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In Search of Distress Risk in Emerging Markets

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Abstract

Although the non-financial corporate sector accounts for the lion's share of the post-Global Financial Crisis surge in emerging-market leverage, there is little systematic research on factors that impact corporate distress risk in emerging markets. Existing bankruptcy risk models developed using US data have low predictive power when applied to emerging market firms. We suggest that these models do not account for emerging market vulnerabilities to global shocks such as advanced economy monetary policy changes, US dollar movements, or shifts in global liquidity and risk-aversion. A novel multi-country dataset of corporate defaults allows us to quantify the importance of global shocks on emerging market corporate distress. Using a set of accounting, market, and macroeconomic variables, we develop a model of distress risk specific to emerging markets with comparable forecasting power to that of existing models based on US data. We also explore the asset pricing implications of our model by testing whether equity returns accurately reflect default risk. We find that global factors like US interest rates and credit risk contribute more predictive power for corporate default risk than domestic macroeconomic variables, especially for those firms whose stock returns are most sensitive to global financial conditions.

Keywords: emerging markets, corporate distress, bankruptcy risk models, global factors, asset prices

JEL classification: F3, G15, G33

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1 Introduction

Non-financial corporate debt in emerging markets surged from US$4 trillion in 2004 to over US$25 trillion in 2016 (IIF, 2017). In view of heightened levels of leverage and worsening solvency positions, there is rising concern about the deteriorating health of emerging market firms (IMF, 2015).[1] Recent evidence also suggests that the share of debt held by troubled firms is the highest in over a decade (IMF, 2015). Whether through links with the global financial system or through macroeconomic effects, a wave of corporate defaults in emerging markets could trigger broader financial stress (Shin, 2013; McCauley et al., 2015; Acharya et al.; 2015, Beltran et al., 2017).

Yet there is little systematic research on the determinants of corporate distress specific to emerging markets.[2] An exception is Altman (2005), who adapts a longstanding bankruptcy risk model to the idiosyncrasies of emerging market firms. Recent approaches principally focused on US data have made significant strides to further develop the methodologies to measure probabilities of default. Notable examples are the frailty factor models introduced by Duffie et al. (2009); the forward-intensity model in Duan et al. (2012); and the logit models put forth by Shumway (2001) and refined by Campbell, Hilscher, and Szilagyi (2008). However, out-of-sample testing suggests that existing models proposed for US firms perform sub-optimally when applied directly to the emerging market context.

This paper uses a novel dataset on emerging market corporate defaults to fill the existing gap. We suggest that extant models do not account for emerging market vulnerabilities to global macro shocks such as advanced economy monetary policy changes, US dollar movements or shifts in global liquidity and risk aversion. Our objective is to develop an optimal model of distress risk that allows us to quantify the importance of global shocks on corporate distress in emerging markets as a class of assets. Given the documented spillover effects of advanced economy monetary shocks (Fratzscher, Lo Duca, and Straub, 2018; Chen, Mancini Griffoli, and Sahay, 2014) and the impact of changes in international investor risk tolerance on emerging market capital flows (Rey, 2015; Chari, Dilts, and Lundblad, 2017), we suggest that a set of global financial variables play an important role in predicting corporate distress in emerging markets.

For instance, the currency denomination of emerging market corporate debt is a significant source of concern. US dollar appreciation raises the local currency value of dollar-denominated liabilities

[1] "IMF Flashes Warning Lights for $18 Trillion in Emerging-Market Corporate Debt," *Wall Street Journal*, September 25, 2015.

[2] We use "default risk" and "distress risk" interchangeably throughout the paper.

with adverse effects on firm balance sheets (Calvo et al., 2008; Schneider and Tornell, 2004). Borrowers residing in emerging markets account for over a third of global dollar credit to non-banks outside the US, and dollar bond issuance doubled between 2009 and 2015 (McCauley et al., 2015). Bruno and Shin (2016) use BIS data to show that issuance of international debt securities in foreign currency by non-financial corporations also rose significantly between 2001 and 2015. Changes in global monetary conditions exacerbate fears about currency risk. In particular, monetary policy normalisation in advanced economies is a key risk for emerging market firms. Powell (2014) highlights concerns about global debt paired with other macro conditions, such as the risk of asset price drops and currency depreciation, that could damage the ability of emerging market firms to repay their debts.[3]

We pay specific attention to the corporate sector in Asia. Historically, emerging market crises arose from sovereign debt problems, and twin banking and currency crises (Reinhart and Rogoff, 2009). However, during the Asian Financial Crisis, corporate debt vulnerabilities were significant underlying microeconomic roots (Pomerleano,1998; Corsetti et al. 1999) in addition to implicit guarantees and moral hazard (Krugman 1998, Craig, et al. 2003). The crisis was accompanied by widespread corporate failures due to adverse balance sheet effects via currency and maturity mismatches at the firm level. Given the importance of corporate sector vulnerabilities during the Asian Financial Crisis, we believe it is useful to assess corporate distress risk in Asia today.

We estimate a logit model of probability of corporate default on a set of firm-specific accounting and market variables, domestic macroeconomic variables, and variables reflecting global financial conditions. The evidence suggests that the 5-year US Treasury rate, the Fed funds rate, and the TED spread are correlated with distress risk, even after controlling for firm-specific variables and the domestic macro environment. For the Asia-only sample, the global variables that help predict default are the 5-year Treasury rate and the change in the exchange rate against the US dollar, consistent with a history of currency depreciations playing a major role in economic crises. Furthermore, introducing a dummy variable indicating whether a firm has defaulted in the past has a very positive impact on the model's predictive power – a novel result in the literature, to the best of our knowledge. A model that includes all three types of variables and the prior-default dummy yields a much higher explanatory power for emerging market firms than Campbell et al.'s (2008) specification of accounting and market variables. The model performs well when including all emerging market countries in our sample and when focusing on firms in Asian countries. While both domestic and global macro variables seem

[3]"Prospects for Emerging Market Economies in a Normalizing Global Economy," Speech by Jerome Powell, October 12 2017.

important in the understanding of default risk, global variables contribute more to default prediction when included in the model.

In a related exercise, we focus on firms whose returns are most sensitive to global financial conditions in order to explore if stock returns carry information about the impact of the global financial environment on default risk. We label these sensitivities "global betas" that are extracted from firm-specific time series regressions of stock returns on a global variable, controlling for market returns. Introducing dummies for the tercile of firms with most negative global betas (i.e., firms most negatively affected by US dollar appreciation, sovereign spreads, US interest rates, VIX, and TED spread) reveals that, for 5-year rates, VIX, and TED spread, the effect of the global variable on the probability of default differs for firms with most negative betas. Furthermore, a composite global beta measure helps us show that the effect of a global risk-off environment on distress risk is greater for firms whose returns respond more negatively to such global conditions. This last finding does not hold when restricting our sample to firms in Asian countries.

Finally, we move on to the asset pricing implications of our measure of distress risk. Asset pricing theory suggests investors should demand a premium for holding stocks at risk of default. However, prior literature using US data and our global beta results seem to indicate that distress risk and stock returns move in opposite directions. We construct ten portfolios sorted by firms' predicted probability of default and find strong evidence of the presence of a distress risk premium in emerging market stocks. Future 12-month stock returns are almost monotonically increasing in the probability of corporate default, a trend that holds true after controlling for the Fama-French three factors.

Our paper contributes to the existing corporate default literature in three ways. First, it precisely determines which accounting, market and macroeconomic variables are associated with corporate distress risk in emerging markets – and compares them to those in advanced economies. A number of fundamental idiosyncrasies suggest a modified approach to analyse corporate vulnerabilities in an emerging market setting. For example, Mendoza and Terrones (2008) find that corporate credit booms in emerging markets are followed by larger macroeconomic responses, such as drops in output, investment, and consumption, than in advanced economies. Further, credit expansions are determined by different factors in the two sets of economies: financial reforms and productivity gains in advanced economies and large capital inflows in emerging markets. Given the surge in "search for yield" flows from advanced economies to emerging markets during the unconventional monetary policy period, concerns about reversals in these flows during monetary policy normalisation in advanced economies could exacerbate corporate distress risk in emerging markets.

Second, the paper improves current tools to predict corporate distress in emerging markets. Instead of simply estimating US-based models using emerging market data, our specification includes a set of explanatory variables that maximises predictive power for emerging markets. Additionally, the introduction of stock returns' sensitivities to global factors adds a new dimension to our understanding of how distress risk operates through financial markets. Third, we find a positive default risk premium in emerging market stocks by examining the pricing of financially distressed firms. We use the probability of failure measure developed in the main part of the paper to explore the performance of distressed stocks between 2002 and 2016.

Related Literature: Shumway (2001) combines accounting data with a set of market variables comprised of 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) improve forecasting by shortening the observation intervals to monthly frequency and find the existence of an industry effect. Campbell et al. (2008) build on the work of Shumway (2001). Their paper uses US data 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.[4] An important asset pricing implication of Campbell et al. (2008) is that stocks of distressed companies experience abnormally low returns.

A small set of papers develop bankruptcy models for emerging markets. Notably, to adjust the Z-Score to the different environment in emerging markets Altman (2005) introduces the modified Z-score.[5] 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 crisis. Subsequent studies focus on expanding the types of variables included in the predictive model (Hernandez-Tinoco and Wilson, 2013) and applying US-specific determinants of bankruptcy without modification to other countries (e.g. Kordlar and Nikbakht, 2011; Xu and Zhang, 2009; Bauer and Agarwal, 2014; NUS-RMI, 2016).

Other related research focuses on specific financial sheet variables to identify country-wide cor-

[4] The authors define distress as either filing for bankruptcy, being delisted, or receiving a D rating. The authors 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, they study default forecasts at different horizons, finding market capitalization, market-book ratio, and equity volatility the most consistently predictive characteristics of corporate distress, and demonstrating the increased importance of balance sheet versus market variables as the horizon increases.

[5] More information on the specifics of the modified Z-score model derivation can be found in Altman (2005).

porate distress risk. Alfaro et al. (2017) use firm-level data to show that corporate fragility is currently less severe but more widespread in emerging markets than during the build-up of the Asian Financial Crisis. The paper shows that the correlation between leverage and corporate fragility is time-varying and strongest for large firms and times of local currency devaluations. 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 non-financial corporations in emerging markets. The 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 between advanced and emerging economies. Hence, the traditional belief that cash increases a firm's repaying ability may not hold in the current environment.

There has been limited research on the drivers and consequences of high currency exposure due to the shortage of reliable data on currency composition of debt.[6] However, the view most widely held is that foreign-currency liabilities are in fact a concern for emerging market non-financial corporations and particularly troubling for firms that do not have natural currency hedges in place (e.g. firms in non-tradable industries).[7] Harvey and Roper (1999) show that high foreign currency-denominated leverage and low profitability were important factors spreading the Asian Financial Crisis. Dell'Ariccia et al. (2016) corroborate the idea that foreign currency borrowing increases systemic risk and exposes lenders to the risk of default when the borrower's currency plunges.

There is substantial academic and policy research showing concern about the health of the non-financial sector in emerging markets. However, the literature so far has not been able to show whether a heightened risk of default is correlated with suggested indicators of corporate distress. To the best of our knowledge, ours is the first paper that estimates firm-specific probabilities of default in emerging markets and quantifies how the balance sheets of firms and the macroeconomic environment they operate in can affect their ability to remain solvent. Additionally, having a more reliable measure of corporate default risk allows us to explore the behaviour of distressed stocks in emerging markets.

The rest of the paper is organised as follows. Section 2 explains the methodology. Section 3 describes the data. Section 4 presents the results of logit regressions of the probability of default and introduces global betas as predictors of default. Section 5 shows preliminary asset pricing implications of our measure of distress risk. Section 6 presents robustness checks and additional tests. Section 7

[6] The two major issues in compiling accurate data on debt currency composition are: (a) Many corporate reports present the currency composition of their liabilities in the notes of the reports and not in hard data, and (b) 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.

