use data from the United Kingdom and the United States.

Since market data is fairly accessible, the value of this dataset resides in the broad coverage of financial statement data and, especially, of monthly bankruptcy-like events. As the tables below show, I can get detailed information about a company's reason for default or exit from the exchange. This is important because different countries have different definitions of default.

Default	
Action Type	**Subcategory**
Bankruptcy filling	Administration, Arrangement, Canadian CCAA, Chapter 7, Chapter 11, Chapter 15, Conservatorship, Insolvency , Japanese CRL, Judicial Management, Liquidation, Pre-Negotiation Chapter 11, Protection, Receivership, Rehabilitation, Rehabilitation (Thailand 1997), Reorganization, Restructuring, Section 304, Supreme court declaration, Winding up, Work out, Sued by creditor, Petition Withdrawn, Other
Delisting	Bankruptcy
Default Corporate Action	Bankruptcy, Coupon & Principal Payment, Coupon Payment Only, Debt Restructuring, Interest Payment, Loan Payment, Principal Payment, ADR (Japan only), Declared Sick (India Only), Regulatory Action (Taiwan only), Financial Difficulty and Shutdown (Taiwan only), Buyback option, Other

Other Exits	
Action Type	**Subcategory**
Delisting	Acquired/Merged, Assimilated with underlying shares, Bid price below minimum, Cancellation of listing, Failure to meet listing requirements, Failure to pay listing fees, Inactive security, Insufficient assets, Insufficient capital and surplus, Insufficient number of market makers, Issue postponed, Lack of market maker interest, Lack of public interest, Liquidated, Not available, Not current in required filings, NP/FP finished, Privatized, Reorganization, Security called for redemptions, the company's request, Scheme of arrangement, Selective capital reduction of the company, From exchange to OTC, Privatised, Other

To get a better idea of the contents of the bankruptcy data, the table below shows how many firms defaulted or had "other exits" in Brazil per year.

Economy: BRA

Year	Defaults	Others
1994	1	0
1995	2	1
1996	0	1
1997	7	21
1998	8	47
1999	3	48
2000	2	49
2001	0	50
2002	3	35
2003	2	33
2004	1	24
2005	1	24
2006	0	26
2007	0	14
2008	0	29
2009	0	23
2010	0	21
2011	0	20
2012	6	16
2013	10	6
2014	6	14
2015	2	6

The next table shows the variables I plan on using for my model. Many of them were found to be significant determinants of corporate default in the literature, and I chose others that measure some of the EM-specific risks discussed in the introduction. In some cases, I may use slight modifications of these variables; e.g. use an alternative measure of profitability or divide net income by the market value of total assets instead of book value. The list is subject to change based on data availability. The sign to the right of each variable is the expected sign of its correlation with the firm's probability of default.

Variable List	
Type	Variable
Accounting	Retained earnings to total assets (-) Market value of equity to book value of total liabilities (-) Sales to total assets (-) Net income to total assets (-) Total liabilities to total assets (+) Working capital to total assets (-) Current assets to current liabilities (-) Return on assets (-) EBIT to interest expenses (-) Cash holdings (?) Return on Investment (-) Return on Equity (-) Change in Property, Plant, and Equipment (?) Sales abroad (interact with exchange rate) Imported intermediate goods (interact with exchange rate) Liabilities denominated in a foreign currency (?) Bond to loans ratio (?)
Market	Stock returns (-) Volatility of stock returns (+) Bond prices (-) Bond yield spreads (+) Market capitalization (-) Market capitalization relative to country median (-) Market-to-book ratio (?) Returns relative to main stock index in the country (-)
Firm	Firm age (or years listed) (-) Industry classification Credit rating (-) Average loan term (e.g. in months) (-)
Macroeconomic	Interest rates (+) Inflation (+) Change in exchange rate (?) GDP growth (-) Unemployment rate (+) Offshore bond issuance over total bond issuance (+) Change in cash over change in leverage – a measure of offshore intermediation (+) Global liquidity (?) Measures of institutional quality? Terms of trade (-) Capital account openness (?)

