Sovereign Credit Risk, Financial Fragility, and Global Factors

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Abstract

This study explores the relationship between sovereign credit risk, financial fragility, and global factors in emerging market economies, by using a novel model-based semi-parametric metric (JLoss) that computes the expected joint loss of the banking sector conditional on a systemic event. Our metric of financial fragility is positively associated with sovereign bond spreads and negatively associated with higher sovereign credit ratings, after controlling for the standard determinants of sovereign credit risk. The results additionally indicate that countries with more fragile banking sectors are more exposed to global (exogenous) financial factors than those with more resilient banking sectors. These findings underscore that regulators must ensure the stability of the banking sector to improve governments' borrowing costs in international debt markets.

JEL Codes: E43, E44, F30, G12, G15.

Keywords: banks, credit ratings, credit risk, emerging economies, global factors.

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1 Motivation

The global financial crisis of 2008-09 and the European debt crisis, which were characterized by large losses in the banking sector, affected international debt markets severely. They produced a significant deterioration of sovereign credit spreads and ratings with the greater expectation of public support for distressed banks (Mody and Sandri, 2012). Despite a rich body of research on the drivers of sovereign credit risk, a better understanding of the factors influencing sovereign risk and of how these factors can be properly measured in both advanced and emerging economies is of key importance for several reasons. Sovereign credit risk is not only a key determinant of governments' borrowing costs, but also remains a significant determinant of the cost of debt capital for the private sector (Cavallo and Valenzuela, 2010; Borensztein, Cowan, and Valenzuela, 2013). Moreover, sovereign credit risk directly influences the ability of investors to diversify the risk of global debt portfolios and plays a crucial role in determining capital flows across countries (Longstaff et al., 2011).

The literature has recently emphasized that the primary factors that affect sovereign credit risk are macroeconomic fundamentals, global factors, and financial fragility, which have generally been treated as independent determinants of sovereign credit risk. Although macroeconomic fundamentals have substantial explanatory power for sovereign credit spreads in emerging economies (Hilscher and Nosbusch, 2010), sovereign credit risk appears to be mainly driven by global financial factors (González-Rosada and Yeyati, 2008; Longstaff et al., 2011). Financial fragility also seems to influence governments' indebtedness and credit risk. Greater banking-sector fragility predicts larger bank bailouts, larger public debt, and higher sovereign credit risk (Acharya, Drechsler, and Schnabl, 2014; Kallestrup, Lando, and Murgoci, 2016; Farhi and Tirole, 2018). This relationship between bank risk and sovereign risk is particularly strong during periods of financial distress (Fratzscher and Rieth, 2019). Finally, recent empirical evidence also suggests systemic sovereign risk has its roots in financial markets rather than in macroeconomic fundamentals (Dieckmann and Plank, 2012; Ang and Longstaff, 2013). Specifically, Dieckmann and Plank (2012) show the state of the domestic financial market and the state of the global financial system have strong explanatory power for the evolution of sovereign spreads, and that the magnitude of the effect is shaped by the importance of the domestic financial system pre-crisis.

Using a novel model-based semi-parametric metric (JLoss) that computes the expected joint loss of the banking sector in the event of a large financial meltdown, in this study, we explore the relationship between sovereign credit risk, financial fragility, and global financial factors. We study this relationship in a panel data set that covers 19 emerging market economies from 1999:Q1 to 2017:Q3. Consistent with the idea that our metric (JLoss) can be understood as the direct cost of bailing out the whole banking sector, and with recent evidence that shows sovereign spreads increased in the eurozone with the greater expectation of public support for distressed banks (Mody and Sandri, 2012), our results indicate our metric of financial fragility is positively associated with sovereign credit spreads and negatively associated with higher sovereign credit ratings. The results additionally indicate countries with more fragile banking sectors are more exposed to the influence of global (exogenous) financial factors related to market volatility, risk-free interest rates, risk premiums, and aggregate illiquidity. Our results are statistically significant and economically meaningful, even after controlling for country and time fixed effects, the standard determinants of sovereign credit risk, and systemic banking crises. These findings underscore that the stability of the domestic banking sector plays a crucial role in reducing sovereign risk and its exposure to global factors.

This study contributes to the literature in at least three ways. First, it introduces a new measure of financial fragility in the banking sector (JLoss) that reflects the expected joint loss of the domestic banking sector in the event of a large financial meltdown. The calculation of our JLoss metric employs a saddle-point methodology in which the distribution of potential losses in the banking system is a function of the bank-specific probabilities of default, the exposure in case of default, a loss given default (LGD) parameter, and the correlation between the banks' stock market returns and the stock market index returns of each country. Recent academic studies have introduced measures of systemic risk (e.g., see Brownlees and Engle (2016) for a measure of systemic risk for the U.S.). However, given that our metric of the expected joint loss of the domestic banking sector can be interpreted as the direct cost of bailing banks out from a crisis, it should be a particularly significant factor to consider in the pricing of sovereign bonds.

Second, this study explores the relationship between sovereign credit risk and financial fragility in a sample of emerging economies. Thus, this study is a departure from recent studies that have focused their analysis on samples of European countries during the Eurozone sovereign and banking crises. Mody and Sandri (2012) argue that sovereign credit spreads increased in the eurozone with the greater expectation of public support for distressed banks and that this effect was stronger in countries with lower growth prospects and higher debt burdens. Fratzscher and Rieth (2019) show the correlation between CDS spreads of European banks and sovereigns rose from 0.1 in 2007 to 0.8 in 2013, and attribute this higher correlation to a two-way causality between bank credit risk and sovereign credit risk. Although the study of sovereign credit risk in emerging economies has received much attention (Boehmer and Megginson, 1990; Edwards, 1986; Hilscher and Nosbusch, 2010; Longstaff et al., 2011), new research on the relationship between banking fragility and sovereign credit risk in emerging economies has been sparse.

Third, this study takes an additional step beyond the extant literature by exploring a channel (i.e., the fragility of the banking sector) that amplifies the effect of global (exogenous) factors on sovereign credit risk. Although global factors have recently been viewed as push factors in the literature, they have usually been modeled as having homogeneous effects on sovereign credit risk (see, e.g., González-Rosada and Yeyati, 2008). Our analysis suggests that regulations and policies aimed at improving the stability of the domestic banking sector may be helpful in reducing the exposure to global factors, which have become increasingly important in a more financially integrated world.

The remainder of the article is organized as follows. Section 2 presents the JLoss methodology utilized to construct a financial fragility measure. Section 3 describes the sample and variables used in this study. Section 4 presents our empirical strategy and reports the main results. Section 5 conducts a set of robustness checks. Finally, section 6 concludes.

2 Joint Loss (JLoss) Measure

To study the relationship between financial fragility and sovereign credit risk, in this work we construct a novel country-level metric of financial fragility (JLoss). JLoss is a model-based semi-parametric metric of the joint loss of the banking sector conditional on a systemic event. Figure 1 presents an overview of the JLoss methodology.

To calculate our JLoss metric, we first employ a saddle-point methodology that allows us to calculate the aggregated distribution of losses. In this approach the distribution of potential losses in the banking system is a function of the banks' probabilities and exposure at default, a loss given default (LGD) parameter, and the correlation between banks' stock market returns and a systemic component. The individual probabilities of default are calculated following a modification of the Merton's (1974) model. The exposure is proxied by the amount of liabilities of the banks at the moment of default. The LGD for banking debt is set to a 45%, as suggested by the Bank of International Settlements (BIS, 2006). The key assumption in our approach is that bank risks are uncorrelated, conditional on being correlated with a systemic factor, which in our case is the overall stock market performance of each country. With the distribution of potential losses in the banking system, we calculate each bank's marginal contribution to the total risk. Finally, we normalize these contributions to the total risk with respect to total liabilities.

Next, we describe in detail the calculation of the banks' default probabilities and the aggregation of losses with the saddle-point method.

2.1 Individual Probabilities: Distance-to-Default

To calculate default probabilities for each bank, we employ Kealhofer's (2000) approach. This approach is a standard modification of the structural credit risk model introduced by Merton (1974). Table A.1 in the appendix reports the number of banks used in our analyses by country.