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

concludes.

2 Methodology

Although leverage levels receive substantial attention in the corporate default literature, several studies show the importance of other accounting and market variables in forecasting corporate bankruptcies. Earlier static bankruptcy prediction models used accounting ratios to forecast default (See Altman, 1968; Ohlson, 1980; Zmijewski, 1984). Shumway (2001) points out that static models effectively require arbitrary choices about how long ahead of bankruptcy to observe the firms' characteristics – adding selection bias to the process. In contrast, dynamic forecasting using hazard or dynamic logit models use all available information to determine each firm's bankruptcy risk at each point in time. By including each firm-year as a separate observation, the data used for estimation is much larger and controls for the "period at risk," namely that some firms fail after being at risk for many years and others go from healthy to bankrupt much faster. In addition to accounting for duration dependence, hazard models include time-varying covariates, which provide a changing picture of a firm's health. Campbell et al. (2008) build on the work of Shumway (2001) and improve the set of variables used to predict distress. The authors run a logit model on US data, putting more emphasis on market variables as predictors of distress.

Similar to Shumway (2001) and Campbell et al. (2008), we estimate a dynamic panel model of probability of default using a logit specification augmented by domestic and global macroeconomic factors that have particular relevance to emerging market firms. We assume a logistic distribution for the marginal probability of default over the next period, which is given by:

$$P_{t-1}(Y_{i,t} = 1) = \frac{1}{1 + exp(-\alpha - \beta x_{i,t-1})} \tag{1}$$

where $Y_{i,t} = 1$ in the month t prior to firm i defaulting and $Y_{i,t} = 0$ in all periods when the firm does not default the following month. Firms disappear from the sample only after they experience a bankruptcy event. Firms that do not default at any point in the sample have $Y_{i,t} = 0$ throughout the entire period, including in the month of their departure if they leave the sample for reasons other than default (e.g. merger). The vector of explanatory variables, $x_{i,t-1}$, is known at the end of the previous period. A higher level of $\alpha + \beta x_{i,t-1}$ implies a higher probability of default.

We suggest that the domestic macroeconomic environment may affect the financial health of emerging market firms through demand for their goods and services, wage and borrowing costs, and other input costs. Evidence from the credit risk literature suggests that the incidence of firm failures rises during recessions (Pearce and Michael, 2006; Altman and Brady, 2001) and that GDP growth and an indicator of recession improve the predictive power of credit risk models (Bangia et al., 2002; Richardson et al., 1998; Helwege and Kleiman, 1996). Further, inflation risk affects economic growth and creates uncertainty about the domestic economy. For example, Hernandez-Tinoco et al. (2013) find a significant relationship between default risk and both domestic inflation and interest rates in UK firms. To analyse the impact of the domestic economic conditions for predicting default in emerging markets, we augment the model in Campbell et al. (2008) by including a set of domestic macro variables in the estimations. For variables with lower frequency than our monthly prediction period, we use the last available data point.

Furthermore, the globalisation and increased interconnectedness of financial markets propagates the transmission of financial and economic conditions from developed to emerging markets. For instance, a 2015 report by the IMF shows that the increase in corporate debt in emerging markets was driven by global factors. Shin (2013) argues that global liquidity increased in response to the Global Financial Crisis. Jotikasthira et al. (2012) report that "global funds substantially alter portfolio allocations in emerging markets in response to funding shocks from their investor base." Due to their high reliance on international markets for funding, the listed firms that make up our dataset are likely affected by these changes in global conditions. For this reason, we also include a number of global variables that may influence the distress risk of emerging market firms. Section 4.2 discusses in detail the methodology to compute global betas as a measure of emerging market risk exposure to a range of global factors.

2.1 Model Performance

The existing literature uses a number of measures of a model's predictive power, most of which involve ranking firms by their estimated probability of default. However, studies differ in the number of firms and defaults, size of quantiles to group firms into, and allocation of distressed firms across quantiles, making comparisons across models difficult. Chava and Jarrow (2004) and Wu et al. (2010), among others, improve comparability by relying on the Receiver Operating Characteristics (ROC) score. The ROC score, also known as "area under the power" or "area under the curve" (AUC), uses 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 "Good Model" curve tells us that the 20% of firms that a particular model identifies as most likely to default include 70% of the firms that go on to default the next month. Point B in the "Bad Model" curve signals that it takes 50% of firms ordered from most to least likely to default for the model to identify 70% of defaulting companies. We compare the two models by computing the area under each of the curves, known as Area Under the Curve (AUC) or ROC score. A larger area indicates that the model is correctly predicting more distressed firms as being likely to fail. An AUC of 0.5 indicates no discriminatory power, and the closer the score gets to 1 the better the model identifies distressed firms.[8] Contributing to the interpretation of the AUC, Hanley and McNeil (1982) show that the score obtained by ranking observations by estimated likelihood of failure represents the probability a failed subject will be ranked ahead of a randomly chosen healthy subject.

We also use the AUC to measure predicting power out of sample. We compute out-of-sample AUC scores in two ways. First, we estimate the probability of default model using data from the earliest 70% of our sample and use the estimates to compute the AUC for each month in the remaining 30% of the sample. Second, we estimate the model on a rolling basis increasing the estimation window every month and predicting default on the following month. Predicting default out of sample is important to validate our in-sample results, particularly given the large ratio of observations to defaults in the sample.

To measure goodness of fit, we use McFadden's pseudo-R^2, which compares the model's likelihood (L) to that of a model consisting of only a constant (L_0), i.e. the average default rate in the sample. Specifically, it is computed as $1 - \frac{log(L)}{log(L_0)}$ and can be interpreted in the same manner as the standard R^2 (between 0 and 1, increasing in model fit).

3 Data

Our dataset consists of corporate default events and a set of firm-specific and macroeconomic explanatory variables. A majority of the data come from the CRI database, the Credit Research Initiative of the National University of Singapore, accessed on December 1, 2016. The CRI database contains detailed default, accounting, and market data for over 60,000 exchange-listed firms in 119 countries between 1990 and 2016. The countries in our analysis are those classified as Emerging Markets by MSCI during the majority of our sample period (1995-2016): Argentina, Brazil, Chile, China, Colom-

[8] See Sobehart and Keenan (2001) for more details on the ROC score.

bia, Czech Republic, Egypt, Hungary, India, Indonesia, Jordan, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, Turkey, and Vietnam.

The dataset is novel in its broad coverage of balance sheet variables and, especially, of default events in emerging markets.[9] As Table 1 shows, it contains information on firms' bankruptcies and other corporate default actions. This is important because countries differ in their definitions of default. To construct our measure of financial distress, we define a default to be any of the events in the "Bankruptcy Filing" (excluding "Petitions Withdrawn"), the "Delisting," and the "Default Corporate Action" (excluding "Buyback options") groups.[10] Delayed payments made within a grace period are not counted as defaults.

Table B1 in Appendix B shows our distress indicator over time for firms with sufficient data to replicate benchmark specifications from existing US studies. The first column shows the number of firm-months of data in each year, the second column the number of default events per year, and the third column the corresponding percentage of firms that experienced a default event. The average default rate in the sample is close to 0.1% per year, with some variation within years. Importantly, there is no strong clustering across time, as the distress indicator displays considerable cross-time variation in the distribution of corporate defaults. Coverage of accounting variables varies. The number of firm-months and defaults with data for *any* of the variables in Campbell et al.'s (2008) specification is 2,724,716 and 2,150, respectively. However, in order to run the logit model we require every observation have data for *all* explanatory variables included in the regression specification. Due to missing observations and the sparsity of some accounting data, the final sample includes 437,492 observations and 412 default events. This data serves as the basis for our benchmark regression specification.

As seen in Table B2 in Appendix B, the data coverage varies substantially by country, possibly influencing the lack of a clear pattern in the percentage of defaults by year. Even though Thailand is the only Asian country with data during the Asian Financial Crisis, the default rate is higher than average in 1998-2000, with 1999 having the highest share of defaults in our sample. Comparing our sample against prior studies using US firms, we find that the ratio of defaults to firms is lower in emerging markets than in the United States. This could be due to several reasons. First, governments own a percentage of many large firms in emerging markets and might be more inclined to bail out or recapitalise struggling companies. Second, large firms may benefit from corruption in governments

[9]Market data from emerging markets on stock prices and related variables are fairly accessible from sources such as Datastream, Bloomberg, etc.

[10]The number of Default Corporate Action events is lower than the sum of its sub-components because some events include multiple actions (e.g. Missed Loan Payment and Missed Coupon Payment)

to get help staying solvent. Third, the lower percentage of firms that are publicly listed implies less small firms in our sample.[11]

The set of covariates consists of three types of variables: firm-specific accounting and market variables; domestic macroeconomic variables; and global variables, i.e. variables from outside the emerging market region. Consistent with Campbell et. al. (2008), the monthly firm-specific market variables are: log excess stock returns relative to the country's main index (EXRET), log of price per share (PRICE), volatility of daily returns over the prior month (VOL), and the log ratio of market cap relative to the total market cap of all listed firms in the country (RELSIZE). The accounting variables have quarterly frequency and include the ratio of net income to the market value of total assets (NIMTA), the ratio of total liabilities to the market value of total assets (TLMTA), the ratio of cash and short-term assets to the market value of total assets (CASHMTA), and the market-to-book ratio (MB).[12] In some of our specifications we include a dummy variable that equals one if the firm has experienced a default event in the past.[13]

To control for large outliers and possible errors in the balance sheet and market data, we winsorize the firm-specific variables at the 1^{st} and 99^{th} percentiles of their distributions[14]. We also lag the accounting ratios (TLMTA, NIMTA, CASHMTA, and MB) by three months to ensure the balance sheet data was publicly available at the time we predict default.

To capture the domestic macro environment within which firms operate, we include four domestic macro variables for each country. These include the unemployment rate to capture slack in the economy, retrieved from the World Bank. Inflation is the monthly change in CPI from the Bank for International Settlements, which reflects pricing pressures in the local economy. Real interest rates come also from the World Bank, and we include them as a proxy for local borrowing costs and liquidity. Lastly, the JP Morgan Emerging Markets Bonds Spread, which measures the average spread on US dollar-denominated bonds issued by sovereign entities over US Treasuries incorporates international investors' perception of the government's credit risk.

Lastly, we include a number of variables that capture global financial conditions (many US-based

[11]Campbell et al. (2008), Ohlson (1980), and others show firm size is negatively correlated with default risk.

[12]Campbell et al. (2008) include time-weighted averages of NIMTA over the previous four quarters and EXRET over the previous twelve months. Due to the sparsity of emerging market data, we would lose too many observations if we required one consecutive year of data for those two variables. We used the single-period definition instead.

[13]Although we would have liked to include a variable indicating the firm's age or listing date, unfortunately good quality data are not available for the firms in our sample.

[14]Market-to-book ratio is winsorized at the 5^{th} and 95^{th} percentiles in order to deal with firm-months with very small or negative book-to-equity values, which in turn make MB very large.

variables) and each emerging market country's exposure to them. Our motivation for focusing on US-based variables as global variables stems from the extensive literature on the global financial cycle that attributes importance to global shocks stemming from the US (see Rey (2014) and the related literature on the global financial cycle). For example, even though VIX measures implied volatility in the S&P 500, it is now widely used as a proxy for global risk aversion. Similarly, short-term US government debt is considered the safest financial asset; hence, the Fed funds rate is used as the benchmark (risk-free rate) against which to measure the performance of all other investments and is a key determinant of financial flows into emerging markets (e.g. see Chari, Dilts and Lundblad, 2017, Fratzscher, 2012 provides a nice survey).

