Sovereign CDS Spreads with Credit Rating*

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JEL Classification: G22, G33

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> *"... we live again in a two-superpower world. There is the US and there is Moody's. The US can destroy a country by leveling it with bombs; Moody's can destroy a country by downgrading its bonds."*
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> ——Thomas L. Friedman, The New York Times, Feb 22, 1995

1 Introduction

The Eurozone debt crisis has highlighted the importance of sovereign credit risk in global financial markets. The repeated occurrence of sovereign debt crises, such as the "Baring Crisis" of the 1890s, the Latin American debt crisis of the 1980s and the Mexican and Russian debt crisis of the 1990s, over the past two centuries has inspired a large and constantly growing literature on sovereign credit risk.[1] One of the most important issues for understanding sovereign debt is the properties of sovereign credit risk in both the time-series and cross-sectional perspectives. Earlier related studies are based on either syndicated loans, such as Boehmer and Megginson (1990), or bond prices (yields), such as Mauro et al. (2002). Mauro et al. (2002) document that sovereign bond spreads of emerging markets in the 1990s comove in a significantly higher degree than those in 1870 to 1913.

The fast growing market for credit default swap (CDS) contracts offers a unique data set for studying sovereign credit risk because of their simplicity in contract terms and existing partial or full term structures. These advantages of CDS data spur a series of important papers that study sovereign credit risk[2] and associated risk premium under the reduced-form framework of Duffie and Singleton (1999; 2003). These studies show that time-series fluctuations of sovereign credit spreads are mostly driven by common risk factors. For example, Pan and Singleton (2008) show that one common principal component explains more than 90% of the variations of the CDS spreads of three geographically dispersed countries: Mexico, Turkey, and Korea. Longstaff et al. (2011) conclude that the CDS spreads of 26 developed and emerging market countries are primarily driven by the VIX index, US equity, and high-yield factors. Based on a sovereign credit risk model with a common and a country-specific factor, Ang and Longstaff (2013) show that the

[1] See Tomz and Wright (2013) for a recent review of the related empirical literature. Also see Cruces and Trebesch (2013) for a study on investor losses in 180 cases of sovereign default in 68 countries during 1970 to 2010.

[2] Papers that use CDS spreads to study corporate credit risk include Duffie (1999), Longstaff et al. (2005), and others.

US and European systemic factors extracted from the CDS spreads of the US government, 10 individual US states, and 11 EMU sovereigns are highly correlated with one another and are strongly related to financial market variables. Augustin (2016) shows that the slope of the CDS term structure can affect the relative importance of global and country-specific macroeconomic variables in explaining sovereign credit risk.[3]

Despite the important insights provided by these studies, most existing reduced-form models have ignored credit rating as a determinant of sovereign CDS spreads. Casual empirics and empirical studies, such as Cantor and Packer (1996), show that credit ratings play a central role in sovereign credit markets.[4] By grouping borrowers into broad categories based on similar credit qualities, credit rating provides a first-order approximation of the level of default risk. As a result, rating transition represents a discrete and material change in borrower credit quality. Therefore, credit rating can provide a new perspective on sovereign credit risk that is absent from the existing reduced-form models of sovereign credit risk.

In this paper, we study the role of credit rating in determining sovereign CDS spreads in a *reduced-form* framework by adopting a rating-based *reduced-form* model for corporate credit risk developed by Li (2000) to sovereign credit markets.[5] Although, as shown by Eaton and Gersovitz (1981) and Duffie et al. (2003), some distinctive characteristics of sovereign credit risk, such as political risk, repudiation risk, and foreign reserves, are important for pricing sovereign credit risk, our *reduced-form* approach, which is also employed by Pan and Singleton (2008) and Longstaff et al. (2011) among others, does not consider these distinctive characteristics explicitly. Rather, we assume that these important sovereign characteristics are embedded in sovereign credit ratings, as suggested by Cantor and Packer (1996) and claimed by rating agencies.

[3]Other studies on sovereign credit risk include bond-based Duffie et al. (2003) and Geyer et al. (2004), CDS-based Zhang (2008), Augustin and Tédongap (2016) and others. Studies on commonality and correlation in corporate credit risk include Duffie et al. (2007), Das et al. (2007), Duffie et al. (2009), and Farnsworth and Li (2007). Please refer to Augustin et al. (2014) and Augustin (2014) for comprehensive reviews on CDS literature.

[4]Cantor and Packer (1996) is one of the first systematic studies about the determinants and effects of sovereign credit ratings. A recent similar study is Afonso et al. (2011). Other regression-based studies on the links between sovereign credit ratings and sovereign credit risk (either bond yield or CDS spread) include Eichengreen and Mody (1998a,b), Ismailescu and Kazemi (2010), Gärtner et al. (2011), Afonso et al. (2012), Kiff et al. (2012), and many others. This literature shows that sovereign credit rating reflects the macroeconomic fundamentals of a country and that there are significant variations in sovereign credit spreads across different rating classes. However, this literature does not impose no-arbitrage restriction, and thus, has no implications on term structures of credit risk and risk premium.

[5]A series of studies, such as Jarrow et al. (1997), Lando (1998), Lando and Mortensen (2005), Kijima (1998), Kijima and Komoribayashi (1998), Das and Hanouna (1996), Arvanitis et al. (1999), Huge and Lando (1999), Trueck and Rachev (2009), and Farnsworth and Li (2007), have considered credit rating for the pricing of corporate default risk.

In the model, the credit rating of each country follows a continuous-time Markov chain characterized by a common transition matrix, and countries within a given rating category share a similar level of systematic default intensity. Following Ang and Longstaff (2013), we assume that the default risk of a sovereign borrower is driven by a common and a country-specific factor. The common factor drives the rating transition matrix, as well as the systematic component of default risk, and the default intensities of countries in different rating categories have different loadings on the common factor. The country-specific factor captures the idiosyncratic component and/or within-rating variation of the default risk of each individual country.[6] The number of parameters in the model does not increase with the number of countries, given that all countries share the same set of parameters for the country-specific factor.

The rating-based model explicitly incorporates the well-known cross-sectional and time-series properties of sovereign credit spreads and provides closed-form solutions for a wide range of credit derivatives. One of the most appealing features of the rating-based approach is that it can simultaneously capture the credit spreads of multiple countries under a parsimonious and unified modeling framework. Given the strong dependence of sovereign credit spreads on credit rating, incorporating rating information into the existing reduced-form models significantly enhances the capability of these models to capture the time-series and cross-sectional variations of sovereign credit spreads. Therefore, while the existing reduced-form models mostly focus on pricing the credit risk of individual countries, the rating-based model makes it possible to capture the credit spreads of all countries in a unified framework, which facilitates the analysis of the default risk of portfolios of sovereign credit instruments.

Another important advantage of the rating-based model is that it naturally captures both continuous evolution and discrete change in the default risk of a sovereign borrower due to rating transition. Existing reduced-form models, which assume that the default intensity of a sovereign borrower follows a continuous diffusion process, would have difficulty in capturing the dramatic increases in the default risk of sovereign borrowers due to rating downgrades. Historically, a highly rated borrower rarely defaults directly. Instead, such borrower is more

[6] Ang and Longstaff (2013) use Germany as the systemic factor for European countries and the US for individual states. This modeling choice is perfectly sensible given the purpose of their research. Given that we want to price CDS spreads of countries from different parts of the world, such as Europe, North and Latin America, Asia, and Middle East, we allow each country to have its own country-specific factor in our model.

likely to be downgraded before defaults. Therefore, the credit risk of a sovereign borrower consists of the risk of default, as well as the risk of downgrading. Moreover, rating downgrades (particularly from investment grade to non-investment grade) can seriously affect the market perception of the credit quality of a borrower, thus limiting the access of this borrower to capital markets. Therefore, incorporating rating information into existing reduced-form sovereign credit risk models can help capture the default risk of sovereign borrowers more completely and yield better insights about the sovereign credit market.[7]

By incorporating fundamental information and other sovereign characteristics such as political uncertainty (summarized in credit ratings) into existing reduced-form models, the rating-based approach avoids overfitting the data and improves the efficiency of model estimation. While existing reduced-form models choose latent default factors to match the observed credit spreads of individual countries, our approach requires countries with similar credit ratings to share a similar level of default risk. As a result, pricing errors under the model reflect inconsistencies between observed credit spreads and underlying credit rating and could thus be strong signs of future rating changes. Given that countries with the same credit rating share similar level of default risk, our approach jointly uses the credit spreads of all countries to estimate the model and significantly increases the estimation efficiency of the common default factor. This case is similar to the portfolio approach in the equity literature, which estimates asset pricing models with portfolios of securities with similar risk exposures instead of individual securities.

Consistent with our objective, we apply a parsimonious rating-based model with only 17 parameters, one common and one country-specific factor, to capture the term structure of the CDS spreads of 68 countries between January 2004 and March 2012. The ratings of these countries are obtained from Standard & Poor's and are grouped into 7 broad rating categories: AAA, AA, A, BBB, BB, B, and CCC. For our main estimation, we split the sample countries in half according to the number of observations of their CDS spreads during the sample period. We use the first half with more observations in CDS spreads as in-sample countries and the other half as

[7] Our paper is most closely related to Farnsworth and Li (2007) and Remolona et al. (2008). Remolona et al. (2008) directly use credit rating to approximate a country's credit risk. Meanwhile Farnsworth and Li (2007) apply a rating-based model to study corporate bonds, our paper is one of the first that studies the effect of rating on the pricing of sovereign CDS spreads in a dynamic reduced-form setting. Farnsworth and Li (2007) adopt a recovery of market value (RMV) approach that is convenient for bond pricing, but in the current paper, we adopt a recovery of face value (RFV) approach that is more realistic and natural for CDS pricing.

out-of-sample countries. Arguably, the CDS spreads with most observations are the most liquid ones, such that they may collectively represent the aggregate market better. Existing models for sovereign credit risk are typically estimated country by country. By contrast, we estimate the rating-based model simultaneously by using the term structure of CDS spreads of the 34 in-sample countries via maximum likelihood. We then use the estimated model to price the CDS spreads of the 34 out-of-sample countries as an out-of-sample performance evaluation of the model. We choose the common factor to match the average CDS spreads of the in-sample countries across all maturities and use this factor to price the out-of-sample countries. We choose the country-specific factor to match the average CDS spreads of each in-sample and out-of-sample country over all maturities given the common factor.

Although we find relatively large pricing errors for certain countries during certain parts of our sample period, the pricing errors reflect inaccuracies in the credit ratings of these countries in almost all cases. For example, in 2004 and 2005, the model has large pricing errors for some Latin American countries, such as Brazil and Colombia. News reports during this time suggest that the macroeconomic conditions of these countries are improving and that their ratings do not fully reflect the improved macroeconomic fundamentals due to rising exports, declining deficits, and strengthening local currencies. The large pricing errors disappear as the countries are gradually upgraded. We also find relatively large pricing errors for some of the Eurozone countries during the 2008 global financial crisis and the 2010 to 2011 European debt crisis. The unstable ratings of these countries, as evidenced by their subsequent credit downgrades and negative credit watches, significantly affect their CDS spreads.

Overall, the rating-based model can capture the term structure of the CDS spreads of the 34 in-sample countries reasonably well. The model has small average absolute pricing errors relative to the average bid-ask spreads of the CDS spreads, particularly for intermediate maturities and ratings. More importantly, the extremely parsimonious model has comparable pricing performance for the 34 out-of-sample countries. To further assess the importance of ratings in conjunction with the common factor to determine sovereign CDS spreads, we compare the model CDS spreads with all country-specific factors being set to zero with the data. On average, these model spreads without the country-specific factors can explain more than 60% of the variations of the observed CDS spreads of the 34 in-sample and 34 out-of-sample countries. This captured commonality in the sovereign CDS spreads is consistent with that of the Principal Component Analysis (PCA) of the observed CDS spreads. Thus, the cross-sectional variable, credit ratings and a common time-series variable can collaboratively capture the majority of the variations of the CDS spreads of most countries. Furthermore, the common-factor model spreads also naturally lead us to define a model *implied* credit rating. When we replace the observed ratings with the model implied ratings, the explanatory power of the common-factor model spreads in explaining the observed CDS spreads exceeds 80% for both the in-sample and out-of-sample countries. This indicates the commonality is significantly underestimated with the observed rating due to rating staleness.

Following existing studies, we then explore the economic forces that drive the common factor, the market price of default risk, and the credit risk premium. The common factor extracted from the model can explain a large fraction of the CDS spreads of most countries and has close connections to financial market variables. Particularly, we find that the volatility index VIX and the MSCI world stock index can explain more than 50% of the variations of the common factor and credit risk premium. The credit risk premium of the sovereign CDS spreads across all ratings and maturities increases significantly during the global financial crisis and the European debt crisis. So does the estimated price of (sovereign credit) risk, which varies between 0.1 to 0.9 most of the time during the sample period. This estimated variation of price of risk is comparable to that estimated in other financial markets, e.g., stock markets.

The rest of the paper is organized as follows. In Section 2, we develop a general rating-based continuous-time model for sovereign credit risk. We discuss the data used in our empirical study and the estimation method in Section 3 and report the main estimation and empirical results in Section 4. Section 4.6 shows that the main estimation is robust to alternative sample selections and credit ratings. Section 5 concludes the paper.

2 Rating-Based Sovereign Credit Risk Model

In this section, we first adopt a general rating-based continuous-time model for corporate credit risk developed by Li (2000) to sovereign credit markets,[8] particularly, to derive rating-based CDS spreads. We then consider a special version of the model with one common and one country-specific factor with closed-form solutions for a wide range credit derivatives. Throughout the analysis, we assume that there exists a risk-neutral probability space $(\Omega, \mathcal{F}, \mathbf{F}, \mathcal{Q})$, under which all securities can be priced appropriately. In this paper, all expectations are taken under this risk-neutral probability measure $\mathcal{Q}$, unless otherwise stated.

2.1 General Pricing with Credit Ratings

Suppose all sovereign borrowers can be classified into K possible credit rating categories and that the rating for each country follows a continuous-time Markov chain characterized by a common $K \times K$ transition *rate* matrix[9]

$$Q(t) = \{q_{ik}(t)\}_{\{i,k=1,\dots,K\}},$$

where $\sum_{k=1}^{K} q_{ik}(t) = 0$ and $q_{ik}(t) \geq 0$ for all $i \neq k$ and t. Intuitively, q_{ik} is the *rate* (*intensity*) of rating transition from i to $k \neq i$: over a short horizon Δt, the conditional probability for a rating change from i to $k \neq i$ is approximately $q_{ik}\Delta t$, and the conditional probability of staying in i is $1 + q_{ii}\Delta t$, therefore, $q_{ii} = -\sum_{k\neq i}^{K} q_{ik} < 0$.[10]

If a country is rated

$$CR(t) \in \{1, \cdots, K\},$$

then its hazard rate of default is $h_{CR(t-)}(t)$. Let H be a $K \times K$ diagonal matrix with its diagonal element $H_{ii} = h_i(t)$, which represents the default intensity of a country with a rating i. Let $P(t, T)$

[8]Unlike the *structural* approach of Merton (1974), the *reduced-form* formation of credit risk does not depend on the detailed structure of fundamentals. Thus, the idea of modeling corporate credit risk can be directly applied to modeling sovereign credit risk.

[9]This is also known as intensity matrix or infinitesimal generator matrix.

[10]When Q is a constant matrix, the transition probability matrix $\tilde{Q}_t$ (over a time interval of length t) admits a simple form as

$$\tilde{Q}_t = e^{tQ} = I + \sum_{n=1}^{\infty} t^n \frac{Q^n}{n!},$$

where I is the identity matrix. We can therefore see that summation over rows of $\tilde{Q}$ being 1 is equivalent to summation over rows of Q equal to 0, e.g., $Q\mathbf{1} = \mathbf{0}$ implies $\tilde{Q}_t\mathbf{1} = \mathbf{1}$, and *vice versa*, where $\mathbf{1}$ is a vector of 1s.

be the $K \times 1$ price vector associated with a $K \times 1$ payoff $P(T)$ at maturity T. Our goal is to derive a pricing equation for $P(t,T)$.[11]

Let $CR(t-) = i$. By applying Itô's Lemma to $P_{CR(t)}(t,T)$

$$E_t\left[dP_{CR(t)}(t,T)\right] = E_t\left[dP_i(t,T)\right] + \sum_{k=1}^{K} q_{ik}\left(P_k(t,T) - P_i(t,T)\right)dt + h_i(t)\left(P_i^D(t) - P_i(t,T)\right)dt,$$

where P_i^D is the payoff, given that the reference country defaults directly from rating i. As no-arbitrage requires $E_t\left[dP_{CR(t)}(t,T)\right] = r(t)P_{CR(t-)}(t,T)\,dt$, we have

$$E_t[dP_i(t,T)] + \sum_{k=1}^{K} q_{ik}\left(P_k(t,T) - P_i(t,T)\right)dt + h_i(t)\left(P_i^D(t) - P_i(t,T)\right)dt = r(t)P_i(t,T)\,dt,$$

where r is the risk-free interest rate. Let I be the $K \times K$ identity matrix. By the fact that $\sum_{k=1}^{K} q_{ik} = 0$, we can rewrite the equation in terms of vectors and matrices as

$$E_t[dP(t,T)] = [r(t)I + H(t)]P(t,T)\,dt - Q(t)P(t,T)\,dt - H(t)P^D(t)\,dt, \tag{1}$$

where Q, H, and P^D (a $K \times 1$ vector) are some suitable measurable stochastic processes.

It can be shown that pricing equation (1) is equivalent to

$$\begin{aligned} P(t,T) = E_t\bigg[&\exp\left(-\int_t^T r(s)\,ds\right)\Phi(t,T)P(T) \\ &+ \int_t^T \exp\left(-\int_t^s r(a)da\right)\Phi(t,s)H(s)P^D(s)\,ds\bigg], \end{aligned} \tag{2}$$

where $\Phi(t,s)$ is defined as the solution to the following matrix differential equation[12]

$$\frac{d\Phi(t,s)}{dt} = -[Q(t) - H(t)]\Phi(t,s),\ 0 \le t < s \tag{3}$$

with terminal condition $\Phi(s,s) = I$.

Pricing equation (2) has a natural and intuitive interpretation. Here, $\Phi(t,s)$ is the probability

[11] For a coupon bond, $P(T) = \mathbf{1}$. The model can easily price credit linked notes by setting appropriate rating-dependent terminal payoff $P(T)$.

[12] For any squared matrix A, the matrix exponential is defined as $e^A = \sum_{n=0}^{\infty} \frac{A^n}{n!}$. If $Q(t) - H(t)$ is a constant matrix $Q - H$, we have $\Phi(t,s) = e^{(s-t)(Q-H)}$.

matrix that the security has not defaulted up to time s, $H(s)ds$ is the default probability matrix over ds, $P^D(s)$ is the cash flow vector when the security defaults, and $P(T)$ is the cash flow vector if the security does not default up to T. Thus, the summation (integration) over all expected discounted cash flows under the risk-neutral probability yields the price of the security.

A single-country CDS buyer pays a constant premium c in exchange for a one-time cash flow $\mathbf{1} - P^D(s) = L(s)\mathbf{1}$ when a reference country defaults at date s. Here $\mathbf{1}$ is a $K \times 1$ vector with all elements being 1. The protection buyer also stops paying any remaining premium after default. To compute for the value of the premium (fixed) leg of a CDS contract, we simply substitute $P(T) = c\Delta t\mathbf{1}$ and $P^D(s) = 0$ in equation (2) for $T = T_m$, $m = 1, \cdots, M$.[13] Thus, the value of the fixed leg is $cP_{fx}(t, T)$, where

$$P_{fx}(t,T) = \Delta t \sum_{m=1}^{M} E_t \left[\exp\left(-\int_t^{T_m} r(s)\, ds \right) \Phi(t, T_m) \right] \mathbf{1}, \tag{4}$$

$\Delta t = T_{m+1} - T_m$, and $T_M = T$.

For the default (floating) leg, substituting $P(T) = 0$ and $P^D(s) = L(s)\mathbf{1}$ into equation (1) yields the value of the floating leg:

$$P_{fl}(t,T) = E_t \left[\int_t^T \exp\left(-\int_t^s r(a)\, da \right) \Phi(t,s) H(s) L(s)\, ds \right] \mathbf{1}. \tag{5}$$

If the reference country is rated i at t, then the premium c is given by

$$\mathrm{CDS}_i(t,T) = \frac{\mathbf{1}_i^\top P_{fl}(t,T)}{\mathbf{1}_i^\top P_{fx}(t,T)}, \tag{6}$$

where $\mathbf{1}_i$ is a $K \times 1$ vector of zeros except that its ith element equals 1.

[13] Accruals can be easily accounted by setting $P^D(s) = (s - n_s\Delta t)\mathbf{1}$, where n_s is the greatest integer that is smaller than $s/\Delta t$. In this case, we have

$$\begin{aligned} P_{fx}(t,T) \quad = \quad & \Delta t \sum_{m=1}^{M} E_t \left[\exp\left(-\int_t^{T_m} r(s)\, ds \right) \Phi(t, T_m) \right] \mathbf{1} \\ & + E_t \left[\int_t^T \exp\left(-\int_t^s r(a)\, da \right) \Phi(t,s) H(s) \left(s - n_s \Delta t \right)\, ds \right] \mathbf{1}. \end{aligned}$$

The extra term is similar to the valuation of the floating leg of a CDS.

2.2 Specific Setup with One Common and One Country-Specific Factor

In this section, we develop a special version of the model with one common factor z, which affects the rating transition matrix[14] and the sovereign default risk of all countries, and one country-specific factor y, which captures the idiosyncratic component and/or within-rating variation of the default risk of individual countries. In particular, we have

$$Q(t) = \bar{Q}(\alpha + z_t), \quad H(t) = \bar{H}(\alpha + z_t) + I y_t,$$

where $\bar{Q}$ is a constant $K \times K$ transition rate matrix, and $\bar{H}$ is a constant $K \times K$ diagonal matrix. These assumptions imply that the common factor z affects both the default risk across credit ratings and the transition of credit ratings. When z increases, the overall default risk increases, and credit ratings become less stable. The country-specific factor y only affects the default risk of a specific country and has no effect on the transition matrix of credit ratings.

We assume that the common factor z follows a CIR (Cox et al., 1985) process under the risk-neutral measure, which is given by

$$dz_t = \kappa_z(\theta_z - z_t)\, dt + \sigma_z \sqrt{z_t}\, dW_t, \tag{7}$$

where W_t is a Brownian motion, and κ_z, θ_z, and σ_z are positive constants.[15] Following Bakshi and Wu (2010) and Carr and Wu (2010), we assume that the price of risk for the common factor has the following form:[16]

$$\lambda(t) = \lambda_z \sqrt{z_t}. \tag{8}$$

Thus, the dynamics of z_t under the physical measure is given by

$$dz_t = \kappa_z^P \left(\theta_z^P - z_t\right)\, dt + \sigma_z \sqrt{z_t}\, dW_t^P, \tag{9}$$

[14]Since the common factor z is stochastic, the rating migration follows a *nonhomogeneous* Markov chain, which, as documented in Bluhm and Overbeck (2007), can generate very rich term structure for probability of default.

[15]In general, z_t could also be a linear function of several processes as that in the affine term structure models.

[16]This form implies equation (10). The second equality in (10) makes it easier to maintain the equivalent condition between the physical and risk-neutral probability measures.

where W_t^P is the Brownian motion under the physical measure, and

$$\kappa_z^P = \kappa_z - \sigma_z \lambda_z, \quad \theta_z^P = \kappa_z \cdot \theta_z / \kappa_z^P. \tag{10}$$

Given this physical dynamics, it is straightforward to derive the transition probability and the likelihood of the systematic factor. Although we do not explicitly specify the price of risk for rating transitions, it is indirectly modeled through the process of z. The expected transition probability of ratings under the risk-neutral measure is $E_t\left[\exp\left(\int_t^s \bar{Q}(\alpha + z_a)\, da\right)\right]$, which is different under the physical measure because of z.

The country-specific factor y, which carries no risk premium, follows a Vasicek (1977) process[17]

$$dy_t = -\kappa_y\, y_t\, dt + \sigma_y\, dW_t^y,$$

where W^y is independent of W.

There are different ways to model the loss at default process L. Although we could allow each country to have its own loss at default or countries in the same rating category to share the same level of loss of default, for convenience, we assume that all countries share the same level of loss of default. We also assume that the risk-free interest rate r is independent of z.[18] This independence assumption enables us to separate the expectations between the risk-free rate and default risk components, thus simplifying the computation of CDS spreads. In addition, our empirical results suggest that the dependence between interest rate and z is very weak (see Table 13).

The key to the computation of the pricing formulae (4) and (5) is to compute the following expectations:

$$E_t[\Phi(t,s)] \text{ and } E_t[\Phi(t,s)H(s)].$$

[17] Including a Vasicek process in the credit risk may cause problem since it can take negative values. However, this approach is convenient and necessary in a cross-sectional context; all country-specific factors are washed out at the aggregate level. If the country-specific factors cannot be diversified away, then the undiversified portion becomes systematic. In the cross-sectional sense, the country-specific factor y acts as "error" term.

[18] This independence assumption can be relaxed through a linear relation between r and z, such as $r(s) = X(s) + \rho z_t$, where X and z are independent, and X represents other factors that affect the default-free term structure.

