The Term Structure of CDS Spreads and Sovereign Credit Risk

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First Version: October 2012
This Version: October 2013

Abstract

The shape of the term structure of credit default swap spreads is an informative signal about the relative importance of global and domestic risk factors to the time variation of sovereign credit spreads. A model illustrates how global shocks determine spread changes when the slope is positive, while a negative slope indicates that domestic shocks are relatively more important. These theoretically motivated results are empirically validated using a geographically dispersed panel of 44 countries. Overall, the results suggest that both global risk factors and country-specific fundamentals are important sources of sovereign credit risk. They simply matter at different times.

Keywords: Credit Default Swaps, Default Risk, Sovereign Debt, Term Structure

JEL Classification: C1, E43, E44, G12, G15

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1 Introduction

The defaults of several emerging market economies over the last two decades and the six recent European government bailouts have revived the interest in understanding the pricing of sovereign credit risk.[1] Yet the literature is inconclusive about the relative importance of global and country-specific risk factors to the time variation of sovereign credit spreads, in particular at high frequencies.

Until the end of the financial crisis, there seemed to be some consensus on the counter-intuitive findings that sovereign credit risk is explained to a large extent by global factors (Pan and Singleton 2008, Borri and Verdelhan 2012, Ang and Longstaff 2013) and that it is relatively better explained by U.S. financial market variables than by country-specific fundamentals (Longstaff et al. 2010). These results are widely motivated by the strong co-movement of credit spreads across countries. Since the beginning of the sovereign crisis though, Acharya et al. (2011) and Kallestrup et al. (2012), among others, have established a link between sovereign distress and domestic financial risk. The above studies usually focus their analysis on one specific maturity of spreads. But the term structure of spreads also exhibits significant variation over time, with richer cross-sectional dynamics and less commonality than the level of spreads. While the slope tends to be positive in good times, it often inverts during times of economic distress. On that account, the term structure of spreads may contain useful information on potentially state-dependent sources of risk.

I study the term structure of sovereign credit default swap spreads (henceforth CDS spreads) to understand how global and country-specific risk factors determine the dynamics of sovereign credit risk. The main conclusion is that both factors matter, but they matter in different periods. Global shocks are the primary source of variation for spreads when the term structure is upward-sloping. A negative slope, in contrast, indicates that local shocks

[1] Greece was bailed out twice on 2 May 2010 and 21 July 2011 with 110 and 109 billion Euro respectively, and officially defaulted in March 2012. Ireland received an 85 billion Euro lifeline on 28 November 2010 and Portugal was hit on 20 May 2011 when it was forced to accept a bailout loan of 78 billion Euro. Spain was implicitly bailed out when it received a 100 billion Euro package to save Spanish banks on 11 June 2012. Cyprus endorsed a 10 billion Euro bailout package on 30 April 2013.

dominate. This suggests that the shape of the term structure conveys useful information on the relative importance of the underlying sources of risk. Their influence can be inferred in real time as CDS spreads are observable at a daily frequency. My conclusions are based on both theoretical and empirical analysis.

First, I develop a recursive preference-based model with long-run risk for CDS spreads. The underlying default process, modulating expectations about future default rates, depends both on global macroeconomic uncertainty and country-specific shocks. This contrasts strongly with the reduced-form Duffie and Singleton (2003) pricing framework with latent default intensities.[2] The model generates time variation in the slope of the term structure through the following mechanism: As a proxy for global risk, systematic shocks in the default process are a priced source of risk for the marginal investor. Being a risk-averse Epstein-Zin agent with a preference for early resolution of uncertainty, she commands a distress risk premium that increases with maturity. This generates a positive slope. Country-specific shocks, on the other hand, are assumed to be unpriced. As a result of negative domestic shocks, the level of and uncertainty about future default rates rise. This translates into higher loss expectations, especially at short maturities. Because of mean reversion in default risk, expected losses are characterized by a steep negative slope. A flat or weakly increasing term structure of risk premia is insufficient to offset the steep decline in long-term expected losses. The net effect is a downward-sloping term structure. Patterns of term structure inversions in response to local distress are consistent with empirical observations. This model has the advantage of providing an economic explanation for the time variation in the slope of the term structure based on the joint dynamics of aggregate macroeconomic and country-specific shocks, as well as investor preferences. Although one could think of other frameworks to generate similar implications, the long-run risk specification is a convenient tool to guarantee consistent outcomes for the risk-free rate, the equity premium, the variance premium and

[2] The continuous-time pricing in reduced form has been applied to sovereigns in Duffie et al. (2003) and Zhang (2008) to study the Russian and Argentinian defaults. More recently, it has been applied to a large panel of countries by Pan and Singleton (2008), Longstaff et al. (2010) and Ang and Longstaff (2013).

the nominal term structure of interest rates. In addition, it allows for closed-form solutions of conditional CDS spreads.