The set of global macro variables specific to each country includes the monthly change in a country's exchange rate against the US dollar and the monthly change in the sovereign spread. The exchange rate against the US dollar is often the most important exchange rate for emerging market firms if, for example, a significant proportion of external debts are dollar denominated or via trade linkages. [15] While the sovereign spread in levels included as a domestic macro variable serves more as a country fixed effect, the monthly change focuses on the change in the country's perceived credit quality compared to the United States, often driven by increases or decreases in capital flows to the emerging country's financial markets.

Moving on to variables computed only with developed-market data, the CBOE Volatility Index, known commonly as the VIX, measures the market's expectation for 30-day volatility in the S&P 500. A higher VIX typically denotes a general increase in the risk premium and, consequently, an increase in borrowing costs of emerging market firms. Rey (2015) finds one global factor correlated with the VIX that drives the price of risky assets around the world while Forbes and Warnock (2012) show that changes in the VIX explain international capital flows. The effect of changes in US rates on capital flows to emerging markets has also been established in the literature (Chari, Dilts and Lundblad, 2017), and Bruno and Shin (2015) introduce bank leverage as a mechanism through which changes in US monetary policy impact international capital flows. To address the interest rate effect, we include both the US federal funds rate and the 5-year US Treasury rate. The federal funds rate is indicative of monetary conditions and changes in monetary policy in the United States, whereas the 5-year Treasury rate serves as the risk-free rate against which investors in advanced economies evaluate the payoffs of all other assets of similar maturities. Lastly, the TED spread is a proxy for

[15] The percentage of corporate debt denominated in US dollars has increased dramatically since the Global Financial Crisis, as shown by IMF (2015) and others.

perceived credit risk in the US economy, and it is computed by subtracting the 3-month Treasury bill rate from the 3-month LIBOR rate. Due to the correlation between TED spread and VIX, we use the orthogonal component of the two, i.e. the residual of a regression of the TED spread on VIX similar to Fratzscher (2012). These global variables have monthly frequency and are common to all firms in the sample.[16] Appendix A defines variables and their sources in greater detail. In later exercises we compute firm exposures to these global variables and incorporate the firm-specific exposures into our distress prediction specifications.

3.1 Summary Statistics

Table 2 reports simple equally-weighted means of the explanatory variables, as well as t-tests for means. The first column presents statistics for the full sample, the second column for the Default group, and the third for the Bankruptcy group – a subset of the Default group. The fourth and fifth columns show whether there is a statistically significant difference in means between the full sample and the Default and Bankrupt groups, respectively.

The firm-specific covariates show that firms in the Default group exhibit lower excess returns, stock prices, and volatility. Firms under duress are also smaller, the average firm in the group comprising 0.01% of the country's market cap, compared to 0.04% for the average firm in the full sample. This is not surprising, since smaller firms may find it more difficult to access temporary financing when facing default.

Looking at firm balance sheets, firms one month away from default differ from the full sample in the expected direction – and the difference in all four mean accounting ratios is larger for firms in the Bankrupt group. Distressed firms have lower profitability and are on average making losses the month before failing to pay their obligations, compared to an average net income to total assets of 0.005 in the full sample. These firms also have higher leverage, 0.577 and 0.785 for Default and Bankrupt groups, respectively, than the overall population (0.365), as well as lower cash holdings over total assets – 0.043 and 0.025 for the Default and Bankrupt groups, compared to a full sample average of 0.081. Both ratios are suggestive of firms' diminishing ability to repay their upcoming liabilities. Lastly, troubled firms have low book value of equity relative to their market capitalisation, resulting in higher market-to-book ratios of 2.756 (Default) and 4.283 (Bankrupt), compared to 2.140 for the full sample. All summary statistics described so far are consistent with those in Shumway

[16] Except the bilateral exchange rate (local/USD) and changes in the sovereign spread, which we include as global factors because they are most important for firms with exposure to the rest of the world.

(2001) and Campbell et al. (2008), except for the fact that volatility of stock returns is lower for firms one month away from default.

We also introduce a variable that, to the best of our knowledge, has not been used in the literature: an indicator of whether a firm has defaulted in the past. Comparing the means of distressed firms and the full sample, we find in the Default and Bankrupt groups a much higher percentage of firms which have already suffered a default event.

The interpretation of the differences in the means of the domestic macroeconomic variables is less clear, given that some countries will have structurally higher levels of interest rates, inflation, unemployment or sovereign spreads than others throughout the sample. In any case, we find that domestic macroeconomic environment for the Default group is characterised by lower unemployment, real interest rates, and sovereign spreads.

On the other hand, the direction of the effect of global variables on corporate distress is more predictable, as they affect firms' ability to roll over or pay off their financial obligations to avoid default. We would expect an environment of high interest rates in the US to lower the search for yield and corresponding demand for riskier emerging market debt instruments. The summary statistics support this hypothesis, with firms defaulting in times of higher 5-year Treasury and Fed funds rates – 2.906% and 1.900%, respectively, compared to 2.382% and 1.285% in the full sample. Also as expected, defaults occur on average during times where a country's sovereign spread is increasing more than on average during our sample period. Lastly, the Default group is characterised by having a higher TED spread; that is, higher global liquidity risk. VIX levels and exchange rate dynamics are not significantly different between distressed firms and the full sample.

4 Results

4.1 A General Model of Default Risk

To test the prior that firm-specific predictors are the same for US and emerging markets, we computed 17 different accounting ratios and market-based variables as predictors of default in emerging markets: Retained Earnings to Total Assets, Market Value of Equity to Book Value of Liabilities, Revenue to Total Assets, Working Capital to Total Assets, Current Assets to Current Liabilities, Interest Coverage Ratio, Asset Tangibility, EBIT to Total Assets, and Current Liabilities to Total Liabilities. Using LASSO to inform our variable selection, we don't find strong evidence that any subset of accounting and market variables specific to emerging markets outperforms those used by Campbell et al.

(2008) (referred to as CHS intermittently hereafter). Even though the level of market efficiency might be weaker in emerging markets, we find that all four market-based variables in CHS contribute to model fit for the probability of default for our emerging market firms. While we are agnostic with respect to market efficiency, our results suggest that the market-based variables are correlated with the probability of default in our emerging market sample. We therefore use the CHS specification with accounting and market variables as a baseline and examine whether including domestic and global macro variables enhances model performance.

Before moving on to our general model of default risk, we address multicollinearity concerns associated with our multivariate framework. Table B3 in Appendix B shows the correlation matrix of the variables in our model and, in the last two rows, two popular measures of multicollinearlity, the Tolerance value (TOL) and its reciprocal Variance Inflation Factor (VIF), for each of the regressors. VIF is computed as $1/(1-R_k^2)$, where R_k^2 is the R^2 value of a regression of factor k on all others. TOL is simply $1-R_k^2$. VIF values larger than 10 are typically considered suggestive of multicollinearity in a model. In our specification, no variable has VIF ≥ 10, and only the Fed Funds Rate and 5-year Treasury rate have VIF > 5, presumably due to the high correlation between the two. The correlation between Fed Funds Rate and 5-year Treasury rates is 0.88, the only pairwise correlation larger than 0.55 in absolute value among all our variables.

To understand the contribution of domestic and global variables to the probability of default of emerging market firms, we estimate a number of specifications. Table 3 shows the results of these multivariate logistic regressions. As a benchmark, we estimate in Column 1 the CHS model, which yields a pseudo-R^2 of 0.142 and an AUC of 0.88. All coefficients are significant and have the same sign Campbell et al. (2008) find, except for volatility of returns. The results imply that a firm is more likely to default next month if it has lower excess stock returns, a lower stock price, lower volatility of returns, lower market cap, lower profitability, higher leverage, less cash, and a higher market-to-book ratio.

Next, we add a dummy variable signalling whether a firm has defaulted in the past, and we find that it greatly increases explained variation and predictive power (Column 2). The pseudo-R^2 goes up to 0.241 and the AUC to 0.921. We keep the prior default event dummy in the set of firm-specific variables moving forward. To the best of our knowledge ours is the first paper to include this explanatory variable that is remarkably robust across specifications. Including a wider subset of events as "Default" rather than outright bankruptcy, allows us to examine the impact of prior distress states on the current probability of default.

In the third column we add the domestic macro variables – unemployment, inflation, real interest rates, and sovereign spreads – to the regression. The pseudo-R^2 increases to 0.261, but the AUC falls to 0.916, suggesting a better model fit but not better predictive power. We find that default is associated with lower real interest rates and lower sovereign spreads, after controlling for firm-specific accounting and market variables. The coefficient on real interest rate is negative both when controlling for CHS variables and in the specification restricted to domestic variables (Column 6). Sovereign spreads have a significantly negative coefficient only when CHS variables are included, and the coefficients on unemployment and inflation lose their negative significance when we estimate them along with accounting and market variables (Column 3).

Column 4 presents the results of a model that consists of CHS, the prior default dummy, and global variables. This specification yields the highest AUC (0.922) and a pseudo-R^2 of 0.255. When compared against the specification in Column 3, the results suggest that domestic macro variables do a better job fitting the data (pseudo-R^2) but that global variables contribute more predictive power (AUC) after controlling for firm-specific covariates. The coefficients in this specification tell us that default risk is associated with higher 5-year Treasury rates, lower Fed funds rates, likely an adjustment for the 5-year rates, since Fed funds rates are unconditionally positively correlated with default, and a higher TED spread. In other words, after controlling for firm-specific accounting and market variables, emerging market firms are more likely to default when US 5-year rates are high, Fed funds rates are low, and credit risk in the US is more prevalent. While the change in sovereign spreads and the VIX are not associated with changes in the probability of default in Column 4, they have positive coefficients when regressing global variables by themselves (Column 7).

Finally, a specification that includes all variables yields a pseudo-R^2 of 0.265, but it underperforms slightly in prediction power (AUC = 0.916) against the specification in Column 4. Out-of-sample forecasts show that estimating the model one time with 70% of the sample yields AUC = 0.838 when predicting on the remaining 30% of our data and AUC = 0.879 using the recursive approach, such that the smallest window includes the earliest 60% of our sample. The in-sample ROC curve associated with this model is shown in Figure 2. As in the CHS benchmark, we find that a firm is more likely to default next month if it has low excess returns, market cap, profitability, and cash; as well as high leverage and market-to-book ratio. When including domestic and global macro variables to the specification, however, the effects of volatility of returns and stock price on default risk disappear.

4.2 Global Betas

Some emerging market firms are more dependent on or exposed to global markets than others. When we include global variables in our baseline model of probability of default, the average effect of these factors on our entire sample might hide stronger coefficients and predictive power for the more global-facing firms. However, if stock returns accurately carry information about the impact of global factors on firms, we may expect the default risk of corporations with returns more sensitive to global factors to be more correlated with such variables.

In order to test this hypothesis, we compute firm-specific betas of stock returns to each of the global factors in our model. Specifically, we run a time series regression for each firm and global factor, conditional on having at least two years of data on returns and the global variable. The dependent variable is the firm's stock returns and the explanatory variables are the global factor and the returns of the country's main stock index. The resulting coefficient on each global factor is what we take to represent the sensitivity of the firm's returns to the global factor, after controlling for the country's returns. Having computed betas for each of the global factors, we select the tercile of firms with most negative betas, i.e. whose returns fall most with increases in the global factor.[17] Once our firms are sorted by betas, we create a dummy variable that indicates whether a firm belongs to the top tercile.

