Credit Risk Premia Embedded in the Sovereign Credit Default Swaps

Rob Sperna Weiland*

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Abstract

In this paper, I analyze in more detail credit risk premia embedded in sovereign CDS spreads. In particular, I explicitly take into account "default event risk premia", which are risk premia related to the timing of default events. These premia have been investigated in the corporate credit risk literature, but did not receive much attention in the sovereign credit risk literature.

I propose a novel model for the term-structure of sovereign credit risk in which sovereign defaults can be triggered by shocks in either a common or country-specific factor. Both factors are modeled as self-exciting processes, allowing the model to capture apparent features in the data such as the high degree of commonality of sovereign credit risk and the clustering of credit shocks over time and across countries.

The model allows for a natural decomposition of CDS spreads in two dimensions: First, I can decompose CDS spreads in country-specific and systemic risk components. I find a similar decomposition across rating classes in which approximately 65% of CDS spreads can be attributed to country-specific risk and 35% of CDS spreads can be attributed to systemic risk. Second, I can decompose CDS spreads into risk premia and a default risk component. I find that the default event risk premium is heavily priced in CDS spreads and is more important for lower credit ratings. For example, the default event risk premium accounts on average for 22% of (5-year) CDS spreads of A-rated countries and up to 52% for B-rated countries. In the term-structure dimension, I find that default event risk is more important for shorter maturities.

Keywords: Sovereign default risk, Distress risk premium, default risk premium, Sovereign CDS

*Corresponding author: Phone: +31 6 38951188. E-mail: R.C.SpernaWeiland@uva.nl. Postal address: Amsterdam Business School, Section Finance, Plantage Muidergracht 12, 1018 TV Amsterdam, The Netherlands.

1. Introduction

It has been well documented that there is a high degree of commonality and contagion in sovereign credit risk. As argued by Jarrow et al. (2005), this systemic nature of sovereign credit risk makes it plausible that investors do not only demand a risk premium for the risk of unexpected variations in credit spreads (hereafter referred to as the "distress risk premium"), but also for the risk of the credit events itself (hereafter referred to as the "default event risk premium"). Evidence for such default event risk premia has, for example, been found in corporate bond and CDS contexts (see, e.g., Driessen, 2005, Saita, 2006, and Berndt et al., 2008). In the sovereign credit literature, however, a detailed empirical analysis of both distress and default event risk premia is still lacking.

The main aim of this paper is, therefore, to investigate in more detail the distress and default event risk premia embedded in sovereign CDS data. I contribute to the literature by introducing a new model, and corresponding estimation methodology, that is able to capture the high degree of commonality in sovereign credit risk and clustering of large credit shocks over time and across countries in a parsimonious way. Furthermore, the model gives rise to a suitable decomposition of sovereign credit default swap (CDS) spreads, allowing me to analyze the risk premia in more detail.

In particular, I propose a new model for the term-structure of sovereign credit risk and assume that the default of a country can be triggered by either a common, systemic factor, or by an independent country-specific factor. By modeling a common factor, I explicitly take into account the high degree of commonality in the sovereign credit risk. The novelty of the model is that I specify both the common and country-specific factors to be self-exciting jump processes. In this way, the model can capture the clustering of large credit shocks over time and across countries, apparent in the data, in a parsimonious way.

The model facilitates a multi-step estimation procedure. In a first step, I estimate the model parameters by a Bayesian MCMC procedure. In this step, I use data on the term-structure of sovereign CDS spreads of 28 geographically dispersed countries with ratings ranging from A to B over the period 01-01-2008 until 30-12-2016. Since CDS spreads only contain information about risk-neutral default probabilities, I follow Driessen (2005) and use historical sovereign default rates by rating class from S&P to estimate the default event risk premium in a second step.

The first step of the estimation procedure seems to properly capture both systemic and country-specific factors. For example, I find clear clusters of systemic shocks around the default of Lehman Brothers and at the peak of the European sovereign debt crisis. The default event risk premium estimate I find in the second step is in line with the corporate credit risk literature.

Using the estimated model parameters, the model allows for a natural decomposition of CDS spreads along two dimensions. First, I can decompose CDS spreads in country-specific and systemic risk components. I find a similar decomposition across rating classes in which approximately 65% of (5-year) CDS spreads can be attributed to country-specific risk and 35% of CDS spreads can be attributed to systemic risk. Second, I can decompose CDS spreads into distress risk premia, default event risk premia, and default risk components. I find that the distress risk premium is mainly relevant for higher rated countries, whereas the default event risk premium and default risk component are more important for lower credit ratings. For example, the default event risk premium accounts on average for 22% of (5-year) CDS spreads of A-rated countries and up to 52% for B-rated countries. These results confirm indeed that default event risk premia are heavily priced into CDS spreads and should not be ignored.

In the term-structure dimension, I find that default event risk is more important for shorter maturities, whereas distress risk is more important for longer maturities. This suggests that investors care relatively more about default events in the short-term, whereas the uncertainty regarding future default arrival rates is more important in the long-term.

Although there is a large literature on sovereign credit risk, this paper is most closely related to Pan and Singleton (2008), Remolona et al. (2008) Longstaff et al. (2011), Ang and Longstaff (2013), Zinna (2013), Aït-Sahalia et al. (2014), and Monfort et al. (2018). In particular, Pan and Singleton (2008), Longstaff et al. (2011), and Zinna (2013) all consider distress risk premia embedded in sovereign CDS spreads, and show that these have a high level of commonality and are closely related to global and macroeconomic factors. They do, however, not consider default event risk premia.

Ang and Longstaff (2013) do not consider risk premia, but instead propose a model structure similar to mine, in which countries can default due to either shocks in a systemic or country-specific factor. They use this model set-up to investigate the commonality of sovereign credit risk in more detail, and show that there is less systemic risk in the US than in the Eurozone and that the systemic risk component is mainly related to financial market variables. Aït-Sahalia et al. (2014) use self- and cross-exciting processes to investigate spillovers of credit shocks across European countries. The main differences between my model set-up and theirs is that I explicitly take into account a common factor, whereas they only allow for commonality of sovereign credit risk in an implicit way through contagion effects. As a consequence, the number of parameters they need to estimate grows quadratically in the number of countries under consideration. In my model set-up, however, I only need to estimate one common factor (and loadings to this factor) to capture commonality. As a result, my model can be estimated on a broader cross-section of countries than theirs. Furthermore, Aït-Sahalia et al. (2014) also not take into account risk premia.

Two papers that do take into account default event risk premia in a sovereign context are Remolona et al. (2008) and Monfort et al. (2018). Remolona et al. (2008) use credit rating data to extract actual default arrival intensities, and construct a measure of expected loss in case of default. They define the difference between the CDS spread and their expected loss measure to be the risk premium embedded in the CDS spread and show that it can be substantial. Since they do not use a formal pricing model, their risk premium measure essentially captures the total risk premium component, but is not able to distinguish between distress and default risk premia. My model, on the other hand, allows for an explicit decomposition of CDS spreads in both distress and default risk premia allowing me to study these separately. Monfort et al. (2018) develop a discrete-time pricing framework in which they also explicitly allow for commonality, default event risk premia, and contagion. In one of the applications of their framework they briefly consider sovereign credit risk and focus on sovereign CDS data of four European countries. Although their framework is of a similar flavour as this paper, their main focus is on the development of their pricing framework (which is considerably different from this paper), and not on sovereign credit risk.

The remainder of this paper is structured as follows: Sections 2 and Section 3 describe the data and model set-up, respectively. The estimation methodology and results are discussed in 4. Section 5 considers a decomposition of CDS spreads into systemic and country-specific risk and risk premia components, and Section 6 concludes.

2. Data

In the empirical analysis, I consider daily sovereign CDS data of 28 geographically dispersed countries over the period 01-01-2008 until 30-12-2016.[1] In particular, I consider for every country the term-structure of CDS spreads and obtain the daily 2-, 3-, 5-, and 10-year CDS spreads from Datastream. All CDS contracts are denominated in dollars.

[1]For some countries, CDS data was only available from a date later than 01-01-2008. The exact start date of the sample for every country is reported in Table 1.

Table 1 presents summary statistics. For every country, the average S&P credit rating is determined by mapping prevailing credit rating grades to a numerical scale and taking the average over the sample period. As expected, countries with higher credit ratings have, in general, lower CDS spreads than countries with lower credit ratings. Furthermore, all countries, except Venezuela, have, on average, upwards-sloping term structures of CDS spreads.[2] The standard deviations and minimum/maximum values show that there is substantial time-series variation in the CDS spreads.

Figure 1 plots the 5-year CDS spreads grouped by average rating for all countries in our sample and illustrates two eminent features of the data: 1) A high degree of commonality across countries, and 2) the occurrences of clusters of large jumps in CDS spreads (see, e.g., the distressed period 2008-2009). A principal component analysis on the correlation matrix of the 5-year CDS levels reveals that over 60% of the daily variation in CDS levels is explained by the first principal component. When restricting the sample period to the distressed period 2008-2009, however, the first principal component explains over 90% of the daily variation in CDS levels, suggesting that the commonality is larger in crisis periods. Similar results hold when looking at a monthly frequency. Table 1 also reports the variation of CDS spreads explained by the first principal component across different maturities within each country. For most countries, the first principal component explains well over 90% of the variation across different maturities. This high degree of commonality in sovereign credit risk is not specific to our sample and has been well-documented and investigated in the literature before (see, e.g., Longstaff et al., 2011, and Ang and Longstaff, 2013).

Apart from sovereign CDS data, I use historical sovereign default data. In particular, I use

[2]Augustin (2016) argues that the slope of the term structure of CDS spreads contains information on the relative importance of global and domestic risk factors. He finds that country-specific factors influence spreads mainly when there is a negative slope of the term structure. Indeed, throughout our sample period Venezuela was prone to many country-specific risk factors such as high inflation and political unrest. This is also reflected in the very large CDS spreads throughout our sample period.

the average cumulative default rates per rating category as provided by Standard & Poor's (S&P). These default rates are averages of default rates of cohorts of countries that are formed each year. More specifically, each cohort starts on a specific start date and consists of all countries with a similar rating on that start date. The countries of each cohort are followed from the start date onwards, and cumulative default rates are constructed. Finally, in order to filter out time and cohort effects, the average cumulative default rates across cohorts is taken. In the sample, I focus on countries with an average credit rating of A and below. The reason for this is that there are no historical records of sovereign defaults for countries with a credit rating higher than A, and as such the historical default rates are not very informative for countries with a high credit rating.

Table 1 About Here

Figure 1 About Here

3. The model

Motivated by the apparent features of the data and recent literature on the modeling of sovereign credit risk, I propose a semi-closed-form model for the term structure of sovereign CDS spreads. Similar to Ang and Longstaff (2013), I assume that defaults can occur via two channels: Both a systemic shock, affecting all sovereigns, as well as independent country-specific factors can induce a country to default. A key distinction of my model compared to Ang and Longstaff (2013), however, is that it departs from the diffusive setting and uses self-exciting jump processes to model the country-specific and systemic factors (see also Aït-Sahalia et al., 2014). This feature allows the model to capture the empirical observation that large credit shocks tend to cluster both in time as well as between countries (see Figure 1). A major difference between my model and Aït-Sahalia et al. (2014), on the other hand, is that I explicitly account for the commonality in sovereign credit risk by modeling a common factor. Aït-Sahalia et al. (2014) allow for commonality of sovereign credit risk in an implicit way through contagion effects which they model as cross-exciting jumps. The main advantage of my approach over theirs is that I only need to estimate one common factor (and loadings to this factor) to capture commonality, whereas the number of parameters they need to estimate grows quadratically in the number of countries under consideration. As a result, my model can be estimated on a broader cross-section of countries than theirs. Furthermore, Ang and Longstaff (2013) and Aït-Sahalia et al. (2014) do not consider the estimation of risk premia, which is the core focus of this paper.

Specifically, every country $i, i = 1, 2, \ldots, K$, can be hit by country-specific shocks, N_i, or shocks in a common, systemic factor, N_c, where the subscript c refers to "common".[3] Every time a country is hit by a country-specific shock there is a probability γ_i that this country defaults. Similarly, when a country is hit by a common shock, there is a probability of γ_i^c of going into default. The probabilities γ_i^c are thus sovereign-specific and can be viewed as loadings to the common factor. Since both systemic and country-specific shocks can trigger a default event, the CDS spread of country i depends on both the systemic as well as the ith country-specific factors (see equation (6) in Section 3.1 below). The $N_j, j \in \{c, 1, 2, \ldots, K\}$, are independent counting processes with each an underlying shock arrival intensity process $\lambda_{j,t}^{\mathbb{P}}$ under the actual probability measure $\mathbb{P}$, and an arrival intensity process $\lambda_{j,t}^{\mathbb{Q}}$ under

[3]The common factor shocks can be interpreted in two ways: The most straightforward interpretation is that they represent exogeneous shocks hitting all countries at the same time. A slightly different interpretation could be that they are not purely exogeneous shocks, but that they represent country-specific shocks that, through instantaneous contagion, also directly affect other countries. In this second interpretation, the shocks are thus qualitatively different from country-specific shocks that only affect the country itself. For example, high inflation or political unrest can be viewed as country-specific shocks, not directly affecting other countries, whereas a shock in the banking system of a certain country may directly spread to other countries due to the interconnectedness of the financial system. In a strict sense, I could specify contagion more directly by allowing country-specific shocks to cross-excite the default intensities of other countries. However, the main reason I specify a common factor is exactly to avoid this, as this would blow up the number of parameters to be estimated.

the risk-neutral measure $\mathbb{Q}$. The difference between the actual and risk-neutral intensities constitute the risk premia related to default event risk.

In particular, assuming absence of arbitrage, it can be shown that there exists the following relation between the default intensity processes under the actual probability measure $\mathbb{P}$ and the risk-neutral measure $\mathbb{Q}$ (see, e.g., Jarrow et al., 2005):

$$\lambda_{j,t}^{\mathbb{Q}} = \mu \lambda_{j,t}^{\mathbb{P}}, \quad j \in \{c, 1, 2, \ldots, K\}. \tag{1}$$

Here μ is the risk premium associated with the (unpredictable) default event itself. More specifically, if $\mu > 1$ default event risk is priced as investors overestimate the (instantaneous) probability of default under the risk-neutral measure. In principle, μ can be time-varying and different across $j, j \in \{c, 1, 2, \ldots, K\}$. To estimate μ, data on real-world sovereign default probabilities (see Yu, 2002) is needed. However, since sovereign default events are scarce, it is not feasible to construct accurate time-varying and/or country-specific estimates of real-world default probabilities, and, therefore I assume μ to be constant over time and the same for all country-specific and common factors.[4]

Jarrow et al. (2005) argue that there are in principle two reasons for why default event risk could be priced. First, default event risk is priced when there is a positive probability of countries defaulting at the same time (i.e., conditional on the state vectors driving the default intensities, sovereign defaults are not independent). Second, default event risk is priced when there are only a finite number of entities/assets, even if defaults are conditionally independent. It is plausible that, especially in a sovereign context, both these conditions are met, and that default event risk should be taken into account.

In addition to default event risk, captured by the difference between the default intensities

[4] In estimating μ I perform a robustness check and estimate μ per rating class. Except for the A-rated countries, I find little variation across these rating-specific estimates, suggesting that this assumption is reasonable.

under $\mathbb{P}$ ($\lambda_{j,t}^{\mathbb{P}}$) and $\mathbb{Q}$ ($\lambda_{j,t}^{\mathbb{Q}}$), another source of risk stems from the fact that the likelihood of default changes over time. In the case that fluctuations in the intensities over time are priced, the dynamics of $\lambda_{j,t}^{\mathbb{P}}$ and $\lambda_{j,t}^{\mathbb{Q}}$ also differ under both measures. Risk premia related to changes of default risk over time have been investigated in a sovereign context before (see, e.g., Pan and Singleton, 2008, and Longstaff et al., 2011), and I refer to these risk premia as 'distress risk premia'. In total there are thus four configurations of probability measures associated with the default intensity processes and their dynamics: The $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda_{j,t}^{\mathbb{P}}$, and the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda_{j,t}^{\mathbb{Q}}$, $j \in \{c, 1, 2, \ldots, K\}$.[5]

I assume that the $\mathbb{P}$-dynamics of $\lambda_{j,t}^{\mathbb{Q}}$ are given by the following self-exciting dynamics:

$$\mathrm{d}\lambda_{j,t}^{\mathbb{Q}} = \alpha_j^{\mathbb{P}}(\lambda_{j,\infty}^{\mathbb{P}} - \lambda_{j,t}^{\mathbb{Q}})\mathrm{d}t + \sigma_j\sqrt{\lambda_{j,t}^{\mathbb{Q}}}\mathrm{d}W_{j,t}^{\mathbb{P}} + Z_j\mathrm{d}N_{j,t}, \quad j \in \{c, 1, 2, \ldots, K\}, \tag{2}$$

where $W_{j,t}^{\mathbb{P}}$ are independent $\mathbb{P}$-Brownian motions and $N_{j,t}$ are the independent credit shock arrival processes with intensity processes $\lambda_{j,t}^{\mathbb{Q}}$ themselves. Every time the counting process $N_{j,t}$ jumps (i.e., a common or country-specific credit event occurs), $\lambda_{j,t}^{\mathbb{Q}}$ jumps by $Z_j > 0$. This again induces an increase in the probability of another jump in $N_{j,t}$, since this jump process is driven by $\lambda_{j,t}^{\mathbb{Q}}$. This self-exciting specification allows the model to capture the clustering of large credit shocks in time and across countries.[6]

Consistent with the literature, I assume that the market prices of risk underlying the change

[5]Throughout this paper, the actual and risk-neutral default intensities are denoted with superscripts $\mathbb{P}$ and $\mathbb{Q}$, respectively. Similarly, where necessary, the parameters governing the $\mathbb{P}$- and $\mathbb{Q}$-dynamics are also denoted with superscripts $\mathbb{P}$ and $\mathbb{Q}$, respectively.