Given the affine structure of the model, Φ has a closed-form solution as follows:

$$\Phi(t,s) = \Omega \exp\left(\Lambda \int_t^s (\alpha + z_a)\, da - I \int_t^s y_a\, da\right) \Omega^{-1},$$

where $\Omega\Lambda\Omega^{-1} = \bar{Q} - \bar{H}$, and Λ is a $K \times K$ diagonal matrix with its diagonal elements $\Lambda_{ii},\ i = 1,\ldots,K$, being eigenvalues of $\bar{Q} - \bar{H}$. Since Λ is a diagonal matrix, we have that

$$\exp\left(\Lambda \int_t^s (\alpha + z_a)\, da - I \int_t^s y_a\, da\right)$$

is also a diagonal matrix with its ith diagonal element being

$$\exp\left(\Lambda_{ii} \int_t^s (\alpha + z_a)\, da - \int_t^s y_a\, da\right).$$

It is straightforward to show that

$$E_t[\Phi(t,s)] = \hat{p}_1(\tau, y_t)\Omega\, \Gamma^1(\tau, z_t)\Omega^{-1}, \tag{11}$$

where $\tau = s - t$, and Γ^1 is a diagonal matrix with its diagonal elements equal to

$$\Gamma^1_{ii}(\tau, z_t) = p_0(\tau, \alpha\Lambda_{ii}) p_1(\tau, z_t, \Lambda_{ii}),\ i = 1,\ldots,K.$$

We can also show that

$$E_t[\Phi(t,s)H(s)] = \Omega\, [\hat{p}_1(\tau, y_t)\Gamma^2(\tau, z_t) + \hat{p}_2(\tau, y_t)\Gamma^1(\tau, z_t)]\Omega^{-1}\bar{H}, \tag{12}$$

where Γ^2 is a diagonal matrix with its diagonal elements equal to

$$\Gamma^2_{ii}(\tau, z_t) = p_0(\tau, \alpha\Lambda_{ii})[\alpha p_1(\tau, z_t, \Lambda_{ii}) + p_2(\tau, z_t, \Lambda_{ii})],\ i = 1,\ldots,K.$$

Here, for $\tau = s - t$, p_0, p_1, and p_2 are given by

$$p_0(\tau, \beta) \quad = \quad \exp(\beta\tau),$$

$$
\begin{aligned}
p_1(\tau, z_t, \beta) &= E_t\left[\exp\left(\beta\int_t^s z_a\,da\right)\right] = A(\beta,\tau)e^{B(\beta,\tau)z_t}, \\
p_2(\tau, z_t, \beta) &= E_t\left[z_s\exp\left(\beta\int_t^s z_a\,da\right)\right] = [C(\beta,\tau)+D(\beta,\tau)z_t]e^{B(\beta,\tau)z_t},
\end{aligned}
$$

and, for any β,

$$
\begin{aligned}
A(\beta,\tau) &= \exp\left(\frac{\kappa_z\theta_z(\phi+\kappa_z)}{\sigma_z^2}\tau\right)\left(\frac{1-\gamma}{1-\gamma e^{\phi\tau}}\right)^{\frac{2\kappa_z\theta_z}{\sigma_z^2}}, \\
B(\beta,\tau) &= \frac{\kappa_z-\phi}{\sigma_z^2}+\frac{2\phi}{\sigma_z^2(1-\gamma e^{\phi\tau})}, \\
C(\beta,\tau) &= \frac{\kappa_z\theta_z}{\phi}(e^{\phi\tau}-1)\exp\left(\frac{\kappa_z\theta_z(\phi+\kappa_z)}{\sigma_z^2}\tau\right)\left(\frac{1-\gamma}{1-\gamma e^{\phi\tau}}\right)^{\frac{2\kappa_z\theta_z}{\sigma_z^2}+1}, \\
D(\beta,\tau) &= \exp\left(\frac{\kappa_z\theta_z(\phi+\kappa_z)+\phi\sigma_z^2}{\sigma^2}\tau\right)\left(\frac{1-\gamma}{1-\gamma e^{\phi\tau}}\right)^{\frac{2\kappa_z\theta_z}{\sigma_z^2}+2}, \\
\phi &= \sqrt{-2\beta\sigma_z^2+\kappa_z^2}, \qquad \gamma = \frac{\kappa_z+\phi}{\kappa_z-\phi}.
\end{aligned}
$$

Meanwhile, $\hat{p}_1$ and $\hat{p}_2$ are given by (see, e.g., Jamshidian, 1989)

$$
\begin{aligned}
\hat{p}_1(\tau, y_t) &= E_t\left[\exp\left(-\int_t^s y_a da\right)\right] = \hat{A}(\tau)e^{-\hat{B}(\tau)y_t}, \\
\hat{p}_2(\tau, y_t) &= E_t\left[y_s\exp\left(-\int_t^s y_a da\right)\right] = \left[\hat{C}(\tau)+\hat{D}(\tau)y_t\right]e^{-\hat{B}(\tau)y_t},
\end{aligned}
$$

where $\tau = s-t$, and

$$
\begin{aligned}
\hat{A}(\tau) &= \exp\left(-\frac{\sigma_y^2}{2\kappa_y^2}(\hat{B}(\tau)-\tau)-\frac{\sigma_y^2\hat{B}^2(\tau)}{4\kappa_y}\right), \\
\hat{B}(\tau) &= \frac{1-e^{-\kappa_y\tau}}{\kappa_y}, \qquad \hat{C}(\tau) = -\frac{\sigma_y^2\hat{B}^2(\tau)}{2}\hat{A}(\tau), \qquad \hat{D}(\tau) = e^{-\kappa_y\tau}\hat{A}(\tau).
\end{aligned}
$$

Substituting formulae (11) and (12) together with the default-free bond price

$$
P_0(t,s) = E_t\left[\exp\left(-\int_t^s r_a\,da\right)\right] \tag{13}
$$

into equations (4), (5), and (6) yields the CDS spreads. A numerical integration is needed to compute (5) for the floating leg

$$P_{fl}(t,T) = \Omega \left[\int_t^T P_0(t,s) \left[\hat{p}_1(\tau, y_t)\Gamma^2(\tau, z_t) + \hat{p}_2(\tau, y_t)\Gamma^1(\tau, z_t) \right] ds \right] \Omega^{-1}\bar{H}L\mathbf{1},$$

where $\tau = s - t$ and $P_0(t,s)$ is the price of default-free zero coupon bonds.

Notice that the common and the country-specific factors are entangled together in the CDS spreads. However, we can compute the common component of CDS spread, called z-spread, by setting $y = 0$ in the formulae. In the empirical exercise, we use the z-spread to study the explanatory power of the common factor, in conjunction with credit rating, to explain the cross-sectional and time-series variations of the sovereign CDS spreads.

3 Data and Estimation Method

In this section, we first introduce the data used in our empirical analysis. These data include the term structure of CDS spreads, the corresponding bid-ask spreads, and the credit ratings of the 68 countries. We then discuss the estimation of the rating-based sovereign credit risk model with one common and one country-specific factor using maximum likelihood.

3.1 Data

We obtain the sovereign CDS spreads from Credit Market Analysis Ltd (CMA), which collects OTC market data on credit derivatives. The sample consists of monthly (the last Wednesday of each month) quotes of CDS spreads with maturities of 1, 2, 3, 5, 7, and 10 years from January 2004 to March 2012.[19] The dataset includes 69 countries, which have CDS contracts traded during the sample period, from North America, Europe, Asia/Pacific, Middle East, Latin America, and Africa. We exclude Malta, which has only 6 monthly observations, from our analysis for ease of presentation. The discount bond prices $P_0(t,u)$ in the valuation formula are the US Treasury zero bonds taken from a dataset provided by Gurkaynak et al. (2006).

[19] Although the quotes of CDS spreads with maturities of 0.5, 0.75, 4, 6, 8, and 9 years are also available, we exclude them from our analysis due to their low liquidity. The restructuring type of CDS contracts is complete restructuring (CR) for all sovereigns. In our sample, the seniority for all CDS contracts is senior. All CDS contracts are quoted based on the US dollar, except for contracts referring the United States of America, which are quoted based on the Euro.

Table 1 provides a summary of important information of the 68 countries, which includes credit rating, average 5-year CDS spread, average bid-ask spread of 5-year CDS spread, number of observations, and number of rating changes for each country. The maximum number of observations for each country is 99 months. We use the top 34 countries with the most complete observations of the term structure of CDS spreads to estimate the model in the sample. We then use the estimated model to price the CDS spreads of the other 34 countries with fewer observations out of sample. We split the data sample as described above with two major considerations. First, the CDS contracts of countries with the most observations are the most liquid traded contracts and may thus reflect the underlying market conditions better. Second, using the in-sample estimated model to price the out-of-sample countries offers a strong cross-sectional test on the validity of our model, which uses credit rating as the key cross-sectional factor in sovereign credit risk market.

All the CDS spreads are denoted in basis points based on a unit notional principal. We use Standard & Poor's credit ratings obtained from Bloomberg. Following previous literature, we ignore such minor adjustments as "+" or "-" to baseline ratings and obtain seven broad rating categories from AAA to CCC (C and CC are merged into CCC). Ratings reported in Table 1 represent the rating of each country at the end of the sample period.[20] While the ratings of 25 countries (12 in-sample and 13 out-of-sample) remain constant throughout the sample, certain countries experience up to 5 rating changes during the sample period. The average 5-year CDS spreads generally increase when ratings deteriorate. Among the in-sample countries, the most common rating is BBB, whereas the least common ones are AAA (Germany) and CCC (Greece).[21] Panel A (in-sample countries) of Table 2 reports the frequency of rating changes of the 34 countries used for in-sample model estimation. In total, the 34 countries have experienced 40 rating changes (under our reclassification of ratings) during the sample period. Interestingly, rating transitions typically occur between two adjacent ratings, for example, there were 4 rating changes from A to AA for the in-sample countries. A similar observation also holds for the 34 out-of-sample

[20] In the empirical section, we report the complete history of the evolution of the ratings of each country.

[21] After Greece's downgrade by the S&P to Selective Default (SD) on February 27, 2012, the CDS spreads of the country became extremely high. For example, the Greece 1-year CDS spreads were 57,166 and 57,644 basis points on February 29, 2012 and March 30, 2012, respectively. Thus, we remove the last two month CDS spreads of Greece in our in-sample estimation and all subsequent analyses.

countries. This empirical fact motivates our parametrization of the rating transition matrix as a tridiagonal matrix in Section 3.2. The top-left panel of Figure 1 plots the numbers of quarterly rating changes and the average 5-year CDS spreads of the 34 in-sample countries. The top-right panel of Figure 1 also reports the number of rating downgrades during the sample period. Notably, rating changes and downgrades tend to increase when the CDS spreads widen.

Panel B of Table 2 reports the average CDS spreads for countries in different rating categories and at different maturities. Panel C of Table 2 also reports the average bid-ask spreads at different maturities and credit ratings. On average, we find an upward sloping term structure of CDS spreads for ratings above BB. For the CCC rating, the term structure of CDS spreads is downward sloping. The CDS spreads increase monotonically when ratings worsen. The bottom two panels of Figure 1 provide time-series plots of the average 5-year CDS spreads at different ratings. We observe a monotonically negative relation between rating and average CDS spreads. We also see huge spikes in the CDS spreads during the global financial crisis and European debt crisis.

Note that, both the mean CDS spreads and bid-ask spreads are quite different between the in-sample and out-of-sample countries. One major reason for the large differences is the uneven sample dates during the sample period, in which the CDS spreads varied greatly as shown in Figure 1. By selection, most of the in-sample quotes cover the entire sample period, whereas most of the out-of-sample quotes occur in the late part of the sample period when the sovereign risk elevates and becomes volatile.

Many studies, including the cited references, do not distinguish whether a CDS spread quote is observed or derived.[22] For dynamic models such as ours, a full term structure of CDS spreads is preferred and is sometimes necessary for model identification. Table 3 reports the portions of observed data in the data sample. Following common practice in the literature, we use both observed and derived data in our main empirical studies. Finally, we also estimate the model with observed data only as a robustness check.

[22]The data provider offers the derived quotes based on observed spreads. Those quotes are used for mark-to-market purpose by the CDS traders.

3.2 Maximum Likelihood Estimation

We use the model with one common and one country-specific factor presented in Section 2.2 in our empirical analysis. As in Pan and Singleton (2008) and Longstaff et al. (2011), we assume that the loss rate is 75% for all countries regardless of their ratings. To reduce the parameter space, all countries share the same set of parameters for y_j, although we allow each country to have its own local factor y_j.[23] Moreover, although the y_{jt} factor is supposed to capture the idiosyncratic component of a country's default risk, it might also capture small deviations from the average default risk for a particular sovereign credit rating due to our coarse re-classification of the observed credit ratings.

We estimate the parameters using maximum likelihood. We back out the common factor z and country-specific factor y as follows: in each month, we assume that the sum of the model z-spreads of all in-sample countries (based on their current ratings) and all maturities is equal to the sum of the corresponding market CDS spreads, such that the pricing function can be inverted to obtain the common factor z. Then, for each country, we assume that the sum of CDS spreads over all maturities implied by the model with both the common and country-specific factors is equal to the sum of the observed market quotes, such that we can back out the country-specific factor y_j given z. For the j-th country, the contract with maturity M is assumed to be priced with normally distributed pricing errors with mean zero and standard error σ_{jM}. The pricing errors are assumed to be independent across countries and maturities.

To estimate the model, we have to compute the log-likelihood of the observed data and the model-implied z and y_j. Let ϵ_{jt} be the vector of pricing errors across maturities for the CDS contracts for country j at time t, and $CR_j(t)$ the ratings for country j at time t, then the likelihood function includes the following four components:

- The likelihood of the pricing error ϵ_{jt} at time t given z_t, y_{jt}, and $CR_j(t)$, which is independent Gaussian by assumption, across countries;
- The likelihood of rating $CR_j(t)$ at time t given $CR_j(t-\Delta)$, $z_{t-\Delta}$, and z_t across countries;

[23]This condition may look odd at first sight. For example, the country-specific factors of Germany and Greece have the same dynamics. However, as a key point of the model that is supported by our empirical studies, the main cross-sectional differences in sovereign credit risk are captured by the common factor in conjunction with credit ratings.

- The likelihood of y_{jt} given $y_{j(t-\Delta)}$, which is Gaussian (see, e.g., Jamshidian, 1989), across countries; and

- The likelihood of z_t given $z_{t-\Delta}$, which is non-central χ^2 (see, e.g., Cox et al., 1985).

Similar to that in Farnsworth and Li (2007), we assume that the transition rate matrix of ratings is 7×7 tridiagonal and has the following form:

$$\bar{Q} = \begin{pmatrix} -\bar{Q}_{12} & \bar{Q}_{12} & 0 & 0 & 0 & 0 & 0 \\ \bar{Q}_{21} & -\bar{Q}_{21}-\bar{Q}_{23} & \bar{Q}_{23} & 0 & 0 & 0 & 0 \\ 0 & \bar{Q}_{21} & -\bar{Q}_{21}-\bar{Q}_{23} & \bar{Q}_{23} & 0 & 0 & 0 \\ 0 & 0 & \bar{Q}_{21} & -\bar{Q}_{21}-\bar{Q}_{23} & \bar{Q}_{23} & 0 & 0 \\ 0 & 0 & 0 & \bar{Q}_{21} & -\bar{Q}_{21}-\bar{Q}_{23} & \bar{Q}_{23} & 0 \\ 0 & 0 & 0 & 0 & \bar{Q}_{21} & -\bar{Q}_{21}-\bar{Q}_{23} & \bar{Q}_{23} \\ 0 & 0 & 0 & 0 & 0 & \bar{Q}_{76} & -\bar{Q}_{76} \end{pmatrix},$$

where $\bar{Q}_{12} > 0$, $\bar{Q}_{23} > 0$, $\bar{Q}_{21} > 0$, and $\bar{Q}_{76} > 0$.[24] This assumption significantly reduces the parameter space and is roughly consistent with the frequency of rating transitions reported in Table 2.[25] The transition probabilities of ratings between $t-\Delta$ and t are given by

$$\exp\left(\int_{t-\Delta}^{t} \bar{Q}(\alpha + z_a)\, da\right).$$

However, since we do not have a continuous observation of z_a, we use the following to approximate the transition probabilities

$$E_t^P\left[\exp\left(\int_{t-\Delta}^{t} \bar{Q}(\alpha + z_a)\, da\right)\bigg|\, z_{t-\Delta}, z_t\right],$$

where the expectation is under the physical probability measure.[26]

[24]We also estimate the model with all elements of the upper and lower diagonals as independent parameters. However, there seems to be some identification problems with a full tridiagonal setup. A sensible restriction would be to require that credit ratings have a stationary distribution at the long-run mean of z. Our current setup is the easiest one, although it restricts parameter space and, hence, the model's ability to fit the data. However, our experiment with more flexible setups indicates that the current setup does not have significant effect on the model's performance.

[25]This simple setting can generate similar rating migration behaviors as those reported by rating agencies as well as that reported in literature; see, e.g., Jarrow et al. (1997) and Fuertes and Kalotychou (2007).

[26]The details of the approximation can be found in the Appendix of Farnsworth and Li (2007).

Given that we reclassify the observed ratings into 7 categories, $\bar{H}$ is a 7×7 diagonal matrix. To avoid potential identification problems between $\bar{H}$ and the common factor z, we fix the value of $\bar{H}_{33}$ at 1.

Our model seems to be quite complex compared with other classical reduced-form models (see, e.g., Carr and Wu 2007 and Longstaff et al. 2011); however, it can be estimated through a set of CDS spreads of multiple countries at one time. The classical reduced-form model is usually estimated country by country, that is, if we apply a classical reduced-form model with only 5 parameters to N countries, we will need $5 \times N$ parameters; if $N = 34$, we will need 170 parameters. Meanwhile, the number of parameters (which is 17) in our rating-based model keeps unchanged regardless of the number of countries.

4 Empirical Results

In this section, we present the results of our main estimation and discuss some key empirical implications of the estimated model. We are particularly interested in both in-sample and out-of-sample pricing performance of the model and how much credit rating, along with the common factor, can explain the cross-sectional and time-series variations of sovereign CDS spreads. Finally, we also estimate the model with alternative data sample to gauge the robustness of our main estimation.

4.1 Parameter Estimates

Table 4 reports the maximum likelihood estimates of the parameters of three different versions of the rating-based model. Model I is the full model as described previously. All the parameter estimates of Model I are highly significant, except for α. To examine the incremental contribution of rating transition, we consider Model II, which maintains rating-dependent default intensities but does not allow transitions between different ratings. Finally, we consider Model III, which does not allow any distinctions between ratings. Likelihood ratio tests highlight the importance of credit rating in model performance and overwhelmingly reject Model III against Model II and Model II against Model I. All subsequent analyses and discussions are solely based on the estimation results of Model I reported in Table 4.

We first highlight the cross-sectional differences in default risk for different rating categories. The loading of each rating group on the common factor $\bar{H}_{ii}$ monotonically increases from 0.59 for the AAA rating to 59.90 for the CCC rating. These estimates are consistent with the idea that rating captures the relative ranking of default risk of borrowers and show that rating is an important factor of capturing the cross-sectional variations of CDS spreads.

The highly significant parameter estimates of the transition matrix $\bar{Q}$ highlight the importance of rating changes. In Table 5, we translate these estimated parameters into the transition probabilities of rating changes over a one-year horizon. We find that ratings tend to be very stable and persistent. Under normal market conditions, a country has more than 87% probability to remain in its current rating over a one-year horizon. Rating transitions become more likely when the general level of default risk measured by the common factor increases. Ratings are also more stable under the physical than the risk-neutral measure.[27]

Under our framework, systematic credit risk has two components: default risk (measured by current credit rating) and rating transition risk due to rating upgrades or downgrades. To examine the importance of rating change, Table 6 reports the proportions of CDS spreads caused by potential rating transitions. We find that the rating transition risk component tends to be a relatively small, but significant, percentage of the total CDS spread. On average, the portion of CDS spreads explained by rating transition risk is 19.2%, which tends to be larger at short (1-year and 2-year) maturities. Moreover, a better rating results in the larger fraction of CDS spread that can be explained by rating transition risk. The relatively small rating transition component of CDS spreads is consistent with the fact that the ratings for sovereigns are very stable with only 40 transitions for 34 countries over 8 years. Consistent with Pan and Singleton (2008) and Longstaff et al. (2011), our parameter estimates show that $\theta_z > \theta_z^P$ and $\kappa_z < \kappa_z^P$, which suggests that the default intensity has higher mean and is more persistent under the risk-neutral measure.

Table 7 reports the standard deviations of the pricing errors at different maturities for the 34 in-sample countries. These in-sample pricing errors are comparable with that in the literature, e.g., Longstaff et al. (2011). The model fits most of the term structures quite well. We also find

[27] Our rating migration matrix are similar to those reported by rating agencies such as Moody's, Standard & Poor's, and Fitch Rating. Also, many scholars report similar rating transition behavior as ours; see, e.g., Hu et al. (2002), Lando and Skodeberg (2002), Wei (2003), and Hill et al. (2010).

that σ_{jM} increases as ratings worsen. In particular, for the 1-year CDS contract on Greece, the average pricing error is close to 600 basis points. The pricing error, however, remains reasonable relative to the bid-ask spreads of CDS contracts on Greece during the ongoing European debt crisis: the 1-year CDS spreads of Greece exceed 10,000 basis points, whereas the bid-ask spreads exceed 1,000 basis points.

4.2 In-Sample and Out-of-Sample Pricing Performances

While existing reduced-form models on sovereign credit risk are typically estimated using the CDS spreads of individual countries, the main purpose of the rating-based model is to price the CDS spreads of all countries (with ratings) simultaneously. Thus, one natural evaluation of our model is its cross-sectional out-of-sample pricing performance. Given the in-sample estimated model parameters and the common factor z, the common component of CDS spreads of any out-of-sample country is determined by its credit rating. Meanwhile, the country-specific factor, which shares a common set of parameters, can directly be determined by matching average observed spreads and model spreads over all maturities.

4.2.1 Overall Performance

The left (right) panel of Table 8 reports the mean absolute pricing error relative to the bid-ask spread for the 34 in-sample (out-of-sample) countries over the sample period. In general, the model pricing errors are quite small compared with the observed bid-ask spreads. For most countries at intermediate maturities (2 to 7 years), the average absolute pricing errors are comparable with the average bid-ask spreads. The relative pricing errors are larger for 1- and 10-year maturities. Notably, the relative pricing errors for the out-of-sample countries are generally smaller than that of the in-sample countries. One of the main reasons for this disparity is that the bid-ask spreads of CDS spreads for the out-of-sample countries are generally greater than that for the in-sample countries.

4.2.2 Non-Eurozone Countries

In this section, we report on the pricing performance of the model for each of the 28 in-sample and 28 out-of-sample non-Eurozone countries. We discuss the pricing performance separately for the Eurozone countries. Then, for each country, we provide time-series plots of the average absolute pricing errors (across all maturities), the corresponding average bid-ask spreads, credit rating changes, positive/negative credit watches, model implied credit ratings, and default events. We delay the discussion on the *implied* credit ratings in Section 4.3.1.

Figure 2 provides the results for 18 in-sample countries with small relative pricing errors. These countries include Bulgaria, Chile, Croatia, Czech Republic, Iceland, Indonesia, Israel, Korea, Malaysia, Panama, Poland, Qatar, Romania, Russia, Slovakia, South Africa, Thailand, and Ukraine. Taking Chile as an example, while the rating at the end of the sample was A+, the prior rating A was upgraded on December 18, 2007. The general conclusion from these graphs is that the model can capture the CDS spreads of these countries quite well. The average absolute pricing errors are generally smaller than the average bid-ask spreads for most countries and at most times, although the pricing errors become relatively large during the global financial crisis and during the Eurozone debt crisis.

Figure 3 provides time-series plots of the average absolute pricing errors of CDS spreads across all maturities for 28 out-of-sample countries, as well as the average bid-ask spreads for these countries. The countries, which represent all the non-Eurozone out-of-sample countries, include Abu Dhabi, Argentina, Australia, Bahrain, Costa Rica, Cyprus, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Guatemala, Hong Kong, Kazakhstan, Latvia, Lebanon, Lithuania, Morocco, New Zealand, Norway, Pakistan, Saudi Arabia, Slovenia, Sweden, Switzerland, USA, and Vietnam. Interestingly, the model seems to exhibit better performances for these 28 out-of-sample countries than for the 18 in-sample countries; the pricing errors are generally smaller than the average bid-ask spreads for most of the 28 countries and most of the time.

Figure 4 shows that the model does have relatively large pricing errors for the 10 in-sample countries, which include Brazil, China, Colombia, Hungary, Japan, Mexico, Peru, Philippines, Turkey, and Venezuela. These large pricing errors indicate that the underlying credit rating does not fully reflect the economic fundamentals of the borrowers or, at least, the economic fundamentals are inconsistent with that of other countries in similar rating categories. The large relative pricing errors of the 10 in-sample countries can be explained by roughly dividing them into three groups.