Panel A in Table 5 reports the results of logit regressions of probability of default where the explanatory variables are the global variable and the interaction of that global variable with the top–tercile beta dummy. The coefficient on the interaction term tells us whether the magnitude of the impact of each global factor on the probability of default differs for the subset of firms with most sensitive returns to that factor. We find significant coefficients in the top-third dummy interactions for 5-year Treasury rates, VIX, and TED spread (p-value = 0.15), implying that the effect of these variables on the probability of default differs for the stocks with highest sensitivity to those variables. Specifically, the coefficients on the 5-year Treasury dummy interaction is positive, implying that the risk of default increases more with higher rates for firms with most negative betas. The same holds true for the TED spread. While the coefficient on VIX is not significant by itself, the interaction of VIX and the top-tercile dummy is significantly negative, suggesting that a decrease in the VIX is associated with a higher probability of default for stocks with high negative exposure to the volatility index. This finding is a bit of a puzzle since intuitively we would expect that a rise in global risk aversion cap-

[17] In the case of the change in the exchange rate, we choose the tercile of firms with most positive betas; that is, whose returns fall most with increases in the rate of change of the US dollar relative to the local currency.

tured by a rising VIX would increase the probability of default. However, the counter-intuitive inverse correlation between the VIX exposure and default probabilities may suggest that distress risk rises in an environment of low global risk aversion that in turn leads to credit booms and high international liquidity especially for firms with the highest negative exposure to the VIX.

To verify that the difference in effect between firms with more or less sensitive returns is not due to different firm characteristics between the two groups, in Panel B we control for the firm-specific accounting and market variables in the benchmark model. We also find positive signs on the 5-year Treasury rate and its interaction with the top-tercile dummy, as well as a negative sign on the VIX top-tercile dummy interaction term. The TED spread dummy interaction is no longer significant. The VIX and 5-year Treasury results shown in Table 5 are also robust to including dummies for firms with above-median betas rather than the top-tercile (available on request).

Combining all global variables into one global factor yields further evidence that the sensitivity of returns to global financial conditions is related to the effect those global conditions have on firms' probability of default. We construct an index of return sensitivity to the global environment – which we call the Global Beta Z score – by combining the betas of the six global variables in our model. We standardize the beta for each global factor by subtracting the mean beta across firms and dividing by the standard deviation. We then add the resulting values of the six factors.[18] The result is a combined measure that gives equal weight to each beta and serves as proxy for how much a firm's returns respond to global financial conditions. A lower Global Beta Z score implies that a firm's returns are more negatively affected by increases in the global variables. We compute a Global Variable Z in the same manner, using the global variables as inputs instead of the betas. A higher Global Variable Z score is associated with a more difficult environment for emerging markets to finance themselves (what is often known as a "risk-off" environment).

In Table 6 we show the results of a logit regression of the probability of default on Global Beta Z, Global Variable Z, and the interaction of the two. We control for firm-specific and domestic macro variables. The coefficient on Global Beta Z is not statistically significant, implying that exposure to global financial conditions per se is not a predictor of default. On the other hand, Global Variable Z is positively correlated with default risk; i.e. a firm is more likely to default in global risk-off conditions. Additionally, the interaction of the two returns a significant, negative coefficient. This tells us that the effect of a risk-off environment on default risk is larger for firms whose returns respond more

[18]We subtract the change in the exchange rate since we want an increase in the US dollar to impact the Global Beta Z in the same direction as an increase in rates, VIX, sovereign spread, and TED spread.

negatively to such global conditions.

We can therefore conclude that, for some global factors like 5-year Treasury rates and for a composite global factor, how sensitive a firm's returns are to the factor(s) affects how much its solvency depends on the level of such factor(s). There are at least two possible explanations behind this connection between default risk and market betas. First, the stock market captures the effect of global conditions on the firms' probability of default, and the price responds more sharply than for other firms. Second, the fact that returns respond more strongly to the global environment increases the firm's probability of default. In other words, the larger response of returns in some firms accentuates the direct impact of the global conditions on the firm's ability to remain solvent. Should the first explanation hold, it would suggest a distress risk premium exists in emerging market stock returns. We explore this and other asset pricing implications of our measure of probability of default in the next section.

5 Asset Pricing

We use our estimated probability of default to study the stock returns of distressed firms in emerging markets. As was the case with the distress risk measure, research on the distress risk premium has been mostly focused on US equities (e.g. Fama and French, 1996; Vassalou and Xing, 2004; Da and Gao, 2010; Campbell et al., 2008). Asset pricing theory suggests investors should demand a premium for holding stocks at risk of default. However, Vassalou and Xing (2004) and Campbell et al. (2008), among others, find the opposite: stocks of firms with a high probability of default yield lower returns than their safer or more solvent counterparts. Campbell et al. (2008) show this result holds even after controlling for Fama-French factors and a momentum factor. This result has important implications for the understanding of risk factors in asset prices, since distress risk is often argued to be the reason behind the small cap and value premia (Chan and Chen, 1991; Fama and French, 1996).

We test whether the distress risk premium puzzle exists also in emerging market stocks. Every month between January 2002 and September 2016 we estimate our measure of distress risk using all prior data in the sample to prevent look-ahead bias. In the first month, we sort all stocks based on this predicted probability of default and construct ten portfolios of equal size, placing those with lowest distress risk in Portfolio 1 and those most likely to default in Portfolio 10. We rebalance the portfolios every month thereafter based on the stocks' updated distress risk, again placing the least and most likely to default in Portfolios 1 and 10, respectively.

Table 7 shows each portfolio's average returns in excess of the market, along with other summary statistics. There is a large spread in the average probability of default across the portfolios: firms in the portfolio of lowest default risk have just 0.01% probability of failing next month, compared to 1% for stocks in the riskiest decile. The performance of Portfolios 2 through 10 suggests a *negative* risk premium associated with distress, consistent with similar exercises on US equities – the average excess return falls monotonically with the average probability of default. Surprisingly, the least distressed portfolio, Portfolio 1, experiences negative returns on average during the sample. Notably, even though stock-specific volatility of returns does not predict default in the estimation of our distress risk measure, the standard deviation of the portfolios' excess returns has a positive correlation with the average probability of default. Because we rebalance our portfolios every month the standard deviation of returns is very low, but the difference in volatility across portfolios is large in relative terms – the decile of stocks with highest risk of failure is almost 6 times as volatile as the decile with lowest default risk. Figure 4 shows the cumulative returns of each portfolio throughout our sample period.

As a robustness test, we follow Campbell et al. (2008) and give more weight to the tails of the distress risk distribution when constructing our portfolios.[19] We find that the relationship between distress risk and future excess returns is still negative, though not as clearly as when the portfolios match the deciles of the distribution.

These results don't necessarily imply a negative distress risk premium in emerging market stocks, since our measure of distress risk may be associated with other economic forces and factors that demand premia of their own. For example, excess returns is one of the predictors we use in our probability of default measure, which implies that the distressed stocks have negative momentum we must try to control for. In a future version of this paper we will explore how to single out the relationship between probability of default and stock returns that cannot be explained by known factors in the literature.

6 The Asian Experience

Unlike most emerging market crises, which arose from sovereign debt problems or combinations of banking and currency troubles, the Asian Financial Crisis was characterized by corporate vulnerabilities. Currency and maturity mismatches coupled with stretched balance sheets to cause widespread

[19] Campbell et al. (2008) construct portfolios that contain stocks in percentiles 0 to 5, 5 to 10, 10 to 20, 20 to 40, 40 to 60, 60 to 80, 80 to 90, 90 to 95, 95 to 99, and 99 to 100 of the failure risk distribution.

corporate failures. In this section, we model distress risk specifically for the subset of Asian firms, using the entire emerging market sample as benchmark to compare against. Even though the majority of our sample is comprised of firms in Asian countries (China, India, Indonesia, Malaysia, Pakistan, Philippines, South Korea, Taiwan, Thailand, and Vietnam), focusing on the behaviour of firms in this region yields slightly different results from the entire emerging market sample.

Table D1 shows the summary statistics for Asian firms are very similar to those in the emerging market sample. The only notable exception is the unemployment rate, which is higher for the default group in the Asian sample and lower in the emerging market sample. In Table D2, we run the same logit regressions as in Table 3 for the subsample of Asian countries. We focus on Column 5 since it is our measure of probability of default. The signs and significance of the coefficients on accounting and market variables are the same as the emerging market sample, except for the stock price. The Asia results show that a high stock price increases a firm's risk of default, whereas the coefficient was not significant when including all emerging market countries. More notably, though, all four domestic macro variables have significant coefficients, the average firm being more likely to default in an environment of high unemployment, low inflation, low real interest rates, and a high sovereign spread. Global financial conditions affect default risk differently, too. The coefficients on TED spread and Fed funds rate are no longer significant, and appreciations of the local currency versus the US dollar are negatively correlated with default risk. The 5-year Treasury rate keeps its positive, statistically significant coefficient. Consistent with the emerging market sample, the set of global variables contributes more to predictive power than the domestic macro covariates, after controlling for firm-specific covariates. Lastly, the specification in Column 5 yields an AUC of 0.914, up from the 0.87 returned by the CHS specification. Out-of-sample forecasts return AUC = 0.737 when estimating one time on the earliest 70% of the sample and predicting default on the remaining 30%, and AUC = 0.850 when estimating in a recursive manner.

We continue our analysis of the Asian subset of firms by computing global betas; i.e. the sensitivity of stock returns to the global variables in our model. We sort our firms by global beta and create a dummy that equals 1 for the tercile of firms with most negative betas.[20] We then run logit regressions (one for each global variable) of the probability of default next month on the global variable and its interaction with the top tercile dummy. Table D3 presents the results. Panel A shows that the probability of default of firms outside the top tercile of betas increases with the TED spread, Fed funds

[20] We select the tercile with most positive betas in the case of ΔFX to focus on those firms whose returns are most negatively affected by an appreciation of the US dollar versus the local currency.

rate, 5-year Treasury rates, and changes in the sovereign spread. We also find a positive coefficient on the interaction terms for 5-year Treasury, VIX, and Fed Funds rate. These results hold when controlling for firm-specific variables in Panel B.

Our last exercise involves looking at the effect of global financial conditions as a whole on firms' default risk. Table D4 contains the results of logit regressions of probability of default on Global Beta Z, Global Variable Z, and the interaction of the two, after controlling for firm-specific and domestic macro variables. Recall that Global Variable Z and Global Beta Z are the sum of standardized global variables and their betas, respectively. As in the emerging market sample, the coefficient on Global Variable Z is positive and statistically significant, implying that a risk-off environment contributes to default risk. Unlike the emerging market sample, however, the coefficient on the interaction of Global Variable Z and Global Beta Z is not significantly different from zero. This suggests that the effect of a risk-off environment on default risk is no different for firms whose returns are more sensitive to such global environment. This result is somewhat surprising given that half of the global variables yield a positive and significant coefficient in Table D3 when interacted with the top tercile dummy. One possible explanation is that the effect is partly captured by the domestic macro variables, which we don't control for in Table D3.

7 Conclusion

There is a dearth of rigorous research on the determinants of corporate distress in emerging markets. The goal of this paper is to shed light on factors that adversely impact the solvency of emerging market firms. We believe that developing a framework that allows policymakers to anticipate corporate defaults in emerging markets may inform efforts to mitigate their regional and global impact.

We find that while existing models proposed for US firms yield reasonable forecasting power, the performance is suboptimal compared to developing model specifications particular to the emerging market context. We suggest that these models do not account for emerging market vulnerabilities to global shocks such as advanced economy monetary policy changes, US dollar movements, or shifts in global liquidity and risk-aversion. A novel multi-country dataset of corporate defaults allows us to quantify the importance of global shocks on emerging market corporate distress. Using a set of accounting, market, and macroeconomic variables, we develop a model of distress risk specific to emerging markets with comparable forecasting power to that of existing models based on US data. The model performs well when including all emerging market countries in our sample and when focusing on firms in Asian countries. We also explore the asset pricing implications of our model by testing whether equity returns accurately reflect default risk.

