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 in the event of a large financial meltdown. 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 and 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 it also remains a significant determinant of the cost of debt capital for the private sector (Cavallo and Valenzuela, 2010; Borensztein, Cowan, 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 of sovereign credit spreads in emerging economies (Hilscher and Nosbusch, 2010), it seems that sovereign credit risk is 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, there is also recent empirical evidence that suggest that 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 that the state of the domestic financial market as well as of the global financial system have strong explanatory power for the evolution of sovereign spreads. They emphasize 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 that sovereign spreads increased in the eurozone with the greater expectation of public support for distressed banks (Mody and Sandri, 2012), our results indicate that our metric of financial fragility is positively associated with sovereign credit spreads and negatively associated with higher sovereign credit ratings. The results additionally indicate that countries with more fragile banking sectors are more exposed to the influence of global 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 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 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. Recent academic studies have introduced measures of systemic risk (see, for example, Brownlees and Engle (2016)). 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 in 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 that 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 in the past (Boehmer and Megginson, 1990; Edwards, 1986; Hilscher and Nosbusch, 2010; Longstaff et al., 2011), new research on the relationship 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 factors on sovereign credit risk. Although global factors have recently been viewed as push factors in the literature, they have been usually modeled as having homogeneous effects on sovereign credit risk (see, for example,González-Rosada and Yeyati, 2008). Our analysis suggest that regulations and policies aimed to improve the stability of the domestic banking sector may be helpful to reduce 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 describes the sample and variables used in this study. Section 3 presents the regression analysis and reports the main results. Section 4 conducts a set of robustness checks. Finally, section 5 concludes.

2 Data

To empirically test the relationship between sovereign credit risk, financial fragility, and global factors, we employ a quarterly panel data set of 19 emerging economies over the period 1999:Q1 to 2017:Q3. Our panel data set 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 EMBI Global and those for the ones 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.1 in Appendix A presents the description and sources of all the variables. Our final sample consists of 1,187 country-time observations in the spreads regressions and of 1,243 country-time observations in the rating regressions. Table 1 reports summary statistics of all the variables used in the regression analysis for the overall sample.

2.1 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 with the J. P. Morgan Emerging Markets Bonds Index (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 foreign currency.[1] 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, for example, Borensztein et al., 2013), with the 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.2 in the Appendix A reports the numerical values for each credit rating category.

Tables 2 and 3 provides summary information for the sovereign credit spreads

[1]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."

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 that there is also significant variations 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.

2.2 Domestic Financial Fragility

Our key explanatory variable of interest is a novel metric of financial fragility. Our metric, JLoss, is a model-based semi-parametric estimation of the expected joint loss of the banking sector after liquidating the collateral. The JLoss calculation utilizes as inputs bank-level probabilities of default generated on a Merton (1974) contingent claims approach, which are calculated by 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.3 in Appendix reports the number of banks by each country. Using bank-level default probabilities, we apply a semi-parametric method for calculating an aggregate measure of the systemic credit risk at the country level. This method is based on the saddle point approximation technique discussed in Martin, Thompson, and Browne (2001). It requires as inputs the bank-specific probabilities of default, the exposure in case of default (banks liabilities), a loss given default (LGD) parameter, and an estimate of the correlation between assets and the systemic component. Appendix B describes in detail the methodology used in the construction of our JLoss metric, including the calculation of the JLoss metric and of the default probabilities as well as the saddle point method. Figure 1 displays our aggregate JLoss metric. Figure 2 displays the JLoss metric for each of the 19 emerging countries in the sample.

Although Jloss is not the only attempt at literature to measure financial stability, this is one of the few that performs an aggregation work that allows us to have a metric that reflects financial stability at country level. For example, the SRISK metric (Brownless & Engle, 2016) is an index that computes the expected deficit to the capital of individual financial firms. Brownless & Engle (2016) agregation procedure consist on adding up all the capital loses of a particular financial system. Thus the aggregate metric does not consider the correlation between the financial institutions. In addition, since the SRISK is a metric that is based on capital deficits given a praticular stressted scenario, the metric is more crisis-oriented than identifying periods of vulnerability.

On the other hand, the CIMDO-copula of Segviano (Goodhart, Segoviano 2009) is a metric more similar to the Jloss in methodological terms. However, the difference between the Jloss and the Segovian CIMDO-copula is that in the first case with the assumptions of conditional independence and the semi-parametric calculation allow us to improve efficience in capturing the changes of variation and, in addition, offers advantages from the computational point of view, being an approximation, but with high precision.

2.3 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 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 for 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 of emerging economies. The 10-year U.S. Treasury rate address 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 global financial market. We employ the 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.[2] 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.

2.4 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 country's exchange rate against the U.S. dollar. We added this variable as 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 domestic financial sector. Sovereign credit ratings are credit rating agencies's opinion of a government's overall capacity to meet its foreign-

[2]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).

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).

