CORPORATE DEBT AND DISTRESS RISK IN EMERGING MARKETS

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A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics.

Chapel Hill
2018

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ABSTRACT

Gonzalo De Asis Ruiz: Corporate Debt and Distress Risk in Emerging Markets
(Under the direction of Anusha Chari)

This dissertation consists of two papers in the field of international finance, both under the general theme of corporate distress in emerging markets. In the first paper, I explore how the leverage and size of emerging market firms relates to their financial fragility. I also show that idiosyncratic shocks to large firms have macroeconomic effects. In the second paper, I estimate an emerging market-specific measure of distress risk and explore its asset pricing implications. I find that global financial conditions help explain changes in firms' probability of default, and that distressed stocks earn a premium over their safer counterparts.

To Courtney, for your love, patience, and unwavering support throughout this journey.
And to my parents, for encouraging and helping feed my curiosity from the start.

ACKNOWLEDGMENTS

This dissertation and my academic development has greatly benefitted from the incessant effort, support, and guidance of my advisor, Anusha Chari, to whom I am enormously grateful. I am also deeply indebted to my other dissertation committee members – Christian Lundblad, Eric Ghysels, Peter Hansen, and Mike Aguilar – for their time and helpful comments. Working with Laura Alfaro and Ugo Panizza has been a very rewarding experience, both personally and professionally. I am thankful to my peers and friends in the Economics Department at UNC – Chapel Hill for their constructive criticism and extended discussion of my work. Lastly, I thank the Risk Management Institute at the National University of Singapore for hosting me and granting me access to their CRI database, without which this project would have never been completed.

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CHAPTER 1: IN SEARCH OF DISTRESS RISK IN EMERGING MARKETS[1]

1.1 Overview

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. We suggest that bankruptcy risk models developed using US data 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 develop a logit model of distress risk specific to emerging markets, as well as quantify the importance of global shocks on emerging market corporate distress. While Leverage, Cash, and Profitability have the largest marginal effects on the probability of default, US interest rates and US equity volatility are positively correlated with default risk. We also find that the set of global factors contributes more predictive power than domestic macroeconomic variables and that the effect of a global "risk-off" environment on default risk is greater for firms whose returns respond more negatively to such global conditions. Using our best measure of probability of default, we construct distress-sorted portfolios and find monotonically increasing 12-month realized returns in distress risk, even after controlling for Fama-French factors, momentum, short-term reversal, and long-term reversal. A number of robustness tests confirm the presence of a positive distress risk premium in emerging market equities.

[1] Co-authored by Asis, G., and Chari, A.

1.2 Introduction

Non-financial corporate debt in emerging markets surged from $4 trillion in 2004 to over $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).[2] 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.[3] An exception is Altman (2005), who adapts a longstanding bankruptcy risk model (Altman, 1968) 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, we find that logit 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

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

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

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, 2016; 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 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 normalization 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.[4]

We estimate a logit model of probability of corporate default on a set of firm-specific accounting and market variables, as well as variables reflecting global financial conditions. The evidence suggests that the 5-year US Treasury rate, the Fed funds rate, and the VIX are

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

correlated with distress risk, even after controlling for firm-specific variables and country fixed effects. 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 both 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. Furthermore, their model has lower predictive power in sample than ours out of sample.

Computing marginal effects of our probability of default model allows us to speak about the economic significance of our coefficients. Leverage and Cash have the largest average marginal effects on the probability of default – a one-standard-deviation increase in the predictor is associated with 0.4 and -0.52 percentage point changes in the probability of default, respectively. From the set of global variables, DFX and 5-year Treasury Rate have the largest average marginal effects. Plots of predicted probabilities – for all values of each explanatory variable while keeping all other predictors constant at their mean – reveal variations in the range and curvature of these marginal effects.

Next, we focus on firms whose returns are most sensitive to global financial conditions in order to explore whether stock returns carry information about the impact of the global financial environment on default risk. We label these sensitivities "global betas", and they 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 increases in the US dollar, sovereign spreads, US interest rates, VIX, and TED spread) reveals that, for 5-year Treasury rates, VIX, and TED spread, the effect of increases in the global variable on the probability of default is larger 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.

Lastly, we explore 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 finds that distress risk and future 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 monotonically increasing in the probability of corporate default, a trend that holds true after controlling for the Fama-French three factors, momentum, short-term reversal, and long-term reversal.

Our paper contributes to the existing corporate default literature in three ways. First, it determines precisely 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 analyze 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 normalization 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 maximizes 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 distress risk premium in emerging market stocks by examining the pricing of financially distressed firms. We use the probability of default measure developed in the first part of the paper to explore the performance of distressed stocks between 2002 and 2015.

Related Literature: Shumway (2001) introduces a multiple logit model that 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-to-book ratios, and lower prices per share.[5] An important asset pricing implication

[5] The authors define distress as either filing for bankruptcy, getting 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-to-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.

of Campbell et al. (2008) is that stocks of distressed companies experience abnormally low returns.

Das et al. (2007) prove that the models mentioned above don't explain all the systematic risk that contributes to firms' probability of default. Duffie et al. (2009) introduce frailty factors – latent common factors – that help explain these shared risks, though at the expense of computational ease. In an attempt to reduce the computational burden, Duan and Fulop (2013) combine frailty factors with a forward intensity approach first developed in Duan et al. (2012). Another recent alternative is proposed by Creal et al. (2013) through Generalized Autoregressive Score (GAS) models, expanded by Chen et al. (2016) by incorporating multiple frailty factors.

Although not as closely related to this paper, a branch of the literature has developed structural models of default risk. The most influential structural approach was pioneered by Merton (1974) and improved by Oldrich Vasicek and Stephen Kealhofer (Vasicek, 1984; Kealhofer, 2003a; Kealhofer, 2003b) in what became known as the Vasicek-Kealhofer (VK) model. Crosbie and Bohn (2003) base on these prior works their Distance to Default (DTD) measure: DTD = Firm Net Worth / (Market Value of Assets · Asset Volatility). Because a firm will default when its net worth reaches zero, its distance to default will also equal zero at that point. The authors then translate this structure into a probability of default by empirically mapping DTD and historical US default data.

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.[6] Pomerleano (1998) uses accounting ratios to study the build-up of the Asian Financial Crisis, finding excess leverage and poor capital performance in the years leading

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

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 to other countries (e.g. Kordlar and Nikbakht, 2011; Xu and Zhang, 2009; Bauer and Agarwal, 2013; NUS-RMI, 2016).

Other related research focuses on specific financial sheet variables to identify country-wide corporate 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.[7] However, the view most widely held is that foreign-currency liabilities are a concern for emerging market non-financial corporations and particularly troubling for firms that do not have natural currency

[7] The two major issues 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.

hedges in place (e.g. firms in non-tradable industries).[8] 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. (2015) 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 emerging market-specific probabilities of corporate default and quantifies how the global macroeconomic environment they operate in can affect their ability to remain solvent. Additionally, having a reliable measure of corporate default risk allows us to explore the behavior of distressed stocks in emerging markets.

The rest of the paper is organized as follows. Section 1.3 explains the methodology. Section 1.4 describes the data. Section 1.5 presents the results of logit regressions of the probability of default and introduces global betas as predictors of default. Section 1.6 shows the asset pricing implications of our measure of distress risk. Section 1.7 concludes.

1.3 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

[8] Kalemli-Ozcan et al. (2016) and others find that currency exposure is not as risky for companies with natural hedges.

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 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, 1997). Further, inflation risk affects economic growth and 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 control for the impact of the domestic economic conditions in the probability of default of emerging market firms, we include a number of domestic macroeconomic indicators and country fixed effects in different specifications of the model.

Furthermore, the globalization 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, while 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 1.5.2 Global Betas discusses in detail the methodology to compute global betas as a measure of emerging market risk exposure to a range of global factors.

1.3.1 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 1.1 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 (AUC). 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.[9] 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 that a failed subject will be ranked ahead of a randomly chosen healthy subject.

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

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).

1.3.2 Variable Selection

Given the large number of default predictors found by the literature and the lack of studies specific to emerging markets, we want to make sure we include only the most relevant set of explanatory variables in our specification. Hence, in a robustness exercise we add the Least Absolute Shrinkage and Selection Operator (LASSO) routine to our estimation. This procedure allows us to select, from a large set of explanatory variables, the subset with highest predictive power. The LASSO constrains the sum of the absolute value of the coefficients during the maximum likelihood estimation, forcing some coefficients to equal zero.[10] Specifically, it minimizes the following (negative) likelihood function, which includes a constraint on the sum of the coefficients:

$$\sum_{i=1}^{n}\left(-Y_{i,t+1}\left(\alpha + \beta x_{i,t}\right) + \log\left(1 + \exp\left\{-\alpha - \beta x_{i,t-1}\right\}\right)\right) + \lambda\left(\sum_{k=1}^{p} |\beta_k|\right) \tag{2}$$

We use cross-validation to determine the level of λ that gives the best model fit. Next, we choose the set of variables within one standard error of the optimal λ that maximizes the in-sample ROC. The result is enhanced prediction accuracy and ease of interpretation of the coefficients. Tian, Yu, and Guo (2015) employ this routine on US data, and their resulting set of accounting and market variables achieves higher in- and out-of-sample predictability than

[10] The variables that enter the LASSO procedure are standardized in advance in order for LASSO to accurately compare the importance of each variable. Dummy variables are standardized as well, which prevents us from interpreting their LASSO coefficient in the usual manner – this is not problematic since we re-run our model using the set of variables selected by LASSO.

Campbell et al. (2008). Starting from theoretical arguments and existing advanced-economy specifications, the LASSO routine allows us to add statistical rigor to the variable-selection component of the exercise.

1.4 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, Colombia, 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.[11] As Table 1.1 shows, the CRI database 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.[12] Delayed payments made within a grace period are not counted as defaults.

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

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

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. The two years with highest share of defaults coincide with the depth of the Asian Financial Crisis. 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 671,762 observations and 590 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. 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 a couple of reasons. First, governments own a percentage of many listed firms in emerging markets and might be more inclined to bail out or recapitalize struggling companies. Second, large firms may benefit from corruption in governments to get help staying solvent.

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).[13] In some of our specifications we include a dummy variable that equals one if the firm has experienced a default event in the past.[14]

To control for large outliers and possible errors in the balance sheet and market data, we winsorize the firm-specific variables at the 1st and 99th percentile of their distributions [15]. 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 in which firms operate, we incorporate four domestic macro variables for each country. The first is 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

[13] 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 use the single-period definition instead.

[14] 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.

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

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.

The set of global macro variables includes the monthly change in a country's exchange rate against the US dollar, since it is a major determinant of firms' revenues from abroad and their ability to repay debts denominated in dollars.[16] We also include the monthly change in the sovereign spread measures 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

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

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 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).

The global variables have monthly frequency and are common to all firms in the sample.[17] Appendix A defines variables and their sources in greater detail.

1.4.1 Summary Statistics

Table 1.2 reports simple equally-weighted means of the explanatory variables, as well as t-tests for means. The first column presents means for the full sample, the second column for the Default group, and the third for the Bankrupt 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 over 0.04% for the average firm in the full sample.

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

[17] 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.

income to total assets of 0.004 in the full sample. These firms also have higher leverage (0.578 and 0.759 for Default and Bankrupt groups, respectively) than the overall population (0.366), as well as lower cash holdings over total assets: 0.045 and 0.024 for the Default and Bankrupt groups, compared to a full sample average of 0.082. 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 capitalization, resulting in higher market-to-book ratios of 2.673 (Default) and 4.400 (Bankrupt), compared to 2.121 for the full sample. All summary statistics described so far are consistent with those in Shumway (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 characterized by lower unemployment and real interest rates.

On the other hand, the direction of the effect of global variables on corporate distress is intuitive based on how 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: 2.890% and 1.869%, respectively, compared to 2.363% and 1.235% in the full sample. Also as expected, defaults occur on average during times when a country's sovereign spread is increasing more than on average during our sample period. Lastly, the Default group is characterized 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.

1.5 Results

1.5.1 A General Model of Default Risk

As a first step to tailoring the default risk model to emerging market firms, we run a variable selection exercise using the Least Absolute Shrinkage and Selection Operator (LASSO) to choose from a set of accounting and market variables the combination with highest predictive power for emerging markets.[18] While Campbell et al. (2008) (referred to as CHS intermittently hereafter) show their model outperforms other prior specifications in the US-based literature, we do not assume the same combination of firm-specific variables will achieve the highest prediction power for emerging market firms. Therefore, we construct nine other accounting ratios that show some explanatory power in the existing literature, and we add them to the eight accounting and market variables in CHS. The results of the LASSO procedure do not show strong evidence that any subset of accounting and market variables specific to emerging markets outperforms those used by CHS. 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.

[18] Methodology section provides details.

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 multicollinearity, 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 0.888, the only pairwise correlation larger than 0.6 in absolute value among all our variables

In order to estimate the model with country fixed effects we must drop any country with no defaults during the period being used for estimation. The effect on our sample is small: the sample size only falls from 671,762 to 589,224 firm-months, and we are left with firms from Argentina, Brazil, China, India, Indonesia, Malaysia, Mexico, Philippines, Poland, South Korea, and Thailand.

Table 1.3 shows the results of six iterations of the multivariate logistic regression. As a benchmark, we estimate in Column 1 the CHS model, which yields a pseudo-R^2 of 0.124 and an AUC of 0.865. All coefficients are significant and have the same sign Campbell et al. (2008) find, except for volatility of returns (opposite sign) and market capitalization (not significant). 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 profitability, higher leverage, less cash, and a higher market-to-book ratio.

Next, we add a dummy variable signaling 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 0.2 and the AUC to 0.907. 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 0.235, but the AUC falls to 0.888, suggesting a better model fit but not better predictive power. We find that default is associated with higher unemployment, lower real interest rates, and lower sovereign spreads, after controlling for firm-specific accounting and market variables. The inclusion of the domestic macro environment makes firm size negatively correlated with the probability of default.

Column 4 presents the results of a model that consists of CHS, the prior default dummy, and global variables. The higher AUC than in Column 3 suggests that global variables contribute more predictive power than domestic variables after controlling for firm-specific covariates. The coefficients suggest 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 Fund 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.

A specification that includes both domestic and global variables is presented in Column 5. Notable results are the significantly positive coefficient on VIX and the fact that real interest rates are the only domestic macro variable to remain (negatively) associated with default risk.

Before introducing country fixed effects, we again rely on LASSO to verify that no subset of variables would deliver a model with better fit. Figure C1 shows the path of the coefficients during the LASSO estimation, with decreasing *l* (from left to right) loosening the constraint on the absolute value of the standardized coefficients and allowing more variables to enter the regression. The coefficients the procedure returns for the *l* that yields the best fit are shown in Column 2 of Table C1. LASSO eliminates all global variables but the 5-year Treasury rate, as well as volatility of returns, firm size, and cash. When we run a logit regression using the explanatory variables selected by LASSO (Column 3), the sign and significance levels of the coefficients match those of our benchmark model (Column 1). The AUC of the LASSO model is only marginally larger than that of the full model, suggesting that the entire set of explanatory variables is almost as good at explaining and predicting default as the best subset as selected by LASSO.

Finally, a specification that includes country fixed effects yields the best predictive power, with an AUC of 0.914. Including country fixed effects allows us to control for country-specific differences in characteristics like legal system, bankruptcy laws, and state intervention, all of which are difficult to quantify. The ROC curve associated with this and CHS's model is shown in Figure 1.2. Figure 1.3 plots, for each quarter, the number of defaults predicted by this model against the number of actual defaults. As in the CHS benchmark, we find that a firm is more likely to default next month if it has low excess returns, price, profitability, and cash; as well as high leverage and market-to-book ratio. Adding country fixed effects causes relative size (a firm's market cap divided by the total market cap of all listed firms in the country) to be positively correlated with the probability of default. While the corporate default literature finds the opposite relationship for firms in advanced economies (e.g. Campbell et al., 2008; Hernandez-Tinoco et al., 2013), Alfaro et al. (2017) find that firm size is positively correlated with corporate fragility, measured by Altman's Z-score. Volatility of returns is no longer significant, and VIX becomes statistically significant and positively correlated with default, at the expense of the TED spread, which loses its significance.

Being the specification with highest predictive power, we use Column 6 as our measure of probability of default in the remainder of the paper. We test the robustness of our estimates by running two out-of-sample tests of predictive power. First, we estimate the probability of default model one time 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 in a recursive manner (increasing the estimation window every month, starting with the earliest 60% of data) and predict default on the following month. Both methods yield an AUC of 0.88, compared to an in-sample AUC of 0.914.

Lastly, we compute average marginal effects of each individual regressor, presented in Table 1.5. This allows us to speak about the economic significance of the coefficients; i.e., the effect on the probability of default of changes in a specific predictor variable while keeping all other predictors constant. We find that Leverage and Cash have the largest average marginal effects, such that a one-standard-deviation increase in the predictor is associated with 0.4 and -0.52 percentage point changes in the probability of default, respectively. From the set of global variables, DFX and 5-year Treasury Rate have the largest average marginal effects. Figures 1.4-1.7 show the vectors of predicted probabilities for the entire range of each explanatory variable in our model, while keeping all the other predictors constant at their means. The plots reveal the curvature in variables like size, leverage, and profitability, and they allow us to compare the probability of default at various levels of each variable for the average firm.

1.5.2 Global Betas

Not captured by the global variables in the logistic regression is the fact that 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.[19] Once our firms are sorted by betas, we create a dummy variable that indicates whether a firm belongs to the top tercile.

[19] 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.

Panel A in Table 1.4 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 positive, statistically significant coefficients in the top-third dummy interactions for 5-year Treasury rates, VIX, and Fed funds rate. This implies that the harmful effect on the probability of default of increases in these variables is larger for the stocks which fall most during increases in those variables. For instance, the risk of default increases more with VIX for firms with most negative VIX betas. Panel B shows that the difference in effect between firms with more or less sensitive returns is not due to different firm characteristics between the two groups.

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.[20] 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

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

environment for emerging markets to finance themselves (what is often known as a "risk-off" environment).

In Table 1.6 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 negatively to such global conditions, all else equal.[21]

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.

[21] It is worth noting that the coefficient of the interaction term is not significant when computing the global betas using local currency returns rather than US-dollar returns.

1.6 Asset Pricing

We use our estimated probability of default (Column 6 in Table 1.3) 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. The findings have 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 December 2015 we estimate our measure of next-month probability of default 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 the stocks with lowest distress risk in Portfolio 1 and those most likely to default in Portfolio.

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. As a proxy for expected returns, we use average realized returns over the 12 months after distress risk is computed. Next-month realized returns leave little room for information surprises to cancel out, and, by looking at returns over a longer horizon, we average out temporary over- and under-performance due to idiosyncratic events unrelated to firm health.

Table 1.7 shows each portfolio's average estimated probability of default and 12-month average monthly returns. The spread in the probability of default across portfolios is large: the average firm in the portfolio with lowest default risk has just a 0.005% probability of failing next month, compared to 1.17% for the average firm in the riskiest decile. The average 12-month returns reported in the second row are monotonically increasing in probability of default, consistent with a positive risk premium associated with distress. The safest and riskiest portfolios return 0.5% and 1.4% per month, respectively. However, these results don't necessarily imply the existence of a distress risk premium in emerging market stocks, since our measure of distress risk may be associated with other factors that demand premia of their own. To address this, we control for six common factors from the literature in order to separate the distress risk premium from other sources of risk premia that may be present in our sample. These are the three factors from Fama and French (1993), momentum, short-term reversal, and long-term reversal. Appendix A describes the computation of these factors in detail.

We find that high failure risk portfolios have higher betas on SMB, HML, and RM. These coefficients imply that the larger returns of riskier portfolios can be partly explained by Fama and French's three factors; correcting for them reduces the outperformance of distressed stocks that can be attributed to distress risk. The constant, or alpha, of this regression can be interpreted as the portion of returns not explained by the factors. We observe alphas that are increasing in default risk. This allows us to conclude that, even after correcting for the sources of risk captured by the factors, investors can expect a higher return on portfolios comprised of stocks at high risk of default. Figures 1.8 and 1.9 graphically depict the returns, alphas, and factor loadings from the 6-factor regression. Figure 1.10 plots the 6-factor alphas and their 95% confidence intervals, which show that the alpha on Portfolio 10 (highest probability of default) is significantly larger than the alphas on Portfolios 5 and lower, and the alpha on Portfolio 1 (lowest probability of default) is significantly smaller than all other portfolios' alphas.

We run a number of different exercises in order to test the statistical significance of these results. First, we form two "long-short" portfolios, LS90-10 and LS80-20 – the first long the most distressed portfolio (Portfolio 10) and short the portfolio with least distressed stocks (Portfolio 1), and the second long the two most distressed portfolios and short the two with least distressed stocks. We run a 6-factor regression using the 12-month average return of LS90-10 and LS80-20, and the results are shown in Table 1.8. The positive, statistically significant alphas confirm that the factor-adjusted compensation is in fact larger for the portfolios with higher distress risk.

An alternative method to compute 6-factor alphas using returns over a 12-month period is to run, for every month of the year following portfolio formation, a regression of that month's returns on the six factors computed in that same month. By doing this, the timing of the returns corresponds with the timing of the factors, instead of using the factors computed only on the month following portfolio formation as controls for the average 12-month returns. The two main results described above – the monotonically increasing alphas in distress risk and the positive, statistically significant alphas on the long-short portfolios – also hold when running the factor regressions in this manner.

To further test of the robustness of our findings, we run firm-level Fama Macbeth regressions of 12-month average returns on firms' probability of default. We find a positive, statistically significant coefficient in the second stage cross-sectional regression, also confirming the presence of a distress risk premium in emerging market stocks.

Lastly, we use valuation ratios instead of realized returns to extract the distress risk premium. While realized returns are unbiased estimates of expected returns, their use as proxies for expected returns in the short and medium term has been questioned in the literature (e.g. Elton, 1999; Lundblad, 2007). Valuation measures like implied cost of capital, dividend yield, and earnings-to-price ratio are commonly suggested alternatives (e.g. Pastor et al, 2008), on the basis that they are a better reflection of investors' expectations of future stock performance. We don't have enough data to compute dividend yield or implied cost of capital; however, in early testing we don't find much of a relationship between the net income-to-price ratio and our measure of probability of default.

1.7 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 and explore whether investors are compensated for taking on distress risk. 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.