We find that, controlling for firm-specific variables and the domestic macro environment, the 5-year US Treasury rate, the Fed funds rate, and the TED spread are correlated with distress risk. The VIX does not have significant power in predicting default risk at a one-month horizon, but it is positively correlated with the probability that an emerging market firm will default at some point in the next three months. For the Asia-only sample, the global variables that help predict default are the 5-year Treasury rate and the change in the exchange rate against the US dollar, consistent with a history of currency depreciations playing a major role in economic crises. For both samples, introducing a dummy variable indicating whether a firm has defaulted in the past has a very positive impact on the model's predictive power. To the best of our knowledge this is a novel result. A model that includes accounting, market, domestic and global macro variables along with the prior-default dummy yields a much higher explanatory power for emerging market firms than Campbell et al.'s (2008) specification. While both domestic and global macro variables seem important in the understanding of default risk, global variables contribute more to default prediction when included in the model. Future directions regarding the distress risk measure will focus on the prediction of corporate default at longer horizons.

We also analyse the asset pricing implications of our findings by examining the connection between distress risk and stock returns. We first do so by focusing on firms whose returns are most sensitive to global financial conditions. Analysis of these global betas reveals that the effect of the global variable on the probability of default differs for firms with most negative betas. Furthermore, a composite global beta measure we call the Global Beta Z helps us show that the effect of a global risk-off environment on distress risk is greater for firms whose returns respond more negatively to such global conditions. However, this last finding does not hold when restricting our sample to firms in Asian countries. Finally, we present preliminary analysis on the asset pricing implications of our distress risk measure. Consistent with prior studies using US data, we find that future stock returns are almost monotonically decreasing in default risk. Given the co-movement of distress risk with other risk factors, our next steps include disentangling the distress risk premium from other sources of risk.

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Tables and Figures

Figure 1: Example of Receiver Operating Characteristics curve

Point A in the "good model" ROC curve shows that the 22% of firms with highest probability of default include 70% of the firms that default the following month. Point B in the "bad model" curve indicates that to capture 70% of firms that default next month one needs to include the top 50% firms with highest probability of default.

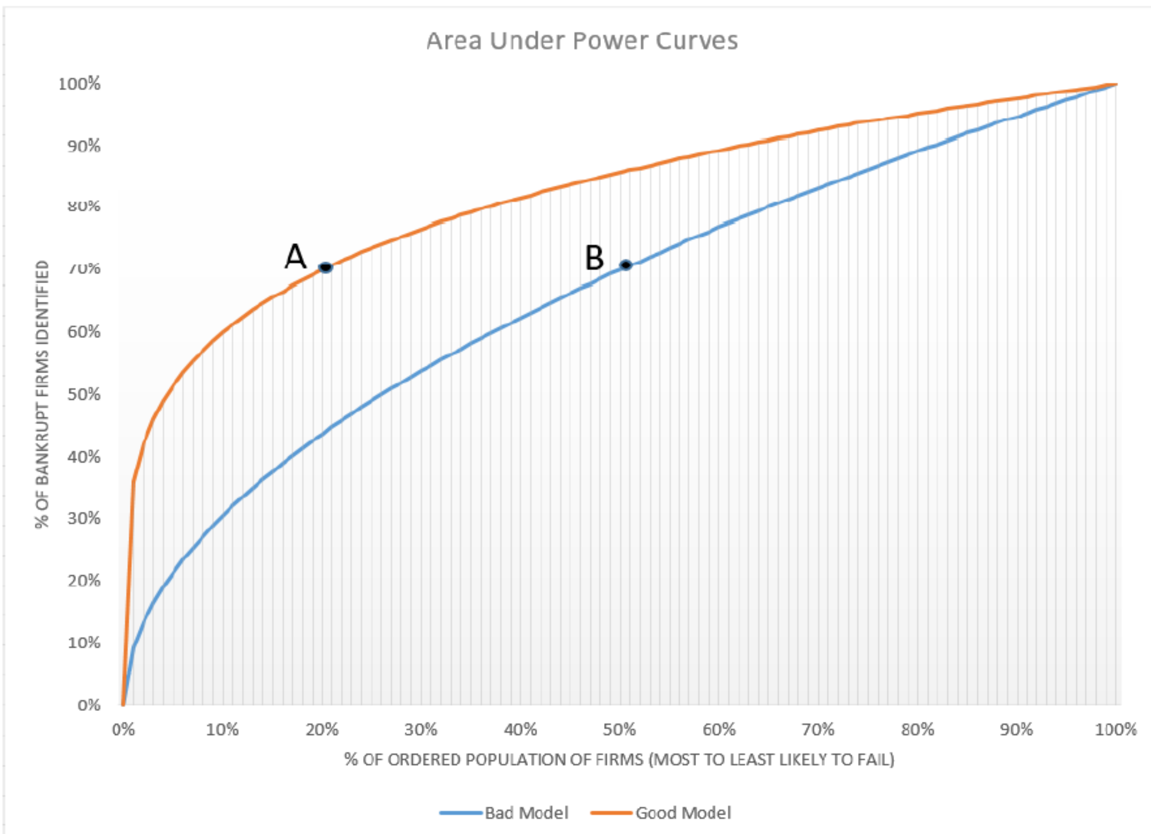


Figure 2: ROC of Full Model on EM Firms

This figure shows the Receiver Operating Characteristics curve for our model of distress risk. The curve shown is the average of the ROC curves in each month in the sample.

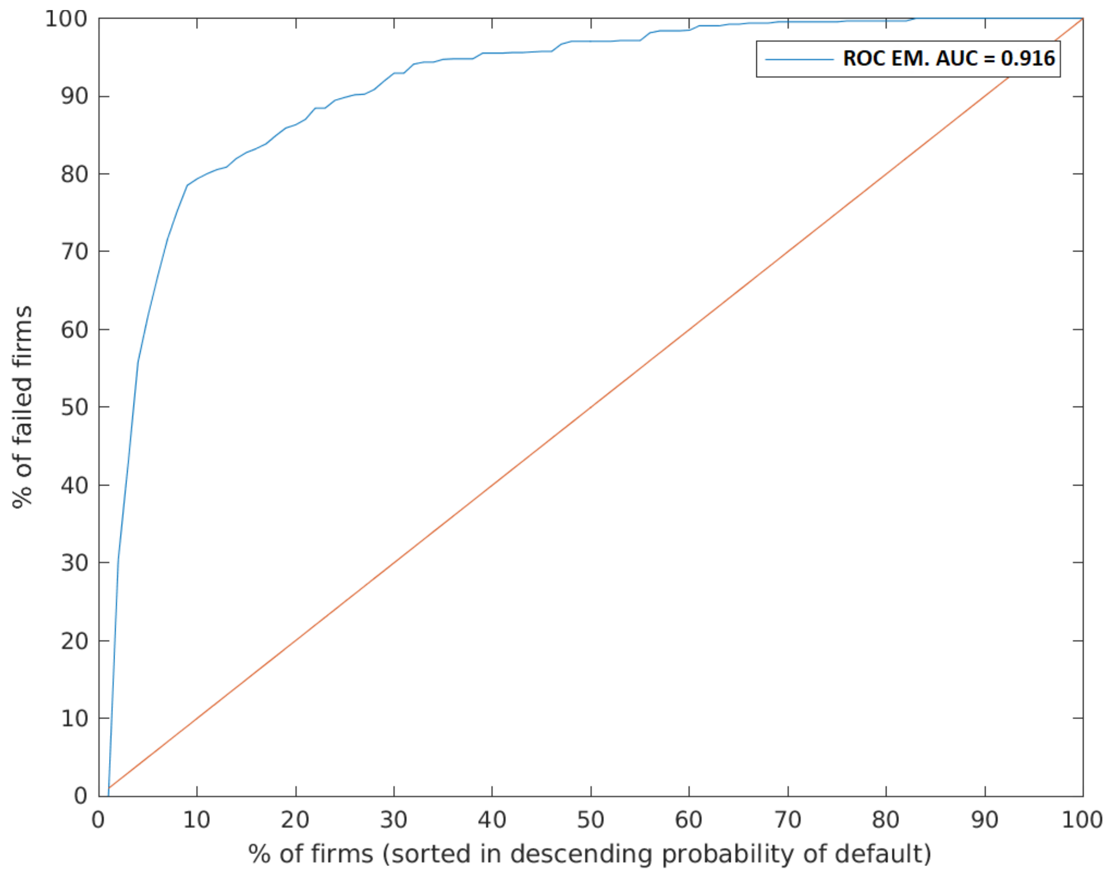


Figure 3: Time Series of Actual and Predicted Defaults

This figure shows the number of actual defaults per quarter and number of defaults predicted by our model. The number of predicted defaults in a quarter is the sum of the estimated probabilities of default of each firm-month.

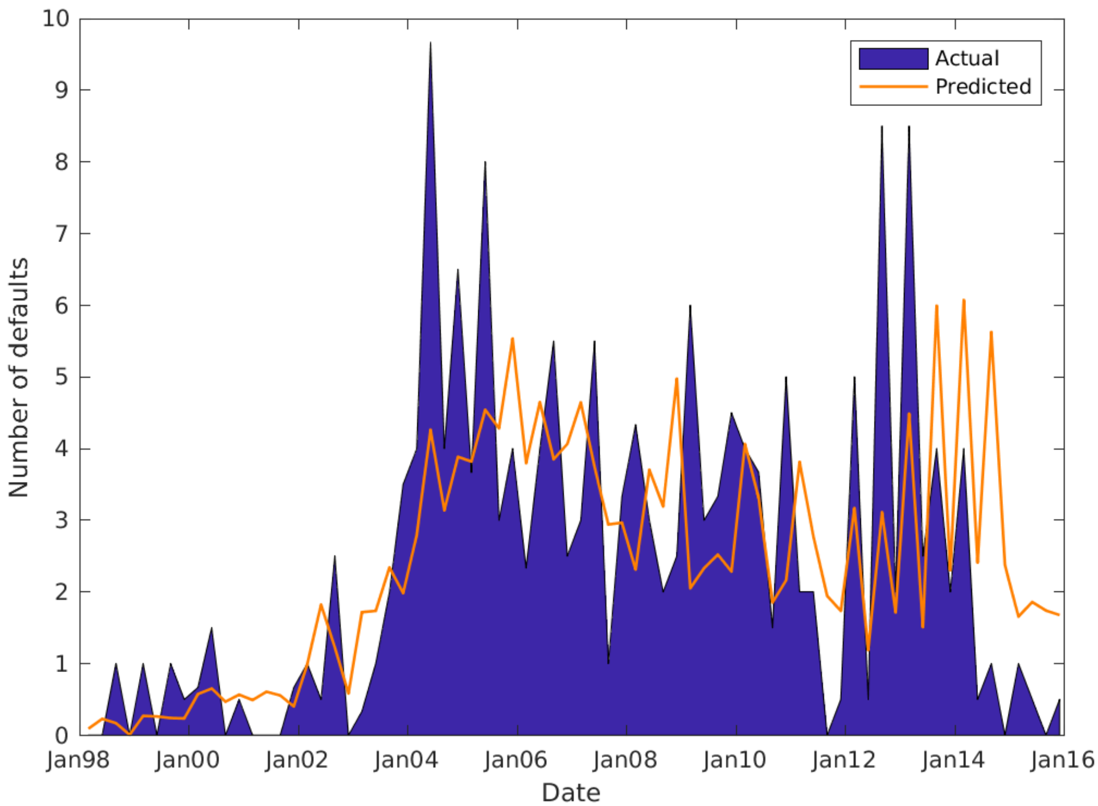


Figure 4: Cumulative Stock Returns by Probability of Default

This figure shows the returns over time of portfolios sorted by distress risk, such that each portfolio contains 10% of firms at each point in time. Portfolio 1 holds the firms least likely to default next month and Portfolio 10 those with highest distress risk. The portfolios are rebalanced monthly.