The first group consists of four Latin American countries, namely, Brazil, Colombia, Mexico, and Peru, which had large relative pricing errors from 2004 to early 2006. These economies had been recovering from the Latin American and Asian financial crisis in the late 1990s. However, owing to the unexpected US economic improvement in early 2004, the market expected that the US Federal Reserve would hike the fed fund rate soon. This widespread expectation caused some institutions to unwind their carry trade positions and subsequently withdraw funds from the respective emerging markets.[28] The unwinding of carry trade had especially high impact on these Latin American countries and led market participants to speculate on the stability of their credit worthiness, as evidenced by the sharp increases in the pricing errors during early 2004. Apparently, the economic fundamentals of these countries had been consistently improved during this time, given the rising exports of natural resources and government policies that have resulted in lower deficits, more reserves, and rising local currencies. These countries actually ended up buying back some of their Brady bonds issued in the 1990s, and the pricing errors of these countries had declined toward the level of average bid-ask spreads with credit upgrades.

The second group includes the Philippines, Turkey, and Venezuela. These countries share problems similar to those of the first group of countries caused by the expectation of changes in the US monetary policy. However, the economic fundamentals of these countries became worse than that reflected in credit ratings. While the Philippines had a BB rating in 2004, its economic fundamentals were significantly worse than those with similar or even worse credit ratings. For example, the country's debt-to-GDP ratio was more than 80% (could be 100% if the debt of some state firms are counted) with half denominated in foreign currencies. By contrast, countries with BB rating, such as Brazil, Turkey, Ukraine and Vietnam, had a median debt-to-GDP ratio of 60%. The debt-to-GDP ratio of the Philippines was even higher than that of some B-rated countries, such as Pakistan and Indonesia. Turkey was the second worst among the aforementioned

[28] The 1980s Latin American sovereign debt crisis was triggered by the US Federal Reserve aggressively hiking the fed fund rate to fight inflation under the Volcker regime.

countries. A major factor that haunted the Turkish economy for a long time was high inflation and currency (Lira) depreciation. From 2005 to 2008, the "New Turkish Lira" (1 new Lira = 1 million old Lira) was introduced to replace the old Turkish Lira, and the "New" was removed since 2009. The relative pricing errors of Turkish CDS contracts fluctuated and remained high during this currency transition period. Aside from some unusual idiosyncratic behaviors of the government,[29] Venezuela's economy depends heavily on world oil price. Large relative pricing errors tend to emerge when the world oil price declines during the global financial crisis and the Eurozone debt crisis.

China, Hungary, and Japan form the third group. The large relative pricing errors for these countries emerged during the global financial crisis and the Eurozone debt crisis. While Japan has a AA rating, its extremely high debt-to-GDP ratio and budget deficit dimmed future prospects for the country's economic growth. As a result, the default risk of Japan is probably higher than that of the other AA-rated counties. Although China had the largest foreign reserve, the huge amount of debt carried by its local governments also caused concerns during the global financial crisis and lingered through the Eurozone debt crisis. This concern became more apparent after China's rating was upgraded. Finally, Hungary was downgraded to junk status because of its poor economic outlook in the middle of the Eurozone debt crisis, thus causing pricing errors to shoot up around the downgrade.

The relations between large model pricing errors and stale (inaccurate) ratings are best illustrated by the two rating changes for two in-sample countries: China and Venezuela. When China was upgraded from BBB+ to A- on July 20, 2005, the absolute average pricing errors of China CDS spreads immediately declined toward the level of the average bid-ask spreads. Evidently, BBB+ did not accurately reflect the credit risk of China at that time. After Venezuela was downgraded on August 25, 2011, the absolute pricing errors jumped up to a much higher level. In this case, the market seemed to be settled with Venezuela's rating before the downgrade, which failed to change the market assessment of Venezuela's credit risk.[30] To illustrate further

[29]For example, Venezuela missed a payment on local debt because the person supposed to sign the check was not available in 1998; see p.18 in Moody's (2012). Venezuela also delayed a payment almost for a month in 2005 and was subsequently rated "Selective Default" for a short period by S&P.

[30]This downgrade of Venezuela is not based on any new related developments but rather reflect that S&P revised rating methodology that assigns heavier weight on political risk, which is a credit weakness for Venezuela.

the relation between the model pricing errors and rating accuracy, Figure 5 provides the pricing errors at different maturities for China and Venezuela before and after the rating changes. Jumps in the pricing errors mainly come from the model's capability to capture the term structure of the CDS spreads, which depends on credit ratings and their transitions.

4.2.3 Eurozone Countries

As discussed previously, the global financial crisis and the Eurozone debt crisis had clear effects on sovereign credit risk for many countries. The countries that were the most affected by these events were, of course, the Eurozone countries. The 2008 global financial crisis served as a real-time stress test, which exposed the hidden problems of some Eurozone countries inherited by these welfare states with stretched low economic growth coupled with relatively high growth in sovereign debt. Since the 2008 global financial crisis, sovereign market participants started to re-assess the credit worthiness of the Eurozone countries, and the standing credit ratings did not reflect the underlying credit risk of these countries, especially for the GIIPS countries (Greece, Ireland, Italy, Portugal, and Spain). Greece was the first one to fall; all three major rating agencies, namely, Fitch, Moody's, and S&P, downgraded Greece to CCC in January 2011. The Eurozone debt crisis reached its peak on December 5, 2011, on which S&P placed Germany, France, and 13 other Eurozone countries (Austria, Belgium, Estonia, Finland, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovak, Slovenia, and Spain) on negative credit watch. One month later, on January 13, 2012, S&P cut the ratings of Cyprus, Italy, Spain, and Portugal by two notches and the standings of Austria, France, Malta, Slovakia, and Slovenia by one notch each.

The time-series pricing errors for the 12 Eurozone countries in our dataset well reflect the unfolding of the Eurozone debt crisis but from a different perspective, as shown in Figure 6. Before the 2008 global financial crisis, the pricing errors for both in-sample and out-of-sample countries were relative small and stable. The pricing errors for some countries during this period were higher than the bid-ask spreads. However, parts of the relatively "large" pricing errors might be attributed to very low bid-ask spreads, usually in low single digits of basis points. The pricing errors jumped to significantly higher levels and became unstable, especially for the

GIIPS[31] countries, since the 2008 global financial crisis. The in-sample countries include three GIIPS countries, Greece, Italy, and Portugal. S&P went through a series of negative watches and subsequent downgrades on the credit standing of Greece. However, these downgrades failed to catch up with the rapid deterioration of Greek economic growth, fiscal conditions, and political uncertainty caused by austerity measure. The average absolute pricing errors for Greece reached in the 2,000s in basis points before the country's default in February 2012. The countries with the second and third highest pricing errors during this period were Portugal and Italy, respectively. The relative magnitude of the pricing errors reflected the severity of the default risk of each of the three in-sample GIIPS countries. As expected, the other three in-sample countries had much smaller pricing errors due to their relatively strong underlying economies and relatively lower debt levels. However, we do see some market concerns for Austria and Belgium, which were downgraded in January 2012. Although Germany was also placed on the negative watch list by S&P in December 2011, the major concern was that Germany might have to bail out the troubled Eurozone countries; still, it survived the possible downgrade.

The time-series pricing errors of the six out-of-sample Eurozone countries paint a similar picture as that of the in-sample countries. Among the out-of-sample countries during the crisis period, the two out-of-sample GIIPS countries, Ireland and Spain, had the largest pricing errors, followed by France and England. Meanwhile, Finland and Netherlands did not fully participate in the crisis due to their relatively strong fiscal conditions. Although these two countries were also on the negative watch list in December 2011, their triple-A ratings survived the credit reviews.

As indicated by the pricing analyses, the model can well capture the CDS spreads for both in-sample and out-of-sample countries with stable ratings. However, the model tends to have larger pricing errors for countries that undergo dramatic economic developments, which may cause their ratings to change. This feature of the model, however, does not necessarily represent a shortcoming. Large pricing error provides a warning sign to investors for potential rating changes in the near future. By contrast, although existing reduced-form models might be capable

[31] Several versions of acronym of GIIPS emerged to refer the troubled Eurozone countries during the European debt crisis in the popular press. Other versions include GIPS (without Italy), GIIIPS (adding Iceland), and GGIIPS (adding Great Britain).

of selecting the latent factors to fit individual CDS spreads well, these models may have difficulty in providing insights into whether the changes in CDS spreads are actually due to changes in the economic fundamentals of the sovereign borrower.

4.3 Credit Ratings and the Common Components of CDS Spreads

We now investigate the systematic components of sovereign CDS spreads and the impacts of rating staleness through model implied ratings. Sovereign credit risk consists of two components in our model: common (systematic) factor and country-specific factor. We are interested in how much the z-spreads, with the observed credit ratings or with the model implied credit ratings, explain cross-sectional and time-series variations of the observed sovereign CDS spreads.

4.3.1 Implied Credit Ratings

One of the advantages of our rating-based model is that we can compute the model *implied credit ratings* based on the model estimation. The average CDS spread for a given rating is determined by the common factor z only. We call this common component of the model CDS spread z-spread, which can be computed in the model by setting the country-specific factor zero. At time t, for a country with observed rating $\tilde{k} \in \{1 = \text{AAA}, \cdots, 7 = \text{CCC}\}$, we define the model *implied* credit rating as the nearest number $k \in \{1 = \text{AAA}, \cdots, 7 = \text{CCC}\}$ to $\tilde{k}$ such that

$$\begin{aligned} z\text{-spread}_t(k-1) + 0.4 \times \big(z\text{-spread}_t(k) - z\text{-spread}_t(k-1)\big) \leqslant \\ \text{either } \textbf{bid spread quote} \text{ or } \textbf{ask spread quote} \text{ at } t \\ < z\text{-spread}_t(k) + 0.4 \times \big(z\text{-spread}_t(k+1) - z\text{-spread}_t(k)\big), \end{aligned} \quad (14)$$

with the convention z-spread(0) = 0 and z-spread(8) = ∞.[32] Notice that we can take both quote and z-spread for a particular maturity, e.g., 5 years, or average over all observed maturities in equation (14). The reported implied ratings hereafter are based on the maturity of 5 years. The resutls are similar if we use the average over all observed maturities.

[32] We choose 0.4 as the cutoff between ratings in considering the relatively high default intensity for worse ratings (high k, see the estimates of $\bar{H}_{kk}$ reported Table 4).

The mean absolute pricing errors relative to the bid-ask spreads with the implied ratings (Table 9) are comparable to or smaller than that with the original ratings (Table 8) across all maturities for both the in-sample and out-of-sample countries. This indicates that the way we define the implied rating does not sacrifice the model pricing performance and that country-specific factor y mainly captures the idiosyncratic, within-rating variations of a country's credit risk.

4.3.2 Cross-Sectional Variations

To examine the cross-sectional explanatory power of sovereign ratings, we run a regression of 5-year data CDS spreads on the 5-year z-components with the observed ratings across countries for every month.[33] Figure 7 plots the resulting R^2s for the in-sample countries (top), the out-of-sample countries (middle), and then a combination of both (bottom). The average R^2 over the sample period is 56% (74%) for the in-sample (out-of-sample) countries.

The in-sample cross-sectional R^2 varies from low twenties to near 90% and peaks in early 2004, late 2006 to early 2007, late 2008 to late 2009 and early 2011 to late 2011, which correspond to the "unwinding carry trade," the "subprime mortgage crisis," the "global financial crisis" and the "Eurozone debt crisis," respectively. This observation suggests that the global sovereign risk comoves more during crisis periods. Three periods exist in between the peaks when the R^2s fall notably below the sample average. These periods are from January 2005 to January 2006, March 2008 to August 2008, and January 2010 to March 2011. After the crisis, the fundamentals of some countries may have changed dramatically, and the credit ratings of these countries may fail to reflect their credit worthiness.

To examine the effects of rating staleness, we use the model *implied* ratings as defined by equation (14). We loosely call an observed rating *stale* if it is different from the model implied rating. We re-run the cross-sectional regressions by removing observations with stale ratings, and the resulting R^2s ($\tilde{R}^2$, dash line in Figure 7) are plotted in the same graph. As shown in the plot, the R^2s increase dramatically, on average from 56% to 85%, after removing the countries with stale ratings. We also repeat the cross-sectional regressions with the implied ratings and

[33]We also redo this exercise with average CDS spreads over maturities, and obtained similar results.

the resulting R^2s ($\hat{R}^2$, dot-dash line in Figure 7) become even higher, reaching 90% on average, and less volatile over time.

As for the out-of-sample countries, the cross-sectional R^2s with the observed ratings dropped during the global financial crisis and the Eurozone debt crisis when the countries with stale ratings emerged. After removing the observations with stale ratings, the average cross-sectional R^2 dramatically increased from 74% to 94%, and settled at 91% with the model implied ratings. The bottom panel of Figure 7 depicts the cross-sectional R^2s for the combined both the in-sample and out-of-sample countries with the observed rating, without stale ratings, and with the implied ratings. With the model implied ratings, the resulting cross-sectional R^2s for the pooled sample vary between 70% to almost 100% over the sample period. These different sampling results show that credit rating is the key cross-sectional variable that drives the main cross-sectional variations in the sovereign CDS spreads.

The proportion of rating staleness implied by our model is 46% (28%) for the in-sample (out-of-sample) countries. In general, the cross-sectional R^2 tends to be negatively correlated with the proportion of the rating staleness. The details of the observed ratings and the implied ratings for each country are reported in Figures 2-4, and 6. In general, the model implied ratings are relatively stable over time; thus, the improvements on the cross-sectional R^2s are not through high frequency changes of the implied ratings. As shown in Figures 4 and 6, our discussions on the rating staleness in the previous section based on the pricing errors are mostly consistent with the model implied ratings.

4.3.3 Time Series Variations

To examine the time-series explanatory power of credit ratings, along with estimated common factor z, we regress the 5-year market CDS spreads on the corresponding z-spreads with the observed ratings, without stale ratings, and with the implied ratings. The left and right panels of Table 10 report the regression results for the in-sample and out-of-sample countries, respectively.

We find that the z-spread can explain, on average, approximately 65% of the variations of the CDS spreads of both the in-sample and out-of-sample countries; the mean R^2 for the in-sample (out-of-sample) countries is 66% (65%), whereas the median R^2 for the in-sample (out-of-sample) countries is 75% (68%). After removing the observations with stale ratings identified in the cross-sectional exercise, the mean and median R^2 become 87% (83%) and 93% (89%), respectively, for the in-sample (out-of-sample) countries. Moreover, the mean and median R^2s with the implied ratings become 90% (83%) and 91% (88%) for the in-sample (out-of-sample) countries, respectively. The R^2s of the time-series regressions for most of the countries increases significantly after removing or correcting the stale ratings. For example, the time-series R^2 of the Philippines jumps from 0.3% to 91%. In general, the results of the time-series regressions are consistent with those of the cross-sectional regressions.

We also find that the z-spreads can well capture the average level of the CDS spreads of both the in-sample and out-of-sample countries. The estimated values of β in Table 10 are close to 1, suggesting that rating is correctly priced on average. For example, the mean β for the in-sample (out-of-sample) countries is 0.99 (1.06), whereas the median β for the in-sample (out-of-sample) countries is 0.92 (1.13). However, for some specific countries, the ratings seem to be mismatched with their credit quality measured by their CDS spreads. Table 10 shows that most Eurozone countries, such as Austria, Belgium, Iceland, Portugal, France, Greece, Italy, Spain and Ireland, are significantly overrated because their βs are significantly higher than 1. This observation is consistent with the fact that most of these countries have inherent problems and are downgraded or placed on negative credit watch during the financial crisis, as previously discussed. Meanwhile, countries with low time-series R^2s in Table 10, such as Colombia, Panama and the Philippines, seem to be underrated. These observations are supported by the time-series regressions after removing data with stale ratings (with the implied ratings); all the corresponding regression coefficients $\tilde{\beta}$ ($\hat{\beta}$) move to the right directions and the standard deviations of the regression coefficients are significantly reduced.

Overall, credit ratings, in conjunction with the common factor, capture the majority of both cross-sectional and time-series variations of sovereign CDS spreads of both in-sample and out-of-sample countries in the dataset. The existence of strong commonality in sovereign CDS spreads is consistent with Pan and Singleton (2008) and Longstaff et al. (2011). However, we use credit ratings as the only cross-sectional variable, and the method that is used to model and estimate the common factor is different from that used in the existing sovereign credit risk models.[34]

4.4 Comparison with Principal Component Analysis

How well does the rating-based model capture the commonality in the Sovereign CDS market? To answer this question, we conduct a principal component analysis, following Longstaff et al. (2011), on the 5-year CDS spreads of the in-sample countries. Table 11 reports the results of regressions on the extracted first-two principal components for the 5-year CDS spreads of both in-sample and out-of-sample countries. On average, the first principal component explains 66% of the variations of the in-sample CDS spreads, which is comparable with the in-sample performance of our model with the *observed* ratings. However, as for the out-of-sample countries,[35] our model outperforms the simple principal component analysis by a large margin in terms of regression R^2s (65% vs 52%, the difference is significant at the 5% level). A similar conclusion can be made based on the median R^2s. In addition to the true out-of-sample nature offered by the rating-based model, it also captures well the commonality embedded in both the in-sample and out-of-sample market CDS spreads.

To further demonstrate the advantages of our rating-based credit risk model, which yields consistent term structures of credit risk, we repeat the regression exercises in Tables 10 and 11 for different maturities and report the resulting average R^2s in Table 12. The rating-based model enjoys a much consistent performance across maturities for both in-sample and out-of-sample countries and with both the observed and implied ratings. Whereas the principle components extracted from the 5-year CDS spreads of the in-sample countries does not explain CDS spreads well, less consistently across different maturities. Clearly, the rating-based model with the implied rating shows much more commonality existed in the Sovereign CDS spreads than the principle component analysis implied, which is purely data driven without any consistent no-arbitrage restrictions.

[34] For example, Ang and Longstaff (2013) take Germany and the US as the systemic factor for the European countries and individual US states, respectively. We extend their analysis by allowing the possibility that each country has its own idiosyncratic default component. As shown in Table 10, the R^2s for Germany and the US are 67% and 48%, respectively, suggesting that the CDS spreads of even the highest-rated countries contain significant idiosyncratic components.

[35] Performing a strict out-of-sample analysis for the principal component analysis is not possible due to the fact that we have to estimate the coefficients on the in-sample principal components for the out-of-sample countries.

In sum, we show that the rating-based model offers a parsimonious and consistent framework to jointly capture the credit risk of *multiple* countries well for both in-sample and out-of-sample countries. The rating-base model has good cross-sectional predictability, and it can generate model implied ratings that can, at least partially, address the problem of rating staleness. Equipped with internally consistent term structures of credit risk, the rating-based model can be used to price sovereign bonds and other related sovereign credit derivatives.

4.5 Nature of the Common Factor and Risk Premium

Given the importance of the common factor, we study the economic forces that drive the fluctuations of z_t and the sovereign credit risk premium. For maturity τ and credit rating i, the risk premium is defined as (see Pan and Singleton 2008)

$$CRP_i(t, t+\tau) \equiv CDS_i(t, t+\tau) - CDS_i^P(t, t+\tau), \tag{15}$$

where $CDS_i(t, t+\tau)$ is the τ-year CDS spreads, and $CDS_i^P(t, t+\tau)$ is the τ-year CDS spreads obtained from (6) by setting the price of risk to zero [e.g., setting $\lambda_z = 0$ in (8)]. We are also interested in the risk premium fraction of CDS spread defined as

$$RPF_i(t, t+\tau) \equiv \frac{CDS_i(t, t+\tau) - CDS_i^P(t, t+\tau)}{CDS_i(t, t+\tau)}. \tag{16}$$

Table 13 reports the regressions of changes in z_t and the credit risk premium (5-year CRP average over all 7 ratings) on six key market variables, namely, the volatility VIX index, the MSCI World stock index, the DAX stock index, the S&P 500 stock index, corporate credit risk index [CDX NA IG (North America, Investment Grade)], and the 5-year constant maturity Treasury yield, individually and collectively. Individually, all these market variables, except the Treasury yield, are highly significant and can explain close to or more than 30% of the variations of the common factor z. All three stock indexes are negatively correlated with the common factor and credit risk premium, such that when the World economy improves, so does the World sovereign credit risk. As expected, the volatility index VIX and the corporate credit risk index CDX are positively correlated with the World sovereign credit risk.

Collectively, only the volatility index VIX and the MSCI World stock index still remain highly significant in explaining the common factor z and sovereign credit risk premium. Jointly, the VIX and MSCI World stock indices explain more than 50% of the variations of the common factor and sovereign credit risk premium. On the other hand, the S&P 500 stock index of the US, the DAX stock index of Germany, and the corporate credit risk index CDX become insignificant, and the improvement in the regression R^2 also becomes insignificant by including these three market indexes as additional explanatory variables.

One important advantage of the rating-based model is that we can jointly use the CDS spreads of all in-sample countries to estimate the common default factor, which considerably increases estimation efficiency. Thus, the model structure and estimation method significantly improve our ability to identify the common factor.

Figure 8 plots the time series of the common factor z (top-left panel) and the average credit risk premium CRP at different ratings (middle-left panel) and maturities (bottom-left panel) during our sample period. Notably, both the common factor and the risk premium CRP for all ratings increased dramatically during the global financial crisis and the European debt crisis. The right panels in Figure 8 plot the time series of price of risk, average fractions of credit risk premium of CDS spreads at different ratings and maturities. The price of risk varies between 0.02 to 0.92 and peaks around 0.9 during the global financial crisis and European debt crisis. Meanwhile, the fractions of risk premium are relatively stable, varying around 30% for the top 5 ratings and around 20% for the 2 bottom ratings. Whereas the average fraction of risk premium increases with maturities, varying around 10% for 1-year CDS contracts to 45% for 10-year CDS contracts. We also report the average credit risk premium and fraction of risk premium across maturities for each country in Table 14.

We also conduct some analyses about the economic forces that drive the fluctuations of the country-specific factor y_t and report the results in Table 15. We find that, on average, more than half of the variations of country-specific factors can be explained by five macro economic variables (GDP growth rate, GDP per capita, government effectiveness, stock market return of the country, and total reserve of the country). The resulting regression coefficients, reported in Table 15, vary dramatically across countries in signs, magnitudes and significance. This reflects the idiosyncratic nature of the country-specific factors.

4.6 Alternative Estimations and Robustness

Several potential concerns of the main estimation regarding the selection of in-sample countries and the use of the S&P ratings may arise. As for the ratings, we repeat the estimations with either Moody's ratings or Fitch ratings, both of which are almost identical to the main estimation with the S&P ratings. As for the in-sample data selection, we re-estimate the model with (1) all CDS spreads of all 68 countries in the data set (Full Sample), (2) 34 in-sample countries with most observations rating-by-rating (Even Sample), and (3) only the observed CDS spreads of all 68 countries (Observed Sample). We then compare the pricing performance of these alternative estimations with that of our main estimation. The overall pricing errors of the full-sample estimation reported in Table 16 are comparable with that of the main estimation; the pricing errors of the 34 in-sample countries in the main estimation are slightly worsened, whereas those of the out-of-sample countries in the main estimation are slightly improved. Overall, the pricing errors of the full-sample estimation are similar to those in our main estimation.

Recall that we split data into in-sample and out-of-sample countries by the number of observations, i.e., the top half countries with the most complete observations of the term structure of CDS spreads form in-sample. While this approach can pick up the countries with the most complete term structure, it also leads to uneven distribution countries in each rating class between in-sample and out-of-sample countries (see Table 1). Moreover, as reported in Table 2, the averages of CDS spreads in some rating categories for in-sample countries are much lower than those for out-of-sample countries. To address this concern, we re-estimate the model with an alternative selection of in-sample and out-of-sample countries as follows. Within each rating class, the top half countries with the most complete observations belong to the in-sample group. Table 17 reports the mean absolute pricing error relative to bid-ask spread for this alternative in-sample selection. We find that these results are similar to those reported in Table 8. The results (not reported) about time-series regressions of market CDS spread on the common-factor model spreads are also quite similar to those reported in Table 10.

As shown in Table 3, large portions of the data are derived by the data provider, especially for the out-of-sample countries. Thus, an estimation with the observed data only may offer a better assessment on our main estimation. Table 18 reports the pricing errors of the estimation with the observed CDS spreads of all countries. As can be seen, the pricing errors of 5-year contracts for both in-sample and out-of-sample countries in the main estimation are significantly improved. Such improvements are attributed to the fact that 5-year contracts dominate in the observed data and, in particular, these contracts can be perfectly priced in the absence of other term CDS spreads. The pricing errors of other terms are basically the same as those in the main estimation, except for the countries with extremely few observations. The estimated parameters (not reported) are close to those in the main estimation. All results related to these robustness checks are available upon request. Overall, these alternative estimations show that our main estimation is robust to alternative selections of data sample and credit ratings.

5 Conclusion

In this paper, we consider a rating-based continuous-time model of sovereign credit risk, which simultaneously captures the cross-sectional and time-series properties of sovereign credit spreads and offers closed-form solutions for a wide range of credit derivatives. In the model, rating transition follows a continuous-time Markov chain, and countries with the same credit rating share similar levels of default risk. One of the greatest advantages of our approach is that it offers a parsimonious and unified framework to capture the credit risk of multiple countries. A simple version of this model, with only 17 parameters, one common and one country-specific factor, can simultaneously capture the term structure of CDS spreads of 34 in-sample and 34 out-of-sample countries well. On average, the common factor, along with credit ratings, explains more than 60% of the variations of the CDS spreads of both the in-sample and out-of-sample countries, whereas more than 50% of the variations of the common factor and risk premium are explained by the CBOE VIX index and the MSCI World stock index. Our model also yields a natural *implied* credit rating. With the model implied ratings, the explanatory power of the common factor in explaining sovereign CDS spreads increases to more than 80%.