The model is calibrated to 44 countries from January 2001 to February 2012. Low relative root-mean-square errors, ranging from 2 to 26% for 5-year spreads, suggest that the model describes the data reasonably well. Countries with upward-sloping term structures on average load heavily on aggregate risk. Risk premia rise with maturity and the average risk compensation for 5-year spreads is 10% of the level of the spreads. For countries that, on average, have downward-sloping term structures, on the other hand, the leverage factor on global risk is small and the default intensity depends mainly on idiosyncratic shocks. Using time-series information on spreads, expected consumption growth and volatility, I decompose spreads into their local and global components. The average local spread as a fraction of the total spread increases with the duration of distress, proxied by the number of months for which the term structure is inverted. Similarly, a variance decomposition indicates that the variance explained by idiosyncratic shocks increases with the distress duration.

I evaluate the model's implications using three empirical tests. First, the co-movement of sovereign credit spreads should be lower during a sovereign crisis. Second, on the premise that a downward-sloping term structure characterizes distress, country-specific fundamentals should explain relatively more of the variation in spread changes for distressed countries. Third, the variation in spreads explained by country-specific risk should increase with the duration of distress. I confirm these predictions using a dataset similar to that in Longstaff et al. (2010). Overall, these findings support the view that the shape of the CDS term structure conveys useful information on the relative importance of global and domestic risk factors for the dynamics of sovereign credit risk.

These facts reconcile previous conclusions, which have stressed the importance of either global or country-specific risk. On the one hand, the results rationalize the observed relationship between sovereign default risk and the domestic financial sector during times of distress. Acharya et al. (2011), for example, demonstrate how a risk transfer from the banks to the sovereign balance sheet may feed back into the financial sector through a dilution of the implicit bailout guarantee and collateral damage to the banks' sovereign bond holdings. Gennaioli et al. (2012) provide evidence that the government's decision to default and its borrowing costs depend on the development of the financial sector. Likewise, Kallestrup et al. (2012) establish a relationship between sovereign credit risk and banks' foreign sovereign bond holdings.[3] On the other hand, my findings confirm the link between sovereign CDS spreads and global factors during financially benign times. Pan and Singleton (2008), for example, show that risk premia in the CDS term structures of Korea, Mexico and Turkey are strongly associated with the VIX volatility index. Longstaff et al. (2010) conclude that US equity returns, volatility and bond risk premia explain time variations in both sovereign risk premia and expected losses of 26 countries. In the same spirit, Ang and Longstaff (2013) compare CDS spreads of federal states in the United States and European countries. They estimate a systemic risk component in spreads, which they link to global financial factors. Evidence in favor of both domestic and global risk factors is provided in Remolona et al. (2008). They conclude that global risk aversion is the dominant determinant of sovereign risk premia, while country-specific fundamentals and market liquidity matter more for expected losses. The relative importance of global financial risk and country fundamentals for the dynamics of sovereign bond spreads is also investigated by Gilchrist et al. (2012). For a more detailed review of the sovereign CDS literature, I refer the reader to Augustin (2012).[4]

In addition to the tension surrounding the role of global vs. domestic risk, the literature discusses whether the source of global risk for sovereign credit is financial or macroeconomic in nature (Ang and Longstaff 2013). In my model, global financial assets are explained

[3]For additional evidence on the link between sovereign credit and domestic financial risk, see also Altman and Rijken (2011) or Dieckmann and Plank (2011). As an alternative, Hilscher and Nosbusch (2010) suggest that volatility of the terms of trade accounts for annual variation in government bond spreads.

[4]Additional literature establishing a link between global factors from the United States and sovereign CDS premia is provided in Dooley and Hutchison (2009) and Wang and Moore (2012). Authors stressing the effect of shocks to the US economy on sovereign bonds include Uribe and Yue (2006), Reinhart and Rogoff (2008) and Obstfeld and Rogoff (2009). Mauro et al. (2002), Geyer et al. (2004), Baek et al. (2005), Weigel and Gemmill (2006), González-Rozada and Yeyati (2008) and Ciarlone et al. (2009) stress more generally the importance of global factors for sovereign fixed income.

through macroeconomic shocks. Hence the model reconciles the documented connection between sovereign credit spreads and U.S. financial risk. Simultaneously, it maintains the relationship between sovereign credit risk and fundamental macroeconomic risk over and above financial risk as documented in Augustin and Tédongap (2012). They provide empirical evidence that the first two common components of 38 countries are strongly associated with expected consumption growth and macroeconomic uncertainty in the United States. Their modeling framework is conceptually related to this paper. In contrast though, I incorporate continuous state space dynamics as opposed to a Markov regime-switching setup. Furthermore, I focus on the country dynamics of, as well as the cross-sectional differences in the term structure. As an alternative to the long-run risk framework, Borri and Verdelhan (2012) apply the Campbell and Cochrane (1999) habit framework to show that the U.S business cycle is a systematically priced factor in the cross-section of emerging market bond returns. The consumption-based modeling setup has also been used recently by Chen et al. (2009) and Bhamra et al. (2010) to address the corporate credit spread puzzle.

Importantly, among the above papers studying sovereign CDS spreads, almost none use the information embedded in the term structure. Notable exceptions are Pan and Singleton (2008), who study three countries only, and Longstaff et al. (2010), who use the cross-sectional information in the term structure to estimate the risk-neutral parameters of the default process. Arellano and Ramanarayanan (2012), on the other hand, illustrate how the endogenous choice of debt maturity may lead to an inverted sovereign yield curve. Hoerdahl and Tristani (2012) and Renne (2012) suggest alternative no-arbitrage approaches without preferences to model the real effects on the government yield curve by exogenously specifying the interest rate as a function of macroeconomic observables.

