DOCUMENTOS DE TRABAJO

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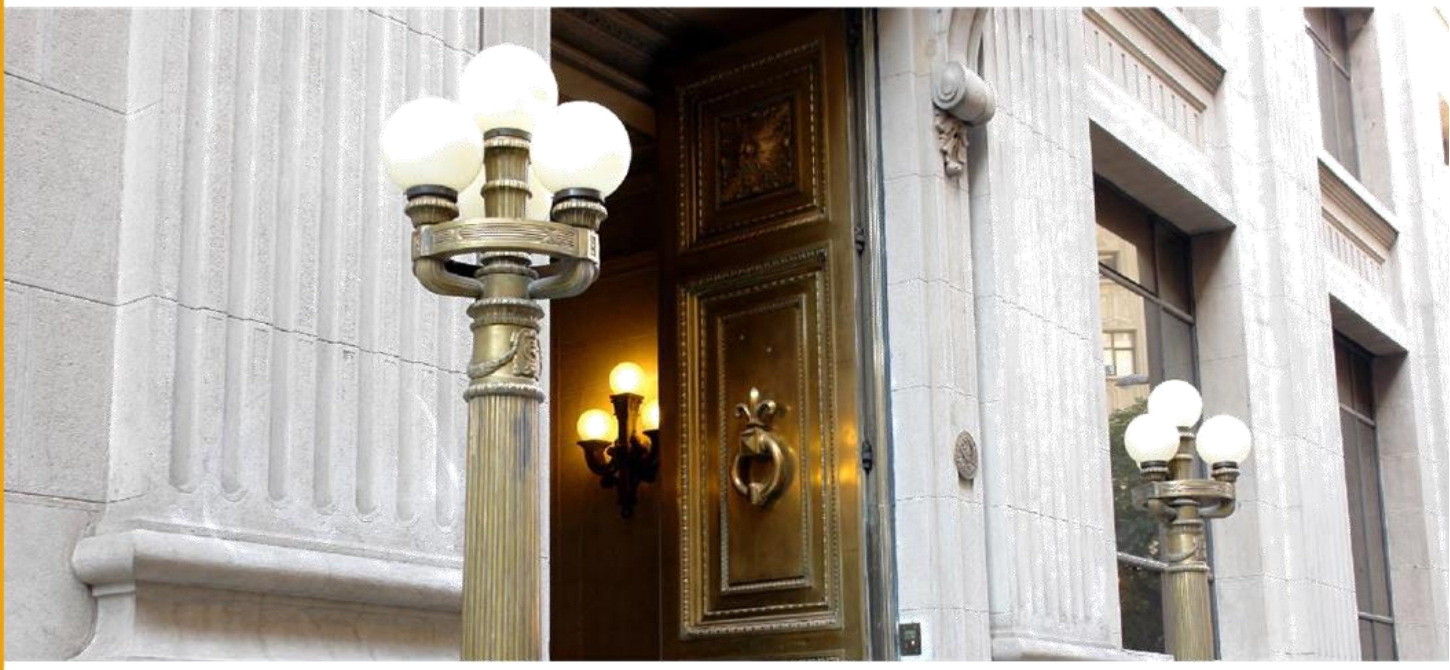
N° 957 Mayo 2022
BANCO CENTRAL DE CHILE



Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 38822311

Documento de Trabajo N° 957

Working Paper N° 957

Sovereign Credit Spreads, Banking Fragility, and Global Factors*

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Abstract

This study explores the relationship between sovereign credit risk, banking fragility, and global financial factors in a large panel database of emerging market economies. To measure banking fragility, we construct 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 banking fragility is positively associated with sovereign credit spreads, after controlling for the standard determinants of sovereign credit risk, a comprehensive set of measures of systemic risk, and country and time fixed effects. 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.

Resumen

Este estudio explora la relación entre el riesgo de crédito soberano, la fragilidad financiera y los factores financieros globales en una base de datos panel que contiene economías emergentes. Para medir la fragilidad financiera, construimos una métrica con una metodología semi paramétrica (Jloss) que calcula la pérdida conjunta esperada del sistema bancario condicional a un evento sistémico. Nuestra métrica de fragilidad financiera se encuentra positivamente asociada con los spreads de crédito soberano, controlando por los determinantes estándar del riesgo de crédito, un conjunto de medidas de riesgo sistémico, y efectos fijos por país y tiempo. Los resultados adicionalmente indican que economías con sectores bancarios más frágiles están más expuestos a factores financieros globales que aquellos con sectores bancarios más resilientes. Estos descubrimientos destacan que los reguladores deben asegurar la estabilidad financiera en el sector bancario para mejorar los costos de financiamiento de los gobiernos en el mercado internación de deuda.

*We wish to thank Charles Goodhart, Dimitrios Tsomocos, Jose Vicente Martinez, Oren Sussman, and participants at the First Conference on Financial Stability and Sustainability for insightful comments on an earlier version of this paper. Valenzuela acknowledges financial support from Fondecyt Project 1200070 and the Institute for Research in Market Imperfections and Public Policy, MIPP (ICS13002 ANID). Contact: fgarces@bcentral.cl, jmartinez@bcentral.cl

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 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 banking 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). Banking 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 spreads, banking fragility, and global financial factors. We study this relationship in a panel data set that covers 19 emerging market economies from 2000:Q1 to 2021:Q4. 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 banking fragility is positively associated with sovereign credit spreads. 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 liquidity. Our results are statistically significant and economically meaningful, even after controlling for the standard determinants of sovereign credit risk, a comprehensive set of systemic risk measures, and country and time fixed effects. Our results are also robust during periods of financial distress and periods of financial stability as well as to controlling for additional heterogeneous effects of global financial factors on sovereign spreads. 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 banking 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 banking 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. Bruyckere et al. (2013) examine contagion between the banking sector and sovereign default risk in Europe from 2007 to 2012, and find that banks with a weak capital buffer, a weak funding structure and less traditional banking activities are particularly vulnerable to risk spillovers. Black et al. (2016) measure the systemic risk of European banks by using a distress insurance premium (DIP), which integrates the characteristics of bank size, probability of default, and correlation. 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 financial 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). An exception is the study by Georgoutsosa and Migiakisb (2013), which explores the determinants of euro area sovereign bond yield spreads and find significant country-level heterogeneity on the effects on spreads. Specifically, 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 our banking 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 banking fragility and sovereign credit risk, in this work we construct a novel country-level metric of banking 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 ($\hat{\sigma_A}$):

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

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

[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.

asset volatility ($\hat{\sigma_A}$). Finally, we assume normality to obtain the expected default frequency (EDF) as

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

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.