[6]In principle, the model can be generalized in a few ways: As mentioned above, the model could also take into account direct spillover effects from country-specific shocks to other countries by allowing for cross-excitation effects. In this case, one can explicitly differentiate between direct contagion effects and common shocks. The number of parameters to be estimated would, however, be much larger and identification would become infeasible. Therefore, I use the common component to capture both direct contagion and exogenous shocks. Another possible generalization of the model is to allow for stochastic jump sizes Z_j. The reason I take fixed jump size parameters $Z_j > 0$ instead of stochastic jump sizes is again that the number of parameters to be identified and estimated (i.e., additional distribution and risk premia parameters) would be too large.

of measure from $\mathbb{P}$ to $\mathbb{Q}$ are dependent on the current levels of the default intensities and are given by

$$\xi_{j,t} = \frac{\delta_{j,0}}{\sqrt{\lambda^{\mathbb{Q}}_{j,t}}} + \delta_{j,1}\sqrt{\lambda^{\mathbb{Q}}_{j,t}}, \quad j \in \{c, 1, 2, \ldots, K\}. \tag{3}$$

These market prices of risk assure that the $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}_{j,t}$ are of a similar form as the $\mathbb{P}$-dynamics and are given by

$$\mathrm{d}\lambda^{\mathbb{Q}}_{j,t} = \alpha^{\mathbb{Q}}_{j}(\lambda^{\mathbb{Q}}_{j,\infty} - \lambda^{\mathbb{Q}}_{j,t})\mathrm{d}t + \sigma_j\sqrt{\lambda^{\mathbb{Q}}_{j,t}}\mathrm{d}W^{\mathbb{Q}}_{j,t} + Z_j\mathrm{d}N_{j,t}, \tag{4}$$

where $\alpha^{\mathbb{Q}}_{j} = \alpha^{\mathbb{P}}_{j} + \delta_{j,1}\sigma_j$, $\alpha^{\mathbb{Q}}_{j}\lambda^{\mathbb{Q}}_{j,\infty} = \alpha^{\mathbb{P}}_{j}\lambda^{\mathbb{P}}_{j,\infty} - \delta_{j,0}\sigma_j$, and $W^{\mathbb{Q}}_{j,t}$ are independent $\mathbb{Q}$-Brownian motions. Note that the difference between the $\mathbb{P}$ -and $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}_{j,t}$ stem from the change of measure in the Brownian motions. The market price of risk parameters capture the risk premia investors require with respect to changes in default risk.

Since $\lambda^{\mathbb{Q}}$ and $\lambda^{\mathbb{P}}$ are related through the constant parameter μ, the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{P}}_{j,t}$ are of a similar form as the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}_{j,t}$. In the estimation procedure, detailed in Section 4, I first use sovereign CDS spread data to estimate the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of the risk-neutral default intensity processes, $\lambda^{\mathbb{Q}}_{j,t}$. After that, I use historical sovereign default rates obtained from S&P to estimate the default event risk premium parameter μ.

3.1. CDS Pricing

The time t level of the CDS spread of country i with maturity M, $CDS_{i,t}(M)$ is determined by equating the payoff value for the protection buyer to the payoff value for the protection seller. I will make the standard simplifying assumption that the risk-free rate is independent from the common and country-specific factors, and denote $D(t,T) = \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_t^T r_s \mathrm{d}s}\middle| \mathcal{F}_t\right] = \mathbb{E}^{\mathbb{Q}}_t\left[e^{-\int_t^T r_s \mathrm{d}s}\right]$. I use US Treasury rates to construct the risk-free discount factors $D(t,T)$.

Specifically, I get (see, e.g., Duffie and Singleton, 2003)

$$
\begin{aligned}
&\frac{1}{4}CDS_{i,t}(M)\sum_{j=1}^{4M} D(t,t+0.25j)\mathbb{E}_t^{\mathbb{Q}}\left[(1-\gamma_i)^{N_{i,t+0.25j}-N_{i,t}}\right]\mathbb{E}_t^{\mathbb{Q}}\left[(1-\gamma_i^c)^{N_{c,t+0.25j}-N_{c,t}}\right] \\
&\qquad = (1-R)\int_t^{t+M} D(t,u)\mathbb{E}_t^{\mathbb{Q}}\left[\left(\gamma_i\lambda_{i,u}^{\mathbb{Q}}+\gamma_i^c\lambda_{c,u}^{\mathbb{Q}}\right)(1-\gamma_i)^{N_{i,u}-N_{i,t}}(1-\gamma_i^c)^{N_{c,u}-N_{c,t}}\right]\mathrm{d}u. \quad (5)
\end{aligned}
$$

The left-hand side of (5) reflects the present value of the (quarterly) premium payments that the buyer makes to the seller, contingent upon a default event not having occurred. A default can occur either through a country-specific shock, $N_{i,t}$, or through a shock in the common factor, $N_{c,t}$. The right-hand side of (5) reflects the present value of the payout that the seller makes in case of default. I assume fractional recovery of face value of the underlying bond and let R denote the constant recovery rate.[7]

Solving for $CDS_{i,t}(M)$ gives the following CDS pricing formula:

$$
CDS_{i,t}(M) = \frac{(1-R)\int_t^{t+M} D(t,u)\mathbb{E}_t^{\mathbb{Q}}\left[\left(\gamma_i\lambda_{i,u}^{\mathbb{Q}}+\gamma_i^c\lambda_{c,u}^{\mathbb{Q}}\right)(1-\gamma_i)^{N_{i,u}-N_{i,t}}(1-\gamma_i^c)^{N_{c,u}-N_{c,t}}\right]\mathrm{d}u}{\frac{1}{4}\sum_{j=1}^{4M} D(t,t+0.25j)\mathbb{E}_t^{\mathbb{Q}}\left[(1-\gamma_i)^{N_{i,t+0.25j}-N_{i,t}}\right]\mathbb{E}_t^{\mathbb{Q}}\left[(1-\gamma_i^c)^{N_{c,t+0.25j}-N_{c,t}}\right]}. \quad (6)
$$

The expectations appearing in (6) can be computed in closed-form (up to a system of ODEs) by exploiting the affine structure of the model and using the framework outlined in Duffie et al. (2000). The computations are detailed in Appendix A.

4. Estimation methodology

Similar to Driessen (2005), the model setup is such that it can be estimated in two steps. In the first step, I estimate the model governing the risk-neutral intensities $\lambda_{j,t}^{\mathbb{Q}}$, $j \in \{c, 1, 2, \ldots, K\}$ using sovereign CDS data. In the second step, I estimate the default event risk premium

[7]Following the literature, I assume a constant recovery rate of 25% for all countries and abstract away from recovery rate risk premia (see, e.g., Longstaff et al., 2011).

parameter μ using S&P historical sovereign default data. The global outline and results of the first and second steps of the estimation procedure are described in Section 4.1, and Section 4.2, respectively.

4.1. Estimation risk-neutral intensities $\lambda^{\mathbb{Q}}_{j,t}$

In estimating the model of the risk-neutral intensities, I use a Bayesian Markov chain Monte Carlo (MCMC) procedure similar to Sperna Weiland et al. (2018). This procedure makes use of the sovereign CDS spreads and provides estimates for the parameters driving the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}_{j,t}$, values of the latent risk-neutral intensity processes, and latent jump times.

I estimate the parameters governing the common and the country-specific factors in three steps. First, I estimate the common factor by pooling the CDS data of all countries and ignoring the country-specific factors. In the second step, I estimate the country-specific factors, keeping the common factor results from the first step fixed. In a third step, I re-estimate the common factor, but now fixing the country-specific factors obtained in step two. In this way, the estimation of the common factor explicitly takes into account the presence of country-specific factors. I investigated whether applying more iterations of steps two and three would lead to significant changes in the parameter estimates, but found this not to be the case.

The main challenges in estimating the (risk-neutral intensity) model are that the intensity processes and jump times are latent, and that, due to self-excitation, their transition densities are not known. The key of dealing with these issues is to properly discretize and orderly sample the intensity processes defined in (2). To see this, consider the following discretized version of (2):

$$\lambda^{\mathbb{Q}}_{j,t+1} - \lambda^{\mathbb{Q}}_{j,t} = \alpha^{\mathbb{P}}_j \lambda^{\mathbb{P}}_{j,\infty} \Delta_{t+1} - \alpha^{\mathbb{P}}_j \lambda^{\mathbb{P}}_{j,t} \Delta_{t+1} + \sigma_j \sqrt{\lambda^{\mathbb{Q}}_{j,t} \Delta_{t+1}} \epsilon_{j,t+1} + Z_c N_{j,t+1}, \quad j \in \{c, 1, 2, \ldots, K\}, \tag{7}$$

where Δ_{t+1} is the time interval between t and $t+1$ (i.e., a business day), $\epsilon_{j,t+1}$ an independent standard normal random variable, and $N_{j,t+1} = 1$ indicates a jump arrival. The jump counters $N_{j,t+1}$ are Bernoulli random variables with non-constant success probabilities $\lambda^{\mathbb{Q}}_{j,t}\Delta_{t+1}$. The discretization thus assumes that at most one jump can occur in the time-interval Δ_{t+1}, which follows from the small-time property of self-exciting processes stating that $\mathbb{P}\left[N_{j,t+\Delta} - N_{j,t} > 1 | \mathcal{F}_t\right] = o(\Delta)$. Sperna Weiland et al. (2018) show in a Monte Carlo study that this discretization on a daily frequency does not impose notable biases.

Using the discretization refEqn:: Discretized inensity process and denoting $X^j_t = \{N_{j,t}, \lambda^{\mathbb{Q}}_{j,t}\}$ and $\bar{\Theta}$ the vector with parameters, the transition density can be decomposed as

$$p(X^j_t | X^j_{t-1}, \bar{\Theta}) = p(\lambda^{\mathbb{Q}}_{j,t} | N_{j,t}, X^j_{t-1}, \bar{\Theta}) p(N_{j,t} | X^j_{t-1}, \bar{\Theta}), \tag{8}$$

where $p(\lambda^{\mathbb{Q}}_{j,t} | N_{j,t}, X^j_{t-1}, \bar{\Theta})$ is Gaussian, and $p(N_{j,t} | X^j_{t-1}, \bar{\Theta})$ Bernoulli with success probability $\lambda^{\mathbb{Q}}_{j,t-1}\Delta_t$. That is, under the above discretization the transition density is a mixture of normal densities, allowing me to sequentially draw $N_{j,t}$ from the Bernoulli densities $p(N_{j,t} | X^j_{t-1}, \Theta)$ and $\lambda^{\mathbb{Q}}_{j,t}$ from $p(\lambda^{\mathbb{Q}}_{j,t}, | N_{j,t}, X^j_{t-1}, \Theta)$ using the newly drawn $N_{j,t}$ in the conditioning information. The discretization above thus simplifies the transition densities, which play a crucial role in determining the posterior densities necessary for Bayesian inference. The details of the estimation procedure are explained in Appendix B.

4.1.1. Estimation results risk-neutral intensities

Table 2 reports the posterior means and standard deviations of the parameter estimates of the common and country-specific risk-neutral intensities, the number of estimated jumps in each of the factors, and the average relative pricing errors of the CDS spreads per country.

Table 2 shows that the speed-of-mean-reversion parameters governing the $\mathbb{P}$-dynamics of the intensity processes ($\alpha_j^{\mathbb{P}}$) are larger than the speed-of-mean-reversion parameters governing the $\mathbb{Q}$-dynamics of the intensity processes ($\alpha_j^{\mathbb{Q}}$) for all systemic and country-specific factors. That is, under the risk-neutral dynamics, distressed periods are more persistent. The $\alpha_j^{\mathbb{P}}\lambda_{j,\infty}^{\mathbb{P}}$ parameters, on the other hand, are all larger than the $\alpha_j^{\mathbb{Q}}\lambda_{j,\infty}^{\mathbb{Q}}$ parameters. However, backing out the implied long-term average intensity values, $\lambda_{j,\infty}^{\mathbb{P}}$ and $\lambda_{j,\infty}^{\mathbb{Q}}$, reveals that the long-term average intensities are higher under the $\mathbb{Q}$-dynamics than under the $\mathbb{P}$-dynamics for the systemic factor and most of the country-specific factors. Only for the Dominican Republic, Egypt, and Venezuela the opposite result holds. In principle, the slower speed-of-mean-reversions and higher long-term average default intensities under the risk-neutral dynamics suggest the presence of distress risk premia (i.e., risk premia related to the differences in process dynamics under the actual and risk-neutral measures). In Section 5, I study these risk premia in more detail.

The upper panel of Figure 2 plots the estimated systemic default risk intensities. The model seems to capture systemic risk well. For example, the systemic risk factor was especially large during the 2008-2009 crisis period in which the CDS spreads of all countries spiked up. Furthermore, there is an increase in the systemic risk factor during the second half of 2011, reflecting the peak of the European sovereign debt crisis. The bottom panel of Figure 2 shows the estimated (self-exciting) jumps in the systemic risk factor.[8] I find a cluster of systemic jumps shortly after the default of Lehman Brothers. Furthermore, I find a systemic

[8]For both the systemic and country-specific factors, I take those days for which the estimated jump probability is larger than 0.25 to be the jump dates.

jump on September 22nd, 2011. On this date, global stock markets dropped over 3% and the VIX index spiked with 11% as a result of increasing fear of investors regarding spillovers of the European sovereign debt crisis.

To illustrate the performance of the model regarding country-specific factors, I plot in Figure 3 the model-fit of 5-year CDS spreads (upper panels), estimated country-specific intensities (middle panels), and estimated country-specific jump probabilities of Brazil (left column) and Russia (right column). I focus on these countries, since their model-fit is close to the average relative pricing error of 9% over all countries. Furthermore, both Brazil and Russia experienced country-specific distress periods during the sample period, making it appropriate candidates to evaluate the model performance. The middle panels show that the country-specific factors indeed seem to pick up country-specific distress. For Brazil, the intensities spike up from 2015 onwards, coinciding with the start of an economic recession and increased political unrest. Similarly, Russia also experienced a recession in 2015-2016 as a result of international sanctions in response to the Ukraine conflict, sharp declines in oil prices, and strong depreciation of the currency. Again, the country-specific intensities seem to capture this episode of distress well.

As Table 2 indicates, I find a relatively large number of jumps in some country-specific factors, whereas in other country-specific factors I do not find evidence of any jumps. This suggests that the self-exciting specification is not per se appropriate for some countries, and an easier diffusive specification would suffice. However, to keep the model consistent and comparable across countries, I take the same specification for all country-specific factors. For those countries without any estimated jumps the jump size parameter Z_i should be interpreted with care.

TABLE 2 ABOUT HERE

Figure 2 About Here

Figure 3 About Here

4.2. Estimation default event risk premium parameter

In the second step, I estimate the default event risk premium parameter μ, which defines the difference between the actual and risk-neutral default intensities (i.e., $\lambda^{\mathbb{Q}}_{j,t} = \mu\lambda^{\mathbb{P}}_{j,t}$, $j \in \{c, 1, 2, \ldots, K\}$). In principle, this parameter can be time-varying, but, given the scarcity of historic sovereign default data, I assume it to be constant. This means that I focus on the average risk premium on default events rather than exploring time-varying aspects of it.