The rest of this paper proceeds as follows. Section 2 develops and derives the model. Asset pricing implications and the dynamics of the model are discussed in section 3. The model is empirically evaluated in section 4. I conclude in section 5. All model derivations not directly related to the CDS results are contained in an external appendix.

2 A Preference-based Model for Credit Default Swaps

I embed a reduced-form default process into a consumption-based asset pricing framework with recursive preferences and a long-run risk economy. The individual ingredients are discussed successively in the following sections. I start by defining the pricing of CDS spreads.

2.1 Pricing credit default swaps

Sovereign CDSs are insurance contracts protecting against sovereign default. The protection buyer purchases insurance against a contingent credit event on a specified part of the capital structure of the underlying reference entity by paying a constant premium to the protection seller. The annualized fee, quoted as a percentage of the insured face value, is the CDS spread.[5] The maturity of the product defines the time horizon over which insurance is provided. Conceptually, pricing CDS spreads in a preference-based framework is standard. The difference is that expected cash-flows are discounted using a pricing kernel defined in terms of investor preferences and economic fundamentals.

To derive the general equilibrium valuation of CDS spreads, I follow Augustin and Tédongap (2012), who discretize the continuous framework in Duffie (1999). Without loss of generality, I consider monthly spreads. Each coupon period n contains J trading months, and a K-period swap thus has a maturity of KJ months.[6] A fairly priced CDS must equalize at inception the net present values of cash-flows for the protection buyer and the protection

[5] For a further description of the institutional details, see Augustin (2012).

[6] Note that each coupon period n contains the trading months $(n-1)\,J+j,\ j=1,\ldots,J$. In the calibration exercise, I assume without loss of generality that swap premia are paid on a yearly basis. The assumption of yearly payments assures that the model results can be translated directly into annualized spreads. However, the model can easily accommodate bi-annual and quarterly payment frequencies. On the other hand, this increases the importance of keeping the accrual payments in the equation.

seller. The protection buyer's leg π_t^{pb} is defined as

$$\pi_t^{pb} = CDS_t\left(K\right)\left(\sum_{k=1}^{K} E_t\left[M_{t,t+kJ} I\left(\tau > t+kJ\right)\right] + E_t\left[M_{t,\tau}\left(\frac{\tau-t}{J} - \left\lfloor \frac{\tau-t}{J} \right\rfloor\right) I\left(\tau \leq t+KJ\right)\right]\right), \tag{1}$$

where $CDS_t\left(K\right)$ is the constant premium of a K-period CDS defined in month t and to be paid until the earlier of either maturity (month $t+KJ$) or a credit event occurring at a random month τ.[7] $M_{t,t+j}$ denotes the stochastic discount factor that values in month t any financial payoff to be claimed at a future month $t+j$. Note that $\lfloor \cdot \rfloor$ rounds a real number to the nearest lower integer, and $I\left(\cdot\right)$ is an indicator function taking the value 1 if the condition is met and 0 otherwise. The protection leg in equation 1 is the sum of two parts. The first part relates to the payments made by the protection buyer contingent on no credit event. The second part defines the accrual payments in case of default in between two payment dates.

The protection seller's leg π_t^{ps} is defined as the net present value of expected losses incurred by the protection buyer upon the occurrence of a credit event. π_t^{ps} is described by

$$\pi_t^{ps} = E_t\left[M_{t,\tau}\left(1-R_\tau\right) I\left(\tau \leq t+KJ\right)\right], \tag{2}$$

where R_τ represents the random post-default recovery rate and may contain claimed accruals from the defaulted reference obligation. A fairly priced CDS at any date t is thus obtained by equating the two legs of the transaction, which yields the K-maturity CDS spread

$$CDS_t\left(K\right) = \frac{E_t\left[M_{t,\tau}\left(1-R_\tau\right) I\left(\tau \leq t+KJ\right)\right]}{\sum_{k=1}^{K} E_t\left[M_{t,t+kJ} I\left(\tau > t+kJ\right)\right] + E_t\left[M_{t,\tau}\left(\frac{\tau-t}{J} - \left\lfloor \frac{\tau-t}{J} \right\rfloor\right) I\left(\tau \leq t+KJ\right)\right]}, \tag{3}$$

which I rewrite using the Law of Iterated Expectations for the numerator and the denomi-

[7] It is assumed that default can only occur at the end of each month.

