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ABSTRACT

This paper employs a novel multi-country dataset of corporate defaults to develop a model of distress risk specific to emerging markets. The data suggest that global financial variables such as US interest rates and shifts in global liquidity and risk aversion have significant predictive power for forecasting corporate distress risk in emerging markets. We document a positive distress risk premium in emerging market equities and show that the impact of a global "risk-off" environment on default risk is greater for firms whose returns are more sensitive to a composite global factor.

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1 Introduction

Non-financial corporate debt in emerging markets surged from $4 trillion in 2004 to over $30 trillion in 2019 (IIF, 2020). There is rising concern about the deteriorating health of emerging market firms given heightened leverage levels and worsening solvency positions—recent evidence suggests that the share of debt held by troubled firms is the highest its been in over a decade (IMF, 2015).[1] Whether through links with the global financial system or 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). Fed Chair Jerome Powell warned that global debt paired with other macro conditions, such as the risk of asset price drops and currency depreciation, could damage the ability of emerging-market firms to repay their debts.[2]

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 U.S. data further develop the methodologies to measure probabilities of default (Shumway, 2001; Campbell, Hilscher, and Szilagyi, 2008).

This paper uses a novel multi-country dataset on corporate defaults to study factors that drive corporate distress in emerging markets. We note that extant models do not account for emerging market vulnerabilities to global financial conditions such as advanced-economy monetary policy changes, U.S. dollar movements, or shifts in global liquidity and risk aversion. Depending on the extent of global exposure, deteriorating international credit market conditions can affect the ability of emerging market firms to repay their debts. Consequently, model specifications developed using U.S. data have low predictive power when applied to the emerging market context. Our objective is to disentangle the economic mechanisms through which global financial conditions may drive corporate distress in emerging markets.

Our paper makes two main contributions. First, we explore how global financial conditions affect financial distress in emerging economies. Second, we show that the "distress risk premium puzzle" identified by Campbell et al. (2008) for developed economies does not seem to apply to emerging

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

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

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

economies: riskier firms in emerging economies command a larger risk premium.

In settings with borrowing constrained firms and endogenous default, theoretically, there can be a range of alternative mechanisms by which global financial shocks can impact corporate default rates. Greater corporate leverage can, for example, make firms more vulnerable to adverse shocks to their cash flows and asset values, driving up probabilities of default. Tightening global financial conditions can exacerbate rollover and currency risks. In the absence of sufficient hedging, currency depreciation can impose a more significant strain on the ability of emerging-market firms to service any FX-denominated debts. Deteriorating global financial conditions can, therefore, directly impact credit risk, elevating probabilities of corporate default, particularly for firms with weak fundamentals.

The capital flows literature points to possible international transmission mechanisms, i.e., perturbations that originate in global financial markets that can impact corporate default probabilities in emerging markets.[4] We suggest a cost of external finance channel that operates through different types of global funding shocks. Rising US interest rates, shortfalls in global liquidity, and foreign investor risk appetite can increase the cost of borrowing and hamper the ability of firms in emerging markets to repay their debts. Evidence suggests that tightening U.S. monetary policy shocks are correlated with increasing bond yields and lower equity prices in emerging markets (Chari et al., 2020), which in turn increase financing costs (Bruno and Shin (2015 a,b)). Through asset price and exchange rate changes, financial shocks can affect collateral values, the borrowing capacity of firms, and corporate default probabilities. Also, rollover risk can impact the ability to refinance corporate debt and trigger corporate default events.

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.[5] The database contains detailed default, accounting, and market data for over 60,000 exchange-listed firms in 119 countries between 1990 and 2016. The dataset is novel in its broad coverage of balance sheet variables and, especially, of default events in emerging markets.

Existing models that forecast corporate default incorporate accounting and market variables such as stock prices to estimate default probabilities. In our setting, empirically, a simultaneity issue arises as global financial conditions can jointly determine stock prices and probabilities of default. Once

[4]For example, papers on the global financial cycle (Miranda-Agrippino and Rey, 2019; Rey, 2015) and capital flow surges and retrenchments (Forbes and Warnock, 2012) focus on flows and returns responses to global financial shocks. The literature on exchange rate changes paired with foreign currency-denominated borrowing and the risk-bearing capacity of foreign intermediaries suggest that global financial shocks can impact collateral constraints and have adverse balance sheet effects (Cespedes, Chang and Velasco, 2008; Bruno and Shin, 2015 a, b).

[5]CRI is the Credit Research Initiative of the Risk Management Institute at the National University of Singapore.

we control for stock prices that embed relevant information about a firm's global exposures through foreign sales dependence or foreign financing sources, it is not clear what additional information the global variables themselves may have for forecasting default. It is entirely conceivable that a firm's stock price movements capture much of the effect of global financial shocks.

To address the issue of simultaneity, we begin by examining the effect of global financial conditions on both stock prices and probabilities of default. In doing so, we first capture the impact of accounting and global variables on market variables such as stock prices and volatility of returns, and then use the orthogonalized values of these variables to predict default.[6] Separately, the strategy also allows us to summarize information about the relationship between global variables and corporate distress using fitted values to identify how the global transmission of shocks occurs.

Introducing stock return sensitivities to global factors adds a new dimension to our understanding of how distress risk operates through financial markets. To analyze the distress risk premium in emerging market stocks, 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. We find that emerging market stock returns embed a positive distress risk premium, a novel contribution to the literature on predicting corporate default risk.

We begin by estimating a logit model of the probability of corporate default on a set of firm-specific accounting , as well as variables reflecting the domestic economic backdrop and global financial conditions. Controlling for corporate fundamentals and domestic economic conditions, we find that emerging market firms are more likely to default when the U.S. Fed funds rate is high, the U.S. Treasury yield curve is steep, U.S. monetary policy tightens, and funding liquidity is reduced. We also find that firms who have defaulted in the past are more likely to do so again, to the best of our knowledge a novel result in the literature. Our findings on the effect of broad U.S. dollar appreciation are more subtle. While we expected a strong broad U.S. dollar (often a sign of investor risk aversion) to be a drag on emerging market solvency, bilateral local currency strength vs. the U.S. dollar dominates when both are appreciating and contributes to a lower risk of default.

Introducing orthogonalized market variables in the model reveals that falling stock returns contribute to firms' probability of default in ways that are not captured by global financial conditions or corporate fundamentals, likely a result of collateral constraints. Importantly, though, we find that

[6] Note that a structural model would involve two simultaneous equations with the stock price and the risk of default both depending on some unobservable financial condition variable that is determined by firm-specific idiosyncratic shocks, country-level shocks, and global variables.

the accounting and global variables also operate through market variables such as excess returns to impact probabilities of default.

Computing marginal effects of the model's coefficients allows us to quantify the economic impact (i.e., the change in the probability of default) of changes in each of the model's variables. Among accounting variables, one-standard-deviation changes in leverage and cash have the greatest impact (positive and negative, respectively) on firms' default risk. Among global variables, the Fed funds rate and Treasury yield curve slope have the largest marginal effects. For instance, a one-standard-deviation increase in the Fed funds rate increases the predicted number of corporate defaults in our sample by 11%.

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[7] reveals that, for the Fed Funds rate, five-year Treasury rates, and the VIX, the effect of increases in the global variable on the probability of default is larger for firms with most negative betas. Further, a composite global beta measure helps us show that the effect of a global risk-off environment on distress risk is higher for firms whose returns are more sensitive to global factors.

Finally, 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 U.S. data finds an inverse correlation between distress risk and future stock returns (Campbell, Hilscher, and Szilagyi, 2008). 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 twelve-month stock returns are monotonically increasing in the probability of corporate default, a trend that is robust to the inclusion of controls for the Fama-French three factors, momentum, short-term reversal, and long-term reversal.

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, the idiosyncratic standard deviation of stock returns, net income to total assets, and total liabilities to total assets.[8]

[7] I.e., firms most negatively affected by increases in U.S. interest rates, VIX, the TED spread, and the U.S. dollar

[8] Chava and Jarrow (2004) improve forecasting by shortening the observation intervals to the monthly frequency and find the existence of an industry effect.

Campbell et al. (2008) builds on the work of Shumway (2001) to show that firms are more likely to enter distress if they have higher leverage, lower profitability, lower market capitalization, lower past stock returns, more volatile past stock returns, lower cash holdings, higher market-book ratios, and lower prices per share.[9,10] An important asset pricing implication of Campbell et al. (2008) is that stocks of distressed companies experience abnormally low returns.

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 the correlation between leverage and corporate fragility is time-varying and strongest for large firms and times of local currency devaluations.[11] The research on the drivers and consequences of high currency exposure is limited given the shortage of reliable data on the currency composition of debt.[12] 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 hedges in place (e.g. firms in non-tradable industries).[13]

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 2 describes alternative transmission mecha-

[9]The authors define distress as either filing for bankruptcy, getting delisted, or receiving a D rating. The authors use Shumway's (2001) specification as a base and make modifications that improve the model's predictive power. First, they divide net income and leverage (both explanatory variables) by the market value of assets instead of book value. Second, they add corporate cash holdings, Tobin's Q, and price per share to the set of explanatory variables. Third, they study default forecasts at different horizons, finding market capitalization, market-book ratio, and equity volatility the most consistently predictive characteristics of corporate distress, and demonstrating the increased importance of balance sheet versus market variables as the horizon increases.

[10]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. 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 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., NUS-RMI, 2016).

[11]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.

[12]The two significant 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 Avdjiev et al. (2014).

[13]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.

nisms through which global financial shocks may impact the probability of corporate default in emerging markets. Section 3 explains the methodology and describes the data. Section 4 presents the results on default probabilities and introduces global betas as predictors of default. Section 5 shows the asset pricing implications of our measure of distress risk. Section 6 concludes.

2 Global Shocks and Corporate Default Probabilities: Alternative Transmission Mechanisms

This section surveys alternative transmission mechanisms through which global financial shocks may impact the probabilities of corporate default in emerging markets. At the aggregate level, several studies beginning with the seminal work of Calvo et al. (1996) and Calvo (1998) show that countries with higher levels of default risk are more sensitive to U.S. interest rates. The existing literature focuses on the sovereign default risk implications of external shocks. To the best of our knowledge, the literature does not provide micro evidence on the link between global financial conditions and corporate default risk in emerging markets.

Evidence from papers on boom-bust cycles in emerging markets demonstrates that episodes of capital inflow surges lead to credit booms and high leverage (Tornell and Schneider, 2007; Mendoza and Terrones, 2008; Lorenzoni, 2008) followed by credit busts, asset price collapses and painful deleveraging (Gourinchas and Obstfeld, 2012; Rey, 2015). These papers focus on the impact of capital flows on aggregate credit creation and the build-up of leverage in emerging markets. Search for yield flows or returns chasing capital inflows can lead to falling bond yields and rising equity prices. In turn, rising asset values can relax firm-level borrowing constraints due to the availability of lower-cost funding as well as appreciated collateral values (Bernanke, Gertler, and Gilchrist, 1996). Higher leverage has also been associated with, on average, rising foreign currency exposures (IMF, 2015). A natural next step is to explicitly examine the link between global shocks, firm characteristics, and corporate default probabilities.

Candidate global financial shocks that receive attention in the capital flows literature primarily fall into three inter-related categories: (i) U.S./advanced economy monetary policy shocks, (ii) shocks that impact foreign investor risk aversion and liquidity in international financial markets, and (iii) exchange rate shocks. For example, Forbes and Warnock (2012) and Fratzscher (2012) show that global risk factors drive capital flows in and out of emerging markets. Jotikasthira et al. (2012) report that "global funds substantially alter portfolio allocations in emerging markets in response to funding shocks from their investor base." Focusing on U.S. monetary policy, market risk and investor sentiments, Bekaert et al. (2013), Miranda-Agrippino and Rey (2019) and many others use the VIX as a proxy to measure the risk appetite of global investors. Fratzscher (2012) includes the TED spread as a measure of credit risk and liquidity in international capital markets. Chari et al. (2020) make use of high-frequency identification to extract U.S. monetary policy shocks using Treasury derivatives data to show that capital flows to emerging markets are sensitive to term premium shocks in the U.S. yield curve. In this paper, we examine the link between alternative global shocks and the probabilities of corporate default. To understand potential transmission mechanisms through which these alternative shocks can impact corporate default probabilities, let us consider them in turn.

Evidence suggests that there is a correlation between expansionary monetary policy in the U.S. and a "risk-on" environment in financial markets that drives capital flows to emerging markets, increases asset prices and drives up leverage (Bruno and Shin, 20015 a,b; Chari et al., 2020; Gourinchas and Obstfeld, 2012). Conversely, tightening monetary policy shocks lead to a "risk-off" environment with capital outflows, falling asset prices, and deleveraging in emerging markets. Risk-on and risk-off states of the world also correlate with movements in measures of uncertainty and risk such as the VIX that capture foreign investor risk sentiments and the TED spread that captures perceptions of credit risk and liquidity in financial markets.[14] We suggest that there is a correlation between corporate default probabilities in emerging markets and an amalgam of the U.S. interest rate environment, foreign investor risk appetites, and liquidity in global financial markets.

To fix ideas, consider the following. Chari et al. (2020) disentangle the channels through which U.S. monetary policy shocks can alter expectations hypothesis-driven yields and risk premia in the term structure of U.S. interest rates. Via portfolio rebalancing and signaling, changes in domestic yields and risk premia can have a significant impact on equity prices and bond yields in emerging markets.[15] In particular, tightening U.S. monetary policy shocks are correlated with increasing bond yields and lower equity prices in emerging markets–both of which can increase the cost of raising external finance and impact expected probabilities of corporate default.

Closely related to the cost of external finance is the rollover risk associated with the refinancing of existing debt. Rollover risk specifically pertains to prevailing financial market conditions such as

[14] Bekaert et al., 2013; Miranda-Agrippino and Rey, 2019; and Bruno and Shin, 2015a) show that U.S. monetary policy changes impact global risk—higher U.S. rates correspond to rising risk premia.

[15] In addition to using high-frequency monetary policy shocks, we also consider the predictive power of the decomposed values of short-term yields and term premia from a US-based term structure model on corporate default probabilities.

liquidity in credit markets and the state of the economy versus the financial position of borrowers. If interest rates rise, market liquidity deteriorates, and credit market conditions tighten; the cost of refinancing debt also rises and can impact corporate default probabilities. He and Xiong (2012) present theoretical arguments to demonstrate the complex interaction between illiquidity in debt markets and the corporate default premium, highlighting the role of short-term debt in exacerbating rollover risk. Broner et al. (2013) suggest that the maturity composition of emerging market debt is predominantly short-term because of a risk sharing problem between emerging economies subject to rollover risk and risk averse international investors.

Rollover risk is of particular concern for foreign currency-denominated emerging market debt.[16]. Lenders (foreign and domestic) are often unwilling to renew expiring loans during risk-off states of the world when collateral values can drop if asset prices fall. Risk-on shocks and capital inflows that drive up asset prices in emerging markets can also relax collateral constraints, making it easier for firms to borrow and lever up. At the same time, risk-off shocks can lead to opposite effects. Together these factors suggest that a global risk-off environment can directly impact the probabilities of corporate default in emerging markets.

Some facts worth bearing in mind are that \$4.3 trillion of the total \$20 trillion in global bonds and loans that come due through the end of 2020 are in emerging markets (IIF, 2020). Approximately, \$772 billion of emerging market corporate debt is due to mature between 2020-2024 of which 26% is of speculative-grade (S&P Global, 2020).[17] Also, emerging markets will need to refinance \$730 billion in total foreign-currency denominated debt through the end of 2020. Across emerging markets with available data, foreign-currency denominated corporate debt stood at 26 percent of GDP in 2018 (World Bank, 2020). Further, a greater share of corporate debt is owed by firms with riskier financial profiles (Beltran and Collins, 2018; Feyen et al., 2017).