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Table 1: General Information of Sovereign CDS Contracts of 68 Countries. This table provides general information on the 34 in-sample and 34 out-of-sample countries between January 2004 and March 2012. We have monthly observations of the term structure of CDS spreads with bid-ask spreads and credit ratings from the S&P's. MoCDS represents the monthly average of 5-year CDS spreads, MoBAS represents the monthly average of the bid-ask spreads of 5-year CDS spreads, NoO is the number of observations, and NoTR is the number of rating transitions (under our reclassification of ratings) during the sample period. The reported rating for each country is the S&P's rating in the last month of the sample period. For the case of Greece, the reported rating is the one before its default.

In-Sample Countries							Out-of-Sample Countries						
SN	Rating	Country	MoCDS	MoBAS	NoO	NoRT	SN	Rating	Country	MoCDS	MoBAS	NoO	NoRT
1	AAA	Germany	23.5	2.6	99	0	35	AAA	Australia	62.0	5.8	45	0
2	AA	Austria	47.9	3.5	97	1	36	AAA	Denmark	48.2	4.8	59	0
3	AA	Belgium	59.7	4.2	99	0	37	AAA	Finland	33.3	4.2	56	0
4	AA	China	62.4	4.8	99	2	38	AAA	Hong Kong	39.8	6.0	86	2
5	AA	Czech	57.7	6.6	99	1	39	AAA	Netherlands	41.0	4.3	65	0
6	AA	Japan	38.6	3.7	98	0	40	AAA	Norway	25.4	4.6	49	0
7	AA	Qatar	75.3	10.3	95	1	41	AAA	Sweden	41.4	4.5	58	1
8	A	Chile	66.9	10.0	94	0	42	AAA	Switzerland	55.2	9.0	39	0
9	A	Israel	89.0	10.8	95	0	43	AAA	UK	57.8	4.0	59	0
10	A	Korea	93.0	5.1	99	0	44	AA	Abu Dhabi	152.6	13.1	36	0
11	A	Malaysia	77.1	5.6	99	0	45	AA	Estonia	180.5	19.1	54	1
12	A	Poland	89.9	5.9	99	1	46	AA	France	46.7	2.9	80	1
13	A	Slovakia	60.7	7.7	94	1	47	AA	New Zealand	75.0	7.1	39	0
14	BBB	Brazil	211.2	6.2	97	2	48	AA	Saudi Arabia	136.5	19.5	33	1
15	BBB	Bulgaria	167.2	11.7	99	1	49	AA	USA	34.8	4.7	58	1
16	BBB	Colombia	207.7	9.4	99	1	50	A	Slovenia	111.8	9.8	49	2
17	BBB	Croatia	166.7	13.5	99	0	51	A	Spain	143.3	5.0	65	3
18	BBB	Iceland	213.1	24.4	96	3	52	BBB	Bahrain	276.3	31.3	45	1
19	BBB	Italy	94.0	3.8	99	2	53	BBB	Ireland	304.9	12.1	58	3
20	BBB	Mexico	121.0	4.4	98	0	54	BBB	Kazakhstan	233.5	15.4	80	1
21	BBB	Panama	165.8	11.3	99	1	55	BBB	Lithuania	253.7	19.7	62	2
22	BBB	Peru	178.2	10.5	96	1	56	BBB	Morocco	188.6	29.8	41	1
23	BBB	Russia	177.8	5.6	94	1	57	BB	Costa Rica	193.7	28.1	37	0
24	BBB	South Africa	129.6	8.2	99	0	58	BB	Cyprus	140.7	6.3	9	2
25	BBB	Thailand	92.5	6.6	99	0	59	BB	El Salvador	229.2	30.3	34	0
26	BB	Hungary	174.8	6.3	99	2	60	BB	Guatemala	177.5	33.6	23	0
27	BB	Indonesia	232.7	14.0	90	1	61	BB	Latvia	335.8	24.3	58	3
28	BB	Philippines	251.5	9.2	99	0	62	BB	Vietnam	238.7	24.6	86	0
29	BB	Portugal	201.5	8.2	99	3	63	B	Argentina	902.7	34.4	82	1
30	BB	Romania	186.7	12.4	94	2	64	B	Dominican	299.5	73.5	10	1
31	BB	Turkey	240.1	7.1	95	1	65	B	Ecuador	992.4	111.7	18	5
32	B	Ukraine	663.8	35.3	92	4	66	B	Egypt	343.3	31.8	49	1
33	B	Venezuela	765.4	25.1	95	4	67	B	Lebanon	380.8	32.9	52	2
34	CCC	Greece	597.9	28.6	97	4	68	B	Pakistan	656.5	112.8	80	2

Table 2: Summary Information of Rating Transitions, CDS Spreads, and Bid/Ask Spreads. Panel A reports the number of rating transitions (40 times for the 34 in-sample countries and 37 times for the 34 out-of-sample countries) between January 2004 and March 2012. The left column represents the rating before rating transitions, and the upper row represents the rating after transitions. Panels B and C report the average monthly CDS spreads and bid-ask spreads by rating and maturity, respectively. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country. NoO is the number of observations for each rating.

In-Sample Countries

Panel A: Number of Rating Transitions							
	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	0	3	0	0	0	0
A	0	4	0	5	0	0	0
BBB	0	0	3	0	4	0	0
BB	0	0	0	7	0	3	0
B	0	0	0	0	5	0	3
CCC	0	0	0	0	0	2	0
Panel B: Mean of CDS Spreads							
	AAA	AA	A	BBB	BB	B	CCC
1	20.4	32.1	50.1	115.9	190.3	426.1	4399.4
2	24.7	40.1	59.8	132.7	226.5	501.7	3614.9
3	28.7	47.4	67.8	143.3	253.6	547.3	3189.9
5	33.5	51.5	79.2	160.6	299.5	574.8	2767.3
7	39.5	65.2	86.5	168.6	320.6	615.7	2528.0
10	41.7	70.5	91.9	175.8	337.4	630.1	2350.1
Slope	21.3	38.4	41.7	60.0	147.0	204.0	-2049.3
Panel C: Mean of Bid-Ask Spreads							
	AAA	AA	A	BBB	BB	B	CCC
1	3.3	6.9	10.6	20.7	23.6	46.2	403.0
2	3.3	6.4	9.4	16.6	19.3	38.7	265.1
3	3.2	6.1	8.7	13.9	17.6	36.2	207.8
5	2.9	4.6	7.0	9.4	12.2	29.8	154.2
7	3.3	5.2	7.3	10.0	14.4	31.8	141.6
10	3.5	5.3	7.3	10.1	13.7	30.8	133.4
NoO	193	399	945	931	708	101	23

Out-of-Sample Countries

Panel A: Number of Rating Transitions							
	AAA	AA	A	BBB	BB	B	CCC
AAA	0	4	0	0	0	0	0
AA	3	0	3	0	0	0	0
A	0	4	0	5	0	0	0
BBB	0	0	2	0	2	0	0
BB	0	0	0	2	0	1	0
B	0	0	0	0	0	0	4
CCC	0	0	0	0	0	7	0
Panel B: Mean of CDS Spreads							
	AAA	AA	A	BBB	BB	B	CCC
1	25.7	81.4	134.3	255.0	191.3	512.4	1818.5
2	31.1	93.5	150.6	277.5	215.3	558.6	1715.9
3	35.9	102.6	163.2	290.1	234.7	586.6	1655.8
5	44.5	114.9	179.4	299.4	259.7	625.7	1537.4
7	48.2	119.6	180.7	302.5	276.5	641.1	1512.4
10	51.1	123.6	179.4	300.5	285.9	653.6	1472.8
Slope	25.5	42.2	45.1	45.5	94.6	141.3	-345.7
Panel C: Mean of Bid-Ask Spreads							
	AAA	AA	A	BBB	BB	B	CCC
1	6.1	15.8	34.5	46.6	46.7	86.0	469.4
2	5.7	13.8	28.7	36.9	39.3	69.0	385.1
3	5.3	11.9	24.4	30.0	33.1	57.2	323.5
5	4.7	9.5	18.3	21.1	28.8	49.3	298.8
7	4.9	9.1	17.7	21.6	25.1	44.5	309.2
10	5.1	8.9	16.6	20.4	22.8	42.3	283.0
NoO	621	289	133	185	279	230	17

Table 3: Proportion (%) of Observed Data for In-Sample and Out-of-Sample Countries. The proportion is calculated by using the formula $\frac{\text{N. of Observed Data}}{\text{N. of Observed Data + N. of Derived Data}} \times 100$. We also report the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012.

In-Sample Countries								Out-of-Sample Countries							
Rating	Country	1y	2y	3y	5y	7y	10y	Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Germany	0.0	0.0	1.3	62.6	8.8	50.0	AAA	Australia	0.0	0.0	0.0	77.8	0.0	0.0
AA	Austria	0.0	0.0	2.1	60.8	0.0	43.3	AAA	Denmark	0.0	0.0	1.7	62.7	0.0	47.5
AA	Belgium	0.0	0.0	2.7	67.7	0.0	58.7	AAA	Finland	0.0	0.0	1.8	78.6	0.0	62.5
AA	China	15.2	11.1	6.1	93.9	15.2	28.3	AAA	Hong Kong	0.0	0.0	1.2	46.5	4.7	10.5
AA	Czech	0.0	0.0	0.0	54.5	2.0	17.2	AAA	Netherlands	0.0	0.0	3.1	67.7	0.0	52.3
AA	Japan	0.0	0.0	1.0	61.2	1.0	9.2	AAA	Norway	0.0	0.0	2.0	81.6	0.0	42.9
AA	Qatar	7.4	4.2	1.1	64.2	4.2	10.5	AAA	Sweden	0.0	0.0	0.0	75.9	0.0	58.6
A	Chile	11.7	6.4	4.3	50.0	8.5	17.0	AAA	Switzerland	0.0	0.0	0.0	17.9	0.0	15.4
A	Israel	7.5	4.3	2.2	61.1	1.1	20.4	AAA	UK	0.0	0.0	3.4	78.0	0.0	61.0
A	Korea	16.2	9.1	8.1	92.9	20.2	35.4	AA	Abu Dhabi	0.0	0.0	0.0	86.1	0.0	0.0
A	Malaysia	17.9	9.5	10.5	91.9	15.8	30.5	AA	Estonia	0.0	1.9	0.0	79.6	0.0	3.7
A	Poland	17.2	14.1	9.1	78.8	6.1	41.4	AA	France	0.0	0.0	2.5	76.3	5.0	57.5
A	Slovakia	10.6	11.7	6.4	66.0	4.3	22.3	AA	New Zealand	0.0	0.0	0.0	82.1	0.0	0.0
BBB	Brazil	54.3	53.2	47.9	92.8	29.8	64.9	AA	Saudi Arabia	0.0	0.0	0.0	81.8	0.0	0.0
BBB	Bulgaria	28.3	23.2	13.1	88.9	17.2	44.4	AA	USA	1.7	0.0	1.7	72.4	0.0	41.4
BBB	Colombia	38.3	42.6	46.8	87.9	23.4	55.3	A	Slovenia	0.0	0.0	0.0	67.3	0.0	2.0
BBB	Croatia	23.2	19.2	9.1	78.8	14.1	44.4	A	Spain	1.5	1.5	3.1	78.5	0.0	84.6
BBB	Iceland	4.3	0.0	0.0	32.3	0.0	24.6	BBB	Bahrain	0.0	0.0	0.0	84.4	0.0	0.0
BBB	Italy	2.0	1.0	7.1	66.7	5.1	50.5	BBB	Ireland	1.7	1.7	0.0	82.8	1.7	79.3
BBB	Mexico	34.7	35.7	32.7	89.8	19.4	63.3	BBB	Kazakhstan	7.7	5.1	1.3	90.0	12.8	33.3
BBB	Panama	16.2	21.2	20.2	80.8	10.1	26.3	BBB	Lithuania	0.0	0.0	1.6	54.8	0.0	3.2
BBB	Peru	35.4	39.6	39.6	84.4	13.5	45.8	BBB	Morocco	0.0	0.0	0.0	61.0	0.0	0.0
BBB	Russia	21.3	25.5	26.6	94.7	18.1	58.5	BB	Costa Rica	0.0	0.0	0.0	2.7	0.0	0.0
BBB	South Africa	33.3	30.3	24.2	88.9	16.2	56.6	BB	Cyprus	0.0	0.0	11.1	22.2	0.0	22.2
BBB	Thailand	22.2	12.1	8.1	93.9	13.1	28.3	BB	El Salvador	0.0	0.0	0.0	2.9	0.0	0.0
BB	Hungary	29.6	29.6	21.4	81.8	9.2	58.2	BB	Guatemala	0.0	0.0	0.0	0.0	0.0	0.0
BB	Indonesia	23.3	14.0	26.7	88.9	22.1	39.5	BB	Latvia	3.4	0.0	1.7	75.9	0.0	8.6
BB	Philippines	30.3	31.3	36.4	91.9	35.4	45.5	BB	Vietnam	8.5	0.0	2.8	83.7	4.2	11.3
BB	Portugal	3.8	3.8	8.8	63.6	10.0	61.3	B	Argentina	50.0	53.7	53.7	92.7	28.0	50.0
BB	Romania	23.6	22.5	7.9	87.2	20.2	48.3	B	Dominican	0.0	0.0	0.0	0.0	0.0	0.0
BB	Turkey	50.5	60.4	57.1	92.6	20.9	62.6	B	Ecuador	0.0	11.1	11.1	11.1	0.0	11.1
B	Ukraine	35.2	38.6	37.5	82.6	15.9	38.6	B	Egypt	0.0	0.0	0.0	59.2	0.0	0.0
B	Venezuela	47.9	53.2	53.2	91.6	23.4	46.8	B	Lebanon	0.0	0.0	0.0	57.7	0.0	0.0
CCC	Greece	9.4	9.4	12.5	66.3	15.6	54.2	B	Pakistan	0.0	0.0	1.3	32.5	0.0	6.3
—	AAA	0.0	0.0	0.6	61.1	4.0	45.4	—	AAA	0.2	0.0	1.1	67.1	0.6	47.8
—	AA	1.2	0.3	4.1	61.2	3.8	22.5	—	AA	0.3	0.3	1.7	77.2	1.4	21.8
—	A	10.6	7.2	5.3	69.8	8.5	33.5	—	A	0.0	0.8	0.8	67.7	0.0	7.5
—	BBB	24.1	22.1	17.1	87.2	13.4	46.9	—	BBB	3.8	2.7	1.1	81.1	6.0	20.8
—	BB	38.5	42.0	41.9	88.3	23.7	51.1	—	BB	3.0	0.0	1.5	49.8	1.1	4.5
—	B	37.2	36.0	39.5	75.2	25.6	45.3	—	B	17.9	19.2	19.7	59.1	10.0	20.1
—	CCC	41.7	29.2	37.5	87.5	25.0	33.3	—	CCC	0.0	11.8	11.8	11.8	0.0	11.8
—	Overall	20.0	19.0	17.6	77.4	13.1	41.1	—	Overall	3.3	3.1	3.8	66.0	2.6	27.0

Table 4: Parameter Estimates of Rating-Based Sovereign CDS Models. Model I is the full model, Model II allows dependence of default risk on rating but no transitions between ratings, and Model III allows neither. $\bar{H}_{33}$ is fixed at 1 for all models. Likelihood ratio test between Model I and Model II (III) has a χ^2 distribution with 4 (10) degrees of freedom, with critical value at the 99.99 percentile of 23.51 (35.56). There is overwhelming evidence that both $\bar{Q}$ and $\bar{H}$ are important factors for CDS pricing.

parameter	estimate	std. error	parameter	estimate	std. error
Model I: full model					
Q_{12}	7.6538	0.3460	H_{77}	59.8975	0.6609
Q_{21}	37.5411	0.6019	α	1e-06	1e-05
Q_{23}	28.0941	0.6496	κ_z^p	0.2017	0.0936
Q_{76}	74.4700	2.8453	$\kappa_z^p \theta_z^p$	0.0007	6e-06
H_{11}	0.5851	0.0084	σ_z	0.0286	0.0004
H_{22}	0.6445	0.0108	λ_z	-7.0456	3.2837
H_{44}	3.2012	0.0308	κ_y	0.0475	0.0023
H_{55}	3.5085	0.0464	σ_y	0.0076	5e-05
H_{66}	27.7768	0.5426	LogLikeli	1103.65	—
Model II: $\bar{Q} = 0$					
H_{11}	0.4006	2e-05	κ_z^p	0.1522	1e-05
H_{22}	0.7177	0.0001	$\kappa_z^p \theta_z^p$	0.0009	9e-07
H_{44}	2.0774	0.0001	σ_z	0.0303	3e-06
H_{55}	4.6256	0.0003	λ_z	-5.0210	0.0006
H_{66}	10.8648	2e-05	κ_y	0.0033	0.0003
H_{77}	17.1201	0.0984	σ_y	0.0076	1e-05
α	1e-06	3e-07	LogLikeli	1057.67	—
Model III: $\bar{H} = I$ ($\bar{Q} = 0$)					
α	1e-07	2e-07	λ_z	-3.1569	0.0001
κ_z^p	0.1308	6e-06	κ_y	0.0949	0.0001
$\kappa_z^p \theta_z^p$	0.0020	3e-07	σ_y	0.0300	1e-05
σ_z	0.0414	7e-07	LogLikeli	954.13	—
Likelihood Ratio Test:					
	$p_{99\%}$ of $\chi^2(4)$	13.28	Model I vs. Model II: tested value		
	$p_{99.99\%}$ of $\chi^2(4)$	23.51	$2 \times (1103.65 - 1057.67) = 91.96$		
	$p_{99\%}$ of $\chi^2(10)$	23.21	Model I vs. Model III: tested value		
	$p_{99.99\%}$ of $\chi^2(10)$	35.56	$2 \times (1103.65 - 954.13) = 299.03$		

Table 5: One-Year Rating Transition Probabilities. Expected (conditional) rating transition probabilities are computed under the physical measure and the risk-neutral measure with the estimated model parameters, that is, $E_t^P\left[e^{\int_t^{t+1}\bar{Q}(\alpha+z_u)du}\right]$ and $E_t\left[e^{\int_t^{t+1}\bar{Q}(\alpha+z_u)du}\right]$. This table reports results (in percent) when z_t is the 10th percentile, the median, and the 90th percentile of the estimated time series for the common factor z.

	Under Physical Measure							Under Risk-Neutral Measure						
Ratings	AAA	AA	A	BBB	BB	B	CCC	AAA	AA	A	BBB	BB	B	CCC
	Normal Period: $z_t = 0.0027$							Normal Period: $z_t = 0.0027$						
AAA	98.01	1.91	0.08	0.00	0.00	0.00	0.00	97.83	2.08	0.09	0.00	0.00	0.00	0.00
AA	9.36	83.93	6.43	0.27	0.01	0.00	0.00	10.19	82.53	6.94	0.32	0.01	0.00	0.00
A	0.51	8.59	84.18	6.44	0.27	0.01	0.00	0.61	9.28	82.83	6.95	0.32	0.01	0.00
BBB	0.02	0.48	8.60	84.19	6.44	0.27	0.01	0.03	0.57	9.29	82.84	6.95	0.32	0.01
BB	0.00	0.02	0.48	8.60	84.19	6.45	0.27	0.00	0.02	0.57	9.29	82.84	6.97	0.31
B	0.00	0.00	0.02	0.48	8.62	84.53	6.35	0.00	0.00	0.02	0.57	9.31	83.24	6.85
CCC	0.00	0.00	0.00	0.04	0.94	16.84	82.18	0.00	0.00	0.00	0.05	1.11	18.17	80.67
	Tranquil Period: $z_t = 0.0004$							Tranquil Period: $z_t = 0.0004$						
AAA	99.50	0.50	0.01	0.00	0.00	0.00	0.00	99.46	0.54	0.01	0.00	0.00	0.00	0.00
AA	2.43	95.77	1.78	0.02	0.00	0.00	0.00	2.64	95.41	1.92	0.02	0.00	0.00	0.00
A	0.04	2.37	95.79	1.78	0.02	0.00	0.00	0.05	2.57	95.44	1.92	0.02	0.00	0.00
BBB	0.00	0.04	2.38	95.79	1.78	0.02	0.00	0.00	0.04	2.57	95.44	1.92	0.02	0.00
BB	0.00	0.00	0.04	2.38	95.79	1.78	0.02	0.00	0.00	0.04	2.57	95.44	1.92	0.02
B	0.00	0.00	0.00	0.04	2.38	95.82	1.77	0.00	0.00	0.00	0.04	2.57	95.47	1.91
CCC	0.00	0.00	0.00	0.00	0.07	4.69	95.23	0.00	0.00	0.00	0.00	0.09	5.08	94.84
	Turbulent Period: $z_t = 0.0114$							Turbulent Period: $z_t = 0.0114$						
AAA	93.44	5.71	0.77	0.08	0.01	0.00	0.00	92.90	6.09	0.90	0.10	0.01	0.00	0.00
AA	27.98	54.02	15.44	2.30	0.23	0.02	0.00	29.88	51.17	16.01	2.62	0.29	0.03	0.00
A	5.08	20.64	56.06	15.66	2.32	0.24	0.02	5.90	21.39	53.47	16.27	2.64	0.30	0.02
BBB	0.66	4.11	20.92	56.08	15.66	2.34	0.23	0.84	4.68	21.74	53.50	16.28	2.67	0.29
BB	0.07	0.56	4.14	20.93	56.11	15.95	2.24	0.09	0.70	4.72	21.75	53.54	16.64	2.55
B	0.01	0.06	0.57	4.18	21.32	58.93	14.94	0.01	0.08	0.71	4.78	22.24	56.73	15.46
CCC	0.00	0.01	0.11	1.09	7.95	39.60	51.23	0.00	0.01	0.16	1.36	9.03	40.97	48.46

Table 6: Proportion of Model Implied CDS Spread Attributed to Rating Transition Risk. For each country and at each maturity, we report the time series average of the ratio $|CDS^0 - CDS|/CDS$, where CDS is the model implied CDS spread and CDS^0 is obtained by setting $\bar{Q} \equiv 0$ in the CDS pricing formula, given the in-sample estimated values of z and y_i. The first column reports the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country.

Rating	Country	1y	2y	3y	5y	7y	10y	Mean
AAA	Germany	0.131	0.115	0.138	0.035	0.034	0.104	0.093
AA	Austria	0.090	0.101	0.136	0.050	0.030	0.097	0.084
AA	Belgium	0.332	0.237	0.148	0.076	0.116	0.227	0.189
AA	China	0.563	0.385	0.206	0.047	0.127	0.209	0.256
AA	Czech	0.504	0.373	0.454	0.084	0.165	0.269	0.308
AA	Japan	0.458	0.393	0.407	0.079	0.117	0.239	0.282
AA	Qatar	0.365	0.250	0.150	0.033	0.117	0.220	0.189
A	Chile	0.581	0.359	0.194	0.052	0.145	0.238	0.262
A	Israel	0.416	0.265	0.147	0.046	0.136	0.224	0.206
A	Korea	0.448	0.283	0.157	0.047	0.137	0.227	0.216
A	Malaysia	0.482	0.302	0.166	0.047	0.140	0.231	0.228
A	Poland	0.426	0.327	0.348	0.059	0.112	0.167	0.240
A	Slovakia	0.547	0.372	0.423	0.082	0.153	0.241	0.303
BBB	Brazil	0.409	0.259	0.118	0.061	0.121	0.145	0.186
BBB	Bulgaria	0.228	0.143	0.117	0.046	0.055	0.075	0.111
BBB	Colombia	0.627	0.295	0.115	0.091	0.152	0.170	0.242
BBB	Croatia	0.150	0.128	0.094	0.039	0.048	0.067	0.088
BBB	Iceland	0.185	0.159	0.133	0.046	0.079	0.133	0.122
BBB	Italy	0.486	0.413	0.307	0.069	0.128	0.225	0.271
BBB	Mexico	0.094	0.075	0.055	0.037	0.044	0.061	0.061
BBB	Panama	0.611	0.333	0.134	0.087	0.151	0.171	0.248
BBB	Peru	0.470	0.290	0.125	0.072	0.132	0.153	0.207
BBB	Russia	0.137	0.090	0.055	0.044	0.056	0.072	0.076
BBB	South Africa	0.113	0.082	0.060	0.038	0.045	0.063	0.067
BBB	Thailand	0.242	0.129	0.081	0.041	0.049	0.065	0.101
BB	Hungary	0.357	0.268	0.156	0.042	0.076	0.125	0.170
BB	Indonesia	0.615	0.238	0.095	0.082	0.127	0.152	0.218
BB	Philippines	0.586	0.254	0.097	0.100	0.152	0.172	0.227
BB	Portugal	0.442	0.359	0.214	0.054	0.102	0.186	0.226
BB	Romania	0.322	0.277	0.145	0.073	0.096	0.118	0.172
BB	Turkey	0.552	0.248	0.099	0.095	0.150	0.171	0.219
B	Ukraine	0.403	0.235	0.105	0.070	0.175	0.256	0.207
B	Venezuela	0.367	0.184	0.083	0.069	0.129	0.172	0.167
CCC	Greece	0.456	0.409	0.396	0.077	0.150	0.243	0.288
—	AAA	0.105	0.106	0.138	0.043	0.030	0.098	0.087
—	AA	0.401	0.347	0.258	0.061	0.110	0.224	0.234
—	A	0.505	0.351	0.267	0.060	0.147	0.242	0.262
—	BBB	0.149	0.108	0.097	0.042	0.049	0.063	0.085
—	BB	0.611	0.313	0.127	0.093	0.160	0.185	0.248
—	B	0.325	0.164	0.082	0.036	0.126	0.224	0.160
—	CCC	0.231	0.122	0.035	0.094	0.188	0.294	0.161
—	Overall	0.393	0.252	0.171	0.061	0.110	0.167	0.192

Table 7: Estimated Standard Deviations of Pricing Errors σ_{jM} Across Countries and Maturities. The first column reports the last-month rating for each country. The average for each rating is computed according to the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012.

Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Germany	11.2	8.3	4.7	5.8	8.5	10.2
AA	Austria	13.9	8.1	4.7	8.8	8.8	9.6
AA	Belgium	16.1	8.9	9.3	7.9	9.0	13.6
AA	China	12.6	9.2	6.1	5.7	9.5	14.9
AA	Czech	11.3	7.0	4.8	5.0	7.0	13.2
AA	Japan	15.6	9.5	4.9	7.2	10.6	13.0
AA	Qatar	16.1	8.1	3.3	6.8	8.5	11.9
A	Chile	13.3	7.8	3.3	8.0	8.2	9.3
A	Israel	15.0	6.8	4.2	8.2	7.7	9.9
A	Korea	21.2	12.4	5.3	10.9	13.8	14.8
A	Malaysia	12.7	7.9	4.5	6.7	7.9	12.2
A	Poland	22.3	11.2	6.9	7.8	12.5	19.4
A	Slovakia	14.1	8.9	5.9	5.3	9.0	16.5
BBB	Brazil	71.4	30.1	10.3	25.1	35.7	46.8
BBB	Bulgaria	30.3	13.8	11.5	12.7	14.9	24.5
BBB	Colombia	49.6	29.8	14.4	21.4	28.7	37.4
BBB	Croatia	28.1	14.7	12.8	10.4	15.6	27.5
BBB	Iceland	101.6	52.2	16.4	28.8	53.0	67.2
BBB	Italy	26.7	13.2	8.6	11.9	15.3	17.9
BBB	Mexico	21.4	12.2	8.1	8.4	12.8	21.0
BBB	Panama	32.0	21.4	14.1	11.5	20.9	34.2
BBB	Peru	36.7	23.4	10.8	15.8	22.8	31.0
BBB	Russia	62.7	22.0	11.6	29.4	30.8	24.4
BBB	South Africa	25.8	13.2	7.9	10.9	13.3	21.3
BBB	Thailand	13.5	10.0	6.9	6.0	9.7	17.1
BB	Hungary	37.2	17.2	11.4	16.3	19.8	26.0
BB	Indonesia	36.2	34.1	23.1	13.2	28.6	48.8
BB	Philippines	47.1	30.2	19.0	21.0	27.4	41.8
BB	Portugal	120.6	100.9	42.9	52.6	88.7	103.7
BB	Romania	41.4	23.8	19.4	17.8	24.1	37.1
BB	Turkey	35.1	20.0	14.1	14.2	18.8	29.0
B	Ukraine	257.0	129.0	42.4	77.0	140.0	204.0
B	Venezuela	169.1	87.9	56.7	63.1	88.2	118.6
CCC	Greece	496.6	119.4	87.2	159.5	192.3	209.4
Average	AAA	11.2	8.3	4.7	5.8	8.5	10.2
Average	AA	14.3	8.5	5.5	6.9	8.9	12.7
Average	A	16.4	9.2	5.0	7.8	9.9	13.7
Average	BBB	41.7	21.3	11.1	16.0	22.8	30.9
Average	BB	52.9	37.7	21.6	22.5	34.6	47.7
Average	B	213.0	108.4	49.5	70.0	114.1	161.3
Overall	Mean	56.9	27.4	15.2	21.2	30.1	39.9
Overall	SD	92.8	32.4	17.5	29.5	40.3	49.0
Overall	Min	11.2	6.8	3.3	5.0	7.0	9.3
Overall	Med	27.4	13.5	9.8	11.2	15.1	22.8
Overall	Max	496.6	129.0	87.2	159.5	192.3	209.4

Table 8: Mean Absolute Pricing Error Relative to Bid-Ask Spread for In-Sample and Out-of-Sample Countries. We also report the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012.

In-Sample Countries								Out-of-Sample Countries							
Rating	Country	1y	2y	3y	5y	7y	10y	Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Germany	3.7	2.6	1.3	1.3	2.2	3.2	AAA	Australia	1.5	0.8	0.2	1.3	1.3	0.6
AA	Austria	2.0	1.4	0.9	1.2	1.6	2.4	AAA	Denmark	2.1	1.0	0.6	1.0	1.2	1.6
AA	Belgium	1.7	0.9	1.1	0.8	1.2	2.7	AAA	Finland	3.0	1.2	0.5	1.1	1.1	1.4
AA	China	2.1	1.6	1.0	1.2	1.5	2.7	AAA	Hong Kong	0.7	0.6	0.5	0.3	0.8	1.5
AA	Czech	1.0	0.8	0.8	0.5	1.1	2.8	AAA	Netherlands	1.9	1.2	0.6	1.0	1.3	1.8
AA	Japan	4.9	2.4	1.2	1.4	2.1	3.0	AAA	Norway	1.3	1.1	0.7	0.8	0.9	1.3
AA	Qatar	1.2	0.6	0.3	0.8	0.8	1.0	AAA	Sweden	2.4	1.4	0.5	1.2	1.2	1.5
A	Chile	0.7	0.5	0.3	0.6	0.5	0.9	AAA	Switzerland	1.2	1.0	0.5	0.9	1.1	0.8
A	Israel	1.1	0.4	0.3	0.8	0.6	0.7	AAA	UK	5.3	3.2	1.4	2.2	2.3	2.2
A	Korea	1.3	0.9	0.6	1.2	1.2	1.9	AA	Abu Dhabi	2.2	1.4	0.7	1.1	1.2	2.1
A	Malaysia	1.8	1.1	0.5	1.2	1.0	1.5	AA	Estonia	1.6	0.7	0.6	0.8	1.1	1.6
A	Poland	2.1	1.1	0.9	1.1	1.9	3.5	AA	France	3.3	2.2	1.0	1.7	2.0	2.6
A	Slovakia	0.8	0.8	0.8	0.5	1.2	2.8	AA	New Zealand	0.3	0.7	1.0	0.6	0.8	2.4
BBB	Brazil	3.9	2.4	1.1	2.6	2.6	4.0	AA	Saudi Arabia	0.4	0.4	0.2	0.5	0.4	0.8
BBB	Bulgaria	1.6	0.9	0.7	0.7	1.3	2.5	AA	USA	0.9	0.7	0.6	0.6	1.1	1.7
BBB	Colombia	3.2	1.8	0.9	1.7	2.0	2.8	A	Slovenia	1.6	0.8	0.5	1.0	1.1	1.2
BBB	Croatia	1.1	0.8	0.7	0.5	1.1	2.1	A	Spain	2.1	1.5	1.4	1.8	1.9	2.6
BBB	Iceland	0.8	0.8	0.4	0.5	1.3	2.2	BBB	Bahrain	0.5	0.4	0.5	0.6	0.6	1.6
BBB	Italy	1.5	1.2	1.1	1.2	1.5	2.7	BBB	Ireland	1.3	1.4	1.2	1.5	2.5	3.5
BBB	Mexico	2.8	1.5	0.8	1.7	1.7	2.8	BBB	Kazakhstan	2.1	0.6	0.5	1.4	1.1	1.7
BBB	Panama	1.5	0.9	0.6	0.7	1.1	1.9	BBB	Lithuania	1.4	1.0	0.6	0.7	1.6	2.7
BBB	Peru	2.0	1.0	0.6	1.0	1.2	2.1	BBB	Morocco	0.7	0.6	0.4	0.3	0.9	1.5
BBB	Russia	3.4	1.2	0.9	2.4	2.0	2.9	BB	Costa Rica	0.9	1.0	0.9	0.3	1.1	1.9
BBB	South Africa	2.6	1.2	0.6	1.5	1.3	2.0	BB	Cyprus	1.0	1.1	0.9	0.6	1.8	3.1
BBB	Thailand	1.3	1.0	0.8	0.7	1.0	2.1	BB	El Salvador	0.7	0.5	0.5	0.4	0.7	1.3
BB	Hungary	2.1	1.1	0.8	1.6	1.8	2.9	BB	Guatemala	0.7	0.5	0.3	0.3	0.7	0.7
BB	Indonesia	1.5	1.4	1.5	1.1	1.4	2.5	BB	Latvia	1.7	1.3	0.7	1.4	2.1	2.8
BB	Philippines	2.3	1.9	1.5	1.9	1.8	2.8	BB	Vietnam	1.2	0.9	0.8	0.9	1.4	1.9
BB	Portugal	1.3	1.3	1.0	1.1	2.3	3.3	B	Argentina	5.4	3.1	1.6	2.9	4.2	7.4
BB	Romania	1.8	1.3	0.8	1.1	2.1	3.4	B	Dominican	0.9	0.5	0.3	0.4	0.6	1.0
BB	Turkey	3.4	2.5	1.4	2.7	2.8	4.8	B	Ecuador	2.4	1.2	0.8	1.7	2.8	3.2
B	Ukraine	2.5	1.5	0.8	1.8	2.2	3.6	B	Egypt	1.4	0.9	0.7	1.0	1.6	2.1
B	Venezuela	3.2	2.0	0.9	2.8	3.5	4.4	B	Lebanon	1.1	1.2	1.2	0.5	1.4	2.9
CCC	Greece	1.6	1.2	0.7	1.7	2.8	4.1	B	Pakistan	1.5	0.9	0.7	0.6	1.2	1.6
—	AAA	2.8	2.0	1.1	1.2	1.9	2.8	—	AAA	2.3	1.4	0.7	1.2	1.4	1.6
—	AA	2.7	1.4	0.9	1.0	1.5	2.3	—	AA	1.3	0.9	0.8	1.0	1.1	1.9
—	A	1.2	0.8	0.7	0.9	1.1	2.1	—	A	1.3	1.0	0.7	0.7	1.4	2.3
—	BBB	2.1	1.1	0.8	1.3	1.6	2.8	—	BBB	1.6	0.8	0.6	1.1	1.4	2.1
—	BB	2.4	1.8	1.1	2.0	2.2	3.2	—	BB	1.1	0.8	0.6	0.8	1.3	1.8
—	B	4.2	2.3	1.1	2.0	3.6	5.4	—	B	2.8	1.8	1.1	1.4	2.4	4.1
—	CCC	1.0	0.5	0.5	1.1	1.4	1.7	—	CCC	2.2	1.1	0.5	1.7	2.4	2.8
—	Overall	2.1	1.3	0.8	1.3	1.6	2.7	—	Overall	1.9	1.2	0.7	1.1	1.5	2.1

Table 9: Mean Absolute Pricing Error (with Implied Ratings) Relative to Bid-Ask Spread for In-Sample and Out-of-Sample Countries. This table re-calculate the model implied CDS spreads by using the implied ratings obtained as per equation (14). Reported are the averaged absolute pricing error relative to bid-ask spread. The first column of each panel reports the last-month rating for each country. The average for each rating is computed according to the *implied* rating when the price is quoted. The sample consists of monthly observations between January 2004 and March 2012.

In-Sample Countries								Out-of-Sample Countries							
Rating	Country	1y	2y	3y	5y	7y	10y	Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Germany	4.5	5.5	6.4	3.5	25.0	50.2	AAA	Australia	6.3	7.8	8.8	0.9	16.2	36.2
AA	Austria	4.3	5.3	6.1	5.2	23.7	47.6	AAA	Denmark	4.2	5.3	5.9	2.1	15.2	33.2
AA	Belgium	5.2	6.6	7.6	3.9	22.4	47.2	AAA	Finland	3.7	4.7	5.3	2.0	13.5	29.2
AA	China	5.2	7.1	8.2	2.2	23.0	48.6	AAA	Hong Kong	2.7	3.5	4.0	1.9	14.1	28.7
AA	Czech	3.4	4.2	4.9	2.1	15.3	33.4	AAA	Netherlands	4.1	5.1	5.8	2.5	15.2	34.2
AA	Japan	4.9	6.3	7.0	2.8	18.6	39.0	AAA	Norway	2.7	3.4	4.1	1.7	11.6	25.8
AA	Qatar	3.9	5.2	6.2	1.2	16.3	35.8	AAA	Sweden	4.1	5.1	5.9	1.9	14.7	33.7
A	Chile	2.8	3.9	4.4	1.1	13.9	31.3	AAA	Switzerland	3.3	4.1	4.7	0.6	8.0	18.6
A	Israel	3.6	5.2	6.1	2.0	16.8	37.1	AAA	UK	6.7	8.4	9.6	2.1	18.5	40.4
A	Korea	6.0	8.1	9.6	3.8	26.1	54.1	AA	Abu Dhabi	6.9	8.9	10.0	3.0	21.8	44.9
A	Malaysia	5.0	7.0	8.3	2.5	22.3	47.0	AA	Estonia	3.9	4.8	5.4	2.4	14.0	28.2
A	Poland	5.6	7.3	8.5	5.5	27.9	55.6	AA	France	5.9	7.5	8.5	5.1	26.2	48.5
A	Slovakia	2.8	3.6	4.1	2.2	14.6	30.7	AA	New Zealand	5.4	6.7	7.8	0.9	16.3	36.6
BBB	Brazil	9.2	14.6	17.6	25.5	66.8	139.2	AA	Saudi Arabia	4.8	6.1	6.6	1.4	13.0	29.2
BBB	Bulgaria	4.7	6.5	7.1	5.4	27.1	54.3	AA	USA	3.2	4.0	4.7	3.3	16.5	29.9
BBB	Colombia	7.0	9.7	11.8	11.5	42.5	83.9	A	Slovenia	4.7	5.7	6.3	2.1	16.7	34.9
BBB	Croatia	4.9	6.4	6.7	5.6	25.9	51.9	A	Spain	9.6	12.7	13.8	8.4	35.4	61.7
BBB	Iceland	3.3	4.1	4.1	3.0	14.3	28.4	BBB	Bahrain	4.6	5.7	6.3	3.6	16.5	34.0
BBB	Italy	6.4	8.4	10.0	7.9	29.0	48.9	BBB	Ireland	8.7	10.8	10.1	9.1	30.0	50.6
BBB	Mexico	8.7	11.8	13.9	11.4	42.1	86.2	BBB	Kazakhstan	5.7	8.3	9.7	8.1	32.6	64.7
BBB	Panama	5.3	7.2	8.5	4.1	27.0	57.4	BBB	Lithuania	5.5	7.3	7.5	5.2	20.7	41.8
BBB	Peru	6.1	8.3	9.8	6.3	32.0	69.6	BBB	Morocco	3.4	4.4	5.1	3.0	15.0	30.4
BBB	Russia	9.1	13.4	16.0	18.0	64.8	118.4	BB	Costa Rica	3.5	4.7	5.6	2.5	13.7	26.8
BBB	South Africa	5.3	8.2	9.9	8.7	34.8	66.4	BB	Cyprus	2.2	2.9	2.2	5.3	17.7	30.1
BBB	Thailand	4.9	6.8	8.1	5.9	26.9	57.7	BB	El Salvador	5.3	7.3	7.8	4.0	26.9	56.2
BB	Hungary	7.2	10.0	10.2	9.8	36.5	71.0	BB	Guatemala	3.2	4.5	5.9	2.8	18.1	37.3
BB	Indonesia	7.0	9.7	11.8	10.7	39.2	76.2	BB	Latvia	6.5	8.0	7.8	6.4	23.1	44.4
BB	Philippines	7.8	10.8	14.0	23.1	50.8	94.0	BB	Vietnam	6.1	8.2	9.4	5.6	32.1	64.4
BB	Portugal	5.8	7.1	6.9	6.6	26.2	47.8	B	Argentina	11.5	16.5	14.9	56.9	90.8	145.8
BB	Romania	5.2	7.0	8.0	7.2	32.7	67.5	B	Dominican	1.7	2.3	3.0	1.5	7.2	15.1
BB	Turkey	11.0	18.2	21.6	16.4	66.9	130.6	B	Ecuador	8.1	10.3	14.2	22.2	55.1	96.0
B	Ukraine	9.0	13.9	14.5	10.8	44.6	87.4	B	Egypt	6.6	8.3	9.1	6.1	25.4	49.6
B	Venezuela	9.9	14.1	11.9	32.1	67.1	111.4	B	Lebanon	5.5	7.3	8.6	11.8	32.4	54.2
CCC	Greece	5.5	7.2	5.9	10.1	30.5	51.6	B	Pakistan	4.1	6.1	6.7	9.5	42.5	65.1
—	AAA	4.3	5.3	6.1	4.3	24.3	49.0	—	AAA	4.4	5.5	6.2	2.5	16.7	35.0
—	AA	4.7	6.1	7.0	3.2	20.4	42.2	—	AA	6.2	8.0	8.9	3.5	20.9	40.2
—	A	4.5	6.0	7.1	3.4	21.6	44.0	—	A	4.0	5.2	5.6	3.8	17.3	33.3
—	BBB	6.6	9.0	10.1	8.4	33.6	65.7	—	BBB	6.2	8.2	8.6	7.1	26.4	51.1
—	BB	7.5	11.4	13.1	16.3	50.5	100.3	—	BB	5.4	7.1	7.9	4.8	24.1	48.3
—	B	8.9	12.5	12.2	18.8	49.6	79.0	—	B	7.2	10.2	10.1	26.7	56.0	89.4
—	CCC	6.4	6.1	2.1	10.5	20.4	28.9	—	CCC	7.1	8.4	11.8	20.9	47.3	86.5
—	Overall	5.9	8.2	9.3	8.1	32.2	63.6	—	Overall	5.4	7.0	7.7	7.0	25.1	47.2

Table 10: Results of Time Series Regressions. This table reports the time series regressions of 5-year market CDS spreads on 5-year z-spreads. We obtain the z-spreads by setting the country-specific factors to zero in estimated Model I based on the 34 in-sample countries. The sample consists of monthly observations between January 2004 and March 2012. We also report $\widetilde{\beta}$ and $\widetilde{R}^2$ of regressions without the observations with "stale rating", and $\hat{\beta}$ and $\hat{R}^2$ of regressions using "implied rating". t-statistics of regression β-s are also reported. Column N reports the number of observations with "stale rating".

In-Sample Countries

Rating	Country	β	t_{stat}	$\widetilde{\beta}$	t_{stat}	$\hat{\beta}$	t_{stat}	R^2	$\widetilde{R}^2$	$\hat{R}^2$	N
AAA	Germany	1.00	14.0	0.84	17.8	0.93	23.2	67.0	80.1	84.7	18
AA	Austria	2.28	21.7	0.96	25.6	0.94	51.2	83.2	92.4	96.5	41
AA	Belgium	1.58	9.4	0.84	15.1	0.95	32.8	47.9	94.6	91.7	84
AA	China	0.77	15.5	0.82	32.9	0.83	40.6	71.2	94.6	94.4	35
AA	Czech	1.01	24.2	0.83	14.2	0.93	35.5	85.8	83.5	92.8	57
AA	Japan	0.81	10.4	1.06	13.9	0.98	31.8	52.8	93.2	91.3	82
AA	Qatar	1.71	18.9	1.00	35.4	1.00	32.7	79.3	96.7	92.0	50
A	Chile	0.85	28.4	0.97	44.5	0.97	44.9	89.7	95.8	95.6	5
A	Israel	0.90	20.9	0.92	29.2	0.82	25.8	82.4	91.6	87.7	15
A	Korea	1.32	20.6	1.13	38.2	0.88	33.5	81.3	95.0	92.1	20
A	Malaysia	0.94	23.3	1.03	34.4	1.01	33.0	84.8	93.1	91.8	9
A	Poland	1.33	15.4	1.10	14.7	0.83	28.7	71.1	90.4	89.4	74
A	Slovakia	0.95	13.9	1.05	13.5	1.00	32.3	67.7	83.8	91.9	57
BBB	Brazil	0.69	9.9	0.90	25.3	0.77	28.1	50.6	92.8	89.3	45
BBB	Bulgaria	1.14	30.0	1.09	30.9	1.00	33.2	90.2	93.4	91.9	30
BBB	Colombia	0.14	2.4	0.47	2.9	0.60	28.8	5.7	21.1	89.5	65
BBB	Croatia	1.17	26.8	1.11	28.0	1.03	31.9	88.1	91.5	91.3	24
BBB	Iceland	1.63	16.1	0.72	8.2	1.09	41.5	73.4	76.2	94.8	73
BBB	Italy	1.30	12.9	1.13	23.1	0.96	41.0	63.1	95.3	94.5	71
BBB	Mexico	0.54	16.4	0.78	34.4	0.79	29.5	73.8	94.5	90.1	27
BBB	Panama	0.28	9.0	1.31	8.6	0.80	16.4	45.3	60.9	73.5	49
BBB	Peru	0.43	5.0	0.65	9.7	0.60	18.6	21.2	60.4	78.6	32
BBB	Russia	1.17	16.8	0.98	20.2	0.84	38.1	75.5	84.7	94.0	18
BBB	South Africa	0.68	20.0	0.84	35.7	0.83	34.1	80.5	94.0	92.3	16
BBB	Thailand	0.52	27.4	0.71	35.8	0.79	25.5	88.6	96.7	87.0	53
BB	Hungary	1.02	24.3	1.02	24.8	0.91	30.0	85.9	91.8	90.3	42
BB	Indonesia	0.46	9.4	0.67	14.3	0.69	16.1	50.3	83.3	74.7	47
BB	Philippines	0.03	0.5	0.60	17.8	0.66	32.2	0.3	91.4	91.5	67
BB	Portugal	2.57	19.5	0.74	7.8	0.87	31.8	79.7	85.9	91.2	87
BB	Romania	0.63	33.6	0.73	39.3	0.86	27.9	92.5	97.4	89.4	50
BB	Turkey	0.24	7.1	0.59	15.4	0.55	15.4	35.1	84.0	71.8	48
B	Ukraine	0.86	16.6	0.97	27.7	0.94	38.5	75.4	93.5	94.3	37
B	Venezuela	0.65	4.8	0.65	21.6	1.00	34.5	19.9	93.4	92.9	60
CCC	Greece	2.00	37.8	2.05	19.7	1.78	24.8	93.8	93.3	86.6	69
Overall	Mean	0.99	17.1	0.92	23.0	0.90	31.3	66.3	87.1	89.5	46
Overall	SD	0.58	8.9	0.28	10.7	0.20	8.0	25.2	14.6	6.1	23
Overall	Min	0.03	0.5	0.47	2.9	0.55	15.4	0.3	21.1	71.8	5
Overall	Med	0.92	16.5	0.91	22.4	0.90	32.1	74.6	92.6	91.4	48
Overall	Max	2.57	37.8	2.05	44.5	1.78	51.2	93.8	97.4	96.5	87

Out-of-Sample Countries

Rating	Country	β	t_{stat}	$\widetilde{\beta}$	t_{stat}	$\hat{\beta}$	t_{stat}	R^2	$\widetilde{R}^2$	$\hat{R}^2$	N
AAA	Australia	1.17	13.4	1.09	13.1	0.95	22.6	80.6	93.5	92.2	31
AAA	Denmark	1.50	13.2	1.25	21.3	1.02	25.0	75.3	92.3	91.7	19
AAA	Finland	0.80	11.5	0.81	15.0	0.84	14.3	71.0	81.9	79.2	4
AAA	Hong Kong	1.01	21.3	0.93	20.9	0.97	33.6	84.4	92.7	93.1	50
AAA	Netherlands	1.24	13.7	1.13	18.8	1.09	26.2	74.9	89.2	91.6	20
AAA	Norway	0.47	10.9	0.47	10.9	0.47	10.9	71.7	—	—	0
AAA	Sweden	1.24	15.0	1.00	22.5	0.96	29.3	80.0	93.3	93.9	20
AAA	Switzerland	1.18	8.4	0.54	6.5	0.93	18.3	65.7	70.3	90.0	19
AAA	UK	1.25	11.0	1.15	18.3	0.99	20.4	67.8	94.1	88.0	36
AA	Abu Dhabi	1.34	5.5	0.34	1.5	0.81	13.3	47.3	53.5	83.8	74
AA	Estonia	2.40	17.1	1.32	7.2	1.24	41.0	84.8	77.7	97.0	37
AA	France	1.58	9.1	0.78	23.1	0.94	37.7	51.3	91.3	94.8	27
AA	New Zealand	0.84	11.8	1.01	16.8	0.87	12.1	78.9	91.3	79.9	10
AA	Saudi Arabia	1.16	8.2	0.41	2.1	0.82	15.5	68.5	69.0	88.6	29
AA	USA	0.47	7.2	0.80	13.4	0.76	13.6	48.3	83.7	76.8	21
A	Slovenia	1.89	8.3	1.13	10.9	0.87	27.6	59.7	89.4	94.2	33
A	Spain	2.09	6.6	1.04	26.9	0.89	30.0	40.8	97.4	93.4	44
BBB	Bahrain	0.76	6.4	0.66	9.6	0.84	13.3	48.5	92.1	80.5	35
BBB	Ireland	2.00	10.1	1.36	36.7	0.95	16.5	64.5	99.3	82.9	46
BBB	Kazakhstan	1.50	11.3	1.00	18.4	0.81	30.5	62.2	86.6	92.3	26
BBB	Lithuania	1.10	15.0	0.89	10.4	0.87	26.8	78.9	79.5	92.3	32
BBB	Morocco	0.22	6.6	0.53	4.2	0.67	9.0	52.4	55.7	67.6	25
BB	Costa Rica	0.29	10.8	NaN	NaN	0.57	9.8	76.9	NaN	73.1	35
BB	Cyprus	3.03	27.6	NaN	NaN	1.05	160.4	99.1	NaN	100.0	8
BB	El Salvador	0.50	17.2	0.70	16.9	0.74	9.6	90.2	93.8	74.2	13
BB	Guatemala	-0.16	-1.5	0.54	5.2	0.54	6.4	9.1	79.3	66.2	14
BB	Latvia	0.71	6.9	1.06	8.9	0.99	18.9	45.6	80.0	86.5	36
BB	Vietnam	0.51	19.5	0.74	17.9	0.83	20.4	81.8	84.9	83.1	27
B	Argentina	1.36	11.6	0.90	17.4	1.05	36.1	62.5	84.8	94.2	43
B	Dominican	-0.03	-0.1	NaN	NaN	0.21	1.0	0.2	NaN	10.7	14
B	Ecuador	1.31	14.0	1.29	14.1	1.28	15.5	92.5	93.4	93.7	8
B	Egypt	0.30	8.0	0.72	17.5	0.70	13.6	57.8	92.1	79.7	21
B	Lebanon	0.12	4.9	1.10	1.8	0.64	7.9	32.8	34.6	55.8	44
B	Pakistan	0.85	23.4	0.98	38.8	0.92	29.7	87.5	96.6	91.9	25
Overall	Mean	1.06	11.3	0.89	15.1	0.85	24.0	64.5	83.4	83.1	27
Overall	SD	0.71	6.1	0.28	9.0	0.21	26.0	22.0	14.5	16.3	15
Overall	Min	-0.16	-1.5	0.34	1.5	0.21	1.0	0.2	34.6	10.7	0
Overall	Med	1.13	10.9	0.93	15.0	0.87	18.6	68.2	89.2	88.3	27
Overall	Max	3.03	27.6	1.36	38.8	1.28	160.4	99.1	99.3	100.0	74

Table 11: Results of Time Series Regressions on Principal Components. This table reports the time series regressions of 5-year market CDS spreads on their principal components. We obtain the principal components by conducting the principal components analysis of the correlation matrix of the changes of CDS spreads for in-sample countries. The average for each rating is computed according to the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012. $\hat{\beta}_i$ is the loading on the i-th principal component in the two-PC regression. The column t_i reports t-statistics of $\hat{\beta}_i$. R_1^2 (R_2^2) denotes the adjusted R-square for the regression using the first (first two) principal component(s). Column N reports the number of rating transitions (under our reclassification of ratings) during the sample period. At the bottom of this table, we report the time series regressions of market CDS spreads for different maturities on the principal components of 5-year market CDS spreads for in-sample countries.