nator as

$$CDS_t\left(K\right) = \frac{\sum_{j=1}^{KJ} E_t\left[M_{t,t+j}\left(1-R_{t+j}\right)\left(S_{t+j-1}-S_{t+j}\right)\right]}{\sum_{k=1}^{K} E_t\left[M_{t,t+kJ}S_{t+kJ}\right] + \sum_{j=1}^{KJ}\left(\frac{j}{J}-\lfloor\frac{j}{J}\rfloor\right)E_t\left[M_{t,t+j}\left(S_{t+j-1}-S_{t+j}\right)\right]}, \tag{4}$$

and where the process S_t denotes the survival probability conditional on the time-t information set $\mathcal{I}_t$, i.e $S_t \equiv Prob\left(\tau > t \mid \mathcal{I}_t\right)$.[8] Survival probabilities are functions of an underlying hazard rate h_t

$$S_t = S_0 \prod_{j=1}^{t}\left(1-h_j\right) \quad \text{for} \quad t \geq 1, \tag{5}$$

which defines the instantaneous probability of default conditional on no earlier default, that is $h_t \equiv Prob\left(\tau = t \mid \tau \geq t; \mathcal{I}_t\right)$. Equation 4 contains three main ingredients, the pricing kernel $M_{t,t+j}$, the survival probabilities S_t and the recovery rate R_t. These are defined in terms of investor preferences and the aggregate economy, which are described in the next section.

Before concluding this section, it is nevertheless important to address some institutional features of CDS spreads, which are not taken into account in the modeling framework. Counterparty risk is clearly a concern on theoretical grounds. However, the quantitative effects are empirically debated. Arora et al. (2012) show using a proprietary dataset of corporate spreads that counterparty risk is statistically priced, but that its economic significance is negligible.[9] In addition, CDS spreads could be affected by the introduction of the Big Bang and Small Bang protocols in the United States and Europe respectively.[10] These regulatory changes mainly reflect a shift towards a standardization of insurance premia, whereby differences in prices are settled through a one-time up-front payment. The quotation of running spreads nevertheless remains the market convention. Collin-Dufresne et al. (2012)

[8] Note the assumption that $Prob\left(\tau = t \mid \mathcal{I}_T\right) = Prob\left(\tau = t \mid \mathcal{I}_{\min(t,T)}\right)$ for all integers t and T.

[9] The authors show that counterparty risk would need to increase by 6 percentage points to move spreads by 1 basis point.

[10] I am grateful to Itamar Drechsler for raising this point.

also demonstrate that ignoring this detail has no crucial quantitative implications. Likewise, differential liquidity in contracts of different maturities may affect the slope of the term structure. While these details would certainly make the model more realistic, they would at best have an effect on the convexity of the slope, and would not bias the economic insights of this paper. This motivates my decision to remain as parsimonious as possible.

2.2 Preferences

The marginal investor has Epstein and Zin (1989)-Weil (1989) recursive preferences. She maximizes her utility V_t, defined as

$$V_t = \left\{ (1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left[\mathcal{R}_t \left(V_{t+1} \right) \right]^{1-\frac{1}{\psi}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \quad \text{if } \psi \neq 1, \tag{6}$$

over a weighted average of current consumption C_t and all future consumption streams, summarized by the certainty equivalent of her future lifetime utility $\mathcal{R}_t \left(V_{t+1} \right)$. The weights are based on the time preference parameter δ, and ψ refers to the elasticity of intertemporal substitution (EIS). The Kreps and Porteus (1978) certainty equivalent $\mathcal{R}_t \left(V_{t+1} \right)$ is implicitly defined as

$$\mathcal{R}_t \left(V_{t+1} \right) = \left(E_t \left[V_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{1-\gamma}} \quad \text{if } \ \gamma > 0, \tag{7}$$

where γ is the coefficient of relative risk aversion.[11] This preference specification allows us to separate the choice of asset allocations over time and across risky states, as it disentangles the coefficient of relative risk aversion $\gamma \geq 0$ and the EIS $\psi \geq 0$. At the same time, it nests the time-separable expected utility framework with constant relative risk aversion if $\gamma = \frac{1}{\psi}$. This is illustrated more clearly by Hansen et al. (2008), who show that the stochastic

[11] If $\psi = 1$, we have $V_t = C_t^{1-\delta} \left[\mathcal{R}_t \left(V_{t+1} \right) \right]^{\delta}$, and if $\gamma = 1$, the KP certainty equivalent reduces to $\mathcal{R}_t \left(V_{t+1} \right) = \log \left(V_{t+1} \right)$.

discount factor $M_{t,t+1}$ described by

$$M_{t,t+1} = \delta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left(\frac{V_{t+1}}{\mathcal{R}_t \left(V_{t+1} \right)} \right)^{\frac{1}{\psi} - \gamma} \tag{8}$$

may be rewritten in terms of the continuation value of consumption utility.[12] It is assumed that the agent prefers early resolution of uncertainty, i.e. $\gamma > \frac{1}{\psi}$. In this case, Bansal and Yaron (2004) show that the long-run risk channel coupled with recursive preferences has important implications for asset prices as revisions about future growth rates drive a wedge between future utility V_{t+1} and the certainty equivalent of all future consumption streams $\mathcal{R}_t \left(V_{t+1} \right)$. Epstein and Zin (1989) rewrite the ratio of continuation utility to the certainty equivalent of future lifetime utility in equation 8 as a function of consumption growth Δc_{t+1} and the simple gross return on a claim on aggregate wealth $R_{c,t+1}$. Using this transformation, it is possible to rewrite the logarithm of the stochastic discount factor from equation 8 as the well-known expression

$$m_{t,t+1} = \theta \ln \delta - \frac{\theta}{\psi} \Delta c_{t+1} - (1 - \theta) \, r_{c,t+1}, \tag{9}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ and $r_{c,t+1}$ denotes the logarithm of the gross wealth return.