In estimating μ, I follow the procedure proposed by Driessen (2005). That is, I estimate μ by using moment conditions for the conditional default probabilities, which are defined as the probabilities of defaulting in year $t+n$, conditional upon no default between time t and $t+n-1$ (and the average credit rating during the sample period). These moment conditions are given by

$$\mathbb{E}^{\mathbb{P}}_t \left[Z_{i,t+n} | R_{i,t} = R, Z_{i,t} + Z_{i,t+1} + \ldots + Z_{i,t+n-1} = 0\right] = q_{n,R}(\mu, \phi), \qquad n = 0, \ldots, 9, R = A, BBB, BB, B, \quad (9)$$

where $Z_{i,t}$ is a variable that is equal to 1 if country i defaults in the annual time interval $[t, t+1]$, R is the average credit rating of the country during the sample period, and $q_{n,R}(\mu, \phi)$ is the model-implied conditional default probability under the actual probability measure, and ϕ is a parameter vector containing all other parameters of the model.

The model-implied conditional default rates can be computed explicitly. First, I note that the actual probability that country i defaults within the next n years, conditional upon that no default has occurred yet, is given by

$$\begin{aligned} p_{i,n,R}(t,\mu,\phi) &= \mathbb{E}^{\mathbb{P}}[Z_{i,t} + Z_{i,t+1} + \ldots + Z_{i,t+n-1} | R_i = R] \\ &= 1 - \mathbb{E}_t^{\mathbb{P}}\left[(1-\gamma_i)^{N_{i,t+n}-N_{i,t}}\right] \mathbb{E}_t^{\mathbb{P}}\left[(1-\gamma_i^c)^{N_{c,t+n}-N_{c,t}}\right]. \end{aligned} \tag{10}$$

Because of the affine structure of the model, expression (10) can be computed explicitly up to a system of ODEs (see Appendix A). I average out (10) over all days in our sample period and denote the obtained probabilities by $p_{i,n,R}(\mu,\phi)$. The yearly conditional default rates are now given by $q_{i,n,R}(\mu,\phi) = 1 - (1 - p_{i,n+1,R}(\mu,\phi))/(1 - p_{i,n,R}(\mu,\phi))$. In a last step, I average the conditional default probabilities over all countries in a given rating category to obtain $q_{n,R}(\mu,\phi)$.

I use average historical cumulative default rates provided by S&P to consistently estimate the left-hand side of (9). I use the cumulative default rates up to 10 years, since the longest maturity contract in our sample is 10 year. I convert the cumulative default probabilities into yearly conditional default rates $q_{n,R}^{Data}$.

I now estimate μ by using the first step of the generalized method of moments and minimize the sum of squared differences between the model-implied and observed conditional default rates over μ, inserting the estimates for the other parameters $\hat{\phi}$:

$$\min_{\mu} \left[\sum_{R=A,BBB,BB,B} \sum_{n=0}^{9} \left(q_{n,R}(\mu,\hat{\phi}) - q_{n,R}^{Data} \right)^2 \right]. \tag{11}$$

4.2.1. Estimation results default event risk premium parameter

Using the estimation procedure detailed in the previous section, I find $\hat{\mu} = 2.07$. This implies that investors multiply (instantaneous) default probabilities with a factor of over 2 when pricing sovereign credit default swaps. The estimated value $\hat{\mu}$ is in line with values of default event risk premia found previously in the literature on corporate default risk (see, e.g., Driessen, 2005, and Berndt et al., 2008)

In Figure 4, I illustrate the effect of the risk premium parameter μ on default probabilities. For every rating class, the line "Risk-neutral" depicts the risk-neutral model-implied conditional default probabilities (i.e., using the $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}$ in calculating the default probabilities). The line "$\mu = 1$" plots the actual model-implied default probabilities, assuming that there is no default event risk premium (i.e., using the $\mathbb{P}$-dynamics of $\lambda^{\mathbb{Q}}$ and assuming $\mu = 1$ in calculating the default probabilities). The difference between these lines is completely caused by the risk premia related to changes in default risk over time (i.e., distress risk premia).

Next, the line "S&P historical data" presents the empirical conditional default probabilities based on S&P historical default data. For all rating classes except A, the historical default probabilities lie completely below the "Risk-neutral" and "$\mu = 1$" lines, indicating that distress risk premia can not sufficiently explain observed default rates. Finally, the line "$\mu = 2.07$" depicts the model-implied actual default probabilities, using $\mu = 2.07$. Taking into account default event risk premia clearly improves the fit of historical default probabilities for the BBB, BB and B ratings.

<u>FIGURE 4 ABOUT HERE</u>

As a robustness check, I also estimate the default event risk premium parameter μ per rating class. For the BBB, BB, and B rating classes I find $\hat{\mu} = 2.03$, $\hat{\mu} = 1.59$, and $\hat{\mu} = 2.12$, respectively. Hence, for all these rating classes I find $\mu > 1$, implying a positive default event risk premium. Furthermore, these results are reasonably close to the total estimate $\hat{\mu} = 2.07$, indicating that there is not much variation in the default event risk premium across countries from these rating classes. For the A rating class, however, I find $\hat{\mu} = 0.75$, which indicates that there is even a negative default event risk premium for A-rated countries. The reason for this deviating value is that the estimated historical default rates are (relatively) very high for A-rated countries as a result of the recent double default of Greece. Greece rated A in 2009, and, therefore, still plays a role in some of the A-rated cohorts used by S&P to construct the historical cumulative default rates. Since sovereign defaults are scarce, especially for higher rated countries, one or two default events can result in substantial upwards biases in the historical default probability estimates, thereby affecting the default event risk premium estimate. This thus reveals that there are limitations in using historical default rates for higher rated countries.

5. CDS spread decomposition

The differences in the parameters governing the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}$ and the estimated value of the default event risk parameter μ indicate the presence of both distress and default event risk premia in sovereign CDS spreads. In this section, I explore the economic significance of these risk premia in more detail, and decompose CDS spreads into distress risk premia, default event risk premia, and actual default risk components.

Similar to Pan and Singleton (2008) and Longstaff et al. (2011), I quantify the magnitude of the distress risk premium by computing the difference in CDS spreads implied by the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda^{\mathbb{Q}}_{j,t}$. The CDS spread of country i implied by the $\mathbb{Q}$-dynamics of risk-neutral intensities is given by equation (6). This CDS spread includes the market prices of risk $\xi_{c,t}$ and $\xi_{i,t}$ related to the dynamics of the common and country-specific factors, respectively, and the default event risk premium parameter μ. The CDS spread of country i implied by the $\mathbb{P}$-dynamics of the risk-neutral intensities, on the other hand, does not include these market prices of risk (i.e., $\xi_{c,t} = \xi_{i,t} = 0$), and the difference between the CDS spreads computed in these ways thus constitutes the distress risk premium embedded in the CDS spread.

I denote the CDS spread of country i implied by the $\mathbb{P}$-dynamics of the risk-neutral intensities by $CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M)$. Here, the first superscript ($\mathbb{P}$) refers to the probability measure governing the dynamics of the intensity process, and the second superscript ($\mathbb{Q}$) refers to the probability measure under which we consider the intensity values (i.e., the superscript $\mathbb{P}\mathbb{Q}$ denotes the $\mathbb{P}$-dynamics of $\lambda^{\mathbb{Q}}$). The pseudo-CDS spread $CDS_{i,t}^{\mathbb{P}\mathbb{Q}}$(M) can thus be computed by using (6) and taking expectations with respect to the $\mathbb{P}$-dynamics of the risk-neutral intensities implied by (2). That is,

$$CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M) = \frac{(1-R)\int_t^{t+M} D(t,u)\mathbb{E}_t^{\mathbb{P}\mathbb{Q}}\left[\left(\gamma_i\lambda_{i,u}^{\mathbb{Q}} + \gamma_i^c\lambda_{c,u}^{\mathbb{Q}}\right)(1-\gamma_i)^{N_{i,u}-N_{i,t}}(1-\gamma_i^c)^{N_{c,u}-N_{c,t}}\right]\mathrm{d}u.}{\frac{1}{4}\sum_{j=1}^{4M} D(t,t+0.25j)\mathbb{E}_t^{\mathbb{P}\mathbb{Q}}\left[(1-\gamma_i)^{N_{i,t+0.25j}-N_{i,t}}\right]\mathbb{E}_t^{\mathbb{P}\mathbb{Q}}\left[(1-\gamma_i^c)^{N_{c,t+0.25j}-N_{c,t}}\right]}. \tag{12}$$

Clearly, if the market prices of risk $\xi_{c,t}$ and $\xi_{i,t}$ are zero, $CDS_{i,t}(M)$ and $CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M)$ are the same, and there is no distress risk premium. If, on the other hand, $\xi_{c,t}$ or $\xi_{i,t}$ are non-zero, $CDS_{i,t}(M)$ and $CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M)$ differ and the difference between the two, $[CDS_{i,t}(M) - CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M)]$, constitutes the distress risk premium. I also investigate the distress risk premium in relative terms, which is given by $[CDS_{i,t}(M) - CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M)]/CDS_{i,t}(M)$.

Both $CDS_{i,t}(M)$ and $CDS_{i,t}^{\mathbb{P}\mathbb{Q}}(M)$ still contain the default event risk premium parameter μ, since they consider the risk-neutral common and country-specific intensities $\lambda_{c,t}^{\mathbb{Q}}$ and $\lambda_{i,t}^{\mathbb{Q}}$, respectively. To extract the default event risk premium, I can thus go one step further and compute the CDS spreads implied by the $\mathbb{P}$-dynamics of $\lambda_{j,t}^{\mathbb{P}}$, which I denote by $CDS_{i,t}^{\mathbb{P}\mathbb{P}}(M)$:

$$CDS_{i,t}^{\mathbb{P}\mathbb{P}}(M) = \frac{(1-R)\int_t^{t+M} D(t,u)\mathbb{E}_t^{\mathbb{P}\mathbb{P}}\left[\left(\gamma_i\lambda_{i,u}^{\mathbb{P}} + \gamma_i^c\lambda_{c,u}^{\mathbb{P}}\right)(1-\gamma_i)^{N_{i,u}-N_{i,t}}(1-\gamma_i^c)^{N_{c,u}-N_{c,t}}\right]\mathrm{d}u.}{\frac{1}{4}\sum_{j=1}^{4M} D(t,t+0.25j)\mathbb{E}_t^{\mathbb{P}\mathbb{P}}\left[(1-\gamma_i)^{N_{i,t+0.25j}-N_{i,t}}\right]\mathbb{E}_t^{\mathbb{P}\mathbb{P}}\left[(1-\gamma_i^c)^{N_{c,t+0.25j}-N_{c,t}}\right]}. \tag{13}$$

$CDS^{\mathbb{PP}}_{i,t}(M)$ thus represents the CDS spread absent of any risk premia and is a measure of actual default risk. The difference between $CDS^{\mathbb{PQ}}_{i,t}(M)$ and $CDS^{\mathbb{PP}}_{i,t}(M)$, $[CDS^{\mathbb{PQ}}_{i,t}(M) - CDS^{\mathbb{PP}}_{i,t}(M)]$ is then the default event risk premium embedded in the CDS spread. The relative default event risk premium is given by $[CDS^{\mathbb{PQ}}_{i,t}(M) - CDS^{\mathbb{PP}}_{i,t}(M)]/CDS_{i,t}(M)$.

Table 3 reports summary statistics on the average decomposition of 5-year CDS spreads, both on the country level as well as the rating class level.[9] Considering the results on the rating class level, a few clear patterns emerge: First, I find a strong decreasing pattern in the relative distress risk premia as the rating gets lower. For example, the distress risk premium makes up, on average, 60.8% of CDS spreads of A-rated countries, but only 5.9% of CDS spreads of B-rated countries. Second, I find increasing patterns in both the relative default event risk premia and default risk components as the rating gets lower. The default event risk premium and default risk component constitute, on average, 22.0%, and 17.2% of the CDS spread of A-rated countries, respectively. For B-rated countries these relative weights are 52.9%, and 41.3%, respectively. Intuitively, as a default event becomes more likely (i.e., countries with a lower credit rating), investors start caring relatively more about default event risk than distress risk. Figure 5 shows the evolution of the decomposition over time for four countries of different rating classes. In particular, I plot the decomposition for Chile (A), Croatia (BBB), Vietnam (BB), and Lebanon (B).

Table 3 About Here

Figure 5 About Here

[9]The results on the rating class level are obtained by taking the average of the countries in that rating class. Since Venezuela is quite different from the other countries under consideration, I also report the results for B-rated countries excluding Venezuela. I find that all results stay qualitatively the same when excluding Venezuela from the sample.

The results discussed above focus on the decomposition of 5-year CDS spreads. Table 4, however, reports the average relative decomposition of CDS spreads for different maturities. Again a few interesting patterns emerge. For all countries, I find that the portion attributable to the distress risk premium increases, whereas the portions attributable to the default event risk premium and default risk component decrease as the maturity gets longer. This suggests that investors mainly worry about actual default events in short-term horizons. For longer horizons, on the other hand, investors worry more about the increasing uncertainty around future default probabilities.

<u>Table 4 About Here</u>

In addition to decomposing CDS spreads in risk premia and default risk components, the model also allows for a decomposition of CDS spreads in systemic risk and country-specific risk components. To compute the systemic risk component, I take (6) and ignore the country-specific part. That is,

$$CDS_{i,t}^{\text{systemic}}(M) = \frac{(1-R)\int_t^{t+M} D(t,u)\mathbb{E}_t^{\mathbb{Q}}\left[\gamma_i^c \lambda_{c,u}^{\mathbb{Q}}(1-\gamma_i^c)^{N_{c,u}-N_{c,t}}\right]\mathrm{d}u.}{\frac{1}{4}\sum_{j=1}^{4M} D(t,t+0.25j)\mathbb{E}_t^{\mathbb{Q}}\left[(1-\gamma_i^c)^{N_{c,t+0.25j}-N_{c,t}}\right]}. \tag{14}$$

Similarly, to compute the country-specific risk component, I take (6) and ignore the common factor. That is,

$$CDS_{i,t}^{\text{country}}(M) = \frac{(1-R)\int_t^{t+M} D(t,u)\mathbb{E}_t^{\mathbb{Q}}\left[\gamma_i \lambda_{i,u}^{\mathbb{Q}}(1-\gamma_i)^{N_{i,u}-N_{i,t}}\right]\mathrm{d}u.}{\frac{1}{4}\sum_{j=1}^{4M} D(t,t+0.25j)\mathbb{E}_t^{\mathbb{Q}}\left[(1-\gamma_i)^{N_{i,t+0.25j}-N_{i,t}}\right]}. \tag{15}$$

Table 5 displays the results of the decomposition of 5-year CDS spreads in systemic and country-specific risk parts. I find a relatively stable decomposition across rating classes, where the country-specific and systemic components account for approximately 65% and

35% of CDS spreads, respectively. Figure 6 displays the average relative decomposition of 5-year CDS spreads in the country-specific and systemic risk components for all countries.

Table 5 About Here

Figure 6 About Here

The decompositions outlined above can also be combined. In Table 6 and Figure 7 I show the results of this two-dimensional decomposition in which I first decompose the spreads in country-specific and systemic risk components, and then decompose both these parts in the risk premia and default risk components. I find that the sub-decomposition of the systemic part is very similar across rating classes: The systemic distress risk premium, systemic default event risk premium, and systemic default risk component account for roughly 20%, 9%, and 6% of CDS spreads across rating classes. The sub-decomposition of the country-specific component, however, differ substantially across rating classes. I find a strong decreasing pattern in the relative importance of country-specific distress risk premia as the rating gets lower. The country-specific default event risk premium and country-specific default risk component, on the other hand, become relatively more important as the rating gets lower. These results thus show that the patterns found in Table 3 are mainly due to the differences in the country-specific components across rating classes.

Table 6 About Here

Figure 7 About Here

6. Conclusions

In this paper, I investigate credit risk premia embedded in sovereign CDS spreads. In particular, I consider risk premia related to unpredictable changes in future default arrival rates (i.e., 'distress risk premium'), and risk premia related to (the unpredictable timing of) default events themselves (i.e., default event risk premium), which, until now, have largely been ignored in the sovereign credit risk literature.

I propose a novel way of modeling the term-structure of sovereign credit risk and assume that the default of a country can be triggered by either a common, systemic factor, or by an independent country-specific factor. By modeling a common factor, I explicitly take into account the high degree of commonality in the sovereign credit risk. The novelty of the model is that I specify both the common and country-specific factors to be self-exciting jump processes. In this way, the model can capture the clustering of large credit shocks over time and across countries, apparent in the data, in a parsimonious way.

I estimate the model using sovereign CDS data and historical sovereign default rates per rating class from S&P. The model allows for a decomposition of CDS spreads along two dimensions. First, I can decompose CDS spreads in country-specific and systemic risk components. I find a similar decomposition across rating classes in which approximately 65% of (5-year) CDS spreads can be attributed to country-specific risk and 35% of CDS spreads can be attributed to systemic risk. Second, I can decompose CDS spreads into distress risk premia, default event risk premia, and default risk components. I find that the distress risk premium is mainly relevant for higher rated countries, whereas the default event risk premium and default risk component are more important for lower credit ratings. These results are mainly driven by differences in country-specific risk. In the term-structure dimension, I find that default event risk is more important for shorter maturities, whereas distress risk is more important for longer maturities. This suggests that investors care relatively more about actual default events in the short-term, whereas the uncertainty regarding future default arrival rates is more important in the long-term.