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

[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.

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

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:

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

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:

[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.

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

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:

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

In order to further simplify the calculations, we use the *cumulant* generating functions (K), defined as the logarithm of the MGF. Thus, $K\left(s|V\right) = \log\left(M\left(s|V\right)\right)$. 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 $K'\left(s=0\right) = \mathbb{E}\left(x\right)$ and $K''\left(s=0\right) = \mathbb{V}\text{ar}\left(x\right)$.

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:

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

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 $\frac{d}{ds}\left(K\left(s\right) - sx\right)$, 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:

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

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:

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

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:

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

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. 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

[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.

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, banking fragility, and global factors, we employ a quarterly panel data set of 19 emerging economies over the period 1999:Q1 to 2021:Q4. Our panel data set contains variables related to sovereign credit spreads, financial fragility in the banking sector, country-specific macroeconomic conditions, global financial factors, and measures of systemic risk. 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 bank-level 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, Philippines, Poland, Russia, South Africa, Turkey, and Venezuela.

Table A.1 in Appendix A presents the description and sources of all the variables used in our regression analysis. Our final sample consists of 1,406 country-time observations. Table 2 reports summary basic statistics of all the variables used in the regression analysis for the overall sample.

3.1 Sovereign Credit Risk

The sovereign-credit-risk measure used in this study is the sovereign credit spread. This variable is obtained from the Bloomberg system that collects data from industry sources. Emerging-market sovereign credit 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. We control for sovereign credit ratings. 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).

Table 3 provides summary information for the sovereign credit spreads by country. The average values of the spreads range widely across countries. The lowest average is 135 basis points for China; the highest average is 1,405 basis points for Argentina. Both the standard deviations and the minimum/maximum values indicate significant variations also exist over time within countries. For example, the credit spread for Argentina ranges from 204 to 7,078 basis points during the sample period.

3.2 Banking Fragility

Our key explanatory variable of interest is our metric of banking 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.2 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.

[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."

As shown in Figure 1, in most countries our JLoss metric captures both periods of global financial distress and periods of country-specific idiosyncratic banking fragility. In many countries, idiosyncratic factors seems to have stronger effects on banking 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 banking fragility than global banking fragility.

3.3 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. As previously mentioned, 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.

3.4 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 liquidity. 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, as we explain in the next section, we also control for a large number of measures of systemic risk proposed in the literature.

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. Lastly, 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.

3.5 Systemic Risk Measures

Finally, for robustness purpose, in some regressions we augment our baseline specification with 19 systemic risk measures: Absorption, AIM, CoVaR, CoVaR, MES, MES-BE, Book leverage, CatFin, DCI, Def. spr, Absorption, Intl. spillover, GZ, Size conc., Mkt lvg., Volatility, TED spr., Term spr., and Turbulence. We also employ the systemic risk index (PQR) of the mentioned systemic risk measures. We obtain this data from Giglio, Kellya and Pruitt (2016). Given that these measures are constructed to capture systemic risk stemming from the core of the financial system, these measures are based on data for financial institutions identified by

[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).

two-digit SIC codes 60 through 67 (finance, insurance, and real estate). Although these measures are available for three regions (US, UK, and EU), for space considerations, we only report the results that use U.S. data.

4 Regression Analysis and Results

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

$$Spread_{c,t} = \alpha_c + \gamma_t + \beta JLoss_{c,t} + \omega X_{c,t} + \epsilon_{c,t}, \tag{6}$$

where $Spread_{c,t}$ is the sovereign credit spread of country c at time t. $JLoss_{c,t}$ is our metric of fragility in the banking sector, which computes the joint loss distribution of the banking sector conditional on a systemic event. Both $Spreads_{c,t}$ 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. The term α_c represents a vector of country fixed effects that control for all time-invariant country-specific factors affecting both credit spreads and banking 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 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 banking fragility, the sovereign bond spreads 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 spreads is stronger in countries with more vulnerable banking sectors. To explore this hypothesis, we estimate the following model:

$$Spread_{c,t} = \alpha_c + \beta JLoss_{c,t} + \gamma Global_t + \theta JLoss_{c,t} \; x \; Global_t + \omega X_{c,t} + \epsilon_{c,t}, \quad (7)$$

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 spreads differs in countries with different degrees of banking 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 Banking Fragility

Table 4 presents the results from the estimation of equation (6) with different sets of control variables. 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 our set 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, each of our estimated coefficients represent an elasticity. In terms of the economic magnitude of our findings, the coefficient reported in column 1 suggests that, on average, a 100-percent increase in our JLoss measure raises the sovereign credit spread by 22 percent. The coefficient reported in column 3 suggests that a comparable increase in JLoss raises the average spread by 13 percent. Our regressions appear to support the view that banking fragility exerts a strong influence on the pricing of emerging-market sovereign bonds.

Despite the high correlation in our country-level control variables, most of the estimated coefficients of our control variables are statistically significant in the expected direction. On the one hand, the results show that sovereign credit ratings and bank profits are negatively related to credit spreads. On the other hand, the results show indebtedness, global financial instability, exchange rate volatility, global premiums, and aggregate market illiquidity are positively related to spreads.

4.2 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.