The choice of preferences is partly motivated by the need for closed-form solutions of the model. In addition, the perception of a sovereign's future solvency is likely linked to future states of the economy. Although one could think of a way to yield similar implications in a habit framework, for this specific application, it seems plausible that the stochastic discount factor used to price sovereign default risk is formed from expectations about future economic outlooks rather than from a sequence of past consumption streams.

I should also emphasize that I take the perspective of a U.S.-based investor selling USD-denominated insurance contracts. This assumption is consistent with empirical evidence in

[12]The derivation is based on Euler's Theorem and is feasible because the recursion with constant elasticity of substitution is homogeneous of degree 1. See Hansen et al. (2007).

Longstaff et al. (2010), who conclude in favor of a global investor using only international factors from the United States. As the largest economy in the world, its importance for the sovereign debt market is widely documented. A further justification is the strong concentration of CDS trading in the OTC dealer market for credit default swaps.[13] Finally, as long as assets are priced in USD (which sovereign CDS spreads are), the results will carry through for a non-U.S. investor as long as markets are complete and all shocks are spanned by exchange rates.[14] While the case of incomplete markets is interesting, this scenario arises in no structural model that I am currently aware of, as is also pointed out by Borri and Verdelhan (2012) and Koijen et al. (2010).

2.3 Economy

Aggregate consumption growth Δc_{t+1} embeds a slowly mean-reverting predictable component x_t, which determines the conditional expectation of consumption growth,

$$\Delta c_{t+1} = x_t + \sigma_t \varepsilon_{c,t+1} \tag{10}$$

$$x_{t+1} = \mu_x + \phi_x \left(x_t - \mu_x \right) + \nu_x \sigma_t \varepsilon_{x,t+1}, \tag{11}$$

where the short-run and long-run consumption shocks $\varepsilon_{c,t+1}$ and $\varepsilon_{x,t+1}$ are independent and identically distributed normal errors with zero mean and unit variance. The parameter ϕ_x modulates the persistence of expected growth, whose long-run mean is defined by μ_x, and whose sensitivity to long-run shocks is guided by ν_x. Hansen et al. (2008) and Bansal et al. (2009) have demonstrated evidence in favor of a low frequency component in expected growth. This feature of the model also seems attractive for the pricing of sovereign default risk, as it may be influenced by expectations about future growth rates.

Consumption growth and its conditional mean inherit the same stochastic volatility pro-

[13] See Giglio (2011) and Augustin (2012) among others.
[14] See Borri and Verdelhan (2012) for a theoretical explanation of this argument.

cess σ_t^2, modeled as an autoregressive gamma process

$$\sigma_{t+1}^2 \sim ARG\left(\nu_\sigma, \phi_\sigma \sigma_t^2, c_\sigma\right), \tag{12}$$

where the parameter ϕ_σ modulates the persistence of volatility.[15] The parameters $\nu_\sigma > 0$ and $c_\sigma > 0$ are linked to the unconditional mean μ_σ and variance ω_σ of the volatility process by

$$\mu_\sigma = \frac{\nu_\sigma c_\sigma}{1-\phi_\sigma} \quad \text{and} \quad \omega_\sigma = \frac{\nu_\sigma c_\sigma^2}{\left(1-\phi_\sigma\right)^2}, \tag{13}$$

with conditional first and second moments given by

$$E_t\left[\sigma_{t+1}^2\right] = \phi_\sigma \sigma_t^2 + \nu_\sigma c_\sigma \quad \text{and} \quad V_t\left[\sigma_{t+1}^2\right] = 2c_\sigma \phi_\sigma \sigma_t^2 + \nu_\sigma c_\sigma^2. \tag{14}$$

Stochastic volatility is consistent with empirical evidence of conditional volatility in consumption growth, as supported by Kandel and Stambaugh (1990) and Stock and Watson (2002), and relates to the co-movement between macroeconomic volatility and asset prices, as documented by Bansal et al. (2005) and Lettau et al. (2006). The autoregressive gamma dynamics are based on the work of Gourieroux and Jasiak (2006) and have been generalized by Le et al. (2010) with an application to the term structure of nominal bonds in a habit framework.[16] They have also been applied to the long-run risk framework in Hansen et al. (2007). With this specification, the model remains nested in the class of general affine equilibrium models described by Eraker (2008) and it ensures that consumption volatility is a

[15]Stijn Van Nieuwerburgh pointed out to me that a model with two volatilities, such as in Bansal and Shaliastovich (2012) and Koijen et al. (2010), may be more appropriate for studying default risk, given that sovereign CDS spreads may depend on more than one global factor. An extensive calibration exercise over permissible parameter values has proven to obtain similar model implications. All derivations for the augmented model are available from the author upon request.