Bruno and Shin (2015 a, b) suggest that liquidity in dollar funding markets such as during phases of expansionary monetary policy increases the risk-bearing capacity of financial intermediaries and drives international banking flows to emerging markets. If the debt is in foreign currencies, the resulting currency appreciations allow firms (and banks) to borrow more, possibly worsening currency mismatches on balance sheets. Alfaro et al. (2019) show that the negative impact of exchange rate shocks has a more acute impact on the more highly levered firms. This paper suggests that bilateral

[16]For example, the World Bank cautioned that "Rollover risks are potentially acute for Indonesia and Thailand, given their sizable stocks of short-term debt (around \$50 billion and \$63 billion, respectively)," World Bank 2018

[17]https://www.spglobal.com/ratings/en/research/articles/200203-credit-trends-global-refinancing-rated-corporate-debt-due-through-2024-nears-11-trillion-11329293

exchange rate depreciation can have adverse balance sheet effects, making it harder for firms to repay their debts and driving up predicted probabilities of default.

In addition, exchange rate changes can affect foreign-currency-denominated sales, input, and borrowing costs and, consequently, firm earnings and interest coverage ratios (interest expenses/EBIT, where EBIT is a measure of earnings). Here, there can be a contemporaneous impact on both stock prices via firm income and default probabilities. Exchange rate changes can also impact the net worth of firms (especially for foreign currency-denominated liabilities).

The impact on expected probabilities of default is inextricably tied to firm fundamentals, such as profitability, leverage, and the cash that firms have on hand. In addition to global variables, our baseline specification, therefore, includes firm-level accounting measures to condition on corporate fundamentals. For example, Alfaro et al. (2019) show that firm size plays a critical role in the relationship between leverage, firm fragility, and exchange rate movements in emerging markets.

Further, the primarily US-focused bankruptcy literature in corporate finance shows that there is predictive power in market variables such as stock returns, stock prices, market-to-book ratios, and the volatility of returns for forecasting default. A simultaneity challenge arises if global financial shocks and asset prices are jointly determined and together have an impact on corporate default probabilities.

To overcome the issue of joint determination, therefore, our empirical investigation takes a two-pronged approach. First, given that stock prices can be jointly determined by firm fundamentals that impact expected future cash flows or discount rates as well as global financial shocks, we project firm-level stock returns onto a set of firm financials and the set of global financial shocks. We then use the orthogonalized component of the market variables in our baseline specification to see if they comprise any additional information to predict corporate default.

Second, note that these corporate fundamentals can also impact asset prices. To examine the channel through which market variables operate and impact corporate default probabilities, we use fitted values of asset returns on (i) firm-specific accounting variables that capture information about firm fundamentals and (ii) global variables in a separate exercise. Our empirical investigation, therefore, focuses on the link between global financial shocks, firm fundamentals, and corporate default probabilities.

3 The Data and Methodology

3.1 Methodology: Predicting Corporate Distress in Emerging Markets

Several studies from the corporate default literature show the importance of other accounting and market variables (including leverage) in forecasting corporate bankruptcies. Earlier static bankruptcy prediction models used accounting ratios to forecast default (See Altman, 1968; Ohlson, 1980; Zmijewski, 1984). Shumway (2001) point out that static models effectively require arbitrary choices about how long ahead of bankruptcy to observe firm 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 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 (Altman and Brady, 2001). 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.

As outlined in Section 2 the globalization and increased interconnectedness of financial markets propagates the transmission of financial and economic conditions from developed to emerging markets. 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 include a number of global variables that may influence the distress risk of emerging market firms. Section 4.5 discusses in detail the methodology to compute global betas as a measure of emerging market risk exposure to a range of global factors.

3.2 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, the size of the quantiles to group firms, and the allocation of distressed firms across quantiles, making comparisons across models difficult. Chava and Jarrow (2004) 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. The ROC curve plots the true positive rate (i.e., firms that actually default) against the false positive rate (i.e., firms that are predicted to default but do not in fact default) for different threshold settings. In machine learning, the true-positive rate is referred to as the sensitivity, or the probability of detection.

Appendix Figure B1 presents an example. Point A on the "High-Sensitivity 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 "Low-Sensitivity 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.[18] 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.

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

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

sample. Specifically, it is computed as $1 - \frac{log(L)}{log(L_0)}$ and can be interpreted in the same manner as the standard R^2 (between 0 and 1, increasing in model fit).

3.3 The 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.[19] As Table 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.[20] Delayed payments made within a grace period are not counted as defaults.

Table B1 in Appendix B shows our distress indicator over time for firms with sufficient data to replicate our benchmark specification.[21] 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

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

[20] 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)

[21] In order to run the logit model, we need every observation to have data for each explanatory variable.

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 in our baseline specification includes 589,224 observations and 589 default events. This data provides the widest coverage of default events with sufficient accounting data to conduct the estimations and serves as the basis for our benchmark regression specification.[22]

As seen in Tables B2 and B3 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 few 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, politically connected large firms may benefit from government bail-outs. Legal system inefficiencies and lengthy court delays, common institutional features in many emerging market economies, may also lead to lower bankruptcy rates.

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 countries and usually related to financial conditions in advanced economies. 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).[23] In some of our specifications we include a dummy variable that equals one if the firm has experienced a default event in the past. Although we would have liked to include a variable indicating the firm's age or listing date, unfortunately good quality data are not

[22]Coverage of country-specific macro variables is more sparse and in specifications with local macro variables, the sample of observations falls as logit estimation does not allow for missing observations for any covariate. However, our preferred benchmark specification includes country-fixed effects so that the observation count is 589,224 and includes all available data on market, accounting and global variables.

[23]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.

available for the firms in our sample.

To control for large outliers and possible errors in the balance sheet and market data, we winsorize the firm-specific variables at the 1^{st} and 99^{th} percentile of their distributions[24]. 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 five 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 interest rates come also from the World Bank, and we include them as a proxy for local borrowing costs and liquidity. 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. We include the 12-month average of the monthly change in a country's bilateral exchange rate against the US dollar, as it is a major determinant of firms' revenues from abroad and their ability to repay debts denominated in dollars.[25]

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 the US Fed funds rate and the yield curve slope as calculated by the difference between a the 5-year Treasury and the Fed funds rates. The Federal Funds rate is indicative of monetary conditions and changes in monetary policy in the United States, whereas the slope of the yield curve captures how the bond market expects short-term interest rates (as a reflection of economic activity and future levels of inflation) to move in the future, and therefore borrowing costs at longer maturities.

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

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

In addition, to capture the period of unconventional monetary policy, we turn to two different approaches. The first is to use that measure of monetary policy surprises extracted from 5-year Treasury futures using high-frequency identification from Chari et al. (2017). The second is to use the yield curve decomposition of the 5-year and 10-year Treasury rate into expected short rates and term premia based on the model in Adrian, Crump and Moensch (2013).

Given that the bilateral dollar is a country variable that it is outside the control of small open economies (Rey (2015), we include changes in the broad US$ index as a global variable. This is the trade weighted Broad US dollar index from FRED. 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. Appendix A defines variables and their sources in greater detail. In later exercises we compute firm exposures to these global variables and incorporate the firm-specific exposures into our distress prediction specifications.

3.4 Summary Statistics

Table 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 0.034% for the average firm in the full sample. This is not surprising, since smaller firms may find it more difficult to access temporary financing when facing default.

Looking at firm balance sheets, firms one month away from default differ from the full sample in the expected direction – and the difference in all four mean accounting ratios is larger for firms in the Bankrupt group. Distressed firms have lower profitability and are on average making losses in the months prior to failing to pay their obligations, compared to an average net income to total assets of 0.004 in the full sample. These firms also have higher leverage (0.599 and 0.759 for Default and Bankrupt groups, respectively) than the overall population (0.370), as well as lower cash holdings over total assets: 0.041 and 0.024 for the Default and Bankrupt groups, compared to a full sample average of 0.084. 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 2.869 (Default) and 4.400 (Bankrupt), compared to 2.084 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; 54.5% and 42.9% compared to 6.1% for the full sample.

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 Bankrupt group is characterized by higher unemployment and real interest rates.

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 expect an environment of high interest rates in the US to lower the search for yield and demand for riskier emerging market debt instruments. Summary statistics support this hypothesis, with firms defaulting in times of a higher Fed Funds rate: 1.806%, compared to 1.239% in the full sample. Lastly, the Default group is characterized by having a higher TED spread; that is, higher global liquidity risk. VIX levels are not significantly different between distressed firms and the full sample, while the broad dollar index appears to decrease by 0.2%.

4 Results

4.1 Firm Fundamentals, Asset Prices and Global Financial Conditions

In this section, we investigate the impact of global financial conditions on corporate default probabilities through different channels. In section 2, we suggest that in theoretical settings with borrowing constrained firms and endogenous default, perturbations that originate in global financial markets can impact corporate default probabilities in emerging markets through alternative channels. In particular, changes in international credit market conditions can impact firms with different degrees of global exposure. As a result, default rates can vary conditional on the impact of global financial conditions on corporate fundamentals (such as profitability and leverage).

These shocks can alter the cost of external finance that impact the ability of firms to repay their debts. Capital flows and retrenchments, changing investor risk appetites and global liquidity conditions have direct effects on external financing costs. Collateral constraints can affect the borrowing capacity of firms. These constraints can bind via changes in stock prices and exchange rates and have balance sheet effects that in turn impact the net worth of firms and limit access to capital markets.

The global financial shocks we investigate in this section fall into the following categories: (1) US monetary policy changes; (2) changes in international investor risk aversion; (3) liquidity conditions in international financial markets, and (4) exchange rate configurations.

4.2 Benchmark Specification

Existing closed-economy models of corporate default focus on domestic shocks to determine the ability of firms to repay their debts. We extend the analysis to an open-economy setting where global shocks can interact with firm fundamentals and impact corporate default probabilities.

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.

To avoid the potentially confounding effects of simultaneously including market, accounting and global variables in our baseline specification, we conduct the analysis in three steps. First, we estimate a baseline regression that examines the impact of accounting and global variables on predicted probabilities of default to capture the direct effect of firm fundamentals (accounting) and global financial conditions on default risk (Table 3, Columns 1-6). At this stage we do not include any firm-level market variables such as stock prices, excess returns or volatility. Second, to capture asset price exposure to global financial conditions and firm fundamentals (e.g. profitability and leverage), we estimate the impact of global and accounting variables on firm-level stock market variables (Appendix Table B5). In the third stage, we use the orthogonalized component of the firm-level market variables to discern the additional impact (if any) of these variables along with accounting and global variables on default probabilities (Table 3, Columns 7 & 8). The benchmark specification in Table 3 (Column 8) includes market variables that are expunged of global and accounting factors to discern their impact on default risk.

Table 3 shows the results of six iterations of the multivariate logistic regression without any market variables. Column 1 estimates a baseline specification, using a set of accounting variables commonly used in U.S. bankruptcy models. The results in Column 1 suggest that profitability and cash are inversely correlated with the probability of default, while leverage is positively correlated with the probability of default. These coefficients are statistically significant at the 1% level and are consistent with the findings in the previous literature (Altman, 1968; Zmieliewski, 1984; Shumway, 2001; Campbell et al., 2008). The specification yields a pseudo-R^2 of 0.097 and an AUC of 0.839. The results imply that firms are more likely to default in the next month if they are less profitable, highly levered, have less cash, and lower book-to-market ratios. In sum, weak corporate fundamentals make firms more vulnerable to default.

Next, we add a dummy variable signaling whether a firm has defaulted in the past. Including a wider subset of events in our definition of "Default" rather than being restricted to outright bankruptcy, allows us to examine the impact of prior distress states on the current probability of default. We find that this "prior default" dummy greatly increases explained variation and predictive power (Column 2). The coefficient is positive and highly significant at the 1% level, suggesting that if a firm has defaulted on interest or principal payments in the past, it is more likely to default in the future. The pseudo-R^2 for the specification goes up to 0.175 and the AUC rises to 0.902. The strong significance of the prior default dummy suggests there is something about prior defaulters' risk of default which is not captured by firm-specific observable accounting and market variables. This could indeed be the result of sectoral differences in handling corporate distress, or just the mechanical transition from more minor defaults towards bankruptcy. To the best of our knowledge ours is the first paper to include this explanatory variable that is remarkably robust across specifications. Due to its strong statistical and economic significance, we find it worth including as a control in the specifications moving forward.

In the third column we add to the regression the domestic macro variables – unemployment, inflation, real interest rates, a 12-month trailing average of the change in the bilateral exchange rate with the U.S. dollar and sovereign spreads. The pseudo-R^2 increases to 0.183, but the AUC falls to 0.889, suggesting a better model fit but not better predictive power. Controlling for firm-specific accounting variables, lower real interest rates and lower inflation rates are significant predictors of default. Consistent with the exchange rate channel, bilateral appreciation of the U.S. dollar is significantly positively correlated with the probability of default.

Column 4 presents the results of a model that consists of the baseline accounting variables, the prior default dummy, and global variables. The AUC of 0.902, similar to that in Column 3, suggests that global variables contribute more to predictive power than domestic variables after controlling for firm-specific covariates. The coefficients suggest that default risk is associated with a higher Fed Funds rate, a steeper yield curve, tightening monetary policy surprises and a higher TED spread. The Fed Funds rate and the yield curve are significant at the 1% level, the TED spread at the 5% level, the monetary policy surprise and the broad dollat at the 10% level, and the VIX at the 15% level. After controlling for firm-specific accounting variables it appears that emerging market firms are more likely to default when US Fed Funds rates are high, the yield curve is steep, there is a tightening monetary policy stance in the U.S., and funding conditions are less liquid. In terms of transmission mechanisms it appears that the most salient factors pertain to the U.S. monetary policy environment and global liquidity conditions.[26]

Regarding the US dollar, we find that broad dollar appreciations lower probabilities of default.[27]

[26] Also, note that since we explicitly include the yield curve slope in the specification, increases in the Fed Funds rate can be interpreted as level increases in the yield curve. The implication here is that the yield curve term incorporates expectations of the future short-term rates (i.e., the 5-year Treasury rate).

[27] The broad dollar is said to appreciate when the index value rises and *vice versa*. The bilateral dollar is expressed as $

At first pass this appears to be a counter-intuitive finding. Dollar appreciation is often a sign of a risk-off environment, which has an adverse impact on capital flows to emerging markets and also for firms with dollar-denominated debts. On the other hand, dollar appreciation is beneficial for exporters- a weaker domestic currency implies greater export competitiveness. The sign of the coefficient on the broad dollar variable as a predictor of corporate default probabilities depends on which effect dominates–improved export competitiveness or the adverse balance sheet impact.

A specification that includes both domestic and global variables is presented in Column 5. The specification in Column 5 includes both the bilateral dollar and the broad dollar. A notable result is that the statistical significance of the coefficient on the 12-month trailing average change in the U.S. dollar (bilateral) rises to 5%. Bilateral U.S. dollar appreciation ($ per foreign currency unit) is significantly correlated with the predicted probability of default.

The negative coefficient on the broad dollar suggests the contrary. One interpretation of these opposite sign coefficients on the bilateral and broad dollar is that controlling for the bilateral dollar effect (the leverage channel that impacts dollar-denominated debts), a broad dollar appreciation is beneficial for emerging market firms via the trade channel. However, Avdjiev et al., 2018 suggest that broad dollar strength may lead to contractions in cross-border lending and is a key barometer of risk-taking capacity in global capital markets. Caution is therefore warranted in interpreting the negative coefficient on the broad dollar as the more intuitive and straightforward prior would be that conditional on leverage, broad dollar strength drives up probabilities of default, in which case we would expect a positive sign on the coefficient on the broad dollar.

Finally, in Column 6, a specification that includes country fixed effects yields the best predictive power yet, with an AUC of 0.907. 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. To estimate the model with country fixed effects we must drop local macroeconomic variables, as well as any country with no defaults during the period being used for estimation. As in the baseline specification, we find that a firm is more likely to default next month if it has low profitability, and cash, as well as high leverage and market-to-book ratios. The VIX, our measure of global investor risk appetite, becomes statistically significant and positively correlated with default, at the expense of the TED spread, which loses some significance. The Fed funds rate and the slope of the yield curve remain highly significant predictors of default and the monetary policy

per foreign currency unit, which implies that the dollar appreciates when the bilateral dollar value declines.

surprise variable gains significance (5% level) in predicting the probability of default.