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Appendices

Appendix A Closed-form price formulas

In this Appendix, I show how the expectations appearing in the CDS pricing formula (6) can be computed explicitly (up to a system of ODEs).

Let $X_{j,t} = (N_{j,t}, \lambda^{\mathbb{Q}}_{j,t})'$, $j \in \{c, 1, 2, \dots, K\}$. The dynamics of $X_{j,t}$ are given by

$$
\begin{aligned}
\mathrm{d}X_{j,t} &= \mathrm{d}\begin{pmatrix} N_{j,t} \\ \lambda^{\mathbb{Q}}_{j,t} \end{pmatrix} \\
&= \begin{pmatrix} 0 \\ \alpha^{\mathbb{Q}}_j(\lambda^{\mathbb{Q}}_{j,\infty} - \lambda^{\mathbb{Q}}_{j,t}) \end{pmatrix} \mathrm{d}t + \begin{pmatrix} 0 & 0 \\ 0 & \sigma_j \sqrt{\lambda^{\mathbb{Q}}_{j,t}} \end{pmatrix} \mathrm{d}\begin{pmatrix} 0 \\ W^{\mathbb{Q}}_{j,t} \end{pmatrix} \\
&\quad + \begin{pmatrix} 1 \\ Z_j \end{pmatrix} \mathrm{d}N_{j,t}.
\end{aligned} \tag{16}
$$

From this specification it is clear that the process $X_{j,t}$ falls into the generalized affine jump-diffusion framework and, therefore, I can use the framework of Duffie et al. (2000) and prove the following Propositions:

Proposition 1.

$$\mathbb{E}^{\mathbb{Q}}\left[(1-\gamma_j)^{N_{j,T}} \,\middle|\, \mathcal{F}_t\right] = e^{\alpha(t)+\beta_1(t)N_{j,t}+\beta_2(t)\lambda^{\mathbb{Q}}_{j,t}},$$

with

$$
\begin{aligned}
\dot{\alpha}(t) &= -\alpha_j^{\mathbb{Q}}\lambda_{j,\infty}^{\mathbb{Q}}\beta_2(t), \\
\alpha(T) &= 0, \\
\dot{\beta}_1(t) &= 0, \\
\beta_1(T) &= \beta_1(s) = \log(1-\gamma_j) \quad t \leq s \leq T, \\
\dot{\beta}_2(t) &= \alpha_j^{\mathbb{Q}}\beta_2(t) - \frac{1}{2}\beta_2^2(t)\sigma_j^2 - \left(e^{\beta_1(t)+Z_j\beta_2(t)} - 1\right), \\
\beta_2(T) &= 0.
\end{aligned}
$$

Proof. Consider an affine jump-diffusion process X in some state space $D \subset \mathbb{R}^n$ solving the stochastic differential equation

$$
\mathrm{d}X_t = \mu(X_t)\mathrm{d}t + \sigma(X_t)\mathrm{d}W_t + \sum_{i=1}^{m} \mathrm{d}Z_t^i,
$$

where Z^i are pure jump processes whose jumps have a fixed probability distribution ν^i on $\mathbb{R}^n$ and arrive with intensity $\lambda^i(X_t)$ for some $\lambda^i : D \to [0,\infty)$. Let us fix an affine process $R : D \to \mathbb{R}$. Then we have that the complete affine structure of the model is captured by:

$$
\begin{aligned}
\mu(x) &= K_0 + K_1 x, \text{ for } K = (K_0, K_1) \in \mathbb{R}^n \times \mathbb{R}^{n\times n}. \\
\sigma(x)\sigma(x)^\top &= H_0 + \sum_{k=1}^{n} H_1^{(k)} x_k, \text{ for } H = (H_0, H_1) \in \mathbb{R}^{n\times n} \times \mathbb{R}^{n\times n\times n}. \\
\lambda^i(x) &= l_0^i + l_1^i \cdot x, \text{ for } l = (l_0, l_1) \in \mathbb{R} \times \mathbb{R}^n. \\
R(x) &= \rho_0 + \rho_1 \cdot x, \text{ for } \rho = (\rho_0, \rho_1) \in \mathbb{R} \times \mathbb{R}^n.
\end{aligned}
$$

Let us furthermore denote the jump-transforms, which determine the jump-size distributions, as $\theta^i(c) = \int_{\mathbb{R}^n} \exp(c \cdot z)\, \mathrm{d}\nu^i(z)$ for $c \in \mathbb{C}^n$. We want to compute an expression of the form

$$\phi^X(u, X, t, T) = \mathbb{E}^X \left[\exp\left(- \int_t^T R(X_s) \mathrm{d}s \right) e^{u \cdot X_T} \middle| \mathcal{F}_t \right].$$

According to Proposition 1 of Duffie et al. (2000), we have, under some technical assumptions on the processes being well-behaved, that we can write

$$\phi^X(u, x, t, T) = e^{\alpha(t) + \beta(t) \cdot x},$$

where β and α satisfy the following (complex-valued) ODEs:

$$\begin{aligned} \dot{\beta}(t) &= \rho_1 - K_1^\top \beta(t) - \frac{1}{2} \beta(t)^\top H_1 \beta(t) - \sum_{i=1}^m l_1^i (\theta^i(\beta(t)) - 1) \\ \dot{\alpha}(t) &= \rho_0 - K_0 \cdot \beta_t - \frac{1}{2} \beta(t)^\top H_0 \beta(t) - \sum_{i=1}^m l_0^i (\theta^i(\beta(t)) - 1), \end{aligned}$$

with boundary conditions $\beta(T) = u$ and $\alpha(T) = 0$.

Applying the situation described above to the process defined in (16), we have $n = 2$, $m = 1$, $K_0 = (0, \alpha_j^{\mathbb{Q}} \lambda_{j,\infty}^{\mathbb{Q}})^\top$,

$$K_1 = \begin{pmatrix} 0 & 0 \\ 0 & -\alpha_j^{\mathbb{Q}} \end{pmatrix},$$

$H_0 = \mathbf{0}$,

$$H_1^1 = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}, H_1^2 = \begin{pmatrix} 0 & 0 \\ 0 & \sigma_j^2 \end{pmatrix}$$

$l_0^1 = 0$ and $l_1^1 = (0, 1)^\top$. Since $N_{j,t}^{\mathbb{Q}}$ is a counting process, and the coefficient Z_j is a constant, we have fixed jump sizes and therefore $\theta^1(c) = \exp(c_1 + Z_j c_2)$. Since we want to compute $\mathbb{E}^{\mathbb{Q}} \left[(1 - \gamma_j)^{N_{j,T}} \middle| \mathcal{F}_t \right]$, we have that $\rho_0 = 0$, $\rho_1 = (0, 0)^\top$ and $u = (\log(1 - \gamma_j), 0)^\top$. The result thus follows by applying Proposition 1 of Duffie et al. (2000). $\square$

Proposition 2.

$$\mathbb{E}^{\mathbb{Q}}\left[\gamma_j \lambda^{\mathbb{Q}}_{j,T}(1-\gamma_j)^{N_{j,T}} \,\middle|\, \mathcal{F}_t\right] = e^{\alpha(t)+\log(1-\gamma_j)N_{j,t}+\beta_2(t)\lambda^{\mathbb{Q}}_{j,t}} \times (A(t)+B_2(t)\lambda^{\mathbb{Q}}_{j,t}),$$

with

$$\begin{aligned}
-\dot{A}(t) &= \alpha^{\mathbb{Q}}_j \lambda^{\mathbb{Q}}_{j,\infty} B_2(t), \\
-\dot{B}_2(t) &= -\alpha^{\mathbb{Q}}_j B_2(t) + \beta_2(t)\sigma_j^2 B_2(t) + (1-\gamma_j) Z_j e^{Z_j \beta_2(t)}, \\
B_2(T) &= \gamma_j, \\
A(T) &= 0,
\end{aligned}$$

and $\alpha(t)$ *and* $\beta(t)$ *satisfy the ODEs in the previous proposition.*

Proof. Proposition 3 of Duffie et al. (2000) with
$u = (\log(1-\gamma_j), 0)^\top$ and $v = (0, \gamma_j)^\top$ yields the result. □

Appendix B MCMC details

In this Appendix, I provide more details of the estimation methodology used to estimate the model of the risk-neutral intensities. As explained in Section 4.1, the estimation of the risk-neutral model is divided into three steps. Since all these steps rely on the same MCMC procedure, I briefly explain the set-up of the first and third steps in which I keep the country-specific factors fixed and only consider the common factor with country-specific loadings γ_i^c to this factor. I denote the fixed country-specific parts of the model with Ψ. That is, Ψ contains all parameters related to the country-specific factors, as well as the country-specific jump times and intensities.[10]

[10] In the first substep, I ignore the country-specific factors, which essentially boils down to setting all country-specific parameters and intensities equal to zero. In the third substep, I fix the country-specific

I first denote the right-hand side of the CDS pricing formula (6) as a function F of a vector with the common factor parameters and country-specific loadings to this factor, $\Theta_i = \{\alpha_c^{\mathbb{Q}}, \alpha_c^{\mathbb{Q}}\lambda_{c,\infty}^{\mathbb{Q}}, \sigma_c^2, Z_c, \gamma_i^c\}$, $i = 1, \ldots, K$, state variables $X_t = \{N_{c,t}, \lambda_{c,t}^{\mathbb{Q}}\}$, maturity M, and fixed country-specific parts. That is

$$CDS_{i,t}(M) = F\left(X_t, \Theta_i, M, \Psi\right). \tag{17}$$

Since the data does not start on the same date for all countries, I let $S(t)$ denote the set of CDS contracts for which I have an observation on day $t, t = 1, \ldots, N$. I assume that the (log) CDS spreads $Y_{t,k}$, $k \in S(t)$ are observed with normally distributed pricing errors, that is

$$Y_{t,k} = log\left(F\left(X_t, \Theta_k, M, \Psi\right)\right) + \xi_{t,k}, \quad \forall k \in S(t), t = 1, \ldots, N, \tag{18}$$

with $\xi_{t,k} \sim \mathcal{N}(0, h_c^2)$.[11]

Let $Y = \{Y_{t,k} : t = 1, \ldots, N, k \in S(t)\}$ denote the vector of all CDS price observations, $X = \{X_t : t = 1 \ldots, N\}$ the vector with all states, and $\bar{\Theta} = \{h_c^2, \alpha_c^{\mathbb{Q}}, \alpha_c^{\mathbb{Q}}\lambda_{c,\infty}^{\mathbb{Q}}, \sigma_c^2, Z_c, \{\gamma_i^c\}_{i=1}^K, \alpha_c^{\mathbb{P}}, \alpha_c^{\mathbb{P}}\lambda_{c,\infty}^{\mathbb{P}}\}$ the vector with all parameters related to the common factor (i.e., both the parameters governing the $\mathbb{P}$- and $\mathbb{Q}$-dynamics of $\lambda_{c,t}^{\mathbb{Q}}$). Furthermore, for notational convenience, I from now on drop the fixed Ψ from the notation. Then the conditional density of the joint observations can be written as

$$\begin{aligned} p(Y|X, \bar{\Theta}) &\propto \prod_{t=1}^{N} \prod_{k \in S(t)} \phi(Y_{t,k}; F(X_{k,t}, \Theta_k, M), h^2) \\ &=: \prod_{t=1}^{N} p(Y_t|X_t, \Theta), \end{aligned} \tag{19}$$

components to the estimates found in substep two.

[11] For every country, the pricing formula (6) of the 2-, 3-, 5-, and 10-year maturity CDS spreads depend on the same parameters and state variables. Therefore Θ_k is the same for CDS spreads of the same country across different maturities.

where $\phi(x; m, s^2)$ denotes a normal density with mean m and variance s^2 evaluated at x.

The full joint posterior density $p(Y, X, \bar{\Theta})$ is then given by

$$p(Y, X, \bar{\Theta}) \propto p(Y|X, \bar{\Theta})p(X|\bar{\Theta})p(\bar{\Theta}), \tag{20}$$

where $p(\bar{\Theta})$ is the prior for $\bar{\Theta}$. I choose our priors to be proper but in such a way that they impose little information.

Using the Markovian property of the joint intensity and jump process (see Aït-Sahalia et al., 2014), I can rewrite this as a product over the observations times:

$$p(Y, X, \bar{\Theta}) \propto p(\bar{\Theta}) \prod_{t=1}^{N} p(Y_t|X_t, \bar{\Theta})p(X_t|X_{t-1}, \bar{\Theta}), \tag{21}$$

where $p(X_t|X_{t-1}, \bar{\Theta})$ is the transition density of the state process. As explained in Section 4.1, I use a discrete-time approximation of the transition densities, making it possible to express the transition density in closed-form.

Ultimately, the goal is to sample from the joint conditional posterior density $p(\bar{\Theta}, X|\bar{Y})$. The reason for this is that, by Bayes theorem, $p(\bar{\Theta}|Y) \propto p(\bar{\Theta}, X|Y)$. Hence, the sample average of $\bar{\Theta}^{(1)}, \bar{\Theta}^{(2)}, \ldots, \bar{\Theta}^{(G)}$, $\hat{\bar{\Theta}} = \frac{1}{G}\sum_{g=1}^{G} \bar{\Theta}^{(g)}$, can be used as the estimate of $\bar{\Theta}$. In a similar way, the latent jump intensities can be estimated by considering the sample averages $\lambda_{j,t}^{\mathbb{Q}(g)}$ for all $t = 1, \ldots, N$. To estimate the jump times, i.e., to decide whether a jump occurred at time t, $t = 1, \ldots, N$, I define a threshold, $\omega > 0$, and say that a jump occurred at time t if $\frac{1}{G}\sum_{g=1}^{G} N_{j,t}^{(g)} > \omega$ (see Johannes et al., 1999).

Since the joint conditional posterior density is high-dimensional and nonstandard, it is not possible to sample from this density directly. In order to overcome these problems, I employ a Gibbs sampler, which sequentially draws all random variables from the joint posterior density.

The Gibbs sampler consists of the following steps, initialized by an appropriate set of starting values for X and $\bar{\Theta}$ when $g = 0$:

For $g = 1, \ldots, G, t = 1, \ldots, N$, simulate

1. $X_t^{(g+1)}$ from $p(X_t | X_{1:N_{\setminus t}}^{(g)}, \bar{\Theta}^{(g)}, \bar{Y})$, and
2. $\bar{\Theta}^{(g+1)}$ from $p(\bar{\Theta} | X^{(g+1)}, \bar{Y})$,

where $X_{1:N_{\setminus t}}$ denotes the collection of state vectors X_s at all $s = 1, \ldots, N$ except at $s = t$. In the sections below, I first explain the details of the steps involved in drawing the new states, and next those of drawing the new parameters.

B.1 Metropolis Step for Simulating the States

The drawing of the state vectors requires alternating between two different sampling schemes. This is to deal with the latency of the states, which makes it challenging for the algorithm to initialize the drawing of jumps. For a more detailed discussion on this, I refer to Sperna Weiland et al. (2018).

B.1.1 State Simulation Scheme 1

In the first simulation scheme, I use that $p(X_t | X_{1:N_{\setminus t}}^{(g)}, \bar{\Theta}^{(g)}, \bar{Y})$ is characterized by its full conditionals. Therefore, the drawing of $X_t^{(g+1)}$ can be split into the following two steps:

1. draw $N_{j,t}^{(g+1)}$ from $p(N_{j,t} | \lambda_{j,t}^{\mathbb{Q}(g)}, X_{1:N_{\setminus t}}^{(g)}, \bar{\Theta}^{(g)}, Y)$;
2. draw $\lambda_{j,t}^{\mathbb{Q}(g+1)}$ from $p(\lambda_{j,t}^{\mathbb{Q}} | N_{j,t}^{(g+1)}, X_{1:N_{\setminus t}}^{(g)}, \bar{\Theta}^{(g)}, Y)$.