[16]Note that the conditional density of an autoregressive gamma process is obtained as a convolution of the standard gamma and Poisson distributions in the sense that $\frac{\sigma_{t+1}^2}{c_\sigma} \mid \left(\mathcal{P}, \sigma_t^2\right) \sim Gamma\left(\nu_\sigma + \mathcal{P}\right)$, where $\mathcal{P} \mid \sigma_t^2 \sim Poisson\left(\frac{\phi_\sigma \sigma_t^2}{c_\sigma}\right)$.

positive process, avoiding the need to replace negative realizations in model simulations with an arbitrary small number.[17] More importantly, it allows me to easily introduce aggregate macroeconomic uncertainty as a proxy for global risk into the underlying default process to generate dynamics in the term structure of CDS spreads.

The more novel contribution of this paper is the way I specify dynamics for sovereign default risk and recovery upon default. Equation 5 in section 2.1 describes how survival probabilities depend on the hazard rate h_t. This hazard rate is driven by the country-specific default intensity λ^i_{t+1} through the relationship

$$h^i_{t+1} = 1 - \exp\left(-\lambda^i_{t+1}\right), \tag{15}$$

where the superscript i will subsequently be dropped for ease of exposition. To ensure that the hazard rate is bounded between zero and one, the default process must be strictly positive. Furthermore, it should inherit both global and country-specific shocks. To attain these goals, the default process λ_{t+1} is modeled as a bivariate autoregressive gamma process:

$$\lambda_{t+1} \sim ARG\left(\nu_\lambda, \phi_{\lambda\sigma}\sigma^2_t + \phi_\lambda \lambda_t, c_\lambda\right), \tag{16}$$

where the parameters $\phi_{\lambda\sigma} > 0$ and $0 < \phi_\lambda < 1$ modulate the sensitivity of the default process to the global factor and its own past respectively. Thus, macroeconomic uncertainty σ^2_t may feed directly into expectations about future defaults. The unconditional mean μ_λ and variance ω_λ are related to the parameters $\nu_\lambda > 0$ and $c_\lambda > 0$ as

$$\mu_\lambda = \frac{\phi_{\lambda\sigma}\mu_\sigma + \nu_\lambda c_\lambda}{1 - \phi_\lambda} \quad \text{and} \quad \omega_\lambda = \frac{2c_\lambda\left(\phi_{\lambda\sigma}\mu_\sigma + \phi_\lambda\mu_\lambda\right) + \phi^2_{\lambda\sigma}\omega_\sigma + \nu_\lambda c^2_\lambda}{1 - \phi^2_\lambda}, \tag{17}$$

where the functional form of the unconditional moments reflects that the mean default μ_λ (volatility ω_λ) is high when macroeconomic uncertainty μ_σ (volatility of macroeconomic

[17] W.Feller (1951) proved that the condition $\nu_\sigma > 1$ is sufficient to guarantee positivity of the process.

uncertainty ω_σ) is high and the exposure $\phi_{\lambda\sigma}$ is large, or when the default process is very persistent, that is ϕ_λ is close to one. In addition, the default process features time-varying conditional first and second moments given by

$$E_t\left[\lambda_{t+1}\right] = \phi_{\lambda\sigma}\sigma_t^2 + \phi_\lambda\lambda_t + \nu_\lambda c_\lambda \quad \text{and} \quad V_t\left[\lambda_{t+1}\right] = 2c_\lambda\left(\phi_{\lambda\sigma}\sigma_t^2 + \phi_\lambda\lambda_t\right) + \nu_\lambda c_\lambda^2, \tag{18}$$

where time-varying second moments are necessary to generate time-varying correlations in spreads across countries. To be more explicit about the process, it is useful to illustrate its autoregressive form

$$\lambda_{t+1} = \mu_\lambda + \phi_{\lambda\sigma}\left(\sigma_t^2 - \mu_\sigma\right) + \phi_\lambda\left(\lambda_t - \mu_\lambda\right) + \sqrt{\omega_{\lambda_t}}\eta_{\lambda,t+1}, \tag{19}$$

where the parameter $\eta_{\lambda,t+1}$ is a zero mean and unit variance shock. The common factor introduces co-movement in spreads across countries. Moreover, the default process is driven by shocks to macroeconomic uncertainty through its dependence on σ_t^2. However, it also inherits idiosyncratic shocks $\eta_{\lambda,t+1}$, which are uncorrelated across countries.[18] Sensitivity to global shocks is modulated through $\phi_{\lambda\sigma}$. If $\phi_{\lambda\sigma}$ is zero, the default process becomes purely idiosyncratic.[19]

To conclude the specification of the economy, I characterize the dynamics of the recovery rate R_t. Defined as a fraction of face value, the recovery rate is a function of the loss intensity η_{t+1},

$$R_{t+1} = \exp\left(-\eta_{t+1}\right), \tag{20}$$

where η_{t+1} must be non-negative to guarantee a bounded recovery between zero and one.

[18] I assume that the country-specific shocks are uncorrelated as I focus on the relative dynamics of global and loal risk factors within countries. It is possible to think of extensions with correlated country-specific shocks to address other research questions such as contagion. This is however not the goal of this paper.

[19] Observe that we do not allow for default risk to feed back into the pricing kernel nor into the consumption process of the marginal investor. Such alternative specifications would be interesting avenues for future research.