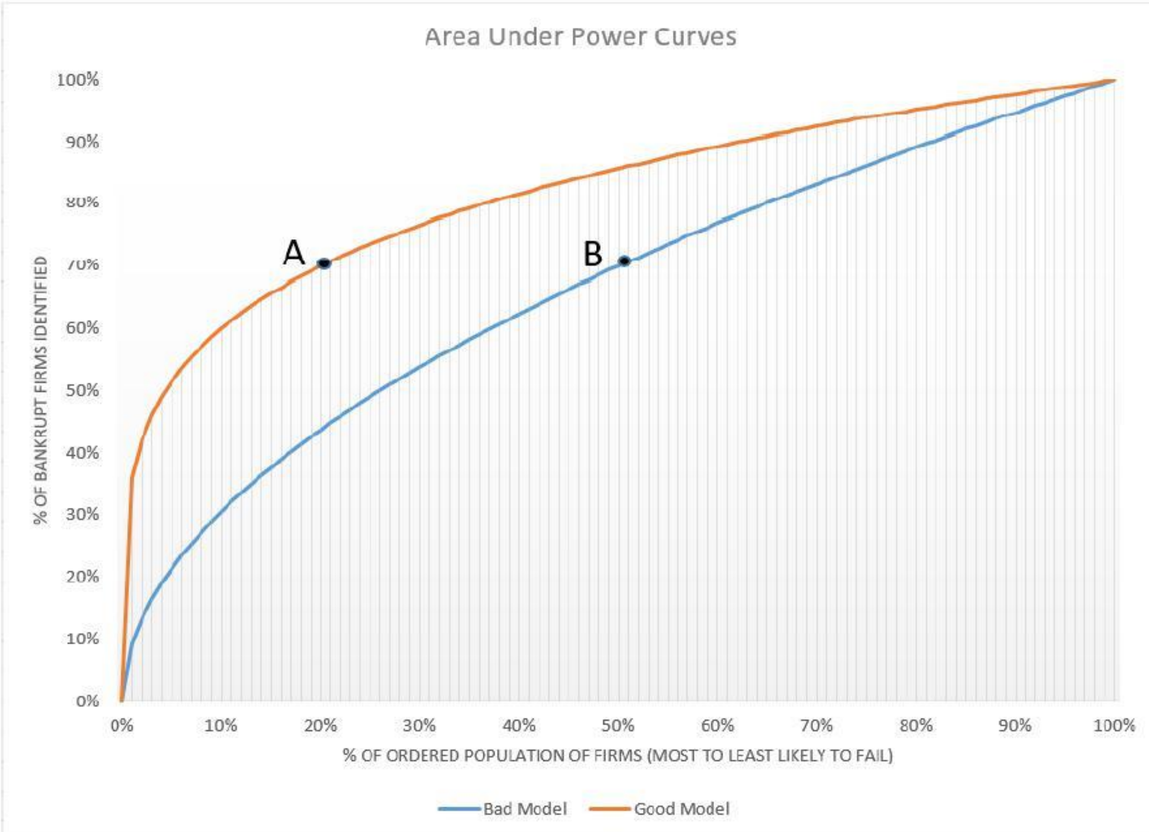
We argue that, while existing models proposed for US firms yield reasonable forecasting power, they do not account for vulnerabilities specific to emerging market companies, such as advanced economy monetary policy changes, US dollar movements, or shifts in global liquidity and risk aversion. A novel multi-country dataset of corporate defaults allows us to develop a model of distress risk specific to emerging markets, as well as quantify the importance of global shocks on emerging market corporate distress.

We find that, controlling for firm-specific variables and country fixed effects, the 5-year US Treasury rate, the Fed funds rate, and the VIX are correlated with distress risk. 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. To the best of our knowledge this is a novel result. A model that includes accounting, market, and global macro variables along with country fixed effects and the prior-default dummy yields a much higher explanatory power for emerging market firms than Campbell et al.'s (2008) specification.

We also explore whether information about default risk is embedded in 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 is larger 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.

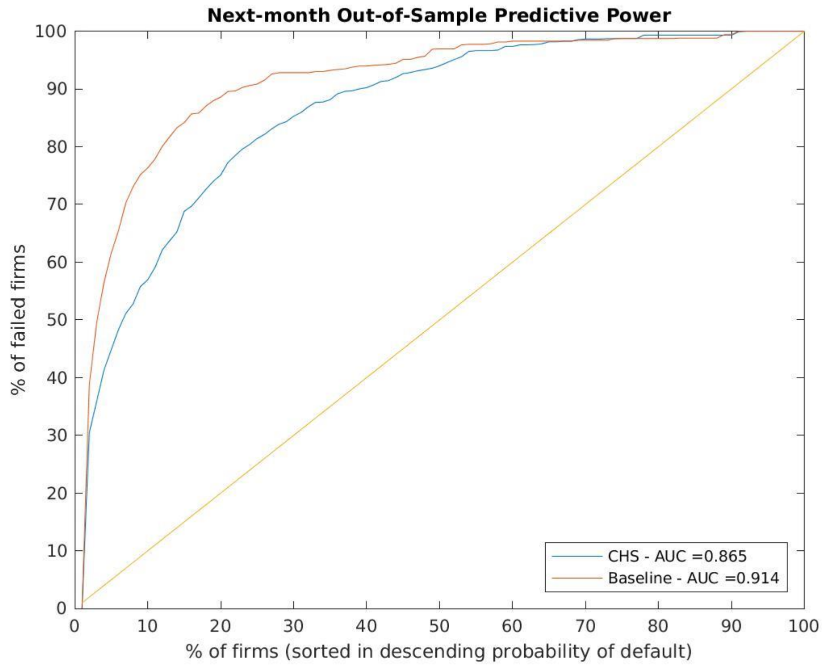
Finally, we explore the asset pricing implications of our probability of default measure. Previous studies using reduced-form measures of default risk have struggled to identify a positive distress risk premium in US equities. We, on the other hand, find strong evidence of the presence of a distress risk premium in emerging market stocks. Future 12-month stock returns are monotonically increasing in the probability of corporate default, a trend that holds true after controlling for six popular factors. A number of robustness tests confirm the statistical significance of our findings.

1.8 Tables and Figures



Point A in the "good model" ROC curve shows that the 20% 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 1.1: Example of Receiver Operating Characteristics Curve



This figure shows the Receiver Operating Characteristics (ROC) curve for our best model of distress risk and for the specification in Campbell et al. (2008). The curves shown are the average of the ROC curves in each month in the sample.

Figure 1.2: In-sample Predictive Power

Table 1.1: Types of Default Events

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-Negotiation Chapter 11, Protection, Receivership, Rehabilitation, Rehabilitation (Thailand 1997), Reorganization, Restructuring, Section 304, Supreme court declaration, Winding up, Work out, Sued by creditor, Petition Withdrawn, Other
Delisting	Bankruptcy
Default Corporate Action	Bankruptcy, Coupon & Principal Payment, Coupon Payment Only, Debt Restructuring, Interest Payment, Loan Payment, Principal Payment, ADR (Japan only), Declared Sick (India only), Regulatory Action (Taiwan only), Financial Difficulty and Shutdown (Taiwan only), Buyback option, Other

PANEL B

Action Type	Count
Bankruptcy	74
Delisting	3
Default Corporate Action	509
Bankruptcy Corporate Action	11
Coupon & Principal Payment	19
Coupon Payment	19
Restructuring	133
Interest Payment	10
Loan Payment	320
Principal Payment	10
Other	2
Unknown	12

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 its 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.

Table 1.2: Summary Statistics

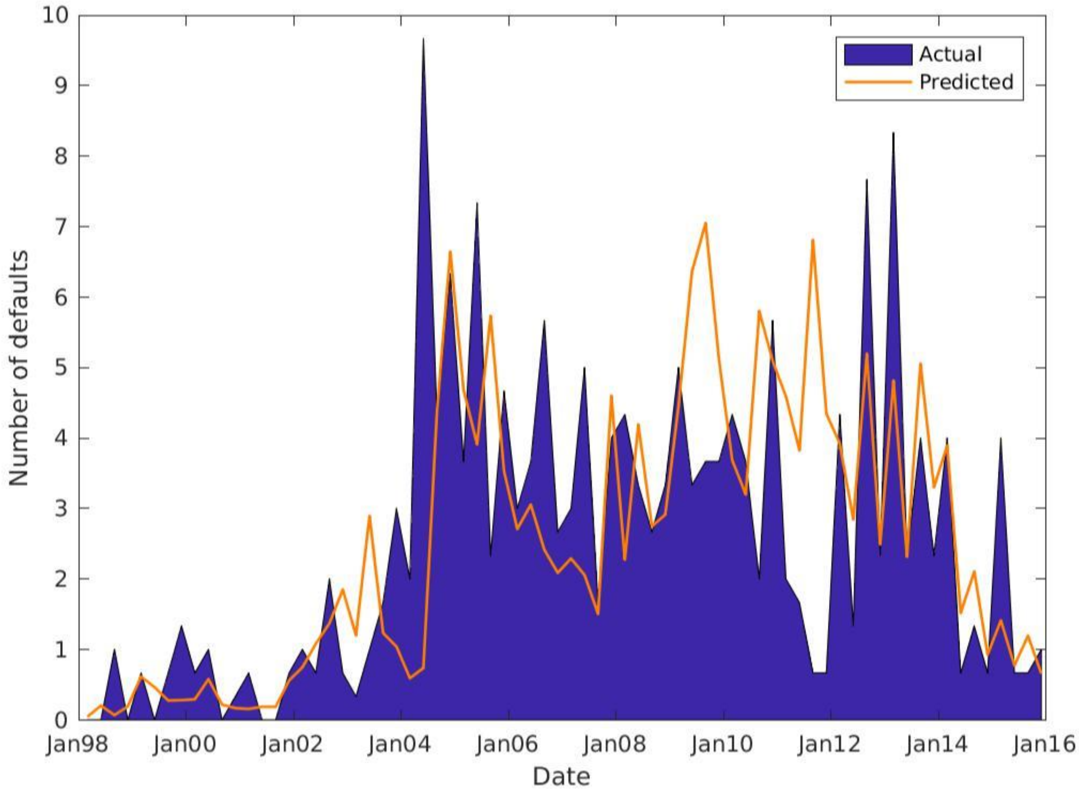
	Means			t-Tests	
	Full Sample	Default	Bankrupt	Default	Bankrupt
Excess returns	-0.008	-0.050	-0.06	***	***
Stock price	2.636	1.305	0.156	***	***
Volatility of returns	1.580	0.714	0.727	**	
Market capitalization	-7.735	-9.130	-9.233	***	***
Profitability	0.004	-0.017	-0.049	***	***
Leverage	0.366	0.578	0.759	***	***
Cash	0.082	0.045	0.024	***	***
Market-to-book ratio	2.121	2.673	4.400	***	***
Prior default	0.058	0.609	0.429	***	***
Unemployment rate	4.683	4.306	5.471	***	**
Inflation	0.036	0.035	0.031		
Real interest rate	4.123	1.929	8.113	***	***
Sovereign spread	2.541	2.503	1.965		*
ΔSovereign spread	0.009	0.022	-0.003	**	
ΔFX	0	0	-0.003		
5-year Treasury	2.363	2.890	2.785	***	**
VIX	19.52	19.59	21.31		*
Fed funds rate	1.235	1.869	1.547	***	
TED spread	-0.067	0.035	-0.111	***	

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 $p < 0.10$.

Table 1.3: Logit Regressions of Probability of Default Next Month

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-7.470***	-8.108***	-8.297***	-9.360***	-9.478***	-9.973***
Excess returns	-1.354***	-1.493***	-1.309***	-1.195***	-1.222***	-1.344***
Stock price	-0.224***	-0.168***	-0.079***	-0.080***	-0.054**	-0.193***
Volatility of returns	-0.074**	-0.071**	-0.058*	-0.077**	-0.065*	-0.022
Market capitalization	0.027	-0.002	-0.045*	-0.063***	-0.082***	0.164***
Profitability	-6.543***	-5.997***	-6.416***	-6.330***	-6.570***	-7.141***
Leverage	2.583***	2.102***	2.197***	1.904***	2.041***	3.136***
Cash	-4.837***	-3.235***	-4.195***	-3.451***	-3.717***	-5.993***
Market-to-book ratio	0.206***	0.119***	0.089***	0.082***	0.087***	0.051***
Prior default		2.502***	2.491***	2.560***	2.515***	2.234**
Unemployment rate			0.054**		0.032	
Inflation			-3.488		-2.587	
Real interest rate			-0.048***		-0.038***	
Sovereign spread			-0.037**		-0.018	
ΔSovereign spread				0.193	0.093	0.127
ΔFX				1.194	-1.129	0.878
5-year Treasury				0.351***	0.320***	0.349***
VIX				0.007	0.009*	0.015***
Fed funds rate				-0.119**	-0.110*	-0.109*
TED spread				0.270**	0.218*	0.088
Pseudo-R^2	0.124	0.200	0.235	0.232	0.241	0.221
AUC	0.865	0.907	0.888	0.899	0.893	0.914
Observations	589,224	589,224	372,673	402,253	372,158	402,253
Defaults	589	589	524	544	522	544
Country FE						X

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 macro variables, Column 4 includes global variables, and Column 5 has both domestic and global. Column 6 is our baseline specification, which incorporates country fixed effects to the model in Column 4. 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.



This figure shows the number of actual defaults per month (averaged by quarter) and number of defaults predicted by our model. The number of predicted defaults in a month is the sum of the estimated probabilities of default of all firms.

Figure 1.3: Time Series of Actual and Predicted Defaults

Table 1.4: Top Tercile Betas by Global Variable

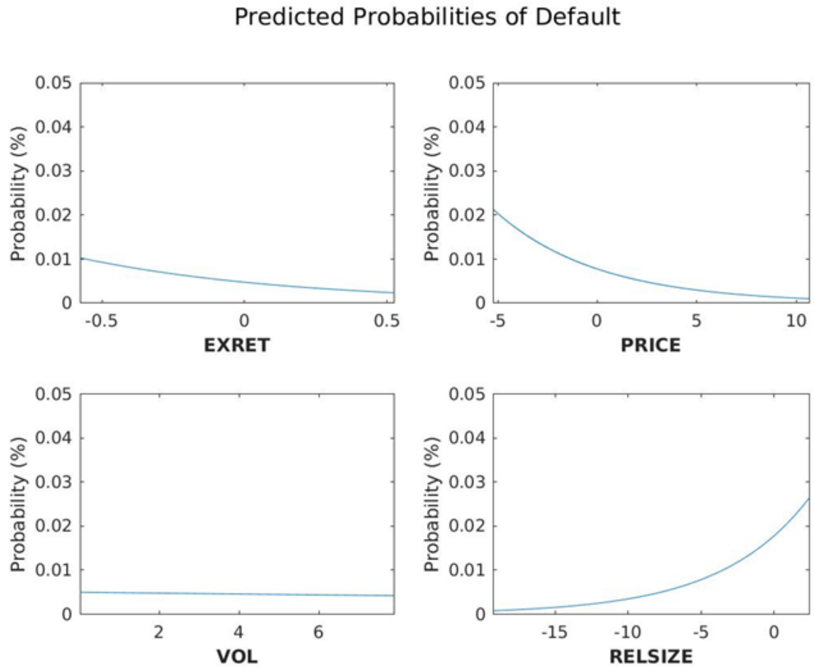
	ΔSov. spread	ΔFX	5-year Treasury	VIX	Fed funds	TED spread
PANEL A						
Constant	-6.662***	-7.020***	-7.708***	-7.136***	-7.229***	-7.015***
Global variable	0.469	-0.378	0.245***	-0.002	0.129***	0.244**
Global variable * Top-tercile	0.376	1.063	0.082***	0.020***	0.060**	0.210
Pseudo-R^2	0.003	0	0.01	0.003	0.006	0.001
Observations	479,438	774,705	774,705	774,705	774,705	774,705
Defaults	617	692	692	692	692	692
PANEL B						
	ΔSov. spread	**ΔFX**	**5-year Treasury**	**VIX**	**Fed funds**	**TED spread**
Constant	-7.417	-7.447***	-8.363***	-7.529***	-7.824***	-7.503***
Excess returns	-1.094***	-1.317***	-1.295***	-1.334***	-1.304***	-1.264***
Stock price	-0.160***	-0.224***	-0.198***	-0.222***	-0.207***	-0.219***
Volatility of returns	-0.100***	-0.083**	-0.088***	-0.078**	-0.088**	-0.084***
Market capitalization	0.009	0.027	-0.016	0.024	0.003	0.021
Profitability	-7.019***	-6.539***	-6.631***	-6.489***	-6.661***	-6.660***
Leverage	2.416***	2.559***	2.473***	2.651***	2.501***	2.560***
Cash	-5.725***	-4.966***	-4.751***	-5.191***	-4.796***	-4.941***
Market-to-book ratio	0.184***	0.204***	0.204***	0.200***	0.205***	0.205***
Global variable	0.612*	1.434	0.182***	-0.009*	0.092***	0.381***
Global variable * Top-tercile	-0.201	0.890	0.075***	0.026***	0.059*	-0.013
Pseudo-R^2	0.102	0.123	0.129	0.128	0.126	0.125
Observations	398,601	586,985	586,985	586,985	586,985	586,985
Defaults	536	586	586	586	586	586

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 three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

Table 1.5: Marginal Effects

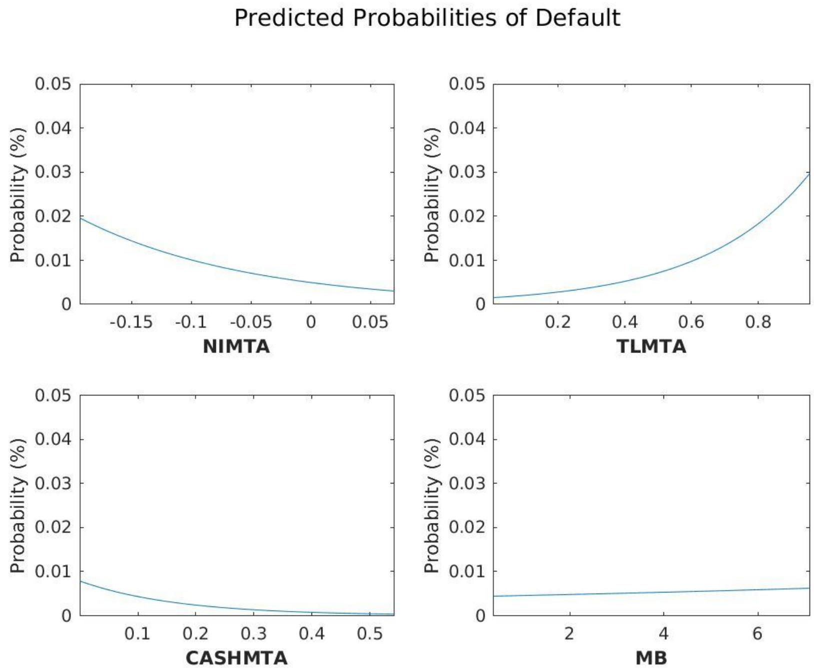
	MEM	AME
Cash	-0.111	-0.403
Profitability	-0.067	-0.242
Excess returns	-0.056	-0.204
Stock price	-0.009	-0.032
Fed funds rate	-0.003	-0.009
Volatility of returns	-0.001	-0.003
VIX	0.001	0.002
ΔSovereign spread	0.001	0.002
TED spread	0.002	0.006
Market-to-book ratio	0.003	0.013
Market capitalization	0.005	0.019
5-year Treasury	0.010	0.038
ΔFX	0.037	0.132
Prior default	0.084	0.304
Leverage	0.125	0.450

This table reports marginal effects of each individual regressor in the logit model, sorted from smallest to largest. The AME column shows average marginal effects. The MEM column presents marginal effects at the mean; i.e. the marginal effect of each regressor when all other regressors are kept at their mean.



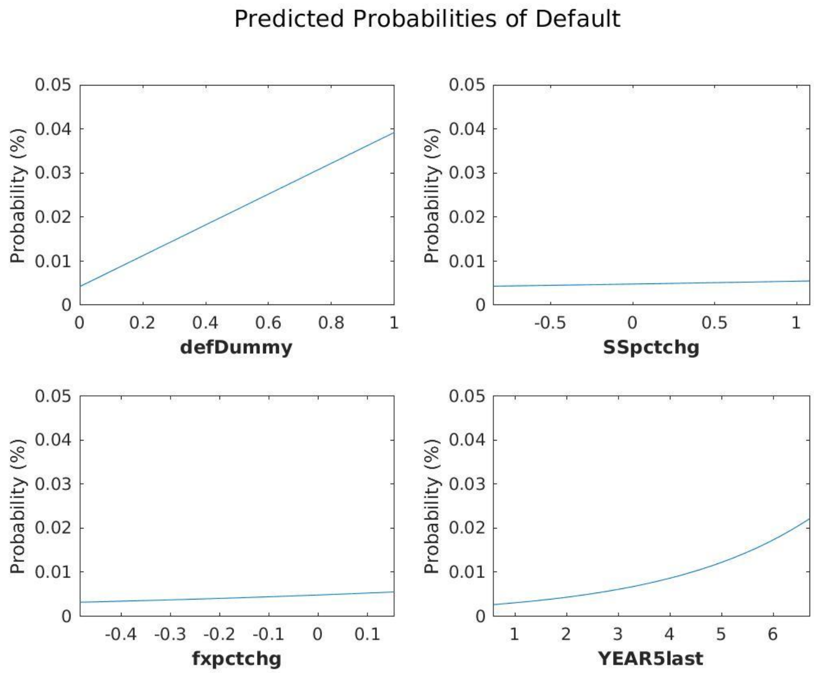
This figure shows predicted probabilities for all values of each variable, keeping all other predictors constant at their mean.

Figure 1.4: Predicted Probabilities I



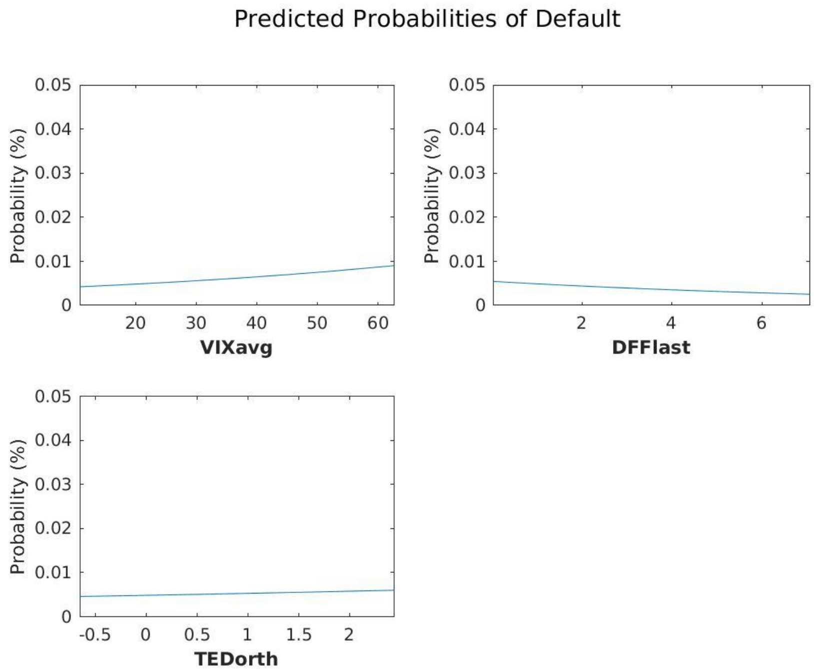
This figure shows predicted probabilities for all values of each variable, keeping all other predictors constant at their mean.