Under the discretization of the state transition dynamics introduced in (7), the full posterior of $N_{j,t}$ is a Bernoulli density with success probability

$$p(N_{j,t}=1|\lambda_{j,t}^{\mathbb{Q}(g)}, X_{1:N_{\setminus t}}^{(g)}, \bar{\Theta}^{(g)}, Y) = \frac{p(\lambda_{j,t}^{\mathbb{Q}(g)}|N_{j,t}=1, X_{t-1}^{(g+1)}, \bar{\Theta}^{(g)})p(N_{j,t}=1|X_{t-1}^{(g+1)})}{\sum_{s=0,1} p(\lambda_{j,t}^{\mathbb{Q}(g)}|N_{j,t}=s, X_{t-1}^{(g+1)}, \bar{\Theta}^{(g)})p(N_{j,t}=s|X_{t-1}^{(g+1)})}. \tag{22}$$

(22) is easy to compute, since $p(\lambda_{j,t}^{\mathbb{Q}(g)}|N_{j,t}=s, X_{t-1}^{(g+1)}, \bar{\Theta}^{(g)})$ is a normal density and $p(N_{j,t}=s|X_{t-1}^{(g+1)})$ a Bernoulli with success probability $\lambda_{j,t-1}^{\mathbb{Q}(g+1)}\Delta_t$. The credit jump probability does not depend on Y, since the CDS prices only depend on the intensities and parameter vector. Therefore, the jump probabilities are determined only by the state transition equations and not by the measurement equations. This makes it hard for the algorithm to draw initial jumps. For this reason, I alternate between this sampling scheme and the one explained below, which does take into account the measurement equations.

After having drawn $N_{j,t}^{(g+1)}$, the new intensity $\lambda_{j,t}^{\mathbb{Q}(g+1)}$ is drawn from the density

$$\begin{aligned} p(\lambda_{j,t}^{\mathbb{Q}}|N_{j,t}^{(g+1)}, X_{1:N_{\setminus t}}^{(g)}, \bar{\Theta}^{(g)}, Y) \propto p(Y_t|\lambda_{j,t}^{\mathbb{Q}}, N_{j,t}^{(g+1)}, \bar{\Theta}^{(g)})p(\lambda_{j,t+1}^{\mathbb{Q}(g)}|\lambda_{j,t}^{\mathbb{Q}}, N_{j,t+1}^{(g)}, \bar{\Theta}^{(g)}) \\ \times p(\lambda_{j,t}^{\mathbb{Q}}|\lambda_{j,t-1}^{\mathbb{Q}(g+1)}, N_{j,t}^{(g+1)}, \bar{\Theta}^{(g)}), \end{aligned}$$

which is the product of a multivariate normal density and two univariate normal densities. This density is non-standard, and, therefore, I use a Metropolis step with proposal density $p(\lambda_{j,t}^{\mathbb{Q}}|\lambda_{j,t-1}^{\mathbb{Q}(g+1)}, N_{j,t}^{(g+1)}, \bar{\Theta}^{(g)})$, which is a normal distribution with mean $\lambda_{j,t-1}^{\mathbb{Q}(g+1)} + \alpha_j^{\mathbb{P}(g)}\lambda_{j,\infty}^{\mathbb{P}(g)}\Delta_t - \alpha_j^{\mathbb{P}(g)}\lambda_{j,t-1}^{\mathbb{Q}(g+1)}\Delta_t + Z_j^{(g)}N_{j,t}^{(g+1)}$ and variance $\sigma_j^{2(g)}\lambda_{j,t-1}^{\mathbb{Q}(g+1)}\Delta_t$

Using this proposal density, the acceptance criterion becomes

$$\min\left(\frac{p(Y_t|X_t^{(g+1)}, \bar{\Theta}^{(g)})p(\lambda_{j,t+1}^{\mathbb{Q}(g)}|N_{j,t+1}^{(g)}, X_t^{(g+1)}, \bar{\Theta}^{(g)})}{p(Y_t|X_t^{(g)}, \bar{\Theta}^{(g)})p(\lambda_{j,t+1}^{\mathbb{Q}(g)}|N_{j,t+1}^{(g)}, X_t^{(g)}, \bar{\Theta}^{(g)})}, 1\right).$$

For the end point $t = N$ the acceptance criterion simplifies, since the terms $p(\lambda_{j,t+1}^{\mathbb{Q}(g)}|N_{j,t+1}^{(g)}, X_t^{(g+1)}, \bar{\Theta}^{(g)})$ and $p(\lambda_{j,t+1}^{\mathbb{Q}(g)}|N_{j,t+1}^{(g)}, X_t^{(g)}, \bar{\Theta}^{(g)})$ do not appear anymore in the numerator and denominator, respectively. For the starting point $t = 1$, I use a slightly different proposal density, since I cannot condition on X_{t-1}. I therefore draw $\lambda_{j,1}^{\mathbb{Q}(g+1)}$ from a normal density with mean $\lambda_{j,2}^{\mathbb{Q}(g)}$ and variance $\sigma_j^2 \lambda_{j,2}^{\mathbb{Q}(g)} \Delta_2$. Denoting this proposal density as $q(\lambda_{j,1}^{\mathbb{Q}(g+1)}|\lambda_{j,2}^{\mathbb{Q}(g)}, \bar{\Theta})$ gives the following acceptance criterion:

$$\min \left(\frac{p(Y_1|X_1^{(g+1)}, \bar{\Theta}^{(g)}) p(\lambda_{j,2}^{\mathbb{Q}(g)}|N_{j,2}^{(g)}, X_1^{(g+1)}, \bar{\Theta}^{(g)}) q(\lambda_{j,1}^{\mathbb{Q}(g)}|\lambda_{j,2}^{\mathbb{Q}(g)}, \bar{\Theta}^{(g)})}{p(Y_1|X_1^{(g)}, \bar{\Theta}^{(g)}) p(\lambda_{j,2}^{\mathbb{Q}(g)}|N_{j,2}^{(g)}, X_1^{(g)}, \bar{\Theta}^{(g)}) q(\lambda_{j,1}^{\mathbb{Q}(g+1)}|\lambda_{j,2}^{\mathbb{Q}(g)}, \bar{\Theta}^{(g)})}, 1 \right).$$

B.1.2 State Simulation Scheme 2

In the second simulation scheme, instead of drawing X_t in two steps, I sample the complete vector X_t at once from $p(X_t|X_{1:N_{\setminus t}}, \bar{\Theta}, Y)$. Equation (21) shows that the Markovian property of the state processes implies that I only need to consider the terms in (21) where (parts of) X_t enters directly. This gives

$$p(X_t|X_{1:N_{\setminus t}}^{(g-1)}, \bar{\Theta}, Y) \propto p(Y_t|X_t, \bar{\Theta}) p(X_t|X_{t-1}^{(g)}, \bar{\Theta}) p(X_{t+1}^{(g-1)}|X_t, \bar{\Theta}). \tag{23}$$

In this density, both the likelihoods as well as the transition densities play a role, and, therefore, the drawing of jumps depends on both the measurement equations as well as the transition densities of the states. By assumption of the normally distributed error terms $p(Y_t|X_t, \bar{\Theta})$ is multivariate normal with dimension equal to the number of observations at time t.

According to (8), the transition density can be written as

$$p(X_t|X_{t-1}, \bar{\Theta}) = p(\lambda_{j,t}^{\mathbb{Q}}|N_{j,t}, X_{t-1}, \bar{\Theta}) p(N_{j,t}|X_{t-1}, \bar{\Theta}), \tag{24}$$

In order to draw $X_t^{(g+1)}$ from (23), I use the following proposal density

$$
\begin{aligned}
q(X_t|X^{(g)}_{1:N_{\backslash t}}, \bar{\Theta}^{(g)}) &= p(X_t|X^{(g+1)}_{t-1}, \bar{\Theta}^{(g)}) \\
&= p(\lambda^{\mathbb{Q}}_{j,t}|N_{j,t}, N^l_t, X^{(g+1)}_{t-1}, \bar{\Theta}^{(g)})p(N_{j,t}|X^{(g+1)}_{t-1}, \bar{\Theta}^{(g)}).
\end{aligned}
$$

Under the discretization of the intensity processes, this is a mixture of normal distributions. When drawing from this distribution, one can first draw $N^{(g+1)}_{j,t}$ from an independent Bernoulli distribution with success probability $\lambda^{\mathbb{Q}(g+1)}_{j,t-1}\Delta_t$, and then, given the outcome, draw $p(\lambda^{\mathbb{Q}}_{j,t}|N^{(g+1)}_{j,t}, X^{(g+1)}_{t-1}, \Theta^{(g)})$ from a normal distribution with the appropriate mean (depending on outcome of the draw of $N^{(g+1)}_{j,t}$).

Using this proposal density, the acceptance criterion is as follows:

$$
\min\left(\frac{p(Y_t|X^{(g+1)}_t, \Theta^{(g)})p(\lambda^{\mathbb{Q}(g)}_{j,t+1}, N^{(g)}_{j,t+1}|X^{(g+1)}_t, \Theta^{(g)})}{p(Y_t|X^{(g)}_t, \Theta^{(g)})p(\lambda^{\mathbb{Q}(g)}_{j,t+1}, N^{(g)}_{j,t+1}|X^{(g)}_t, \Theta^{(g)})}, 1\right),
$$

where $p(\lambda^{\mathbb{Q}(g)}_{j,t+1}, N^{(g)}_{j,t+1}|X^{(g+1)}_t, \bar{\Theta}^{(g)}) = p(\lambda^{\mathbb{Q}(g)}_{j,t+1}|N^{c(g)}_{t+1}, X^{(g+1)}_t, \bar{\Theta}^{(g)}) \times p(N^{(g)}_{j,t+1}|X^{(g+1)}_t, \bar{\Theta}^{(g)})$. Since all densities are standard (i.e., multivariate normal, univariate normal or bernoulli), evaluating this acceptance criterion is straightforward. For the end points $t = 1$ and $t = N$ similar comments apply as in simulation scheme 1.

B.2 Metropolis Step for Simulating the Parameters

Next I explain the Metropolis step for estimating the parameters $\bar{\Theta}^{(g+1)}$ from $p(\bar{\Theta}|X^{(g+1)}, \bar{Y})$ in more detail.

For h^2_j, $j \in \{c, 1, 2, \ldots, K\}$, the inverse gamma distribution is a conjugate prior. This follows from $p(h^2_j|\bar{\Theta}\backslash\{h^2_j\}, X, Y) \propto p(Y|\bar{\Theta}, X)p(h^2_j)$, where $p(Y|\bar{\Theta}, X)$ is multivariate normal with diagonal variance matrix with h^2_j as variance and $p(h^2_j)$ the prior inverse gamma density. Explicit computations are standard and are therefore omitted.

For the other parameters I rely on Metropolis steps. I use random-walk Metropolis steps with Gaussian proposal densities with as mean vectors the previous draws and with a diagonal covariance matrices. I choose the priors on all parameters to be proper but uninformative in the sense that the prior variances should be high compared to the estimated posterior variances. I use the following priors:

- $\alpha_j^{\mathbb{Q}}$, $\alpha_j^{\mathbb{P}}$, $\alpha_j^{\mathbb{Q}}\lambda_{j,\infty}^{\mathbb{Q}}$, $\alpha_j^{\mathbb{Q}}\lambda_{j,\infty}^{\mathbb{Q}}$, σ_j^2, Z_j, $j \in \{c, 1, 2, \ldots, K\}$: $Gamma(0.02, 10)$
- γ_i and γ_i^c, $i \in \{1, 2, \ldots, K\}$: $Uniform(0, 1)$
- h_j^2, $j \in \{c, 1, 2, \ldots, K\}$: $IG(3, 0.1)$

In line with theoretical parameter restrictions for nonnegativity and stationarity of the processes, I impose some parameters to be nonnegative by using gamma priors. Since γ_i and γ_i^c are the probability of going into default in the case a country-specific or common credit shock arrives, respectively, I use $Uniform(0, 1)$ priors. In general, the means and variances of all parameters are chosen arbitrarily, but such that the means are small and positive for all parameters and the variances relatively large compared to their means. All-in-all, results are robust against prior specification, since typically the likelihood contribution of the priors is small compared to the likelihood contribution of the data in the acceptance criteria. Furthermore, the posterior standard deviations are also much smaller than the prior standard deviations, indicating that our priors do not impose much information.

B.3 Estimation country-specific components

In the second substep of the estimation procedure, the common factor part of the model is fixed and the country-specific factors are estimated. In the notation of above, I now denote the fixed common factor part of the model by Ψ, and write the right-hand side of the CDS pricing formula (6) as a function F of a vector with the country-specific parameters $\bar{\Theta} =$

$\{h_i^2, \alpha_i^{\mathbb{Q}}, \alpha_i^{\mathbb{Q}}\lambda_{i,\infty}^{\mathbb{Q}}, \sigma_i^2, Z_i, \gamma_i, \gamma_i^c, \alpha_i^{\mathbb{P}}, \alpha_i^{\mathbb{P}}\lambda_{i,\infty}^{\mathbb{P}}\}$, country-specific states $X_t = \{N_{i,t}, \lambda_{i,t}^{\mathbb{Q}}\}$, maturity M, and fixed common component Ψ. That is,

$$CDS_{i,t}(M) = F(\bar{\Theta}, X_{i,t}, M, \Psi). \tag{25}$$

Apart from this change, the mechanics of the estimation methodology are exactly identical to those of the first and third substeps outlined in this Appendix.

Figures

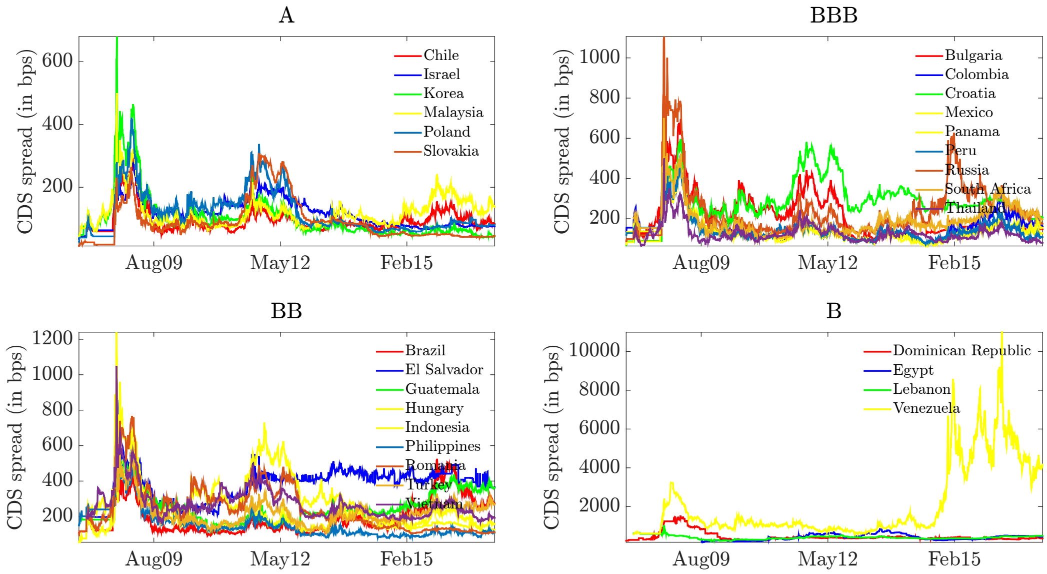

Figure 1. 5y CDS spreads. This figure plots the 5y CDS spreads for A-rated (upper left panel), BBB-rated (upper right panel), BB-rated (bottom left panel), and B-rated (bottom right panel) countries. Source: Datastream.

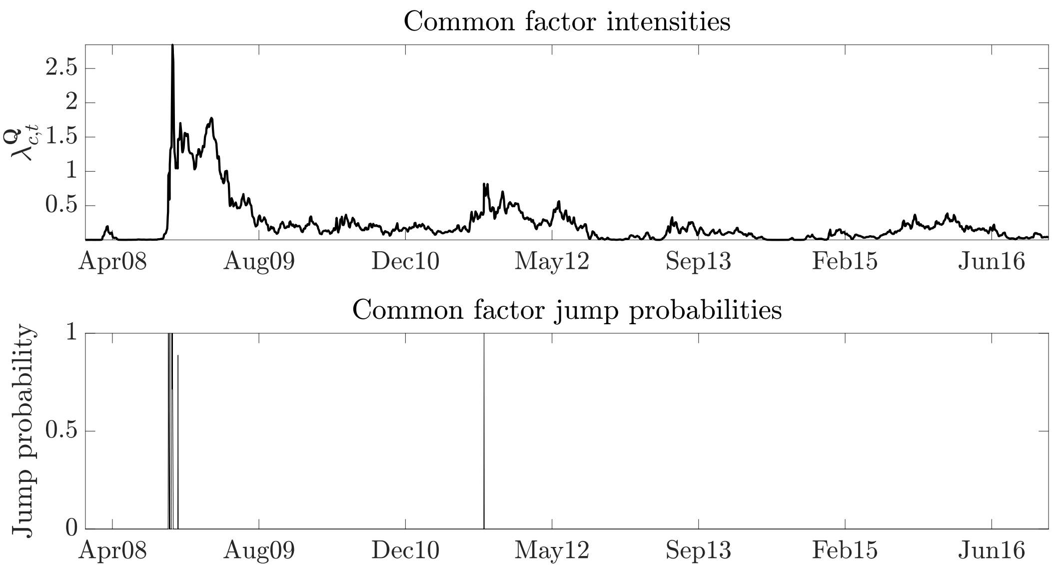

Figure 2. Estimated common factor intensities and jump times. This figure plots the estimated common factor intensities (upper panel) and estimated probabilities of arrivals of large systemic credit shocks (bottom panel).