4.3 The Joint Determination of Asset Prices, Global Factors and Default Probabilities

Market participants typically discount the market equity of firms in distress or close to bankruptcy. Existing bankruptcy studies therefore include market variables in addition to accounting variables to predict probabilities of default. Shumway (2001) and Campbell et al. (2008) show that stock prices, past excess returns and relative market capitalization contain valuable information for predicting corporate distress. Similarly, firms with more variable cash flows tend to have more volatile stock returns. Therefore, the idiosyncratic volatility of stock returns is also an important predictor of corporate financial distress.

However, global variables may jointly determine both asset prices (market variables) and probabilities of default. Incorporating global variables into the specification to disentangle their impact on default probabilities, therefore presents an empirical challenge. To address the simultaneity issue and to more effectively estimate default probabilities whilst including global variables into the benchmark specification, we introduce orthogonalized components of the market variables into our baseline specification.

To extract the orthogonalized values of the market variables, we estimate the impact of global and accounting variables on firm-level stock market variables. This exercise captures firm exposures to global financial conditions as well as firm characteristics such as profitability and leverage. We do this by regressing the firm-level market variables using ordinary least squares (OLS) on the full set of accounting and global variables. Appendix Table B5, Panel C reports the results.

Using the coefficient estimates from the OLS estimation, we extract the orthogonalized components of the market variables- the aforementioned firm-level stock prices, excess returns, stock return volatility and relative market capitalization. The subsequent analysis uses the orthogonalized component of the firm-level market variables to discern the additional impact (if any) of these variables along with accounting, local, and global variables on default probabilities (Table 3, Columns 7 & 8). In other words, the baseline regression is modified to include market variables expunged of global and accounting factors to discern their impact on default risk.

The results show that the orthogonalized components of the market variables contribute significantly to default probabilities. Controlling for accounting, domestic macro and global variables, falling orthogonalized excess returns and stock prices predict increases in probabilities of default. The results suggest that stock prices convey additional information about distress risk over and above factors such as firm profitability, leverage, cash as well as the domestic and global macro conditions. The pattern of results also holds in specification 8 which includes country-fixed effects. It is encouraging to note that across the board, with a few exceptions, the coefficient estimates for the firm-specific and global variables remain remarkably stable with the inclusion of the orthogonalized market variables.

Our dataset contains missing observations for a number of local macroeconomic variables, reducing the sample size for specifications that include these factors. In contrast, specifications which include country fixed effects retain many of these observations. The sample used for our benchmark specification including fixed effects (Column 8) contains 589,224 firm-months, 589 distress events, and we are left with firms from Argentina, Brazil, China, India, Indonesia, Malaysia, Mexico, Philippines, Poland, South Korea, and Thailand. Being the specification with highest predictive power, we use Column 8 as our measure of probability of default in the remainder of the paper.

As noted before, the extant literature on distress risk does not account for exposure of emerging market firms to global macroeconomic shocks, the analysis of which is the main focus of our paper. The ROC curve associated with the baseline specification (8), that including local macroeconomic variables (7), and model (1) with accounting variables, is shown in Figure 1. Figure 3 plots, for each quarter, the number of defaults predicted by these same models against the number of actual defaults.

The Receiver Operating Characteristics (ROC) curves illustrate the importance of global factors in the identification of distressed firms (Figure 1). Our benchmark model (Table 3, Column 8) performs substantially better in identifying at-risk firms. Over 80% of the defaulting firms are included in the top 10% of firms when ranked by predicted default probability (blue curve). The specification in Column 1 that includes only accounting variables takes nearly 40% of the sample to get to this same rate of identification (red curve).

Figure 3 also shows a visible benefit in terms of matching the time series dynamics of default clustering and timing. Our benchmark specification is less flat through the majority of the sample and matches some of the default clustering that we see in the data. The additional information captured in these global monetary and macroeconomic variables influence the model more drastically in times of global turmoil, as evidenced by the widening spread between the models in 2005-2006 and in 2009.

An econometric model that includes frailty or contagion (or both) has the potential to improve upon our ability to match the surges in defaults around 2004, 2012, and 2014. However, the model structure in leading contagion/frailty papers rely on unobservable, underlying factor analysis to analyze correlated defaults. For example, in Azizpour et al. (2018), the main focus is on the number of defaults in a period, but it generalizes away from firm-level heterogeneity and only incorporates one observable macro factor. The default intensity model in Duffie et al. (2009) imposes similar restrictions in terms of number of covariates. Both types of models lack the ability to analyze the impact of an array of global factors, which is our primary goal.[28]

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 0.913, compared to an in-sample AUC of 0.922.[29]

Having accounted for the simultaneity issue we are reassured of the the independent impact of global financial conditions on default probabilities. Note that since we use lagged values of the firm fundamental variables such as profitability and leverage to predict default, simultaneity is less of a concern when including accounting variables into the specification. Next, we exploit the fitted components of the market variables to identify the channels through which firm fundamentals and global financial conditions impact probabilities of default.

Recall that in Appendix Table B5, Panel C we examine the impact of the full set of accounting and global variables on the market variables. We also regress the market variables separately on the set of accounting variables (Panel A) and global variables (Panel B). We now use the fitted values of the market variables to examine the channels through which firm fundamentals and global variables operate via market variables to impact probabilities of default. Given that we are using the same set of accounting and global variables to fit the market variables, we encounter co-linearity issues and can enter the fitted variables only one by one into the baseline specification. Table 5 presents the results for excess returns in specifications with local macro variables and country fixed effects. Appendix Tables

[28]The analysis of contagion and correlated defaults while outside the scope of this paper, could be a fruitful avenue for future research.

[29]We are cognizant of the multicollinearity concerns associated with our multivariate framework. Table B4 in Appendix B shows the correlation matrix of the variables in our model and, in the last two rows, two popular measures of multicollinearlity, the Tolerance value (TOL) and its reciprocal Variance Inflation Factor (VIF), for each of the regressors. VIF is computed as $1/(1 - R_k^2)$, where R_k^2 is the R^2 value of a regression of factor k on all others. TOL is simply $1 - R_k^2$. VIF values larger than 10 are typically considered suggestive of multicollinearity in a model. In our specification, no variable has VIF ≥ 10, and only the Fed Funds Rate and yield curve slope have VIF > 2, presumably due to the high correlation between the two. The correlation between Fed Funds Rate and yield curve slope is -0.678, the only pairwise correlation larger than 0.6 in absolute value among all our variables.

B6, B7, and B8 present the results of stock prices, the volatility of returns and the relative market capitalization respectively.

We see that both accounting and global variables also operate through excess returns to impact probabilities of default. Column 2 examines the impact of excess returns fitted on the set of accounting variables that proxy for firm financial health and shows that that the coefficient of the fitted excess return variable is a negative and highly significant predictor of default. The global variables continue to have the same pattern of predictive power for the probabilities of default. A higher Fed funds rate, steeper yield curve, tightening monetary policy surprises and a rising VIX predict increases in probabilities of default, while a strengthening broad dollar appears to predict reductions in default probabilities.

Column 3 conducts the same exercise with excess returns fitted on global variables. Firm-level accounting variables enter the specification as additional controls. We see that in a a composite sense the impact of global variables operating through excess returns has a highly significant impact on default probabilities. In particular, an overall rise in global variables, mostly representing a high interest rate environment in the United States, rising VIX levels and less liquid financial markets have a negative impact on excess returns. In turn, lowered excess returns predict increases in the probability of default.

Collectively, the pattern of results from the orthogonalized and fitted components of market variables on default probabilities suggests the following. First, market variables such as excess returns and stock prices carry independent information about default probabilities. Second, accounting variables that impact corporate financial fragility such as profitability, leverage and cash on hand as well as variables that summarize the state of the global financial environment also operate through market variables to impact probabilities of default. From the orthogonalized market variables specification we can quantify the total impact of global variables on default probabilities whereas the fitted market variables allow us to quantify the indirect effects of global variables operating through market variables on default risk.

4.3.1 Alternative Global Variables

Global Illiquidity: We consider two alternative measures of global illiquidity. The first is the noise measure of illiquidity from Hu, Pan and Wang (2013) in US Treasury bills, notes, and bonds markets.[30] The measure has the advantage that it uses information from the entire yield curve as opposed to focusing on a single maturity bond. Additionally, we use the on-/off-the-run 10-year yield spread, which is calculated as the difference in yields between 10-year on-the-run and off-the-run Treasury bonds. We find that the coefficients on all these alternative measures of illiquidity are positive and statistically significant (Table 10, Columns 2 & 3). They predict increases in default probabilities as global financial markets (US and Europe) become more illiquid.

Monetary Policy: We decompose the 5-year Treasury rate into an expected short rate and a term premium component based on the model in Adrian, Crump and Moensch (2013). The coefficients on both the short rate and term premium components are positive and statistically significant and predict increases in default probabilities as short rates and term premia rise (Table 10, Columns 4 & 5). The results are robust to the inclusion of the alternative measures of monetary policy as well as the decomposed shocks. It is interesting to note that the decomposed monetary policy shock components are highly correlated with the VIX and therefore the coefficient on the VIX loses significance in the specification that includes the decomposed variables.

4.4 Marginal Effects and Predicted Defaults

Ultimately, the economic significance of the coefficients from the logit specification lies in predicting actual defaults. Marginal effects allow us to examine the impact of changes in a specific predictor variable on the probability of default, holding all other predictors constant.

To calculate marginal effects, we take the first derivative of equation (1). Using the chain rule implies that the change in the probability of default with respect to a change in the conditioning variable is:

$$\frac{dP_{t-1}(Y_{i,t}=1|X_{i,t-1})}{dx_j} = \frac{\beta_j exp(-\alpha - \beta x_{i,t-1})}{(1+exp(-\alpha-\beta x_{i,t-1}))^2} = \beta_j(1-P_{t-1}(Y_{i,t}=1|X_{i,t-1}))\cdot(P_{t-1}(Y_{i,t}=1|X_{i,t-1})) \tag{2}$$

[30]The illiquidity measure is modeled based on a smooth zero-coupon yield curve which is used to calculate prices for all available bond maturities. The measure is constructed by aggregating the deviations (RMSE) between the model and market yields.

That is, a one-unit change in X_i creates a change in the probability equal to the coefficient β_i times one minus the probability times the probability.

Note that, in contrast to a linear model such as OLS, the partial derivative in Equation 2 is not exclusively based on the regression coefficient (β_j) for the variable of interest. In fact, all model coefficients (βs) and variables (the vector $x_{i,t-1}$) influence this partial derivative through multiplicative terms and influence the magnitude of any derived marginal effects for any given variable j. The non-linearity of the logit model allows us analyze how firm heterogeneity and evolving global financial conditions are interdependent and jointly enter into our marginal analysis. In other words, the marginal impact of global variables on default probabilities is conditional on all other aspects of firm health and the levels of all other global variables.

In this section we begin by computing marginal effects, then use alternative methods to explore the non-linear response in default probabilities to changes in covariate values, and finally translate our marginal effects into estimated predicted defaults.

4.4.1 Marginal Effects at the Mean (MEM) and Average Marginal Effects (AME)

We begin by computing marginal effects at the mean (MEM)-the effect of a one standard deviation change in an explanatory variable on the probability of default for a representative firm with accounting, market and global variables held at their respective sample means. We calculate average marginal effects (AME) by taking averages of the individual marginal effects for one standard deviation changes in the explanatory variables for each firm evaluated at their true accounting, market and global variable values across the sample.

Specifically, from equation (2), letting $h_t(X) = P_{t-1}(Y_{i,t} = 1|X)$, MEM and AME for the j^{th} covariate are calculated as:

$$MEM_j = \frac{dh_t(\bar{X})}{dx_j} = \beta_j(1 - h_t(\bar{X})) \cdot (h_t(\bar{X})) \tag{3}$$

$$AME_j = \frac{1}{N \times T} \sum_{i,t}^{N,T} \frac{dh_t(X_{i,t-1})}{dx_j} = \beta_j \left(\frac{1}{N \times T} \sum_{i,t}^{N,T} (1 - h_t(X_{i,t-1})) \cdot (h_t(X_{i,t-1})) \right) \tag{4}$$

Table 4 presents the results using the coefficient estimates from the benchmark specification (Column 8) with country fixed effects and orthogonalized market variables. Columns 1 and 2 present the standard deviations of each variable and marginal effects at the mean (MEM). Column 3 presents the average marginal effects (AME).[31] We see that the marginal effects for the firm-specific variables and the monetary policy variables are quite large. It is important to remember that although at first blush the magnitude of the global variables may appear small, these are systemic effects and can translate to large numbers of predicted defaults when aggregated across firms.

We find that among the accounting variables, leverage and cash have the largest average marginal effects, such that a one-standard-deviation increase in the predictor is associated with 0.088 and -0.048 percentage point changes in the probability of default, respectively. From the set of global variables, Fed funds rate and the yield curve slope have the largest average marginal effects at 0.051 and 0.041, respectively.

4.4.2 Global Variables, Firm Characteristics and Predicted Default Probabilities

It is important to recognize that the MEM and AME-style marginal effects of the logit model depend on the values of other covariates. To illustrate this dependence, we examine predicted probabilities of default for "healthy" firms as well as those that default in the next month. Specifically, we simulate a healthy firm in 2006 by setting all firm accounting and market variables equal to their respective means for the subset of non-defaulting firms for that year. We simulate an unhealthy firm in a similar manner using data from the subset of firms that defaulted in the next month. All macroeconomic variables for both firms are set to their mean values in 2006.

Figure 2 shows the probability of default for our healthy (blue) and un-healthy (red) firms across the entire sample range of each global variable, as in Appendix Figure B2.[32] The stark difference

[31] The two approaches yield estimated marginal effects of different magnitudes for the following reasons. First, since the logit model specification is non-linear, marginal effects for continuous variables vary depending on the point in the sample space at which we evaluate them. To see this, Appendix Figure B2 plots predicted probabilities across the sample range of each variable, holding all other variables at their means. The slopes of the individual covariate curves at their respective mean values give the MEM value. Second, since AME is the average of individual marginal effects, higher moments of the distribution for each of the covariates will influence AME. For example, highly skewed covariates will see larger differences between AME and MEM if their skew is towards values that increase the probability of default (this depends both on the distribution of covariates and the degree of convexity of the response function). Further, the marginal effects of each variable will also depend on the values of all other covariates.

[32] Due to the non-linearity of the logit model, marginal effects are somewhat harder to interpret than in OLS. To better visualize the response of default probabilities to changes in covariates we include Appendix Figure B2, which shows the paths 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 grey shaded areas are 95% confidence intervals, computed using the 95% confidence intervals of each variable's coefficient in the logit regression. The plots allow us to compare the probability of default at various levels of each variable for the "average firm". The convexity in the pattern of stock price and relative size predicted probabilities stands out against the more linear excess returns and volatility of returns. The patterns suggest that the tails of the two former variables are relatively more harmful to firms than that of the latter. The flatness of the volatility of returns plot as well as the wide error shading is consistent with its coefficient's lack of statistical significance in the logit regression (Column 8 in Table 3). The leverage plot reveals a large spread in the probability of default between the two extremes, which increases faster at high leverage levels. Since Prior default is a dummy, the line in the plot is simply connecting firms' probability of default when the variable equals zero (no prior default) and one (the firm has defaulted in the past).

in the levels and slopes of these two curves illustrates that firm characteristics play a large role in determining the impact of global shocks on default probabilities. The figure illustrates that, in contrast to their healthy peers, unhealthy firms are, for all values of the global variables, more likely to default. The impact of adverse global shocks is similarly far greater for unhealthy firms since a firm's marginal effect is proportional to its probability of default conditional on values for firm characteristics such as leverage, profitability, and so on.

An insight we gain from computing marginal effects by firm health status is that even without explicitly including interaction terms in our logit specification, we can examine how firm heterogeneity may interact with global financial conditions in determining default probabilities. We explore the cross-sectional variation in the global exposures of firms further in Section 4.5.