Figure 1.5: Predicted Probabilities II



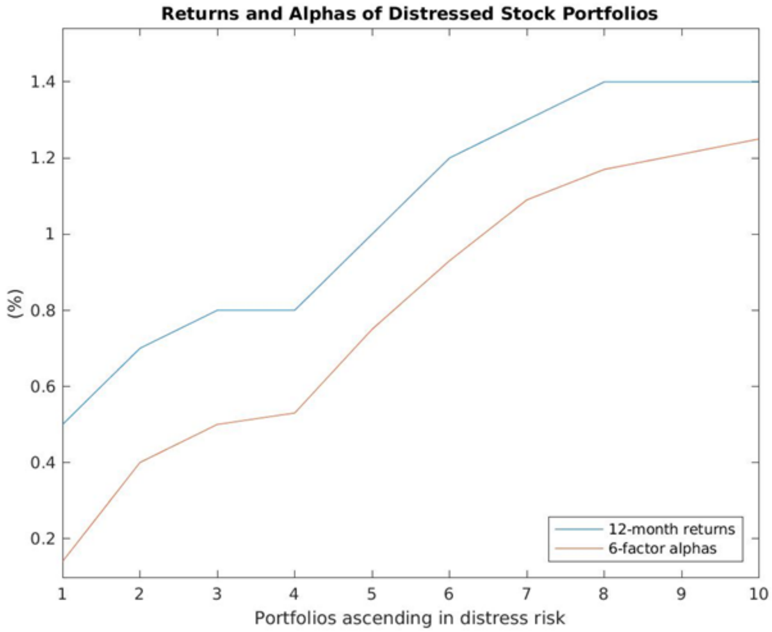
This figure shows predicted probabilities for all values of each variable, keeping all other predictors constant at their mean.

Figure 1.6: Predicted Probabilities III



This figure shows predicted probabilities for all values of each variable, keeping all other predictors constant at their mean.

Figure 1.7: Predicted Probabilities IV



For each portfolio ordered from least to most distressed, this figure shows 12-month average future returns and alphas from the 6-factor regression on market, size, value, momentum, short-term reversal, and long-term reversal factors.

Figure 1.8: Portfolio Returns and Alphas

Table 1.6: Composite Global Beta Z Score as Predictor of Default

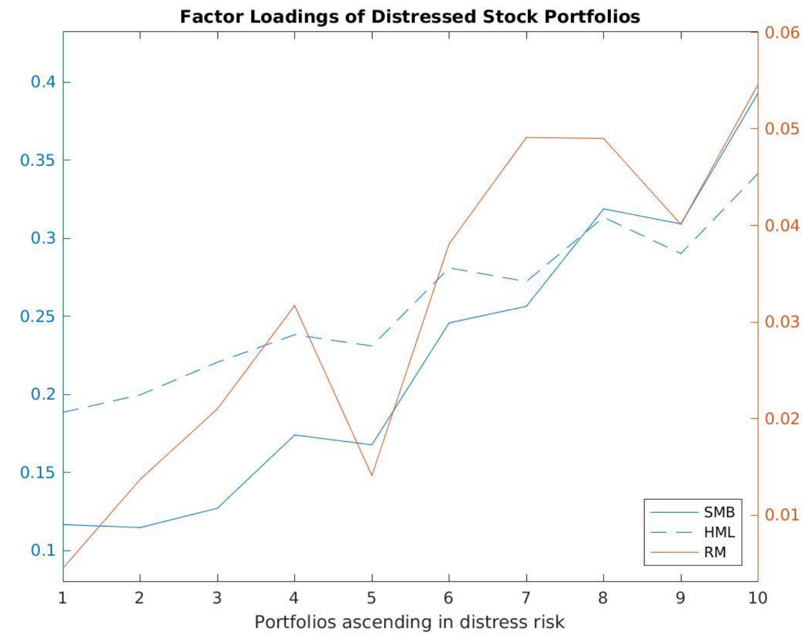
	(1)
Constant	-8.386***
Excess returns	-1.187***
Stock price	-0.063**
Volatility of returns	-0.066*
Market capitalization	-0.068***
Profitability	-6.515***
Leverage	2.113***
Cash	-3.947***
Market-to-book ratio	0.082***
Prior default	2.567***
Unemployment rate	0.034†
Inflation	-4.259*
Real interest rate	-0.041***
Sovereign spread	-0.027
Beta Z	-0.013
Variable Z	0.073***
Beta Z * Variable Z	-0.011†
Pseudo-R^2	0.202
AUC	0.893
Observations	386,884
Defaults	515

Results of logit regression of probability of default on a composite global factor, controlling for firm-specific variables. Beta Z and Variable 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: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$, respectively.

Table 1.7: Returns on Portfolios Sorted by Distress Risk

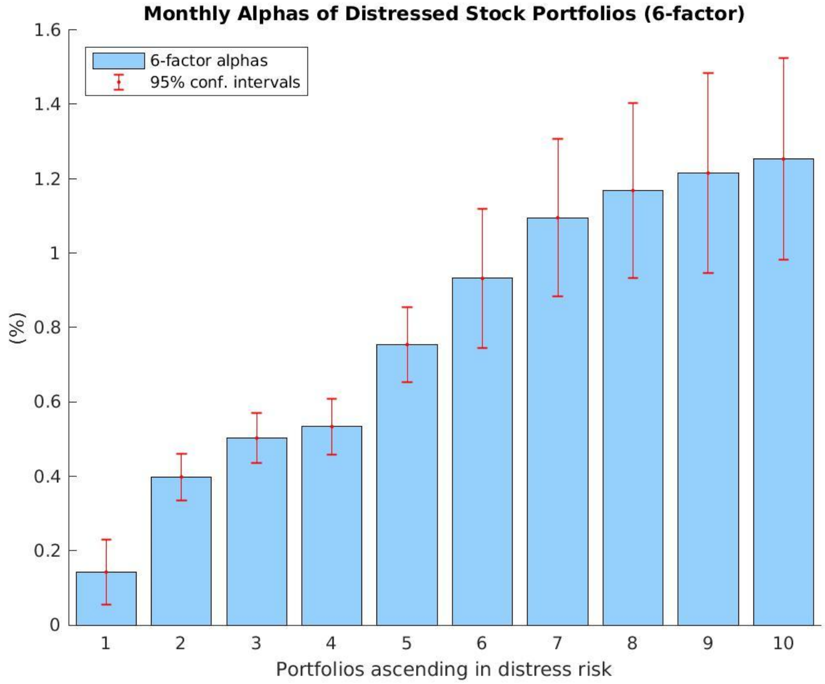
	1	2	3	4	5	6	7	8	9	10
Mean P(default) (%)	0.005	0.010	0.016	0.025	0.038	0.058	0.079	0.110	0.171	1.169
Mean 12-month returns	0.005	0.007	0.008	0.008	0.010	0.012	0.013	0.014	0.014	0.014
6-factor alpha	0.0014	0.0040	0.0050	0.0053	0.0075	0.0093	0.0109	0.0117	0.0121	0.0125
RM	0.0045	0.0137	0.0210	0.0317	0.0141	0.0381	0.0491	0.0490	0.0401	0.0546
SMB	0.1166	0.1147	0.1271	0.174	0.1677	0.2458	0.2564	0.3188	0.3092	0.3930
HML	0.1885	0.1997	0.2206	0.2382	0.231	0.281	0.2723	0.3134	0.2902	0.3415

Stocks sorted monthly based on our predicted probability of default and placed in ten portfolios of equal size. Portfolio 1 contains the firms with the lowest probability of default and Portfolio 10 those with highest predicted distress risk. We rebalance the portfolios every month from January 2002 to December 2015 based on the stocks' updated distress risk. This table shows, for each portfolio, average estimated probability of default, average monthly returns for the 12 months following portfolio formation, and coefficients from a 6-factor regression: RM equals the return of a weighted average of country index returns minus the risk-free rate, and SMB and HML are the returns of factor-mimicking portfolios constructed as in Fama and French (1993). The other factors (coefficients not shown) are momentum, short-term reversal, and long-term reversal.



For each portfolio ordered from least to most distressed, this figure shows the coefficients on the Fama-French factors from the 6-factor regression.

Figure 1.9: Portfolio Factor Loadings



This figure plots six-factor alphas and their respective 95% confidence intervals for 10 portfolios sorted by distress risk.

Figure 1.10: Six-Factor Alphas

Table 1.8: Returns on Long-Short Portfolios

	LS90-10	LS80-20
Mean 12-month returns	0.013†	0.011†
6-factor alpha	0.011***	0.010***
RM	0.050	0.038
SMB	0.276***	0.235***
HML	0.153**	0.122*

For long-short portfolios LS90-10 and LS80-20 (long the riskiest and short the safest one and two deciles, respectively), this table shows average 12-month future returns and alphas and Fama-French factors from a six-factor regression. ***, **, and * indicate three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. † indicate $p < 0.01$ in a t-test of means.

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CHAPTER 2: LESSONS UNLEARNED? CORPORATE DEBT IN EMERGING MARKETS[22]

2.1 Overview

This paper documents a set of new stylized facts about leverage and financial fragility for emerging market firms following the Global Financial Crisis (GFC). Corporate debt vulnerability indicators during the Asian Financial Crisis (AFC) attributed to corporate financial roots provide a benchmark for comparison. Firm-level data show that post-GFC, emerging market corporate balance sheet indicators have not deteriorated to AFC crisis-country levels. However, more countries are close to or in the "vulnerable" range of Altman's Z-score, and average leverage for the entire emerging market sample is higher in the post-GFC period than during the AFC. Regression estimates suggest that the relationship between leverage, exchange rate depreciations, and corporate financial distress is time varying. Also, a central finding is that firm size is correlated with corporate distress and, further, that currency depreciations amplify the impact of leverage on financial vulnerability for large firms during a crisis. Consistent with Gabaix (2011) the paper finds a granularity effect in that large firms are systemically important—idiosyncratic shocks to the sales growth of large firms significantly correlate with GDP growth in our emerging markets sample. Relatedly, the sales growth of large firms with higher leverage is more adversely impacted by exchange rate shocks. While this result holds for the average country in our sample, there is substantial cross-country heterogeneity.

[22] Alfaro, L.; Asis, G., Chari, A. and Panizza, U. Lessons Unlearned? Corporate Debt in Emerging Markets. *Journal of International Economics.* Submitted, 2018.

2.2 Introduction

There was a rapid credit expansion in emerging-market countries in the aftermath of the Global Financial Crisis (GFC). A surge in foreign borrowing and deterioration in net external debt positions accompanied the increase in domestic credit (BIS, 2014; IMF, 2015). The non-financial corporate sector accounts for the lion's share of this surge in leverage, which also accounts for large increases in international bond issuance (BIS, 2016). The total domestic and international debt of emerging market-based non-financial firms rose from $2.4 trillion to $3.7 trillion, and outstanding international bonds grew from $360 billion to $1.1 trillion between 2007 and 2015 (BIS, 2016).

The impact of monetary policy reversals in advanced economies on emerging-market sovereign debt premia, in conjunction with low corporate profitability and market valuations, have the potential to cause severe liquidity problems for emerging market firms.[23] Nearly $1 trillion flowed out of emerging markets in the first three-quarters of 2015, eclipsing the outflows during the GFC.[24] Understanding potential vulnerabilities require knowing more about the state of emerging market corporate balance sheets and their potential impact on the macroeconomy. Our paper fills this gap.

In this paper, we show that the relationships between leverage, exchange rate depreciations, and corporate financial distress are time varying—this result is new. In particular, controlling for firm characteristics, the relationship between (i) leverage and distress scores and

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[23] The growth in corporate profits has slowed considerably and the return on invested capital in emerging-market firms has significantly declined since the financial crisis. As evidence, emerging markets usually trade at a lower valuation than their advanced-economy counterparts, and while these relative valuations increased in the aftermath of the GFC, emerging markets are trading at a discount again.

[24] A number of direct and indirect channels can transmit shocks to highly leveraged non-financial corporates to the domestic economy. For example, a deterioration of credit quality of corporate borrowers or a sudden withdrawal of funds from the domestic financial system by firms that are unable to roll-over their international obligations can impair the domestic banking system (Acharya et. al., 2015).

(ii) leverage, currency depreciation and distress scores varies across the crisis and tranquil periods in our sample. A key finding is that firm size plays a critical role in the relationship between these three variables. Specifically, there is an inverse correlation between firm size and corporate distress scores and, further, currency depreciations amplify the impact of leverage on financial vulnerability for large firms during a crisis. Therefore, we go on to investigate the role of large firms and the amplification of macroeconomic vulnerabilities in emerging markets. To the best of our knowledge, this is the first paper to document these facts and implications.

The analysis proceeds in the following steps. First, we examine differences in leverage and other indicators of corporate vulnerability immediately prior and during the Asian Financial Crisis (AFC), the intervening tranquil period and the post-GFC period. Then, we present a formal regression analysis that highlights the importance of the interaction between leverage and exchange rate movements on corporate distress scores in the different sub-periods. This interaction provides indirect evidence for the relative importance of foreign currency debt in different periods, a variable that is not observable in balance sheet data. The regression analysis also brings to light the importance of firm size as it shows that, all else equal, it is the larger firms that are more vulnerable.

Next, we explore the role of large firms and their importance for the overall economic performance in emerging markets. We believe that this is the first paper to formally test the role of Gabaix (2011) and others' granularity idea using emerging market data. We find that while large firms are less leveraged than small firms, they may have a more risky type of leverage as large firms corporate distress scores deteriorate more significantly in response to exchange rate depreciations. In conjunction with the contributions that large firms make to the overall economic performance in emerging markets, the leverage vulnerabilities of these firms may, therefore, warrant particular attention from policy makers.

Note again that there is considerable concern about the recent increase in dollar borrowing by emerging market firms (BIS, 2015, Avdjiev et al., 2014, and Acharya et al., 2015). Our paper is the first to provide evidence of the macroeconomic consequences of the links between leverage, currency movements, and firm size. Given that disaggregate data on the liability composition (currency, maturity, type of lender) of non-financial firms are not available, our tests are a valuable and novel contribution to the literature. The details of the analysis follow below.

To reiterate, the first objective of this paper is to document a set of stylized facts about leverage and financial fragility in the non-financial corporate sector in emerging markets. We use detailed firm-level data to document stylized facts about the evolution of corporate leverage and its relationship to financial fragility in emerging markets over the last twenty years. With this data in hand, we compare corporate debt immediately before and during the Asian Financial Crisis (AFC) with corporate debt in emerging markets in the aftermath of the GFC. The AFC serves as the benchmark that allows us to answer the following question: How do corporate debt vulnerability indicators in emerging markets today compare with these indicators on the eve of the AFC?[25] In particular, how is corporate financial fragility related to leverage and other pertinent firm characteristics? While research on the state of corporate balance sheets in emerging markets shows that leverage and foreign currency exposure of emerging-market-based

[25] Chari and Henry (2015) use this methodological approach to compare and contrast the fiscal policy response and its impact on the recovery of GDP growth in the aftermath of the AFC to examine Europe's pivot from stimulus to austerity and the impact on European growth in the aftermath of its crisis.

corporates have increased, a lack of relevant benchmarks prevents prior studies from assessing the magnitude of the risks brought about by these trends (IMF 2015).

The second objective of our paper is to provide such a benchmark by comparing the current situation with the evolution of corporate balance sheets during the AFC. Why the AFC? Historically, emerging market crises arose from sovereign debt problems, and twin banking and currency crises (Reinhart and Rogoff, 2009). However, the underlying microeconomic roots attributed to the AFC include corporate debt vulnerabilities (Pomerleano,1998; Corsetti et al. 1999) as well as 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. Corporate debt levels associated with the AFC, therefore, serve as a natural benchmark to assess corporate sector vulnerabilities in emerging markets today.

Third, we ask whether leverage poses a risk to the health of emerging market firms. To test this, we regress corporate fragility on leverage and other firm characteristics and macroeconomic control variables, focusing on different periods, sectors, and exchange rate regimes.

Fourth, as noted by Gabaix (2011), the largest firms dominate economic activity across many countries and shocks to the largest firms can affect total output as these shocks do not get diversified in the aggregate data.[26,27] The role of large firms is particularly critical in many emerging markets.

[26] See also Acemoglu et al. (2016) and Acemoglu et al. (2017).

[27] Note that weak bank balance sheets and non-performing loans leading up to the AFC were arguably associated with corporate sector weaknesses (see Corsetti et al., 1999).

The final objective of the paper is to carefully examine whether the most levered and financially fragile firms are also the most systemically important. In particular, implicitly the vulnerabilities of systemically large firms are intimately linked to bailout guarantees and moral hazard issues in emerging market lending where widespread corporate debt vulnerabilities can turn into full-blown financial crises.

We compile extensive firm-level data between 1992 and 2014 from Worldscope and Osiris for 26 countries classified as emerging markets by the Bank of International Settlements (Argentina, Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Jordan, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, South Korea, Taiwan, Thailand, Turkey, and Vietnam). We exclude financial firms from our analysis. The firm-level data provide different indicators from the balance sheets and income statements to analyze cash flows, leverage, liquidity, solvency, and profitability ratios—the returns on equity and invested capital.

To document the stylized facts, we split the sample into two subperiods: AFC (1996-1998) and post-GFC (2008-2014). We compare the post-GFC indicators to two benchmarks: (i) a within-country comparison relative to 1996-1998 values for a given indicator; and (ii) a crisis-country comparison to the 1996-1998 average of the five Asian countries involved in the AFC (Asian Crisis Five).[28,29] We find that the within-country cross-time benchmark and the Asian Crisis Five benchmark yield varying cross-country patterns of results.

[28] Indonesia, Malaysia, Philippines, South Korea and Thailand.

[29] In robustness analyses, we also exclude, obtaining similar results, the period 1999-2002 to avoid contaminating our tests with emerging market crises which were associated with sovereign debt episodes as the Russian, Brazilian, and Argentine crises of the late 1990s early 2000s were not clearly attributable to corporate leverage, (see Reinhart and Rogoff, 2009).

In particular, the data reveal the following stylized facts. First, over half of the emerging markets in our sample display increased leverage in the post-GFC period. However, no emerging market country has leverage ratios that exceed the average of the Asian Crisis Five on the eve and during the Asian Financial crisis. Second, half our sample countries have higher short-term liquidity needs measured by current to total liabilities compared to the Asian Crisis Five. Third, about 91% of countries in the sample have stronger solvency positions, measured by coverage ratios, in the post-GFC period than the Asian Crisis Five during the AFC.[30] Fourth, a measure of corporate financial fragility (Altman's (2005) emerging-market Z-score) shows that post-GFC, a larger number of countries are in or close to the grey or "vulnerable zone" than in the AFC period. However, while South Korea was in the distress zone during the AFC, there are no countries in the distress zone in the post-GFC period. In summary, our data show that post-GFC, emerging market corporate balance sheet indicators have not deteriorated to AFC crisis-country levels. However, more countries are close to or in the "vulnerable" range of Altman's Z-score (in the "grey zone" or barely above the threshold) and average leverage for the entire emerging market sample is higher in the post-GFC sub period than during the AFC.

Next, we formally analyze the relationship between leverage and corporate financial fragility at the firm level controlling for a variety of firm, sector, and country-level (macroeconomic) factors. Regression estimates confirm that during the AFC and in the aftermath of the GFC, there is a negative and statistically significant correlation between leverage and firm financial fragility. In other words, firms with higher leverage have Z-scores that are closer to the financial distress range. The data also show that currency depreciation amplifies the negative impact of leverage Z-scores during the Asian Financial Crisis.

[30] This could be a result of higher liabilities, lower profitability or a combination of the two.

To examine whether the leverage and corporate financial fragility patterns can portend adverse macroeconomic consequences, we examine the role of large firms in the macroeconomy. Consistent with Gabaix (2011) we find that large firms are systemically important—idiosyncratic shocks to large firms significantly correlate with GDP growth in our sample of emerging markets. We also find that while large firms are, on average, less leveraged than smaller firms, the more-levered large firms are more vulnerable to exchange rate shocks than smaller firms with comparable levels of leverage. While this result holds for the average country in our sample, we also find that there is substantial cross-country heterogeneity.

Our paper is related to several strands of literature. First, the paper contributes to the literature on the recent evolution of corporate debt in the aftermath of the GFC. IMF (2015) documents the main trends and shows that global factors drive the increase in corporate leverage following the GFC. This finding is in line with Shin's (2013) view that the response to the crisis led to a sudden increase in global liquidity. Acharya et al. (2015) present several case studies and evaluate vulnerabilities and potential policy responses.

The paper is also related to the literature on the origins of the AFC. Several papers suggest that weak fundamentals and excessive risk-taking by corporates caused the crisis. The "crony capitalism" view suggests that the increase in corporate leverage was due to moral hazard attributed to weak banking supervision and implicit guarantees for well-connected borrowers (Corsetti et al., 1998, Claessens and Glaessner, 1997, Krugman, 1998, Johnson et al., 2000; Burnside et al., 2001, 2003).[31] Pomerleano (1998) uses firm-level data and finds that excessive

[31] An alternative view as in Furman and Stiglitz (1998), Radelet and Sachs (1998), and Stiglitz and Bhattacharya (2000) maintains that there was nothing particularly wrong with the pre-crisis fundamentals of most East Asian economies.

leverage and poor financial performance in the corporate sector caused the AFC.[32] More generally, this paper relates to the literature documenting the association between rapid credit growth and the building of corporate leverage and financial crises (Mendoza and Terrones 2008, and Schularick and Taylor, 2012).

The paper proceeds as follows. Section 2.3 presents trends in broad macro-indicators to motivate the analysis. Section 2.4 describes the firm-level data. Section 2.5 uses the AFC as a benchmark to detail stylized facts about leverage and corporate financial fragility, and Section 2.6 presents formal firm-level regression results. Section 2.7 analyzes the interplay between emerging-market corporate fragility and the macroeconomy. Section 2.8 concludes.