In-Sample Countries									Out-of-Sample Countries								
Rating	Country	$\hat{\beta}_1$	t_1	$\hat{\beta}_2$	t_2	R_1^2	R_2^2	N	Rating	Country	$\hat{\beta}_1$	t_1	$\hat{\beta}_2$	t_2	R_1^2	R_2^2	N
AAA	Germany	0.15	17.4	0.34	13.6	52.0	83.6	0	AAA	Australia	0.13	11.3	0.06	1.7	74.4	75.5	0
AA	Austria	0.16	16.3	0.30	10.9	56.2	80.8	1	AAA	Denmark	0.11	8.2	0.21	5.4	46.0	64.1	0
AA	Belgium	0.12	9.4	0.36	10.2	30.8	66.6	0	AAA	Finland	0.12	11.6	0.20	6.4	60.7	78.0	0
AA	China	0.20	24.2	-0.00	-0.2	85.9	85.8	2	AAA	Hong Kong	0.17	14.3	-0.02	-0.7	71.7	71.5	2
AA	Czech	0.19	25.2	0.12	5.3	83.7	87.3	1	AAA	Netherlands	0.12	12.2	0.24	8.0	55.8	78.2	0
AA	Japan	0.16	12.2	0.07	1.8	60.2	61.2	0	AAA	Norway	0.12	10.0	0.13	3.7	64.6	72.6	0
AA	Qatar	0.18	16.3	-0.02	-0.6	74.3	74.1	1	AAA	Sweden	0.11	7.9	0.18	4.2	48.2	60.8	1
A	Chile	0.18	18.2	-0.06	-2.0	77.5	78.3	0	AAA	Switzerland	0.18	7.6	-0.03	-0.5	73.9	73.4	0
A	Israel	0.19	18.3	-0.02	-0.8	78.3	78.3	0	AAA	UK	0.11	8.9	0.24	6.6	46.7	69.9	0
A	Korea	0.19	27.7	-0.16	-8.1	82.4	89.5	0	AA	Abu Dhabi	0.10	7.8	0.05	1.1	64.4	64.6	0
A	Malaysia	0.20	31.1	-0.11	-6.2	87.7	91.1	0	AA	Estonia	0.14	17.0	-0.03	-1.2	85.6	85.7	1
A	Poland	0.19	28.1	0.20	10.5	79.3	90.4	1	AA	France	0.11	9.8	0.34	9.9	36.8	72.2	1
A	Slovakia	0.18	22.8	0.18	7.4	77.9	86.2	1	AA	New Zealand	0.20	8.4	-0.09	-1.6	73.3	74.3	0
BBB	Brazil	0.14	10.0	-0.20	-4.8	45.8	56.2	2	AA	Saudi Arabia	0.11	10.6	-0.00	-0.1	79.3	78.5	1
BBB	Bulgaria	0.19	22.2	0.11	4.5	80.9	84.1	1	AA	USA	0.10	6.1	0.17	3.6	37.0	48.2	1
BBB	Colombia	0.16	11.6	-0.15	-4.0	54.3	60.4	1	A	Slovenia	0.09	6.7	0.20	4.6	42.8	61.8	2
BBB	Croatia	0.19	23.1	0.10	4.1	82.6	85.1	0	A	Spain	0.07	4.3	0.23	4.5	19.1	38.5	3
BBB	Iceland	0.16	12.3	-0.07	-1.7	61.2	62.0	3	BBB	Bahrain	0.12	8.6	-0.01	-0.3	63.5	62.7	1
BBB	Italy	0.13	9.7	0.33	8.9	34.8	64.1	2	BBB	Ireland	0.05	2.5	0.14	2.4	9.2	16.5	3
BBB	Mexico	0.20	34.4	-0.10	-6.1	89.9	92.7	0	BBB	Kazakhstan	0.15	11.9	0.04	1.0	64.6	64.6	1
BBB	Panama	0.16	13.0	-0.17	-4.8	58.3	66.1	1	BBB	Lithuania	0.15	17.1	0.03	1.0	83.7	83.6	2
BBB	Peru	0.17	13.9	-0.16	-4.8	62.1	69.3	1	BBB	Morocco	0.10	6.9	0.10	2.3	54.2	58.9	1
BBB	Russia	0.19	26.7	-0.13	-6.1	84.5	88.9	1	BB	Costa Rica	0.24	4.5	-0.07	-0.8	47.2	46.6	0
BBB	South Africa	0.20	32.0	-0.07	-4.1	90.0	91.4	0	BB	Cyprus	1.26	0.3	-2.91	-0.4	20.6	0.0	2
BBB	Thailand	0.20	24.2	-0.09	-4.1	83.8	86.1	0	BB	El Salvador	0.18	3.1	-0.07	-0.5	28.9	26.8	0
BB	Hungary	0.18	20.4	0.17	6.7	74.7	82.6	2	BB	Guatemala	0.32	3.5	0.01	0.1	49.3	46.1	0
BB	Indonesia	0.18	25.1	-0.21	-10.1	76.4	89.1	1	BB	Latvia	0.14	12.2	-0.01	-0.3	73.5	73.1	3
BB	Philippines	0.18	21.2	-0.21	-8.6	72.4	84.2	0	BB	Vietnam	0.17	16.3	-0.15	-5.1	70.3	77.2	0
BB	Portugal	0.05	2.5	0.14	2.5	4.9	9.7	3	B	Argentina	0.14	9.8	-0.18	-4.4	48.0	57.7	1
BB	Romania	0.19	23.3	0.08	3.4	84.2	85.8	2	B	Dominican	0.54	4.5	-0.80	-4.2	0.1	70.9	1
BB	Turkey	0.18	17.4	-0.17	-5.8	70.2	77.9	1	B	Ecuador	0.14	4.0	0.57	4.1	0.0	57.7	5
B	Ukraine	0.18	15.3	-0.07	-2.0	71.2	72.1	4	B	Egypt	0.12	9.8	-0.10	-2.8	64.7	69.6	1
B	Venezuela	0.14	8.5	-0.13	-2.8	42.0	46.0	4	B	Lebanon	0.11	7.6	-0.19	-4.4	44.0	60.3	2
CCC	Greece	0.06	3.2	0.30	5.6	6.1	29.2	4	B	Pakistan	0.17	13.8	-0.18	-5.2	68.2	76.6	2
Average	AAA	0.15	17.4	0.34	13.6	52.0	83.6	0.0	Average	AAA	0.13	10.2	0.13	3.9	60.2	71.5	0.3
Average	AA	0.17	17.3	0.14	4.6	65.2	76.0	0.8	Average	AA	0.13	9.9	0.07	2.0	62.7	70.6	0.7
Average	A	0.19	24.4	0.00	0.1	80.5	85.6	0.3	Average	A	0.08	5.5	0.21	4.6	31.0	50.1	2.5
Average	BBB	0.17	19.4	-0.05	-1.9	69.0	75.5	1.0	Average	BBB	0.12	9.4	0.06	1.3	55.0	57.3	1.6
Average	BB	0.16	18.3	-0.03	-2.0	63.8	71.6	1.5	Average	BB	0.39	6.7	-0.53	-1.2	48.3	45.0	0.8
Average	B	0.16	11.9	-0.10	-2.4	56.6	59.1	4.0	Average	B	0.20	8.3	-0.15	-2.8	37.5	65.5	2.0
Overall	Mean	0.17	18.7	0.01	0.2	66.4	74.6	1.2	Overall	Mean	0.18	8.8	-0.05	1.1	52.1	62.3	1.1
Overall	SD	0.04	8.0	0.18	6.4	22.1	18.4	1.2	Overall	SD	0.21	4.2	0.55	3.8	22.8	18.9	1.2
Overall	Min	0.05	2.5	-0.21	-10.1	4.9	9.7	0.0	Overall	Min	0.05	0.3	-2.91	-5.2	0.0	0.0	0.0
Overall	Med	0.18	18.3	-0.04	-1.2	74.5	81.7	1.0	Overall	Med	0.12	8.5	0.02	0.5	55.0	67.1	1.0
Overall	Max	0.20	34.4	0.36	13.6	90.0	92.7	4.0	Overall	Max	1.26	17.1	0.57	9.9	85.6	85.7	5.0

Table 12: Results of Time Series Regressions for All Maturities. In Panel A, we redo the exercise in Table 10 for each of the six different maturities. Reported are the averages of R^2, $\widetilde{R}^2$, and $\hat{R}^2$ for each maturity. In Panel B, we redo the exercise in Table 11 for each of the six different maturities. Reported are the averages of R_1^2 and R_2^2 for each maturity. In this table, R^2, $\widetilde{R}^2$, and $\hat{R}^2$ have the same meanings as those in Table 10; similarly, R_1^2 and R_2^2 have the same meanings as those in Table 11.

In-Sample Countries							Out-of-Sample Countries						
Panel A: Time Series Regressions on Model Spreads													
	Maturity							Maturity					
	1y	2y	3y	5y	7y	10y		1y	2y	3y	5y	7y	10y
Average R^2	70.0	70.4	68.5	66.3	63.9	62.4	Average R^2	58.5	62.0	64.3	64.5	64.0	63.8
Average $\widetilde{R}^2$	84.5	87.0	87.2	87.1	84.7	83.0	Average $\widetilde{R}^2$	75.3	79.8	82.4	83.4	82.4	80.9
Average $\hat{R}^2$	77.7	84.4	87.9	89.5	87.7	85.7	Average $\hat{R}^2$	76.3	79.6	82.0	83.1	81.9	80.2
Panel B: Time Series Regressions on Principal Components													
	Maturity							Maturity					
	1y	2y	3y	5y	7y	10y		1y	2y	3y	5y	7y	10y
Average R_1^2	51.8	59.1	63.8	66.4	65.2	61.9	Average R_1^2	40.3	45.7	49.6	52.1	51.6	49.2
Average R_2^2	60.7	68.1	72.8	74.6	73.2	69.6	Average R_2^2	50.1	55.7	60.0	62.3	61.7	59.4

Table 13: Regression Results for the Common Factor z and Credit Risk Premium. The table reports the regressions of changes in the estimated common factor z (in percent) and the 5-year credit risk premium (in percent, computed by (15), averaged over all 7 ratings) on changes in the CBOE VIX index, the CDX NA IG index, the 5-Year US Treasury rate, as well as the returns in the MSCI World stock market index, the S&P 500 Index, and the DAX index. t-statistics are reported in square brackets. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Common Factor z								5-y Risk Premium							
Intercept	VIX	MSCI	DAX	S&P 500	CDX	Treasury	R^2(%)	Intercept	VIX	MSCI	DAX	S&P 500	CDX	Treasury	R^2(%)
0.00	1.83***						40.58	0.01	1.95***						45.61
[0.31]	[8.10]							[0.53]	[8.97]						
0.01		-2.27***					45.63	0.01		-2.41***					51.08
[0.71]		[-8.98]						[0.98]		[-10.01]					
0.01			-1.57***				28.38	0.02			-1.67***				31.76
[0.86]			[-6.17]					[1.09]			[-6.68]				
0.01				-2.34***			40.60	0.01				-2.45***			44.18
[0.69]				[-8.10]				[0.92]				[-8.72]			
0.00					0.73***		32.85	0.00					0.80***		39.67
[0.10]					[6.85]			[0.27]					[7.95]		
0.00						-0.08	1.61	0.00						-0.12*	3.64
[0.13]						[-1.25]		[0.23]						[-1.91]	
0.01	0.93***	-1.51***					51.00	0.01	0.99***	-1.60***					57.18
[0.62]	[3.23]	[-4.49]						[0.90]	[3.68]	[-5.07]					
0.01	0.91***	-1.91***	0.40				51.49	0.01	0.98***	-2.03***	0.42				57.73
[0.51]	[3.17]	[-3.62]	[0.98]					[0.77]	[3.62]	[-4.09]	[1.11]				
0.01	0.89***	-2.57**	0.37	0.76			51.73	0.01	0.94***	-3.26***	0.36	1.43			58.57
[0.50]	[3.09]	[-2.33]	[0.89]	[0.68]				[0.77]	[3.50]	[-3.17]	[0.96]	[1.37]			
0.01	0.85***	-2.46**	0.40	0.83	0.12		52.05	0.01	0.87***	-3.07***	0.42	1.55	0.21		59.58
[0.42]	[2.89]	[-2.21]	[0.96]	[0.74]	[0.79]			[0.62]	[3.19]	[-2.98]	[1.10]	[1.49]	[1.51]		
0.01	0.84***	-2.46**	0.34	0.86	0.13	0.02	52.16	0.01	0.88***	-3.07***	0.44	1.53	0.20	-0.01	59.61
[0.46]	[2.82]	[-2.19]	[0.80]	[0.76]	[0.86]	[0.46]		[0.58]	[3.18]	[-2.97]	[1.12]	[1.47]	[1.42]	[-0.26]	

Table 14: Credit Risk Premium. This table reports the time-series averages for the difference (in basis point) $CDS(M) - CDS^P(M)$ and the credit risk premium (in percent) $[CDS(M) - CDS^P(M)]/CDS(M)$. The first column reports the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted. The sample consists of monthly observations between January 2004 and March 2012.

		$CDS(M) - CDS^P(M)$						$[CDS(M) - CDS^P(M)]/CDS(M)$					
Rating	Country	1y	2y	3y	5y	7y	10y	1y	2y	3y	5y	7y	10y
AAA	Germany	3.1	5.7	7.9	9.4	15.9	23.4	22.5	36.5	48.5	73.0	71.4	77.5
AA	Austria	3.1	6.1	8.4	10.5	15.8	23.4	13.9	21.7	34.5	62.1	64.6	69.4
AA	Belgium	3.9	8.9	14.5	15.7	28.7	39.3	9.3	18.7	26.9	65.6	59.7	64.6
AA	China	4.0	8.8	14.6	26.6	37.9	51.6	21.4	35.2	38.8	47.7	55.7	64.6
AA	Czech	5.8	12.4	14.5	24.9	35.5	48.3	15.1	30.2	56.9	66.4	69.1	74.2
AA	Japan	3.4	6.6	8.5	15.0	22.1	31.3	17.7	36.7	55.5	63.7	67.8	73.9
AA	Qatar	2.5	5.9	9.9	18.7	27.4	38.8	6.8	11.8	17.6	28.4	37.5	47.6
A	Chile	4.1	9.6	15.7	28.1	39.0	52.0	11.6	20.7	28.8	42.0	51.7	61.7
A	Israel	4.2	9.9	16.3	29.0	40.5	53.5	6.9	13.9	20.5	32.1	41.3	51.0
A	Korea	4.2	9.8	16.2	28.7	39.5	52.1	7.2	14.2	20.8	32.4	41.5	51.0
A	Malaysia	4.1	9.6	15.9	27.8	39.4	52.4	8.7	16.7	24.1	36.4	46.1	56.0
A	Poland	6.6	13.9	17.1	32.6	46.0	61.0	12.7	29.5	53.1	57.4	60.5	65.5
A	Slovakia	6.6	14.5	16.7	27.4	39.0	52.3	16.4	29.6	56.8	68.2	71.3	76.3
BBB	Brazil	12.7	27.8	43.6	75.1	93.1	113.0	12.8	23.2	31.7	43.1	50.8	57.9
BBB	Bulgaria	11.8	24.1	34.6	56.1	72.0	88.2	19.9	28.5	37.6	43.5	49.5	56.4
BBB	Colombia	17.2	38.9	59.9	93.3	115.7	134.2	20.8	32.8	41.5	51.1	59.4	65.7
BBB	Croatia	11.5	23.3	33.8	54.4	69.9	85.7	16.4	27.5	35.8	42.5	49.0	56.0
BBB	Iceland	14.1	29.9	43.6	45.4	74.0	84.2	7.4	14.5	21.7	48.1	36.4	41.6
BBB	Italy	5.5	11.0	16.5	29.0	38.9	49.7	15.9	35.1	44.7	49.5	55.7	63.2
BBB	Mexico	10.0	21.3	32.8	53.5	69.6	86.4	12.8	22.7	30.9	43.4	52.2	61.1
BBB	Panama	15.5	34.6	53.4	85.3	107.6	127.6	18.3	30.8	40.0	52.2	59.7	67.0
BBB	Peru	11.1	25.1	40.5	68.8	89.9	110.1	13.5	23.6	31.9	43.7	50.9	58.1
BBB	Russia	10.6	23.2	35.8	57.3	73.5	90.0	8.8	16.7	23.8	34.9	42.9	51.2
BBB	South Africa	10.1	21.3	32.8	53.5	69.8	86.9	13.6	22.2	29.9	42.2	51.0	59.9
BBB	Thailand	9.9	21.0	32.4	53.2	69.6	86.9	32.0	39.1	45.5	56.6	64.8	73.4
BB	Hungary	11.8	24.1	35.2	54.1	68.2	82.0	21.8	29.8	34.8	41.4	48.1	55.4
BB	Indonesia	25.0	55.2	81.8	120.4	142.8	160.6	29.0	38.1	45.4	54.4	61.0	66.5
BB	Philippines	19.9	45.2	67.9	102.7	123.9	140.4	20.7	31.7	38.9	48.4	53.8	58.7
BB	Portugal	9.4	18.6	27.5	34.6	50.3	57.8	15.1	31.0	33.7	49.9	46.1	53.5
BB	Romania	24.7	45.7	62.1	89.6	109.5	127.7	20.7	39.0	45.1	49.6	56.5	64.2
BB	Turkey	20.9	47.0	70.9	109.5	130.6	149.4	16.7	27.8	35.9	46.3	53.9	60.5
B	Ukraine	86.2	137.1	170.3	208.5	235.0	255.5	13.6	21.2	27.4	37.2	43.2	50.0
B	Venezuela	42.3	79.2	105.6	136.4	149.6	159.2	8.3	13.9	17.7	23.4	26.9	30.6
CCC	Greece	44.9	58.9	58.5	71.8	84.5	97.1	16.3	29.9	45.6	50.5	53.3	58.4
—	AAA	3.1	5.8	7.9	9.6	15.3	22.8	18.5	29.7	42.2	68.3	68.4	73.7
—	AA	3.2	6.5	10.0	15.3	25.0	34.8	13.6	28.6	37.7	55.7	55.9	63.3
—	A	4.6	10.5	15.8	27.4	38.7	51.4	12.0	22.2	34.7	46.3	52.7	60.9
—	BBB	12.3	25.6	37.1	59.0	75.2	91.1	17.9	28.5	38.5	47.8	54.6	61.8
—	BB	19.3	42.6	63.9	95.7	116.5	133.8	15.3	25.7	32.4	41.5	47.6	53.3
—	B	84.8	139.9	178.9	216.8	253.6	275.4	26.7	32.7	38.3	45.4	53.0	60.4
—	CCC	225.4	312.5	359.5	410.5	440.2	470.7	8.2	13.0	16.4	21.2	24.6	28.4
—	Overall	14.6	28.3	39.3	56.7	72.2	86.6	15.4	26.1	35.9	47.9	53.1	60.2

Table 15: OLS regression of monthly variations of the estimated country-specific factor y on Macro variables (GDP growth rate, GDP per capita, Government effectiveness, Stock market return, and Total reserve) for each country. Reported are the regression beta-s together with there respective statistical significance when all variables are included in the regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. All data are obtained from the World Bank Open Data service. We include an independent variable only if it has at least 9 observations, otherwise we input the mark "NA" indicating not available. In each month, we use the most recent observation if there is no data for that month. In the first column, we report the last-month rating for each country. The last row reports the averaged adjusted-R^2, where the 3rd to 7th column report the results of bivariate regressions.

Rating	Country	GDPgr	GDPpc	GovEff	MarRet	Reserve	Adj-R^2
AAA	Germany	0.12***	-0.31***	0.26	0.16	0.79	53.07
AA	Austria	-0.24	0.66**	0.01**	-0.04	0.02***	56.47
AA	Belgium	-0.03***	0.40	0.41	-0.07	0.80***	72.47
AA	China	0.46	1.15***	-0.52**	-0.12	-0.23***	57.90
AA	Czech Republic	-0.24	-0.50***	0.11**	0.00	1.00***	34.52
AA	Japan	-0.20***	0.71***	0.14***	0.10*	-0.11	45.05
AA	Qatar	-0.32***	0.49	-0.27	-0.03**	0.46***	57.75
A	Chile	-0.12	0.69	0.26***	0.02	-1.28	42.68
A	Israel	0.19**	0.12*	-0.09	0.32	0.43***	28.31
A	Korea	-0.29	0.34***	0.33***	-0.17**	-0.67***	38.71
A	Malaysia	0.05	-0.14*	0.42**	-0.19	0.13***	24.54
A	Poland	-0.08*	0.81	0.35	-0.02	-0.03***	85.73
A	Slovakia	-0.35***	0.15***	-0.08***	NA	NA	15.37
BBB	Brazil	0.34***	0.10	0.05	0.04	-0.84***	74.87
BBB	Bulgaria	-0.09**	1.05	-0.16	-0.07***	-0.49**	58.82
BBB	Colombia	0.35	-0.10*	0.05	0.08**	-0.71***	84.78
BBB	Croatia	-0.11**	0.04***	0.47	0.03	0.13	38.39
BBB	Iceland	-0.34***	0.38*	-0.70	-0.19*	-0.51***	60.59
BBB	Italy	0.08	-0.40	-0.03***	-0.17**	0.91	56.87
BBB	Mexico	0.35***	-0.01	0.00	0.08	-0.76***	66.50
BBB	Panama	-0.16**	-0.53***	-0.11	NA	-0.11	63.80
BBB	Peru	0.16***	-0.22	0.13	0.00	-0.70***	70.43
BBB	Russia	-0.37***	-0.06***	0.37	-0.46	-0.14	50.16
BBB	South Africa	0.17*	-0.11***	0.02***	-0.01	-0.52	40.78
BBB	Thailand	0.32	-0.02***	0.67	0.07*	0.08***	59.43
BB	Hungary	-0.13***	-0.06***	-0.11*	-0.04	0.60***	45.99
BB	Indonesia	0.24***	-0.20***	-0.02***	-0.03***	-0.59*	67.13
BB	Philippines	0.17***	-0.82	0.00***	0.02***	-0.06	85.81
BB	Portugal	0.02***	0.75	-0.09	-0.15	0.63	31.99
BB	Romania	0.41*	-0.61	-0.59	0.28	0.35**	33.25
BB	Turkey	0.31***	-0.51	-0.60***	0.07	0.48	64.48
B	Ukraine	-0.25***	0.21**	0.86***	-0.15	-0.07**	55.77
B	Venezuela	0.05***	0.50	0.08***	-0.17**	0.30	38.91
CCC	Greece	-0.14	0.31***	-0.30	-0.02**	0.28***	32.46
Average	Adj-R^2	9.87	32.38	18.42	1.99	33.04	52.76

Table 16: Mean Absolute Pricing Error Relative to Bid-Ask Spread (Full Sample). The pricing errors are based on the estimated model with both observed and derived data of all 68 countries. We also report the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012.