4.4.3 The Predicted Number of Defaults

Given our interest in predicting actual defaults, we can use the estimates of marginal effects at the mean (MEM) to predict the change in the number of defaults. Column 4 of Table 4 presents the results. Our estimates tell us, for example, that a one standard deviation increase in the Fed funds rate increases the predicted probability of default (at the mean) by 0.011pp. Over our entire sample, this translates to an additional 64 defaults, or an 11% increase.

We use our estimates to simulate changes in probabilities of default at the firm level for different values of the global variables.[33] For example, given the true accounting and market data for each firm, and allowing global variables to be fixed at their means during each time period, our model predicts the total number of defaults as 57, 34, and 46 defaults in 2006, 2007, and 2008 respectively. Simulating a one standard deviation increase in the Fed Funds rate (1.8pp), we predict an increase in the number of defaults (and as a fraction of the total for the year) to be 5 (9%=5/57), 7 (21%), and 15 (33%) in 2006, 2007, and 2008 respectively. Similarly, a one standard deviation increase in the slope of the yield curve (0.85pp) predicts an increase in the number of defaults to be 10 (18%), 7 (21%), and 23 (50%) in 2006, 2007 and 2008 respectively.

We can also analyze the impact that co-movements of our global variables have on predicted probabilities of default. The impact of a simultaneous 1pp increase in the Fed funds rate and a 0.75pp increase in the 5 year Treasury rate yields is 10 (18%), 6 (18%), and 9 (20%) in 2006, 2007, and 2008

[33] Due to the convexity of the probability function as well as the distribution of covariate values, MEM estimates tend to provide a lower bound for predicted defaults while AME estimates provide an upper bound.

respectively. Including a 1pp depreciation in the broad dollar index makes those increases 16 (27%), 10 (29%), and 13 (28%). The marginal effects computations in logit specifications are interactive in nature and therefore greater than the raw effect of any given variable, i.e., the individual β_js. These exercises provide evidence that firm heterogeneity and an amalgam of global variables impact distress probabilities. In the next section, we address the impact of global risk-on/risk-off states of the world in further detail.

What is clear from these results is that US interest rates have far-reaching effects. These findings are consistent with evidence that suggests that the change in emerging market bank leverage following extended monetary policy easing in the United States has a bigger impact on financial leverage than domestic policy. This suggests that the impact of monetary policy tightening in the US can have a significant impact on the increase in median annual defaults. We do not directly explore the feedback effect of US monetary policy on the lagged leverage response. However, it is worth noting that bilateral exchange rates and sovereign spreads can also move in response to US monetary policy tightening, lowering emerging market firm leverage.

4.5 Asset Prices and Cross-Sectional Variation in Global Exposure

If stock returns carry information about the impact of global factors on firms, we may expect the default risk of firms whose returns are more sensitive to global factors to be more correlated with such variables. However, the global variables in the logistic regression mask the fact that some emerging market firms are more dependent on or exposed to global markets than others. In other words, 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 globally-exposed firms. Appendix Table B5 shows that stock returns are correlated with global variables. In this section we further explore the variation in global exposures in the cross-section of firms.

To test the hypothesis that stock returns may contain information that varies across firms by the degree of their global exposure, we compute firm-specific betas of stock returns for each of the global factors in our model. Specifically, we run a time series regression of returns on each global factor for each firm which has 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. We take the resulting coefficient for each global factor 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. In the case of the change in the broad dollar index, we choose the tercile of firms with the most positive betas; that is, whose returns fall most severely with *decreases* in the trade-weighted value of the dollar. Once our firms are sorted by betas, we create a dummy variable that indicates whether a firm belongs to the top tercile.

Panel A in Table 6 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 whose returns are most sensitive to that factor. We find positive, statistically significant coefficients in the top-third dummy interactions for five-year Treasury rates, VIX, and Fed funds rate (Columns 1, 2, and 4). This implies that the adverse impact 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. To verify that this result is robust to the inclusion of firm characteristics, in Panel B we control for the eight accounting and market variables in our baseline regressions. We find that the interaction coefficient is significant for the same three variables - the five-year Treasury rate, the VIX, and Fed funds rate. In addition, the unconditional effects of increases in the TED spread and broad dollar are also significant with directions of magnitude consistent with the results reported throughout the paper. We can therefore conclude that the difference in the impact of the global factors between firms with more or less sensitive returns remains robust to the inclusion of firm characteristics. Further, the firm-specific variables retain the same signs and levels of statistical significance as in Table 3.

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 together the resulting values of the six factors.[34] The result is a

[34]We subtract the change in the broad dollar rate since we want an increase in the US dollar to impact the Global Beta Z

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 (more negative) Global Beta Z score implies that a firm's returns are more negatively affected by increases in the global variables. We compute a Global Variable Z in the same manner, using the global variables as inputs instead of the betas. A higher Global Variable Z score is associated with a more difficult environment for emerging markets to finance themselves (what is often known as a "risk-off" environment).

In Table 7 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. Columns 1, 2 and 3 progressively add firm characteristics, prior default and domestic variables. In the baseline analog in Column 4, we control for firm-specific variables and country fixed effects and find that the coefficient on Global Beta Z is is positive and statistically significant, implying that exposure to global financial conditions is a predictor of default. The Global Variable Z is also positively correlated with default risk and highly statistically significant; i.e. emerging market firms are more likely to default in global risk-off conditions. Additionally, the interaction of the two returns a significant, negative coefficient. This tells us that, all else equal, the effect of a risk-off environment on default risk is larger for firms whose returns respond more negatively to such global conditions.

We can conclude that, for some global factors like the Fed Funds rate, five-year Treasury rates, the VIX and for a composite global factor, the sensitivity of a firm's returns to the factor(s) affects the extent to which 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.

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score in the same direction as an increase in rates, VIX, sovereign spread, and TED spread.

5 The Distress Risk Premium in Emerging Markets

We use our estimated probability of default (Column 8 in Table 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; Campbell et al., 2008). Asset pricing theory suggests investors should demand a premium for holding stocks at risk of default. However, 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 a distress risk premium puzzle exists 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 10. We re-balance 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.

Panel A of Table 8 shows each portfolio's average estimated probability of default, its twelve-month average monthly returns, and the results of a regression of returns on six common factors. The spread in the probability of default across portfolios is large: the average firm in the portfolio with lowest default risk has just a 0.0018% probability of failing next month (Column 1), compared to 0.94% for the average firm in the riskiest decile (Column 10). The average twelve-month returns reported in the second row are broadly increasing in probability of default, consistent with a positive risk premium associated with distress. The safest and riskiest portfolios return 0.95% and 1.55% per month, respectively. 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. The first three factors we control for are the three factors from Fama and French (1993): excess market returns (RM), Small minus Big (SMB), and High value minus Low value (HML). The other three are momentum, short-term reversal, and long-term reversal. Below we describe the computation of these factors for the emerging market firms in our sample in greater detail.

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. For the remaining three factors, momentum is computed as the return in the prior year excluding the prior month, short-term reversal as the return in the prior month, and long-term reversal as the return in the prior five years excluding the prior year.

A regression of 12-month average returns on the six factors returns the following results. We find that high failure risk portfolios have more positive betas on SMB, reflecting the prevalence of small firms among distressed stocks; more negative betas on HML, consistent with growth stocks being more at risk of default; and more positive betas on RM, symptomatic of stocks more exposed to broad market fluctuations also being more likely to default. We include the average market capitalization and market-to-book ratios of the firms in each decile to illustrate the sorting that generates the nearly-monotonically increasing factor loadings for SMB and HML with smaller firms and high market-to-book firms in the highest probabilities of default deciles.

The three Fama-French factors, as well as the firm specific long and short term reversal, and momentum factors, explain a portion of the 12-month average excess returns of each firm's stock. 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. In other words, we find a positive distress risk premium in emerging market stocks.

Figure 4 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 those of the highest two deciles' alphas. Caution is warranted in interpreting any overlap in confidence intervals across deciles as a formal test of the difference in these alpha estimates. In a later robustness test we conduct a t-test to determine the statistical significance of this difference in estimated 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 the first two columns of Table 9. The first row tells us that average returns are 0.55 percentage points larger in the most distressed portfolio than in the least distressed (Column 1), and 0.47 percentage points larger for the 20% riskiest stocks than the 20% safest (Column 2). Both differences are statistically significant. The coefficients on the Fama-French factors confirm that the exposure to SMB or small firms and HML for growth stocks is larger for the portfolios with more distressed stocks. Most importantly, the positive, statistically significant alphas reveal that the factor-adjusted compensation is in fact larger and highly significant for the portfolios with higher distress risk, validating our finding of a positive distress risk premium.

Panel B of Table 8 presents an alternative method for computing 6-factor alphas using returns over a 12-month period. For every month of the year following portfolio formation, we run a regression of 12-month average returns on the six factors computed in that same month. By doing this, the timing of the distress risk portfolio formation corresponds to the timing of the factors, instead of using the factors computed only in January of each year as controls for the average 12-month returns.

Panel B of Table 8 shows monotonically increasing alphas in distress risk, and the long-short regression coefficients in Columns 3 and 4 of Table 9 include positive, statistically significant alphas. We also run a t-test of means on the monthly alphas estimated for the lowest and highest risk portfolios in Panel B. We find the mean of the high risk alphas to be statistically larger than those of the low risk alphas at a confidence level of 1%. In addition, due to the more appropriate factor timing, the factor loadings are more intuitive. We see both growth- *and* value-mimicking portfolio returns as well as mostly positive loadings on the market factor.

To further test 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. Specifically, the average gamma across months is 0.0089 with a t-test p-value less than .01, 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. Panel C in Table 8 does not show a clear pattern in the relationship between the earnings-to-price ratio (using net-income as proxy for earnings) and our measure of probability of default.[35]

[35] We do not have data to compute dividend yield or implied cost of capital.

6 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 there is investor compensation 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 show that global financial conditions can be transmitted to firms in emerging markets through several channels. Although 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, increasing Fed funds rates, a steeper US yield curve, tightening US monetary policy shocks, and poor global liquidity conditions affect default probabilities adversely in emerging markets. Introducing a dummy variable indicating whether a firm has defaulted in the past has a very positive impact on the model's predictive power. The finding is novel. A baseline specification that includes accounting, market, and global financial variables, along with country fixed effects and a prior-default dummy, yields superior explanatory power for emerging market corporate distress than existing US-based bankruptcy forecast models.

We also explore whether stock returns embed information about default risk. 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 more significant for firms with the 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 higher 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 twelve-month stock returns are monotonically increasing in the probability of corporate default, a trend that holds after controlling for six prevalent factors. Several robustness tests confirm the statistical significance of our findings.

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Figure 1: In-sample Predictive Power

This figure shows the Receiver Operating Characteristics (ROC) curve for models 1, 7, and 8 of Table 3. The curves shown are the averages of the ROC curves in each month in the sample.

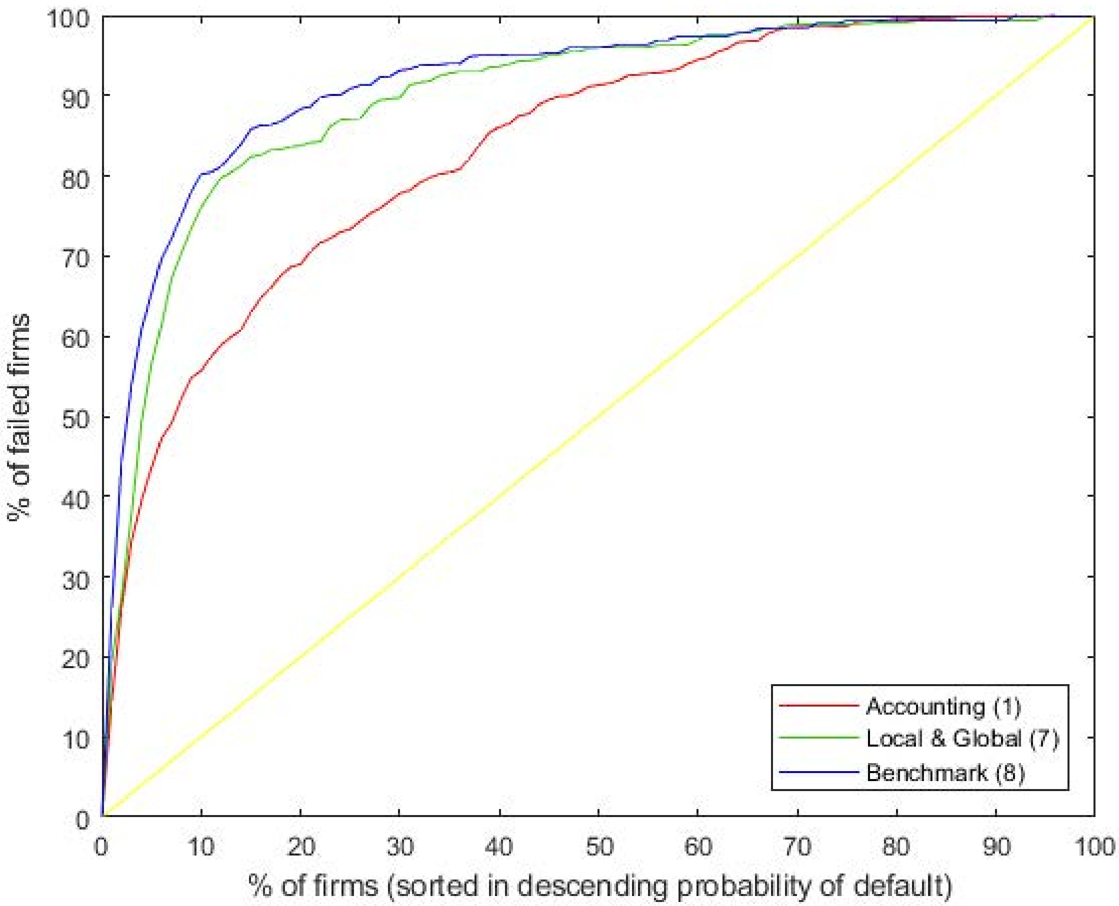

Figure 2: Predicted Probabilities: Healthy vs. Unhealthy Firms

This figure shows predicted probabilities for a 'healthy' firm (in blue) and for an 'unhealthy' firm (in red) for all values of each global variable. All other variables for the 'healthy' firm are set at their means for the subset of firms that do no default the next month. All other variables for the 'unhealthy' firm are set at their means for the subset of firms that do default next month. The shaded grey areas are 95% confidence intervals, computed using the 95% confidence intervals of each variable's coefficient in our benchmark logit regression.