Our measurement approach merges together information on banks' balance sheet and market prices: long and short term liabilities (L_{ST}, L_{LT}), short term assets (A_{ST}), average interest rates (r), time horizon (T), volatility of bank realized returns (σ_V), and market capitalization (E). With this data we construct the default point (D^*), which we formally define as

$$D^* = L_{ST} + \frac{1}{2} L_{LT}.$$

Then we numerically solve the following system of two non-linear equations, by using the Newton-Raphson algorithm (Press et al., 2007), to project banks' value of assets ($\hat{V}$) and implied asset volatility ($\hat{\sigma_A}$):

$$\frac{V}{E}\Phi(d_1) - \frac{e^{-rT}\Phi(d_2)}{E/D^*} - 1 = 0$$
$$\Phi(d_1)\frac{V}{E}\sigma_A - \sigma_E = 0.$$

Where $d_1 = \log\left(V\frac{E}{D^*}\right) + \frac{\frac{1}{2}\sigma_E^2 T}{\sigma_E\sqrt{T}}$ and $d_2 = d_1 - \sigma_E\sqrt{T}$. Φ stands for the cumulative normal distribution function. [1]

Once we get the projected values $\hat{V}$ and $\hat{\sigma_A}$, we insert them into the following distance to default DD equation:

$$DD = \frac{\frac{\hat{V}}{E} - D^*}{\frac{\hat{V}}{E}\hat{\sigma_A}}.$$

This equation is a function of the predicted value of the banks' assets ($\hat{V}$) and asset volatility ($\hat{\sigma_A}$). Finally, we assume normality to obtain the expected default frequency (EDF) as

$$EDF = \Phi(-DD).$$

We compute this quantity for all banks in every country and time periods of our sample, and associate the expected default frequency value to the *unconditional* probability of default (p_{def_i}), which is one of the inputs for the saddle-point method.

[1] We use the realized variance approach to estimate the quarterly equity volatility. Following Barndorff-Nielsen et al. (2002), we compute square root of the sum of squared daily equity returns over a quarter. That is, for every quarter and bank, we calculate $\sigma_E = \sqrt{\sum_{t=1}^{Q} r_t^2}$, where Q is the number of days in a particular quarter.

2.2 Saddle-Point Method and Implementation

The saddle-point method allows us to simplify the calculations of the aggregate distribution of losses by working in a different space. We move from the real numbers space ($\mathbb{R}$) to the moment generating function space (MGF). Then, we apply a transform to come back to the real numbers space. The saddle-point method allows to calculate the distribution of a random variable P that represents the aggregate losses for a portfolio of N banks. Formally, we define P as

$$P = \sum_{i=1}^{N} e_i \mathbb{1}_{D_i},$$

where e_i is the exposure of bank i, and $\mathbb{1}_{D_i}$ is the indicator function that takes a value of zero if banks have repayment capacity and it is equal to one otherwise.

We need a workable description of the problem in the space of a MGF. To determine the MGF, we assume a feasible functional form that is statistically equivalent to the problem in the real and one-dimensional space ($\mathbb{R}$). The Laplace transform naturally connects the two spaces (from $\mathbb{R}$ to MGF), while that the *Bromwich integral* does the reverse process (from MGF to $\mathbb{R}$). This regularity provides a computational advantage with respect to other methods as allow us to reduce the dimensionality of the problem.[2]

For an arbitrary credit portfolio, the relationship between the probability density functions and the MGF is described as

$$M_x(s) = \mathbb{E}\left(e^{sx}\right) = \int e^{sx} f(x)\, dx.$$

Where M_x is the expected value of exponential function (e^{sx}), x is the random variable (of losses, analogous to P), s is the arbitrary Laplace transform parameter, and f represents the probability density function.

If we consider two states for the random variable x (default and no default), we have the following discrete MGF:

[2] Similarly to Martin et al. (2001), when we calculate the *Bromwich integral* through the saddle-point we are taking only the real part of the results since the original results could have imaginary factors.

$$M_i\left(s\right)=\mathbb{E}\left(e^{si}\right)=\sum_{\mathbb{1}_{D_i}=0,1}f\left(\mathbb{1}_{D_i}\right)e^{s\cdot \text{expos}_i\cdot \mathbb{1}_{D_i}}=1-p_{def_i}+p_{def_i}e^{s\cdot \text{expos}_i}.$$

Where p_{def_i} is the *unconditional* default probability and $expos_i$ is the exposure in the defined time horizon for bank i. If we assume *conditional independence*, the relationship between the *unconditional* (p_{def_i}) and *conditional* ($p_{def_i}(\vec{V})$) probabilities of default can be expressed as[3]

$$p_{def_i}=\sum_k p_{def_i}\left(\vec{V_k}\right)h\left(\vec{V_k}\right). \tag{1}$$

Where $\vec{V_k}$ represents the k^{th} set of values of the underlying group of M systemic factors, $\vec{V}=\left\{V^1,V^2,...,V^M\right\}$. Moreover, $h(\vec{V})$ are the probability density of the systemic factor. Following Koylouglu and Hickman (1996), we can write $h(\vec{V})=h^1(V^1)\cdot h^2(V_2)...h^M(V^M)$ as the systemic factors are assumed to be uncorrelated. In this work we consider only one systemic factor: the stock market index return of each specific country.

Without loss of generality and consistent with our method of estimation for the individual probabilities of default, we consider a unifactorial Merton-style model.[4] As in Vasicek(2002), we assume that $h(\vec{V})$ follows a Normal distribution and the conditional probability in equation (1) can be written as:

$$p_{def_i}(V)=P\left(Z\leq\Phi^{-1}\left(p_{def_i}|V\right)\right)=\Phi\left(\frac{\Phi^{-1}\left(p_{def_i}\right)-\rho V}{\sqrt{1-\rho^2}}\right).$$

Where ρ is the correlation between the individual banks' stock market returns and the stock market index return of each specific country. After these calculations, we are able to define the conditional and unconditional MGF, as a function of the underlying systemic factor:

$$M\left(s|V\right)=\prod_{i=1}^{N}M_i\left(s\right)=\prod_{i=1}^{N}\left(1-p_{def_i}\left(V\right)\left(e^{\text{expos}_i s}\right)\right). \tag{2}$$

[3]Conditional independence means that conditional on being correlated to a systemic factor, the banks have uncorrelated probabilities of default. We acknowledge a potential complexity if systemic factors are correlated. However, we assume that they are calculated as orthogonal factor loadings.

[4]This method can be easily extended to allow for multi-factor models.

In order to further simplify the calculations, we use the *cumulant* generating functions (K), defined as the logarithm of the MGF. Thus, $K(s|V) = \log(M(s|V))$. The useful property of this function is that all moments of the distribution described by the probability density $f(\cdot)$ can be generated by calculating the derivatives evaluated at $s = 0$. For instance, for the two first moments we have $K'(s = 0) = \mathbb{E}(x)$ and $K''(s = 0) = \mathbb{V}\mathrm{ar}(x)$.

Once processed the information for the individual banks, the calculations performed, and estimated the correlation structure, we are able to obtain the MGF in equation (2). Next, we reverse the process to come back to the space of real numbers and get the joint probability density of losses. To do that we employ the *Bromwich* integral. Under our *conditional independence* assumption, this integral takes the form:

$$f(x) = \frac{1}{2\pi i} \int_{-\infty}^{+\infty} \left(\int_{-i\infty}^{+i\infty} e^{K(s|V) - sx} ds \right) h(V)\, dV.$$

To solve the above integral, we use a particular property. Close to the saddle-point of the argument of the exponential function, the integral can be approximated with high level of accuracy. If we obtain the first order conditions for the argument of the exponential, we obtain that $\frac{d}{ds}(K(s) - sx)$, and $K'\left(s = \hat{t_V}\right) = x$. In the previous expression, $\hat{t}$ is the saddle point of the integral.

The expression in equation (1) in the continuous case becomes:

$$P(L > x) = \int_{-\infty}^{+\infty} P(L > x|V)\, h(V)\, dV = \frac{1}{2\pi i} \int_{-\infty}^{+\infty} \left(\int_{-i\infty}^{+i\infty} e^{K(s|V) - s \cdot x} ds \right) h(V)\, dV. \tag{3}$$

With the use of the saddle-point property, the distribution of portfolio losses can be approximated by:

$$P(L > x) \approx$$
$$\begin{cases} e^{\left(K\left(\hat{t_V}|V\right) - x \cdot \hat{t_V} + \frac{1}{2}\hat{t_V} K''\left(\hat{t_V}\right)\right)} \Phi\left(-\sqrt{\hat{t_V}^2 K''\left(\hat{t_V}\right)}\right), & \text{if } x \leq \mathbb{E}(L) \\ \frac{1}{2}, & \text{if } x = \mathbb{E}(L) \\ 1 - e^{\left(K\left(\hat{t_V}|V\right) - x \cdot \hat{t_V} + \frac{1}{2}\hat{t_V} K''\left(\hat{t_V}\right)\right)} \Phi\left(-\sqrt{\hat{t_V}^2 K''\left(\hat{t_V}\right)}\right), & \text{if } x > \mathbb{E}(L). \end{cases}$$

In order to be able to manage the integral approximation, we need to discretize the expression in (3). For the general case, in a multi-factor setting, we would have:

$$P(L > x) \approx \sum_{k_1} \dots \sum_{k_M} P\left(L > x | \vec{V} = \{V_{k_1}, \dots, V_{k_M}\}\right) h(V_{k_1}) \dots h(V_{k_M}) \qquad (4)$$

Recall that in our case M, the number of systemic factors, is set to one. We solve the expression in (4) by using a Gauss-Hermite quadrature. By applying the Bayes theorem in (4), we get:

$$P(L > x) \approx \sum_{j} P(j) P(L > x | j) h(V_{k_1}) \dots h(V_{k_M}). \qquad (5)$$

Where j is the state of the underlying systemic factor, thus $P(L > x|j)$ is the probability that the losses are greater than x for the systemic factor configuration V. $P(j)$ is the probability that the economy latent variable V is in the state j and it corresponds to the quadrature weight h_{k_i}. The marginal contributions to the overall risk, from a particular bank to the entire financial system of a country, are obtained following Martin (2001). Finally, to obtain our JLoss metric, we normalized with respect to the total liabilities.