2.3 The Post-GFC Rise in Emerging Market Borrowing

In the aftermath of the GFC, advanced economies were characterized by increases in government borrowing and household and corporate deleveraging.[33] Emerging markets stand in stark contrast. Over 2001-2007 average credit to the non-financial sector in emerging market countries remained close to 120% of GDP. The GFC caused a sudden reduction in credit, which went from 122% of GDP in 2007 to 109% in 2008. Credit started expanding rapidly in 2009 and reached 175% of GDP in 2015, a 67-percentage point increase with respect to the 2008 trough

[32] Ghosh et al. (2002) also show that in 1995–96 several East Asian countries had debt ratios and share of short-term debt which were significantly higher than debt ratios and short-term debt shares in OECD countries. Claessens et al. (2000) suggest that corporate financial risk factors may have been an amplifying factor in the crisis.

[33] Low global interest rates notwithstanding, the higher leverage led to a rapid increase in the debt service ratios of emerging market borrowers. In a period when the average debt service ratio of Advanced Economies decreased from 21 to 18 percent, the average debt service ratio of emerging markets increased from 10 to 12.5 percent. In a subset of emerging economies characterized by rapid credit expansion, debt service ratios surpassed the advanced economy average (BIS credit statistics).

(Figure 2.1). Borrowing by non-financial corporations was a key driver of this surge in leverage—corporate debt went from 57% to 101% of GDP over 2008-15.[34]

There is, however, substantial heterogeneity across emerging market countries (Figure 2.2). By the end of 2015 total domestic credit to the non-financial sector was above 200 percent of GDP in China and South Korea and below 100 percent of GDP in Argentina, Indonesia, Mexico, and Russia. Borrowing by non-financial corporations is important in China, Korea, Hungary, Czech Republic, and Turkey.[35] According to BIS data, in the case of China the total credit-to-GDP ratio for the non-financial sector went from 150% in 2008 to nearly 250% in 2015, with borrowing by non-financial corporations increasing from 100% to 166% of GDP. If we exclude China from our sample of emerging market countries we find a more moderate credit expansion (solid line in Figure 2.1).

Non-financial corporations also played a key role in international bond issuances.[36] Over 2008-2015, outstanding international bonds issued by non-financial corporations grew from $360 billion (approximately 30% of total outstanding bonds) to $1.1 trillion (more than 40% of total outstanding bonds). Issuances by non-financial corporations were particularly important in Asia and Latin America, where they now represent nearly 50% of total outstanding bonds. In addition, by 2015, total claims of BIS reporting banks on emerging markets and outstanding international securities issued by emerging market nationals surpassed $5.8 trillion, representing an 80% increase over emerging-market liabilities in 2007. The largest increases, both in percentage and

[34] Over the same period, household debt increased by 12 percentage points and government debt increased by 9 percentage points.

[35] While borrowing by households is important in Malaysia and Thailand, public sector borrowing is relatively more important in Brazil, India, Indonesia, South Africa, Mexico, and Argentina. See Alfaro and Kanczuk (2013).

[36] In 2015, borrowing by non-financial corporation accounted for about 25 percent of EM cross-border borrowing from BIS reporting banks.

absolute terms, were in Emerging Asia and Latin America (148% and 93%, respectively).[37] The increase in leverage was particularly important in non-tradable cyclical sectors such as construction.

The figures for Asia and, to some extent, Latin America are however driven by two important outliers. As mentioned, liabilities by Chinese nationals increased by 500 percent and, if we remove China from the Asian total, we find a more modest increase in foreign liabilities (a 58% increase compared to 148%). In the case of Latin America, instead, removing Brazil from the total brings down the increase in foreign liabilities from 93% to 76%. Brazil and China account for 48% of the increase in total claims of BIS reporting banks on EMs and outstanding international securities issued by EM nationals, and excluding Brazil and China from the EM total reduces the percentage increase of these liabilities from 80% to 45%.

As the introduction mentions, domestic credit expansion in emerging markets was accompanied by a surge in foreign borrowing.[38] In 2007 foreign currency bonds represented 16 percent of international debt by emerging market-based non-financial corporations and by 2014 the foreign currency share had grown to 22 percent (IMF, 2015).[39] However, the increase in leverage and foreign currency debt documented above took place in an environment of ample global liquidity and record low policy rates in advanced economies. Emerging market-based

[37] Alfaro, Chari, and Kanczuk (2017) analyze the effects of Brazilian capital control policies.

[38] Total cross-border claims on EMs by BIS reporting banks increased from $2.4 trillion in 2008 to a peak of $3.7 trillion on 2014. Data for 2015 indicates a $200 billion retreat, with total cross-border claims standing just below $3.5 trillion (Table 2.2).

[39] The share of dollar-denominated bonds issued by non-financial corporations is higher than the overall share of dollar-denominated bonds.

corporates have therefore borrowed at longer maturities and lower yields.[40] Recent fears are that, as monetary policy conditions in the US normalize, they could trigger a wave of corporate failures in a number of emerging economies.

2.4 Data

Firm-level data are from Worldscope (gathered through Datastream) and Osiris.[41] Our dataset choice is driven by the nature of the exercise. We are not aware of any other firm-level dataset with a better coverage of emerging market countries going back to the 1990s.[42]

Both sources provide detailed historical information for listed and unlisted firms for a wide sample of countries. We compared Worldscope and Osiris' coverage for emerging markets and chose the data source with the most data availability for each country. Osiris had better coverage for China and India, while Worldscope dominated for all other countries. Column 1 in Table D1 shows total sales of firms in our database by country as a percentage of the country's total market capitalization, as computed by the World Bank. We find this a better measure of sample coverage than Sales/GDP because the large majority of the firms in our database are publicly listed, and the size of the listed market relative to GDP varies significantly by country, as Column 2 shows.

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[40] Maturity went from the pre-crisis average of 5 years to more than six years and average yields decreased from 8 to 6 percent (IMF, 2015).

[41] The Worldscope database provides detailed historical financial statement information for the world's leading public and private companies. Osiris, published by Bureau van Dijk, has information as well on listed, and major unlisted/delisted, companies around the world. All data for tangible fixed assets is also from Osiris. When extracting data from Osiris, we restricted the sample to include sales information.

[42] Given that a key objective of our exercise is to compare the current situation with the Asian Crisis period, we need data for the 1990s. In alternative sources such as Orbis data, it is impossible to obtain a consistent data set of private and public firms for our period of interest in particular for emerging markets. For example, Di Giovanni and Levchenko's (2013) show that between 2006 and 2008 there were only 44 countries (mostly OECD and Eastern European countries) for which Orbis had firm-level data on sales for at least 1000 firms.

The sample consists of data on non-financial firms from 1992–2014 for the main countries classified as emerging markets by the Bank of International Settlements. These are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Jordan, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, South Korea, Taiwan, Thailand, Turkey, and Vietnam. Since coverage of Eastern European countries is extremely sparse, we group together firms from Czech Republic, Hungary, Poland, Slovakia, and Slovenia into 'Eastern Europe'.

Overall, the dataset covers primarily larger firms. While a lack of smaller firm coverage tends to pose problems in other settings, a focus on large corporations is to our advantage in this paper. As mentioned in the introduction, large firms have the propensity to contribute more to systemic risk, and thus they are precisely the firms whose financial health is of greatest concern to policy-makers.

Our final sample includes all companies that have data for each indicator of firm performance described below. [43] We exclude outliers and all noticeable errors in the data. The sample varies from a maximum of 8,286 firms with data on return on invested capital totaling (41,888 firm-year observations) to a minimum of 2,986 firms (14,393 observations) with enough data to compute Altman's Emerging Market Z-score. The countries with most firms in the database are China, India, and South Korea, and with the least Eastern Europe.

We use several indicators of corporate financial vulnerabilities and firm performance. For *leverage*, we use as a main indicator the debt to equity ratio (a firm's total debt divided by its common equity), which indicates how much debt a company is using to finance its assets relative

[43] The number of companies with data for every variable and year of interest is too small to create a balanced sample. Nonetheless, we have performed the analysis maintaining a balanced sample during different periods, obtaining similar results (e.g. to analyze yearly debt/assets ratio for the 2008-2014 period, we select for our sample all companies that have data for each indicator of Total Debt, Total Assets, and Sales for each year in 2008-2014).

to its common equity. As a proxy for *liquidity,* we use the current ratio (current to total liabilities). For *solvency*, we compute the coverage ratio, the ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) over total liabilities to measure a company's ability to use their cash flow to pay back its outstanding liabilities.

For firm performance, we analyze as well the increase in tangible fixed assets as a proxy for *investment*. *Profitability* is captured by the return on equity (ROE) and return on invested capital (ROIC). ROE is defined as the amount of net income returned as a percentage of shareholders' equity, and ROIC is the ratio of operating profit (earnings before interest and tax) to invested capital (sum of shareholders' equity and debt liabilities).

As a summary measure of *corporate fragility*, we calculate the Altman (2005) Emerging Market Z-score. The measure weighs four ratios constructed using the firms' financial statements (working capital to total assets, retained earnings to total assets, operating income to total assets, and book value of equity to total liabilities).[44] The measure is an enhanced version of the standard Z-score model, adjusted to incorporate the characteristics of emerging market firms and best suited to assess the relative vulnerability of the sample of countries we consider in this paper. Lower Z-scores are associated with greater vulnerability and likelihood of bankruptcy. Companies with EM Z-scores greater than 5.85 are considered to be in the "safe zone", scores between 5.85 and 3.75 indicate vulnerability, and scores below 3.75 indicate that the firm is in state of distress. The following table from Altman (2005) compares Z-scores with bond ratings.

[44] EM score =6.56 (X_1) + 3.26 (X_2) + 6.72(X_3) + 1.05(X_4) + 3.25, where X_1= working capital/ total assets, X_2=retained earnings /total assets, X_3=operating income /total assets, X_4=book value of equity /total liabilities. The constant term (derived from the median Z`` score for bankrupt US entities) standardizes the analysis so "that a default equivalent (D) is consistent with a score below zero." The use of book value of equity, not market value, was motivated by a concern that equity markets may be less liquid than in developed markets. Altman (2005) adjusts the measure to consider currency devaluation vulnerability, industry adjustments (relative to U.S.); competitiveness position adjustment (dominant firms in the industry due to size, political influence, etc.); special debt issue figure (collateral or bona fide, high-quality guarantor); sovereign spread (comparison to US corporate bond of the same rating).

Table 2.1. Altman's EM Z-Score and Bond Rating

	Z' Score			Rating	Z' Score			Rating	
		>	8.15	AAA	5.65	-	5.85	BBB-	Grey Zone
	7.60	-	8.15	AA+	5.25	-	5.65	BB+	
	7.30	-	7.60	AA	4.95	-	5.25	BB	
	7.00	-	7.30	AA_	4.75	-	4.95	BB-	
	6.85	-	7.00	A+	4.50	-	4.75	B+	
	6.65	-	6.85	A	4.15	-	4.50	B	
Safe Zone	6.40	-	6.65	A-	3.75	-	4.15	B-	
	6.25	-	6.40	BBB+					
	5.85	-	6.25	BBB	3.20	-	3.75	CCC+	Distress Zone
					2.50	-	3.20	CCC	
					1.75	-	2.50	CCC-	
						<	1.75	D	

To further validate our use of Altman's EM Z-score as a proxy for (the inverse of) corporate financial fragility, we test its ability to predict exit from the sample. We find that firms with low Z-scores are more likely to exit the sample the next period. Specifically, a one standard deviation (corresponding to a 4.7%) decrease in the Z-score is associated with a 2% increase in the probability that the firm will not be in the sample in the following year. This outcome allows us to think of the Z-score as a rough proxy for distance to default.[45]

2.5 Corporate Fragility in Emerging Markets: Stylized Facts

We begin by comparing corporate financial fragility indicators during the AFC – which was deemed to have corporate financial roots – with the same indicators following the GFC, a period characterized by the rapid build-up in emerging market corporate debt. To do so, we divide the data into two periods: AFC (1996-1998) and post-GFC (2008-2014).[46] We use the

[45] Specifically, we run a regression where the dependent variable is an "exit" dummy, which takes a value of one if a firm that was in the sample in year t-1and year t-2 is not in the sample in year t and takes a value of zero if a firm that was in the sample in year t-1 and year t-2 is still in the sample in year t. The explanatory variables are the t-1 value of the Z-score and a set of firm fixed effects. We find that the coefficient is -0.005 with a standard error of 0.0019. We would like to thank an anonymous referee for suggesting to check whether the Z score predicts survival.

[46] We also compared results against an average of the period 1992-1997. The main results and implications are similar.

indicators described in Section 2.4 to analyze corporate fragility and profitability using data from the balance sheet, income statements, and cash flows. For different indicators of corporate financial vulnerabilities and firm performance, Table 2.2: Total Claims on Emerging Market Countries, BIS reporting Banks (billion USD) and Figures 2.3-2.6 present several stylized facts via weighted mean values using sales (as a proxy for size) as the weights. The weighted means are calculated for all firms in a country by year. The yearly weighted means are then averaged for each of the two sub-periods, also by country. We also analyze simple means and simple and weighted medians. The Asian Crisis Five include Indonesia, Malaysia, Philippines, South Korea and Thailand.

Leverage: Panel A of Table 2.3 presents the findings for changes in leverage levels (weighted means), measured as the debt to equity ratio for the firms in the sample.[47] It is important to note that the debt to equity ratio provides a more striking perspective on a firm's leverage position than the debt to assets ratio. For example, South Korea's AFC average debt to asset ratio of 68% for the firms in our sample seems less burdensome than its debt to equity ratio of more than 280%, which implies that debt obligations are more than twice as high as shareholder commitments.

We also documented the patterns for the simple means and medians, as well as the weighted median. Here a point about the relevance of the summary statistic used is worth noting. In general, the weighted median measure attenuates the distributional consequences of observations in the tails of a distribution. In many circumstances, this adjustment is warranted to

[47] The debt to equity is a leverage ratio that compares a company's total liabilities to its total shareholder's equity. The measure provides information about the magnitude of the commitments from lenders and creditors to a firm compared to the magnitude of shareholder commitments. The debt to equity ratio therefore provides an alternative lens from which to view a firm's leverage position by comparing total liabilities to shareholders' equity rather than to assets. Similar to the debt to assets ratio, a lower percentage means that a company is using less leverage and has a stronger equity position.

ensure that outliers do not drive the results. In other words, if a few observations skew the weighted mean, the weighted median that adjusts for non-uniform statistical weights and gives the 50% weighted percentile measure is the more appropriate statistic. However, in the case of leverage and measuring the overall riskiness of corporate debt for the financial system in a country, we would like to assess the upper bound of the risk. If a few large firms are also the ones with the highest leverage, it is desirable to give a larger weight to these observations since arguably these firms have the greatest potential to generate systemic risk—we focus on these large firms in Section 2.7. We therefore present the main results using the (sales) weighted mean rather than the weighted median while recognizing that the weighted median provides a useful alternative benchmark.

Columns 1 and 2 present the firm level weighted mean leverage by country for our two periods: one year before and during the AFC (1996-98) and post-GFC (2008-14). Column 1 shows that the average debt to equity ratio in the Asian Crisis Five was close to 145% while the average for the full emerging market sample was 80%. Column 3 counts the number of countries with higher average leverage during the post-GFC than during the AFC, revealing that 56% of countries[48] (10 out of 18) have higher average leverage ratios in the post-GFC period. Column 4 tabulates how many countries have higher average leverage during the post-GFC years than the average of the Asian Crisis Five during the AFC. It shows that all countries have lower leverage post-GFC than the Asian Crisis Five did on the eve and in the midst of the crisis. Figure 2.3 confirms these patterns visually.

For purposes of illustration it is interesting to note the patterns we obtain when we use the (sales) weighted median instead of the weighted mean. First, in the AFC period the weighted

[48] Data for Jordan following the Global Financial crises was patchy for leverage.

median leverage ratios for the Asian Crisis Five and full emerging market sample are much lower than the weighted mean, close to 93% and 67%, respectively. Second, 14 out of 19 countries have a higher post-GFC weighted median. Third, three countries have a higher weighted median compared to the Asian Crisis Five.

Liquidity: Panel B of Table 2.3 provides the (sales) weighted mean of the current to total liabilities ratio by country to analyze the liquidity needs of the firms in our sample.[49] Column 3 suggests that six countries demonstrate a higher current to total liability ratio in the post-GFC sub-period. Column 4 shows that 11 out of the 22 countries have higher short-term liquidity needs compared to the Asian Crisis Five. Figure 2.4 presents a graphical representation of these patterns.

Solvency: The coverage ratio is a measure of a firm's ability to meet its obligations to lenders. Generally, the higher the coverage ratio, the better the ability of the firm to fulfill its debt obligations. Common coverage ratios include the interest coverage ratio, debt service coverage ratio and the asset coverage ratio. The interest payment and debt service ratio data are very sparse in our sample of emerging market firms. We therefore use a modified version of the coverage ratio – the ratio of EBITDA to total liabilities. By definition, this modified ratio will be biased downward as total liabilities exceed interest expenses or other debt obligations used to calculate more standard versions of the coverage ratio. Nevertheless it provides a useful snapshot of a firm's solvency position.

In Panel C of Table 2.3, we see that the pre-crisis coverage ratio average of the Asian Crisis Five has increased. The average for the full emerging markets sample on the other hand

[49] Current liabilities measure a firm's debts and other obligations that are due within one year and include short-term debt, accounts payable, accrued liabilities and other debts. Note that current liabilities provide a more comprehensive measure of a firm's short-term liquidity needs compared to short-term debt since it includes accounts payable and accrued liabilities.

has remained unchanged. Column 3 shows that half of the countries have coverage ratios that are lower than their AFC levels, but 20 countries have coverage ratios that exceed that of the Asian Crisis Five. Figure 2.5 visually confirms these patterns.

Profitability: Next we examine the profitability of the firms in our sample (Panel D, Table 2.3). We use two measures: the return on invested capital (ROIC) and the return on equity (ROE). A concern with increased leverage is that if it is accompanied by a slowdown in profitability, firms will find it more difficult to service their debt obligations. Unlike equity, debt is a non-contingent claim that needs to be met regardless of the state of firm profits. Firm-level liquidity and solvency ratios therefore feature some measure of earnings relative to debt service obligations to provide a measure of a firm's flexibility with respect to these obligations.

Panel D shows that while the ROIC for the Asian Crisis Five during the AFC was close to 7% the number for the overall emerging markets sample was approximately 10%. In the post-GFC period, the average ROIC across all emerging markets in our sample was similar to the AFC sample period. However, 77% of countries (17 out of 22) had higher profitability post-GFC than the Asian Crisis Five during the AFC. The fact that the Asian crisis five countries had significantly worse profitability during the Asian crisis and the emerging market averages for profitability are the same in the AFC and GFC periods suggests that profitability has fallen between the two periods for the countries not involved in the AFC. This pattern indicates that a broader sample of emerging markets have subpar profitability in the post-GFC period.

Interestingly, consistent with an increase in leverage, the return on equity (ROE) shows a much different pattern (not reported in Table D). Note that increased leverage (debt) increases the expected rate of return on the equity simply because leveraged investments are riskier than unlevered ones. The average ROE went from negative to 13% for the Asian Crisis Five across the two sample periods while the overall emerging market average increased from 9% to 14%. More than half the sample of countries has higher ROE values in the post-GFC period compared to the AFC period. Strikingly, post-GFC, most of the countries have higher ROE values compared to the Asian Crisis Five during the AFC.

Corporate Fragility: As mentioned in section 2.4, Altman's Emerging Market Z-score can be used as a composite summary statistic for corporate fragility. The measure is composed of various income statement and balance sheet items: the ratios of working capital, retained earnings, and operating income to total assets, as well as the book value of assets to total liabilities. By combining various aspects of firm operations, it paints an overall picture of corporate health. The advantage of the approach, as the data section shows, is that the different ranges of "safe", "grey" and "distress" can be correlated with corporate ratings letter grades used by credit rating agencies. Altman modifies the summary statistics to account for different structural characteristics of emerging market firms; e.g. he replaces the market value of assets to the book value to adjust for the relative trading illiquidity in emerging markets compared to advanced economies. The Z-score statistics correspond to AAA to BBB for the safe zone, BBB- to B- for the grey zone and CCC+ and below for the distress zone.

Panel E of Table 2.3 and Figure 2.6 present the results. Companies with EM Z-scores greater than 5.85 are considered to be in the "safe zone", scores between 5.85 and 3.75 indicate vulnerability, and scores below 3.75 indicate that the firm is in state of distress. Figure 2.6 shows that among the Asian Crisis Five, South Korea was in the distress zone during the AFC period. Malaysia, Philippines and Thailand were in the grey area, as were China, India, and Pakistan. The only Asian country in the safe zone was Taiwan. In Latin America, while Argentina and Brazil were in the grey zone, Chile, Colombia, Mexico and Peru were in the safe zone. Note also that both Turkey and South Africa were in the safe zone. The average Z-score for the Asian Crisis Five was 5.2 (grey zone) and the AFC emerging market average was 6.1 (safe zone).

The picture changes in the post-GFC period. Countries with higher Z-scores in the post-GFC period are Colombia, Eastern Europe, Malaysia and Indonesia. South Korea moved from the distress zone into the safe zone. China, India and Turkey are in the grey zone as is Mexico. The picture suggests that the issues of corporate vulnerability apply to a broader set of emerging markets in the post-GFC period given the number of countries in or barely above the grey zone. It is worth pointing out that there are no countries in the distress zone post-GFC. Also, note that some of the countries in the safe zone show a fall in their Z-scores compared to their AFC scores and are now barely over the grey zone threshold. If the Altman Z-score provides a leading indicator of the potential for distress, the data suggest that corporate financial vulnerabilities are more widespread now than during the AFC period.

Summary: Thus far, we have contrasted a range of firm-level indicators related to corporate fragility and profitability prior to and during the AFC of 1998 and the aftermath of the GFC of 2008–2009. We compare the indicators using two benchmarks: (i) a within-country cross-time comparison to the 1996-1998 values for a given indicator; and (ii) a comparison relative to the 1996-1998 average of the Asian Crisis Five.

In the 1996-1998 period, East Asian corporates had greater leverage and financial vulnerabilities than corporates in other emerging markets. While there is substantial cross-country heterogeneity in the post-GFC period, our data suggest that more countries have higher leverage and are in or close to the "grey zone" post-GFC than in the AFC period, implying a higher risk of financial distress. It is important to note that the analysis of the East Asian crisis is "ex-post" in that we examine the leverage of the Asian countries that were eventually hit by a crisis. The leverage levels in these countries therefore provide a useful "worst case scenario" benchmark against which to assess leverage-related vulnerabilities in the post-GFC period. Note also that while warning lights are flashing regarding these vulnerabilities, thus far no emerging market country is actually in crisis. Therefore, we do not have a single country with leverage akin to the Asian Crisis Five in the red "distress" zone.