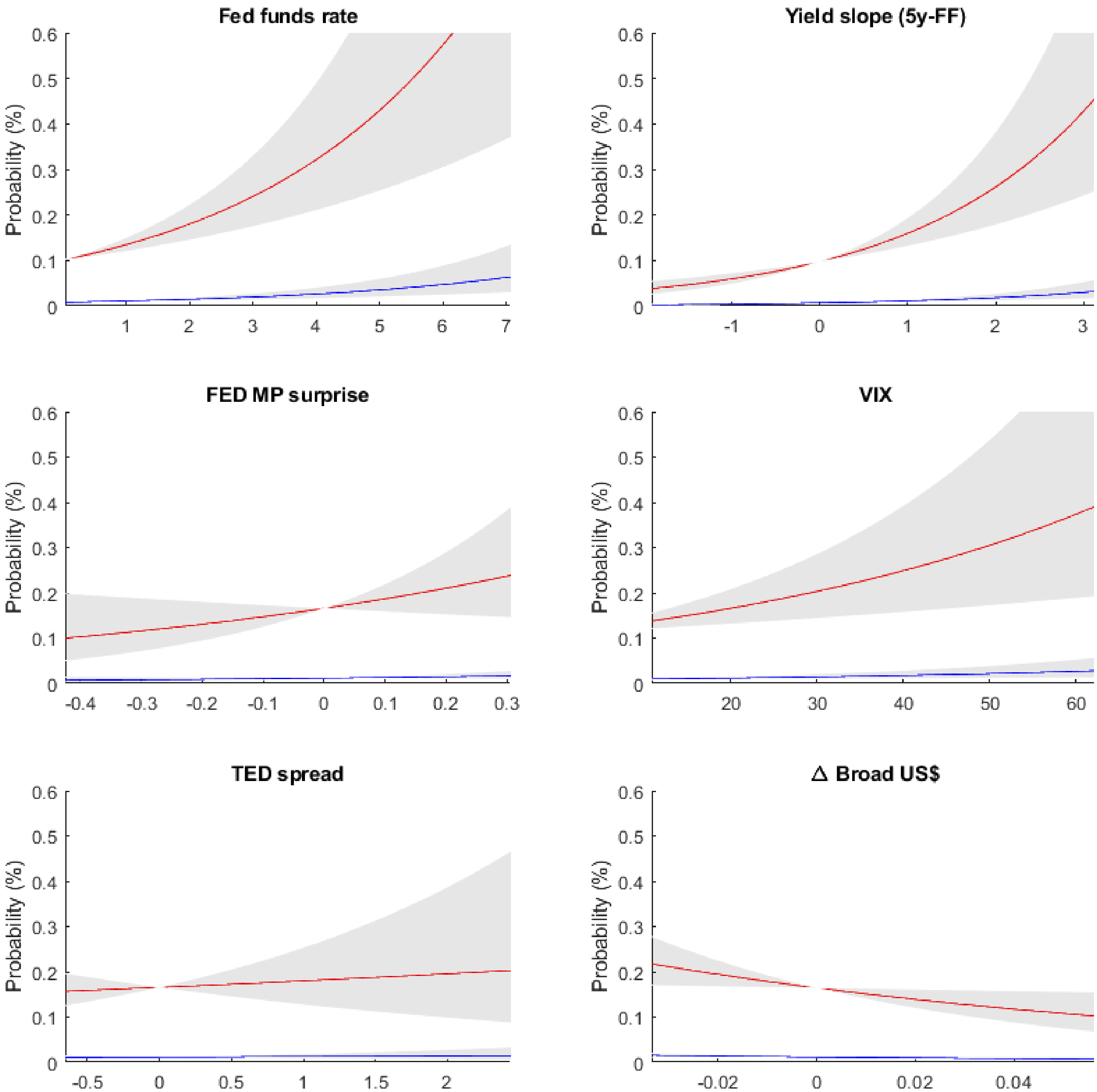

Figure 3: Time Series of Actual and Predicted Defaults

This figure shows the number of actual defaults per month (averaged by quarter) and the number of defaults predicted using models 1, 7, and 8 of Table 3. The number of predicted defaults in a month is the sum of the estimated probabilities of default for all firms.

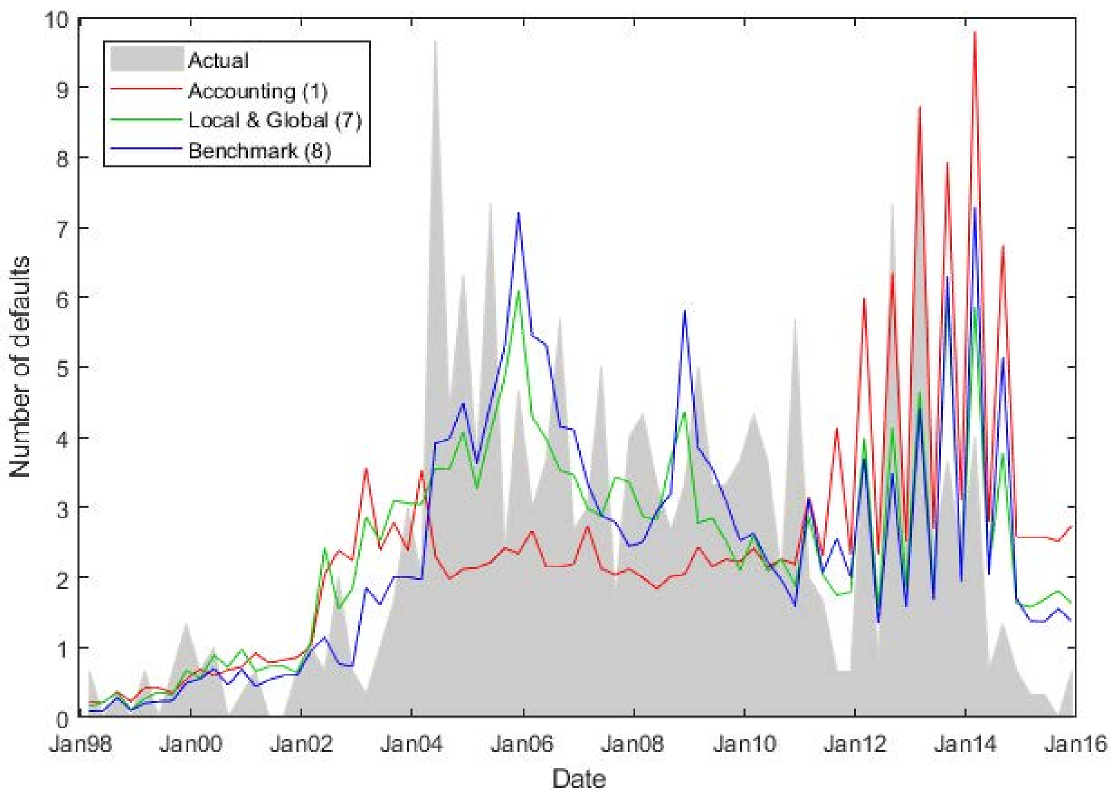

Figure 4: Six-Factor Alphas

This figure plots six-factor alphas from Panel B of Table 8 and their 95% confidence intervals for 10 portfolios sorted by increasing distress risk.

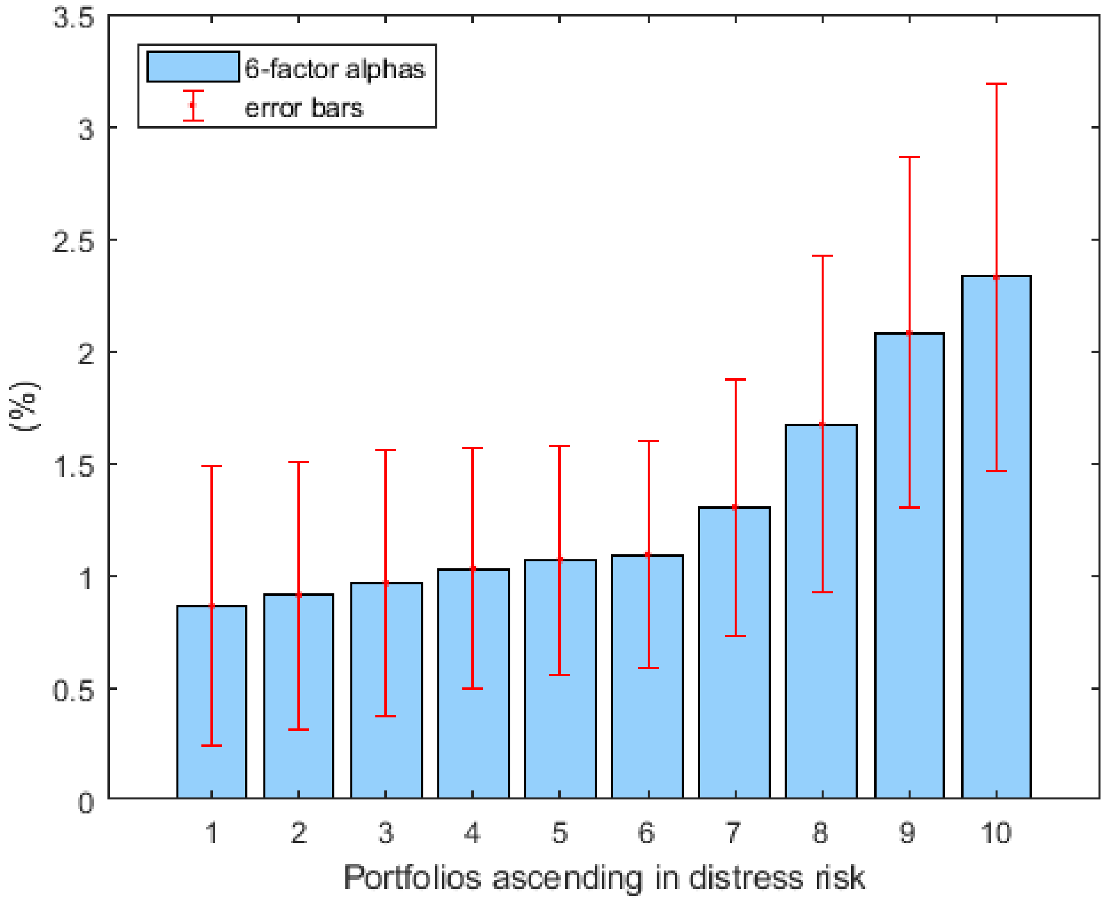

Table 1: Types of default events

Panel A presents the types of default events covered in the CRI database and their classification into Bankruptcy, Delisting, and Corporate Default Action categories, as CRI does in its databaseâĂŹs 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 all accounting and market variables.

PANEL A

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

Table 2: Summary statistics

Summary statistics for firm-months with data for all accounting, market, domestic and global macrovariables. The first three columns show unconditional means, means for those firms that default next month, and means for the subset of firms whose default was listed as a bankruptcy. The last two columns show the results of a two-sample t-test for equal means of each group of distressed firms against the whole sample. ***, **, *, and † indicate $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$.

	Means			t-Tests	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Full Sample	**Default**	**Bankrupt**	**Default**	**Bankrupt**
Excess returns	−0.008	−0.049	−0.060	***	*
Stock price	2.479	1.249	0.156	***	***
Volatility of returns	1.533	0.748	0.727	***	***
Relative size	−7.972	−9.136	−9.233	***	***
Profitability	0.004	−0.019	−0.049	***	***
Leverage	0.370	0.600	0.759	***	***
Cash	0.084	0.041	0.024	***	***
Market-to-book ratio	2.084	2.869	4.400	***	***
Prior default	0.061	0.545	0.429	***	***
Unemployment rate	4.474	4.490	5.471		**
Inflation rate	0.036	0.036	0.031		*
Real interest rate	4.033	2.760	8.113	***	***
Sovereign spread	2.430	2.628	1.965		**
ΔFX 12m avg	−0.000	−0.001	0.001	*	
Fed funds rate	1.239	1.806	1.547	***	
Yield slope (5y-FF)	1.131	1.031	1.238	**	
Fed MP surprise	−0.002	0.001	−0.002	†	
VIX	19.496	19.707	21.311		*
TED spread	−0.070	0.008	−0.111	***	
ΔBroad US$	0.000	−0.002	0.000	***	

Table 3: Logit Regressions of Probability of Default Next Month

Results of logit regression combining accounting and orthogonalized market variables with local and global macro variables to explain the probability of default next month. Column 1 uses firm accounting variables as covariates. 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 incorporates country fixed effects to the model in Column 4. Columns 7 & 8 add orthogonalized firm market variables the specifications in columns 5 & 6. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	−8.926***	−9.013***	−7.908***	−9.934***	−8.477***	−11.290***	−8.667***	−11.477***
Excess returns (orth)							−1.119***	−1.628***
Stock price (orth)							−0.259***	−0.200***
Volatility of returns (orth)							−0.001	−0.024
Relative size (orth)							0.175***	0.191***
Profitability	−7.230***	−7.051***	−7.076***	−6.982***	−7.345***	−8.351***	−8.259***	−8.831***
Leverage	3.283***	2.675***	2.555***	2.636***	2.407***	3.726***	2.407***	3.560***
Cash	−3.459***	−2.576***	−3.791***	−2.432***	−3.355***	−5.467***	−3.781***	−5.597***
Market-to-book ratio	0.232***	0.132***	0.103***	0.134***	0.104***	0.058***	0.108***	0.064***
Prior default		2.538***	2.424***	2.526***	2.437***	2.079***	2.463***	2.143***
Unemployment rate			0.009		−0.018		0.003	
Inflation rate			−10.510***		−10.129***		−8.065***	
Real interest rate			−0.055***		−0.041***		−0.045***	
Sovereign spread			−0.015		0.000		−0.019	
ΔFX 12m avg			−12.566*		−17.966**		−17.338**	
Fed funds rate				0.235***	0.160***	0.275***	0.156***	0.291***
Yield slope (5y-FF)				0.406***	0.288***	0.522***	0.261***	0.495***
Fed MP surprise				1.325*	1.179†	1.744**	0.945	1.191†
VIX				0.007†	0.004	0.015***	0.009†	0.020***
TED spread				0.255**	0.527***	0.181†	0.558***	0.083
ΔBroad US$				−6.105*	−8.077**	−6.177*	−11.327***	−8.376**
Pseudo-R^2	0.097	0.175	0.183	0.182	0.189	0.221	0.201	0.237
AUC	0.839	0.902	0.889	0.902	0.892	0.907	0.903	0.922
Observations	705824	705824	424011	705824	424011	705824	372673	589224
Defaults	681	681	593	681	593	681	524	589
Country FE						✓		✓

Table 4: Marginal effects

Marginal effects from our benchmark model, column 8 of table 3. Column 1 lists standard deviations of each variable. Columns 2 & 3 show MEM and AME estimates for 1 standard deviation increases in each variable. Column 4 shows the estimated change in the number of defaults over the sample due to 1 standard deviation increases in each global variable, calculated using MEM estimates.

	SD	**MEM**	**AME**	**Δ defaults**
Excess returns (orth)	0.138	-0.005^{***}	-0.022^{***}	
Stock price (orth)	1.215	-0.005^{***}	-0.024^{***}	
Volatility of returns (orth)	9.160	-0.005	-0.021^{***}	
Relative size (orth)	1.553	0.006^{***}	0.029^{***}	
Profitability	0.028	-0.005^{***}	-0.024^{***}	
Leverage	0.253	0.019^{***}	0.088^{***}	
Cash	0.089	-0.010^{***}	-0.048^{***}	
Market-to-book ratio	1.533	0.002^{***}	0.009^{***}	
Fed funds rate	1.804	0.011^{***}	0.051^{***}	64
Yield slope (5y-FF)	0.850	0.009^{***}	0.041^{***}	51
Fed MP surprise	0.047	0.001^{*}	0.005^{***}	7
VIX	8.468	0.004^{***}	0.017^{***}	21
TED spread	0.367	0.001	0.003^{***}	4
ΔBroad US$	0.012	-0.002^{**}	-0.010^{***}	-12

Table 5: Transmission of Global Shocks and Firm Fundamentals through Excess Returns

Results of logit regression combining fitted excess returns (generated from the regression detailed in Table B5) and accounting variables with local and global macro variables to explain the probability of default next month. Column 1 uses specification 5 from Table 3 as a baseline, and Columns 2 & 3 add excess returns fitted on accounting and global variables, respectively. Column 4 uses specification 6 from Table 3 as a baseline, and Columns 5 & 6 add excess returns fitted on accounting and global variables, respectively. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-8.477^{***}	-8.189^{***}	-8.167^{***}	-11.290^{***}	-9.810^{***}	-9.985^{***}
Fitted excess returns (accounting)		-28.810^{***}			-34.059^{***}	
Fitted excess returns (global)			-22.824^{**}			-57.455^{***}
Profitability	-7.345^{***}		-7.101^{***}	-8.351^{***}		-8.350^{***}
Leverage	2.407^{***}		2.505^{***}	3.726^{***}		3.699^{***}
Cash	-3.355^{***}		-3.850^{***}	-5.467^{***}		-5.667^{***}
Market-to-book ratio	0.104^{***}		0.100^{***}	0.058^{***}		0.044^{**}
Prior default	2.437^{***}	3.057^{***}	2.549^{***}	2.079^{***}	2.864^{***}	2.203^{***}
Unemployment rate	-0.018	-0.008	$0.030^{\dagger}$			
Inflation rate	-10.129^{***}	-5.929^{**}	-8.251^{***}			
Real interest rate	-0.041^{***}	-0.028^{***}	-0.060^{***}			
Sovereign spread	0.000	0.005	-0.030^{*}			
ΔFX 12m avg	-17.966^{**}	-19.161^{**}	-14.703^{*}			
Fed funds rate	0.160^{***}	0.233^{***}		0.275^{***}	0.357^{***}	
Yield slope (5y-FF)	0.288^{***}	0.334^{***}		0.522^{***}	0.540^{***}	
Fed MP surprise	$1.179^{\dagger}$	1.076		1.744^{**}	1.482^{*}	
VIX	0.004	0.007		0.015^{***}	0.017^{***}	
TED spread	0.527^{***}	0.538^{***}		$0.181^{\dagger}$	0.193	
ΔBroad US$	-8.077^{**}	-12.098^{***}		-6.177^{*}	-9.248^{**}	
Pseudo-R^2	0.189	0.165	0.188	0.221	0.190	0.227
AUC	0.892	0.837	0.889	0.907	0.844	0.916
Observations	424011	372673	372673	705824	589224	589224
Defaults	593	524	524	681	589	589
Country FE				✓	✓	✓

Table 6: Top Tercile Betas by Global Variable

Results of logit regressions 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 accounting and orthogonalized 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 Mc-Fadden'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.