Evidence in favor of pro-cyclical recovery rates, as documented for example by Altman and Kishore (1996), motivates my decision to make recovery depend on the country-specific default intensity λ_t and the global macroeconomic environment σ_t^2. Hence the dynamics of the loss intensity are described by

$$\eta_{t+1} = \mu_\eta + \phi_{\eta\sigma}\left(\sigma_{t+1}^2 - \mu_\sigma\right) + \phi_{\eta\lambda}\left(\lambda_{t+1} - \mu_\lambda\right), \tag{21}$$

where the exposure to the idiosyncratic and common sources of risk are modulated through the parameters $\phi_{\eta\lambda}$ and $\phi_{\eta\sigma}$ respectively. The parameter μ_η describes the mean loss. A common assumption in modeling default (and in pricing CDS spreads) is to assume a constant recovery rate, because of the inherent difficulty in jointly identifying default and recovery.[20] This implies that expected recovery rates are equal under the objective and risk-adjusted probability measure, and hence command no risk premium. As a consequence, the entire risk premium is attributed to default risk. With time-varying recovery, investors will command a premium for unpredictable variation in recovery rates. Although such a setup might allow me to shed some light on the contribution of recovery risk to the overall risk premium embedded in the spreads, I have decided to leave this analysis for future research. Thus, I follow industry practice and standard CDS pricing frameworks by fixing recovery rates at a constant level in the empirical application.

The process driving default risk differs from the literature in several respects, which are worth discussing in more detail. First of all, the process in equation 19 is specified under the objective probability measure and describes the actual default process underlying sovereign default risk. This contrasts with the common reduced-form pricing framework of Duffie (1999), where default intensities are specified under the risk-neutral probability measure. Secondly, the default process describes the risk attributed to unpredictable variation in the probabilities of triggering credit events. Standard ISDA documentation for sovereign CDS

[20] The joint identification is impossible if recovery is defined as a fraction of market value. Pan and Singleton (2008) show how identification can be improved when recovery is assumed to be a fraction of the face value of the contract.

contracts list four different credit events: obligation acceleration, restructuring, failure to pay and repudiation/moratorium. As pointed out by Pan and Singleton (2008), *default* is not listed because of the inexistence of a formal international bankruptcy court for sovereign issuers. The default process therefore appeals to distress risk, which influences the market's perception of sovereign default risk. This is highly relevant from an investment perspective as it applies to marking-to-market portfolios of government debt and CDS positions. Another component of default risk that has received attention in the literature on corporate bonds is jump-at-default risk. This metric is generally measured as the ratio of the risk-neutral to the objective default intensity $\frac{\lambda_t^{\mathbb{Q}}}{\lambda_t^{\mathbb{P}}}$, where the superscript $\mathbb{Q}$ indicates that the dynamic is specified under the risk-adjusted probability measure. Berndt et al. (2008) study this component of default risk by combining estimates of risk-neutral default intensities and Moody's expected default frequencies. Remolona et al. (2008), on the other hand, provide estimates by extracting information on objective default intensities from credit ratings. These are arguably often stale and lag behind forward-looking markets. Similarly to Pan and Singleton (2008) and Longstaff et al. (2010), I remain silent about the jump-at-default risk premium and refer more generally to default risk in the remainder of this text in order to describe a distress premium. An interesting avenue for future research would be to combine the statistically more flexible risk-neutral pricing framework with the present specification to investigate the ratio $\frac{\lambda_t^{\mathbb{Q}}}{\lambda_t^{\mathbb{P}}}$. Thirdly, with respect to the functional form of the default process, I have chosen an autoregressive gamma process, which converges in the limit to a square-root process. This resembles the choice of square-root processes used to study the default risk of Argentina in Zhang (2008) or corporate default risk in Longstaff et al. (2005). Berndt et al. (2008) and Longstaff et al. (2010) settle on a lognormal process. Finally, while the previous papers use a one-factor model consistent with the evidence of strong commonality in spreads, my specification is a two-factor process, which incorporates both global and idiosyncratic shocks.[21]

[21] Ang and Longstaff (2013) also use a two-factor process in the reduced-form continuous-time framework to analyze sovereign CDS spreads of European governments and U.S. states.

For the interpretation of my results, it is crucial to point out another fundamental difference from the reduced-form specification in, for example, Longstaff et al. (2010). Those authors define a risk-adjusted default dynamic $\lambda_t^{\mathbb{Q}}$ under the historical measure $\mathbb{P}$ as a log-normal process, which is linked to its dynamic under the risk-adjusted measure $\mathbb{Q}$ through the price of risk. The latter is assumed to be an affine function of the log default intensity. Both time-series data and the term structure of spreads are then used country by country to extract the coefficients of the price of risk, which in turn define the size of the risk premium. As this procedure is carried out separately for each country, this is equivalent to assuming a different functional form for the stochastic discount factor of each country. While, a priori, nothing is wrong with specifying a different pricing kernel for each country if markets are incomplete, it seems conceptually inconsistent with the empirical conclusion that sovereign spreads and risk premia are linked more to global factors than to country-specific fundamentals, and that they reflect the position of a marginal global investor. I impose the restriction of a unique stochastic discount factor for all countries. Such a restriction has implications for risk premia, which will be discussed together with the asset pricing implications. Moreover, this stochastic discount factor is animated by fundamental macroeconomic shocks and the marginal investor's attitude towards these risks. Consequently, it provides an economic interpretation of how aggregate shocks feed into the term structure of CDS spreads. Although the former specification is statistically more flexible, it provides less insight into the economic mechanism.[22]