2.3 Parameterization

Table 1 shows the parameterization used in the Jloss calculation, once the individual expected default frequencies are calculated. These parameters define the characteristics of the aggregate distribution of losses and the method implemented. Time span is quarterly, we use one systematic factor, and seven nodes for the integral quadrature approximation.[5] The lower bound of losses is fixed at 1 percent, whereas the upper bound is assumed to be 4,8 percent. These values are calibrated to losses in the emerging countries' banking systems. Precision parameter is the 99 percent.

[5]The Gauss-Hermite quadrature solves integrals of the form $I = \frac{1}{2\pi} \int_{-\inf}^{+\inf} e^{-\frac{x^2}{2}} f(x)dx$, as the sum $I = \sum_{i=1}^{n} w_i \cdot f(x_i)$. In our case we are using $n = 7$. Therefore, we need to compute 7 saddle points. In the standard numeric calculus literature, the quadrature is already tabulated to a generic integral. We have just to adjust it to our particular problem.

Finally, the systematic factor is assumed to have a normal distribution with zero mean and variations between -4 and 4 percent. Table A.2 in Appendix A presents the description and sources of all the variables used in the JLoss computation.

2.4 Discussion

A standard way of calculating the credit risk losses is the methodology described in Vasicek (1997). However, this procedure has some shortcomings that can be improved. The calculations require a functional form of the distribution of losses. This assumption is strong because the estimated parameters of the distribution can lead to important errors in the calculation of losses. Moreover, by being a method that works in the space of real numbers, it lacks of a simple mathematical treatment that allows closed form calculations. The semi-parametric saddle-point approach used in this work, which heavily relies on Martin et al. (2001), has three main advantages. First, it allows simple calculations because it has the ability to provide statistical measures associated directly with credit risk. Second, it significantly increases the speed of calculation in the computational implementation as it can be presented in analytical formulas. Therefore, it allow us to construct our measure for a long number of countries. Third, this method makes it possible to reduce a n-dimensional problem to a single value.

Although Jloss is not the only attempt in the literature to measure financial stability, it is one of the few that performs an aggregation work that allows us to have a metric that reflects financial stability at the country level. For example, the SRISK metric introduced by Brownless and Engle (2016) is an index that computes the expected deficit to the capital of individual financial firms. Brownless and Engle's (2016) aggregation procedure consists of adding up all the capital losses of a particular financial system. Thus, the aggregate metric does not consider the correlation between the financial institutions. In addition, because the SRISK is a metric based on capital deficits, given a particular stressed scenario, the metric is more crisis oriented than identifying periods of vulnerability.

The CIMDO-copula introduced by Segoviano (2009) is a metric more similar to the JLoss in methodological terms. However, the difference between the JLoss and the Segoviano CIMDO-copula is that in the first case, the assumptions of conditional independence and the semi-parametric calculation allow us to improve efficiency in capturing the changes of variation and offer advantages from the computational point of view, being an approximation but with high precision.

3 Data

To empirically test the relationship between sovereign credit risk, financial fragility, and global factors, we employ a quarterly panel dataset of 19 emerging economies over the period 1999:Q1 to 2017:Q3. Our panel dataset contains variables related to sovereign credit risk, financial fragility in the banking sector, country-specific macroeconomic conditions, and global financial factors. The countries in our analysis are those classified as emerging markets in the J. P. Morgan Emerging Markets Bonds Index (EMBI Global) and those for which we had data to construct the JLoss metric during our sample period. The countries in our sample are: Argentina, Brazil, Bulgaria, Chile, China, Colombia, Egypt, Indonesia, Malaysia, Mexico, Pakistan, Panama, Peru, Poland, Philippines, Russia, South Africa, Turkey, and Venezuela.

Table A.2 in Appendix A presents the description and sources of all the variables used in our regression analysis. Our final sample consists of 1,187 country-time observations in the spreads regressions and 1,243 country-time observations in the rating regressions. Table 2 reports summary statistics of all the variables used in the regression analysis for the overall sample.

3.1 Sovereign Credit Risk

The sovereign-credit-risk measures used in this study are the sovereign bond spread and the sovereign credit rating. These variables are obtained from the Bloomberg system that collects data from industry sources. Emerging-market sovereign bond spreads are measured using the EMBI Global, which measures the average spread on U.S. dollar-denominated bonds issued by sovereign entities over U.S. Treasuries. It reflects investors' perception of a government's credit risk. Our sovereign-credit-rating variable is constructed based on Standard & Poor's (S&P) ratings for long-term debt in a foreign currency.[6] To compute a quantitative measure of sovereign credit ratings, we follow the existing literature and map the credit-rating categories into 21 numerical values (see, e.g., Borensztein et al., 2013), with a value of 21 corresponding to the highest rating (AAA) and 1 to the lowest (SD/D). For robustness purposes, we also consider Moody's sovereign credit ratings for long-term debt in foreign currency. Table A.3 in the appendix reports the numerical values for each credit-rating category.

Tables 3 and 4 provide summary information for the sovereign credit spreads and sovereign credit ratings by country, respectively. The average values of the spreads range widely across countries. The lowest average is 125 basis points for China; the highest average is 1,395 basis points for Argentina. Both the standard deviations and the minimum/maximum values indicate significant variations also exist over time. For example, the credit spread for Argentina ranges from 204 to 7,078 basis points during the sample period. The average values of the ratings also range widely across countries. The lowest average rating is 6.5 for Argentina; the highest average is 13.2 for Poland. Again, the descriptive statistics indicate significant variations over time. For instance, the credit rating for Russia ranges from 1 to 14 during the sample period.

3.2 Domestic Financial Fragility

Our key explanatory variable of interest is our metric of financial fragility (JLoss). JLoss is calculated using stock market and balance-sheet data of commercial banks that are listed in the stock market of the 19 emerging economies in our sample. Table A.1 in the appendix reports the number of banks by each country. Figure 1 displays the JLoss metric for each of the 19 emerging countries in the sample.

As shown in Figure 1, in most countries our JLoss metric captures both periods

[6] Standard and Poor's (2001) defines a foreign-currency credit rating as "A current opinion of an obligor's overall capacity to meet its foreign-currency-denominated financial obligations. It may take the form of either an issuer or an issue credit rating. As in the case of local currency credit ratings, a foreign currency credit opinion on Standard and Poor's global scale is based on the obligor's individual credit characteristics, including the influence of country or economic risk factors. However, unlike local currency ratings, a foreign currency credit rating includes transfer and other risks related to sovereign actions that may directly affect access to the foreign exchange needed for timely servicing of the rated obligation. Transfer and other direct sovereign risks addressed in such ratings include the likelihood of foreign exchange control and the imposition of other restrictions on the repayment of foreign debt."

of global financial distress and periods of country-specific idiosyncratic financial fragility. In many countries, idiosyncratic factors seems to have stronger effects on financial fragility than global factors. For example, for the case of Argentina our metric shows that the fragility generated by the sub-prime crisis was smaller than the fragility generated by the 2001 Argentinean sovereign default. In Brazil, idiosyncratic factors such as the "Impeachment" of Dilma Rousseff also seem to have a much stronger effect on financial fragility than global financial fragility.

3.3 Global Factors

Far from being autarkies, the emerging economies included in this paper have increasingly become more financially integrated with the rest of the world. Therefore, their ability and willingness to serve their debt may depend not only on macroeconomic domestic conditions, but also on the state of the global economy. To capture broad changes in the state of the global (exogenous) financial markets, we consider a set of global financial factors that reflect financial market volatility, risk-free interest rates, risk premiums, and market illiquidity. Specifically, the global financial factors used in this study are the CBOE Volatility Index, the 10-year U.S. Treasury rate, the 10-year U.S. High Yield spread, and the On/off-the-run U.S. Treasury spread. For robustness, we also employ the noise measure as an additional measure of market illiquidity.