3 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:

$$Credit\ Risk_{c,t} = \alpha_c + \gamma_t + \beta JLoss_{c,t} + \omega X_{c,t} + \epsilon_{c,t}. \tag{1}$$

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 in the event of a financial meltdown. $X_{c,t}$ 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 that this is a plausible assumption, 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 financial factors on sovereign credit risk is stronger in countries with more vulnerable banking sectors. In order to explore this hypothesis, we estimate the following model:

$$Credit\ Risk_{c,t} = \alpha_c + \gamma_t + \beta JLoss_{c,t} + \theta JLoss_{c,t}\ x\ Global_t + \omega X_{c,t} + \epsilon_{c,t}. \quad (2)$$

Where $Global_t$ is a global 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.

3.1 Sovereign Bond Spreads and Financial Fragility

Table 4 presents the results from the estimation of Eq.(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 that 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 exert a strong influence in 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 that indebtness, global financial instability, global premiums, and aggregate market liquidity are positively related to sovereign credit spreads.

3.2 Sovereign Credit Ratings and Financial Fragility

Our previous analysis indicate that 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, it is possible that credit spreads and financial fragility are also linked through a credit-rating channel. While 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.

In order to explore a potential credit-rating channel, Table 5 reports the results from our baseline model by using sovereign credit ratings as our dependent variable. Columns 1 to 2 report the results of our model with country fixed effects and time fixed effects, while that column 3 reports the results of our model including global financial factors instead of time fixed effect. Overall, our results indicate that sovereign credit ratings are negatively related to our JLoss metric. This negative correlation between JLoss and sovereign credit ratings is statistically significant and economically meaningful in all our different specifications.

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

3.3 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, for example, 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 that 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 6 and 7 report the results from the estimation of Eq. (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 reports the estimates of our econometric model including global financial factors instead of time fixed effect (columns 5 to 8). The positive and statistically significant coefficients associated with the interation terms in columns 1 to 4 in Table 6 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 6, that considered the direct effects of global financial factors instead of time fixed effects, produced almost identical results.

Similarly to our previous results, the negative and statistically significant coefficients associated with the interation terms in columns 1 to 4 in Table 7 indicate that a 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 produced almost qualitatively similar results.

4 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 of our sample periods crises. Next, we explore whether our interaction term is capturing other non-linear effect of global factors on sovereign credit spreads. Finally, we consider an alternative sovereign credit rating for long-term debt in foreign currency elaborated by using Moody's sovereign credit rating.

Given that the our metric of financial fragility in the banking sector spikes during periods of systemic banking crises, it is likely that our results are driven by 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 8 reports the results from estimating our baseline regressions controlling for dummy variables associated with periods of systemic banking crises, while columns 3 and 4 reports the results when excluding periods of systemic banking crises. The systemic banking crises dummy variables used in our analysis were constructed by using the dataset introduced by Laeven and Valencia (2018). The results are qualitatively identical to our baseline regressions reported in Tables 4 and 5. As expected the magnitude of our coefficients decrease. However, they remain highly statistically significant in the expected directions.

In view that our primary term of interest in Table 6 is the interaction between the JLoss and our four global factors, it is possible that JLoss captures the effect of another country-specific factor. Table 9 presents the results of a more explicit test of this possibility by including two additional interaction terms. The two added terms correspond to the interaction of the sovereign credit rating and the banking crisis dummy variable with JLoss, respectively. Columns 1 to 4 augments our previous model with the interaction between global factors and sovereign credit ratings, while that columns 5 to 8 augments 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 sovereign credit rating constructed based in the ratings granted by Moody's yielded almost identical results than by using S&P sovereign credit ratings.

5 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, there is a dearth of rigorous research on the nexus between sovereign risk and bank risk in emerging markets. 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. 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 a more healthy banking reduce a country's exposure to global financial factors. A better understanding of the mechanisms through which sovereign credit risk is influenced by global factors 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 a more fragile banking sector are more expose to the influence of global financial factors.

Our results have important policy implications as they underscore that the stability of a country's domestic banking sector plays a crucial role reducing sovereign risk and its sensitivity to global factors. Therefore, countries must ensure the stability of their banking sector to easy access to international funding and reduce potentially undesired effects of integration.

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Tables

Table 1: 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 2: 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 3: 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 4: 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 5: 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 6: Sovereign Bond Spreads, Financial Fragility, and Global 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 7: Sovereign Credit Ratings, Financial Fragility, and Global 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 8: 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***
S&P Rating	-0.116***		-0.110***	
Exchange rate volatility	0.0292	-0.0547	0.0301	-0.00199
Profit margin	0.0311*	-0.0390	0.0332**	-0.0438
Debt to GDP	0.286***	0.00202	0.241***	0.164
GDP per capita	0.243***	2.693***	0.265***	2.792***
Banking crisis	0.417***	-1.043***		
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 9: 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