Rating	Country	1y	2y	3y	5y	7y	10y	Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Germany	3.6	2.6	1.4	1.2	2.2	3.2	AAA	Australia	1.3	0.6	0.2	1.3	1.1	0.5
AA	Austria	2.0	1.4	0.9	1.2	1.5	2.4	AAA	Denmark	2.1	1.0	0.6	1.0	1.2	1.7
AA	Belgium	1.6	1.0	1.2	0.7	1.3	3.1	AAA	Finland	3.0	1.2	0.5	1.1	1.1	1.5
AA	China	1.9	1.5	0.9	1.2	1.4	2.5	AAA	Hong Kong	0.8	0.7	0.5	0.3	0.9	1.6
AA	Czech	0.9	0.8	0.8	0.4	1.1	2.9	AAA	Netherlands	1.9	1.2	0.6	1.0	1.3	1.8
AA	Japan	4.7	2.3	1.1	1.4	2.1	2.9	AAA	Norway	1.3	1.1	0.7	0.8	0.9	1.4
AA	Qatar	1.0	0.5	0.3	0.7	0.7	1.1	AAA	Sweden	2.3	1.4	0.6	1.2	1.2	1.6
A	Chile	0.7	0.5	0.3	0.6	0.5	0.9	AAA	Switzerland	1.2	1.0	0.5	0.9	1.1	0.8
A	Israel	1.1	0.4	0.3	0.8	0.6	0.7	AAA	UK	5.1	3.2	1.4	2.2	2.2	2.2
A	Korea	1.2	0.9	0.6	1.2	1.2	2.0	AA	Abu Dhabi	1.8	1.3	0.7	0.9	1.1	2.2
A	Malaysia	1.7	1.1	0.5	1.1	1.0	1.5	AA	Estonia	1.5	0.7	0.6	0.9	1.1	1.7
A	Poland	2.0	1.1	0.9	1.1	1.8	3.3	AA	France	3.1	2.2	1.0	1.7	2.0	2.6
A	Slovakia	0.8	0.8	0.8	0.5	1.2	2.9	AA	New Zealand	0.4	0.8	1.1	0.6	1.0	2.8
BBB	Brazil	4.9	2.9	1.3	3.4	3.1	4.7	AA	Saudi Arabia	0.4	0.5	0.2	0.4	0.5	1.3
BBB	Bulgaria	1.7	0.8	0.5	0.9	1.2	2.2	AA	USA	0.8	0.7	0.7	0.6	1.1	1.9
BBB	Colombia	3.7	2.1	1.0	1.7	2.3	3.2	A	Slovenia	1.6	0.8	0.6	1.0	1.1	1.5
BBB	Croatia	1.1	0.7	0.6	0.7	1.0	1.8	A	Spain	2.0	1.5	1.5	1.7	2.0	3.1
BBB	Iceland	0.8	0.8	0.4	0.4	1.3	2.4	BBB	Bahrain	0.6	0.4	0.4	0.6	0.7	1.6
BBB	Italy	1.5	1.2	1.1	1.2	1.6	3.0	BBB	Ireland	1.2	1.5	1.3	1.4	2.6	3.9
BBB	Mexico	3.2	1.5	0.8	2.0	1.9	2.8	BBB	Kazakhstan	2.4	0.8	0.4	1.6	1.3	1.6
BBB	Panama	1.9	1.0	0.6	0.8	1.3	2.0	BBB	Lithuania	1.3	0.9	0.6	0.6	1.5	2.5
BBB	Peru	2.5	1.2	0.6	1.3	1.5	2.2	BBB	Morocco	0.5	0.4	0.3	0.2	0.6	1.1
BBB	Russia	3.9	1.3	0.8	2.8	2.3	2.7	BB	Costa Rica	1.1	1.1	0.7	0.3	1.1	1.7
BBB	South Africa	2.9	1.4	0.6	1.8	1.6	2.0	BB	Cyprus	0.9	1.1	0.9	0.5	1.7	3.1
BBB	Thailand	1.3	0.9	0.6	0.9	1.0	1.8	BB	El Salvador	0.9	0.5	0.4	0.4	0.6	1.1
BB	Hungary	2.2	1.1	0.7	1.7	1.7	2.7	BB	Guatemala	0.5	0.5	0.3	0.2	0.5	0.7
BB	Indonesia	1.9	1.9	1.5	1.2	1.8	3.3	BB	Latvia	1.5	1.1	0.6	1.1	1.8	2.5
BB	Philippines	3.0	2.5	1.6	2.3	2.3	3.6	BB	Vietnam	0.7	0.6	0.5	0.6	0.9	1.4
BB	Portugal	1.3	1.3	1.1	1.0	2.4	3.7	B	Argentina	6.6	3.8	1.7	3.2	4.8	8.1
BB	Romania	1.6	1.0	0.6	0.8	1.7	2.8	B	Dominican	1.1	0.4	0.1	0.5	0.6	0.9
BB	Turkey	5.2	3.5	1.7	3.2	3.7	6.3	B	Ecuador	1.5	0.7	0.8	1.1	1.8	2.2
B	Ukraine	3.2	2.1	1.0	2.0	2.8	4.4	B	Egypt	1.0	0.7	0.5	0.6	1.1	1.8
B	Venezuela	3.6	2.4	1.1	2.5	3.7	5.2	B	Lebanon	1.4	1.3	1.0	0.5	1.5	2.8
CCC	Greece	1.5	1.3	0.8	1.5	2.8	4.4	B	Pakistan	1.1	0.9	0.8	0.4	1.1	1.8
—	AAA	2.7	2.0	1.1	1.2	1.9	2.8	—	AAA	2.2	1.4	0.7	1.2	1.4	1.7
—	AA	2.5	1.4	0.9	0.9	1.4	2.4	—	AA	1.2	1.0	0.9	0.9	1.2	2.2
—	A	1.2	0.8	0.7	0.8	1.1	2.2	—	A	1.3	1.0	0.7	0.8	1.4	2.5
—	BBB	2.3	1.1	0.7	1.5	1.7	2.5	—	BBB	1.7	0.8	0.5	1.2	1.5	2.0
—	BB	3.1	2.3	1.2	2.1	2.5	3.9	—	BB	0.9	0.7	0.5	0.5	1.0	1.5
—	B	4.6	2.6	1.0	2.1	3.7	5.6	—	B	3.2	2.1	1.1	1.5	2.6	4.4
—	CCC	1.1	0.5	0.4	1.1	1.5	1.7	—	CCC	1.3	0.6	0.6	1.1	1.5	1.8
—	Overall	2.2	1.4	0.8	1.4	1.7	2.8	—	Overall	1.8	1.2	0.7	1.0	1.4	2.2

Table 17: Mean Absolute Pricing Error Relative to Bid-Ask Spread for In-Sample and Out-of-Sample Countries (Even Sample). We also report the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012.

In-Sample Countries								Out-of-Sample Countries							
Rating	Country	1y	2y	3y	5y	7y	10y	Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Denmark	1.9	0.9	0.6	0.9	1.1	1.6	AAA	Australia	0.8	0.4	0.4	1.2	0.7	1.0
AAA	Germany	3.2	2.3	1.3	1.2	1.9	2.6	AAA	Finland	2.8	1.0	0.5	1.0	1.0	1.4
AAA	Hong Kong	0.8	0.6	0.4	0.3	0.8	1.5	AAA	Norway	1.3	1.1	0.6	0.8	0.9	1.3
AAA	Netherlands	1.7	1.0	0.6	1.0	1.1	1.6	AAA	Sweden	2.1	1.3	0.6	1.2	1.1	1.5
AAA	UK	4.4	2.9	1.2	2.1	2.0	1.8	AAA	Switzerland	1.0	0.9	0.4	0.8	1.0	0.8
AA	Austria	1.7	1.3	0.8	1.1	1.3	2.1	AA	Abu Dhabi	2.4	1.4	0.6	1.2	1.3	2.1
AA	Belgium	1.7	0.9	1.1	0.9	1.4	2.7	AA	Estonia	1.8	0.8	0.6	1.0	1.3	1.6
AA	China	2.3	1.7	0.9	1.3	1.6	2.4	AA	France	2.7	1.8	0.9	1.6	1.6	2.1
AA	Czech	1.0	0.7	0.7	0.6	1.1	2.6	AA	New Zealand	0.3	0.6	1.0	0.7	0.6	2.3
AA	Japan	5.1	2.5	1.2	1.5	2.3	2.9	AA	Saudi Arabia	0.4	0.3	0.2	0.5	0.4	0.9
AA	Qatar	1.3	0.7	0.3	0.8	0.9	1.0	AA	USA	0.7	0.7	0.7	0.5	0.9	1.7
A	Israel	1.4	0.6	0.3	0.8	0.8	0.7	A	Chile	1.0	0.5	0.3	0.6	0.6	0.8
A	Korea	1.5	1.0	0.6	1.2	1.4	1.9	A	Slovakia	0.8	0.7	0.7	0.6	1.2	2.6
A	Malaysia	2.2	1.4	0.5	1.2	1.2	1.6	A	Slovenia	1.6	0.9	0.5	1.0	1.1	1.4
A	Poland	2.5	1.1	0.8	1.4	2.0	3.1	A	Spain	2.0	1.4	1.4	1.8	1.7	2.6
BBB	Bulgaria	1.7	0.8	0.5	0.9	1.2	2.2	BBB	Bahrain	0.6	0.3	0.4	0.8	0.5	1.3
BBB	Colombia	3.8	2.0	0.9	1.9	2.3	2.9	BBB	Brazil	4.9	2.8	1.1	3.8	3.0	4.3
BBB	Croatia	1.1	0.7	0.6	0.7	0.9	1.8	BBB	Iceland	0.8	0.8	0.4	0.4	1.4	2.5
BBB	Italy	1.6	1.1	1.0	1.4	1.4	2.4	BBB	Ireland	1.1	1.4	1.4	1.4	2.4	3.9
BBB	Mexico	3.4	1.6	0.8	2.1	1.9	2.8	BBB	Kazakhstan	2.3	0.7	0.5	1.6	1.3	1.6
BBB	Panama	2.0	1.0	0.5	1.0	1.2	1.8	BBB	Lithuania	1.4	1.0	0.6	0.7	1.6	2.8
BBB	South Africa	3.0	1.4	0.6	1.9	1.7	2.0	BBB	Morocco	0.5	0.4	0.4	0.3	0.7	1.2
BBB	Thailand	1.4	0.9	0.5	0.9	1.0	1.7	BBB	Peru	2.6	1.2	0.5	1.5	1.5	2.0
BB	Hungary	2.2	1.1	0.7	1.8	1.8	2.8	BBB	Russia	4.0	1.3	0.8	3.0	2.4	2.7
BB	Indonesia	1.8	1.6	1.2	1.2	1.6	2.8	BB	Costa Rica	1.1	1.0	0.7	0.3	1.0	1.7
BB	Philippines	3.0	2.3	1.3	2.6	2.2	3.2	BB	Cyprus	0.9	1.1	0.8	0.8	2.1	3.4
BB	Portugal	1.3	1.3	1.1	1.1	2.3	3.5	BB	El Salvador	0.8	0.4	0.3	0.5	0.5	0.7
BB	Romania	1.7	1.1	0.6	1.0	1.8	2.9	BB	Guatemala	0.5	0.5	0.2	0.2	0.6	0.8
BB	Turkey	5.0	3.2	1.4	3.5	3.6	5.3	BB	Latvia	1.6	1.3	0.7	1.2	2.1	3.0
B	Argentina	4.9	2.8	1.2	2.4	3.3	5.7	BB	Vietnam	0.8	0.6	0.5	0.7	1.1	1.5
B	Pakistan	0.8	0.6	0.5	0.4	0.8	1.2	B	Dominican	0.9	0.4	0.1	0.4	0.5	0.8
B	Ukraine	2.6	1.7	0.7	2.0	2.2	3.2	B	Ecuador	2.0	1.0	0.6	1.5	2.4	2.4
B	Venezuela	3.4	2.3	1.1	2.6	4.0	5.3	B	Egypt	1.0	0.7	0.5	0.6	1.2	1.9
CCC	Greece	1.7	1.4	0.8	1.8	3.1	4.5	B	Lebanon	1.2	1.0	0.9	0.5	1.2	2.2
—	AAA	2.4	1.6	0.9	1.2	1.5	2.0	—	AAA	1.6	1.1	0.6	1.0	1.1	1.5
—	AA	2.5	1.4	0.8	1.0	1.5	2.2	—	AA	1.4	1.0	0.9	1.1	1.1	2.0
—	A	1.6	0.9	0.6	1.0	1.2	2.0	—	A	1.1	0.8	0.6	0.7	1.1	1.9
—	BBB	2.2	1.2	0.7	1.4	1.6	2.5	—	BBB	2.5	1.0	0.6	1.7	1.8	2.5
—	BB	2.9	2.1	1.1	2.2	2.6	3.7	—	BB	1.7	1.2	0.6	1.3	1.5	2.1
—	B	3.0	1.7	0.9	1.5	2.3	3.8	—	B	1.6	1.1	0.7	0.6	1.3	2.3
—	CCC	1.0	0.5	0.3	0.9	1.4	1.6	—	CCC	2.4	1.2	0.6	2.0	3.0	3.3
—	Overall	2.3	1.4	0.8	1.4	1.7	2.6	—	Overall	1.7	1.0	0.6	1.2	1.3	2.0

Table 18: Mean Absolute Pricing Error Relative to Bid-Ask Spread (Observed Sample). The pricing errors are based on the estimated model with the observed data of all 68 countries. We also report the last-month rating for each country. The average for each rating is computed according to the actual rating when the price is quoted rather than the last-month rating for each country. The sample consists of monthly observations between January 2004 and March 2012.

Rating	Country	1y	2y	3y	5y	7y	10y	Rating	Country	1y	2y	3y	5y	7y	10y
AAA	Germany	—	—	16.9	0.4	0.8	0.9	AAA	Australia	—	—	—	0.0	—	—
AA	Austria	—	—	0.8	0.7	—	0.9	AAA	Denmark	—	—	2.3	0.3	—	2.0
AA	Belgium	—	—	2.8	1.4	—	2.6	AAA	Finland	—	—	4.5	0.3	—	1.6
AA	China	0.3	0.7	0.2	0.2	0.3	0.4	AAA	Hong Kong	—	—	0.3	0.0	0.3	0.2
AA	Czech	—	—	—	0.2	0.1	0.6	AAA	Netherlands	—	—	2.3	0.4	—	1.6
AA	Japan	—	—	1.4	0.1	0.5	0.3	AAA	Norway	—	—	4.9	0.2	—	0.5
AA	Qatar	0.7	0.3	0.5	0.0	0.3	1.2	AAA	Sweden	—	—	—	0.4	—	1.7
A	Chile	0.5	0.3	0.1	0.1	0.3	0.6	AAA	Switzerland	—	—	—	0.5	—	0.5
A	Israel	1.2	0.7	0.5	0.2	0.7	1.6	AAA	UK	—	—	15.9	0.7	—	1.5
A	Korea	0.8	0.4	0.2	0.3	0.4	0.4	AA	Abu Dhabi	—	—	—	0.0	—	—
A	Malaysia	0.8	1.2	0.5	0.3	0.7	0.6	AA	Estonia	—	0.2	—	0.1	—	0.8
A	Poland	0.8	0.4	0.6	0.3	0.7	0.9	AA	France	—	—	0.8	0.8	0.1	1.0
A	Slovakia	1.0	0.4	0.3	0.2	0.3	0.9	AA	New Zealand	—	—	—	0.0	—	—
BBB	Brazil	5.6	4.4	1.7	2.6	3.7	6.2	AA	Saudi Arabia	—	—	—	0.0	—	—
BBB	Bulgaria	0.9	0.5	0.3	0.2	0.3	1.1	AA	USA	0.5	—	3.5	0.2	—	0.4
BBB	Colombia	5.1	2.9	1.7	1.3	3.2	4.4	A	Slovenia	—	—	—	0.0	—	1.7
BBB	Croatia	0.8	0.5	0.5	0.2	0.4	0.6	A	Spain	0.4	2.2	5.1	4.1	—	3.8
BBB	Iceland	0.9	—	—	0.7	—	2.9	BBB	Bahrain	—	—	—	0.0	—	—
BBB	Italy	3.8	1.2	1.9	2.3	1.4	3.1	BBB	Ireland	4.4	5.2	—	3.4	2.3	3.9
BBB	Mexico	3.2	2.8	1.4	1.4	3.1	3.4	BBB	Kazakhstan	1.1	2.0	0.6	0.2	0.3	0.5
BBB	Panama	1.9	1.5	0.8	0.4	1.4	2.5	BBB	Lithuania	—	—	0.8	0.1	—	1.4
BBB	Peru	2.5	2.1	1.7	0.9	2.1	2.7	BBB	Morocco	—	—	—	0.0	—	—
BBB	Russia	2.4	1.1	1.1	1.5	0.5	1.6	BB	Costa Rica	—	—	—	0.0	—	—
BBB	South Africa	1.8	1.1	1.0	0.8	1.0	1.2	BB	Cyprus	—	—	1.5	1.2	—	1.2
BBB	Thailand	0.6	0.8	0.2	0.2	0.3	0.5	BB	El Salvador	—	—	—	0.0	—	—
BB	Hungary	0.9	1.1	1.0	0.8	1.1	1.6	BB	Guatemala	—	—	—	—	—	—
BB	Indonesia	2.6	2.7	1.8	0.8	1.6	3.4	BB	Latvia	5.4	—	0.3	0.4	—	2.1
BB	Philippines	3.8	2.8	1.4	1.7	2.4	4.1	BB	Vietnam	0.8	—	0.9	0.0	0.3	1.1
BB	Portugal	2.1	3.6	0.6	2.4	0.8	3.0	B	Argentina	8.2	5.1	3.0	2.8	6.3	12.1
BB	Romania	0.6	0.5	0.4	0.2	0.5	0.9	B	Dominican	—	—	—	—	—	—
BB	Turkey	5.7	3.8	1.6	3.3	3.7	7.5	B	Ecuador	—	0.3	0.6	0.5	—	1.5
B	Ukraine	3.5	2.9	1.3	1.8	3.0	6.0	B	Egypt	—	—	—	0.0	—	—
B	Venezuela	4.3	3.0	1.5	2.9	3.7	6.3	B	Lebanon	—	—	—	0.0	—	—
CCC	Greece	2.4	3.3	0.7	2.1	2.8	4.1	B	Pakistan	—	—	1.4	0.2	—	0.8
—	AAA	—	—	16.9	0.5	0.8	0.9	—	AAA	0.5	—	6.9	0.5	0.1	1.6
—	AA	2.2	1.2	1.3	0.5	0.7	2.2	—	AA	0.4	2.2	1.7	1.2	0.3	3.3
—	A	0.7	0.6	0.4	0.6	0.4	1.5	—	A	—	0.2	7.4	0.4	—	3.4
—	BBB	1.6	1.2	1.0	0.7	1.1	1.7	—	BBB	1.5	2.7	0.7	0.4	0.5	1.5
—	BB	4.2	3.1	1.5	1.9	2.8	5.0	—	BB	2.0	—	0.9	0.1	0.3	1.6
—	B	4.9	3.4	1.8	1.4	3.2	6.8	—	B	8.2	5.1	3.0	1.5	6.3	10.9
—	CCC	1.2	0.6	0.3	0.8	3.5	3.2	—	CCC	—	0.3	0.6	0.5	—	1.5
—	Overall	2.7	2.2	1.3	1.0	1.8	2.7	—	Overall	6.3	4.5	3.1	0.7	3.4	2.7

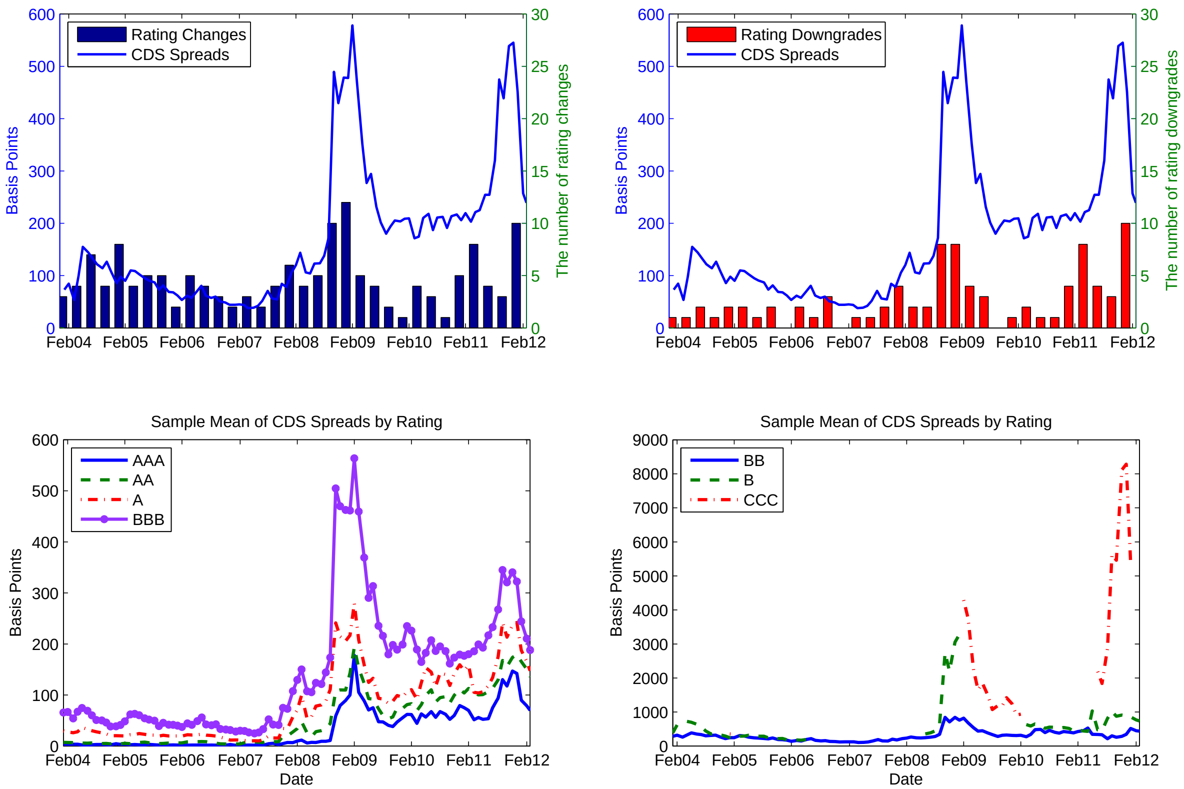

Figure 1: Time Series of Average CDS Spreads and Numbers of Rating Changes for In-Sample Countries. Top Left (Right) Panel: time series of 5-Year CDS Spreads averaged across countries and maturities and quarterly rating changes (downgrades) by one notch or more. Numbers of rating changes here include those with minor changes (e.g., "+" and "-") within each broad rating category. Bottom Panels: time series of 5-Year CDS spreads averaged across countries at seven different ratings.

Figure 2: Pricing Errors of the In-sample Non-Eurozone Countries with Low Relative Pricing Errors. This figure plots the time series of the absolute pricing errors (dash-dot lines) and the Bid-Ask spreads (solid lines) for each country, both series are averaged across maturities. "SD" is for Selective Default, "n" is for negative Credit Watch, and "p" is for positive Credit Watch. Vertical lines represent the dates of either credit rating changes or announcements of Credit Watch.