The appendix includes a table that helps visualize some of our findings through heat maps for leverage and Altman's Z-score. The maps confirm our prior observations that East Asian corporates had greater leverage and financial fragility than corporates in other emerging markets during the AFC, that the AFC period displays the greatest heterogeneity across countries (both in leverage and Z-score), and that leverage and financial fragility have surged for several countries in the post-GFC period.

2.6 Corporate Fragility in Emerging Markets: Firm Level Evidence

In the previous section we found that in the post-GFC period more countries are in Altman's grey zone for corporate fragility or barely above the threshold. In this section we delve further into the firm-level data and run regressions to examine the link between corporate financial fragility and leverage as well as the role of firm-characteristics—in particular firm size. We also examine the impact of macroeconomic and institutional factors such as exchange rates, economic growth, and financial globalization interacted with leverage on the corporate distress scores.

As a first step, we examine whether the relationship between leverage and Z-score is different across time periods by estimating the following model:[50]

$$Z_{i,c,t} = \alpha_i + \delta_{c,t} + (\beta_1 D1 + \beta_2 D2 + \beta_3 D3)L_{i,c,t} + \varepsilon_{i,c,t} \qquad (3)$$

[50] In the regressions, the variables are Winsorized at 5%. The results are robust to using 1% Winsorization as well as no Winsorization.

where $Z_{i,c,t}$ is the Z-score for firm i, country c, year t; $L_{i,c,t}$ is leverage for firm i, country c, year t; α_i are firm fixed effects; $\delta_{c,t}$ are country-year fixed effects; D1 is a dummy that takes a value of 1 for years 1996-98 (the AFC period and its run-up); D2 is a dummy for years 2003-2007 (tranquil period); and D3 is a dummy for years 2008-14 (post-GFC period). In the baseline regression, we exclude 1992-1995 from the regressions because we have a small number of firms for this period. We also exclude 1999-2002 to avoid contaminating our tests with emerging market crises associated with sovereign – not corporate – debt episodes (i.e. Russian, Brazilian, and Argentinean crises). However, as a robustness check we include these years and more generally, find that the results remain robust to alternate specifications of the subsamples.

We begin by examining the unconditional correlation between leverage and the Altman's Z-score across the three sub-periods, i.e., with a specification that does not include compositional controls. In other words, we start by estimating specification (1), but without firm and country-year fixed effects. Column 1 of Table 2.4 examines the impact of leverage on the Altman's Z-score across three sub-periods. $\beta 1,\ \beta 2,$ and $\beta 3$ measure the correlation between leverage ant the Z-score in the Asian Financial Crisis (AFC) period, the tranquil period (Tranquil), and the post-Global Financial Crisis (GFC) periods.

Column 1 shows that leverage is negatively correlated with the Z score, i.e., scores for firms with high leverage are closer to the distress range. The effect is statistically significant at the 1% level in all three periods. A potential concern with the econometric specification in Column 1, however, is that the ratio of Book-Value-of-Equity to Total Liabilities, a component of the Altman's Z-score, is by construction negatively correlated with our measure of leverage. Therefore, one might argue that the relationship between leverage and the Z-score is hard-wired and endogenous. This subtle point is worth emphasizing. On the one hand, at first pass it may appear that “leverage is regressed on leverage.” However, note that this holds because leverage is part of the Z score, but not an entirely correct interpretation because the specification in Column 1 examines whether the relationship between leverage and the Z-score varies over time and hence is not limited to the automatic correlation between leverage and the Z-score. Although, in Column 1, we find that the coefficients are not statistically significantly different from each other, this pattern changes as we include controls for firm observables such as firm size and compositional controls in later specifications.

Nevertheless, to circumvent this concern, we construct a modified Z-score that does not include the leverage term and only includes the ratios of working capital, retained earnings and operating income to total assets. Higher values of these components drive up the Z-score and are a sign of improving corporate health. Column 2 examines the unconditional correlation between leverage and the modified Altman’s Z-score across the three sub-periods. The coefficients on $\beta 1,$ $\beta 2,$ and $\beta 3$, are negative and highly statistically significant. The pattern suggests that there is an inverse unconditional correlation between leverage and the modified Altman’s Z-score as well. This suggests that firms with higher leverage also have a lower index of working capital, retained earnings and operating income relative to total assets.

In Column 3 we introduce firm observables such as investment and firm size. Size is inversely correlated with the modified Z-score, suggesting that, for a given level of leverage, larger firms are more financially fragile. Real investment is positively correlated with firm financial health. Note that the coefficient on 1 , which measures the impact of leverage on the modified Altman’s Z-score during the AFC, loses significance, but the other two coefficients, $\beta 2,$ and $\beta 3$, remain significantly negative. The bottom panel of the table shows that the three coefficients are not significantly different from each other.

The inverse relationship between firm-size and financial health is of interest as the financial vulnerability of large firms is of particular concern to regulators. For example, Chapter 3 of the IMF's World Economic Outlook (October 2015) report explicitly states that it is "important to closely monitor sectors and systemically important firms most exposed to risks and the sectors and large firms closely connected to them, including across the financial system, and to prepare for contingencies."

Since the results in Columns 2 and 3 do not control for time-invariant unobservable heterogeneity at the firm level and time variant unobservable heterogeneity at the country level, we go on to include firm fixed effects, as well as country-year fixed effects to control for compositional effects at the country and year levels. The results, presented in Column 4, suggest that the correlation between leverage and other dimensions of firm resilience captured by the modified Z-score is positive and statistically significant during the tranquil period ($\beta_2 > 0$) and remain negative (albeit not statistically significant) in the other two sub-periods. In other words, once compositional controls are introduced, better firms, i.e., firms with higher working capital, retained earnings and operating income, borrow more during the tranquil sub-period. An important pattern to also note in this regard is that the coefficients on leverage ($\beta 1,\ \beta 2,$ and $\beta 3$), are time-varying and significantly lower during the AFC and post-GFC periods compared to the tranquil period ($\beta_1 - \beta_2 < 0$ and $\beta_3 - \beta_2 < 0$), suggesting that firms with high leverage experienced worsening liquidity, solvency and profitability during the AFC and post-GFC periods.

Column 4 also includes a control for firm size. We find that firm size continues to be negatively correlated with the modified Z score. This implies that, controlling for leverage, larger firms have significantly lower modified Z-scores, i.e., overall lower values of working capital, retained earnings and operating income as fractions of total assets.[51]

Turning to the sector-specific dimension, we use a linear regression with dummy variables to test whether the relationship between leverage and the Z-score differs across sectors. For instance, industries such as energy and mining are traded but exposed to commodity prices. Industries such as construction and utilities tend to be non-traded and therefore particularly exposed to currency risk when they access international capital markets. Currency mismatches associated with excessive foreign currency leverage were one of the root causes of the AFC. However, such mismatches may be less damaging for firms that, by operating in the tradable sector, may have natural hedges through foreign currency revenues.[52]

We observe two patterns. First, in the AFC period the negative correlation between leverage and the modified Z-score is not statistically significant in the tradable sector (Column 5, Table 2.4), positively correlated with the modified Z-score in the tranquil period and inversely correlated in the post-GFC period, mirroring the patterns observed in Column 4. Second, for the non-tradable sector none of the interacted leverage coefficients are statistically significantly related to the Z-score in any sub-period. Post-GFC, it appears that, conditional on leverage, the tradable sector is more financially vulnerable. Firm size continues to be inversely correlated with the Z-score for both tradable and non-tradable sectors.

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[51] We also estimated a specification with a control for the return on assets. The coefficient on firm size remains inversely correlated with the modified Z-score while the return on assets, a measure of profitability, is positively correlated with the modified Z-score.

[52] We start by classifying as non-tradable all firms that have a SIC2 code above 39, but then we also classify as non-tradable firms with SIC2 codes 7 (Agricultural Services), 9 (Fishing, Hunting and Trapping), 15 (Construction - General Contractors & Operative Builders), 16 (Heavy Construction, Except Building Construction, Contractor), 17 (Construction - Special Trade Contractors), 25 (Furniture and Fixtures), 27 (Printing, Publishing and Allied Industries), and 32 (Stone, Clay, Glass, and Concrete Products). This classification yields 5,888 observations in the tradable sector and 4,000 in the non-tradable sector. Our results are robust to using the simpler above 39 and below split.

Next, we examine the impact of the interaction of leverage and three macroeconomic variables - exchange rates, interest rates and GDP growth - on financial fragility. We begin with the exchange rate. This variable stands to play an important role because, in the presence of foreign currency denominated debt, the relationship between leverage and the Z-scores may vary with currency movements. While we do not have data on the currency composition of firm-level debt, the finding that currency movements amplify the correlation between leverage and corporate financial fragility measured by the modified Z-score would be consistent with the presence of currency mismatches. We test this hypothesis by estimating the following equation:

$$Z_{i,c,t} = \alpha_i + \delta_{c,t} + (\beta_1 D1 + \beta_2 D2 + \beta_3 D3)L_{i,c,t} +$$
$$+(\gamma_1 D1 + \gamma_2 D2 + \gamma_3 D3)L_{i,c,t}\Delta EX_{c,t-1} + \varepsilon_{i,c,t} \quad (4)$$

Here, $\Delta EX_{c,t-1}$ is the percentage change in the nominal exchange rate, where $\Delta EX > 0$ represents a currency depreciation. Table 2.5 presents the results. Again, we start by estimating the model without including firms and country-year fixed effects. The first column's negative, statistically significant coefficient on γ_1(AFC×ΔEX×Leverage) suggests that, in the AFC period and conditional on a depreciating currency, leverage has a statistically adverse impact on the firm-fragility score. β_1 the unconditional effect of leverage on the modified Z-score during the AFC period is no longer statistically significant once we include the interaction of leverage and exchange rate changes.

At the same time, β_2 and β_3 , the unconditional effects of leverage on the modified Z-score remain negative and statistically significant and γ_3, the effect of leverage conditional on currency changes in the post-GFC period is not statistically significant. This result is consistent with the fact that in the AFC period firms with high leverage also had currency mismatches. However, currency mismatches do not seem to be important in the post-GFC period, possibly due to the lack of severe currency depreciations. Also, note that while Asian currencies experienced significant depreciations during the AFC, the post-GFC period was generally marked by an appreciation of emerging market currencies with the exception of the period after 2013.

Column 2 of Table 2.5 shows that the interaction effect between leverage and exchange rate change (γ_1) holds when we introduce firm-specific factors like investment in fixed assets (investment) and firm size (log of total assets). Specifically, the modified Z-score continues to be inversely correlated with firm size, and the effect is statistically significant at the 1% level. Column 3 introduces firm and country-year fixed effects. It is interesting to note that once we include compositional controls, the only two coefficients that are statistically significant (and at the 1% level) are the interaction effect between leverage and exchange rate change (γ_1) and the negative coefficient on firm size.

Finally, we split the sample between firms in the tradable and non-tradable sectors. As before, we do not run separate regressions but interact the coefficients with tradable and non-tradable dummies. Column 4 shows that in the AFC period the differences between firms in the tradable and non-tradable sectors are not apparent. The point estimates on γ_1, i.e., the interaction effect of leverage during the AFC period conditional on changes in exchange rates are virtually identical across the two sectors, albeit the coefficient is more precisely estimated for the non-tradable sectors.[53] Taken together, the findings are consistent with the idea that in the AFC period (and immediately before it) the link between leverage and corporate financial fragility indicates the presence of currency mismatches. Further, while, γ_3, the interaction effect between leverage and exchange rate changes in the post-GFC period, is not statistically significant for

[53] As in Table 2.4, Columns 4a and 4b are estimated jointly. In robustness analysis (not shown) the results are robust to including the periods excluded from the table (the excluded periods are 1992-95 and 1999-2002).

either the tradable or the non-tradable sector, β_3, the unconditional relationship between leverage and the modified Z-score continues to be negative and significant in the post-GFC period only for the tradable section. This pattern is similar to that observed in Table 2.6. Post-GFC leverage vulnerabilities appear significant for the tradable sector independent of exchange rate changes as well. Also note that firm size is inversely related to the modified Z-score at the 1% level of statistical significance in all specifications.

One may argue that our results are driven by the fact that exchange rate movements were different in the two periods. In the period following the immediate aftermath of the post-GFC period when international capital flows began their surge towards emerging markets, many emerging markets experienced appreciating currencies (2010-2012) and/or relatively modest depreciations (2012-2014) in comparison to the massive currency depreciations in the AFC period. To examine whether this may be the case, we distinguish between periods of currency appreciation and depreciation. Specifically, we estimate the following model:

$$Z_{i,c,t} = \alpha_i + \delta_{c,t} + (\beta_1 D1 + \beta_2 D2 + \beta_3 D3)L_{i,c,t} +$$

$$+(\gamma_1 D1 + \gamma_2 D2 + \beta\gamma_3 D3)L_{i,c,t}\Delta EX_{c,t-1} +$$

$$+A_{c,t-1}(\theta_1 D1 + \theta_2 D2 + \beta\theta_3 D3)L_{i,c,t}\Delta EX_{c,t-1} + \varepsilon_{i,c,t} \qquad (5)$$

where $A_{c,t-1}$ is a dummy that takes a value of 1 if $\Delta EX_{c,t-1} < 0$ (i.e., if we observe a currency appreciation). The specification captures the differential effects of depreciations and appreciations interacted with leverage on corporate financial fragility. In this set up γ_i measures the joint effect of leverage and change in the exchange rate on Z-scores conditional on a currency depreciation, and $\gamma_i + \theta_i$ measures the effects conditional on an appreciation. We find γ_1 to be negative and statistically significant whereas $\gamma_i + \theta_i$ yields positive but statistically insignificant values (results unreported but available from the authors). This pattern corroborates the hypothesis that leverage interacted with currency depreciation has a statistically significant adverse impact on Z-scores, our measure of corporate financial fragility in emerging markets.

Note that the the objective of this paper is to understand how balance sheets evolve in the run-up to a corporate-driven crisis. With this aim in mind, we limit the pre-AFC period to 1996-1998 as during 1994-1995 there were several emerging-market crises (e.g. Mexico, Brazil, Argentina, Philippines) that could contaminate our focus on the AFC, our benchmark for periods of corporate fragility. However, in the appendix, we show that our regressions results are robust to including 1992-95 in the Asian Financial Crisis period and using this alternative definition for the pre-AFC period (see Tables D3 and D4).[54]

An important concern is whether survivorship bias drives the observed pattern of results. To address this, in Table 2.6 we re-estimate the specification in Column 3 of Table 2.5 with firms that survive or are present in the data for different lengths of time. We limit the sample to firms that are present for at least five years (column 2), for at least ten years (column 3) and for at least fifteen years (column 4). The finding that exchange rate depreciations amplify the negative correlation between leverage and the modified Z-score during the AFC period is robust to restricting the analysis to these subsamples. Interestingly, the correlation rises in magnitude as we proceed from a sample with a fewer number of years in Column 2 to a sample with firms with data for fifteen years in Column 4.

In emerging markets, currency depreciations are often accompanied by economic recessions and tighter financial conditions. The previous results could thus be driven by the fact that highly leveraged firms suffer more during recessions or, in the presence of maturity mismatches, are particularly affected by sudden increases in the interest rate. In Table 2.7, we

[54] Appendix Table D5 also shows the result to be robust to the exclusion of China.

take these underlying macro fundamentals into account by further interacting our three period dummies (AFC, tranquil, and GFC) with lagged GDP growth and the deposit rate (we would have preferred a lending rate but faced data constraints).

The main results from the Tables 2.5 and 2.6 on the adverse impact of leverage conditional on currency depreciations (γ_1) on Z-scores during the AFC period remain unchanged. Column 1 includes lagged real GDP growth as a control and suggests that during the post-GFC period leverage conditional on higher real GDP growth rates is positively but not significantly correlated with Z-scores. It is interesting to point out that in specifications that use the regular Z-score as a dependent variable there is a positive and statistically significant correlation between leverage conditional on real GDP growth in the post-GFC period, suggesting that leverage in growing countries is correlated with less corporate financial vulnerability. Column 2 controls for leverage interacted with lagged values of the interest rate. The coefficient estimates on interest rates interacted with leverage are not statistically significant. Column 3 includes both interaction effects (lagged real GDP growth and lagged interest rates). The interaction effect on lagged real GDP growth continues as positive and that on lagged interest rates remains statistically insignificant. The findings that size is inversely correlated with the modified Z-score while real investment is positively correlated remain robust to the inclusion of these additional macro controls. Note that β_1, the unconditional effect of leverage on the modified Z-score during the AFC period, is positively and significant (Columns 1 and 3) suggesting that controlling for real GDP growth, firms with better prospects were able to borrow more during this period.

Many emerging market countries reacted to the crises of the late 1990s with reforms aimed at improving their institutional and macroeconomic framework. Fourteen of the twenty-five countries included in our sample moved to an inflation-targeting framework between 1997 and 2009. Many countries and also implemented reforms aimed at improving their domestic capital markets (the Asian Bond market Initiative was a specific outcome of the Asian Financial crisis) and promoting financial deepening. In our sample of countries average financial depth went from 50% in 1995 to 72% in 2014. The period we study was also characterized by different phases of financial globalization with an increase of cross-border capital flows over 2002-2007, a collapse over 2007-2009 and a rapid increase in flows to emerging markets after 2010 (Lane and Milesi-Ferretti, 2017).

In Table 2.8 we test whether our results are driven by these factors by examining the effects of leverage conditional on changes in the exchange rate are robust to the inclusion of an index of financial development, inflation targeting regimes, and the updated Lane and Milesi-Ferretti (2007) index of financial globalization. The adverse impact of leverage conditional on currency depreciations (γ_1) on Z-scores during the AFC period remains unchanged to the inclusion of these additional controls. It is important to note that the inverse correlation between firm size and the modified Z-score is salient across all specifications.

2.7 Corporate Fragility in Emerging Markets and the Macroeconomy

A key question is whether the increase in corporate leverage documented above can have large negative macroeconomic consequences when central banks in advanced economies start raising their interest rates (a process already begun by the Federal Reserve). Acharya et al. (2015) suggest this could lead to capital outflows from emerging markets and potential problems associated with the presence of currency mismatches in firm balance sheets.

Note that in all the specifications in Tables 2.4-2.8 that included firm size, size was a significant predictor of financial vulnerability. Moreover the coefficient was highly statistically significant. The inverse correlation between firm size and the Altman’s Z-score (both the standard and modified versions), suggest that in emerging markets firm size or the extent of granularity in the firm-level data may be a novel and powerful indicator of financial vulnerabilities.

We address this question by studying the behavior of large firms. Specifically, we proceed in two steps. First, we follow Gabaix (2011)[55] and show that idiosyncratic shocks to large firms are significantly correlated with GDP growth in our sample of emerging markets.[56] Second, we test whether large firms are particularly vulnerable to exchange rate movements. We find that large firms are, on average, less leveraged than smaller firms. However, we also find that the more-leveraged large firms are more vulnerable to exchange rate shocks compared to equally-leveraged smaller firms. This evidence is consistent with the idea that large firms make a greater use of foreign currency borrowing and that they are not fully hedged against exchange rate movements. While this result holds for the average country in our sample, we also find that there is substantial cross-country heterogeneity.

2.7.1 Granularity in emerging market countries

Gabaix (2011) shows that if the distribution of firm size can be approximated with a fat-tailed power law (formally $P(S > x) = ax^{-\xi}$ where S is firm size and $\xi \geq 1$) idiosyncratic firm-level shocks can play a key role in explaining aggregate fluctuations. He builds a "granularity" index that captures idiosyncratic shocks for the largest 100 US firms and shows that this index is closely correlated with overall US GDP growth.

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[55] Gabaix (2011) shows that idiosyncratic shocks to firms can generate aggregate fluctuations. An intuitive reason is that some firms are very large, and further that initial shocks can be intensified by a variety of generic amplification mechanisms. In the context of exchange rate or other shocks that can adversely impact highly levered firms, an additional concern is that shocks to systemically important firms in emerging markets could have feedback effects for the financial systems in these countries. The financial vulnerability of large firms is inextricably linked to the banking system in particular.

[56] Gabaix (2011) uses data for US listed firms. To the best of our knowledge, we are the first to apply his methodology to emerging market countries and show that the result also holds in this sample of countries.

According to Gabaix, granularity effects are likely to be even more important in countries that are less diversified than the United States. He mentions several emerging market countries and suggests that "It would be interesting to transpose the present analysis to those countries" (Gabaix, 2011 p. 737). We take this suggestion seriously and build a granularity index for our sample of 26 emerging market countries.

Gabaix (2011) measures granularity with the following index:

$$\Gamma_t = \sum_{i=1}^{K} \frac{S_{i,t-1}}{Y_{i,t-1}} \left(g_{i,t} - \bar{g}_t\right) \tag{6}$$

where $S_{i,t-1}$ measures sales of firm i, $Y_{i,t-1}$ is GDP, $g_{i,t}$ is the growth rate of firm i (defined as the growth rate of the sales to employees ratio) and $\bar{g}_t$ is the simple average of the growth rate of the largest Q firms in the economy (with $Q \geq K$, and where firm size is measured by sales). Gabaix sets K=100 and experiments with Q=100 and Q=1000. When Q=100, the index is equal to the weighted growth rate of the 100 largest firms minus the (simple) average growth rate of these same firms. When Q=1000, the index is equal to the weighted growth rate of the 100 largest firms minus the (simple) average growth rate of the largest 1000 firms. It should be noted that the weights ($\frac{S_{i,t-1}}{Y_{i,t-1}}$) do not add up to one because the weights are computed for a subset of firms and the numerator is sales and the denominator is GDP.

In order to build a granularity index for our sample of emerging markets we need to address two issues. The first issue relates to data limitations. As mentioned above, Gabaix measures firm growth as the growth rate of the sales-to-employees ratio. Unfortunately, we do not have a good coverage of firms with data on total employment. Therefore, we measure firm growth by focusing on the growth rate of total sales. Our measure is a good approximation of the sales to employees growth rate as long as most of the variance in the ratio used by Gabaix arises from variations in sales rather than in variations of employment.

The second issue relates to the definition of "large" firms in an emerging market context. While it is reasonable to assume that, in a large and diversified economy like the United States, the largest 100 firms are indeed very large, this assumption is problematic in smaller and less diversified emerging market countries.