Table 5 report the results from the estimation of two specification of equation (7). The table reports the estimates of our econometric model including time fixed effects (columns 1 to 4) and global financial factors instead of time fixed effects (columns 5 to 8). As before, the model is estimated by ordinary least squares (OLS) with robust standard errors. The positive and statistically significant coefficients associated with the interaction terms in columns 1 to 4 in Table 5 indicate that a deterioration in global market volatility, risk-free interest rates, high-yield spreads, and aggregate liquidity 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 the table 5, which consider the direct effects of global financial factors instead of time fixed effects, show almost qualitatively identical results.

To analyze the magnitude of the impact of global factors on sovereign credit spreads across different levels of banking fragility, we show in Figure 3 the partial effect of each of our global factors at different levels of banking fragility.[8] The magnitudes and confidence intervals reported in the figures suggest that the effect of the VIX index and the U.S. high yield on sovereign spreads are either zero or positive, and they become positive and larger in economies with more fragile banking sectors. The marginal effects of the U.S. treasury rate and aggregate illiquidity on sovereign spreads are negative for low levels of banking fragility, zero for moderate levels of banking fragility, and positive for high levels of banking fragility. Given that sovereign spreads measures the average spread on U.S. dollar-denominated bonds issued by sovereign entities over U.S. Treasuries, it is expected the marginal effect of US Treasury rate is negative for low values of banking fragility. Overall, these magnitudes suggest that countries with more fragile banking sectors are more exposed to global (exogenous) financial factors than those with more resilient banking sectors.Thus, our results suggest that stability of the banking sector is a precondition to become more resilient to global shocks and underscore that regulators must ensure the stability of the banking sector to improve governments' borrowing costs in international debt markets.

5 Robustness Checks

We conduct a number of exercises to check the robustness of our main results. First, we split our sample between periods of financial stability and periods of banking crises. Next, we explore whether our interaction terms may be capturing other non-linear effect of global factors on sovereign credit spreads. Finally, we control for a large set of measures of systemic risk proposed in the literature to capture systemic risk stemming from the core of the financial system.

Given that our metric of banking fragility in the banking sector spikes during

[8]It is important to note that if the relationship between global factors and sovereign credit spreads is just a simple correlation caused by common macroeconomic factors rather than by a causal effect, global factors should always affect spreads in a similar way.

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 of Table 6 reports the results from estimating our baseline regressions for the periods of financial stability. Column 2 reports the results for periods of systemic banking crises. The systemic-banking-crises dummy variable used to divide our sample was constructed using the dataset introduced by Laeven and Valencia (2018). The results are qualitatively identical to our baseline regressions reported in Tables 4. As expected, the magnitude of our coefficients decrease for the periods of financial stability and increase for the periods of banking crises. However, in both specifications, they remain highly statistically significant and economically meaningful in the expected directions.

Because our primary term of interest in Table 5 is the interaction between JLoss and our four global factors, it is likely that JLoss may captures the effect of another country-specific factor. Table 7 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 a 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 financial factors and sovereign credit ratings. Columns 5 to 8 augment our previous model with the interaction between global factors and banking crises. Overall, our main findings remain unchanged. That is, the effects of the VIX index, the High Yield spread and the On/off-the-run spread on sovereign spreads is larger in countries with more fragile banking sectors.

Finally, we control for a large collection of systemic risk measures proposed in the literature: Absorption, AIM, CoVaR, CoVaR, MES, MES-BE, Book leverage, CatFin, DCI, Def. spr, Absorption, Intl. spillover, GZ, Size conc., Mkt lvg., Volatility, TED spr., Term spr., and Turbulence. We also employ the systemic risk index (PQR) of the mentioned systemic risk measures. We take these measures from Giglio, Kellya and Pruitt (2016). For space considerations, we only use the measures for the US. The results reported in Table 8 show that the coefficients associated with our JLoss measure remains positive and highly significant in all the 20 models. Our main finding proved to be robust to controlling for a large set of systemic risk measures. Thus, our JLoss metric seems to capture not only systemic risk factors but also idiosyncratic factors that are not capture on global financial measures.

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 banking 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 banking 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 banking 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.

This study on the relationship between our metric of banking fragility (JLoss) and sovereign credit spread is a first approach to explore the validity and power of our metric. Future research should focus on the effect of our JLoss metric on corporate credit risk and firm level performance. More granular data at the firm and bond levels should also allow us to have a more clean identification strategy to examine causal effects of interest.

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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%)

Note: This table reports the parameterization used in the Jloss calculation once the individual expected default frequencies are calculated.

Table 2: Descriptive Statistics

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Sovereign Credit Risk					
EMBI spread	1,406	3.913	6.336	-0.0300	70.78
S&P rating	1,406	11.44	3.545	1	18
Banking fragility					
JLoss	1,406	6.804	9.057	0	47.16
Control Variables					
Profit margin	1,348	20.19	36.34	-789.5	138.6
Exchange rate volatility	1,329	14.38	61.01	0	932.8
Debt to GDP	1,391	45.66	22.21	3.879	147.2
GDP per capita	1,406	7,021	4,278	534	16,056
VIX	1,406	20.07	8.509	9.510	53.54
U.S. treasury rate	1,406	3.211	1.301	0.657	6.442
High yield spread	1,406	5.201	2.583	2.380	17.22
On/off-the-run spread	1,406	0.114	0.112	-0.0182	0.518

Note: This table reports basic descriptive statistics (mean, standard deviation, minimum and maximum values) of the outcome and control variables used in the regression analysis for the overall sample.

Table 3: Descriptive Statistics for Sovereign Credit Spreads

Country	Mean	Standard Deviation	Minimum	Maximum
Argentina	15,60	18,12	2,04	70,78
Brasil	4,36	3,61	1,4	24,12
Chile	1,50	0,54	0,55	3,43
China	1,38	0,616	0,44	2,93
Colombia	2,37	0,96	1,12	4,98
Egypt	3,43	1,99	-0,03	8,78
Indonesia	2,51	1,19	0	7,62
Malaysia	1,59	0,63	0,66	3,7
Mexico	2,65	1,16	1,11	6,53
Pakistan	5,96	4,09	0	21,12
Panama	2,54	1,20	1,14	5,61
Peru	2,79	1,79	1,07	8,8
Philippines	2,49	1,58	0,67	6,71
Poland	1,17	0,72	0,12	3,19
Russia	2,43	1,19	0,92	8,05
South Africa	2,17	1,12	0,73	5,62
Turkey	4,06	2,12	1,77	10,66
Venezuela	14,60	8,31	2,07	31,29
Total	3,91	6,33	-0,03	70,78

Note: This table reports descriptive statistics (mean, standard deviation, minimum and maximum values) for the sovereign credit spreads by country.