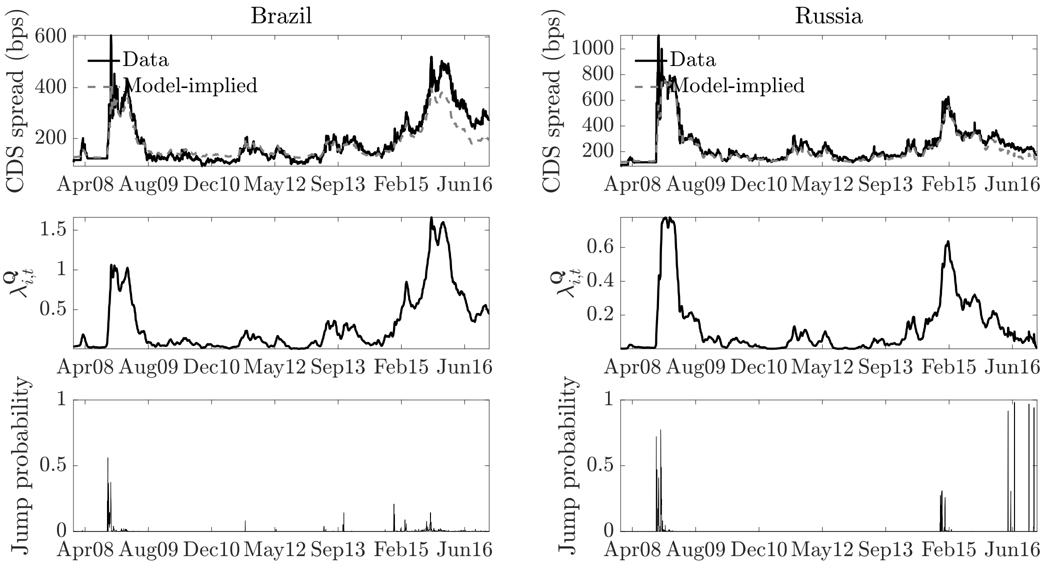

Figure 3. Model-fit and country-specific factors. This figure illustrates the 5-year CDS spread model-fit (upper panels), estimated country-specific intensities (middle panels), and estimated jump times (bottom panels) for Brazil (left column) and Russia (right column).

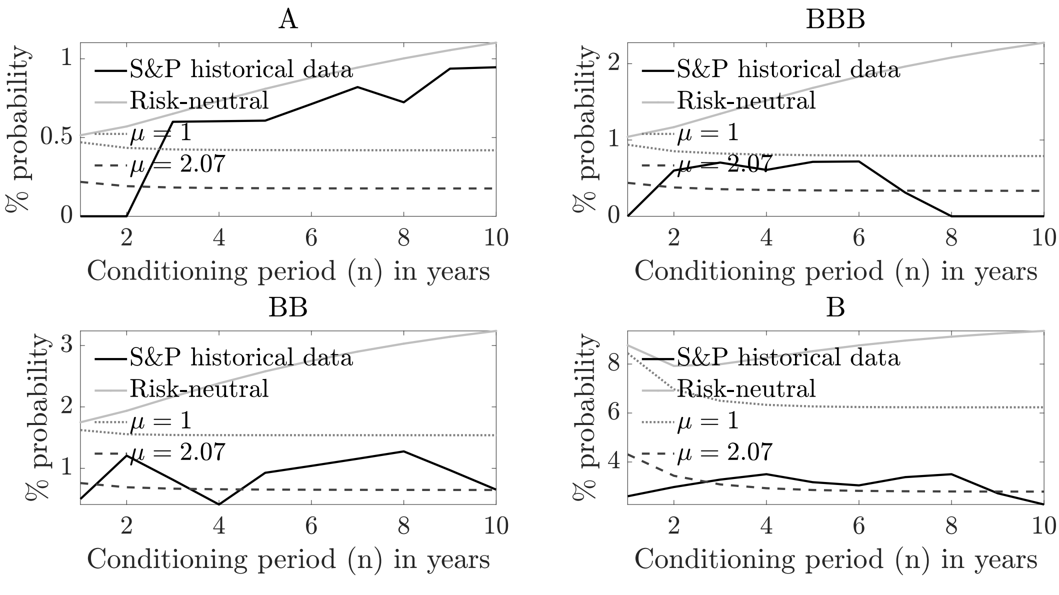

Figure 4. Conditional default probabilities. This figure plots the conditional default probabilities for A-rated (upper left panel), B-rated (upper right panel), BB-rated (bottom left panel), and B-rated (bottom right panel) countries. The conditional default probability is defined as the probability of a country going into default in period $[n, n+1]$ given no default has occurred before year n. The *S&P* historical data line gives the historically estimated conditional default probabilities obtained using S&P data. The line $\mu = 2.07$ represents the model-implied actual conditional default probabilities. The line $\mu = 1$ represents the model-implied actual conditional default probabilities assuming absence of default event risk premia.

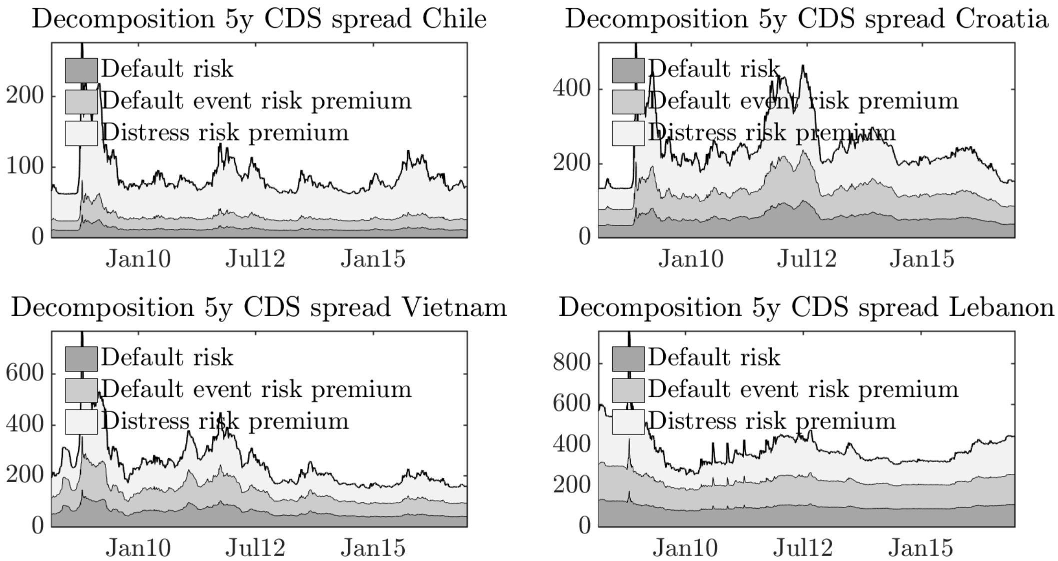

Figure 5. Absolute decomposition 5-year CDS spreads over time. This figure shows the decomposition of 5 year CDS spreads of Chile (upper left panel), Croatia (upper right panel), Vietnam (bottom left panel), and Lebanon (bottom right panel) into distress risk premia, default event risk premia, and default risk components over time.

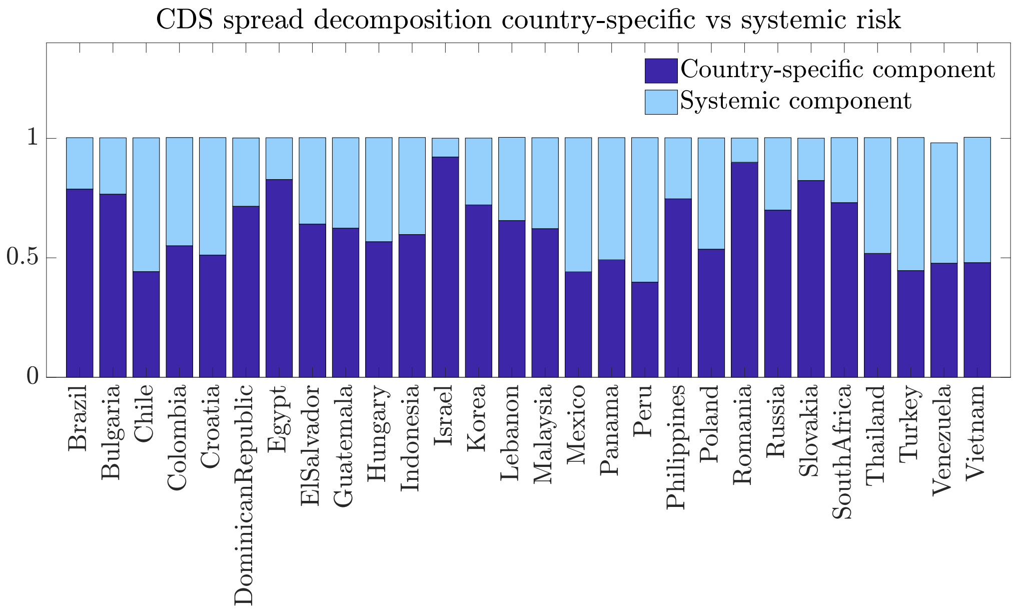

Figure 6. Relative decomposition 5-year CDS spreads into country-specific and systemic risk components. This figure shows the relative decomposition of 5 year CDS spreads into country-specific and systemic risk components.

Tables

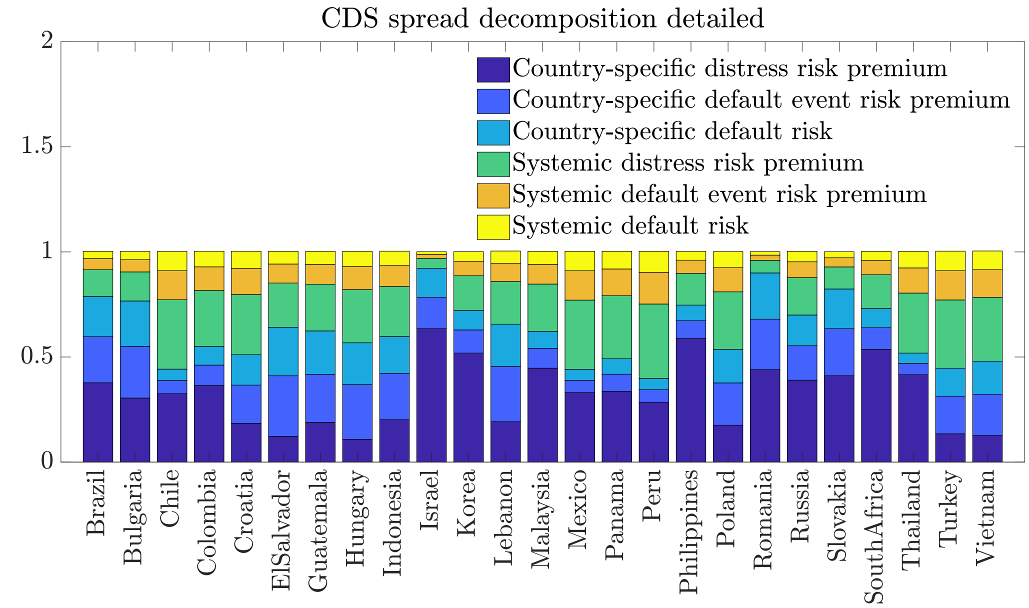

Figure 7. Detailed relative decomposition 5-year CDS spreads. This figure shows the relative decomposition of 5 year CDS spreads into country-specific distress risk premia, country-specific default event risk premia, country-specific default risk,systemic distress risk premia, systemic default event risk premia, and systemic default risk components.

Table 1. Summary statistics. This table reports summary statistics for the CDS spreads of the 28 countries in our sample. The first four columns display the country name, the first date for which observations are available, the total number of (daily) observations, and the average (S%P) rating throughout the sample period, respectively. The average rating is determined by transforming the prevailing ratings to a numerical scale and by taking the average over the sample period. Columns 5 to 8 report the average daily CDS spreads (in basis points) of the 2-, 3-, 5-, and 10-year maturities, respectively. Columns 9 to 12 report the standard deviations of the daily CDS spreads (in basis points) of the 2-, 3-, 5-, and 10-year maturities, respectively. Columns 13 to 16 and 17 to 21 report the sample minimum and maximum CDS spreads (in basis points) of the 2-, 3-, 5-, and 10-year maturities, respectively. The last column reports the percentage of the variation in the levels of the 2-, 3-, 5-, and 10-year CDS spreads explained by the first principal component. The sample period runs from 01-01-2008 until 12-30-2016. Source: Datastream.

				Mean spread				Std. dev. spread				Min spread				Max spread				
Country	Start	Obs	Average rating	2y	3y	5y	10y	2y	3y	5y	10y	2y	3y	5y	10y	2y	3y	5y	10y	% explained 1^{st} PC
Brazil	1-1-2008	2349	BB	119	146	193	236	76	86	98	104	41	61	91	120	587	597	606	628	92.7
Bulgaria	1-2-2008	2348	BBB	160	179	215	243	126	121	110	95	27	45	75	89	715	703	693	668	97.9
Chile	2-29-2008	2306	A	55	69	96	124	31	34	40	41	21	32	49	65	290	285	310	329	95.3
Colombia	1-2-2008	2348	BBB	102	122	161	203	69	71	73	73	26	39	74	120	614	635	669	696	96.0
Croatia	1-2-2008	2348	BBB	215	245	287	317	110	106	103	102	46	54	69	82	602	598	593	602	94.3
Dominican Republic	1-1-2008	2349	B	419	439	454	465	281	274	248	231	130	170	242	245	1784	1552	1547	1474	98.7
Egypt	8-20-2009	1922	B	368	389	415	425	152	153	150	152	147	167	163	177	806	826	844	854	99.0
El Salvador	2-29-2008	2306	BB	318	347	379	403	95	97	95	94	106	143	198	228	815	840	859	886	96.8
Guatemala	1-16-2008	2338	BB	200	224	255	288	86	86	89	90	94	118	123	156	667	677	686	715	97.8
Hungary	1-1-2008	2349	BB	206	232	272	297	151	144	136	123	30	43	55	68	691	692	730	719	97.4
Indonesia	2-29-2008	2306	BB	137	161	216	267	154	145	131	118	34	59	118	163	1240	1240	1240	1240	98.3
Israel	1-2-2008	2348	A	65	80	115	140	44	45	44	38	14	25	35	46	252	268	283	275	89.1
Korea	1-1-2008	2349	A	68	77	104	127	78	77	76	71	13	21	40	55	593	605	680	695	98.3
Lebanon	2-29-2008	2306	B	318	358	408	434	99	94	95	101	169	193	233	233	935	965	1000	1025	94.8
Malaysia	1-1-2008	2349	A	65	82	120	154	43	46	49	52	16	29	44	53	428	475	500	518	88.6
Mexico	1-2-2008	2348	BBB	86	104	139	177	68	69	68	66	22	32	64	89	576	590	613	635	96.5
Panama	1-2-2008	2348	BBB	91	109	145	184	67	69	70	68	24	37	73	113	609	635	677	710	97.4
Peru	1-2-2008	2348	BBB	92	111	148	188	63	65	64	62	25	41	76	123	613	634	664	695	97.2
Philippines	1-1-2008	2349	BB	92	112	156	203	93	90	83	72	21	37	79	134	823	820	840	865	97.6
Poland	1-2-2008	2348	A	75	91	120	152	68	70	69	61	10	19	26	39	418	422	421	396	95.2
Romania	1-2-2008	2348	BB	180	205	245	273	154	145	133	119	35	56	96	99	805	786	768	743	97.9
Russia	1-1-2008	2349	BBB	190	210	243	271	191	169	145	127	39	64	87	106	1107	1106	1106	1092	97.4
Slovakia	1-1-2008	2349	A	60	70	92	117	65	67	66	64	9	10	13	19	278	290	306	318	96.3
South Africa	2-29-2008	2306	BBB	120	148	189	226	81	79	76	71	33	60	101	128	673	701	701	681	93.6
Thailand	2-29-2008	2306	BBB	71	89	127	162	47	47	45	44	22	41	65	80	430	465	500	519	93.5
Turkey	10-8-2008	2148	BB	153	176	223	259	90	86	79	73	50	68	110	145	835	835	835	846	93.7
Venezuela	2-29-2008	2306	B	2267	2192	2095	1912	2312	2115	1917	1694	413	502	571	570	12129	11441	10996	10413	99.4
Vietnam	2-29-2008	2306	BB	191	220	273	318	125	116	90	83	62	100	163	185	1050	1050	1050	1050	96.5

Table 2. Parameter estimates risk-neutral intensities. This table reports the parameter estimates and posterior standard errors (in brackets) of the risk-neutral intensity process parameters. The last two columns report the number of estimated jumps and average relative pricing errors (ARPE), respectively.