One possible way to address this issue is to simply use a smaller number of firms for all countries in our sample. In choosing this number however the number of firms needs to be large enough to capture some variability in idiosyncratic shocks and cover a meaningful share of overall GDP. Among the various possible thresholds, the largest number that allows us to include all the countries in our sample is 25.[57]

An alternative strategy is to use a criterion based on the share of total sales over GDP. For instance, we can rank firms in descending order of size and impose a cumulative sales-to-GDP ratio threshold.[58] Formally, let $f_{1,c,t}$ be total sales of the largest firm (by sales) in country c, year, t, $f_{2,c,t}$, the sales of the second largest and $f_{n,c,t}$ the sales of the nth largest firm. Let *x* be a threshold in terms of cumulated sales of over GDP. Then firm are defined as large up to the point where:

$$\sum_{i=1}^{N} \frac{f_{i,c,t}}{GDP_{c,t}} < x \tag{7}$$

We experimented, with different thresholds and found that most country-years in our sample reach the level of 20% of the cumulative sales-to-GDP ratio. One issue is that in

[57] Note that country heterogeneity poses a challenge. 25 firms are likely to capture a large share of the economy in a relatively small country like Peru, but twill capture a much smaller share of the economy in a larger country like Brazil or China.

[58] As before there are tradeoffs in the choice of the threshold, *x*. If the threshold is too low there will be too few "large" firms and if the threshold is too high there will be many countries in our sample with few listed firms that do not reach a higher threshold.

countries with high degrees of concentration, a very small number of firms are sufficient to breach the threshold.

In the end, we adopt an intermediate strategy: we define as large, the largest firms for whom cumulative sales are below 20 percent of GDP. However, if less than 25 firms are sufficient to reach this threshold, our definition of large is the largest 25 firms. As we do not want to include more firms than what Gabaix includes for the US, we limit the number of large firms to 100. Summing up, we rank firms by sales and we define as large a firm $f_{i,c,t}$ if $i \leq 25$ or $\sum_{i=1}^{N} \frac{f_{i,c,t}}{GDP_{c,t}} < 0.2$, and $i \leq 100$.[59] Table 2.9 replicates Gabaix's results and shows that granularity is positively correlated to GDP growth in our sample of emerging market countries.

2.7.2 Large Firms and Exchange Rate Vulnerabilities

Having established that idiosyncratic shocks to large firms are correlated with GDP growth, we now examine whether leveraged large firms are more vulnerable to currency depreciations. As a first step, we check if there are differences in leverage and other potential measures of fragility between large and smaller firms. Column 1 of Table 2.10 shows that compared to smaller firms, lower levels of leverage characterize the large firms in the sample. Columns 2-4 show that there are no statistically significant differences in other measures of corporate financial vulnerabilities such as solvency, liquidity, and the Z-score.

While large firms have lower leverage with respect to smaller firms, it is possible that they have an "unhealthier" type of leverage. Specifically, in the presence of fixed costs it is easier for large firms to borrow abroad and foreign borrowing tends to be in foreign currency. There is evidence that large firms issue international bonds not only to finance investment

[59] The results are robust to defining as large the largest 25 firms without taking into consideration the cumulative sales-to-GDP ratio.

projects but also to engage into carry trade activities (Bruno and Shin, 2016, Caballero, Panizza, and Powell, 2015). Lack of data on the currency composition of firm liabilities prevents us from directly testing if this is the case for our full sample of countries, but there is some evidence that (i) large Brazilian firms are more likely to have foreign currency debt compared to smaller firms (Bonomo et al.2003); (ii) large firms in US use more foreign currency derivatives (Allayannis and Weston, 2001); (iii) large firms in Finland are more likely to borrow in foreign currencies than small firms (Keloharju and Niskanen, 2001); and larger firms hold a higher fraction of dollar debt in a set of firms from Argentina, Brazil, Chile, Colombia, and Mexico (Bleakley and Cowan, 2005).

Given that we cannot test directly whether currency mismatches are potentially more problematic for larger firms, we test whether sales growth (associated with GDP growth in the granularity regressions of Table 2.9) responds more to exchange rate movements in large and leveraged firms than in equally leveraged smaller firms. As a first step we estimate the following model for our full sample of firms:

$$GR_{i,c,t} = LEV_{i,c,t}(\beta + \gamma DXR_{ct}) + \delta LARGE_{i,c,t} + \theta DXR_{ct} + \alpha_i + \varepsilon_{i,ct,t} \qquad (8)$$

where $GR_{i,c,t}$ is sales growth in firm i, country c, year t, $LEV_{i,c,t}$ is leverage, DXR_{ct} is the percentage change in the exchange rate in country c, year t (positive values are depreciations), $LARGE_{i,c,t}$ is a dummy variable that takes a value of one for large firms (defined as above), and α_i are firm fixed effects.

Column 1 of Table 2.11 shows that currency depreciations and leverage are negatively correlated with sales growth, but that the interaction between leverage and sales growth is not statistically significant. The lack of a significant effect on the interaction between leverage and currency depreciations may be due to the fact that for the average firm in our sample the negative effect of depreciation is not linked to the presence of negative balance sheet effects brought about by the presence of foreign currency debt. Alternatively, the lack of statistical significance may be due to the fact that firms that have currency mismatches are less leveraged on average. As we saw earlier, large firms are less leveraged and may have larger shares of foreign currency debt. When we augment the model with country-year fixed effects (a specification that does not allow us to separately estimate the effect of the exchange rate change, DXR), we find results that are essentially identical to those of the model without country-year fixed effects (compare the first two columns of Table 2.11).

Next, we estimate our model with country-year fixed effects separately for large and small firms. Columns 3 and 4 of Table 2.11 show that leverage and the interaction between leverage and exchange rate movements are statistically significant for large firms and are not statistically significant for smaller firms. There are also large differences in the coefficients. The leverage coefficient is three times larger in the large firms subsample and the interaction between leverage and DXR is ten times larger in the large firms subsample. The point estimates imply that in large firms, a 30% depreciation of the exchange rate (DXR=0.3) yields correlations between leverage and sales growth ranging from -0.045 to -0.195.

In column 3 of Table 2.11, we find that the interactive coefficient takes a value of -0.5. This means that, all else equal, a 30% depreciation (the average in our sample) reduces sales for the large firm with average leverage (the average for large firms is 65% in our sample) by approximately (10% 65*0.3*0.5=9.75%). Assume that these large firms have sales that amount to 50% of GDP. The granularity regressions of Table 2.9 (column 1) say that if there is a 1% shock to sales of the largest firms with total sales accounting for 50% of GDP, GDP growth will decrease by 0.35 percentage points (0.698/2). These back-of-the-envelope calculations imply that the GDP growth effects of a 30% depreciation will be a decrease in growth of 3.5 percentage points.

In column 4, we pool all our observations but allow for the differential effect of firm size by estimating the following model:

$$GR_{i,c,t} = LEV_{i,c,t}\left(\beta + \gamma DXR_{ct} + \phi LARGE_{i,c,t} + \psi LARGE_{i,c,t} \times DXR_{ct}\right) + \\ + \delta LARGE_{i,c,t}(\delta + \lambda DXR_{ct}) + \alpha_i + \chi_{c,t} + \varepsilon_{i,ct,t} \tag{9}$$

where $\chi_{c,t}$ is a country-year fixed effect and all other variables are defined as above. In this case our parameter of interest is ψ, which captures how firm size affects the impact on sales of the interaction between depreciation and leverage. The results are in Column 5 of Table 2.11. We find that ψ is negative, large in absolute value, and statistically significant. This confirms that the interaction between leverage and currency depreciations in absolute value is significantly larger for large firms. We also find that λ is negative and statistically significant, suggesting that large firms are negatively impacted by currency depreciations even in the absence of leverage.

Given that our panel is highly unbalanced with some countries in the sample with more than 400 listed firms while others with only 20 listed firms, we re-estimate our model by keeping a maximum of 150 firms per country-year. The results remain near identical to what we obtain for the full sample of firms (compare columns 5 and 6 of Table 2.11).

Our findings are consistent with the hypothesis that many large firms may have unhedged foreign currency liabilities and are thus vulnerable to sudden currency depreciations. Given our previous evidence that idiosyncratic shocks to large firms affect overall economic activity, one is tempted to conclude that a sudden capital flows reversal could lead to very adverse effects on real output in emerging markets.[60]

Such a pessimistic conclusion is however mitigated by the fact that, while the results of Table 2.11 are valid for the average emerging market country, there is substantial heterogeneity among the countries included in our sample. Figure 2.7 reports the point estimates of the parameter ψ obtained by estimating Equation 9 (without the country-year fixed effects) separately for 16 countries in our sample.[61] The point estimates range between -1 (Pakistan) and 2.5 (Russia). They are negative for 10 countries (statistically significant for 5 countries) and positive for 6 countries (statistically significant for one country). Thus, there is substantial cross-country heterogeneity and one challenge for future research will be to identify the drivers of this heterogeneity.

2.8 Conclusion

This paper addresses widespread concerns about and potential macroeconomic repercussions of the rapid increase in corporate leverage in emerging markets following the GFC. Stylized facts using firm-level data show that post-GFC, emerging market corporate balance sheet indicators have not deteriorated to AFC crisis-country levels. However, more countries are close to or in the "vulnerable" range of Altman's Z-score (in the "grey zone" or barely above the threshold) and average leverage for the entire emerging market sample is higher in the post-GFC sub period than during the AFC. Significantly, we find that the relationships between leverage, exchange rate depreciations, and corporate financial distress scores are time

[60] Please note that all the results are robust to interacting leverage and firm size with financial debt and a measure of financial globalization.

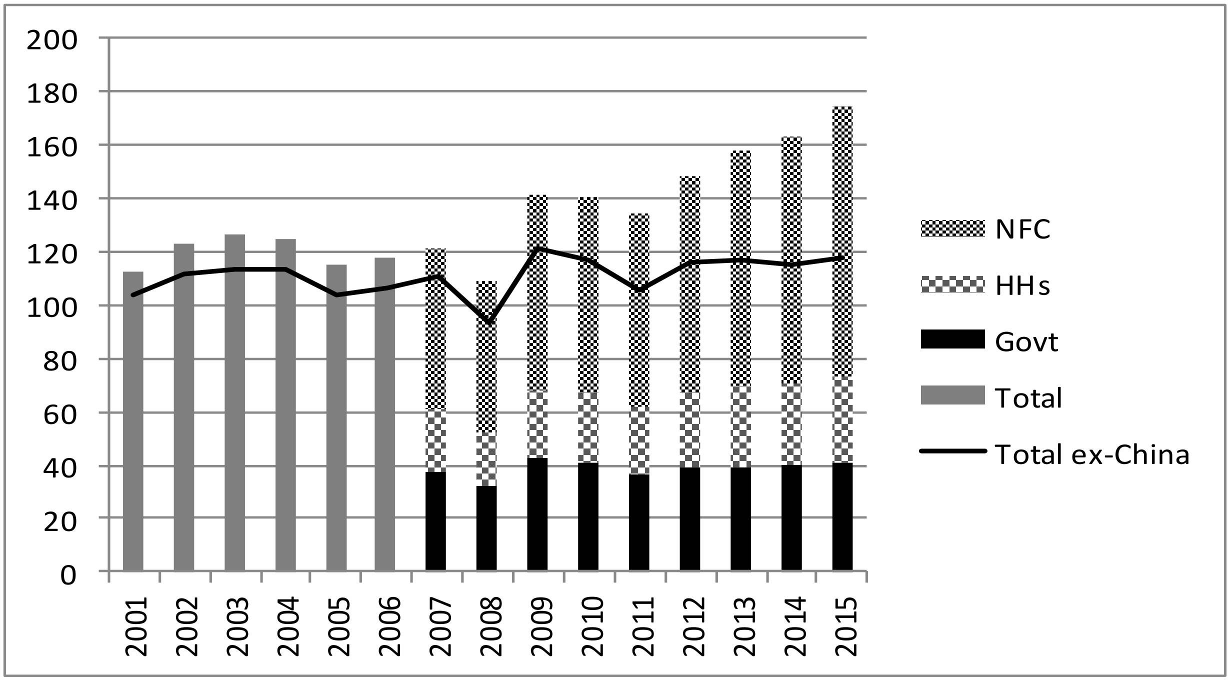
[61] For the remaining countries in our sample, there was not enough information in the data to estimate country-specific coefficients.

varying. Also, a central finding is that firm size is inversely correlated with corporate distress scores and, further, that currency depreciations amplify the impact of leverage on financial vulnerability for large firms during a crisis.

Therefore the question arises whether the corporate financial health of large firms is more important for the macroeconomy than others. Following Gabaix (2011), we find that at a granular level, the sales growth of large firms is a systemically important driver of economic growth. Large firms, therefore, have the potential to transmit corporate distress to other firms in emerging markets via network effects and other spillovers, warranting special attention from policymakers. Although large firms in our sample consistently have less leverage, the sales growth of these firms is more adversely impacted by exchange rate depreciations compared to similarly levered smaller firms, albeit with substantial cross-country heterogeneity in the observed impacts.

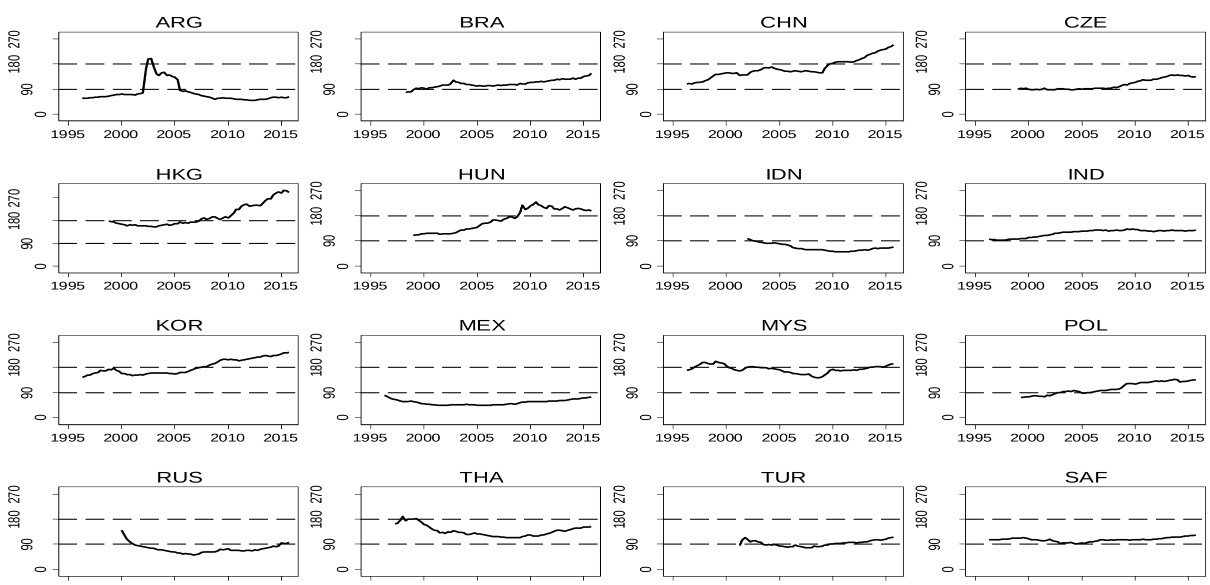
The AFC had corporate financial roots. In particular, increased leverage on firm balance sheets in conjunction with foreign exchange denominated debt made firms vulnerable to the currency devaluations that accompanied the crisis. Currency and maturity mismatches led to widespread firm failures, while implicit bailout guarantees created moral hazard issues related to the increased leverage. Credit to emerging market firms has witnessed an unprecedented and rapid growth since the GFC. Given the systemic importance of large and highly levered firms, our results suggest that policymakers closely monitor this subset of emerging market firms.

2.9 Tables and Figures



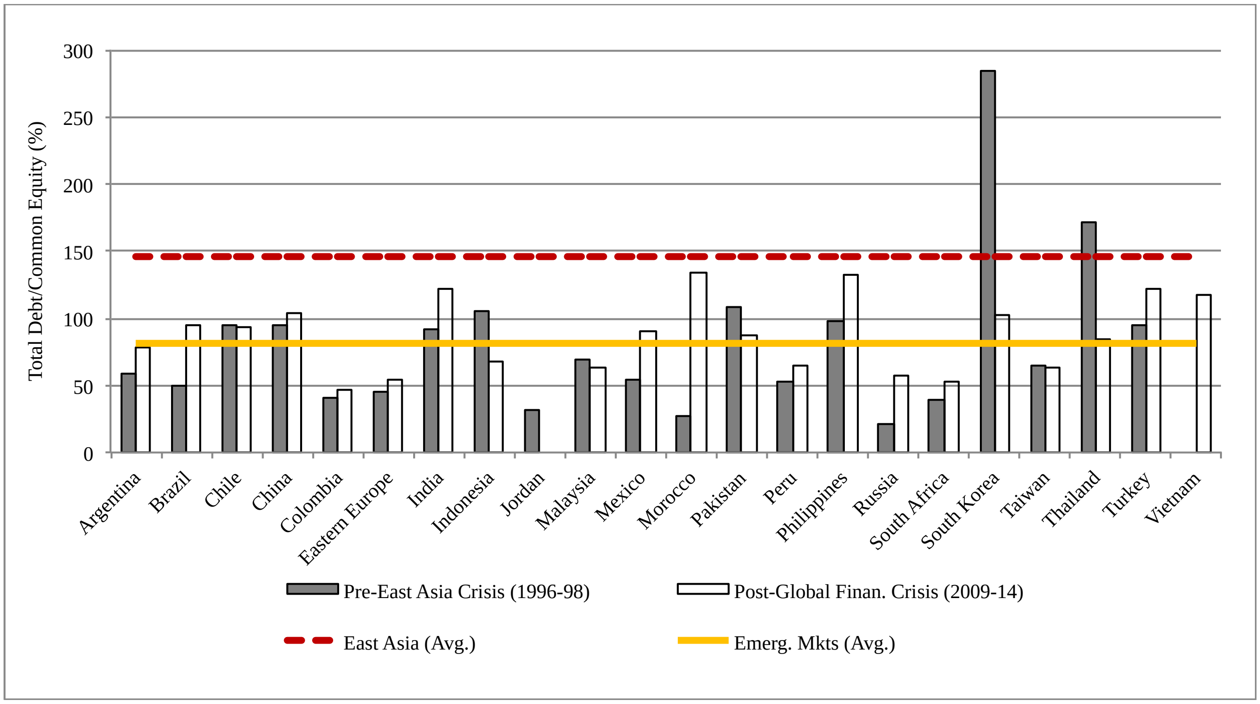
Source: authors calculations based on BIS total credit statistics. (Decomposition across sectors is only available after 2006)

Figure 2.1: Total Credit to the Non-Financial Sector in Emerging Markets (% of GDP)



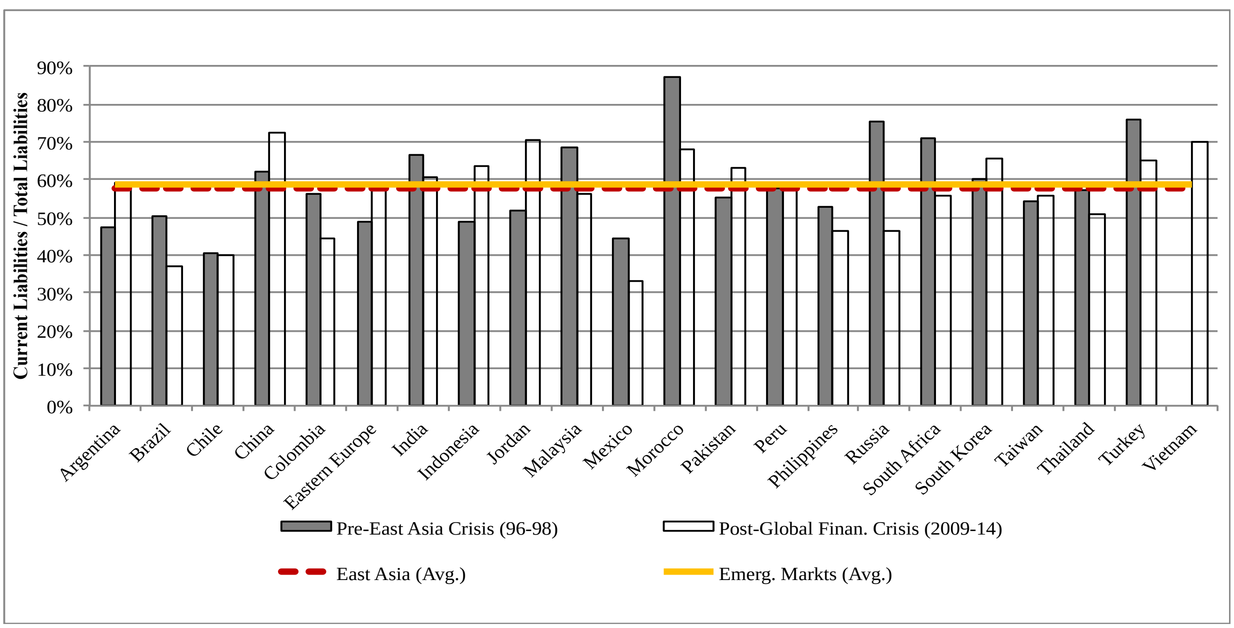
Source: authors calculations based on BIS total credit statistics

Figure 2.2: Total Credit to the Non-Financial Sector in Emerging Markets (% of GDP)



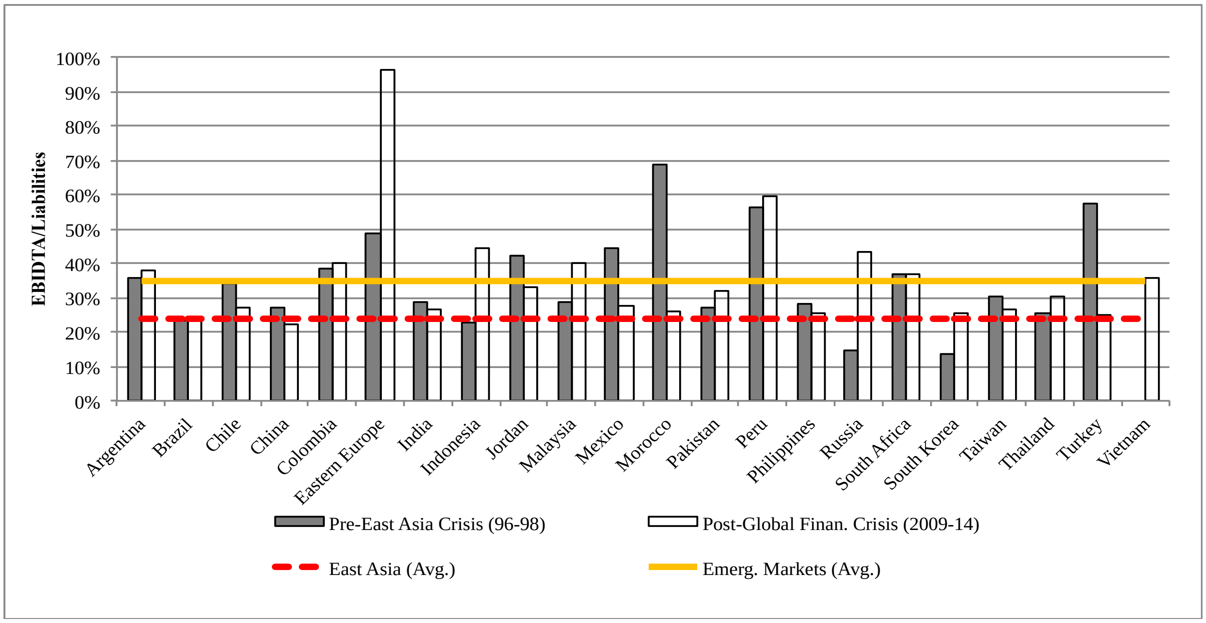
Source: authors calculations based on Worldscope data.