4 Methodology

I divide the sample of firms into two groups: firms that default during the sample period ("bankrupt") and firms that remain healthy throughout ("non-bankrupt"). The dependent variable in the model is a binary variable Y, where $Y_{i,t} = 0$ in the periods that firm i is non-bankrupt and $Y_{i,t} = 1$ in the periods that goes bankrupt.

Following the work of Shumway (2001), Campbell et al. (2008), and others, I will use a hazard model to estimate the probability of bankruptcy. Specifying a hazard model allows explanatory variables to vary through time and increases the number of observations by the number of time periods in the sample compared to a static logit model. Shumway (2001) proves that estimating a multi-period logit model is equivalent to estimating a discrete-time hazard model. He also shows that single-period logit approaches can yield biased, inefficient, and generally inconsistent estimates, and that the hazard model overcomes these econometric problems. To estimate a hazard model in a logit framework, each firm-period (where the period may be a month, quarter, or year based on data availability) is included as a separate observation. Hence, each bankrupt firm only contributes one default observation, and has $y_{i,t} = 0$ for all periods in which it is healthy. The set of explanatory variables is comprised of data from all firms and periods up to the period where bankrupt firms default or exit the sample. When computing test statistics, the correct number of observations must be set to the number of firms and not the number of firm-years, given that the firm-period observations can't be assumed to be independent.

I assume that the marginal probability of default over the next period follows a logistic distribution of the form:

$$P_{t-1} = (1 + exp\{-y_{i,t}\})^{-1}$$

$$y_{i,t} = \alpha + \beta' X_{i,t-1} = \beta' \begin{bmatrix} x_{1,t-1} & \dots & x_{1,t-j} \\ \vdots & \ddots & \vdots \\ x_{n,t-1} & \dots & x_{n,t-j} \end{bmatrix}$$

where $y_{i,t}$ is an indicator that equals one if the firm defaults in period t, and $X_{i,t-1}$ is a vector of explanatory variables known at the end of the previous period. A higher level of $\alpha + \beta' X_{i,t-1}$ implies a higher probability of default.

The large majority of papers choose 'arbitrarily' the set of explanatory variables for their models. Tian, Yu, and Guo (2014) show that one can improve forecasting power by using a variable selection method such as the least absolute shrinkage and selection operator (LASSO). They specifically achieve higher in- and out-of-sample predictability than Campbell et al. (2008) when applying the technique on U.S. data. Given that mine is (to the best of my knowledge) the first attempt to estimate a reduced form model of corporate bankruptcy in emerging markets, I can't blindly incorporate explanatory variables from the U.S.-based literature to my specification. By using a statistical variable selection technique, I will be able to identify from an extensive set of variables a subset made up of the most relevant ones for bankruptcy prediction.

4.1 Further Analysis

Since this is a binary response model, the coefficients from the estimation cannot be interpreted as the variables' marginal effect on the outcome. However, the relationship between each predictor and the probability of default is also of interest. Therefore, in addition to the standard estimation of the dynamic period model, I intend to compute marginal effects, defined as the partial derivative of the probability of default with respect to the explanatory variable.

I also need to measure the model's ability to discriminate between bankrupt and non-bankrupt firms, both in- and out-of-sample. After all, the objective of the exercise is to forecast corporate bankruptcy. Plotting each firm's data into the estimated model returns the probability of default for each firm. One performance measure used in the literature is calculated by creating quantiles based on the probability of bankruptcy and tallying how many bankrupt companies the model places in each quantile. But the most popular in recent work is the Receiver Operating Characteristics (ROC) score described in Section 2. However, this measure depends on the sample used, and the objective of my model is to predict bankruptcy in emerging markets. Hence, I will estimate the most prevalent models in the literature (Altman (1968), Shumway (2001), Campbell et al.(2008), etc.) on my sample and compare their predictive power with that of my specification.