PANEL A

	(1) Fed funds rate	(2) 5y T-bill	(3) FED MP surprise	(4) VIX	(5) TED spread	(6) ΔBroad US$
Constant	−7.229***	−7.708***	−7.019***	−7.135***	−7.015***	−7.022***
Global variable	0.127***	0.245***	1.239	−0.002	0.236**	−7.084*
Global variable * top-tercile	0.065**	0.082***	−1.474	0.020***	0.234	−4.459
Pseudo-R^2	0.006	0.010	0	0.003	0.001	0.001
Observations	774705	774705	774705	774705	774705	774705
Defaults	692	692	692	692	692	692

PANEL B

	(1) Fed funds rate	(2) 5y T-bill	(3) FED MP surprise	(4) VIX	(5) TED spread	(6) ΔBroad US$
Constant	−9.158***	−9.576***	−8.912***	−8.938***	−8.929***	−8.914***
Excess returns (orth)	−1.092***	−1.081***	−1.124***	−1.114***	−1.073***	−1.110***
Stock price (orth)	−0.315***	−0.326***	−0.289***	−0.288***	−0.291***	−0.290***
Volatility of returns (orth)	0.004	0.001	0.004	0.004	0.005*	0.004
Relative size (orth)	0.227***	0.232***	0.214***	0.210***	0.216***	0.215***
Profitability	−7.248***	−7.225***	−7.196***	−7.167***	−7.194***	−7.186***
Leverage	3.215***	3.208***	3.189***	3.293***	3.226***	3.182***
Cash	−3.352***	−3.340***	−3.470***	−3.704***	−3.446***	−3.463***
Market-to-book ratio	0.253***	0.256***	0.250***	0.246***	0.252***	0.251***
Global variable	0.127***	0.228***	1.828*	−0.011**	0.461***	−10.693**
Global variable * top-tercile	0.066**	0.053*	−2.605	0.028***	−0.058	−0.130
Pseudo-R^2	0.107	0.110	0.102	0.107	0.104	0.103
Observations	586985	586985	586985	586985	586985	586985
Defaults	586	586	586	586	586	586

Table 7: Composite Global Beta Z Score as Predictor of Default

Results of logit regressions of probability of default on a composite global factor. Beta Z and Variable Z are the sum of the standardized global betas and global variables, respectively. We control for accounting, orthogonalized market, and 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 four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$, respectively.

	(1)	(2)	(3)	(4)
Constant	-8.862^{***}	-8.971^{***}	-7.884^{***}	-9.719^{***}
Excess returns (orth)	-1.079^{***}	-1.248^{***}	-1.053^{***}	-1.535^{***}
Stock price (orth)	-0.304^{***}	-0.199^{***}	-0.237^{***}	-0.187^{***}
Volatility of returns (orth)	$0.005^{\dagger}$	0.005	0.001	0.005
Relative size (orth)	0.222^{***}	0.135^{***}	0.165^{***}	0.175^{***}
Profitability	-7.249^{***}	-6.927^{***}	-7.761^{***}	-8.542^{***}
Leverage	3.228^{***}	2.550^{***}	2.369^{***}	3.506^{***}
Cash	-3.359^{***}	-2.138^{***}	-4.028^{***}	-6.257^{***}
Market-to-book ratio	0.250^{***}	0.146^{***}	0.101^{***}	0.057^{***}
Prior default		2.605^{***}	2.474^{***}	2.147^{***}
Unemployment rate			0.014	
Inflation rate			-8.442^{***}	
Real interest rate			-0.054^{***}	
Sovereign spread			-0.023	
ΔFX 12m avg			$-12.788^{\dagger}$	
Beta Z	-0.002	0.007	0.018	0.049^{*}
Global Z	0.111^{***}	0.090^{***}	0.083^{***}	0.057^{***}
Beta Z * Global Z	-0.022^{***}	-0.023^{***}	-0.033^{***}	-0.023^{**}
Pseudo-R^2	0.109	0.191	0.198	0.232
AUC	0.848	0.911	0.901	0.920
Observations	586985	586985	371292	586985
Defaults	586	586	522	586
Country FE				✓

Table 8: Returns on Portfolios Sorted by Distress Risk

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. Panel A shows, for each portfolio, average estimated probability of default, average monthly return for the 12 months following portfolio formation, alpha and selected coefficients from a 6-factor regression, and average relative size and market-to-book ratio. 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 panel A, all factors are computed in January. Panel B shows the average coefficients of 12 monthly regressions of average monthly returns for the 12 months following portfolio formation on the factors computed for each respective month. In Panel C, we run the same regression as in Panel A, but using as our dependent variable the net-income-to-price ratio as a proxy for expected returns.

PANEL A: Single Regressions

Portfolios	1	2	3	4	5	6	7	8	9	10
Mean P(default) (%)	0.0018	0.0038	0.0065	0.0104	0.0164	0.0267	0.0485	0.0897	0.1475	0.9374
Mean 12-month returns	0.0095	0.0098	0.0103	0.0099	0.0077	0.0076	0.0089	0.0114	0.0144	0.0155
6-factor alpha	0.0103	0.0104	0.0109	0.0109	0.0091	0.0093	0.0110	0.0133	0.0162	0.0173
RM	−0.0241	−0.0198	−0.0142	−0.0135	0.0064	0.0192	0.0178	0.0190	0.0125	0.0256
SMB	−0.1381	−0.1343	−0.1011	−0.0843	−0.0477	−0.0250	−0.0254	0.0294	0.0890	0.1080
HML	−0.0336	−0.0301	−0.0260	−0.0457	−0.0681	−0.0916	−0.1188	−0.1309	−0.1186	−0.1204
Relative size	−5.1163	−5.1811	−5.6671	−6.3853	−6.8932	−7.3709	−7.8813	−8.2084	−8.4637	−8.7022
Market-to-book ratio	1.5683	1.5670	1.5473	1.5924	1.6908	1.7108	1.8605	2.3392	2.1260	2.3260

PANEL B: Average of Monthly Regressions

Portfolios	1	2	3	4	5	6	7	8	9	10
6-factor alpha	0.0086	0.0091	0.0097	0.0103	0.0107	0.0109	0.0130	0.0167	0.0208	0.0233
RM	−0.0009	0.0032	0.0169	0.0108	0.0143	0.0361	0.0319	0.0769	0.0963	0.0877
SMB	−0.0471	−0.0510	0.0101	0.0228	0.0744	0.0900	0.0845	0.1417	0.1779	0.1794
HML	0.0640	0.0661	0.0749	0.0350	−0.0011	−0.0368	−0.0470	−0.0571	−0.0568	−0.0775

PANEL C: Single Earnings/Price Ratio Regressions

Portfolios	1	2	3	4	5	6	7	8	9	10
Mean E/P ratio	1.1025	0.0160	−0.3489	−0.0092	−0.5994	0.1857	−0.0370	−0.0166	0.0029	−0.1618
6-factor alpha	0.6805	0.0165	−0.6559	−0.0035	−0.0527	0.2352	−0.0426	−0.0165	−0.0095	−0.1789
RM	−2.6830	−0.0353	3.7722	−0.0924	−24.1165	−2.5768	0.3262	−0.1431	0.0054	−0.0246
SMB	−5.8143	−0.0104	−3.8946	−0.0517	−6.4357	3.8457	0.2573	0.0894	−0.4127	−0.0581
HML	31.8551	0.0031	13.5426	−0.1195	−25.9156	0.1286	−0.1671	0.0286	0.7530	1.7765

Table 9: Returns on Long-Short Portfolios

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 monthly returns for the 12 months following portfolio formation and alphas and selected Fama-French factors from a six-factor regression. The first two columns present the results of a regression using factors computed each January, while the last two show the average coefficients of 12 monthly regressions of average monthly returns for the 12 months following portfolio formation using factors computed for each respective month. ***, **, and *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$, respectively.

	Single Regressions		**Average of Monthly Regressions**	
	(1)	**(2)**	**(3)**	**(4)**
	LS90-10	**LS80-20**	**LS90-10**	**LS80-20**
Mean 12-month returns	0.0055	0.0047	0.0055	0.0047
6-factor alpha	0.0065^{***}	0.0059^{***}	0.0142^{***}	0.0127^{***}
RM	$0.0487^{\dagger}$	0.0400	0.0865	0.0887
SMB	0.2452^{***}	0.2338^{***}	0.2283^{*}	0.2295^{**}
HML	-0.0886^{**}	-0.0895^{**}	-0.1440^{**}	-0.1346^{**}

Table 10: Robustness to Alternative Measures

Results of logit regression using our benchmark specification are shown in column 1. Columns 2 & 3 show results from regressions replacing VIX with Noise Illiq. and On/Off-Run spread, respectively. Columns 4 & 5 show results from regressions replacing Fed funds rate and Yield slope with 5-year and 10-year Treasury bond rate decompositions, respectively. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

		VIX robustness		MP robustness	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Constant	−11.477***	−11.023***	−12.538***	−11.417***	−11.834***
Excess returns (orth)	−1.628***	−1.622***	−1.625***	−1.633***	−1.643***
Stock price (orth)	−0.200***	−0.199***	−0.186***	−0.198***	−0.198***
Volatility of returns (orth)	−0.024	−0.013	−0.025	−0.037	−0.031
Relative size (orth)	0.191***	0.191***	0.179***	0.191***	0.194***
Profitability	−8.831***	−8.706***	−8.774***	−8.906***	−8.836***
Leverage	3.560***	3.524***	3.615***	3.655***	3.643***
Cash	−5.597***	−5.657***	−5.549***	−5.527***	−5.561***
Market-to-book ratio	0.064***	0.064***	0.059***	0.061***	0.061***
Prior default	2.143***	2.136***	2.159***	2.152***	2.154***
VIX	0.020***			0.012*	0.009
Noise Illiq.		0.052***			
On/Off-Run spread			0.716***		
Fed funds rate	0.291***	0.253***	0.474***		
Yield slope (5y-FF)	0.495***	0.429***	0.463***		
5y short rate				0.261***	
5y term premium				0.718***	
10y short rate					0.347***
10y term premium					0.545***
Fed MP surprise	1.191†	1.026	0.231	0.737	0.778
TED spread	0.083	0.084	0.031	0.021	−0.005
ΔBroad US$	−8.376**	−9.950***	−3.910	−6.298*	−5.390
Pseudo-R^2	0.237	0.237	0.241	0.239	0.239
AUC	0.922	0.922	0.922	0.921	0.921
Observations	589224	589224	589224	589224	589224
Defaults	589	589	589	589	589
Country FE	✓	✓	✓	✓	✓

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.
Relative size	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 $1 in order to place that firm's market-to-book ratio in the right-hand side of the distribution (Large positive MB instead of a negative MB).
Fed funds rate	Federal Funds Rate, retrieved from FRED, Federal Reserve Bank of St. Louis.
Yield slope (5y-FF)	The slope of the US yield curve calculated as the difference between the US 5-year Treasury rate and the Fed funds rate.
Fed MP surprise	US monetary policy surprise measured as in Chari et. al (2020) as the daily change in 5-year US Treasury futures on FOMC announcement days.
VIX	CBOE Volatility Index.
TED spread	Component of the TED spread orthogonal to VIX. The TED spread is the spread between 3-month LIBOR RATES and 3-month T-bill rates, often used as a measure of liquidity risk in bond markets. Due to collinearity between VIX and the TED spread, we regress the TED spread on the VIX and keep the residual.
Δ **Broad US$**	Monthly percentage change in the broad dollar index, calculated using trade-weighted averages of exchange rates from a broad basket of US trading partners; quoted as international currency units per dollar.
Noise Illiq.	Measure of illquidity in US Treasury bills, notes, and bonds markets, as calculated in Pan, Hu, and Wang (2013). Computed by aggregating the deviations (RMSE) between market and smooth zero-coupon yield curve model implied yields.
On/Off-Run spread	Difference in yields between 10-year off-the-run and on-the-run Treasury bonds.
5y & 10y short rate	Short rate for 5-year and 10-year Treasury bond yield decomposition from Adrian, Crump, and Moench (2013).
5y & 10y term premium	Term premium for 5-year and 10-year Treasury bond yield decomposition from Adrian, Crump, and Moench (2013).

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.

Online Appendix

In Search of Distress Risk in Emerging Markets

Gonzalo Asis   Anusha Chari   Adam Haas

Figure B1: Example of Receiver Operating Characteristics Curve

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.

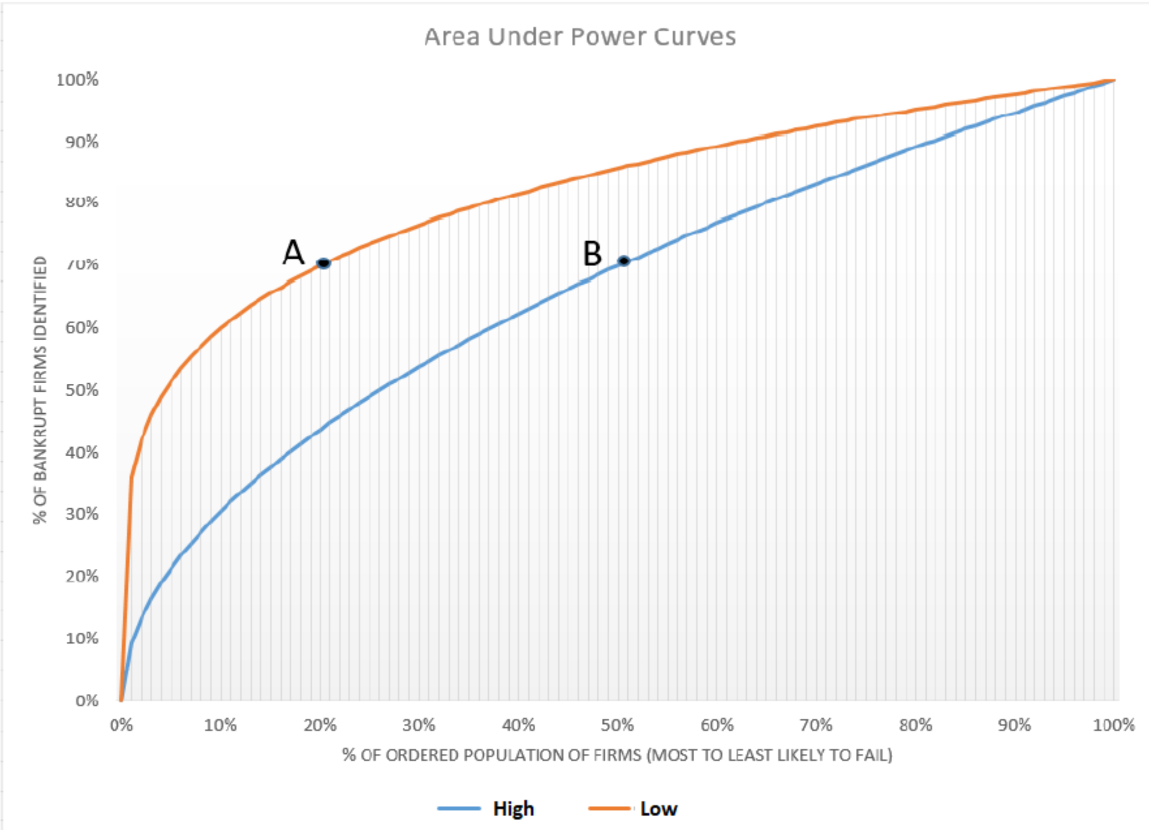

Figure B2: Predicted Probabilites

This figure shows predicted probabilities (in red) for all values of each variable, keeping all other predictors constant at their means. The shaded grey areas are 95% confidence intervals, computed using the 95% confidence intervals of each variable's coefficient in our benchmark logit regression.