The CBOE Volatility Index, known commonly as the VIX, measures the market's expectation for 30-day volatility in the S&P 500. Usually, a higher VIX indicates a general increase in the risk premium and, consequently, an increase in the cost of financing for emerging economies. The 10-year U.S. Treasury rate addresses the interest rate effect. It reflects the risk-free rate against which investors in advanced economies evaluate the payoffs of all other assets of similar maturities. The high-yield spread proxies for the price of risk in the global financial market. We employ J. P. Morgan's High Yield Spread Index, which measures the spread over the U.S. Treasuries yield curve. The On/off-the-run U.S. Treasury spread is the spread between the yield of on-the-run and off-the-run U.S. Treasury bonds. Although the issuer of both types of bonds is the same, on-the-run bonds generally trade at a higher price than similar off-the-run bonds, because of the greater liquidity and specialness of on-the-run bonds in the repo markets.[7] We compute the On/off-the-run U.S. Treasury spread using 10-year bonds, given that the spread tends to be small and noisy at smaller maturities. The data sources used in the construction of this spread are from Gurkaynak et al. (2007) and the Board of Governors of the Federal Reserve System. Lastly, the noise measure captures the amount of aggregate illiquidity in the U.S. bond market (Hu, Pan, and Wang, 2013). It is the aggregation of the price deviations across U.S. Treasury bonds. The primary concept behind this measure is that the lack of arbitrage capital reduces the power of arbitrage and that assets can be traded at prices that deviate from their fundamental values.

3.4 Country-Specific Factors

To capture the domestic macro environment, we also control for a set of time-varying country-level macro variables that may directly affect sovereign credit risk: debt to GDP, exchange-rate volatility, profit margin in the banking sector, and GDP per capita. In the spread regressions, we also control for the long-term foreign-currency sovereign credit rating. The debt-to-GDP ratio captures the degree of the economy indebtedness. Exchange-rate volatility is the volatility of the country's exchange rate against the U.S. dollar. We added this variable because it is considered a major determinant of firms' revenues from abroad and their ability to repay debts denominated in dollars. Profit margin in the banking sector captures the degree of competitiveness in the domestic financial sector. Sovereign credit ratings are credit-rating agencies' opinion of a government's overall capacity to meet its foreign-currency-denominated financial obligations. Finally, for robustness purposes, we also control in a set of regressions for periods of domestic systemic banking crises (Laeven and Valencia, 2018).

[7] This specialness arises from the fact that on-the-run Treasury bond holders are frequently able to pledge these bonds as collateral and borrow in the repo market at considerably lower interest rates than those of similar loans collateralized by off-the-run Treasury bonds (Sundaresan and Wang, 2009).

4 Regression Analysis and Results

The first objective of this study is to explore the relationship between sovereign credit risk and financial fragility, controlling for other factors that might affect sovereign credit risk independently. We estimate the following baseline econometric model:

$$Credit\ Risk_{c,t} = \alpha_c + \gamma_t + \beta JLoss_{c,t} + \omega X_{c,t} + \epsilon_{c,t}, \qquad (6)$$

where $Credit\ Risk_{c,t}$ is either the sovereign credit spread or the sovereign credit rating of country c at time t. $JLoss_{c,t}$ is our metric of financial fragility in the banking sector that computes the joint loss distribution of the banking sector conditional on a systemic event. Both $Credit\ Risk_{c,t}$ and $JLoss_{c,t}$ are expressed in natural logarithm. $X_{c,t}$ is a set of time-varying country-level macro variables, including the sovereign credit rating in the spread regressions. The term α_c represents a vector of country fixed effects that control for all time-invariant country-specific factors affecting both credit risk and financial fragility. The term γ_t captures time fixed effects that control for common and global shocks affecting all countries, such as global financial crises or changes in the world business cycle. $\epsilon_{c,t}$ is the error term.

Our specification including country fixed effects and time fixed effects is analogous to a difference-in-differences estimator in a multiple-treatment-group and multiple-time-period setting (Imbens and Wooldridge, 2009). The identification assumption is that in the absence of domestic financial fragility, the sovereign bond spreads and sovereign credit ratings are exposed to similar global shocks. We believe this assumption is plausible, given the homogeneous nature of our sample (i.e., emerging economies that issue international bonds denominated in U.S. dollars) and that global factors are crucial determinants of sovereign credit risk in emerging economies (González-Rosada and Yeyati, 2008).

The second objective of this study is to examine whether the effect of global (exogenous) financial factors on sovereign credit risk is stronger in countries with more vulnerable banking sectors. To explore this hypothesis, we estimate the following model:

$$Credit\ Risk_{c,t} = \alpha_c + \gamma_t + \beta JLoss_{c,t} + \theta JLoss_{c,t}\ x\ Global_t + \omega X_{c,t} + \epsilon_{c,t}, \quad (7)$$

where $Global_t$ is a global (exogenous) financial factor at time t. The coefficient associated with the interaction term, $JLoss_{c,t}\ x\ Global_t$, captures whether the impact of global financial factors on sovereign credit risk differs in countries with different degrees of financial fragility in their banking sectors. We hypothesize that in a financially integrated world where domestic banks and international capital markets work as substitute sources of capital, a stronger banking sector should attenuate a country's exposure to global financial factors.

4.1 Sovereign Bond Spreads and Financial Fragility

Table 5 presents the results from the estimation of equation (1) by using sovereign credit spreads as our dependent variable. The model is estimated by ordinary least squares (OLS) with robust standard errors. The table also reports the estimates of our econometric model by directly including global financial factors instead of time fixed effects. The results suggest sovereign credit spreads are positively related to our metric of banking fragility (JLoss). This positive correlation between JLoss and sovereign credit spreads is statistically significant and economically meaningful, even after controlling for country and time fixed effects (column 1), for sovereign credit ratings (column 2), and for the standard determinants of sovereign credit risk (column 3). We also find similar results when we control for a number of global financial factors instead of time fixed effects (column 4). Given that both the spread and the JLoss metric are expressed in natural logarithm, our estimated coefficients represent an elasticity. Our regressions appear to support the view that banking fragility exerts a strong influence on the pricing of emerging-market sovereign bonds.

Most of the estimated coefficients of our control variables are statistically significant in the expected direction. The results show, on the one hand, that sovereign credit ratings are negatively related to credit spreads. On the other hand, the results show indebtedness, global financial instability, global premiums, and aggregate market liquidity are positively related to sovereign credit spreads.

4.2 Sovereign Credit Ratings and Financial Fragility

Our previous analysis indicates sovereign credit spreads are larger during periods of fragility in the banking sector, even after controlling for credit ratings and other standard determinants of sovereign credit risk. However, credit spreads and financial fragility could also be linked through a credit-rating channel. Whereas credit spreads are a direct indicator of the effective cost of debt capital, credit ratings are rating agencies' opinions about debt issuers' probability of default. Given that these ratings consider business and financial risk factors, they are likely to capture some components associated with financial fragility.

To explore a potential credit-rating channel, Table 6 reports the results from our baseline model by using sovereign credit ratings as our dependent variable. Columns 1 and 2 report the results of our model with country fixed effects and time fixed effects, and column 3 reports the results of our model including global financial factors instead of time fixed effects. Overall, our results indicate sovereign credit ratings are negatively related to our JLoss metric. Remember that this negative correlation between JLoss and sovereign credit ratings is statistically significant and economically meaningful in all our specifications.

Overall, our results suggest both the market and the credit-rating agencies consider the fragility of the banking sector a crucial determinant of sovereign credit risk in emerging markets.

4.3 Are Countries with Fragile Banking Sectors More Exposed to Global Financial Shocks?

Although the literature has explored the relevance of external factors as significant determinants of sovereign credit risk in emerging economies (see, e.g., González-Rosada and Yeyati, 2008), little research has explored the aspects that make a country more or less resilient to sudden changes in the external context. We explore whether global financial factors affect sovereigns differently depending on the fragility of their banking sectors. Given that the emerging economies included in this paper have increasingly become more financially integrated with the rest of the world and that domestic and international capital markets can provide an alternative source of funding that can complement bank financing, we hypothesize that global financial conditions should typically have a smaller effect on countries with more resilient banking sectors.

Tables 7 and 8 report the results from the estimation of equation (2) by using sovereign credit spreads and sovereign credit ratings as our dependent variables, respectively. As before, the model is estimated by ordinary least squares (OLS) with robust standard errors. The tables also report the estimates of our econometric model including global financial factors instead of time fixed effects (columns 5 to 8). The positive and statistically significant coefficients associated with the interaction terms in columns 1 to 4 in Table 7 indicate that a deterioration in global market volatility, risk-free interest rates, high-yield spreads, and aggregate illiquidity produce a higher increase in sovereign credit spreads of countries with more fragile banking sectors. These effects are highly statistically significant and economically meaningful. Columns 5 to 8 in Table 7, which consider the direct effects of global financial factors instead of time fixed effects, show almost identical results.