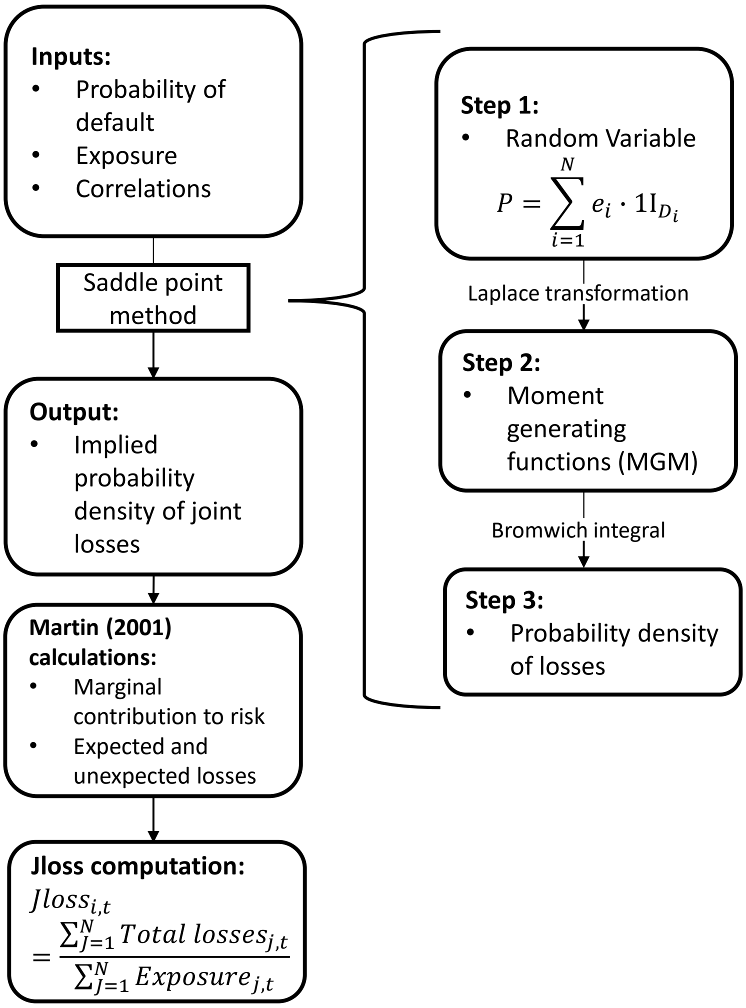

Figure 1: Methology

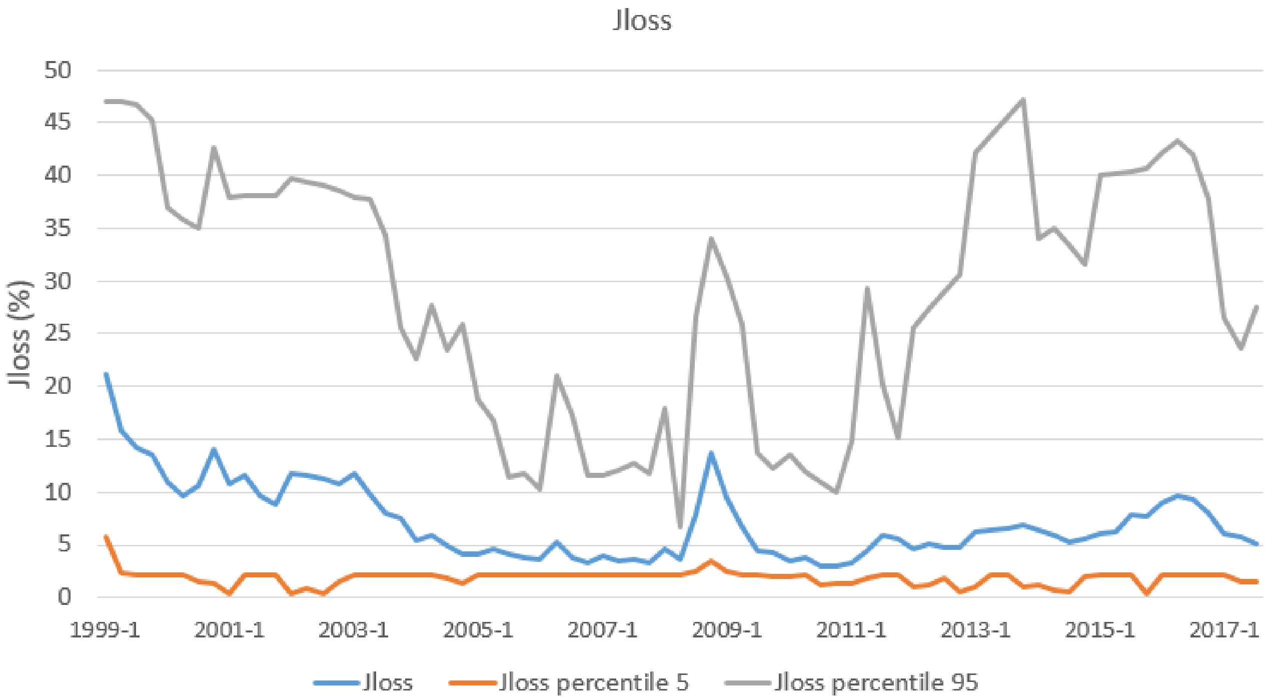

Figure 2: Financial Fragility Measure (JLoss)