Table 4: Sovereign Credit Spreads and Banking fragility

EMBI spread	(1)	(2)	(3)	(4)
Jloss	0.217***	0.152***	0.134***	0.144***
	(0.0221)	(0.0186)	(0.0204)	(0.0188)
Rating S&P		-0.121***	-0.112***	-0.117***
		(0.00884)	(0.00915)	(0.00942)
Exchange rate volatility			0.0681**	0.0536**
			(0.0275)	(0.0268)
Profit Margin			-0.0240	-0.0492***
			(0.0183)	(0.0181)
Debt to GDP			0.199***	0.236***
			(0.0444)	(0.0419)
GDP per capita			0.145***	0.194***
			(0.0545)	(0.0405)
VIX				0.0658
				(0.0447)
US treasury				-0.125**
				(0.0508)
US high yield				0.358***
				(0.0671)
On/Off-the-run spread				0.238
				(0.155)
Observations	1,406	1,406	1,223	1,223
R-squared	0.726	0.798	0.789	0.773
Adjusted R-squared	0.708	0.785	0.773	0.768
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	NO

Note: This table reports estimates from panel regressions of sovereign credit spreads against banking fragility (JLoss) and a comprehensive set of determinants of sovereign credit risk. Models 1 to 3 control for country and time fixed effects. Model 4 controls for global factors instead of time fixed effects. Robust standard errors are in parentheses below each coefficient estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5: Sovereign Credit Spreads, Banking Fragility, and Global Financial Factors

EMBI spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jloss	-0.442***	0.0819	-0.274***	0.0485**	-0.231**	-0.114**	-0.0943	0.0724***
	(0.0823)	(0.0531)	(0.0544)	(0.0218)	(0.106)	(0.0549)	(0.0645)	(0.0219)
Rating S&P	-0.112***	-0.112***	-0.112***	-0.111***	-0.118***	-0.116***	-0.117***	-0.116***
	(0.00912)	(0.00918)	(0.00907)	(0.00910)	(0.00939)	(0.00950)	(0.00938)	(0.00940)
Exchange rate volatility	0.0655**	0.0694**	0.0612**	0.0771***	0.0586**	0.0655**	0.0576**	0.0688***
	(0.0264)	(0.0276)	(0.0261)	(0.0267)	(0.0266)	(0.0267)	(0.0266)	(0.0266)
Profit Margin	-0.0249	-0.0243	-0.0222	-0.0228	-0.0527***	-0.0453**	-0.0516***	-0.0495***
	(0.0175)	(0.0183)	(0.0172)	(0.0175)	(0.0181)	(0.0183)	(0.0181)	(0.0182)
Debt to GDP	0.193***	0.193***	0.201***	0.176***	0.228***	0.206***	0.236***	0.220***
	(0.0447)	(0.0455)	(0.0434)	(0.0443)	(0.0421)	(0.0433)	(0.0415)	(0.0422)
GDP per capita	0.130**	0.139**	0.122**	0.0979*	0.197***	0.168***	0.188***	0.166***
	(0.0548)	(0.0546)	(0.0544)	(0.0543)	(0.0402)	(0.0408)	(0.0403)	(0.0404)
VIX					-0.151**	0.0836*	0.0721	0.0910**
					(0.0716)	(0.0446)	(0.0450)	(0.0445)
US treasury					-0.106**	-0.490***	-0.109**	-0.113**
					(0.0513)	(0.0832)	(0.0509)	(0.0507)
US high yield					0.362***	0.325***	0.137	0.350***
					(0.0668)	(0.0665)	(0.0865)	(0.0662)
On/Off-the-run spread					0.165	0.266*	0.115	-1.010***
					(0.158)	(0.151)	(0.158)	(0.256)
VIX X Jloss	0.191***				0.125***			
	(0.0270)				(0.0352)			
U.S Treasury rate X Jloss		0.0383				0.189***		
		(0.0363)				(0.0382)		
High Yield spread x Jloss			0.223***				0.131***	
			(0.0278)				(0.0339)	
On/Off-the-run spread x Jloss				0.744***				0.596***
				(0.103)				(0.103)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,223	1,223
R-squared	0.801	0.789	0.802	0.799	0.776	0.778	0.776	0.780
Adjusted R-squared	0.785	0.773	0.787	0.784	0.771	0.773	0.771	0.774
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	NO	NO	NO	NO

Note: This table reports estimates from panel regressions of sovereign credit spreads against banking fragility (JLoss) and a comprehensive set of determinants of sovereign credit risk. Models 1 to 4 control for country and time fixed effects. Models 5 to 8 control for global factors instead of time fixed effects. Robust standard errors are in parentheses below each coefficient estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Periods of Financial Stability versus Periods of Crises

EMBI spread	Periods of financial stability	Periods of banking crises
Jloss	0.103***	0.183***
	(0.0226)	(0.0497)
Rating S&P	-0.106***	-0.111***
	(0.00953)	(0.0261)
Exchange rate volatility	0.0715**	0.0869*
	(0.0304)	(0.0485)
Profit Margin	0.00215	-0.0482**
	(0.0201)	(0.0230)
Debt to GDP	0.235***	-0.356
	(0.0525)	(0.236)
GDP per capita	0.132**	-0.0286
	(0.0592)	(0.254)
Observations	1,010	213
R-squared	0.784	0.920
Adjusted R-squared	0.766	0.902
Country FE	YES	YES
Time FE	YES	YES