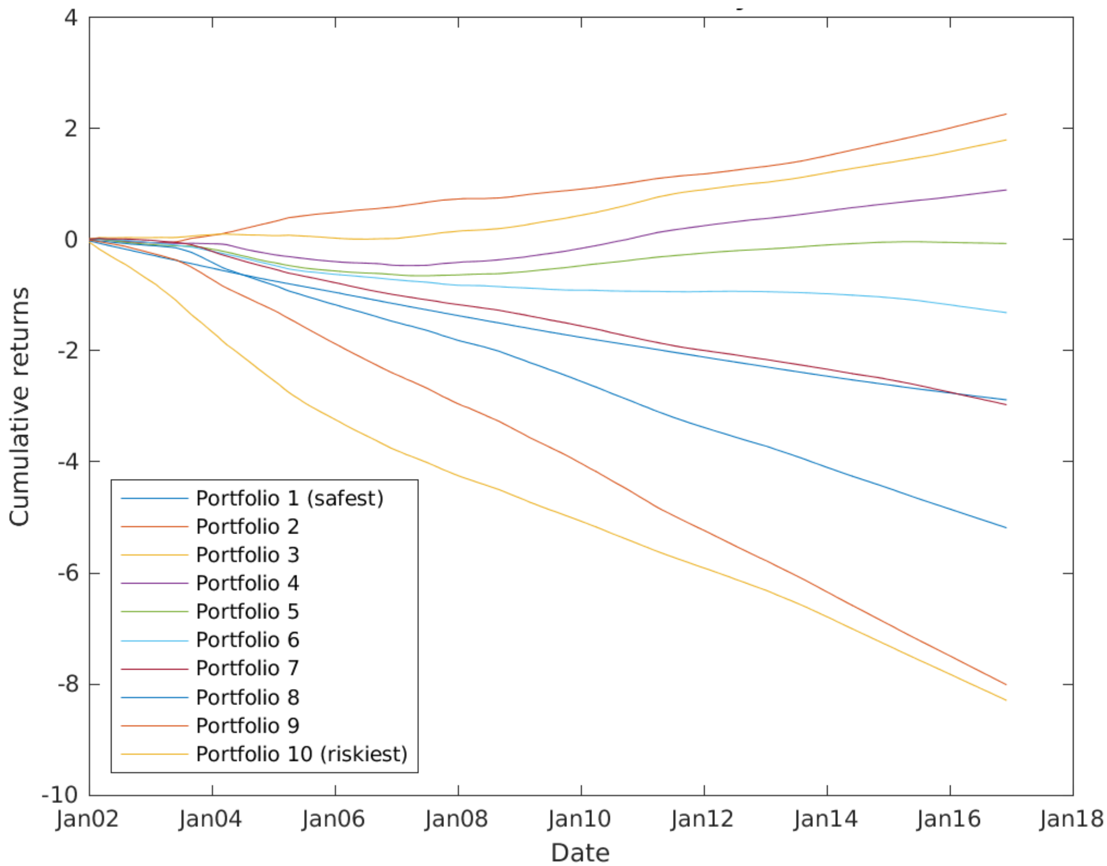


Table 1: Types of Default Events

Panel A presents the types of default events covered in the CRI database and their classification into Bankruptcy, Delisting, and Corporate Default Action categories, as CRI does in the database's technical report (NUS-RMI Technical Report 2016, Table A.9, p. 106). Panel B counts the number of each type of event in our final sample; i.e. the sample of firm-months with data on each of CHS's variables.

PANEL A	
Action Type	**Subcategory**
Bankruptcy Filing	Administration, Arrangement, Canadian CCAA, Chapter 7, Chapter 11, Chapter 15, Conservatorship, Insolvency, Japanese CRL, Judicial Management, Liquidation, Pre-Negotation Chapter 11, Protection, Receivership, Rehabilitation, Rehabilitation (Thailand 1997), Reorganisation, 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

PANEL B	
Action Type	**Count**
Bankruptcy	45
Delisting	2
Default Corporate Action	345
Bankruptcy Corporate Action	7
Coupon & Principal Payment	17
Coupon Payment	11
Restructuring	82
Interest Payment	7
Loan Payment	220
Principal Payment	9
Other	1
Unknown	10

Table 2: Summary Statistics

Summary statistics for all firm-months, for the group of firm-months that experience any default event, and for the group that experiences a bankruptcy next month. The last two columns show the results of a two-sample t-test for equal means, where the "Default" and "Bankrupt" columns refer to the tests of whether the mean for the full sample is different from the default group or the bankrupt group, respectively. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$.

	Means			**t-Tests**	
	Full Sample	**Default**	**Bankrupt**	**Default**	**Bankrupt**
Excess returns	-0.008	-0.042	-0.087	***	***
Stock price	2.594	1.327	0.229	***	***
Volatility of returns	1.589	0.713	0.749	*	
Market capitalization	-7.820	-9.202	-9.242	***	***
Profitability	0.005	-0.015	-0.055	***	***
Leverage	0.365	0.577	0.785	***	***
Cash	0.081	0.043	0.025	***	***
Market-to-book ratio	2.140	2.756	4.283	***	***
Prior default	0.059	0.637	0.433	***	***
ΔSovereign spread	0.007	0.023	0.009	**	
ΔFX	0.001	0.001	-0.005		*
5-year Treasury	2.382	2.906	2.759	***	*
VIX	19.52	19.07	21.07		
Fed funds rate	1.285	1.900	1.491	***	
TED spread	-0.071	0.026	-0.123	***	

Table 3: Logit Regressions of Probability of Default Next Month

Results of logit regression combining CHS's accounting and market variables with local and global macro variables to explain the probability of default next month. Column 1 replicates Campbell et al.'s (2008) specification, which uses only firm-specific accounting and market variables. Column 2 adds a dummy indicating whether a firm has experienced a default event in the past. Column 3 adds domestic macroeconomic variables, while column 4 includes global variables. Column 5 is our baseline specification, which includes all three types of explanatory variables. Columns 6-8 are like columns 3-5 excluding the firm-specific variables. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to McFadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-8.287***	-8.590***	-8.693***	-9.718***	-9.542***	-6.362***	-8.031***	-6.622***
Excess returns	-1.195***	-1.464***	-1.427***	-1.205***	-1.328***			
Stock price	-0.157***	-0.135***	-0.032	-0.049*	-0.018			
Volatility of returns	-0.100**	-0.091**	-0.060	-0.095**	-0.064			
Market capitalization	-0.059***	-0.046**	-0.092***	-0.093***	-0.111***			
Profitability	-6.524***	-5.655***	-5.388***	-5.514***	-5.564***			
Leverage	2.392***	1.917***	2.376***	1.819***	2.217***			
Cash	-4.809***	-2.666***	-4.572***	-3.114***	-4.096***			
Market-to-book ratio	0.206***	0.117***	0.083***	0.083***	0.084***			
Prior default		2.813***	2.653***	2.815***	2.665***			
Unemployment rate			0.040		0.027	-0.049***		-0.048***
Inflation			-1.512		-2.537	-11.42***		-11.92***
Real interest rate			-0.052***		-0.043***	-0.036***		-0.042***
Sovereign spread			-0.112***		-0.068**	-0.008		-0.008
ΔSovereign spread				0.488	0.404		0.398**	0.311*
ΔFX				1.550	-1.702		0.754	-1.602
5-year Treasury				0.421***	0.343***		0.159***	0.051
VIX				0	0		0.009***	0.008***
Fed funds rate				-0.154**	-0.150**		-0.066***	-0.022
TED spread				0.347**	0.300*		0.084	0.263***
Pseudo-R^2	0.146	0.241	0.261	0.255	0.265	0.021	0.005	0.022
AUC	0.880	0.921	0.916	0.922	0.916	0.654	0.537	0.653
Observations	437,492	437,492	256,471	306,360	256,091	3,280,012	3,864,780	3,229,531
Defaults	412	412	374	383	374	2,139	2,182	2,088

Table 4: Logit Regressions of Probability of Default in the Next Three Months

Results of logit regression combining CHS's accounting and market variables with local and global macro variables to explain the probability of default at some point in the next three months. Column 1 replicates Campbell et al.'s (2008) specification, which uses only firm-specific accounting and market variables. Column 2 adds a dummy indicating whether a firm has experienced a default event in the past. Column 3 adds domestic macroeconomic variables, while column 4 includes global variables. Column 5 is our baseline specification, which includes all three types of explanatory variables. Columns 6-8 are like columns 3-5 excluding the firm-specific variables. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event in the following 3 months. Pseudo-R^2 refers to McFadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-7.16***	-7.384***	-7.000***	-8.657***	-8.369***	-5.398***	-7.039***	-5.702***
Excess returns	-0.950***	-1.208***	-1.167***	-1.092***	-1.131***			
Stock price	-0.164***	-0.148***	-0.108***	-0.068***	-0.081***			
Volatility of returns	-0.057***	-0.048***	-0.036*	-0.051***	-0.040**			
Market capitalization	-0.039***	-0.025***	-0.020	-0.074***	-0.062***			
Profitability	-7.698***	-7.153***	-7.153***	-7.084***	-7.185***			
Leverage	2.531***	2.116***	2.293***	1.962***	2.128***			
Cash	-4.637***	-3.396***	-4.633***	-3.567***	-4.202***			
Market-to-book ratio	0.190***	0.114***	0.096***	0.082***	0.094***			
Prior default		2.622***	2.498***	2.666***	2.519***			
Unemployment rate			0.026		0.009	-0.048***		-0.046***
Inflation			-1.546		0.277	-10.45***		-10.91***
Real interest rate			-0.045***		-0.036***	-0.033***		-0.039***
Sovereign spread			-0.034***		-0.018*	-0.003		-0.004
ΔSovereign spread				-0.160	-0.316		0.047	-0.045
ΔFX				0.800	-2.259		1.370***	0.002
5-year Treasury				0.403***	0.382***		0.140***	0.038*
VIX				0.008*	0.010**		0.013***	0.011***
Fed funds rate				-0.145***	-0.146***		-0.053***	-0.014
TED spread				0.312***	0.185*		0.058	0.231***
Pseudo-R^2	0.161	0.252	0.272	0.270	0.279	0.021	0.005	0.023
AUC	0.878	0.924	0.922	0.925	0.923	0.652	0.543	0.654
Observations	437,492	437,492	256,471	306,360	256,091	3,280,012	3,864,780	3,229,531
Defaults	412	412	374	383	374	2,139	2,182	2,088

Table 5: Top Tercile Betas by Global Variable

Results of logit regression of probability of default on each global factor, controlling for firm-specific variables. The explanatory variables in Panel A are the global variable of the same name as each column and the interaction of that variable with a dummy indicating whether a firm's returns are among the top-third most sensitive to the global factor. Panel B also includes CHS's accounting and market variables as controls. The dependent variable is binary, indicating whether a firm experienced a distress event the following month.Pseudo-R^2 refers to McFadden's Pseudo-R^2. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p = 0.15$, respectively.