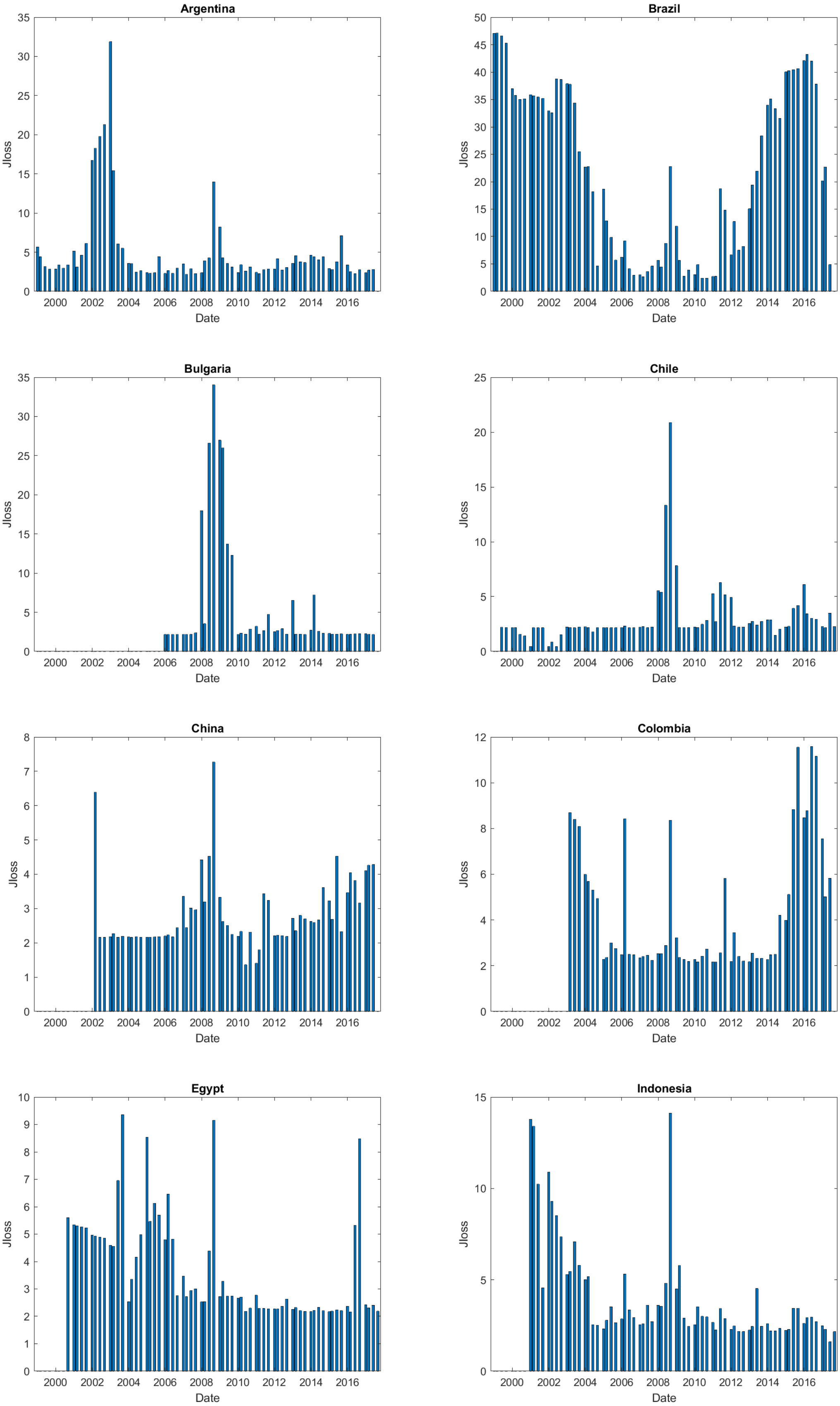

Figure 2A: JLoss by Country

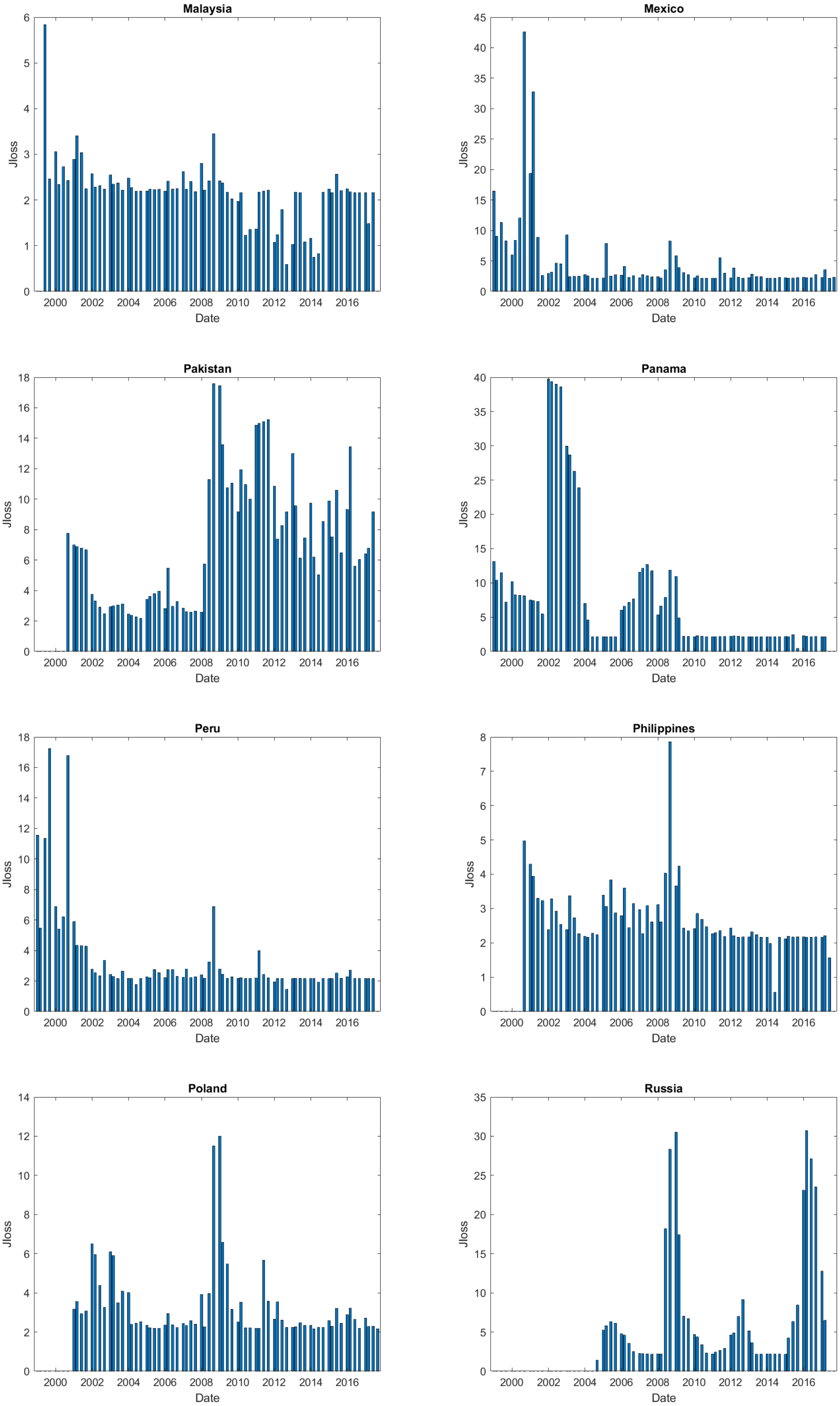

Figure 2B: JLoss by Country

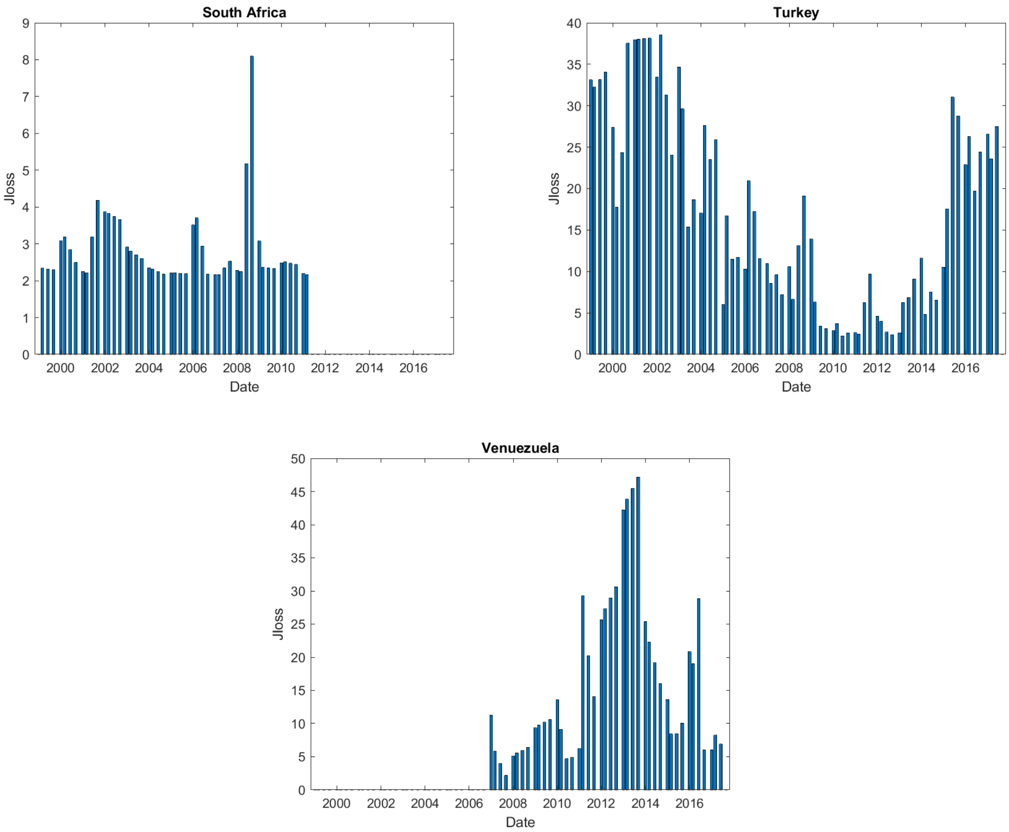

Figure 2C: JLoss by Country

Appendix A

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
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.2 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		