Note: This table reports estimates from panel regressions of sovereign credit spreads against banking fragility (JLoss) and a comprehensive set of determinants of sovereign credit risk. The models control for country and time fixed effects. Robust standard errors are in parentheses below each coefficient estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Robustness: Alternative Non-linear Effects

EMBI spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jloss	-0.408***	0.0885	-0.246***	0.0480**	-0.375***	0.0687	-0.253***	0.0536**
	(0.0882)	(0.0538)	(0.0560)	(0.0217)	(0.0917)	(0.0538)	(0.0675)	(0.0222)
Rating S&P	-0.129***	-0.0710***	-0.134***	-0.111***	-0.112***	-0.111***	-0.112***	-0.111***
	(0.0162)	(0.0136)	(0.0131)	(0.00913)	(0.00909)	(0.00904)	(0.00903)	(0.00908)
Exchange rate volatility	0.0623**	0.0755***	0.0547**	0.0767***	0.0620**	0.0677**	0.0607**	0.0755***
	(0.0267)	(0.0272)	(0.0270)	(0.0267)	(0.0262)	(0.0270)	(0.0260)	(0.0267)
Profit Margin	-0.0238	-0.0239	-0.0213	-0.0228	-0.0229	-0.0205	-0.0221	-0.0228
	(0.0176)	(0.0181)	(0.0173)	(0.0175)	(0.0170)	(0.0174)	(0.0167)	(0.0170)
Debt to GDP	0.197***	0.131***	0.205***	0.178***	0.185***	0.175***	0.193***	0.169***
	(0.0450)	(0.0444)	(0.0437)	(0.0442)	(0.0437)	(0.0444)	(0.0425)	(0.0435)
GDP per capita	0.130**	0.133**	0.126**	0.0982*	0.139**	0.143***	0.131**	0.110**
	(0.0549)	(0.0554)	(0.0543)	(0.0546)	(0.0541)	(0.0541)	(0.0540)	(0.0540)
Banking crisis					-0.611	4.082***	0.123	0.125
					(0.523)	(1.069)	(0.506)	(0.356)
VIX x Jloss	0.180***				0.168***			
	(0.0294)				(0.0306)			
VIX x Rating S&P	0.00598							
	(0.00441)							
VIX x Banking crisis					0.266*			
					(0.137)			
U.S. Treasury rate x Jloss		0.0346				0.0453		
		(0.0366)				(0.0370)		
U.S. Treasury rate x Rating S&P		-0.0355***						
		(0.00953)						
U.S. Treasury rate x Banking crisis						-2.072***		
						(0.540)		
High yield spread x Jloss			0.207***				0.211***	
			(0.0295)				(0.0367)	
High yield spread x Rating S&P			0.0130**					
			(0.00537)					
High yield spread x Banking crisis							0.0429	
							(0.193)	
On/off-the-run spread x Jloss				0.748***				0.695***
				(0.103)				(0.122)
On/off-the-run spread x Rating S&P				0.00356				
				(0.0205)				
On/off-the-run spread x Banking crisis								0.328
								(0.894)
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,223	1,223
R-squared	0.801	0.794	0.803	0.799	0.803	0.795	0.803	0.800
Adjusted R-squared	0.786	0.778	0.788	0.784	0.787	0.779	0.788	0.785
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table reports estimates from panel regressions of sovereign credit spreads against banking fragility (JLoss), a comprehensive set of determinants of sovereign credit risk, and interaction terms. All regressions control for country and time fixed effects. Robust standard errors are in parentheses below each coefficient estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 8: Robustness: Systemic Risk Measures

EMBI spread	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Jloss	0.144***	0.231***	0.216***	0.223***	0.220***	0.219***	0.224***	0.224***	0.220***	0.216***
	(0.0188)	(0.0264)	(0.0265)	(0.0263)	(0.0258)	(0.0266)	(0.0263)	(0.0261)	(0.0266)	(0.0267)
CATFIN	0.0463									
	(0.141)									
PQR		5.343***								
		(1.780)								
Absorption			-0.829***							
			(0.260)							
AIM				5.987						
				(4.216)						
Book - LVG					-5.248***					
					(1.529)					
Covar						-2.323*				
						(1.336)				
DCI							-0.660**			
							(0.264)			
Def - SPR								-0.209***		
								(0.0472)		
Delta Absorption									0.582**	
									(0.252)	
Delta Covar										-6.791***
										(2.614)
Observations	1,223	695	695	695	695	695	695	695	695	695
R-squared	0.773	0.782	0.784	0.780	0.783	0.780	0.781	0.786	0.782	0.781
Adjusted R-squared	0.768	0.773	0.775	0.771	0.775	0.771	0.772	0.777	0.773	0.773
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Note: This table reports estimates from panel regressions of sovereign credit spreads against banking fragility (JLoss) and a comprehensive set of determinants of sovereign credit risk, including 20 alternative measures of systemic risk. Robust standard errors are in parentheses below each coefficient estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

EMBI spread	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Jloss	0.213***	0.206***	0.217***	0.227***	0.219***	0.227***	0.221***	0.228***	0.228***	0.228***
	(0.0286)	(0.0293)	(0.0265)	(0.0264)	(0.0262)	(0.0275)	(0.0263)	(0.0268)	(0.0261)	(0.0269)
GZ	-0.0783**									
	(0.0346)									
Intl. Spillover		-2.46e-06								
		(0.00156)								
MES			-2.318***							
			(0.819)							
MES - be				-7.964***						
				(2.376)						
Market Leverage					-0.0172***					
					(0.00572)					
Real vol.						-1.441				
						(2.058)				
Size Conc.							0.200***			
							(0.0569)			
Ted-SPR								-0.000571**		
								(0.000278)		
Term-SPR									0.0258***	
									(0.00991)	
Turbulence										-0.000640*
										(0.000379)
Observations	612	595	695	695	695	695	695	695	695	695
R-squared	0.792	0.790	0.782	0.783	0.782	0.780	0.783	0.781	0.781	0.781
Adjusted R-squared	0.782	0.781	0.773	0.774	0.773	0.771	0.774	0.772	0.773	0.772
Control variables YES		YES	YES	YES	YES	YES	YES	YES	YES	YES
YES	YES									
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Note: This table reports estimates from panel regressions of sovereign credit spreads against banking fragility (JLoss) and a comprehensive set of determinants of sovereign credit risk, including 20 alternative measures of systemic risk. Robust standard errors are in parentheses below each coefficient estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