How accurately my model forecasts at different horizons is another important measure. It is likely that the data requires a different set of predictors when forecasting one or two periods ahead. Hence, I may have to run both the variable selection and the estimation methods for different horizons and come up a model specification for each. To the best of my knowledge, no other study has done this.

Lastly, I intend to compare how the distribution of predicted defaults in-sample through time compares with the distribution of defaults across time that we see in the data. There is considerable variation in the percentage of firms that go bankrupt across time, and the model would be particularly valuable to policymakers if it can successfully predict waves of corporate defaults.

5 Asset Pricing

I will now explore the asset pricing implications of the model. The objective is to determine whether investors are demanding the appropriate premium for bearing default risk.

The default risk premium can be measured by placing stocks into quantiles (e.g. deciles) based on their probability of default as implied by my model. By treating each decile as a value-weighted portfolio, I can then calculate the average return (across years) of each portfolio in excess of the market. Campbell et al. (2008) perform an exercise of this kind and find a negative risk premium associated with default risk. The average excess returns of their portfolios are "strongly and almost monotonically declining in failure risk" - their safest and riskiest portfolios earned a 3.4% and -17% excess return per year, respectively.

6 Conclusion

With the rise of corporate leverage across the world, it has become difficult to ignore the potential consequences of corporate fragility on the global economy. Economists and policymakers worry that a rapid corporate deleveraging or wave of defaults can turn into a large-scale economic crisis. The consensus is that EMs are now prone to such economic collapse. The usual currency and liquidity risks associated with EM borrowing apply. The volatility of EM securities makes them one of the first assets investors eliminate from their portfolios in times of high risk aversion. Also, an appreciation of the funding currency for EM debts – typically the U.S. dollar – would make it more difficult for firms generating revenues in domestic currencies to cover and roll-over their debts. The current environment raises further concerns, though. First, a commodity bear market has impacted many energy and mining companies, their pain amplified by their leverage. Second, the increase in the share of bonds complicates macro-prudential efforts, since they are more difficult to control than bank loans. Third, healthy firms gaining access to international markets means that domestic banks must lend to smaller, riskier companies. Lastly, the surge in speculative cross-border borrowing by EM NFCs reduces the efficacy of capital controls.

Understanding what variables determine corporate default in emerging markets would help design better prudential policy. Just as important is forecasting the likelihood that firms will in fact default. The early literature focused on accounting ratios to estimate the likelihood of corporate bankruptcy. They used static models and statistical methods like Multiple Discriminant Analysis, which ignored firms' behavior over time. Their samples were small and had a higher percentage of bankrupt firms than the population. Still, they were able to predict with decent accuracy whether a specific firm would or would not fail. Some of the determinants of corporate default these authors found were low efficiency (EBIT to total assets, sales to total assets), poor liquidity (working capital to total assets), small firm size, and high leverage (total liabilities to total assets). Shumway (2001) took a big step forward by introducing the use of the hazard model, allowing more data points and a time-varying picture of the firm's health. Aided by a large dataset and combining accounting and market variables for the first time, he found that his model outperformed all others in predictive power. Many followed his steps, adding industry effects, shortening the time between data points, modifying predictors, and studying default forecasts at different horizons. The determinants of default this group of models found were high leverage, low efficiency, small firm size, low cash holdings, high market to book ratios, low equity returns, high return volatility, and low corporate diversification. In comparative studies, several papers have validated the outperformance of the hazard model over MDA, probit, and standard logit.

Some authors have started adapting the models to international markets. Modifications include adjusting for currency risk and a firm's position in its industry, adding a variable for dependence on banks in Japan, and including macroeconomic variables like inflation and interest rates in the U.K. Besides the larger predictive power of the hazard model, the literature documents improved performance when combining different types of variables.

To the best of my knowledge, there is no research on the determinants of corporate default using a dynamic model specifically for the group of emerging market economies. I hope that this paper will fill this gap using a hazard model with the macroeconomic variables and firm-level market and accounting data most relevant to EM firms.

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