Table A.3 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
Venuezuela	6

Appendix B

Calculation of the JLoss

The *JLoss* calculation uses as inputs the expected default frequencies generated on a Merton (1974) contingent claims approach. We calculate these by using stock market and balance sheet data of commercial banks that are present in the stock market of a set of emerging economies. This is a standard approach. However, it has some limitations, since is relies on market information which does not have a high predictive power. Yet, the reliability and precision of this indicators of individual defaults, in contrast to pure accounting data, is much better. In this analysis, we overcome another limitation of a Merton-like modelling of financial fragility, by considering the correlation structure, using a Vasicek (1977) approach.

Using the individual default probabilities we calculate at individual banks level, we apply an innovative semi-parametric method for calculating the overall JLoss for the banking sector of each country in the sample of emerging economies. This method is the *saddle point* approximation. It uses as inputs the individual probabilities recently described, the exposure in case of default, a loss given default (LGD) parameter, a correlation parameter with a systemic risk factor for each bank in a particular country, and some other parameters we will describe in detail. After we obtain the JLoss, and following Martin (2001) we calculate each country's marginal contribution to the total risk and relativize it with respect to the total liabilities. An overview of the methodology is presented in figure 1.

Individual Probabilities: Distance-to-Default

In this section we describe how we calculate the default probabilities following a standard modification of the widely used Merton (1974) contingent claims distance-to-default approach. The modification we use appears in Kealhofer(2000), which is basically the popular Moody's KMV approach. The disadvantages of this approach include the need of a somewhat subjective estimation of the input parameters, the normality distribution assumption, the lack of use of some important accounting data and the difficulty to distinguish among the assets intrinsic characteristics, such as maturity and collateral. However, despite the disadvantages we mention, it is the relatively best procedure we can follow given the information available. The algorithm is described as follows.

We need information of the banks balance sheets 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 firm (bank) realized returns (σ_V), market capitalization (E) as a percentage. With this data we start constructing the default point (D^*), as in equation (3).

$$D^* = L_{ST} + \frac{1}{2} \cdot L_{LT} \tag{3}$$

On the other hand, we solve a system of two non-linear equations, for the projected value of the assets ($\hat{V}$) and the projected implied asset volatility ($\hat{\sigma_A}$) of the banks. The first equation is the equity value as a function of the value and volatility of the equity (σ_E), which is calculated following a realized variance approach[3], the leverage (K), the average coupon paid (c) assumed equal to zero, and the average interest rate (r). Whereas the second equation relates the asset and equity volatility. The calculations we perform are consistent with our quarterly database. The system we solve appears in (4) and (5).

$$\frac{V}{E} \cdot \Phi\left(d_1\right) - \frac{e^{-rT} \cdot \Phi\left(d_2\right)}{E/D^*} - 1 = 0 \tag{4}$$

$$\Phi\left(d_1\right) \cdot \frac{V}{E}\sigma_A - \sigma_E = 0 \tag{5}$$

Where $d_1 = \log\left(V \cdot \frac{E}{D^*}\right) + \frac{\frac{1}{2}\sigma_E^2 \cdot T}{\sigma_E \cdot \sqrt{T}}$, $d_2 = d_1 - \sigma_E \cdot \sqrt{T}$ and Φ stands for the cumulative normal distribution function. The above system is solved numerically by using the Newton-Raphson algorithm, already programmed in Matlab ®, following Press et al. (2007).

[3] We use the realized variance approach to estimate the quarterly equity volatility. Following Barndorf-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.

Once we get the projected values $\hat{V}$ and $\hat{\sigma_A}$, we insert them into the distance to default DD equation (6). This is a function of the forecasted value of the value of the assets of bank and its forecasted asset volatility. Finally, we obtain the expected default frequency (EDF) as in equation (7), by assuming normality.

$$DD = \frac{\frac{\hat{V}}{E} - D^*}{\frac{\hat{V}}{E} \cdot \hat{\sigma_A}} \tag{6}$$

$$EDF = \Phi\left(-DD\right) \tag{7}$$

We compute this quantity for all of the 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}), one of the inputs for the saddle point method.

Saddle Point Method Description

In this section we describe the semi-parametric saddle point method, used to obtain an aggregate measure of bank projected losses. This section heavily relies on Martin et al (2001). However, as opposed to the individual counterparts focus followed in that work, we apply it to the aggregate financial system. Our goal is to estimate the complete distribution of potential banking system losses, and use this as a measure of credit risk at the national level for emerging economies.