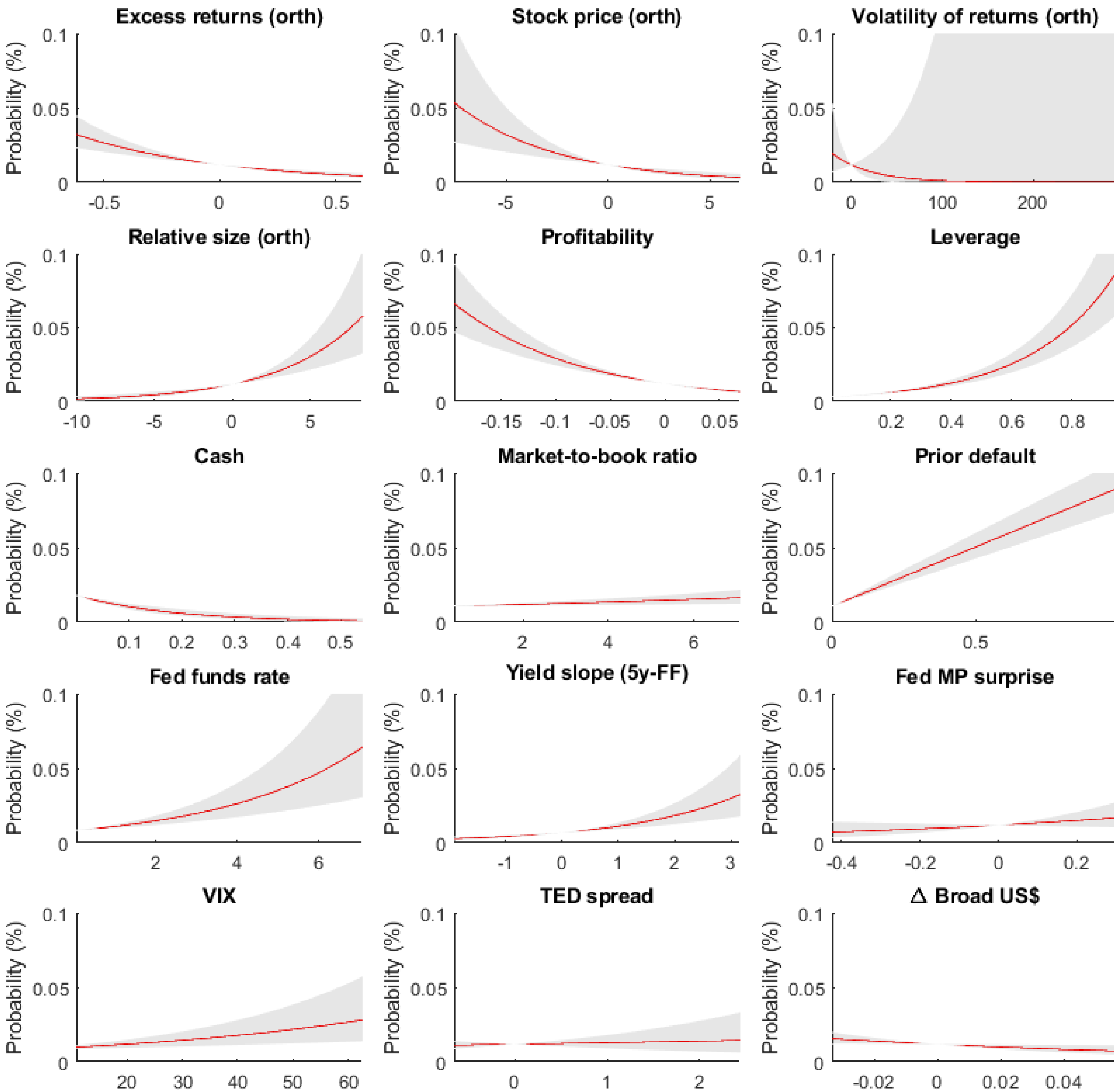

Table B1: Number of Defaults and Observations per Year

This table lists the number of defaults and firm-months per year of our sample, aggregated across countries, for the observations with all data for our benchmark specification.

Year	Firm-Months	Defaults	%
1995	16	.	.
1996	370	.	.
1997	669	.	.
1998	1369	5	0.365
1999	2012	8	0.398
2000	4470	6	0.134
2001	5869	5	0.085
2002	13496	14	0.104
2003	21903	19	0.087
2004	28816	67	0.233
2005	30745	55	0.179
2006	31941	46	0.144
2007	36454	42	0.115
2008	37692	47	0.125
2009	38940	54	0.139
2010	42335	52	0.123
2011	50851	18	0.035
2012	54429	47	0.086
2013	63880	58	0.091
2014	63561	25	0.039
2015	59406	21	0.035
Total	589224	589	0.100

Table B2: Number of Observations per Country and Year

This table lists the number of firm-months with all data for our benchmark specification per country and per year of our sample.

Year	Argentina	Brazil	China	India	Indonesia	Malaysia	Mexico	Philippines	Poland	South Korea	Thailand	Total
1995	.	.	.	.	.	.	.	.	.	.	16	16
1996	.	.	.	.	.	.	123	.	.	.	247	370
1997	27	.	.	.	.	.	225	.	.	.	417	669
1998	42	.	.	.	.	.	255	.	.	.	1072	1369
1999	61	.	.	.	.	173	265	129	.	.	1384	2012
2000	165	373	.	.	33	1817	431	225	57	6	11363	4470
2001	182	457	.	.	308	2270	468	218	301	23	1642	5869
2002	124	493	.	.	454	2469	448	223	402	7077	1806	13496
2003	97	553	4933	27	513	2447	455	235	438	10204	2001	21903
2004	166	609	7720	12	732	4761	507	217	913	11057	2122	28816
2005	304	709	7846	15	869	5556	483	244	1316	11273	2130	30745
2006	359	803	7539	18	948	6099	525	265	1469	11620	2296	31941
2007	422	1188	9682	42	1206	6492	559	320	1732	12341	2470	36454
2008	401	1350	10647	78	1285	5096	521	690	2194	12956	2474	37692
2009	380	1361	11484	105	1329	4872	577	835	2386	13147	2464	38940
2010	376	1444	12991	455	1602	5717	590	912	2571	12892	2785	42335
2011	396	1520	16071	4305	1919	5633	567	1004	2787	13863	2786	50851
2012	311	1441	17919	9626	2079	5536	595	1164	2788	10013	2957	54429
2013	320	1600	18298	12246	2256	5508	610	1124	2814	15942	3162	63880
2014	357	1656	17449	11647	2315	5706	575	1265	2807	16418	3366	63561
2015	371	1545	16958	6791	2341	5472	584	1364	2854	17607	3519	59406
Total	4861	17102	159537	45367	20189	75624	9363	10434	27829	176439	42479	589224

Table B3: Number of Defaults per Country and Year

This table lists the number of defaults per country and per year of our sample.

Year	Argentina	Brazil	China	India	Indonesia	Malaysia	Mexico	Philippines	Poland	South Korea	Thailand	Total
1995	·	·	·	·	·	·	·	·	·	·	·	·
1996	·	·	·	·	·	·	·	·	·	·	·	·
1997	·	·	·	·	·	·	·	·	·	·	·	·
1998	2	·	·	·	·	·	·	·	·	·	3	5
1999	1	·	·	·	·	·	·	3	·	·	4	8
2000	1	·	·	·	·	1	·	1	·	·	3	6
2001	·	·	·	·	1	3	·	·	·	·	1	5
2002	2	1	·	·	1	2	·	4	1	2	1	14
2003	·	1	11	·	1	·	2	2	·	1	1	19
2004	·	·	63	·	·	1	·	2	·	·	1	67
2005	·	1	51	·	·	2	·	·	·	1	·	55
2006	·	·	40	·	·	5	·	·	·	1	·	46
2007	·	·	35	·	·	6	·	·	·	·	1	42
2008	·	·	29	·	·	10	1	1	·	5	1	47
2009	·	·	36	·	2	3	3	2	1	2	5	54
2010	·	·	26	1	1	18	1	·	·	4	1	52
2011	·	·	4	2	1	8	·	·	·	3	·	18
2012	·	3	12	24	·	2	1	·	5	·	·	47
2013	·	7	9	29	·	3	2	·	1	7	·	58
2014	·	4	1	13	1	1	·	·	·	5	·	25
2015	·	·	2	12	·	·	2	·	3	1	1	21
Total	6	17	319	81	8	65	12	15	11	32	23	589

Table B4: Correlation Matrix and Multicollinearity Analysis

The last two rows of this table show the Tolerance Value (TOL) and its reciprocal Variance Inflation Factor (VIF). VIF is computed as $1/(1-R_k^2)$, where R_k^2 is the R^2 value of a regression of variable 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.

Var1	EXRET	PRICE	VOL	RELSIZE	NIMTA	TLMTA	CASH	MB	UR	Inflation	RIR	SovSpread	ΔFX	ΔBDI	Fed funds	Yield slope	MP surprise	VIX	TED spread
EXRET	1.000																		
PRICE	0.025	1.000																	
VOL	0.002	0.057	1.000																
RELSIZE	0.022	0.589	0.037	1.000															
NIMTA	0.048	0.098	0.007	0.108	1.000														
TLMTA	−0.067	−0.139	−0.024	−0.155	−0.142	1.000													
CASH	−0.023	−0.188	−0.033	−0.120	0.093	−0.062	1.000												
MB	0.065	0.165	0.052	0.124	−0.091	−0.466	−0.272	1.000											
UR	0.010	0.211	0.075	0.351	−0.006	0.002	−0.132	0.084	1.000										
Inflation	−0.024	0.234	0.039	0.090	0.007	0.139	−0.134	0.003	0.217	1.000									
RIR	0.010	0.037	0.065	0.074	−0.011	0.110	−0.110	−0.006	0.333	0.114	1.000								
SovSpread	−0.016	0.143	0.033	−0.086	−0.009	0.165	−0.142	−0.035	0.193	0.532	0.151	1.000							
ΔFX	−0.002	−0.004	0.001	0.045	0.025	−0.122	0.044	0.045	−0.016	−0.240	−0.151	−0.382	1.000						
ΔBDI	0.008	−0.024	0.000	−0.011	−0.003	−0.027	0.002	0.025	−0.012	0.059	0.018	0.020	−0.047	1.000					
Fed funds	−0.009	−0.083	0.003	0.119	0.017	0.081	−0.046	−0.078	0.094	−0.004	−0.031	−0.176	0.224	−0.102	1.000				
Yield slope	−0.009	0.125	−0.008	0.041	−0.012	−0.008	0.004	−0.005	−0.024	−0.125	0.033	0.025	−0.089	0.046	−0.678	1.000			
MP surprise	−0.010	0.017	0.002	−0.006	−0.006	−0.019	−0.002	0.021	−0.010	0.012	−0.040	−0.028	0.071	0.077	0.026	−0.089	1.000		
VIX	0.019	0.034	−0.010	0.090	0.010	0.032	0.019	−0.036	0.018	0.023	0.007	0.042	0.043	−0.018	−0.120	0.163	−0.190	1.000	
TED spread	−0.016	−0.140	0.001	−0.004	0.022	−0.017	−0.010	0.029	0.046	0.180	−0.077	−0.043	0.119	0.123	0.477	−0.464	0.031	0.062	1.000
TOL	0.989	0.548	0.988	0.519	0.929	0.667	0.829	0.659	0.722	0.612	0.844	0.577	0.783	0.939	0.411	0.467	0.942	0.888	0.634
VIF	1.011	1.824	1.012	1.928	1.077	1.498	1.207	1.519	1.385	1.635	1.185	1.734	1.277	1.065	2.430	2.140	1.061	1.127	1.578

Table B5: OLS Regression of Market Variables

This table shows OLS regression results of excess returns, stock price, volatility of returns, and relative size on various subsets of our accounting and global covariates. Panel A uses as explanatory variables the set of accounting variables, excluding market-to-book ratios for columns 2 & 4 due to collinearity between stock price and relative size, and market-to-book ratio. Panel B utilizes global variables, and Panel C uses both sets of covariates as explanatory variables.

	Panel A: Accounting variables				**Panel B: Global variables**				**Panel C: Accounting & Global variables**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Returns	**Price**	**Volatility**	**Size**	**Returns**	**Price**	**Volatility**	**Size**	**Returns**	**Price**	**Volatility**	**Size**
Constant	−0.000	2.241***	3.667***	−5.014***	0.008***	1.552***	6.514***	−6.479***	0.006***	2.517***	10.815***	−5.669***
Profitability	0.334***	10.358***	7.955***	9.338***					0.337***	10.399***	9.087***	9.212***
Leverage	−0.020***	−1.783***	−4.264***	−1.460***					−0.020***	−1.755***	−3.534***	−1.522***
Cash	−0.035***	−1.143***	−3.200***	−1.901***					−0.038***	−1.160***	−3.721***	−1.769***
Market-to-book ratio	0.004***		0.047*						0.004***		0.021	
Fed funds rate					−0.002***	−0.037***	−0.826***	0.125***	−0.002***	−0.047***	−1.495***	0.172***
Yield slope (5y-FF)					−0.002***	−0.114***	−1.464***	0.152***	−0.007***	−0.102***	−2.546***	0.215***
Fed MP surprise					−0.020***	0.015	3.398***	0.212***	−0.006*	0.035	8.898***	0.131***
VIX					−0.000***	−0.006***	−0.088***	0.006***	0.000***	−0.005***	−0.110***	0.008***
TED spread					−0.005***	0.193***	3.463***	0.097***	−0.014***	0.032***	4.610***	−0.120***
ΔBroad US$					0.186***	2.362***	−14.323***	4.079***	0.198***	1.672***	−33.132***	4.010***
R^2	0.011	0.860	0.537	0.780	0.002	0.752	0.429	0.742	0.013	0.861	0.540	0.784
Observations	671762	671768	671762	671768	1637846	1637846	1637846	1637846	671762	671768	671762	671768

Table B6: Transmission of Global Shocks and Firm Fundamentals through Stock Price

Results of logit regression combining fitted stock price (generated from the regression detailed in Table B5) and accounting variables with local and global macro variables to explain the probability of default next month. Column 1 uses specification 5 from Table 3 as a baseline, and Columns 2 & 3 add stock price fitted on accounting and global variables, respectively. Column 4 uses specification 6 from Table 3 as a baseline, and Columns 5 & 6 add stock price fitted on accounting and global variables, respectively. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−8.477***	−7.761***	−7.911***	−11.290***	−7.909***	−8.595***
Fitted stock price (accounting)		−0.248***			−1.225***	
Fitted stock price (global)			−0.098***			−0.990***
Profitability	−7.345***		−7.194***	−8.351***		−8.218***
Leverage	2.407***		2.566***	3.726***		3.795***
Cash	−3.355***		−4.213***	−5.467***		−6.296***
Market-to-book ratio	0.104***		0.098***	0.058***		0.045**
Prior default	2.437***	3.089***	2.515***	2.079***	2.527***	2.207***
Unemployment rate	−0.018	−0.033	0.030†			
Inflation rate	−10.129***	2.698	−4.653*			
Real interest rate	−0.041***	−0.011	−0.053***			
Sovereign spread	0.000	0.005	−0.037**			
ΔFX 12m avg	−17.966**	−17.453**	−8.706			
Fed funds rate	0.160***	0.247***		0.275***	0.305***	
Yield slope (5y-FF)	0.288***	0.394***		0.522***	0.507***	
Fed MP surprise	1.179†	1.289†		1.744**	1.473*	
VIX	0.004	0.007		0.015***	0.014***	
TED spread	0.527***	0.282*		0.181†	0.288**	
ΔBroad US$	−8.077**	−11.687***		−6.177*	−9.949***	
Pseudo-R^2	0.189	0.157	0.189	0.221	0.214	0.223
AUC	0.892	0.831	0.891	0.907	0.900	0.915
Observations	424011	372673	372673	705824	589224	589224
Defaults	593	524	524	681	589	589
Country FE				✓	✓	✓