			PANEL A			
	ΔSov. spread	**ΔFX**	**5-year Treasury**	**VIX**	**Fed funds**	**TED spread**
Constant	-6.819***	-7.153***	-7.856***	-7.289***	-7.365***	-7.148***
Global variable	0.561*	0.006	0.242***	0.011***	0.148***	0.223**
Global variable * Top-tercile	0.446	1.718	0.106***	-0.015***	0.001	0.251†
Pseudo-R^2	0.003	0	0.011	0.002	0.005	0.001
Observations	559,498	886,309	886,309	886,309	886,309	886,309
Defaults	616	693	693	693	693	693
			PANEL B			
	ΔSov. spread	**ΔFX**	**5-year Treasury**	**VIX**	**Fed funds**	**TED spread**
Constant	-8.007***	-8.248***	-9.328***	-8.148***	-8.696***	-8.298***
Excess returns	-0.925***	-1.187***	-1.159***	-1.239***	-1.196***	-1.113***
Stock price	-0.106***	-0.158***	-0.124***	-0.172***	-0.140***	-0.156***
Volatility of returns	-0.116**	-0.100**	-0.110**	-0.088**	-0.109**	-0.104**
Market capitalization	-0.049**	-0.058***	-0.105***	-0.052***	-0.086***	-0.064***
Profitability	-6.847***	-6.518***	-6.414***	-6.761***	-6.479***	-6.590***
Leverage	2.330***	2.362***	2.346***	2.468***	2.332***	2.371***
Cash	-5.321***	-4.265***	-4.067***	-4.636***	-4.134***	-4.222***
Market-to-book ratio	0.188***	0.205***	0.206***	0.205***	0.206***	0.207***
Global variable	0.816*	0.993	0.205***	0.006	0.139***	0.463***
Global variable * Top-tercile	-0.177	1.755	0.098***	-0.033***	-0.051	-0.012
Pseudo-R^2	0.108	0.123	0.131	0.129	0.127	0.126
Observations	303,732	435,736	435,736	435,736	435,736	435,736
Defaults	379	410	410	410	410	410

Table 6: Composite Global Beta Z Score as Predictor of Default

Results of logit regression of probability of default on a composite global factor, controlling for firm-specific variables. Beta Z and Global Z are the sum of the standardized global betas and global variables, respectively. We control for the CHS variables and the domestic macro variables. The dependent variable is binary, indicating whether a firm experienced a distress event the following month.Pseudo-R^2 refers to McFadden's Pseudo-R^2. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	(1)
Constant	-8.632***
Excess returns	-1.294***
Stock price	-0.016
Volatility of returns	-0.064
Market capitalization	-0.100***
Profitability	-5.585***
Leverage	2.283***
Cash	-4.510***
Market-to-book ratio	0.077***
Prior default	2.695***
Unemployment rate	0.029
Inflation	-3.824
Real interest rate	-0.044***
Sovereign spread	-0.088***
Beta Z	-0.005
Variable Z	0.069***
Beta Z * Variable Z	-0.016*
Pseudo-R^2	0.263
AUC	0.916
Observations	253,803
Defaults	370

Table 7: Returns on Portfolios Sorted by Distress Risk

Every month between January 2002 and September 2016 we estimate our measure of distress risk using all prior data in the sample to prevent look-ahead bias. We sort all stocks based on this predicted probability of default and construct ten portfolios of equal size. We rebalance the portfolios every month based on the stocks' updated distress risk. This table shows average monthly excess returns (over the market index), standard deviations, and skewness of each portfolio throughout the estimation period. The Probability of Default column shows the average predicted probability of default for each portfolio. Portfolio 1 contains the firms with the lowest probability of default and Portfolio 10 those with highest predicted distress risk.

	Excess Returns	**Volatility of Returns**	**Skewness**	**Probability of Default**
Portfolio 1	-0.0160	0.0028	-0.178	0.0001
Portfolio 2	0.0126	0.0080	-0.919	0.0002
Portfolio 3	0.0100	0.0083	-0.401	0.0002
Portfolio 4	0.0050	0.0105	-0.777	0.0003
Portfolio 5	-0.0004	0.0089	-0.778	0.0004
Portfolio 6	-0.0073	0.0063	-0.663	0.0005
Portfolio 7	-0.0165	0.0063	0.808	0.0006
Portfolio 8	-0.0288	0.0082	1.258	0.0008
Portfolio 9	-0.0445	0.0091	1.994	0.0013
Portfolio 10	-0.0461	0.0141	-1.223	0.0104

Appendix A: Variable and Factor Definitions

Variable Name	Variable Definition
Excess returns	Log (1 + firm returns) - log (1 + country (market) index returns).
Stock price	Log price per share.
Volatility of returns	Standard deviation of daily returns over the previous month.
Market capitalization	Log (Firm market cap) - log (country market cap). The market capitalization of listed domestic companies comes from the World Bank.
Profitability	Ratio of net income to the market value of total assets, where the market value of assets is equal to the sum of the firm's market capitalization and total liabilities.
Leverage	Ratio of total liabilities to the market value of total assets.
Cash	Ratio of cash and cash equivalents to the market value of total assets.
Market-to-book ratio	Ratio of market capitalization to book value of equity, where book value of equity is total assets minus total liabilities. Following Campbell et al. (2008), if a firm has a negative book value of equity, we set its book value of equity equal to $1 in order to place that firm's market-to-book ratio in the right-hand side of the distribution (Large positive MB instead of a negative MB).
ΔFX	Monthly percentage change in the exchange rate between the local currency and the US dollar, quoted as local currency units per dollar and retrieved from Bloomberg.
5-year Treasury rate	Interest rate on US 5-year Treasury notes.
VIX	CBOE Volatility Index.
Fed funds rate	Federal funds rate, retrieved from FRED, Federal Reserve Bank of St. Louis.
TED spread	Component of the TED spread orthogonal to VIX. The TED spread is the spread between 3-month LIBOR rates and 3-month T-bill rates, often used as a measure of liquidity risk in bond markets. Due to collinearity between VIX and the TED spread, we regress the TED spread on the VIX and keep the residual.

Sources: Default data and all accounting and market variables come from the CRI database, the Credit Research Initiative of the National University of Singapore, accessed on December 1, 2016.

Appendix B: Additional Tables and Figures

Table B1: Number of Defaults and Observations per Year

This table lists the number of defaults and observations per year of our sample, aggregated across countries, for the observations with all accounting and market data.

Year	Firm-Months	Defaults	%
1995	11	0	0
1996	194	0	0
1997	505	0	0
1998	1,112	2	0.18
1999	1,384	4	0.29
2000	4,129	6	0.15
2001	5,311	2	0.04
2002	9,181	9	0.1
2003	15,367	15	0.1
2004	19,558	54	0.28
2005	24,328	41	0.17
2006	23,896	32	0.13
2007	27,394	30	0.11
2008	29,533	31	0.1
2009	28,194	36	0.13
2010	31,033	32	0.1
2011	42,561	14	0.03
2012	39,491	37	0.09
2013	43,950	39	0.09
2014	48,503	19	0.04
2015	42,286	9	0.02
Total	437,921	412	0.09

Table B2: Number of Observations per Country and Year

This table lists the number of firm-months with all accounting and market data per country and year of our sample.

	Argentina	Brazil	Chile	China	Colombia	Czech Republic	Hungary	India	Indonesia	Malaysia	Mexico	Pakistan	Peru	Philippines	Poland	South Africa	South Korea	Thailand	Turkey	Vietnam	Total
1995	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	11
1996	0	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	112	0	0	194
1997	15	0	3	0	0	0	0	0	0	0	165	0	0	0	0	0	0	312	10	0	505
1998	25	0	214	0	0	0	0	0	0	0	170	0	0	0	0	0	0	680	23	0	1112
1999	37	0	277	0	0	0	0	0	0	56	156	0	0	84	0	8	0	707	59	0	1384
2000	127	259	371	0	0	0	0	0	22	1166	326	0	0	157	43	26	4	1028	600	0	4129
2001	129	302	321	0	0	0	0	0	207	1518	352	0	0	129	232	33	15	1088	985	0	5311
2002	84	293	257	0	0	7	10	0	267	1650	303	0	4	122	267	38	3913	1051	915	0	9181
2003	66	367	293	3290	0	25	23	27	338	1640	337	0	5	156	327	55	5947	1481	990	0	15367
2004	125	353	263	5556	0	63	61	5	439	3016	346	0	15	132	645	43	6422	1227	847	0	19558
2005	221	528	453	5589	76	97	89	12	644	3685	372	8	112	162	986	43	8452	1599	1200	0	24328
2006	269	538	689	5011	91	84	98	15	557	3568	394	131	160	197	1099	40	7724	1711	1520	0	23896
2007	286	793	675	6458	89	52	68	32	806	4375	420	530	208	187	1155	43	8226	1436	1555	0	27394
2008	272	902	638	6976	95	45	94	62	769	3892	389	358	205	423	1630	53	8593	1678	1383	1076	29533
2009	221	802	664	7632	82	0	120	56	809	2968	392	731	169	351	1607	43	7690	1460	1188	1209	28194
2010	229	849	631	8788	117	0	119	237	960	2924	391	1099	185	473	1703	63	7439	1649	1380	1797	31033
2011	306	1131	803	11899	133	0	90	2210	1262	3799	432	870	218	572	2077	70	10347	2088	1436	2818	42561
2012	192	972	816	12035	118	0	79	6495	1406	3706	449	0	183	693	1868	65	6689	1972	1753	0	39491
2013	165	936	606	10669	91	0	92	8234	1338	3681	408	0	134	662	1640	52	9295	1875	1610	2462	43950
2014	241	1121	682	11615	122	0	109	10029	984	3829	433	0	133	738	1894	79	9552	2228	1793	2921	48503
2015	220	914	685	11318	104	0	108	4586	1378	3227	391	0	128	560	1672	46	10330	2054	1617	2948	42286
Total	3230	11060	9341	106836	1118	373	1160	32000	12186	48700	6708	3727	1859	5798	18845	800	110638	27447	20864	15231	437921

Table B3: Correlation Matrix and Multicollinearity Analysis

The last two rows of this table show the Tolerance Value (TOL) and its reciprocal Variance Inflation Factor (VIF). VIF is computed as $1/(1-R_k^2)$, where R_k^2 is the R^2 value of a regression of factor k on all others. TOL is simply $1-R_k^2$. VIF values larger than 10 are typically considered suggestive of multicollinearity in a model. The rest of the matrix presents pairwise correlations between all variables in our various specifications.

	EXRET	**PRICE**	**VOL**	**RELSIZE**	**NIMTA**	**TLMTA**	**CASHMTA**	**MB**	**ΔsovSpread**	**ΔFX**	**5YEAR**	**VIX**	**DFF**	**TED**
EXRET	1													
PRICE	0.032	1												
VOL	-0.001	0.202	1											
RELSIZE	0.016	0.548	0.090	1										
NIMTA	0.042	0.162	0.064	0.174	1									
TLMTA	-0.071	-0.033	-0.007	-0.035	-0.078	1								
CASHMTA	-0.027	-0.104	-0.074	-0.024	0.149	-0.024	1							
MB	0.078	0.100	0.078	0.024	-0.121	-0.486	-0.273	1						
ΔsovSpread	0.002	-0.007	-0.006	0.004	-0.001	-0.008	0.005	0.026	1					
ΔFX	0.002	0.011	-0.009	0.029	0.009	-0.068	-0.000	0.032	-0.172	1				
5YEAR	0.029	-0.043	0.018	0.220	0.011	0.079	-0.060	-0.093	-0.005	0.133	1			
VIX	0.076	0.042	-0.023	0.112	0.015	0.014	0.021	-0.023	0.335	-0.019	-0.072	1		
DFF	0.048	-0.078	0.025	0.163	0.012	0.069	-0.049	-0.073	0.011	0.152	0.886	-0.126	1	
TED	0.042	-0.138	0.015	0.010	0.020	-0.009	-0.014	0.021	0.183	0.029	0.343	0.031	0.493	1
TOL	0.976	0.571	0.925	0.538	0.903	0.687	0.848	0.648	0.741	0.903	0.189	0.826	0.165	0.641
VIF	1.025	1.751	1.082	1.860	1.108	1.457	1.179	1.544	1.350	1.107	5.292	1.211	6.053	1.559