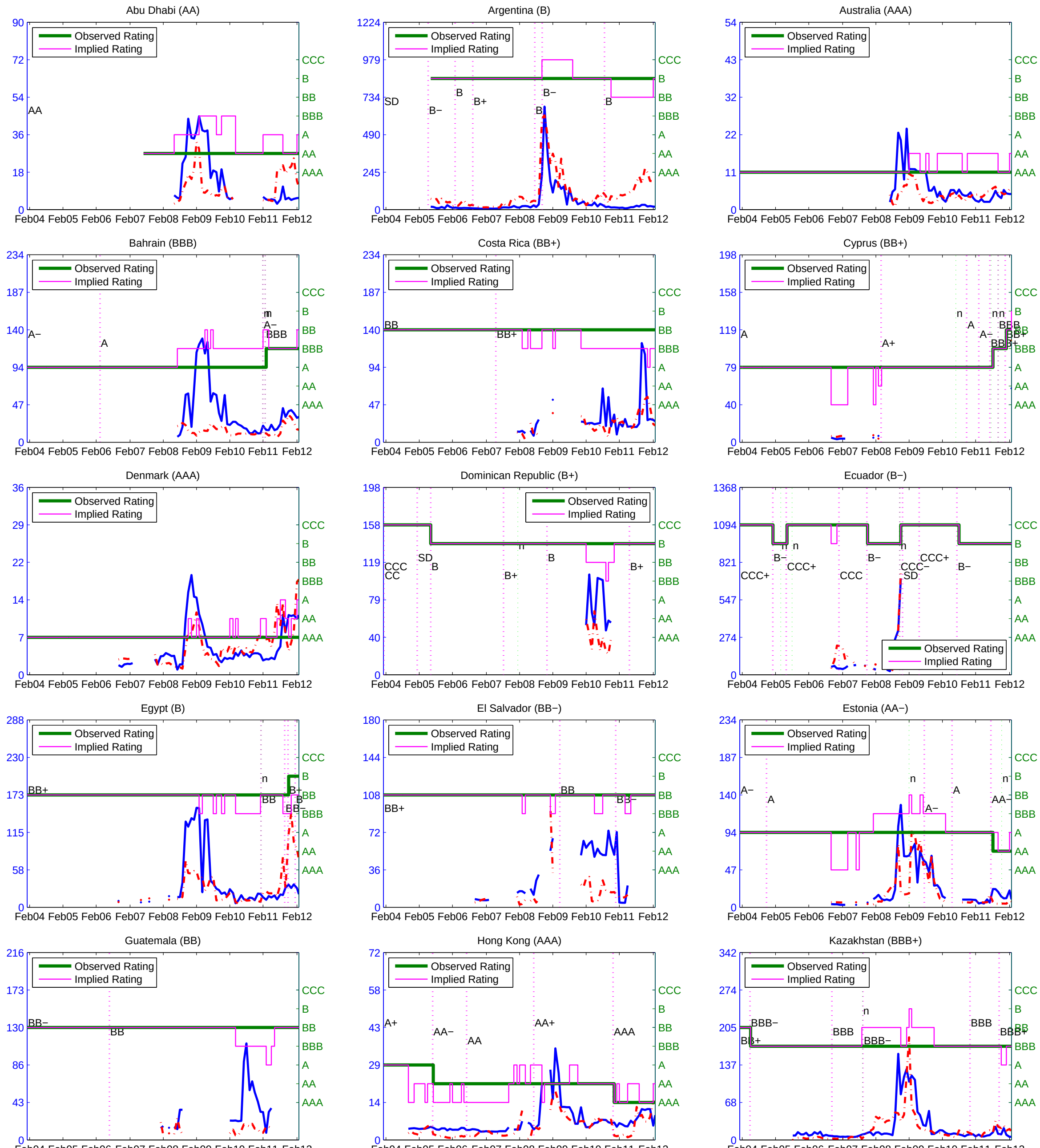

Figure 3: Pricing Errors of the Out-of-Sample Non-Eurozone Countries. This figure plots the time series of the absolute pricing errors (dash-dot lines) and the Bid-Ask spreads (solid lines) for each country, both series are averaged across maturities. “SD” is for Selective Default, “n” is for negative Credit Watch, and “p” is for positive Credit Watch. Vertical lines represent the dates of either credit rating changes or announcements of Credit Watch.

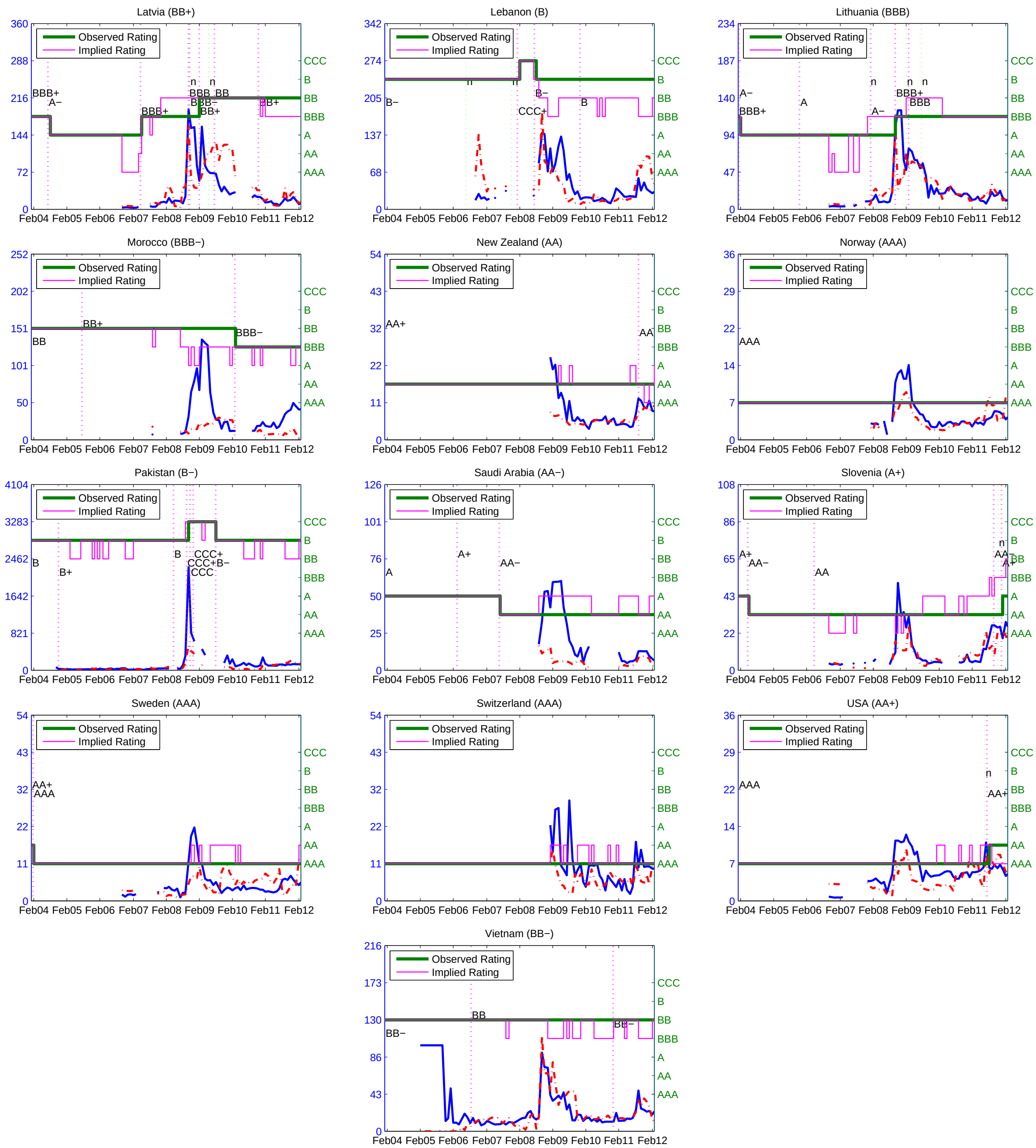

Figure 3: (Continued)

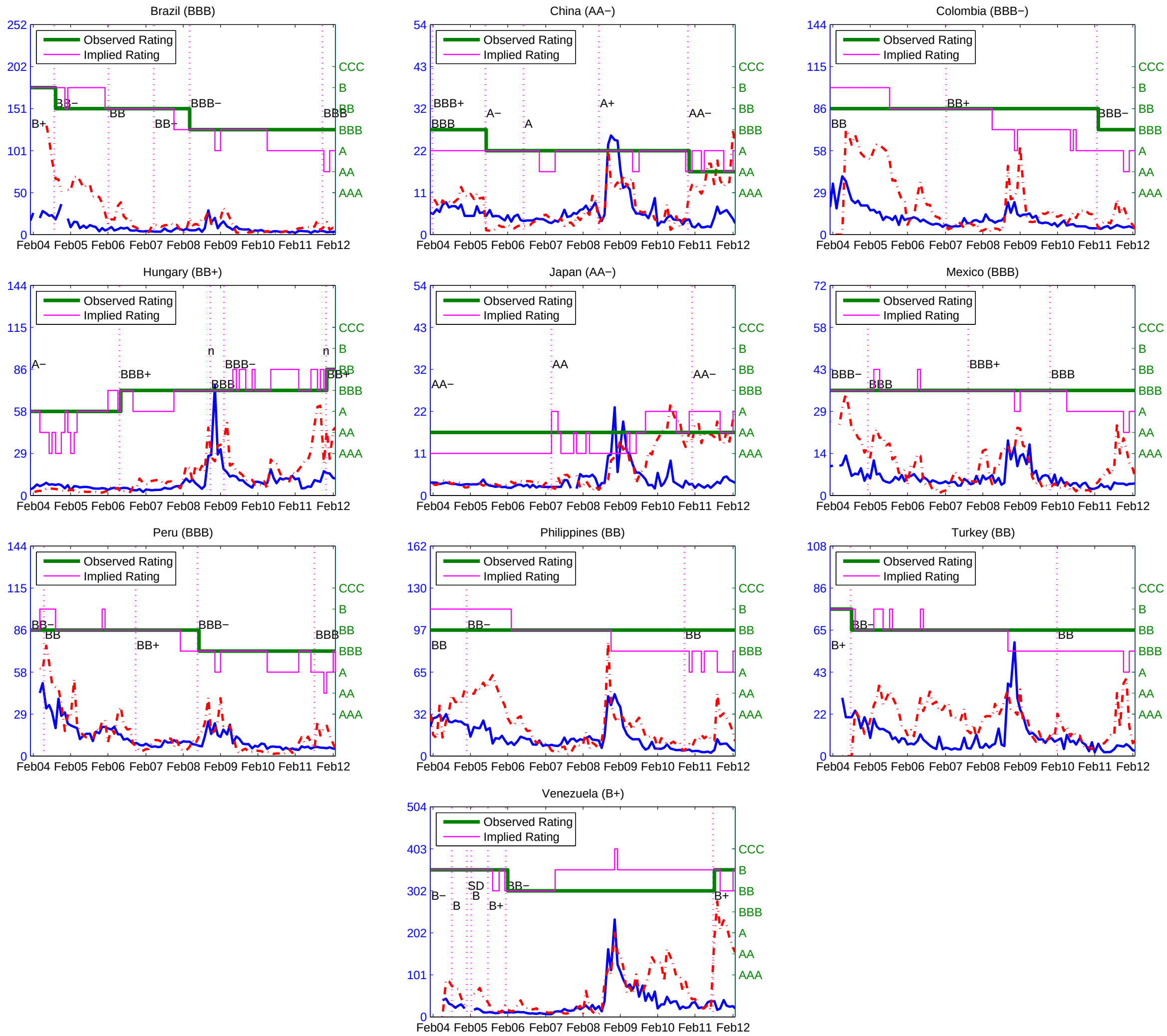

Figure 4: Pricing Errors of the In-Sample Non-Eurozone Countries with High Relative Pricing Errors. This figure plots the time series of the absolute pricing errors (dash-dot lines) and the Bid-Ask spreads (solid lines) for each country, both series are averaged across maturities. "SD" is for Selective Default, "n" is for negative Credit Watch, and "p" is for positive Credit Watch. Vertical lines represent the dates of either credit rating changes or announcements of Credit Watch.

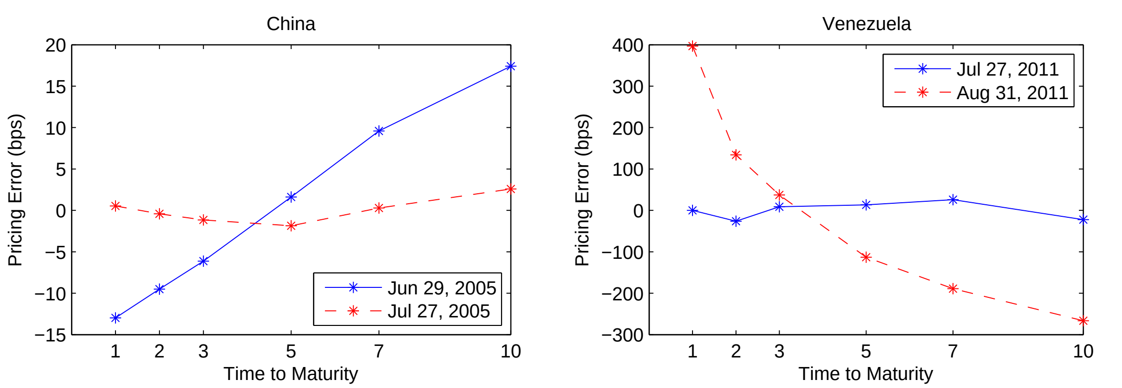

Figure 5: CDS Pricing Errors around Rating Changes. China was upgraded to A- from BBB+ on July 20, 2005, and Venezuela was downgraded to B+ from BB- on August 22, 2011.

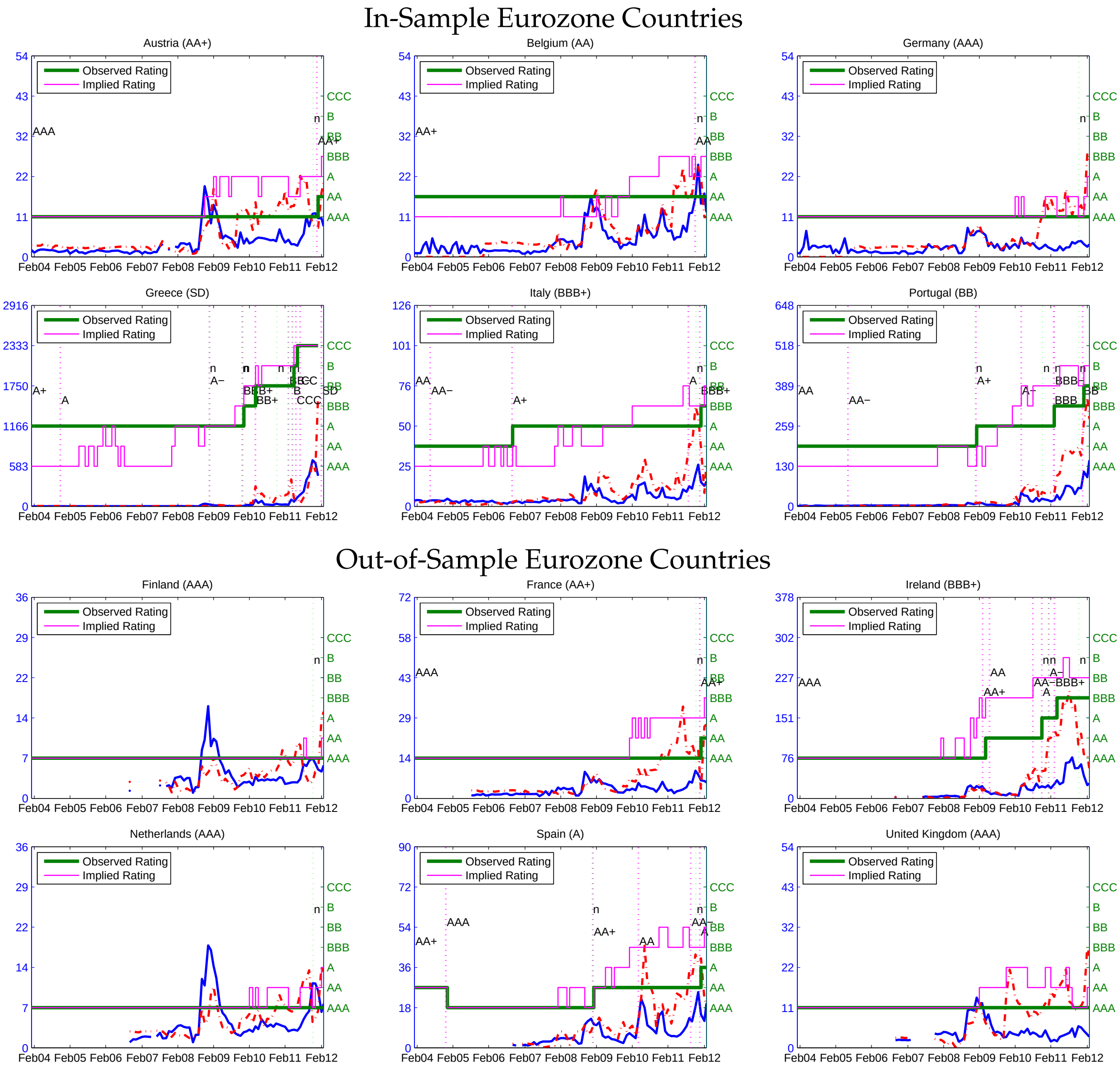

Figure 6: Pricing Errors of the Eurozone Countries. This figure plots the time series of the absolute pricing errors (dash-dot lines) and the Bid-Ask spreads (solid lines) for each country, both series are averaged across maturities. "SD" is for Selective Default, "n" is for negative Credit Watch, and "p" is for positive Credit Watch. Vertical lines represent the dates of either credit rating changes or announcements of Credit Watch.

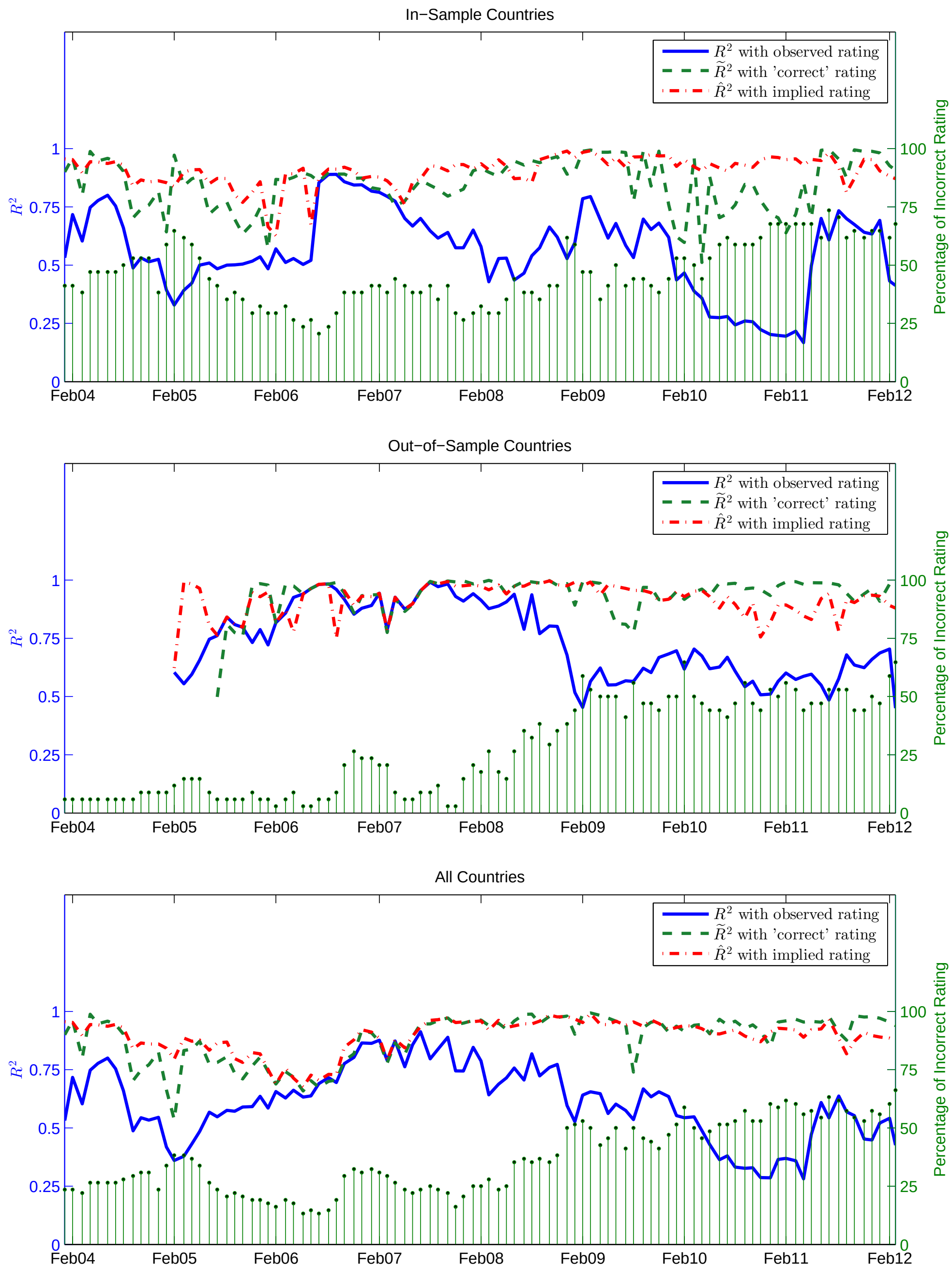

Figure 7: Cross Sectional Regressions. We regress the 5-year market CDS spreads on 5-year model z-spread for each month and plot the resulting R^2s (with observed rating). We repeat the regressions after removing the countries with "stale rating" and plot the resulting $\widetilde{R}^2$s (with 'correct' rating). We also perform the regressions using "implied rating" and plot the resulting $\hat{R}^2$s (with implied rating). For the in-sample countries, the means of R^2, $\widetilde{R}^2$, and $\hat{R}^2$ are 56.1%, 85.0%, and 90.4%, respectively. For the out-of-sample countries, the means of R^2, $\widetilde{R}^2$, and $\hat{R}^2$ are 73.6%, 94.0%, and 91.6%, respectively. Those for all countries are 60.9%, 88.4%, and 89.3%, respectively. The time-series average of the proportion of stale rating for the in-sample countries is 46.3%, that for the out-of-sample countries is 27.5%, and that for all countries is 36.9%.

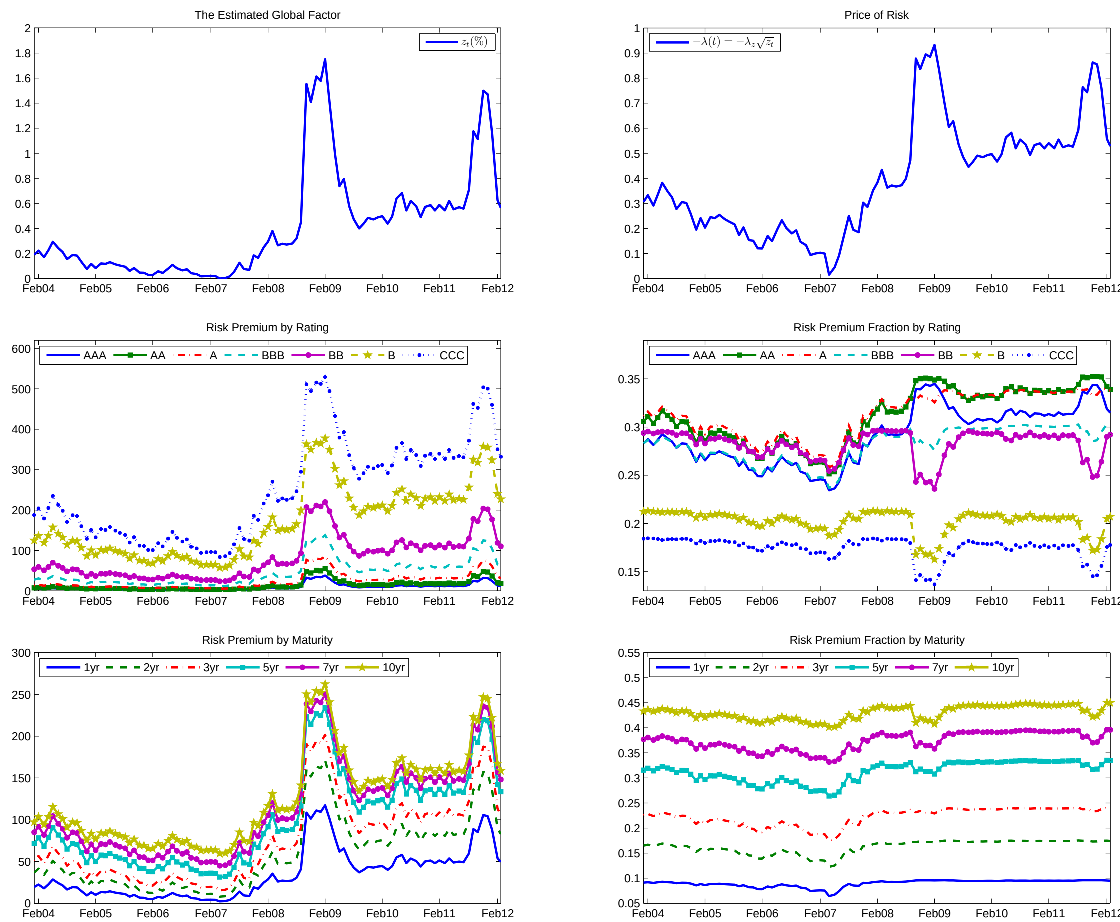

Figure 8: Global Factor, Price of Risk, the Average Risk Premium $CDS(M) - CDS^P(M)$, and the Average Risk Premium Fraction for Different Ratings and Maturities. The risk premium is measured in basis point, and the risk premium fraction is computed by (15). The average for each rating is taken over all 6 maturities (1y, 2y, 3y, 5y, 7y, 10y), and the average for each maturity is taken across all 7 ratings. All calculations are based on the estimation of Model I reported in Table 4 with zero country-specific factor.