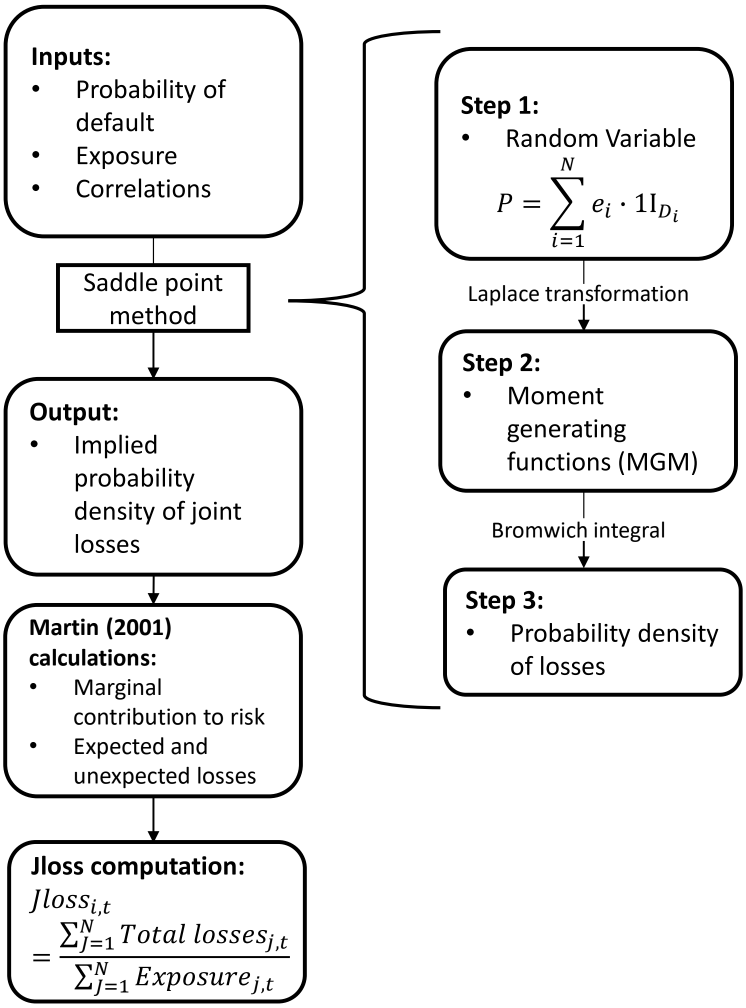

Figure 1: JLoss Methology

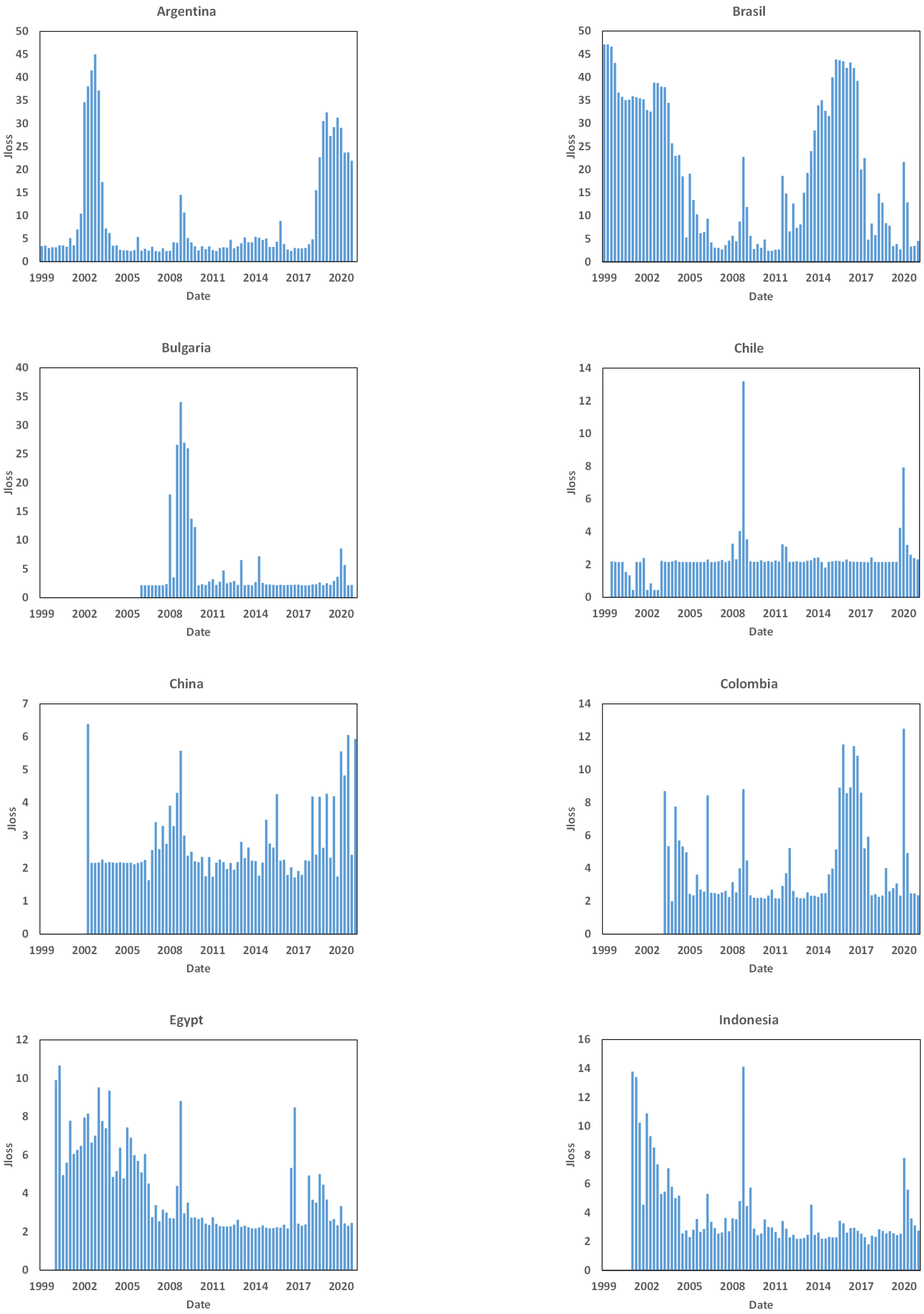