Similar to our previous results, the negative and statistically significant coefficients associated with the interaction terms in columns 1 to 4 in Table 8 indicate that deterioration in global financial market volatility, risk-free interest rates, high-yield spreads, and aggregate illiquidity produced a higher deterioration in sovereign credit ratings of countries with more fragile banking sectors. Columns 5 to 8 in the table report qualitatively similar results.

5 Robustness Checks

We conduct a number of exercises to check the robustness of our main results. First, we control for periods of systemic banking crises. Then, we exclude banking crisis periods of our sample. Next, we explore whether our interaction term is capturing another non-linear effect of global factors on sovereign credit spreads. Finally, we consider Moody's sovereign credit ratings instead of S&P ratings.

Given that our metric of financial fragility in the banking sector spikes during periods of systemic banking crises, our results are likely driven by a few observations that capture a very high correlation between sovereign risk and banking risk during periods of financial turmoil. Columns 1 and 2 of Table 9 report the results from estimating our baseline regressions controlling for dummy variables associated with periods of systemic banking crises, and columns 3 and 4 report the results when excluding periods of systemic banking crises. The systemic-banking-crises dummy variables used in our analysis were constructed using the dataset introduced by Laeven and Valencia (2018). The results are qualitatively identical to our baseline regressions reported in Tables 5 and 6. As expected, the magnitude of our coefficients decrease. However, they remain highly statistically significant in the expected directions.

Because our primary term of interest in Table 7 is the interaction between JLoss and our four global factors, JLoss may captures the effect of another country-specific factor. Table 10 presents the results of a more explicit test of this possibility by including a number of additional interaction terms. The added terms correspond to the interaction of the sovereign credit rating and the banking-crisis dummy variable with our four different measures associated with global factors, respectively. Columns 1 to 4 augment our previous model with the interaction between global factors and sovereign credit ratings, and columns 5 to 8 augment our previous model with the interaction between global factors and banking crises. Overall, our main findings remain unchanged.

Finally, we find in unreported regressions that an alternative measure of the sovereign credit rating constructed based on the ratings granted by Moody's yields results almost identical to all those results obtained using S&P sovereign credit ratings.

6 Conclusion

The global financial crisis of 2008-09 and the European debt crisis generated large losses in the banking sector, triggering a significant deterioration of sovereign credit risk with the greater expectation of public support for distressed banks. These events spurred a renewed interest in generating new measures of financial fragility as well as in understanding the consequences of such vulnerabilities. Despite a new large body of research on the relationship between sovereign risk and bank risk in the eurozone, rigorous research on the nexus between sovereign risk and bank risk in emerging markets is scant. A better understanding of the factors influencing sovereign risk and of how these factors can be properly measured in both advanced and emerging economies is of key importance.

The goal of this paper is to shed light on the relationship between sovereign credit risk and financial fragility in the banking sector. To achieve this goal, we develop a novel model-based semi-parametric metric (JLoss) that computes the joint-loss distribution of a country's banking sector conditional on a systemic event. We find that, controlling for country-level macro variables as well as for country and time fixed effects, our metric of financial fragility (JLoss) is positively associated with sovereign credit spreads and negatively associated with higher sovereign credit ratings in our sample of emerging economies.

We also explore whether bank stability reduce a country's exposure to global financial factors. A better understanding of the mechanisms through which global factors influence sovereign credit risk is crucial. As highlighted by González-Rosada and Yeyati (2008), emerging economies need to formulate mechanisms to reduce their exposure to global financial factors, as the process of financial integration exhibited over the past four decades brings contagion from other advanced and emerging economies. Our results indicate that countries with more fragile banking sectors are more exposed to the influence of global financial factors.

Our results have important policy implications because they underscore that the stability of a country's domestic banking sector plays a crucial role in reducing sovereign risk and its sensitivity to global factors. Therefore, countries must implement policies oriented to improve the stability of their banking sectors to improve their access to international capital and reduce potentially undesired effects of integration.

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Tables

Table 1: Parameters Saddle-Point Estimation

Parameters	Value
Time horizon	1 quarter
Loss given default (LGD)	45%
Approximation nodes	7
Number of systemic factors	1
Loses lower bound	0.010
Loses upper bound	0.048
Number of steps	500
Percentile	0.99
Systemic driver	N(0, 0.16%)

Table 2: Descriptive Statistics

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Sovereign Credit Risk					
EMBI spread	1,187	4.048	6.984	0.410	70.78
S&P rating	1,243	11.15	3.213	1	18
Moody's rating	1,243	11.23	3.438	2	18
Financial Fragility					
JLoss	1,243	6.827	9.113	0.450	47.16
Control Variables					
Profit margin	1,102	15.17	11.74	0.476	99.00
Exchange rate volatility	1,102	0.146	0.642	0	9.681
Debt to GDP	1,102	55.77	36.78	12.70	211.1
GDP per capita	1,102	6,445	3,858	748.0	16,007
VIX	1,102	19.95	8.046	9.510	44.14
U.S. treasury rate	1,102	3.443	1.227	1.471	6.442
High yield spread	1,102	5.396	2.710	2.390	17.22
On/off-the-run spread	1,102	19.59	14.54	2.070	62.91
Noise	1,102	3.138	2.443	0.959	16.17

Table 3: Descriptive Statistics for Sovereign Credit Spreads

Country	Mean	Standard Deviation	Minimum	Maximum
Argentina	13.95	17.35	2.04	70.78
Brazil	5.31	3.98	1.4	24.12
Bulgaria	4.35	4.68	0.65	21.54
Chile	1.49	0.54	0.55	3.43
China	1.25	0.53	0.44	2.93
Colombia	3.33	2.04	1.12	10.66
Egypt	3.1	1.81	0.41	7.64
Indonesia	1.78	0.57	1.02	3.27
Malaysia	1.81	1.32	0.46	10.55
Mexico	3.37	2.42	1.11	15.89
Pakistan	6.39	4.31	1.42	21.12
Panama	2.81	1.24	1.19	5.65
Peru	3.2	1.94	1.14	9.11
Philippines	3.15	1.7	0.91	9.21
Poland	1.78	1.34	0.42	8.71
Russia	6.55	10.88	0.92	57.83
South Africa	2.38	1.15	0.7	6.52
Turkey	3.91	2.23	1.39	10.66
Venuezuela	11.85	8.07	1.83	48.54
Total	4.48	6.69	0.4	70.78

Table 4: Descriptive Statistics for S&P Sovereign Credit Ratings

Country	Mean	Standard Deviation	Minimum	Maximum
Argentina	6.49	2.93	1	9
Brazil	9.48	2	7	13
Bulgaria	10.04	2.7	7	14
Chile	15.7	1.6	13	18
China	15.27	1.9	13	18
Colombia	11.5	1.03	10	13
Egypt	10.32	2.33	5	12
Indonesia	9.45	2.96	1	13
Malaysia	14.85	1.12	12	17
Mexico	12.08	1.45	10	14
Pakistan	6.75	1.45	1	8
Panama	11.25	1.01	10	13
Peru	11	1.68	9	14
Philippines	10.33	1.37	9	13
Poland	13.17	1.92	10	15
Russia	10.05	3.25	1	14
South Africa	12.05	1.48	10	14
Turkey	8.58	1.44	6	11
Venuezuela	7.56	1.89	1	10
Total	10.84	3.24	1	18

Table 5: Sovereign Credit Spreads and Financial Fragility

EMBI spread	(1)	(2)	(3)	(4)
JLoss	0.217***	0.162***	0.121***	0.161***
	(0.0226)	(0.0193)	(0.0209)	(0.0192)
S&P rating		-0.114***	-0.120***	-0.126***
		(0.00955)	(0.00912)	(0.00974)
Exchange rate volatility			0.0272	0.0232
			(0.0263)	(0.0309)
Profit margin			0.0418***	-0.00466
			(0.0161)	(0.0170)
Debt to GDP			0.327***	0.315***
			(0.0496)	(0.0481)
GDP per capita			0.239***	0.0764
			(0.0664)	(0.0503)
VIX				0.159***
				(0.0541)
U.S. Treasury rate				-0.111*
				(0.0568)
High yield spread				0.200***
				(0.0542)
On/off-the-run spread				0.554***
				(0.100)
Observations	1,187	1,187	1,051	1,051
R-squared	0.767	0.828	0.843	0.808
Adjusted R-squared	0.747	0.813	0.827	0.803
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	NO

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Sovereign Credit Ratings and Financial Fragility

S&P rating	(1)	(2)	(3)
JLoss	-0.566***	-0.359***	-0.460***
	(0.0852)	(0.0915)	(0.0781)
Exchange rate volatility		-0.0919	-0.122
		(0.0789)	(0.0866)
Profit margin		-0.0653	0.00429
		(0.0869)	(0.0850)
Debt to GDP		-0.103	-0.286
		(0.256)	(0.241)
GDP per capita		2.754***	2.391***
		(0.295)	(0.182)
VIX			0.286
			(0.257)
U.S. Treasury rate			1.411***
			(0.261)
High yield spread			0.358
			(0.258)
On/off-the-run spread			-0.821*
			(0.454)
Observations	1,243	1,102	1,102
R-squared	0.841	0.821	0.811
Adjusted R-squared	0.828	0.804	0.807
Country FE	YES	YES	YES
Time FE	YES	YES	NO