	$\alpha^{\mathbb{P}}$	$\alpha^{\mathbb{P}}\lambda^{\mathbb{P}}_{\infty}$	σ^2	$\alpha^{\mathbb{Q}}$	$\alpha^{\mathbb{Q}}\lambda^{\mathbb{Q}}_{\infty}$	Z	γ_i	h	γ^c	# jumps	ARPE
Common factor	1.269	0.241	0.470	0.537	0.237	0.462		0.127		7	
	(0.158)	(0.007)	(0.012)	(0.003)	(0.002)	(0.004)		(0.000)			
Brazil	0.928	0.305	0.245	0.197	0.228	0.092	0.027	0.171	0.007	4	9.73%
	(0.522)	(0.029)	(0.033)	(0.071)	(0.050)	(0.018)	(0.001)	(0.052)	(0.00004)		
Bulgaria	0.506	0.016	0.031	0.151	0.015	0.074	0.275	0.118	0.008	2	6.28%
	(0.283)	(0.001)	(0.002)	(0.063)	(0.001)	(0.032)	(0.013)	(0.048)	(0.00005)		
Chile	1.783	0.126	0.155	0.206	0.098	0.159	0.016	0.132	0.009	6	8.77%
	(0.553)	(0.028)	(0.020)	(0.061)	(0.026)	(0.014)	(0.001)	(0.023)	(0.00003)		
Colombia	1.258	0.159	0.169	0.072	0.114	0.030	0.024	0.142	0.012	1	7.23%
	(0.978)	(0.041)	(0.007)	(0.069)	(0.044)	(0.009)	(0.004)	(0.060)	(0.00004)		
Croatia	0.596	0.010	0.015	0.243	0.008	0.239	0.401	0.202	0.023	0	11.59%
	(0.404)	(0.006)	(0.005)	(0.019)	(0.002)	(0.031)	(0.064)	(0.049)	(0.00008)		
Dominican Republic	1.860	0.394	0.074	0.332	0.038	0.150	0.159	0.092	0.020	8	4.59%
	(0.388)	(0.007)	(0.030)	(0.081)	(0.017)	(0.047)	(0.022)	(0.050)	(0.00013)		
Egypt	0.527	0.110	0.052	0.250	0.029	0.197	0.176	0.116	0.012	2	4.32%
	(0.185)	(0.007)	(0.036)	(0.050)	(0.018)	(0.030)	(0.028)	(0.090)	(0.00015)		
El Salvador	0.838	0.073	0.056	0.329	0.028	0.205	0.199	0.077	0.025	4	5.54%
	(0.219)	(0.010)	(0.007)	(0.054)	(0.004)	(0.013)	(0.008)	(0.005)	(0.00010)		
Guatemala	1.570	0.314	0.060	0.086	0.030	0.059	0.059	0.073	0.017	23	5.60%
	(0.701)	(0.028)	(0.003)	(0.018)	(0.002)	(0.005)	(0.001)	(0.016)	(0.00009)		
Hungary	0.397	0.010	0.018	0.251	0.009	0.245	0.358	0.178	0.019	0	9.19%
	(0.109)	(0.005)	(0.008)	(0.009)	(0.004)	(0.028)	(0.045)	(0.072)	(0.00008)		
Indonesia	0.534	0.027	0.040	0.166	0.022	0.166	0.146	0.147	0.012	0	8.25%
	(0.235)	(0.009)	(0.004)	(0.004)	(0.002)	(0.004)	(0.043)	(0.053)	(0.00005)		
Israel	1.406	0.143	0.158	0.038	0.098	0.026	0.029	0.191	0.001	8	11.11%
	(0.870)	(0.027)	(0.021)	(0.034)	(0.023)	(0.009)	(0.006)	(0.070)	(0.00001)		
Korea	1.499	0.006	0.011	0.278	0.006	0.278	0.357	0.249	0.004	0	14.18%
	(0.828)	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)	(0.054)	(0.075)	(0.00002)		
Lebanon	1.118	0.143	0.091	0.470	0.072	0.289	0.128	0.095	0.026	3	6.07%
	(0.338)	(0.023)	(0.006)	(0.166)	(0.019)	(0.059)	(0.008)	(0.023)	(0.00014)		
Malaysia	1.785	0.163	0.168	0.191	0.113	0.175	0.022	0.181	0.008	6	12.66%
	(0.770)	(0.021)	(0.038)	(0.026)	(0.027)	(0.010)	(0.002)	(0.024)	(0.00003)		
Mexico	1.844	0.157	0.186	0.147	0.118	0.108	0.016	0.154	0.012	14	8.32%
	(0.666)	(0.042)	(0.013)	(0.087)	(0.039)	(0.005)	(0.005)	(0.039)	(0.00003)		
Panama	1.347	0.163	0.192	0.129	0.131	0.070	0.018	0.129	0.012	11	7.07%
	(0.803)	(0.037)	(0.017)	(0.103)	(0.039)	(0.017)	(0.002)	(0.043)	(0.00003)		
Peru	1.827	0.180	0.176	0.145	0.119	0.089	0.017	0.119	0.015	14	6.81%
	(0.756)	(0.035)	(0.013)	(0.095)	(0.042)	(0.006)	(0.002)	(0.034)	(0.00003)		
Philippines	1.441	0.010	0.020	0.170	0.013	0.169	0.274	0.139	0.006	1	9.73%
	(0.280)	(0.001)	(0.001)	(0.006)	(0.000)	(0.001)	(0.011)	(0.007)	(0.00005)		
Poland	0.531	0.005	0.009	0.236	0.005	0.236	0.370	0.280	0.008	0	16.13%
	(0.200)	(0.001)	(0.000)	(0.005)	(0.000)	(0.005)	(0.062)	(0.065)	(0.00003)		
Romania	1.819	0.257	0.110	0.053	0.055	0.040	0.066	0.166	0.003	32	8.29%
	(1.351)	(0.057)	(0.023)	(0.012)	(0.012)	(0.014)	(0.012)	(0.096)	(0.00007)		
Russia	1.056	0.053	0.084	0.218	0.042	0.065	0.131	0.142	0.011	16	9.13%
	(0.430)	(0.013)	(0.001)	(0.031)	(0.001)	(0.010)	(0.002)	(0.014)	(0.00005)		
Slovakia	0.695	0.005	0.009	0.187	0.005	0.186	0.404	0.333	0.002	0	22.26%
	(0.303)	(0.001)	(0.001)	(0.003)	(0.000)	(0.003)	(0.046)	(0.058)	(0.00002)		
South Africa	2.123	0.201	0.206	0.207	0.135	0.109	0.039	0.138	0.009	12	8.79%
	(0.330)	(0.011)	(0.030)	(0.058)	(0.031)	(0.012)	(0.003)	(0.031)	(0.00004)		
Thailand	1.994	0.159	0.196	0.095	0.143	0.067	0.016	0.154	0.010	5	9.57%
	(0.424)	(0.039)	(0.035)	(0.053)	(0.039)	(0.033)	(0.003)	(0.030)	(0.00002)		
Turkey	0.474	0.027	0.044	0.210	0.022	0.194	0.106	0.101	0.022	0	7.45%
	(0.174)	(0.004)	(0.002)	(0.007)	(0.001)	(0.014)	(0.005)	(0.009)	(0.00007)		
Venezuela	0.689	0.135	0.098	0.880	0.049	0.196	0.470	0.320	0.138	29	6.69%
	(0.283)	(0.013)	(0.025)	(0.099)	(0.013)	(0.091)	(0.086)	(0.184)	(0.00081)		
Vietnam	0.422	0.027	0.048	0.196	0.024	0.145	0.150	0.103	0.024	0	6.93%
	(0.192)	(0.004)	(0.002)	(0.019)	(0.001)	(0.017)	(0.023)	(0.023)	(0.00008)		

Table 3. Summary statistics 5-year CDS spread decomposition. This table reports summary statistics on the absolute and relative decomposition of 5-year CDS spreads into distress risk premia, default event risk premia, and default risk components.

	Distress Premium			Distress Premium Fraction			Default Event Premium			Default Event Premium Fraction			Default Risk			Default Risk Fraction		
Country	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Brazil	93.36	73.95	45.10	50.2%	48.7%	4.6%	47.55	42.50	11.72	27.3%	28.0%	2.5%	39.32	35.24	9.43	22.6%	23.2%	2.2%
Bulgaria	84.60	63.69	50.22	44.1%	44.0%	2.4%	55.83	43.84	26.63	30.4%	30.5%	1.3%	46.69	36.62	21.95	25.5%	25.5%	1.1%
Chile	56.93	49.12	22.48	65.3%	64.8%	2.6%	16.99	15.73	4.39	20.1%	20.4%	1.4%	12.25	11.39	2.89	14.6%	14.8%	1.2%
Colombia	88.93	81.17	38.18	62.7%	62.8%	3.5%	28.41	26.38	7.15	21.0%	20.8%	2.0%	22.11	20.97	5.16	16.3%	16.3%	1.5%
Croatia	114.20	104.77	41.76	46.6%	46.1%	3.0%	73.12	68.28	19.94	30.6%	30.8%	1.5%	54.37	50.70	14.58	22.8%	23.1%	1.5%
Dominican Republic	63.48	18.61	150.80	7.8%	5.7%	18.9%	174.56	166.44	25.76	50.0%	51.0%	10.0%	147.02	141.34	18.65	42.3%	43.3%	8.8%
Egypt	-7.52	-13.77	49.79	-7.6%	-4.0%	16.5%	204.38	199.87	43.35	60.8%	58.9%	9.0%	156.35	152.73	30.94	46.8%	45.2%	7.5%
El Salvador	124.48	134.06	49.93	32.9%	35.1%	7.2%	133.64	139.77	20.35	37.9%	36.7%	3.9%	102.46	107.24	14.66	29.2%	28.3%	3.3%
Guatemala	107.45	85.32	65.95	40.8%	40.3%	12.0%	72.95	69.90	9.72	32.3%	32.4%	6.5%	60.69	58.25	7.00	26.9%	27.3%	5.5%
Hungary	85.48	75.13	39.72	35.8%	35.4%	3.9%	90.41	84.27	44.67	37.0%	37.1%	2.2%	66.27	62.07	32.14	27.2%	27.4%	1.7%
Indonesia	76.65	60.02	52.92	43.6%	43.5%	3.3%	53.15	44.46	25.38	32.2%	32.2%	1.8%	39.86	33.37	18.28	24.2%	24.3%	1.6%
Israel	61.03	54.59	24.93	68.1%	68.2%	4.6%	14.13	13.39	2.66	16.9%	16.8%	2.4%	12.58	11.96	2.31	15.0%	15.0%	2.2%
Korea	54.41	41.98	36.13	68.2%	67.9%	3.4%	13.18	11.18	5.88	17.9%	18.1%	1.9%	10.18	8.61	4.54	13.8%	14.0%	1.4%
Lebanon	151.02	140.01	49.10	39.1%	38.7%	4.1%	130.83	126.75	18.35	35.0%	35.2%	2.2%	96.81	93.97	12.61	25.9%	26.2%	1.9%
Malaysia	70.83	62.17	28.85	66.9%	66.3%	3.2%	19.12	17.84	4.39	18.8%	19.2%	1.8%	14.45	13.54	3.04	14.3%	14.5%	1.4%
Mexico	73.14	64.95	34.18	65.7%	65.3%	3.0%	21.11	19.47	5.94	19.8%	20.1%	1.7%	15.33	14.27	4.01	14.5%	14.6%	1.3%
Panama	80.23	70.01	38.67	63.3%	63.0%	3.0%	25.34	23.20	7.35	20.9%	21.1%	1.7%	19.04	17.59	5.22	15.8%	15.8%	1.3%
Peru	82.90	73.87	37.18	63.6%	63.4%	3.0%	26.41	24.52	7.15	21.1%	21.2%	1.7%	19.18	17.89	4.74	15.4%	15.4%	1.3%
Philippines	100.83	74.76	62.80	73.6%	72.7%	2.3%	19.13	15.79	8.80	14.8%	15.4%	1.3%	14.95	12.20	6.96	11.6%	11.9%	0.9%
Poland	41.95	32.55	20.75	44.8%	44.4%	2.5%	28.80	21.96	11.61	31.7%	31.8%	1.3%	21.40	16.35	8.49	23.6%	23.8%	1.2%
Romania	117.62	85.08	94.53	49.8%	51.4%	16.6%	45.43	42.44	8.05	26.5%	25.6%	8.8%	40.44	38.01	6.83	23.7%	23.0%	7.9%
Russia	128.65	94.09	91.50	56.4%	55.7%	4.4%	49.60	41.27	22.40	23.9%	24.4%	2.5%	40.73	33.72	18.26	19.6%	20.0%	2.0%
Slovakia	39.02	28.48	29.62	51.5%	51.3%	3.4%	18.73	14.85	11.01	26.8%	26.8%	1.9%	15.13	12.03	8.85	21.7%	21.8%	1.6%
South Africa	119.54	105.01	48.73	69.4%	68.9%	3.2%	28.00	26.26	6.19	17.0%	17.2%	1.8%	22.37	21.11	4.57	13.6%	13.8%	1.4%
Thailand	74.32	67.90	26.40	69.8%	69.5%	2.1%	18.04	16.87	4.60	17.4%	17.6%	1.2%	13.25	12.49	3.06	12.8%	12.9%	0.9%
Turkey	94.48	83.19	40.16	45.6%	45.1%	2.6%	64.29	61.19	18.91	31.8%	32.1%	1.4%	45.48	43.67	12.56	22.6%	22.8%	1.3%
Venezuela	-270.32	-145.82	341.19	-15.8%	-19.2%	11.9%	1049.85	618.43	844.49	65.6%	65.0%	8.4%	738.44	500.30	475.99	50.2%	51.1%	5.4%
Vietnam	104.50	91.68	46.09	42.5%	42.1%	2.6%	79.07	71.82	26.47	32.9%	33.1%	1.3%	58.83	54.18	18.95	24.6%	24.8%	1.3%
A	54.03			60.8%			18.49			22.0%			14.33			17.2%		
BBB	94.06			60.2%			36.21			22.5%			28.12			17.4%		
BB	100.54			46.1%			67.29			30.3%			52.03			23.6%		
B	-15.84			5.9%			389.91			52.9%			284.65			41.3%		
B (w/o Venezuela)	68.99			13.1%			169.92			48.6%			133.39			38.3%		

Table 4. Average decomposition CDS spreads across maturities. This table reports the average decomposition of CDS spreads into distress risk premia, default event risk premia, and default risk across different maturities.