Appendix C: LASSO Estimation

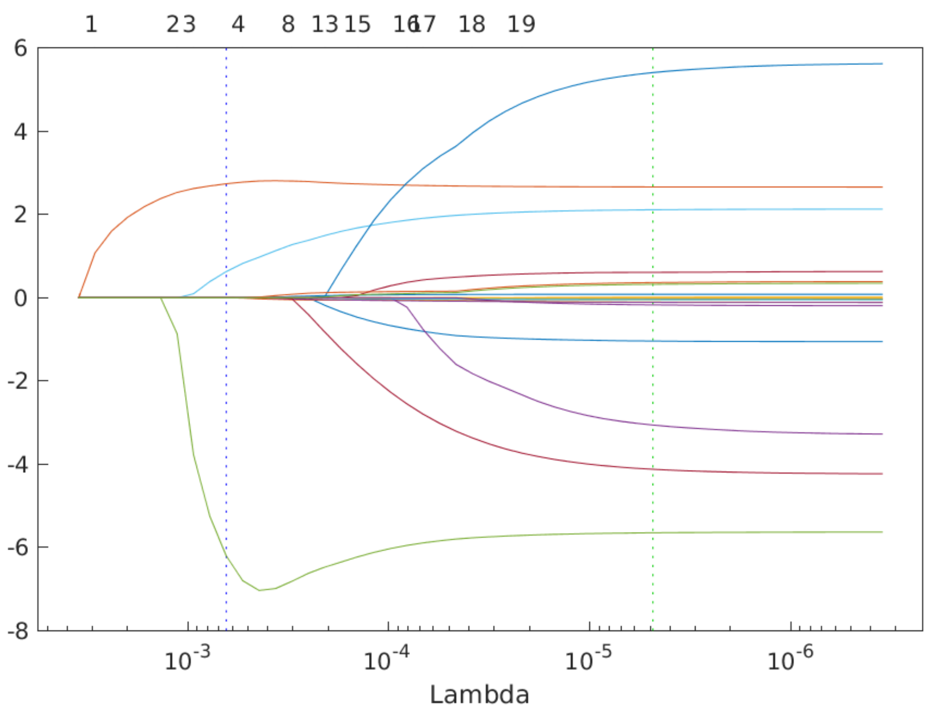
Table C1: Robustness Checks Using LASSO for Variable Selection

Column 1 presents coefficients returned by a simple logit estimation of firms' probability of default on our full set of explanatory variables, while Column 2 shows the coefficients returned by the LASSO procedure. Running a logit regression only on the variables with nonzero coefficients in Column 2 yields the coefficients and statistics in Column 3. In all cases the dependent variable is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to McFadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	(1)	(2)	(3)
Constant			-8.959***
Excess returns	-1.328	-1.140	-1.387***
Stock price	-0.018	-0.041	-0.025
Volatility of returns	-0.064	-0.001	-0.066
Market capitalization	-0.111	-0.068	-0.089***
Profitability	-5.564	-5.834	5.449***
Leverage	2.217	2.030	2.243***
Cash	-4.096	-2.655	-4.151***
Market-to-book ratio	0.084	0.079	0.084***
Prior default	2.665	2.699	2.642***
Unemployment rate	0.027	0	
Inflation	-2.537	-0.377	-2.802
Real interest rate	-0.043	-0.027	-0.043***
Sovereign spread	-0.068	-0.043	-0.068**
ΔSovereign spread	0.404	0.309	0.576
ΔFX	-1.702	0	
5-year Treasury	0.343	0.149	0.158***
VIX	0.000	0	
Fed funds rate	-0.150	0	
TED spread	0.300	0.121	0.179
Pseudo-R^2	0.265		0.262
AUC	0.916		0.916
Observations	256,091		260,665
Defaults	374		377

Figure C1: LASSO Coefficient Path

Coefficient path using LASSO for variable selection on our full set of explanatory variables. The vertical axis reports the value of the coefficients of the standardized explanatory variables. The lower horizontal axis shows the level of λ decreasing from left to right, where a lower λ implies a loosening of the constraint on the sum of the absolute value of the coefficients. The numbers at the top of the figure indicate the degrees of freedom or number of variables with coefficient different from zero for each level of λ.



Appendix D: Asia

Table D1: Summary Statistics of Asian firms

Summary statistics for three groups of firms in Asian countries: the full sample, the group of firm-months that experience any default event, and the group that experiences a bankruptcy next month. Column t-Test shows the results of a two-sample t-test for equal means, where the "Default" and "Bankrupt" columns refer to the tests of whether the mean for the full sample is different from the default group or the bankrupt group, respectively. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$.

	Means			t-Tests	
	Full Sample	**Default**	**Bankrupt**	**Default**	**Bankrupt**
Excess returns	-0.008	-0.041	-0.039	***	
Stock price	2.443	1.33	0.681	***	***
Volatility of returns	1.321	0.684	0.858	*	
Market capitalization	-8.221	-9.251	-9.18	***	**
Profitability	0.004	-0.014	-0.031	***	***
Leverage	0.358	0.568	0.712	***	***
Cash	0.088	0.044	0.024	***	***
Market-to-book ratio	2.127	2.759	4.162	***	***
Prior default	0.064	0.643	0.55	***	***
Unemployment rate	4.021	4.118	4.322	*	
Inflation	0.034	0.034	0.028		
Real interest rates	2.594	1.458	2.145	***	
Sovereign spread	2.3	2.201	1.737		
ΔSovereign spread	0.007	0.024	0.021	**	
ΔFX	0.001	0.001	-0.004		
5-year Treasury rate	2.327	2.93	3.003	***	**
VIX	19.476	18.971	23.159		**
Fed funds rate	1.206	1.93	1.627	***	
TED spread	-0.08	0.025	-0.115	***	

Table D2: Logit Regressions of Probability of Default Next Month in Asia

Results of logit regression combining CHS's accounting and market variables with local and global macro variables to explain the probability of default next month of firms in Asian countries. Column 1 replicates Campbell et al.'s (2008) specification, which uses only firm-specific accounting and market variables. Column 2 adds a dummy indicating whether a firm has experienced a default event in the past. Column 3 adds domestic macroeconomic variables, while column 4 includes global variables. Column 5 is our benchmark specification, which includes all three types of explanatory variables. Columns 6-8 are like columns 3-5 excluding the firm-specific variables. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to McFadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8))**
Constant	-7.316***	-8.042***	-8.973***	-9.415***	-9.640***	-6.520***	-7.730***	-6.740***
Excess returns	-1.282***	-1.477***	-1.296***	-1.153***	-1.198***			
Stock price	-0.253***	-0.170***	0.056	-0.068**	0.076*			
Volatility of returns	-0.058	-0.082*	-0.057	-0.085*	-0.061			
Market capitalization	0.006	-0.014	-0.118***	-0.072**	-0.135***			
Profitability	-5.986***	-4.903***	-4.721***	-4.472***	-4.746***			
Leverage	2.302***	1.830***	2.413***	1.709***	2.180***			
Cash	-5.339***	-3.142***	-4.772***	-3.775***	-4.184***			
Market-to-book ratio	0.232***	0.116***	0.062**	0.074***	0.065**			
Prior default		2.730***	2.703***	2.762***	2.728***			
Unemployment rate			0.204***		0.186***	0.073***		0.067***
Inflation			-24.04***		-27.38***	-10.82***		-11.88***
Real interest rate			-0.224***		-0.228***	-0.081***		-0.094***
Sovereign spread			0.061		0.147***	-0.039***		-0.031**
ΔSovereign spread				0.598	0.229		0.718***	0.145
ΔFX				-1.751	-5.690*		1.508	-1.532
5-year Treasury				0.478***	0.311***		0.159***	0.044
VIX				0.001	-0.006		0.008***	0.006**
Fed funds rate				-0.168**	-0.088		-0.062**	0.006
TED spread				0.295*	0.291		0.202***	0.256***
Pseudo-R^2	0.143	0.232	0.255	0.248	0.261	0.02	0.007	0.022
AUC	0.87	0.915	0.914	0.916	0.914	0.636	0.541	0.635
Observations	362,563	362,563	220,745	234,471	220,470	2,387,466	2,582,021	2,350,689
Defaults	384	384	353	356	353	1,927	1,934	1,879

Table D3: Top Tercile Betas by Global Variable - Asia

Results of logit regression of probability of default of Asian firms on each global factor, controlling for firm-specific variables. The explanatory variables in Panel A are the global variable of the same name as each column and the interaction of that variable with a dummy indicating whether a firm's returns are among the top-third most sensitive to the global factor. Panel B also includes CHS's accounting and market variables as controls. The dependent variable is binary, indicating whether a firm experienced a distress event the following month.Pseudo-R^2 refers to McFadden's Pseudo-R^2. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p = 0.15$, respectively.

PANEL A						
	ΔSov. spread	**ΔFX**	**5-year Treasury**	**VIX**	**Fed funds**	**TED spread**
Constant	-6.651***	-7.073***	-7.916***	-7.204***	-7.332***	-7.066***
Global variable	0.588*	1.289	0.305***	-0.002	0.163***	0.294***
Global variable * Top-tercile	0.612	1.915	0.087***	0.023***	0.072**	0.267
Pseudo-R^2	0.004	0	0.015	0.004	0.009	0.002
Observations	432,546	750,916	750,916	750,916	750,916	750,916
Defaults	564	637	637	637	637	637
PANEL B						
	ΔSov. spread	**ΔFX**	**5-year Treasury**	**VIX**	**Fed funds**	**TED spread**
Constant	-6.914***	-7.316***	-8.371***	-7.310***	-7.710***	-7.366***
Excess returns	-0.956***	-1.247***	-1.235***	-1.263***	-1.243***	-1.207***
Stock price	-0.213***	-0.251***	-0.218***	-0.248***	-0.232***	-0.245***
Volatility of returns	-0.070	-0.060	-0.068	-0.060	-0.066	-0.063
Market capitalization	0.028	0.005	-0.037	0.005	-0.015	0
Profitability	-6.066***	-6.017***	-5.707***	-5.993***	-5.791***	-6.020***
Leverage	2.313***	2.283***	2.254***	2.361***	2.265***	2.289***
Cash	-7.049***	-5.420***	-5.204***	-5.562***	-5.259***	-5.374***
Market-to-book ratio	0.212***	0.233***	0.235***	0.225***	0.237***	0.235***
Global Variable	0.831**	-1.483	0.208***	-0.011	0.088***	0.367**
Global variable * Top-tercile	0.356	0.797	0.106***	0.023***	0.108***	0.021
Pseudo-R^2	0.109	0.127	0.136	0.131	0.132	0.129
Observations	231,817	360,736	360,736	360,736	360,736	360,736
Defaults	353	383	383	383	383	383

Table D4: Composite Global Beta Z Score as Predictor of Default in Asia

Results of logit regression of probability of default of Asian firms on a composite global factor, controlling for firm-specific variables. Beta Z and Global Z are the sum of the standardized global betas and global variables, respectively. We control for the CHS variables and the domestic macro variables. The dependent variable is binary, indicating whether a firm experienced a distress event the following month.Pseudo-R^2 refers to McFadden's Pseudo-R^2. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	(1)
Constant	-9.068***
Excess returns	-1.179***
Stock price	0.075**
Volatility of returns	-0.059
Market capitalization	-0.134***
Profitability	-4.900***
Leverage	2.347***
Cash	-4.696***
Market-to-book ratio	0.056**
Prior default	2.733***
Unemployment rate	0.208***
Inflation	-26.38***
Real interest rate	-0.215***
Sovereign spread	0.078
Beta Z	-0.975
Variable Z	0.053***
Beta Z * Variable Z	-0.320
Pseudo-R^2	0.258
AUC	0.914
Observations	218,107
Defaults	350