Figure 2.3: Leverage – Debt to Equity (Weighted Mean)



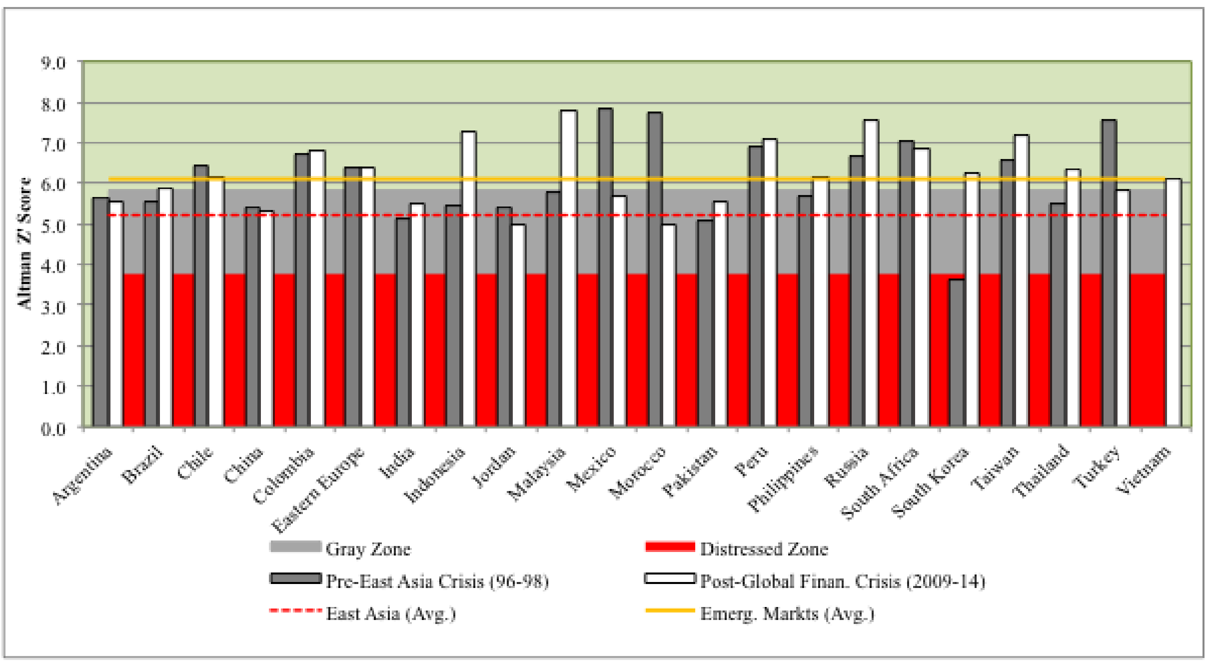
Source: authors calculations based on Worldscope data.

Figure 2.4: Liquidity – Current to Total Liabilities (Weighted Mean)



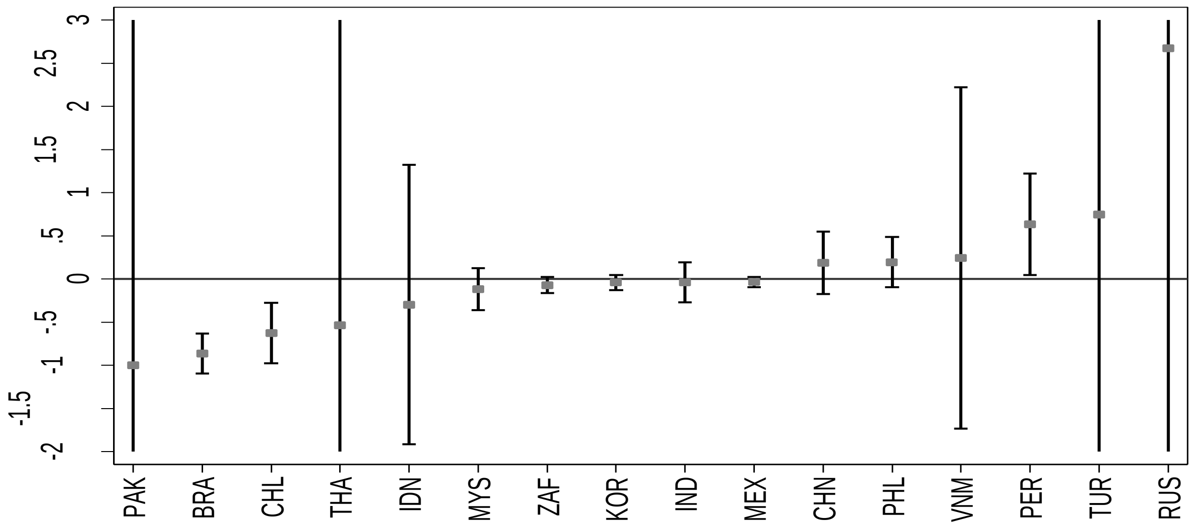
Source: authors calculations based on Worldscope data.

Figure 2.5: Solvency – EBITDA to Total Liabilities (Weighted Mean)



Source: authors calculations based on Worldscope data.

Figure 2.6: Altman Z''-Score EM (Weighted Mean)



Notes: The figure plots the equation the coefficient (with a 95% Confidence Interval) of the Parameter ψ of X4 (Without the country-year fixed effects) estimate one country at a time.

Figure 2.7: Coefficient of the Parameter ψ

Table 2.2: Total Claims on Emerging Market Countries, BIS reporting Banks (billion USD)

	2007	2008	2009	2010	2011	2012	2013	2014	2015Q3
Emerging Markets									
Total	2,419	2,408	2,396	2,807	3,032	3,157	3,640	3,699	3,471
% top 5 curr.	81%	83%	81%	79%	79%	77%	77%	71%	74%
% USD	52%	53%	52%	53%	55%	53%	54%	55%	58%
Emerging Markets Ex-China									
Total	2,231	2,254	2,219	2,476	2,555	2,634	2,740	2,663	2,594
% top 5 curr.	82%	84%	81%	80%	81%	79%	81%	81%	82%
% USD	52%	53%	52%	53%	56%	55%	58%	61%	63%
Asia									
Total	830	738	783	1,064	1,258	1,349	1,801	1,945	1,752
% Total EM	34%	31%	33%	38%	41%	43%	49%	53%	50%
% top 5 curr.	78%	84%	80%	79%	79%	77%	74%	62%	65%
% USD	56%	58%	59%	59%	59%	56%	56%	53%	56%
Asia Ex-China									
Total	641	584	606	733	782	826	901	908	874
% Total EM	26%	24%	25%	26%	26%	26%	25%	25%	25%
% top 5 curr.	81%	86%	84%	82%	85%	83%	84%	82%	83%
% USD	57%	59%	60%	61%	66%	64%	67%	69%	71%
Latin America									
Total	403	410	413	533	602	626	647	633	627
% Total EM	17%	17%	17%	19%	20%	20%	18%	17%	18%
% top 5 curr.	83%	84%	76%	76%	78%	78%	79%	82%	85%
% USD	70%	74%	67%	67%	70%	70%	71%	75%	79%
Developing Europe									
Total	728	786	722	711	690	698	713	609	559
% Total EM	30%	33%	30%	25%	23%	22%	20%	16%	16%
% top 5 curr.	79%	81%	80%	76%	76%	73%	77%	77%	77%
% USD	35%	33%	29%	28%	29%	27%	31%	32%	31%
Africa and Middle East									
Total	459	474	478	499	481	484	479	513	533
% Total EM	19%	20%	20%	18%	16%	15%	13%	14%	15%
% top 5 curr.	87%	84%	85%	84%	86%	83%	84%	83%	84%
% USD	58%	60%	62%	61%	63%	61%	61%	63%	65%

Source: Own elaborations based on BIS Locational Statistics. The data are for total claims (all instruments and all sectors) on residents of counterparty countries. Top five currencies are USD, euro, yen, British pound, and, Swiss franc.

Table 2.3: Asian Financial Crisis vs Post-Global Financial Crisis

	(1)	(2)		(3)	(4)	(5)
Countries	Asian Financial Crisis (1996-1998)	Post-Global Financial Crisis (2008-14)		Post-GFC > AFC (By country)	Post-GFC > Asian Five AFC avg.	Post-GFC > EM AFC avg.
	Panel A: Leverage (Debt to Equity)					
Asian Crisis Five	145.5%	73.9%	Yes	10	0	12
Emerging Markets	80.8%	87.3%	No	8	21	9
	Panel B: Liquidity (Current to Total Liabilities)					
Asian Crisis Five	57.6%	59.5%	Yes	6	11	11
Emerging Markets	58.7%	56.4%	No	12	11	11
	Panel C: Solvency (Coverage ratio: EBITDA to Total Liabilities)					
Asian Crisis Five	23.7%	48.3%	Yes	9	20	9
Emerging Markets	34.9%	35.7%	No	9	2	13
	Panel D: Profitability (Return on Invested Capital)					
Asian Crisis Five	7.3%	11.0%	Yes	9	17	9
Emerging Markets	10.9%	10.7%	No	9	5	13
	Panel E: Emerging-Markets Z-score (Distance to Default)					
Asian Crisis Five	5.2	6.6	Yes	9	20	13
Emerging Markets	6.1	6.2	No	9	2	9

Leverage is measured by the debt to equity ratio: a firm's total debt divided by its common equity. Liquidity is measured by current-to-total liabilities. Solvency is measured by the coverage ratio: earnings before interest, taxes, and depreciation divided by total liabilities. Profitability is measured by the return on invested capital (ROIC): the ratio of operating profit (earnings before interest and tax) to invested capital (sum of shareholders' equity and debt liabilities). Altman's (2005) Emerging Market Z-Score measures the inverse of firm fragility (computation described in the text). The first two columns present the average measure for each group of countries during our two fragile periods: The Asian Financial Crisis (1996-1998) and the post-Global Financial Crisis (2008-2014). The last three columns count the number of countries in our sample that meet (“Yes”) and don’t meet (“No”) the conditions stated in the column headings. The data is weighted by sales by year and then averaged per period per country. Asian Crisis Five countries include Indonesia, Malaysia, Philippines, South Korea, and Thailand. Source: authors calculations based on Worldscope data.

Table 2.4: The Relationship Between Leverage and Distance to Default in Different Time Periods

	(1)	(2)	(3)	(4)	(5)	
	Dep Var: Altman Z-score	Dep Var: Modified Altman Z score				
					(5a) Tradable	(5b) Non-Tradable
β_1 (AFC×Leverage)	-2.666***	-0.389**	-0.225	-0.252	-0.233	-0.270
	(0.229)	(0.179)	(0.201)	(0.259)	(0.332)	(0.338)
β_2 (Tranquil×Leverage)	-3.024***	-0.711***	-0.512***	0.386*	0.495*	0.281
	(0.196)	(0.153)	(0.171)	(0.219)	(0.280)	(0.297)
β_3 (GFC×Leverage)	-2.908***	-0.573***	-0.522***	-0.236	-0.526**	0.177
	(0.183)	(0.143)	(0.157)	(0.201)	(0.249)	(0.289)
Investment			0.066	0.0432	0.769	0.0413
			(0.041)	(0.0392)	(0.623)	(0.0393)
Firm Size			-0.053***	-1.632***	-1.650***	-1.613***
			(0.012)	(0.0731)	(0.0973)	(0.111)
Constant	-2.666***	-0.389**	28.55***			
	(0.229)	(0.179)	(0.203)			
Observations	9,257	9,257	8,015	6,495	6,495	
$\beta_1 - \beta_2$	0.358	0.322	0.287	-0.638**		
P value	0.20	0.13	0.23	0.04		
$\beta_3 - \beta_2$	0.115	0.138	-0.01	-0.622**		
P value	0.62	0.44	0.96	0.02		
$\beta_1 - \beta_3$	0.242	0.185	0.297	-0.016		
P value	0.36	0.37	0.19	0.96		
Firm fixed effects	No	No	No	Yes	Yes	
Country-year fixed effects	No	No	No	Yes	Yes	

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the regular Z-score in column 1 and the modified Z-score in columns 2-5), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1996-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. In column 5 the variables are further interacted with a dummy taking a value of one for firms that operate in tradable sectors (column 5a) and non-tradable sectors (column 5b). In columns 3-5, the model is augmented with a set of firm-specific controls measuring investment and size proxied by the log of total assets. The last two rows display whether a specification includes country-year and firm fixed effects. Robust standard errors clustered at the firm-level in parenthesis.

Table 2.5: Distance to Default, Leverage, and the Exchange Rate

	(1)	(2)	(3)	(4)	(5)	
	Dep Var: Modified Altman Z score					
					(5a) Tradable	(5b) Non-Tradable
β_1 (AFC×Leverage)	-0.225	0.0239	0.245	-0.225	0.336	0.159
	(0.198)	(0.227)	(0.349)	(0.198)	(0.446)	(0.468)
β_2 (Tranquil×Leverage)	-0.731***	-0.550***	0.340	-0.731***	0.425	0.267
	(0.154)	(0.173)	(0.262)	(0.154)	(0.319)	(0.373)
β_3 (GFC×Leverage)	-0.596***	-0.522***	-0.234	-0.596***	-0.499*	0.134
	(0.146)	(0.160)	(0.237)	(0.146)	(0.296)	(0.348)
γ_1 (AFC×ΔEX×Leverage)	-1.747*	-2.333**	-4.800***	-1.747*	-4.881***	-4.822***
	(0.909)	(0.980)	(1.402)	(0.909)	(1.848)	(1.619)
γ_2 (Tranquil×ΔEX×Leverage)	-1.586	-2.699*	-3.131	-1.586	-2.440	0.263
	(1.529)	(1.632)	(1.907)	(1.529)	(2.031)	(2.509)
γ_3 (GFC×ΔEX×Leverage)	1.236	0.336	0.402	1.236	-0.523	1.880
	(1.468)	(1.604)	(2.683)	(1.468)	(3.099)	(3.907)
Investment		0.064	0.042		0.789	0.043
		(0.041)	(0.027)		(0.511)	(0.029)
Firm Size		-0.056***	-1.632***		-1.649***	-1.611***
		(0.012)	(0.089)		(0.120)	(0.134)
Constant	27.64***	28.59***		27.64***		
	(0.0475)	(0.204)		(0.0475)		
Observations	9,257	7,351	6,495	9,257	6,495	
Firm fixed effects	No	No	Yes	Yes	Yes	
Country-year fixed effects	No	No	Yes	Yes	Yes	

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1996-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. These variables are then further interacted with the percentage change in the nominal exchange rate (lagged one period). In columns 2, 3 and 5, the model is augmented with a set of firm-specific controls measuring investment and size proxied by the log of total assets. The last two columns (5a and 5b) estimate separate effects for firms in the tradable and non-tradable sectors. The last two rows display whether a specification includes country-year and firm fixed effects. Robust standard errors clustered at the firm-level in parenthesis.

Table 2.6: Firms that Remain in the Sample

	(1)	(2)	(3)	(4)
	Dep Var: Modified Altman Z score			
β_1 (AFC×Leverage)	0.245	0.191	0.519	0.485
	(0.349)	(0.352)	(0.406)	(0.457)
β_2 (Tranquil×Leverage)	0.340	0.377	0.417	0.393
	(0.262)	(0.263)	(0.329)	(0.477)
β_3 (GFC×Leverage)	-0.234	-0.164	-0.286	0.146
	(0.237)	(0.239)	(0.296)	(0.439)
γ_1 (AF×ΔEX×Leverage)	-4.800***	-4.803***	-5.751***	-7.002**
	(1.402)	(1.395)	(1.750)	(2.696)
γ_2 (Tranquil×ΔEX×Leverage)	-3.131	-2.986	-4.153*	-4.870
	(1.907)	(1.925)	(2.230)	(3.596)
γ_3 (GF×ΔEX×Leverage)	0.402	0.604	0.830	-0.358
	(2.683)	(2.690)	(3.206)	(4.190)
Investment	0.042	0.0444*	-0.317*	0.431
	(0.027)	(0.0259)	(0.192)	(0.712)
Size	-1.632***	-1.597***	-1.665***	-1.941***
	(0.089)	(0.091)	(0.113)	(0.172)
Observations	6,495	6,473	3,940	1,929
Sample	All	At least 5 years	At least 10 years	At least 15 years
Firm fixed effects	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes

This table shows the specification in Table 2.5, column 3 on samples that include firms present for different number of years in the sample. Column 1 uses the entire sample, while columns 2-4 limit the sample to firms with at least 5, 10, and 15 years of data, respectively. The dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1996-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. These variables are then further interacted with the percentage change in the nominal exchange rate (lagged one period). The model is augmented with a set of firm-specific controls measuring investment and size proxied by the log of total assets. All specifications control for country-year and firm fixed effects. Robust standard errors clustered at the firm-level in parenthesis.

Table 2.7: Leverage, Distance to Default, Interest Rate, and Growth

	(1)	(2)	(3)
	Dep Var: Modified Altman Z score		
β_1 (AFC×Leverage)	1.566**	0.736	1.346**
	(0.611)	(0.580)	(0.590)
β_2 (Tranquil×Leverage)	0.163	0.288	0.108
	(0.499)	(0.382)	(0.530)
β_3 (GFC×Leverage)	-0.275	-0.260	-0.308
	(0.368)	(0.436)	(0.440)
γ_1 (AFC*ΔEX)	-3.521**	-4.181**	-4.472***
	(1.634)	(1.731)	(1.707)
γ_2 (Tranquil*ΔEX)	-3.407	-3.172	-3.522
	(3.002)	(3.070)	(3.081)
γ_3 (GFC*ΔEX)	-0.0931	-0.317	-0.145
	(2.738)	(2.764)	(2.797)
AFC*GR	21.33		32.46
	(19.887)		(28.34)
Tranquil*GR	4.287		3.779
	(7.940)		(8.198)
GFC*GR	2.144		1.999
	(5.431)		(6.941)
AFC*IR		-3.933	7.445
		(4.144)	(7.873)
Tranquil*IR		1.652	1.194
		(4.123)	(4.210)
GFC*IR		1.877	0.742
		(7.208)	(9.052)
Investment	0.0434*	0.0443*	0.0436*
	(0.0260)	(0.0259)	(0.0260)
Firm Size	-1.613***	-1.609***	-1.615***
	(0.0892)	(0.0892)	(0.0894)
Observations	6,334	6,334	6,334
Sample	All	All	All
Country-year FE	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1996-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. These variables are then further interacted with the percentage change in the nominal exchange rate (lagged one period), the local interest rate (IR is the deposit rate), and lagged GDP growth (GR). The model is augmented with a set of firm-specific controls measuring investment and size proxied by the log of total assets. All regressions control for country-year and firm fixed effects. Robust standard errors clustered at the firm-level in parenthesis.

Table 2.8: Leverage, Distance to Default, and Macro/Institutional Framework

	(1)	(2)	(3)	(4)
	Dep Var: Modified Altman Z score			
β_1 (AFC×Leverage)	0.331	0.247	0.457	0.549
	(0.622)	(0.349)	(0.781)	(0.801)
β_2 (Tranquil×Leverage)	0.492	0.240	-0.239	-0.331
	(0.528)	(0.455)	(0.826)	(1.021)
β_3 (GFC×Leverage)	-0.505	-0.440	-1.517*	-1.287
	(0.475)	(0.393)	(0.773)	(0.788)
γ_1 (AFC*ΔEX)	-4.865***	-4.804***	-4.842***	-5.077***
	(1.481)	(1.403)	(1.361)	(1.473)
γ_2 (Tranquil*ΔEX)	-1.422	-3.082	-1.517	-2.083
	(1.994)	(1.902)	(2.064)	(2.221)
γ_3 (GFC*ΔEX)	0.604	0.377	-3.626	-3.486
	(2.679)	(2.689)	(2.917)	(2.920)
AFC*FINDEV	-0.001			-0.004
	(0.006)			(0.009)
TRANQ*FINDEV	-0.002			-0.005
	(0.006)			(0.007)
GFC*FINDEV	0.003			-0.004
	(0.005)			(0.008)
AFC*IT		-		-
		0.158		0.255
TRANQ*IT		(0.541)		(0.584)
		0.299		-0.338
GFC*IT		(0.465)		(0.584)
			-0.244	-0.0398
AFC*LMF			(0.769)	(0.963)
			0.426	0.677
TRANQ*LMF			(0.618)	(0.698)
			0.889*	1.109*
GFC*LMF			-0.489	-0.229
			(0.712)	(0.920)
Investment	0.042	0.042	0.082***	0.081***
	(0.02)	(0.027)	(0.011)	(0.01)
Firm Size	-1.630***	-1.630***	-1.619***	-1.618***
	(0.0890)	(0.0889)	(0.108)	(0.108)
Observations	6,473	6,473	4,971	4,971
Sample	All	All	All	All
Country-year FE	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1996-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. These variables are then further interacted with an index of financial development, inflation targeting regimes, and the updated Lane and Milesi-Ferretti (2007) index of financial globalization. The model is augmented with a set of firm-specific controls measuring investment and size (proxied by the log of total assets). All regressions control for country-year and firm fixed effects. Robust standard errors clustered at the firm-level in parenthesis.

Table 2.9: The Granularity Effect

	(1)	(2)	(3)
G	0.698**	0.819***	0.810**
	(0.262)	(0.293)	(0.310)
L.G		0.527**	0.509*
		(0.236)	(0.258)
L2.G			-0.0739
			(0.365)
Observations	486	486	486
Number of countries	26	26	26
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Sample	1994-2014	1994-2014	1994-2014

This table reports a set of regression in which the dependent variable is per-capita GDP growth and the explanatory variables are granularity (G) and its first two lag (L.G and L2.G). All the regressions control for country and year fixed effects. Robust standard errors clustered at the country level in parenthesis.