	Mean Distress Premium				Mean Default Event Premium				Mean Default Risk			
Country	2y	3y	5y	10y	2y	3y	5y	10y	2y	3y	5y	10y
Brazil	28.6%	38.1%	50.2%	63.0%	38.4%	33.5%	27.3%	20.4%	33.0%	28.3%	22.6%	16.6%
Bulgaria	25.4%	33.4%	44.1%	56.6%	39.9%	35.9%	30.4%	23.9%	34.7%	30.7%	25.5%	19.6%
Chile	45.0%	54.4%	65.3%	76.3%	30.8%	26.0%	20.1%	14.0%	24.2%	19.6%	14.6%	9.8%
Colombia	41.7%	51.5%	62.7%	74.1%	31.8%	26.9%	21.0%	14.8%	26.4%	21.7%	16.3%	11.2%
Croatia	27.5%	35.9%	46.6%	58.2%	40.1%	36.1%	30.6%	24.3%	32.4%	28.1%	22.8%	17.4%
Dominican Republic	-0.3%	2.7%	7.8%	15.3%	53.7%	52.4%	50.0%	46.1%	46.6%	44.9%	42.3%	38.6%
Egypt	-8.9%	-9.1%	-7.6%	-2.8%	59.6%	60.6%	60.8%	59.2%	49.3%	48.5%	46.8%	43.6%
El Salvador	18.0%	24.5%	32.9%	42.3%	45.1%	42.1%	37.9%	33.0%	36.9%	33.4%	29.2%	24.7%
Guatemala	24.2%	31.3%	40.8%	52.2%	40.7%	37.1%	32.3%	26.2%	35.2%	31.6%	26.9%	21.5%
Hungary	20.1%	26.7%	35.8%	47.1%	44.3%	41.4%	37.0%	31.2%	35.6%	32.0%	27.2%	21.7%
Indonesia	24.2%	32.4%	43.6%	57.3%	41.8%	37.9%	32.2%	24.8%	34.0%	29.7%	24.2%	17.9%
Israel	45.2%	56.1%	68.1%	79.6%	28.8%	23.1%	16.9%	10.8%	26.1%	20.8%	15.0%	9.6%
Korea	49.3%	58.5%	68.2%	77.2%	27.9%	23.1%	17.9%	13.0%	22.8%	18.4%	13.8%	9.8%
Lebanon	23.9%	30.7%	39.1%	48.1%	42.4%	39.3%	35.0%	30.2%	33.6%	30.1%	25.9%	21.8%
Malaysia	45.5%	55.6%	66.9%	78.1%	30.1%	24.9%	18.8%	12.6%	24.4%	19.5%	14.3%	9.3%
Mexico	45.5%	55.0%	65.7%	76.5%	30.4%	25.6%	19.8%	13.8%	24.1%	19.5%	14.5%	9.7%
Panama	42.7%	52.3%	63.3%	74.4%	31.6%	26.8%	20.9%	14.8%	25.6%	20.9%	15.8%	10.8%
Peru	43.5%	52.8%	63.6%	74.4%	31.6%	26.8%	21.1%	15.0%	25.0%	20.4%	15.4%	10.6%
Philippines	55.1%	64.1%	73.6%	82.2%	24.6%	19.9%	14.8%	10.1%	20.3%	16.0%	11.6%	7.7%
Poland	25.9%	34.0%	44.8%	57.6%	41.0%	37.1%	31.7%	24.7%	33.1%	28.9%	23.6%	17.7%
Romania	26.7%	37.1%	49.8%	63.5%	38.5%	33.1%	26.5%	19.3%	34.8%	29.8%	23.7%	17.1%
Russia	36.8%	45.9%	56.4%	66.7%	34.0%	29.4%	23.9%	18.4%	29.2%	24.7%	19.6%	14.8%
Slovakia	31.0%	40.0%	51.5%	64.4%	37.3%	32.8%	26.8%	19.9%	31.7%	27.3%	21.7%	15.7%
South Africa	51.6%	60.2%	69.4%	78.0%	26.3%	21.8%	17.0%	12.3%	22.1%	17.9%	13.6%	9.7%
Thailand	50.5%	59.6%	69.8%	79.9%	27.6%	22.8%	17.4%	11.8%	22.0%	17.5%	12.8%	8.4%
Turkey	26.7%	34.9%	45.6%	57.7%	41.0%	37.2%	31.8%	25.3%	32.2%	27.9%	22.6%	17.0%
Venezuela	-16.3%	-17.0%	-15.8%	-12.8%	64.0%	65.1%	65.6%	65.4%	52.4%	51.8%	50.2%	47.4%
Vietnam	24.8%	32.5%	42.5%	54.0%	41.6%	38.0%	32.9%	26.8%	33.6%	29.6%	24.6%	19.2%
A	40.3%	49.8%	60.8%	72.2%	32.6%	27.8%	22.0%	15.8%	27.0%	22.4%	17.2%	12.0%
BBB	40.6%	49.6%	60.2%	71.0%	32.6%	28.0%	22.5%	16.6%	26.8%	22.4%	17.4%	12.5%
BB	27.6%	35.7%	46.1%	57.7%	39.6%	35.6%	30.3%	24.1%	32.9%	28.7%	23.6%	18.2%
B	-0.4%	1.8%	5.9%	11.9%	54.9%	54.4%	52.9%	50.2%	45.5%	43.8%	41.3%	37.8%
B without Venezuela	4.9%	8.1%	13.1%	20.2%	51.9%	50.8%	48.6%	45.2%	43.2%	41.2%	38.3%	34.7%

Table 5. Summary statistics for percentage country-specific and systemic risk in 5-year CDS spreads. This table reports summary statistics on the absolute and relative decomposition of 5-year CDS spreads into country-specific and systemic risk components.

	Country-specific				Country-specific Fraction				Systemic Risk				systemic Risk Fraction			
Country	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.
Brazil	143.50	96.96	356.73	59.44	78.8%	63.0%	90.6%	5.3%	37.20	26.88	151.86	14.30	21.5%	9.6%	36.9%	5.3%
Bulgaria	147.25	66.55	484.76	84.91	76.7%	61.7%	87.6%	5.8%	40.16	29.03	163.89	15.43	23.6%	12.6%	38.6%	5.9%
Chile	37.98	26.39	97.47	12.58	44.2%	29.0%	57.2%	4.6%	48.37	34.84	196.44	18.57	56.0%	43.0%	71.0%	4.6%
Colombia	77.49	46.97	206.30	30.63	55.1%	40.4%	69.7%	7.1%	62.38	45.16	254.56	23.92	45.3%	30.7%	59.9%	7.2%
Croatia	126.44	47.40	306.18	57.84	51.2%	10.2%	71.4%	11.7%	115.94	84.16	473.46	44.25	49.2%	28.8%	90.1%	11.7%
Dominican Republic	281.31	114.28	867.37	160.42	71.6%	56.8%	86.2%	6.2%	103.64	75.14	423.16	39.60	28.6%	13.8%	43.1%	6.3%
Egypt	299.25	117.43	642.15	123.51	82.8%	64.0%	92.0%	6.5%	54.77	43.79	101.12	9.07	17.5%	8.2%	36.3%	6.6%
El Salvador	234.19	86.50	445.44	70.29	64.1%	31.8%	82.3%	10.4%	127.30	92.08	517.50	48.53	36.2%	18.0%	67.4%	10.4%
Guatemala	154.51	52.20	298.98	66.18	62.4%	35.7%	80.9%	11.0%	87.18	63.17	355.40	33.35	37.9%	19.5%	64.4%	10.9%
Hungary	147.93	51.82	417.41	95.75	56.8%	26.9%	81.8%	13.5%	94.77	68.68	386.87	36.23	43.5%	18.4%	72.8%	13.6%
Indonesia	105.90	56.02	482.52	75.24	59.8%	44.1%	83.8%	8.0%	64.24	46.32	260.85	24.62	40.6%	16.5%	56.3%	8.1%
Israel	81.12	52.38	180.79	28.12	92.2%	81.8%	95.6%	1.8%	6.67	4.82	27.26	2.57	7.9%	4.5%	18.2%	1.8%
Korea	58.09	30.38	227.55	39.49	72.2%	57.6%	87.3%	6.5%	19.74	14.25	80.60	7.60	28.0%	12.7%	42.6%	6.5%
Lebanon	249.67	136.86	489.86	72.99	65.6%	29.1%	83.5%	9.7%	130.46	94.38	530.40	49.72	34.8%	16.8%	71.2%	9.7%
Malaysia	65.12	45.37	168.76	23.13	62.2%	47.6%	79.2%	5.3%	39.54	28.57	161.38	15.20	38.1%	21.0%	52.7%	5.3%
Mexico	48.92	32.15	162.62	22.39	44.1%	32.0%	57.4%	5.4%	60.94	44.11	248.68	23.37	56.1%	42.9%	68.1%	5.5%
Panama	62.07	39.50	203.87	29.23	49.2%	35.9%	64.9%	6.2%	62.88	45.52	256.58	24.11	51.1%	35.4%	64.4%	6.2%
Peru	51.44	33.44	156.34	21.67	39.8%	27.2%	58.6%	5.8%	77.39	56.07	315.83	29.64	60.5%	41.7%	73.1%	5.8%
Philippines	104.05	58.87	406.17	68.70	74.7%	64.8%	94.4%	6.2%	31.10	22.46	126.95	11.96	25.5%	5.7%	35.5%	6.3%
Poland	51.83	26.71	134.98	30.06	53.6%	21.5%	74.4%	9.7%	40.45	29.25	165.08	15.55	46.5%	25.8%	78.6%	9.7%
Romania	185.81	72.57	545.58	103.81	90.0%	81.2%	95.2%	3.5%	17.88	12.91	73.00	6.89	10.1%	4.9%	19.0%	3.6%
Russia	160.35	77.75	605.81	115.67	70.0%	55.8%	91.0%	8.1%	58.99	42.67	240.75	22.63	30.3%	9.1%	43.5%	8.2%
Slovakia	62.24	29.21	215.81	47.74	82.4%	54.9%	95.1%	5.8%	10.69	7.71	43.68	4.12	17.7%	4.9%	45.1%	5.8%
South Africa	124.78	80.98	308.40	45.31	73.1%	57.6%	83.1%	5.2%	45.59	32.83	185.14	17.50	27.2%	17.1%	42.7%	5.2%
Thailand	54.50	40.06	132.38	16.47	51.9%	34.8%	70.7%	5.2%	51.40	37.03	208.74	19.72	48.4%	29.6%	65.5%	5.2%
Turkey	92.16	41.10	269.20	35.31	44.7%	27.3%	62.8%	8.3%	112.75	80.90	450.07	43.12	55.7%	37.4%	73.2%	8.3%
Venezuela	900.37	177.63	3830.15	973.15	47.7%	9.9%	84.7%	20.6%	569.26	416.71	2466.88	218.94	50.4%	10.7%	87.4%	22.2%
Vietnam	119.27	59.06	278.06	54.02	48.0%	33.6%	71.6%	8.8%	124.05	89.71	504.20	47.30	52.5%	28.9%	66.7%	8.9%
A	59.40				67.8%				27.58				32.3%			
BBB	94.80				56.8%				63.96				43.5%			
BB	143.03				64.4%				77.39				35.9%			
B	432.65				66.9%				214.53				32.8%			
B (w/o Venezuela)	276.74				73.3%				79.21				26.9%			

Table 6. Summary statistics for decomposition of 5-year CDS spreads in country-specific and systemic risk premia. This table reports summary statistics on the relative decomposition of 5-year CDS spreads into country-specific distress risk premia, country-specific default event risk premia, country-specific default risk components, systemic distress risk premia, systemic default event risk premia, and systemic default risk.

	Country-specific Distress Premium			Country-specific Default Event Premium			Country-specific Default Risk			Systemic Distress Premium			Systemic Default Event Premium			Systemic Default Risk		
Country	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Brazil	37.7%	30.8%	54.8%	22.0%	14.3%	24.6%	19.1%	12.3%	21.5%	12.7%	5.7%	24.7%	5.3%	2.3%	7.5%	3.5%	1.5%	4.7%
Bulgaria	30.5%	21.2%	38.9%	24.6%	20.0%	26.3%	21.6%	17.2%	23.1%	13.8%	7.5%	23.5%	5.9%	3.1%	9.1%	3.9%	2.0%	6.0%
Chile	32.5%	22.2%	45.1%	6.3%	3.1%	7.1%	5.4%	2.7%	6.2%	33.0%	25.2%	47.4%	13.8%	10.4%	15.9%	9.1%	6.8%	10.4%
Colombia	36.4%	25.3%	50.7%	9.7%	5.3%	11.0%	8.9%	4.9%	10.1%	26.6%	17.5%	39.4%	11.2%	7.6%	13.9%	7.4%	5.0%	9.1%
Croatia	18.4%	2.4%	30.6%	18.2%	4.3%	23.1%	14.5%	3.5%	18.1%	28.6%	16.6%	59.1%	12.4%	7.1%	19.0%	8.2%	4.7%	11.9%
Dominican Republic	-8.6%	-68.8%	43.5%	42.8%	17.5%	68.7%	37.5%	15.0%	60.7%	16.6%	8.0%	27.2%	7.2%	3.4%	10.7%	4.8%	2.3%	7.2%
Egypt	-17.6%	-61.5%	14.0%	56.5%	44.1%	73.4%	43.9%	33.0%	58.3%	10.2%	4.7%	22.0%	4.3%	2.0%	8.7%	2.9%	1.3%	5.7%
El Salvador	12.3%	-16.9%	31.0%	28.8%	13.6%	36.0%	23.1%	10.9%	29.5%	21.0%	9.9%	44.1%	9.1%	4.8%	14.6%	6.0%	3.2%	9.8%
Guatemala	18.9%	-21.8%	47.8%	22.8%	9.7%	32.0%	20.7%	8.7%	29.1%	22.2%	10.9%	40.7%	9.4%	5.1%	15.4%	6.2%	3.4%	10.2%
Hungary	10.9%	4.1%	19.0%	26.0%	12.2%	36.1%	19.9%	9.3%	26.7%	25.3%	10.7%	48.0%	10.9%	4.6%	16.1%	7.3%	3.1%	10.6%
Indonesia	20.2%	11.3%	38.4%	22.1%	17.1%	25.9%	17.5%	13.6%	20.1%	23.8%	9.5%	34.6%	10.1%	4.2%	13.2%	6.7%	2.8%	8.6%
Israel	63.5%	55.0%	72.3%	15.0%	10.4%	17.8%	13.8%	9.6%	16.4%	4.7%	2.5%	12.3%	1.9%	1.1%	3.7%	1.3%	0.7%	2.3%
Korea	51.9%	39.5%	66.5%	11.0%	8.7%	11.8%	9.3%	7.2%	10.0%	16.5%	7.3%	26.2%	6.9%	3.2%	9.9%	4.6%	2.1%	6.4%
Lebanon	19.2%	3.1%	37.3%	26.2%	14.3%	29.4%	20.1%	10.8%	22.9%	20.3%	9.3%	46.0%	8.7%	4.5%	15.4%	5.8%	3.0%	9.8%
Malaysia	44.7%	33.0%	62.9%	9.4%	5.3%	10.9%	8.1%	4.5%	9.4%	22.5%	12.2%	33.0%	9.4%	5.3%	11.9%	6.2%	3.5%	7.7%
Mexico	33.0%	23.6%	45.3%	5.9%	3.0%	6.7%	5.2%	2.7%	5.9%	33.0%	24.4%	45.2%	14.0%	10.4%	15.9%	9.2%	6.7%	10.5%
Panama	33.6%	23.8%	48.1%	8.2%	4.8%	9.4%	7.3%	4.3%	8.4%	30.0%	20.5%	40.4%	12.7%	8.8%	14.9%	8.4%	5.7%	9.8%
Peru	28.5%	19.3%	46.4%	6.0%	3.1%	7.0%	5.4%	2.8%	6.3%	35.4%	24.0%	46.3%	15.1%	10.4%	16.9%	10.0%	6.9%	11.3%
Philippines	58.8%	50.2%	76.1%	8.5%	7.6%	9.9%	7.4%	6.6%	8.4%	15.1%	3.2%	21.6%	6.3%	1.5%	8.5%	4.2%	1.0%	5.6%
Poland	17.6%	7.1%	29.2%	20.1%	8.0%	25.5%	16.0%	6.3%	19.7%	27.4%	15.4%	52.5%	11.5%	6.2%	16.0%	7.6%	4.1%	10.0%
Romania	44.0%	9.5%	71.0%	24.0%	11.0%	39.0%	22.0%	9.9%	35.9%	6.0%	2.9%	11.7%	2.5%	1.2%	4.4%	1.6%	0.8%	2.9%
Russia	39.0%	27.4%	60.2%	16.4%	10.8%	18.0%	14.6%	9.5%	16.3%	17.8%	5.3%	29.0%	7.5%	2.3%	10.4%	5.0%	1.5%	6.9%
Slovakia	41.1%	28.0%	54.4%	22.5%	14.6%	23.8%	18.8%	12.2%	20.2%	10.5%	2.9%	30.4%	4.3%	1.2%	9.1%	2.9%	0.8%	5.7%
South Africa	53.6%	41.5%	66.4%	10.3%	6.0%	11.9%	9.2%	5.3%	10.6%	16.1%	10.2%	27.8%	6.7%	4.1%	9.4%	4.4%	2.7%	6.0%
Thailand	41.6%	27.2%	59.1%	5.4%	2.9%	6.1%	4.9%	2.6%	5.6%	28.6%	16.6%	43.3%	12.0%	7.8%	14.8%	7.9%	5.2%	9.6%
Turkey	13.5%	5.0%	23.0%	17.9%	12.6%	23.6%	13.3%	9.3%	17.2%	32.5%	21.2%	43.2%	13.9%	9.1%	18.0%	9.3%	6.0%	12.0%
Venezuela	-43.0%	-60.4%	-13.7%	50.9%	12.5%	75.9%	39.9%	11.0%	48.2%	26.3%	5.5%	52.1%	14.0%	3.0%	21.8%	10.1%	2.2%	15.3%
Vietnam	12.6%	6.5%	22.4%	19.7%	12.9%	27.7%	15.7%	10.0%	21.7%	30.4%	15.8%	43.1%	13.2%	7.7%	16.7%	8.8%	5.3%	11.2%
A	41.9%			14.0%			11.9%			19.1%			8.0%			5.3%		
BBB	35.0%			11.6%			10.2%			25.5%			10.8%			7.2%		
BB	25.4%			21.3%			17.6%			21.0%			9.0%			6.0%		
B	-12.5%%			44.1%			35.3%			18.4%			8.5%			5.9%		
B (w/o Venezuela)	-2.3%			41.8%			33.8%			15.7%			6.7%			4.5%		