Table B7: Transmission of Global Shocks and Firm Fundamentals through Volatility of Returns

Results of logit regression combining volatility of returns (generated from the regression detailed in Table B5) and accounting variables with local and global macro variables to explain the probability of default next month. Column 1 uses specification 5 from Table 3 as a baseline, and Columns 2 & 3 add volatility of returns fitted on accounting and global variables, respectively. Column 4 uses specification 6 from Table 3 as a baseline, and Columns 5 & 6 add volatility of returns fitted on accounting and global variables, respectively. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-8.477^{***}	-7.914^{***}	-8.139^{***}	-11.290^{***}	-8.561^{***}	-9.683^{***}
Fitted volatility of returns (accounting)		-0.322^{***}			-0.716^{***}	
Fitted volatility of returns (global)			-0.073^{***}			-0.078^{***}
Profitability	-7.345^{***}		-6.973^{***}	-8.351^{***}		-8.164^{***}
Leverage	2.407^{***}		2.684^{***}	3.726^{***}		3.774^{***}
Cash	-3.355^{***}		-4.134^{***}	-5.467^{***}		-6.224^{***}
Market-to-book ratio	0.104^{***}		0.095^{***}	0.058^{***}		0.045^{**}
Prior default	2.437^{***}	2.966^{***}	2.527^{***}	2.079^{***}	2.666^{***}	2.207^{***}
Unemployment rate	-0.018	0.006	0.043^{**}			
Inflation rate	-10.129^{***}	0.572	-4.948^{**}			
Real interest rate	-0.041^{***}	0.002	-0.056^{***}			
Sovereign spread	0.000	0.010	-0.033^{**}			
ΔFX 12m avg	-17.966^{**}	-16.988^{**}	-11.684			
Fed funds rate	0.160^{***}	0.211^{***}		0.275^{***}	0.314^{***}	
Yield slope (5y-FF)	0.288^{***}	0.324^{***}		0.522^{***}	0.493^{***}	
Fed MP surprise	$1.179^{\dagger}$	1.130		1.744^{**}	1.644^{**}	
VIX	0.004	0.004		0.015^{***}	0.016^{***}	
TED spread	0.527^{***}	0.440^{***}		$0.181^{\dagger}$	$0.202^{\dagger}$	
ΔBroad US$	-8.077^{**}	-11.774^{***}		-6.177^{*}	-9.686^{***}	
Pseudo-R^2	0.189	0.161	0.189	0.221	0.209	0.223
AUC	0.892	0.833	0.893	0.907	0.894	0.915
Observations	424011	372673	372673	705824	589224	589224
Defaults	593	524	524	681	589	589
Country FE				✓	✓	✓

Table B8: Transmission of Global Shocks and Firm Fundamentals through Relative Size

Results of logit regression combining relative size returns (generated from the regression detailed in Table B5) and accounting variables with local and global macro variables to explain the probability of default next month. Column 1 uses specification 5 from Table 3 as a baseline, and Columns 2 & 3 add relative size fitted on accounting and global variables, respectively. Column 4 uses specification 6 from Table 3 as a baseline, and Columns 5 & 6 add relative size fitted on accounting and global variables, respectively. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−8.477***	−14.806***	−9.983***	−11.290***	−17.164***	−0.788
Fitted relative size (accounting)		−0.629***			−1.306***	
Fitted relative size (global)			−0.213***			1.509***
Profitability	−7.345***		−7.258***	−8.351***		−8.230***
Leverage	2.407***		2.645***	3.726***		3.637***
Cash	−3.355***		−4.330***	−5.467***		−5.576***
Market-to-book ratio	0.104***		0.080***	0.058***		0.046**
Prior default	2.437***	3.002***	2.549***	2.079***	2.626***	2.197***
Unemployment rate	−0.018	0.115***	0.085***			
Inflation rate	−10.129***	2.724	−1.620			
Real interest rate	−0.041***	−0.018*	−0.054***			
Sovereign spread	0.000	−0.106***	−0.162***			
ΔFX 12m avg	−17.966**	−31.431***	−15.057*			
Fed funds rate	0.160***	0.393***		0.275***	0.323***	
Yield slope (5y-FF)	0.288***	0.552***		0.522***	0.521***	
Fed MP surprise	1.179†	1.654**		1.744**	1.498*	
VIX	0.004	0.025***		0.015***	0.015***	
TED spread	0.527***	0.188		0.181†	0.268**	
ΔBroad US$	−8.077**	−9.579**		−6.177*	−9.767***	
Pseudo-R^2	0.189	0.183	0.194	0.221	0.208	0.226
AUC	0.892	0.848	0.885	0.907	0.891	0.916
Observations	424011	372673	372673	705824	589224	589224
Defaults	593	524	524	681	589	589
Country FE				✓	✓	✓

Table B9: Returns on Portfolios Sorted by Distress Risk (1 month ahead returns)

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. Panel A shows, for each portfolio, average estimated probability of default, average monthly return for the 12 months following portfolio formation, alpha and selected coefficients from a 6-factor regression, and average relative size and market-to-book ratio. 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 panel A, all factors are computed in January. Panel B shows the average coefficients of 12 monthly regressions of 1 month ahead returns on the factors computed for each respective month. In Panel C, we run the same regression as in Panel A, but using as our dependent variable the net-income-to-price ratio as a proxy for expected returns.

PANEL A: Single Regressions

Portfolios	1	2	3	4	5	6	7	8	9	10
Mean P(default) (%)	0.0018	0.0038	0.0065	0.0104	0.0164	0.0267	0.0485	0.0897	0.1475	0.9374
Mean 12-month returns	0.0095	0.0098	0.0103	0.0099	0.0077	0.0076	0.0089	0.0114	0.0144	0.0155
6-factor alpha	0.0103	0.0104	0.0109	0.0109	0.0091	0.0093	0.0110	0.0133	0.0162	0.0173
RM	−0.0241	−0.0198	−0.0142	−0.0135	0.0064	0.0192	0.0178	0.0190	0.0125	0.0256
SMB	−0.1381	−0.1343	−0.1011	−0.0843	−0.0477	−0.0250	−0.0254	0.0294	0.0890	0.1080
HML	−0.0336	−0.0301	−0.0260	−0.0457	−0.0681	−0.0916	−0.1188	−0.1309	−0.1186	−0.1204
Relative size	−5.1163	−5.1811	−5.6671	−6.3853	−6.8932	−7.3709	−7.8813	−8.2084	−8.4637	−8.7022
Market-to-book ratio	1.5683	1.5670	1.5473	1.5924	1.6908	1.7108	1.8605	2.3392	2.1260	2.3260

PANEL B: Average of Monthly Regressions (1 month ahead returns)

Portfolios	1	2	3	4	5	6	7	8	9	10
6-factor alpha	0.0250	0.0221	0.0253	0.0224	0.0212	0.0252	0.0298	0.0358	0.0357	0.0388
RM	0.1699	0.1817	0.1936	0.2434	0.2252	0.2804	0.2633	0.2942	0.2616	0.2043
SMB	−0.9104	−0.8656	−0.7722	−0.6067	−0.4383	−0.3838	−0.2795	−0.1210	0.0563	0.1748
HML	−0.4291	−0.4186	−0.3965	−0.4432	−0.5197	−0.8513	−0.9997	−1.3489	−1.2799	−1.1835

PANEL C: Single Earnings/Price Ratio Regressions

Portfolios	1	2	3	4	5	6	7	8	9	10
Mean E/P ratio	1.1025	0.0160	−0.3489	−0.0092	−0.5994	0.1857	−0.0370	−0.0166	0.0029	−0.1618
6-factor alpha	0.6805	0.0165	−0.6559	−0.0035	−0.0527	0.2352	−0.0426	−0.0165	−0.0095	−0.1789
RM	−2.6830	−0.0353	3.7722	−0.0924	−24.1165	−2.5768	0.3262	−0.1431	0.0054	−0.0246
SMB	−5.8143	−0.0104	−3.8946	−0.0517	−6.4357	3.8457	0.2573	0.0894	−0.4127	−0.0581
HML	31.8551	0.0031	13.5426	−0.1195	−25.9156	0.1286	−0.1671	0.0286	0.7530	1.7765

Table B10: Returns on Long-Short Portfolios (1 month ahead returns)

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 monthly returns for the 12 months following portfolio formation and alphas and selected Fama-French factors from a six-factor regression. The first two columns present the results of a regression using factors computed each January, while the last two show the average coefficients of 12 monthly regressions of 1 month ahead returns using factors computed for each respective month. ***, **, and *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$, respectively.

	Single Regressions		**Average of Monthly Regressions (1 month ahead returns)**	
	(1)	**(2)**	**(3)**	**(4)**
	LS90-10	**LS80-20**	**LS90-10**	**LS80-20**
Mean returns	0.0055	0.0047	0.0034	0.0047
6-factor alpha	0.0065***	0.0059***	0.0133**	0.0127***
RM	0.0487†	0.0400	0.0323	0.0887
SMB	0.2452***	0.2338***	1.0870***	0.2295**
HML	−0.0886**	−0.0895**	−0.7568***	−0.1346**

Table B11: Logit Regressions of Probability of Default Next Month, Balanced Sample

Results of balanced sample logit regression combining accounting and orthogonalized market variables with local and global macro variables to explain the probability of default next month. Column 1 uses firm accounting variables as covariates. 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 incorporates country fixed effects to the model in Column 4. Columns 7 & 8 add orthogonalized firm market variables the specifications in columns 5 & 6. The dependent variable in all specifications is binary, indicating whether a firm experienced a distress event the following month. Pseudo-R^2 refers to Mc-Fadden's Pseudo-R^2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	−8.074***	−8.356***	−8.057***	−9.102***	−8.609***	−11.206***	−8.667***	−11.545***
Excess returns (orth)							−1.119***	−1.374***
Stock price (orth)							−0.259***	−0.174***
Volatility of returns (orth)							−0.001	−0.019
Relative size (orth)							0.175***	0.161***
Profitability	−9.325***	−7.465***	−7.124***	−7.627***	−7.406***	−7.637***	−8.259***	−8.375***
Leverage	2.771***	2.262***	2.601***	2.272***	2.476***	3.305***	2.407***	3.229***
Cash	−4.799***	−3.231***	−4.082***	−2.947***	−3.638***	−5.511***	−3.781***	−5.613***
Market-to-book ratio	0.197***	0.087***	0.097***	0.088***	0.098***	0.026	0.108***	0.042*
Prior default		2.642***	2.524***	2.626***	2.530***	2.328***	2.463***	2.300***
Unemployment rate			0.034†		0.008		0.003	
Inflation rate			−7.648***		−7.740***		−8.065***	
Real interest rate			−0.063***		−0.046***		−0.045***	
Sovereign spread			−0.033*		−0.015		−0.019	
ΔFX 12m avg			−11.550		−18.523**		−17.338**	
Fed funds rate				0.183***	0.147***	0.298***	0.156***	0.321***
Yield slope (5y-FF)				0.313***	0.259***	0.492***	0.261***	0.509***
Fed MP surprise				1.118	1.037	1.530*	0.945	1.290†
VIX				0.005	0.005	0.016***	0.009†	0.022***
TED spread				0.564***	0.591***	0.223†	0.558***	0.100
ΔBroad US$				−12.149***	−11.118***	−11.424***	−11.327***	−10.594***
Pseudo-R^2	0.089	0.180	0.187	0.189	0.194	0.219	0.201	0.225
AUC	0.839	0.904	0.889	0.904	0.896	0.910	0.903	0.913
Observations	372673	372673	372673	372673	372673	372673	372673	372673
Defaults	524	524	524	524	524	524	524	524
Country FE						✓		✓

Table B12: Top Tercile Betas by Global Variable, Balanced Sample

Results of balanced sample logit regressions 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 accounting and orthogonalized 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 Mc-Fadden'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.

PANEL A

	(1) Fed funds rate	(2) 5y T-bill	(3) FED MP surprise	(4) VIX	(5) TED spread	(6) ΔBroad US$
Constant	−7.229***	−7.708***	−7.019***	−7.135***	−7.015***	−7.022***
Global variable	0.127***	0.245***	1.239	−0.002	0.236**	−7.084*
Global variable * top-tercile	0.065**	0.082***	−1.474	0.020***	0.234	−4.459
Pseudo-R^2	0.006	0.010		0.003	0.001	0.001
Observations	774705	774705	774705	774705	774705	774705
Defaults	692	692	692	692	692	692

PANEL B

	(1) Fed funds rate	(2) 5y T-bill	(3) FED MP surprise	(4) VIX	(5) TED spread	(6) ΔBroad US$
Constant	−9.158***	−9.576***	−8.912***	−8.938***	−8.929***	−8.914***
Excess returns (orth)	−1.092***	−1.081***	−1.124***	−1.114***	−1.073***	−1.110***
Stock price (orth)	−0.315***	−0.326***	−0.289***	−0.288***	−0.291***	−0.290***
Volatility of returns (orth)	0.004	0.001	0.004	0.004	0.005*	0.004
Relative size (orth)	0.227***	0.232***	0.214***	0.210***	0.216***	0.215***
Profitability	−7.248***	−7.225***	−7.196***	−7.167***	−7.194***	−7.186***
Leverage	3.215***	3.208***	3.189***	3.293***	3.226***	3.182***
Cash	−3.352***	−3.340***	−3.470***	−3.704***	−3.446***	−3.463***
Market-to-book ratio	0.253***	0.256***	0.250***	0.246***	0.252***	0.251***
Global variable	0.127***	0.228***	1.828*	−0.011**	0.461***	−10.693**
Global variable * top-tercile	0.066**	0.053*	−2.605	0.028***	−0.058	−0.130
Pseudo-R^2	0.107	0.110	0.102	0.107	0.104	0.103
Observations	586985	586985	586985	586985	586985	586985
Defaults	586	586	586	586	586	586

Table B13: Composite Global Beta Z Score as Predictor of Default, Balanced Sample

Results of balanced sample logit regressions of probability of default on a composite global factor. Beta Z and Variable Z are the sum of the standardized global betas and global variables, respectively. We control for accounting, orthogonalized market, and 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 four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$, respectively.

	(1)	**(2)**	**(3)**	**(4)**
Constant	-8.009^{***}	-8.268^{***}	-7.884^{***}	-9.647^{***}
Excess returns (orth)	-1.035^{***}	-1.076^{***}	-1.053^{***}	-1.261^{***}
Stock price (orth)	-0.314^{***}	-0.220^{***}	-0.237^{***}	-0.160^{***}
Volatility of returns (orth)	0.004	0.004	0.001	0.005
Relative size (orth)	0.207^{***}	0.144^{***}	0.165^{***}	0.145^{***}
Profitability	-9.999^{***}	-8.033^{***}	-7.761^{***}	-8.108^{***}
Leverage	2.680^{***}	2.116^{***}	2.369^{***}	3.198^{***}
Cash	-4.937^{***}	-3.118^{***}	-4.028^{***}	-6.390^{***}
Market-to-book ratio	0.198^{***}	0.090^{***}	0.101^{***}	$0.036^{\dagger}$
Prior default		2.572^{***}	2.474^{***}	2.297^{***}
Unemployment rate			0.014	
Inflation rate			-8.442^{***}	
Real interest rate			-0.054^{***}	
Sovereign spread			-0.023	
ΔFX 12m avg			$-12.788^{\dagger}$	
Beta Z	-0.015	0.001	0.018	0.067^{**}
Global Z	0.128^{***}	0.104^{***}	0.083^{***}	0.072^{***}
Beta Z * Global Z	-0.028^{***}	-0.030^{***}	-0.033^{***}	-0.029^{***}
Pseudo-R^2	0.107	0.192	0.198	0.220
AUC	0.848	0.909	0.901	0.914
Observations	371292	371292	371292	371292
Defaults	522	522	522	522
Country FE				✓