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Sovereign Bond Spreads, Financial Fragility, and Global Financial Factors

EMBI spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JLoss	-0.493***	-0.243***	-0.221***	-0.0329	-0.474***	-0.310***	-0.164**	0.0139
	(0.125)	(0.0655)	(0.0651)	(0.0263)	(0.118)	(0.0606)	(0.0687)	(0.0266)
S&P Rating	-0.117***	-0.114***	-0.117***	-0.115***	-0.124***	-0.118***	-0.125***	-0.123***
	(0.00899)	(0.00910)	(0.00897)	(0.00889)	(0.00960)	(0.00974)	(0.00960)	(0.00949)
Exchange rate volatility	0.0385	0.0340	0.0352	0.0448*	0.0355	0.0369	0.0307	0.0418
	(0.0260)	(0.0275)	(0.0257)	(0.0272)	(0.0298)	(0.0315)	(0.0297)	(0.0306)
Profit margin	0.0405***	0.0435***	0.0395**	0.0392**	-0.00243	0.00227	-0.00504	-0.00235
	(0.0155)	(0.0164)	(0.0156)	(0.0152)	(0.0167)	(0.0170)	(0.0168)	(0.0164)
Debt to GDP	0.354***	0.403***	0.347***	0.391***	0.346***	0.403***	0.338***	0.379***
	(0.0494)	(0.0542)	(0.0488)	(0.0501)	(0.0485)	(0.0508)	(0.0479)	(0.0491)
GDP per capita	0.214***	0.239***	0.220***	0.216***	0.0625	0.0528	0.0631	0.0703
	(0.0642)	(0.0629)	(0.0648)	(0.0611)	(0.0491)	(0.0486)	(0.0497)	(0.0473)
VIX					-0.171**	0.126**	0.185***	0.184***
					(0.0835)	(0.0531)	(0.0551)	(0.0539)
U.S. Treasury spread					-0.128**	-0.689***	-0.124**	-0.102*
					(0.0554)	(0.0879)	(0.0565)	(0.0539)
High yield spread					0.172***	0.204***	-0.128	0.173***
					(0.0547)	(0.0533)	(0.0875)	(0.0542)
On/off-the-run spread					0.512***	0.627***	0.504***	-0.589***
					(0.101)	(0.0981)	(0.0997)	(0.180)
VIX x JLoss	0.203***				0.208***			
	(0.0418)				(0.0386)			
U.S. Treasury rate x JLoss		0.253***				0.320***		
		(0.0440)				(0.0398)		
High yield spread x JLoss			0.183***				0.173***	
			(0.0351)				(0.0356)	
On/off-the-run-spread x JLoss				0.692***				0.625***
				(0.0935)				(0.0918)
Observations	1,051	1,051	1,051	1,051	1,051	1,051	1,051	1,051
R-squared	0.848	0.848	0.847	0.853	0.814	0.819	0.813	0.818
Adjusted R-squared	0.832	0.833	0.832	0.838	0.809	0.814	0.808	0.813
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	NO	NO	NO	NO

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Sovereign Credit Ratings, Financial Fragility, and Global Financial Factors

S&P rating	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JLoss	0.728	0.978***	0.415	-0.113	0.324	1.137***	-0.00644	-0.271**
	(0.498)	(0.327)	(0.291)	(0.135)	(0.474)	(0.283)	(0.267)	(0.121)
Exchange rate volatility	-0.0919	-0.0909	-0.0899	-0.0906	-0.120	-0.127	-0.117	-0.117
	(0.0787)	(0.0793)	(0.0790)	(0.0792)	(0.0884)	(0.0812)	(0.0893)	(0.0901)
Profit margin	-0.0627	-0.0672	-0.0593	-0.0608	0.00169	-0.0205	0.00492	0.00125
	(0.0865)	(0.0854)	(0.0869)	(0.0860)	(0.0850)	(0.0831)	(0.0849)	(0.0845)
Debt to GDP	-0.146	-0.355	-0.143	-0.197	-0.321	-0.549**	-0.315	-0.361
	(0.256)	(0.263)	(0.256)	(0.260)	(0.242)	(0.243)	(0.242)	(0.247)
GDP per capita	2.790***	2.723***	2.783***	2.779***	2.402***	2.418***	2.404***	2.390***
	(0.295)	(0.287)	(0.293)	(0.293)	(0.182)	(0.178)	(0.182)	(0.181)
VIX					0.690**	0.378	0.246	0.249
					(0.336)	(0.254)	(0.260)	(0.258)
U.S. Treasury rate					1.425***	3.309***	1.424***	1.390***
					(0.260)	(0.396)	(0.260)	(0.262)
High yield spread					0.392	0.341	0.814**	0.395
					(0.262)	(0.255)	(0.389)	(0.260)
On/Off-the-run spread					-0.768*	-1.046**	-0.751*	0.631
					(0.455)	(0.448)	(0.454)	(0.766)
VIX x JLoss	-0.359**				-0.257*			
	(0.161)				(0.152)			
U.S. Treasury rate x JLoss		-0.925***				-1.077***		
		(0.217)				(0.178)		
High yield spread x JLoss			-0.414***				-0.241*	
			(0.148)				(0.136)	
On/off-the-run-spread x JLoss				-1.096***				-0.794**
				(0.401)				(0.364)
Observations	1,102	1,102	1,102	1,102	1,102	1,102	1,102	1,102
R-squared	0.821	0.823	0.821	0.822	0.812	0.816	0.812	0.812
Adjusted R-squared	0.804	0.807	0.804	0.805	0.807	0.812	0.807	0.807
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	NO	NO	NO	NO

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Systemic Banking Crises

	Whole sample		Excluding crises	
	(1)	(2)	(3)	(4)
	EMBI spread	S&P rating	EMBI spread	S&P rating
JLoss	0.112***	-0.330***	0.104***	-0.261***
	(0.0197)	(0.0901)	(0.0191)	(0.0894)
S&P Rating	-0.116***		-0.110***	
	(0.00883)		(0.00931)	
Exchange rate volatility	0.0292	-0.0547	0.0301	-0.00199
	(0.0266)	(0.0720)	(0.0268)	(0.0956)
Profit margin	0.0311*	-0.0390	0.0332**	-0.0438
	(0.0159)	(0.0859)	(0.0157)	(0.0872)
Debt to GDP	0.286***	0.00202	0.241***	0.164
	(0.0446)	(0.243)	(0.0477)	(0.256)
GDP per capita	0.243***	2.693***	0.265***	2.792***
	(0.0606)	(0.285)	(0.0604)	(0.285)
Banking crisis	0.417***	-1.043***		
	(0.0868)	(0.356)		
Observations	1,051	1,102	1,024	1,071
R-squared	0.851	0.823	0.828	0.808
Adjusted R-squared	0.835	0.806	0.810	0.789
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness

EMBI spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JLoss	-0.513***	0.0132	-0.274***	0.00459	-0.449***	-0.181***	-0.192***	-0.0298
	(0.138)	(0.0781)	(0.0762)	(0.0273)	(0.125)	(0.0633)	(0.0653)	(0.0260)
S&P rating	-0.129***	0.00581	-0.150***	-0.0998***	-0.114***	-0.110***	-0.113***	-0.113***
	(0.0364)	(0.0248)	(0.0241)	(0.00977)	(0.00871)	(0.00896)	(0.00869)	(0.00873)
Exchange rate volatility	0.0389	0.0299	0.0358	0.0382	0.0392	0.0356	0.0362	0.0452*
	(0.0260)	(0.0268)	(0.0254)	(0.0272)	(0.0263)	(0.0276)	(0.0261)	(0.0274)
Profit margin	0.0406***	0.0196	0.0395**	0.0359**	0.0310**	0.0332**	0.0280*	0.0299**
	(0.0155)	(0.0162)	(0.0155)	(0.0153)	(0.0154)	(0.0160)	(0.0154)	(0.0150)
Debt to GDP	0.355***	0.278***	0.350***	0.352***	0.316***	0.314***	0.303***	0.350***
	(0.0496)	(0.0481)	(0.0497)	(0.0444)	(0.0457)	(0.0507)	(0.0445)	(0.0487)
GDP per capita	0.213***	0.267***	0.224***	0.225***	0.224***	0.251***	0.248***	0.223***
	(0.0645)	(0.0580)	(0.0650)	(0.0570)	(0.0587)	(0.0581)	(0.0592)	(0.0566)
Banking crisis					1.950*	4.286***	2.098**	0.403*
					(1.170)	(0.914)	(0.851)	(0.228)
VIX x JLoss	0.210***				0.186***			
	(0.0458)				(0.0419)			
VIX x S&P rating	0.00415							
	(0.0118)							
VIX x Banking crisis					-0.482			
					(0.354)			
U.S. treasury rate x JLoss		0.0654				0.199***		
		(0.0549)				(0.0418)		
U.S. Treasury rate x S&P rating		-0.0967***						
		(0.0186)						
U.S. Treasury rate x Banking crisis						-2.195***		
						(0.491)		
High yield spread x JLoss			0.212***				0.165***	
			(0.0405)				(0.0352)	
High yield spread x S&P rating			0.0192					
			(0.0129)					
High yield spread x Banking crisis							-0.822**	
							(0.391)	
On/off-the-run spread x JLoss				0.490***				0.639***
				(0.101)				(0.0943)
On/off-the-run spread x S&P rating				-0.112***				
				(0.0257)				
On/off-the-run spread x Banking crisis								-0.0987
								(0.661)
Observations	1,051	1,051	1,051	1,051	1,051	1,051	1,051	1,051
R-squared	0.848	0.859	0.848	0.858	0.855	0.859	0.856	0.859
Adjusted R-squared	0.832	0.844	0.833	0.843	0.840	0.844	0.841	0.845
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figures