Despite being quite useful, the usual way of calculating the credit risk losses (as the one proposed in Basel III accord is based on Vasicek (1984)) has some shortcomings that can be improved. That methodology, requires a functional form of the distribution of losses. Therefore, one should assume that losses are adjusted to it and also assume that this distribution will contain each of the defaults with the frequency assigned. This assumption is quite strong, because the estimated parameters of the distribution can lead to important errors in the calculation of losses. Being a method that works in the space of real numbers, it lacks a simple mathematical treatment that allows closed form calculations. The saddle point procedure allows simple calculations because it has the ability to provide statistical measures associated directly with credit risk. Another advantage is the speed of calculation in the computational implementation, because it can be presented in analytical formulas. It is also quite advantageous when trying to analyze large numbers of credit units. Finally, this method makes it possible to reduce the dimensionality of an n-dimensional problem to a single dimension.

The saddle point methodology procedure allows us to get a measure of the aggregated distribution of losses, which in turn depends on the individual default probabilities, the level of exposure and the loss given a default event. All of these are taken as given and consequently not further modelled. The individual probabilities of default are calculated following a Merton (1974) *distance to default* approach, based on market data for equity and assets, and book data for liabilities. On the other hand, exposure is proxied by the amount of liabilities at the moment of default and the loss given default (LGD) is set to a 45% as suggested by the Bank of International Settlements (BIS, 2006) for banking debt.

The key assumption in this approach is that individual risks are uncorrelated, conditional on being correlated to a systemic factor (or a reduced number of them). The systemic factors can be interpreted as real and/or financial variables. Some natural examples of these components are production or overall stock market performance.

The saddle point procedure allows us to simplify the calculations by previously working in a different space. We move from the real numbers to the moment generating functions space and work on the formulation of the losses there. By making some natural assumptions we apply a transform to come back getting a result in the real numbers space.

Saddle Point Implementation

The saddle point method allows to calculate the distribution of a random variable P that represents the losses for a portfolio of a portfolio of N credit debt-holders.

$$P = \sum_{i=1}^{N} e_i \mathbb{1}_{D_i} \tag{8}$$

Where e_i is the exposure of counterpart i, and $\mathbb{1}_{D_i}$ is the indicator function that takes a value of zero if the client maintains its repayment capacity and it is equal to one otherwise.

The calculation of the losses will be determined by the distribution of the variable P, previously described (recall figure 1).

We need a workable description of the problem in the space of MGF. For it, we need to have the input data, and apply the necessary transform to get the equivalent exposure. Then it is required to determine the MGF, assuming a feasible functional form. That is statistically equivalent to the problem in the real and one-dimensional space. Although MGF do not have a direct economic interpretation, they are useful, since they can be easily constructed. The distribution functions (in $\mathbb{R}$) are equivalent to the MFG. The Laplace transform naturally connects the two spaces (from $\mathbb{R}$ to MGF). The *Bromwich integral* does the reverse process (from MGF to $\mathbb{R}$). From the last calculation it is obtained the name of the procedure, because it uses a mathematical property of this integral, which is that it accurately estimated in the region close to the *saddle point*. This regularity provides a computational advantage with respect to other methods, without any drawback and allow us to reduce the dimensionality of the problem. It is important to note that when we calculate the *Bromwich integral* throught the saddle point we are taking only the real part of the results since the orginal results have imaginary factors. This assumption is the same that Martin (2001) made in his work.

For an arbitrary credit portfolio, the relationship between the probability density functions and the MGF is described in equation (9). The MGF is the expected value of exponential function (e^{sx}), where random variable is x, and s stands for the arbitrary Laplace transform parameter and f represents the probability density function.

$$M_x(s) = \mathbb{E}\left(e^{sx}\right) = \int e^{sx} f(x)\, dx \tag{9}$$

If we consider two states for the random variable (default and no default), we have a discrete MGF, described in (10)

$$M_i(s) = \mathbb{E}\left(e^{si}\right) = \sum_{\mathbb{1}_{D_i}=0,1} f\left(\mathbb{1}_{D_i}\right) e^{s \cdot \text{expos}_i \cdot \mathbb{1}_{D_i}} = 1 - p_{def_i} + p_{def_i} e^{s \cdot \text{expos}_i} \tag{10}$$

In this case p_{def_i} is the *unconditional* default probability and expos_i is the exposure in the defined time horizon for counterpart i. If we assume *conditional independence*[4], under a discrete set of values of an underlying systemic factor, we can write the expression in (11) for the relationship between the *unconditional* (p_{def_i}) and *conditional* ($p_{def_i}(\vec{V})$) probabilities of default.

$$p_{def_i} = \sum_k p_{def_i}\left(\vec{V_k}\right) h\left(\vec{V_k}\right) \tag{11}$$

In the previous expression, $\vec{V_k}$ represents the k^{th} set of values of the underlying group of M systemic factors, $\vec{V} = \left\{V^1, V^2, ..., V^M\right\}$. Among these systemic factors or *credit drivers* we find variables of the economic cycle or fundamentals of the economy. On the other hand, $h(\vec{V})$ are the probability density of the credit drivers. Following Koyluoglu and Hickman (1996), we can write $h(\vec{V}) = h^1(V^1) \cdot h^2(V_2)...h^M(V^M)$, since the systemic factors are assumed to be uncorrelated.