Figure 2: JLoss by Country

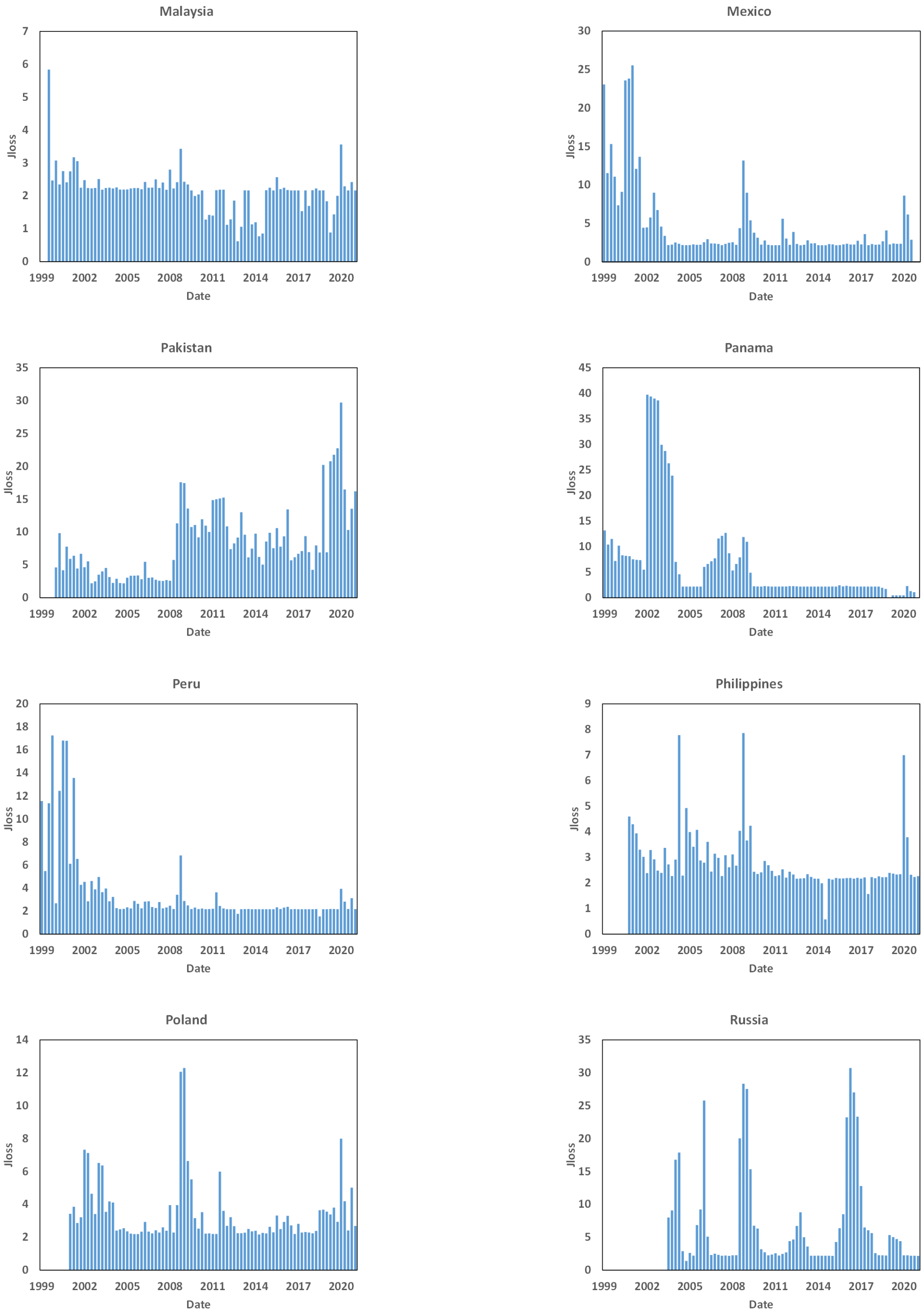

Figure 2: JLoss by Country (continued)