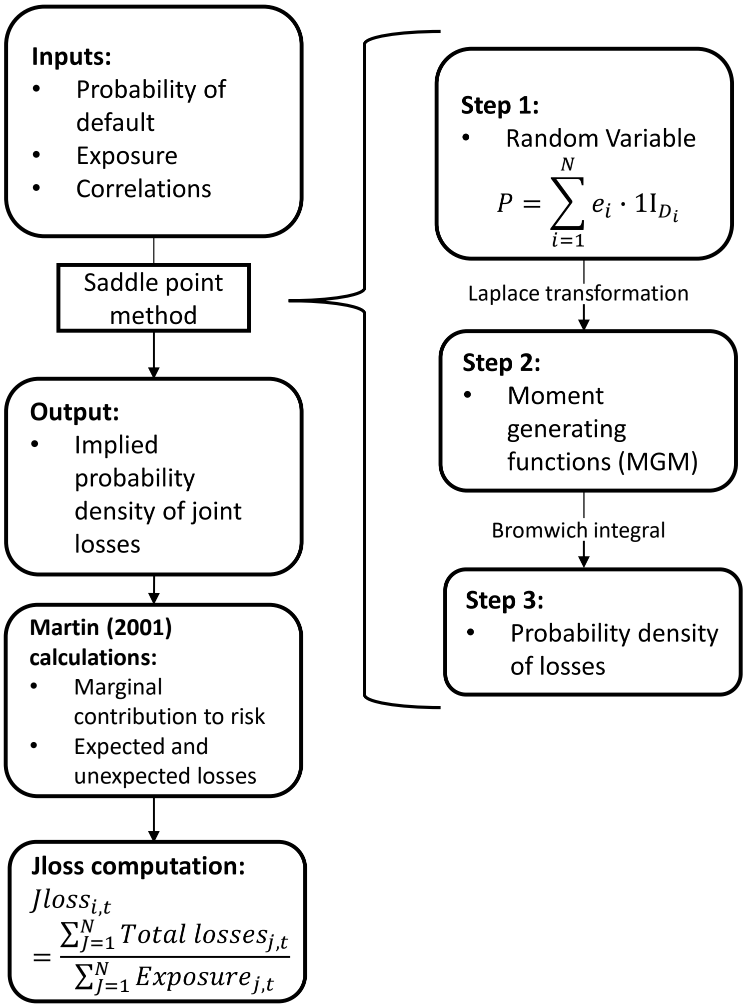

Figure 1: JLoss Methology

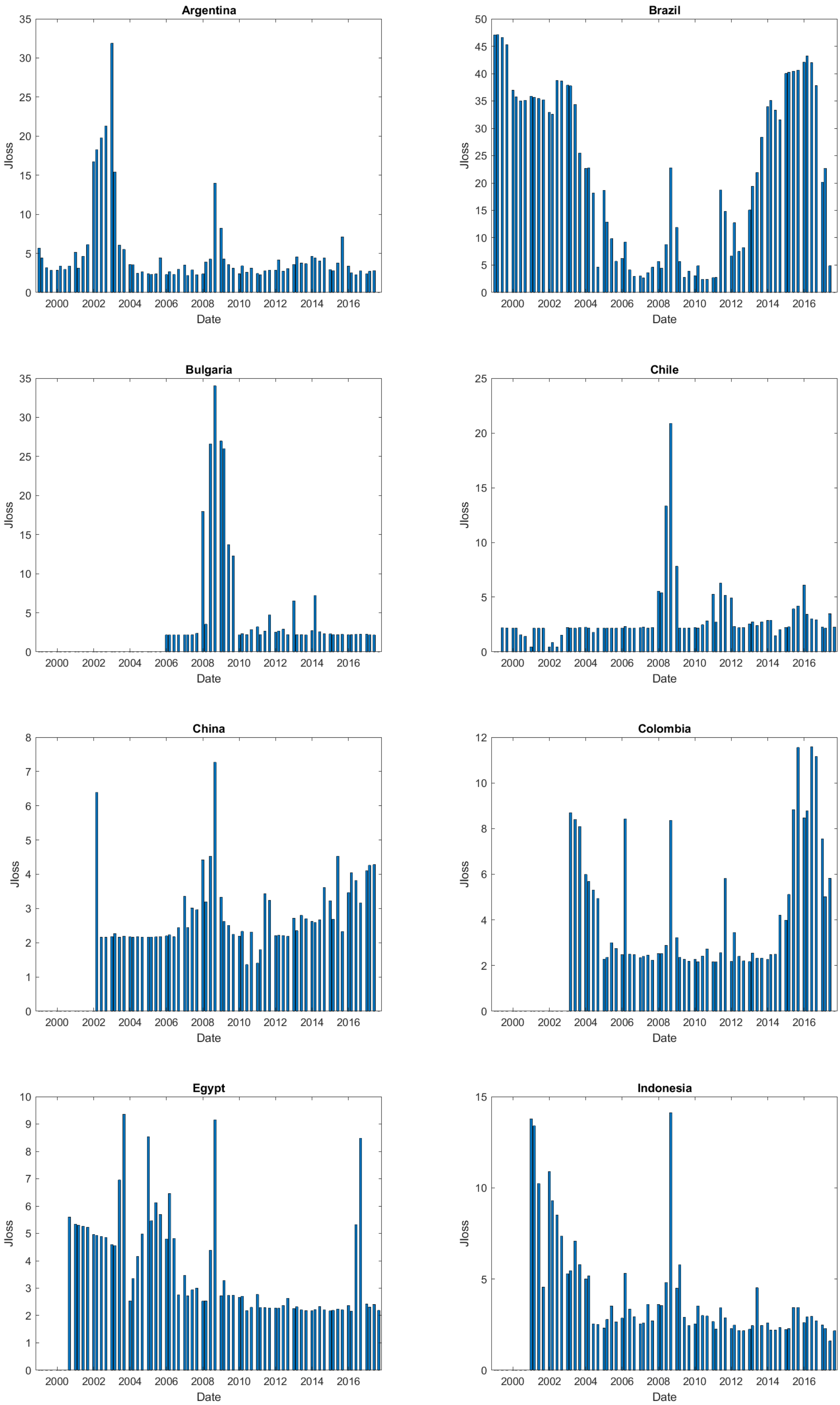

Figure 2: JLoss by Country

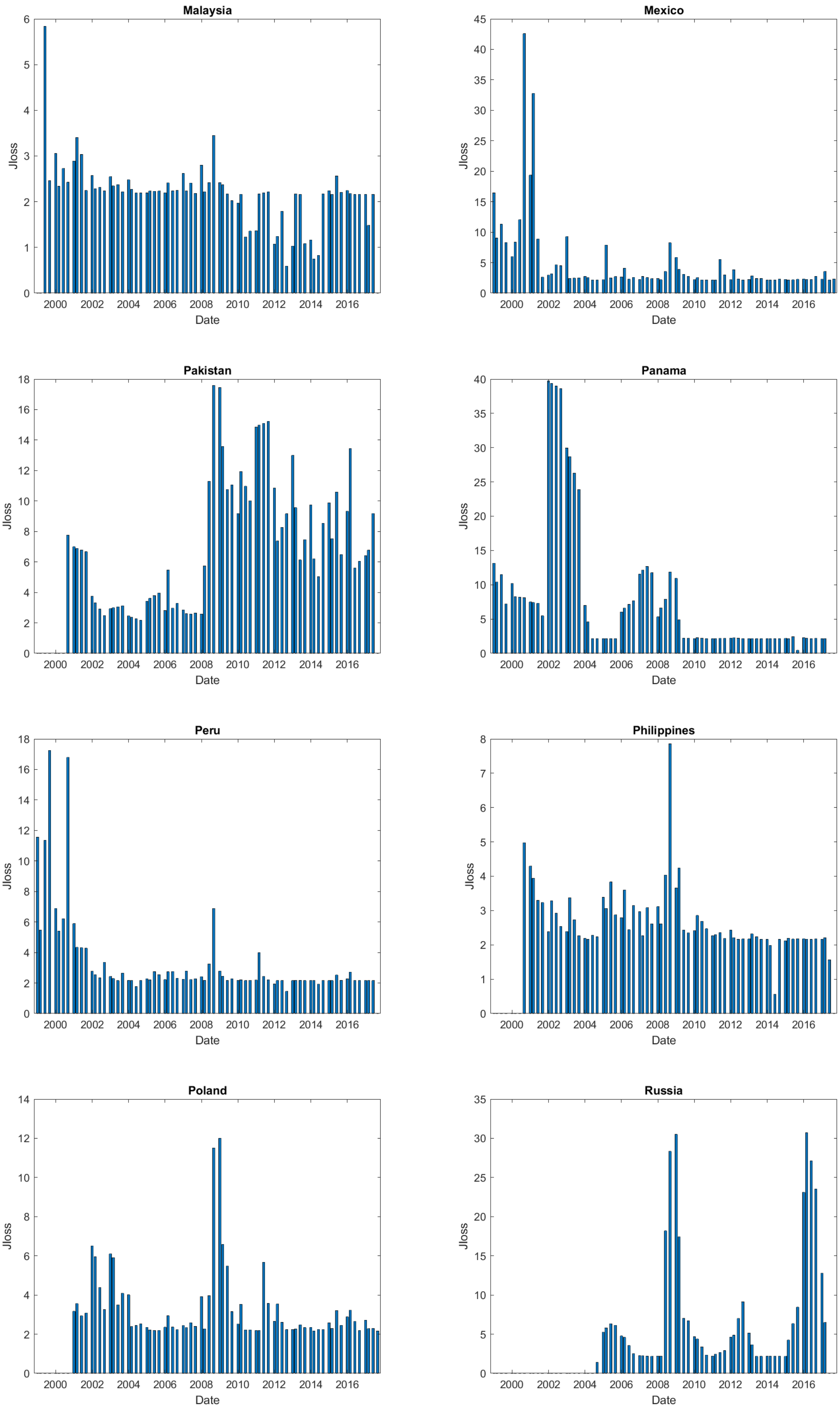

Figure 2: JLoss by Country (continued)

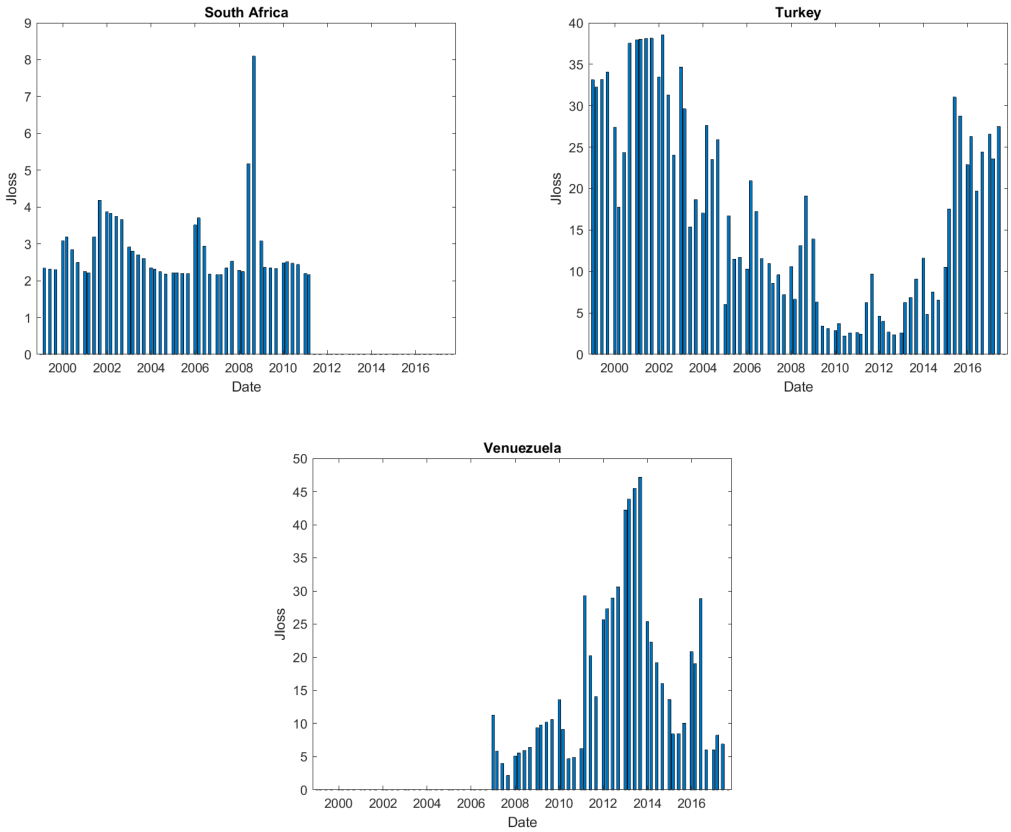

Figure 2: JLoss by Country (continued)

Appendix A

Table A.1 Banks per Country

Country	Number of banks
Argentina	6
Brazil	14
Bulgaria	4
Chile	9
China	40
Colombia	7
Egypt	10
Indonesia	40
Malaysia	8
Mexico	6
Pakistan	21
Panama	7
Peru	22
Philippines	19
Poland	13
Russia	46
South Africa	7
Turkey	13
Venezuela	6

Table A.2 Description of Variables

Name	Level	Description	Frequency	Source
Regression Analysis				
EMBI spread	Country	J.P. Morgan EMBI Global spread (in log)	Quarterly	Bloomberg
S&P rating	Country	S&P sovereign credit rating, long-term debt, foreign currency, 21=AAA - 1=SD (in log)	Quarterly	Bloomberg
Moody's rating	Country	Moody's sovereign rating, foreign currency, 21=AAA - 1=SD (in log)	Quarterly	Bloomberg
GDP per capita	Country	USD GDP per capita (in log)	Quarterly	IFS
Debt to GDP	Country	Debt divided by GDP (in log)	Quarterly	IFS
Profit margin	Country	Profit margin (in log)	Quarterly	Bloomberg
Exchange rate volatility	Country	Exchange rate volatility (percentage points)	Quarterly	Bloomberg
VIX	Global	CBOE Volatility Index (in log)	Quarterly	Bloomberg
U.S. Treasury rate	Global	U.S Treasury yield 10 years (in log)	Quarterly	Bloomberg