Table 2.10: Fragility and Firm Size

	(1)	(2)	(3)	(4)
	Leverage	Solvency	Liquidity	Distance to default
Large	-25.15***	1.737	0.392	-68.66
	(7.849)	(1.648)	(0.944)	(42.46)
Observations	45,104	38,741	39,271	16,687
Sample	All	All	All	All
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports a set of regression in which the dependent variables are various measures of potential or realized fragility (leverage, solvency, liquidity, and distance to default) and the explanatory variable is a dummy variable taking the value of 1 for large firms (Large). All the regressions control for country and year fixed effects. Robust standard errors clustered at the country level in parenthesis.

Table 2.11: Leverage, Depreciation and Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)
LEV	-0.0115*	-0.0119*	-0.0350**	-0.0108	-0.00824	-0.0290
	(0.00674)	(0.00709)	(0.0139)	(0.00865)	(0.00776)	(0.0404)
DXR _LEV	-0.0553	-0.0593	-0.500**	-0.0448	-0.0474	-0.0520
	(0.0495)	(0.0510)	(0.198)	(0.0571)	(0.0501)	(0.0533)
Large	-209.0***	-284.5***			-285.0***	-316.5***
	(19.20)	(24.70)			(24.70)	(27.94)
DXR	0.543					
	(4.742)					
DXR _LARGE					-35.14**	-32.46*
					(17.73)	(17.89)
LARGE_LEV					-0.0316*	-0.0113
					(0.0182)	(0.0466)
LARGE_LEV_DXR					-0.417**	-0.416**
					(0.201)	(0.203)
Observations	42,542	42,542	9,959	32,583	42,542	22,228
Number of firms	7,441	7,441	2,956	6,046	7,441	4,990
Sample	All	All	Large Firms	Other	All	Largest 150
Firm FE	YES	YES	YES	YES	YES	YES
CY FE	NO	YES	YES	YES	YES	YES

This table reports a set of regression in which the dependent variable is sales growth and the explanatory variables are leverage, change in in the exchange rate, firm size and the interactions among these variables. All the regressions control for year fixed effects, and specifications 2-6 control also for country fixed effects. Robust standard errors clustered at the country level in parenthesis.

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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.

Six Factors:

We compute three factors following Fama and French (1993). The **Market** factor, RM, is the return on the market minus the risk-free rate. To account for the various countries in our sample we construct a weighted average of returns of the main index in each country, where the weights are based on the number of stocks from each country in our sample. The Fed Funds rate serves as proxy for the risk-free rate.

The other two factors are **Size** and **Book-to-Market**. Each January, we sort all stocks by market capitalization and divide the sample in two groups of equal size: Small and Big. We also sort all firms by book-to-market and use the 30th and 70th percentiles to divide the cross-section into three groups: Low, Neutral, and High. We then construct 6 portfolios from the intersection of the two sorting results and compute their simple monthly average returns: SL, SN, SH, BL, BN, and BH. Lastly, we find the returns of portfolios mimicking the Size (Small-Minus-Big, or SMB) and Book-to-Market (High-Minus-Low, or HML) factors as in Fama and French (1993):

$$SMB = \frac{1}{3}(SL + SN + SH) - \frac{1}{3}(BL + BN + BH)$$

$$HML = \frac{1}{2}(SH + BH) - \frac{1}{2}(SL + BL)$$

We rebalance the portfolios every January and end up with a monthly time series of returns for each factor-mimicking portfolio.

The other three factors are **Momentum**, **Short-term Reversal**, and **Long-term Reversal**, computed as follows:

- **Momentum** Return in prior year excluding prior month
- **Short-term reversal** Return in prior month
- **Long-term reversal** Return in prior five years excluding prior year

APPENDIX B: CHAPTER 1 ADDITIONAL TABLES AND FIGURES

Table B1: Number of Defaults and Observations per Year

Year	Firm-Months	Defaults	%
1995	16	0	0
1996	370	0	0
1997	692	0	0
1998	1,725	5	0.29
1999	2,561	8	0.31
2000	5,808	6	0.10
2001	7,688	5	0.07
2002	15,406	15	0.10
2003	23,829	19	0.08
2004	30,882	67	0.22
2005	33,640	55	0.16
2006	35,724	46	0.13
2007	40,844	42	0.10
2008	43,601	47	0.11
2009	45,812	54	0.12
2010	50,627	52	0.10
2011	60,405	18	0.03
2012	58,599	47	0.08
2013	72,280	58	0.08
2014	72,730	25	0.03
2015	68,523	21	0.03
Total	671,762	590	0.09

Table B2: Number of Observations per Country and Year

	Argentina	Brazil	Chile	China	Colombia	Czech Rep.	Hungary	India	Indonesia	Malaysia	Mexico	Pakistan	Peru	Philippines	Poland	South Africa	South Korea	Thailand	Turkey	Vietnam	Total
1995	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	16	.	.	16
1996	.	.	.	.	.	.	.	.	.	.	123	.	.	.	.	.	.	247	.	.	370
1997	27	.	8	.	.	.	.	.	.	.	225	.	.	.	.	.	.	417	15	.	692
1998	42	.	324	.	.	.	.	.	.	.	255	.	.	.	.	.	.	1072	32	.	1725
1999	61	.	459	.	.	.	.	.	.	173	265	.	.	129	.	12	.	1384	78	.	2561
2000	165	373	492	.	.	.	.	.	33	1817	431	.	.	225	57	36	6	1363	810	.	5808
2001	182	457	472	.	.	.	.	.	308	2270	468	.	.	218	301	45	23	1642	1302	.	7688
2002	124	493	442	.	.	15	15	.	454	2469	448	.	7	223	402	57	7077	1806	1374	.	15406
2003	97	553	441	4933	.	43	30	27	513	2447	455	.	8	235	438	74	10204	2001	1330	.	23829
2004	166	609	448	7720	.	94	94	12	732	4761	507	.	21	217	913	67	11057	2122	1342	.	30882
2005	304	709	621	7846	104	130	136	15	869	5556	483	12	159	244	1316	57	11273	2130	1676	.	33640
2006	359	803	921	7539	119	109	131	18	948	6099	525	195	217	265	1469	54	11620	2296	2037	.	35724
2007	422	1188	992	9682	115	76	116	42	1206	6492	559	675	307	320	1732	58	12341	2470	2051	.	40844
2008	401	1350	1084	10647	131	76	129	78	1285	5096	521	478	270	690	2194	71	12956	2474	2048	1622	43601
2009	380	1361	1117	11484	120	.	168	105	1329	4872	577	1152	240	835	2386	63	13147	2464	2026	1986	45812
2010	376	1444	1065	12991	170	.	175	455	1602	5717	590	1563	270	912	2571	93	12892	2785	2071	2885	50627
2011	396	1520	1187	16071	176	.	130	4305	1919	5633	567	1316	287	1004	2787	93	13863	2786	2176	4189	60405
2012	311	1441	1200	17919	159	.	136	9626	2079	5536	595	.	245	1164	2788	87	10013	2957	2343	.	58599
2013	320	1600	1227	18298	127	.	162	12246	2256	5508	610	.	197	1124	2814	78	15942	3162	2418	4191	72280
2014	357	1656	1158	17449	164	.	169	11647	2315	5706	575	.	181	1265	2807	106	16418	3366	2400	4991	72730
2015	371	1545	1108	16958	159	.	181	6791	2341	5472	584	.	188	1364	2854	71	17607	3519	2432	4978	68523
Total	4861	17102	14766	159537	1544	543	1772	45367	20189	75624	9363	5391	2597	10434	27829	1122	176439	42479	29961	24842	671762

This table lists the number of firm-months per country and year of our sample with data to replicate Campbell et al.’s (2008) specification.

Table B3: Correlation Matrix and Multicollinearity Analysis

	EXRET	PRICE	VOL	RELSIZE	NIMTA	TLMTA	CASHMTA	MB	Unemp.	Inflation	Real rate	Sov Spread	ΔSov Spread	ΔFX	5Year	VIX	Fed Funds	TED
EXRET	1																	
PRICE	0.024	1																
VOL	0.002	0.057	1															
RELSIZE	0.022	0.589	0.036	1														
NIMTA	0.049	0.098	0.007	0.109	1													
TLMTA	-0.067	-0.139	-0.024	-0.155	-0.142	1												
CASHMTA	-0.023	-0.188	-0.033	-0.120	0.093	-0.061	1											
MB	0.065	0.165	0.052	0.124	-0.091	-0.466	-0.272	1										
Unemployment	0.010	0.211	0.075	0.351	-0.006	0.003	-0.132	0.084	1									
Inflation	-0.025	0.234	0.039	0.089	0.007	0.137	-0.134	0.004	0.219	1								
Real rate	0.010	0.037	0.065	0.074	-0.011	0.110	-0.110	-0.005	0.334	0.113	1							
SovSpread	-0.016	0.143	0.033	-0.087	-0.008	0.164	-0.142	-0.035	0.193	0.532	0.151	1						
ΔSovSpread	-0.016	-0.027	-0.006	-0.021	0	-0.017	0.010	0.027	-0.014	0.109	-0.078	0.02	1					
ΔFX	-0.007	0.017	0.001	-0.026	-0.003	-0.025	-0.009	0.017	-0.016	-0.057	-0.054	-0.067	-0.181	1				
5YEAR	-0.017	-0.031	-0.001	0.181	0.015	0.099	-0.057	-0.105	0.110	-0.089	-0.021	-0.218	-0.009	0.052	1			
VIX	0.019	0.035	-0.010	0.090	0.010	0.031	0.020	-0.036	0.019	0.022	0.006	0.042	0.212	-0.080	-0.056	1		
Fed Funds	-0.009	-0.084	0.003	0.118	0.018	0.078	-0.044	-0.077	0.096	-0.010	-0.032	-0.179	0.011	0.064	0.888	-0.122	1	
TED spread	-0.016	-0.141	0	-0.004	0.022	-0.018	-0.010	0.029	0.046	0.179	-0.077	-0.043	0.140	-0.016	0.336	0.062	0.477	1
TOL	0.989	0.552	0.988	0.521	0.929	0.670	0.828	0.658	0.727	0.609	0.848	0.621	0.893	0.949	0.184	0.887	0.165	0.653
VIF	1.011	1.810	1.012	1.918	1.077	1.493	1.207	1.519	1.376	1.643	1.179	1.612	1.12	1.054	5.425	1.127	6.064	1.531

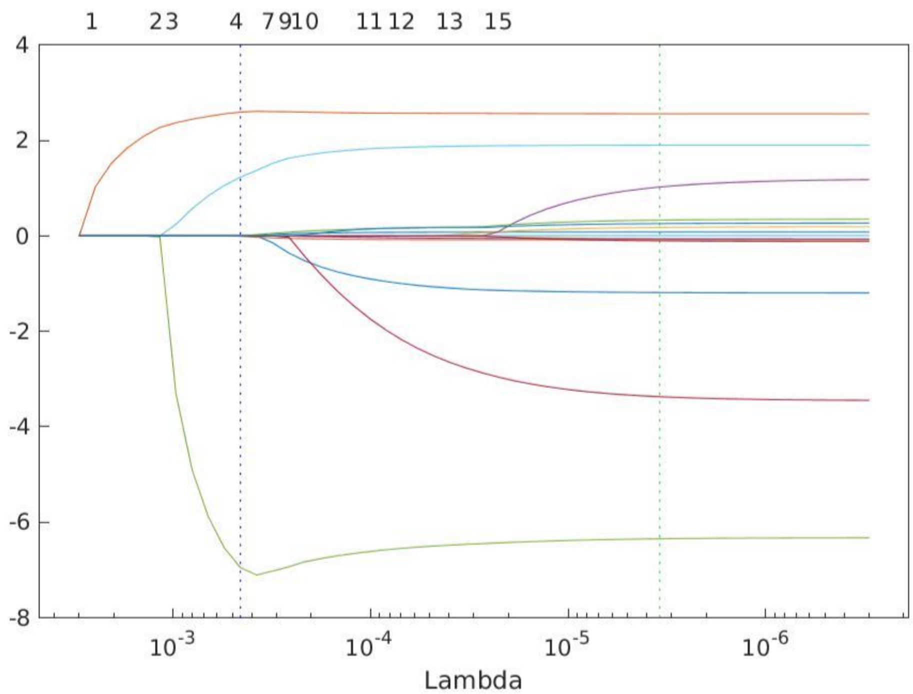
The last two rows of this table show the Tolerance Value (TOL) and its reciprocal Variance Inflation Factor (VIF). VIF is computed as $1/(1 - R_k^2)$, where R_k^2 is the R^2 value of a regression of factor k on all others. TOL is simply $1 - R_k^2$. VIF values larger than 10 are typically considered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

APPENDIX C: LASSO ESTIMATION

Table C1: Robustness Checks Using LASSO for Variable Selection

	(1)	(2)	(3)
Constant			-9.213***
Excess returns	-1.222	-0.159	-1.592***
Stock price	-0.054	-0.040	-0.166***
Volatility of returns	-0.065		
Market capitalization	-0.082		
Profitability	-6.57	-7.372	-6.579***
Leverage	2.041	1.438	2.333***
Cash	-3.717		
Market-to-book ratio	0.087	0.029	0.142***
Prior default	2.515	2.630	2.563***
Unemployment rate	0.032		
Inflation	-2.587		
Real interest rate	-0.038		
Sovereign spread	-0.018		
ΔSovereign spread	0.093		
ΔFX	-1.129		
5-year Treasury	0.32	0.058	0.211***
VIX	0.009		
Fed funds rate	-0.11		
TED spread	0.218		
Pseudo-R^2	0.241		0.218
AUC	0.893		0.911
Observations	372,158		744,197
Defaults	522		617

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.



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.

Figure C1: LASSO Coefficient Path

APPENDIX D: CHAPTER 2 ADDITIONAL TABLES

Table D1: Sample Sales and Country Market Cap and GDP

	(1)	(2)
Country	Sales to Market Cap	Market Cap to GDP
Argentina	52%	14%
Brazil	43%	49%
Chile	51%	111%
China	49%	51%
Colombia	30%	45%
Eastern Europe	100%	34%
India	36%	72%
Indonesia	34%	39%
Jordan*	27%	
Malaysia	46%	146%
Mexico	61%	35%
Morocco*	12%	
Pakistan	107%	16%
Peru	33%	45%
Philippines	32%	69%
Russia	116%	26%
South Africa	23%	225%
South Korea	119%	78%
Taiwan*	93%	
Thailand	59%	75%
Turkey	68%	31%
Vietnam	79%	13%

* No country-level market capitalization data.
Value shows Sales / GDP instead.

This table shows what percentage of a country's economy is captured by firms in our sample. Column 1 reports – by country – the total sales in firms in our sample divided by the country's total market capitalization, as measured by the World Bank. Column 2 shows the ratio of total market capitalization and GDP in each country.

Table D2: Altman's EM Z-score and Leverage Heat Maps

	Altman's EM Z-score			Leverage		
Country	1996-98	2003-07	2008-14	1996-98	2003-07	2008-14
Argentina	5.64	7.38	5.62	59%	45%	74%
Brazil	5.52	6.13	5.88	50%	83%	94%
Chile	6.44	6.44	6.20	95%	82%	93%
China	5.39	5.58	5.28	95%	95%	103%
Colombia	6.71	6.58	6.77	40%	47%	44%
Eastern Europe	6.38	6.49	6.30	45%	48%	55%
India	5.14	5.62	5.55	92%	79%	118%
Indonesia	5.43	6.36	7.13	105%	81%	72%
Jordan	5.39	5.97	5.14	32%	81%	
Malaysia	5.76	6.95	7.77	69%	69%	63%
Mexico	7.83	6.26	5.53	54%	59%	89%
Morocco	7.73	7.47	5.04	28%	42%	128%
Pakistan	5.07	5.26	5.44	108%	56%	84%
Peru	6.88	7.23	6.99	53%	53%	68%
Philippines	5.70	6.02	6.11	98%	103%	131%
Russia	6.69	8.76	7.60	22%	42%	56%
South Africa	7.04	6.71	6.88	39%	50%	54%
South Korea	3.63	5.58	6.11	284%	140%	110%
Taiwan	6.58	6.80	7.03	65%	66%	66%
Thailand	5.51	6.21	6.32	172%	84%	83%
Turkey	7.57	6.30	5.80	95%	104%	124%
Vietnam		6.51	6.18		95%	116%

This table shows average Z-scores and leverage for each country over time. The color scale moves from red (for low Z-scores and high leverage) to green (for high Z-scores and low leverage), going through several shades of orange yellow.

Table D3: Estimates of Table 2.5 Model, Asian Financial Crisis Period Defined as 1992-98

	(1)	(2)	(3)		(4)
	Dep Var: Modified Altman Z score				
				Tradable	Non-Tradable
β_1 (Asian Financial Crisis×Leverage)	-0.249	-0.0376	0.161	0.270	0.0636
	(0.198)	(0.226)	(0.348)	(0.448)	(0.462)
β_2 (Tranquil period×Leverage)	-0.687***	-0.524***	0.383	0.390	0.393
	(0.154)	(0.173)	(0.264)	(0.319)	(0.371)
β_3 (GFC×Leverage)	-0.590***	-0.530***	-0.204	-0.506*	0.213
	(0.146)	(0.160)	(0.239)	(0.296)	(0.345)
γ_1 (AFC×ΔEX×Leverage)	-1.585*	-2.334**	-4.804***	-4.912***	-4.868***
	(0.915)	(0.979)	(1.396)	(1.851)	(1.571)
γ_2 (Tranquil×ΔEX×Leverage)	-1.665	-2.502	-2.952	-1.377	0.673
	(1.526)	(1.631)	(1.937)	(2.042)	(2.559)
γ_3 (GFC×ΔEX×Leverage)	1.191	0.656	0.616	-0.622	2.500
	(1.470)	(1.605)	(2.693)	(3.112)	(3.960)
Investment		0.0568	0.0453*	0.805	0.0463*
		(0.0408)	(0.0252)	(0.507)	(0.0270)
Firm Size		-0.0609***	-1.620***	-1.682***	-1.548***
		(0.0119)	(0.0891)	(0.117)	(0.126)
Constant	30.21***	31.25***			
	(0.0475)	(0.205)			
Observations	9,245	7,351	6,494	6,494	
Firm fixed effects	No	No	Yes	Yes	
Country-year fixed effects	No	No	Yes	Yes	

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1992-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. These variables are then further interacted with the percentage change in the nominal exchange rate (lagged one period). Robust standard errors clustered at the firm-level in parenthesis.

Table D4: Estimates of Table 2.5 Model, Asian Financial Crisis Period Defined as 1992-98 and the Post GFC Period as 2009-2013

	(1)	(2)	(3)		(4)
	Dep Var: Modified Altman Z score				
				Tradable	Non-Tradable
β_1 (Asian Financial Crisis×Leverage)	-0.248	-0.0366	0.162	0.276	0.0660
	(0.198)	(0.226)	(0.348)	(0.448)	(0.462)
β_2 (Tranquil period×Leverage)	-0.609***	-0.466***	0.409	0.313	0.524
	(0.143)	(0.160)	(0.253)	(0.307)	(0.356)
β_3 (GFC×Leverage)	-0.620***	-0.542***	-0.261	-0.494	0.0571
	(0.155)	(0.170)	(0.249)	(0.306)	(0.361)
γ_1 (AFC×ΔEX×Leverage)	-1.585*	-2.330**	-4.793***	-4.910***	-4.867***
	(0.915)	(0.979)	(1.396)	(1.845)	(1.576)
γ_2 (Tranquil×ΔEX×Leverage)	-0.336	-1.032	-1.158	-2.498	1.831
	(1.420)	(1.519)	(2.151)	(2.329)	(2.520)
γ_3 (GFC×ΔEX×Leverage)	0.252	-0.611	-1.711	-3.785	1.518
	(1.554)	(1.699)	(2.705)	(3.071)	(4.162)
Investment		0.0575	0.0454*	0.808	0.0456*
		(0.0408)	(0.0251)	(0.503)	(0.0269)
Firm Size		-0.0597***	-1.622***	-1.688***	-1.547***
		(0.0119)	(0.0892)	(0.117)	(0.127)
Constant	30.21***	31.23***			
	(0.0475)	(0.205)			
Observations	9,245	7,351	6,494	6,494	
Firm fixed effects	No	No	Yes	Yes	
Country-year fixed effects	No	No	Yes	Yes	

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1992-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2009-2013), respectively. These variables are then further interacted with the percentage change in the nominal exchange rate (lagged one period). Robust standard errors clustered at the firm-level in parenthesis.

Table D5: Estimates of Table 2.5 Model, Excluding Chinese Firms from Sample

	(1)	(2)	(3)		(4)
	Dep Var: Modified Altman Z score				
				Tradable	Non-Tradable
β_1 (Asian Financial Crisis×Leverage)	-0.248	-0.0129	0.202	0.355	0.0629
	(0.222)	(0.241)	(0.348)	(0.464)	(0.452)
β_2 (Tranquil period×Leverage)	-0.617***	-0.479***	0.328	0.316	0.357
	(0.167)	(0.183)	(0.273)	(0.332)	(0.379)
β_3 (GFC×Leverage)	-0.587***	-0.489***	-0.156	-0.488	0.286
	(0.161)	(0.173)	(0.245)	(0.304)	(0.355)
γ_1 (AFC×ΔEX×Leverage)	-2.015**	-2.765***	-5.014***	-5.239***	-4.978***
	(0.942)	(0.996)	(1.393)	(1.874)	(1.542)
γ_2 (Tranquil×ΔEX×Leverage)	-1.430	-2.491	-3.031	-1.467	0.641
	(1.521)	(1.626)	(1.928)	(2.037)	(2.559)
γ_3 (GFC×ΔEX×Leverage)	0.0560	-0.414	-0.0801	-1.178	1.616
	(1.524)	(1.647)	(2.731)	(3.138)	(4.063)
Investment		0.0537	0.0405	0.269	0.0447
		(0.0407)	(0.0274)	(1.355)	(0.0277)
Firm Size		-0.0753***	-1.660***	-1.737***	-1.566***
		(0.0122)	(0.0904)	(0.115)	(0.129)
Constant	30.33***	31.59***			
	(0.0512)	(0.212)			
Observations	9,245	7,351	6,494	6,494	
Firm fixed effects	No	No	Yes	Yes	
Country-year fixed effects	No	No	Yes	Yes	

This table shows the results of a set of firm-level regressions where the dependent variable is distance to default (the modified Z-score), and the explanatory variables are the interactions between leverage and each of three dummy variables taking a value of one for the Asian Financial Crisis (1996-1998), tranquil period (2003-2007), and post-Global Financial Crisis (2008-2014), respectively. Excludes Chinese Firms from sample. These variables are then further interacted with the percentage change in the nominal exchange rate (lagged one period). Robust standard errors clustered at the firm-level in parenthesis.