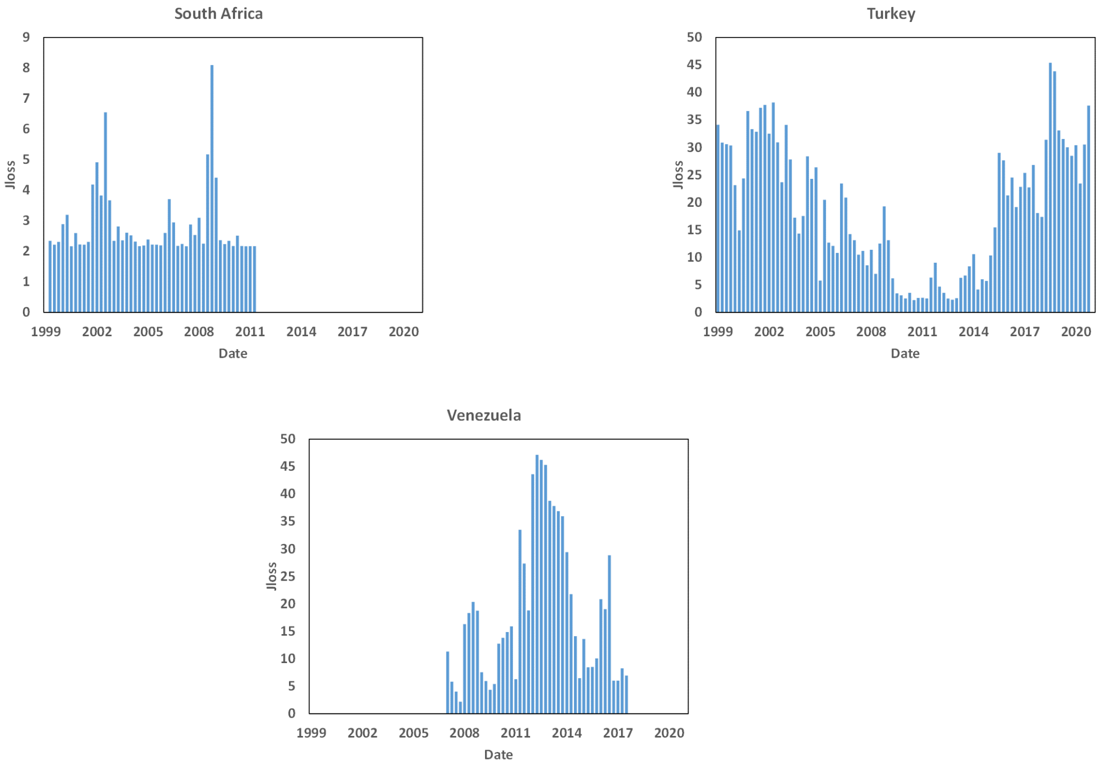

Figure 2: JLoss by Country (continued)

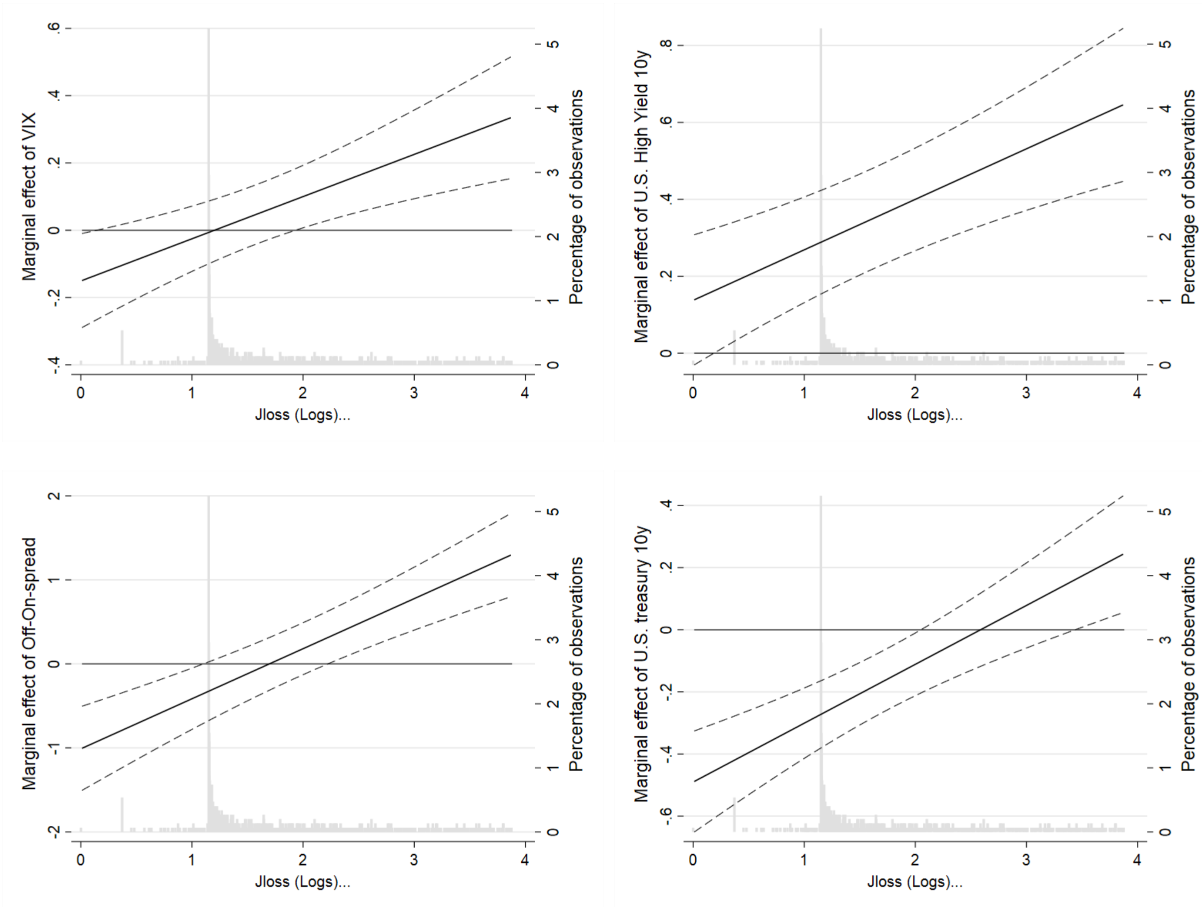

Figure 3: Marginal effects of global factors on sovereign credit spreads conditional on values of banking fragility (Jloss). Dotted lines are 95 percent confidence bands.

Appendix

Table A.1 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
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) the yields from a smooth zero-coupon yield curve (in log)	Quarterly	Board of Governors of the Federal Reserve System
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.2 Banks per Country

Country	Number of banks
Argentina	5
Brazil	11
Bulgaria	3
Chile	6
China	13
Colombia	6
Egypt	9
Indonesia	23
Malaysia	7
Mexico	4
Pakistan	20
Panama	2
Peru	5
Philippines	10
Poland	10
Russia	5
South Africa	3
Turkey	8
Venezuela	3

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