High yield spread	Global	J.P. Morgan high yield spread (in log)	Quarterly	Bloomberg
On/off-the-run spread	Global	Difference between the yield to maturity of 10 years off-the-run and on-the-run Treasury bonds (in log)	Quarterly	Board of Governors of the Federal Reserve System
Noise	Global	Root mean squared distance between market yields and the yields from a smooth zero-coupon yield curve (in log)	Quarterly	Hu, Pan and Wang (2013)
JLoss Computation				
Stock market index	Country	Stock market index	Daily	Bloomberg
Stock price returns	Bank	Stock price returns	Daily	Bloomberg
Long term liabilities	Bank	Long term liabilities	Quarterly	Bloomberg
Short term liabilities	Bank	Short term liabilities	Quarterly	Bloomberg
Average bank interest rates	Bank	Average bank interest rates	Quarterly	Bloomberg
Market capitalization	Bank	Market capitalization	Quarterly	Bloomberg
Volatility of stock price	Bank	Volatility of stock price	Quarterly	Bloomberg
Correlation to systemic factor	Bank	Correlation stock return	Quarterly	Bloomberg

Table A.3 Scale of Foreign Currency Debt Ratings

S&P rating				Moody's rating			
Rating	Conversion	Rating	Conversion	Rating	Conversion	Rating	Conversion
SD	1	BBB-	12	C	1	Baa3	12
CC	2	BBB	13	Ca	2	Baa2	13
CCC-	3	BBB+	14	Caa3	3	Baa1	14
CCC	4	A-	15	Caa2	4	A3	15
CCC+	5	A	16	Caa1	5	A2	16
B-	6	A+	17	B3	6	A1	17
B	7	AA-	18	B2	7	Aa3	18
B+	8	AA	19	B1	8	Aa2	19
BB-	9	AA+	20	Ba3	9	Aa1	20
BB	10	AAA	21	Ba2	10	Aaa	21
BB+	11			Ba1	11		