Without loss of generality, and consistent with our method of estimation for the individual probabilities of default, we consider a unifactorial Merton-style model.[5] Assuming that $h(\vec{V})$ follows a Normal distribution, we have that based on Vasicek(2002), the conditional probability in (11) can be written as in (12).

[4]Conditional independence means that conditional on being correlated to a (group of) systemic factor, the counterparts 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.

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

$$p_{def_i}(V) = P\left(Z \leq \Phi^{-1}\left(p_{def_i}|V\right)\right) = \Phi\left(\frac{\Phi^{-1}\left(p_{def_i}\right) - \rho \cdot V}{\sqrt{1-\rho^2}}\right) \tag{12}$$

Where ρ is the correlation to the systemic factor. In our case we assume the systemic factor is the local stock market return, and compute the sample correlation of the individual counterparts' (banks in our exercise) stock market returns, to the stock market index of its specific country of domicile. After these calculations, we are able to define the conditional and unconditional MGF, as a function of the underlying credit driver.

$$M\left(s|V\right) = \prod_{i=1}^{N} M_i\left(s\right) = \prod_{i=1}^{N}\left(1 - p_{def_i}\left(V\right)\left(e^{\mathrm{expos}_i \cdot s}\right)\right) \tag{13}$$

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 of the 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 $K''\left(s=0\right) = \mathbb{V}\mathrm{ar}\left(x\right)$.

Once processed, the information for the individual counterparts, the calculations performed, and estimated the correlation structure, we are able to obtain the MGF in (13). After this, we need to reverse the process to come back to the space of real numbers and get the joint probability density of losses. To do that we need to calculate the inverse process of the Laplace transform. That is, the *Bromwich* integral. Under our *conditional independence* assumption, this integral takes the form in (14).

$$f(x) = \frac{1}{2\pi i}\int_{-\infty}^{+\infty}\left(\int_{-i\infty}^{+i\infty} e^{K(s|V) - s\cdot x} ds\right) h\left(V\right) dV \tag{14}$$

In order to solve the above integral, we need to use a particular property of this integral. Close to the saddle point of the argument of the exponential function in (14), 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 $\frac{d}{ds}\left(K\left(s\right) - s \cdot x\right)$, solving we have that $K'\left(s = \hat{t_V}\right) = x$. In the previous expression

$\hat{t}$ is the saddle point of the integral. Also recall that s is the Laplace transform parameter and x is the random variable representing the losses due to default.

The expression in equation (11) in the continuous case appears in equation (15).

$$P(L > x) = \int_{-\infty}^{+\infty} P(L > x|V)\, h(V)\, dV = \frac{1}{2\pi i} \int_{-\infty}^{+\infty} \left(\int_{-i\infty}^{+i\infty} e^{K(s|V) - s \cdot x} ds \right) h(V)\, dV \tag{15}$$

With the use of the saddle point property, the distribution of portfolio losses can be approximated by (16).

$$P(L > x) \approx \begin{cases} e^{\left(K\left(\hat{t_V}|V\right) - x \cdot \hat{t_V} + \frac{1}{2}\hat{t_V} K''\left(\hat{t_V}\right)\right)} \Phi\left(-\sqrt{\hat{t_V}^2 K''\left(\hat{t_V}\right)}\right), & \text{if } x \leq \mathbb{E}(L) \\ \frac{1}{2}, & \text{if } x = \mathbb{E}(L) \\ 1 - e^{\left(K\left(\hat{t_V}|V\right) - x \cdot \hat{t_V} + \frac{1}{2}\hat{t_V} K''\left(\hat{t_V}\right)\right)} \Phi\left(-\sqrt{\hat{t_V}^2 K''\left(\hat{t_V}\right)}\right), & \text{if } x > \mathbb{E}(L) \end{cases} \tag{16}$$

In order to be able to manage the integral approximation, we need to discretize the expression in (15). For the general case, in a multi-factor setting, we would have the formula in (17). Recall that in our case M, the number of systemic factors is set to one.

$$P(L > x) \approx \sum_{k_1} ... \sum_{k_M} P\left(L > x|\vec{V} = \{V_{k_1}, ..., V_{k_M}\}\right) h(V_{k_1}) ... h(V_{k_M}) \tag{17}$$

To solve the the expression in (17) it is necessary to use a quadrature. In our case we are using the Gauss-Hermite. By applying the Bayes theorem in (17), we get the expression in (18).

$$P(L > x) \approx \sum_{j} P(j)\, P(L > x|j)\, h(V_{k_1}) ... h(V_{k_M}) \tag{18}$$

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 credit factor configuration V. On the other hand $P(j)$ is the probability that the economy latent variable V is in the state j and it corresponds to the quadrature weight h_{k_i}. Finally, the marginal contributions to the overall risk (from a particular bank, to the entire financial system of a country) are obtained following Martin (2001). [6]

[6] 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.