2.4 Solving the model

Solutions to asset prices rely on the Campbell and Shiller log-linearizations of returns (Campbell and Shiller 1988). The linearized log return of the claim to aggregate wealth $r_{c,t+1}$ obtains

[22] I point out that this economic interpretation would similarly be lost in a simpler framework with an exogenously specified discount factor and a default process depending on two latent factors: one common priced factor, and one country-specific unpriced factor.

as

$$r_{c,t+1} = \kappa_0^c + \Delta c_{t+1} + wc_{t+1} - \kappa_1^c wc_t, \tag{22}$$

where wc_t denotes the wealth-consumption ratio.[23] The linearization constants κ_0^c and κ_1^c are endogenous functions of the mean wealth-consumption ratio A_0^c. Following Bansal and Yaron (2004), I conjecture that the log wealth-consumption ratio is linear in the state variables x_t and σ_t^2:

$$wc_t = A_0^c + A_1^c \left(x_t - \mu_x\right) + A_2^c \left(\sigma_t^2 - \mu_\sigma\right), \tag{23}$$

where the coefficients A_1^c and A_2^c measure the sensitivity of the wealth-consumption ratio to fluctuations in expected consumption growth and macroeconomic uncertainty respectively. Equilibrium restrictions imply that the Euler equation for any continuous return $r_{i,t+1} = \log R_{i,t+1}$ must satisfy

$$E_t \left[M_{t,t+1} R_{i,t+1}\right] = 1, \tag{24}$$

which leads to the endogenous solutions of the mean wealth-consumption ratio A_0^c and the expressions for the loadings on the risk factors A_1^c and A_2^c. While, conceptually, the model derivations are identical to a stochastic volatility specification with Gaussian shocks, and the solution methods are standard, the algebra is economically less intuitive. Hence, detailed derivations and expressions for A_0^c, A_1^c, A_2^c and the linearization constants κ_0^c and κ_1^c are relegated to the external appendix.

If the EIS is larger than one, the substitution effect dominates the wealth effect, and the sensitivity of the wealth-consumption ratio to expected consumption growth A_1^c is positive. This implies that asset valuation ratios rise in response to increases in expected growth. Moreover, the sensitivity is stronger if long-run shocks are more persistent. Furthermore, negative values of the sensitivity to fluctuations in macroeconomic uncertainty A_2^c arise when the EIS is larger than one. Hence, larger uncertainty lowers asset valuation ratios and the

[23]The log-linearization of the wealth-consumption ratio around its mean is the only approximation in the entire model.

effects increase with the persistence of volatility shocks. Using the solutions to the wealth-consumption ratio, the intertemporal marginal rate of substitution can be written explicitly as

$$\begin{aligned} m_{t,t+1} = \bar{m} - \left(\left(1-\theta\right) A_1^c \left(\phi_x - \kappa_1^c\right) + \gamma\right)\left(x_t - \mu_x\right) - \left(1-\theta\right) A_2^c \left(\phi_{\sigma\sigma} - \kappa_1^c\right)\left(\sigma_t^2 - \mu_\sigma\right) \\ - \lambda_c \sigma_t \varepsilon_{c,t+1} - \lambda_x \nu_x \sigma_t \varepsilon_{x,t+1} - \lambda_\sigma \sqrt{\omega_t}\eta_{\sigma,t+1}, \end{aligned} \tag{25}$$

where

$$\bar{m} = \theta \log\left(\delta\right) - \frac{\theta}{\psi}\mu_x - \left(1-\theta\right)\bar{r}^c \quad \text{and} \quad \bar{r}^c = \kappa_0^c + \mu_x + A_0^c\left(1-\kappa_1^c\right), \tag{26}$$

and the prices of risk λ_i are defined as $\lambda_c = \gamma$, $\lambda_x = \left(1-\theta\right) A_1^c$ and $\lambda_\sigma = \left(1-\theta\right) A_2^c$. This expression illustrates that both long-run risk $\varepsilon_{x,t+1}$ and volatility risk $\eta_{\sigma,t+1}$ are priced in addition to short-run consumption risk $\varepsilon_{c,t+1}$, which is not the case for an investor with power utility. Both short-run and long-run consumption risks have positive prices of risk λ_c and λ_x respectively, while volatility carries a negative price of risk λ_σ if the investor prefers early resolution of uncertainty $\left(\gamma > \frac{1}{\psi}\right)$ and both γ and $\frac{1}{\psi}$ exceed one. In contrast to the long-run risk framework with Gaussian volatility, the quantity of volatility risk is time-varying, as seen through the t-subscript in the term $\sqrt{\omega_t}$.

Conditional CDS spreads are obtained analytically by solving the four expressions

$$\begin{aligned} \Psi_{j,t}^* &= E_t\left[M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] \quad \text{and} \quad \Psi_{j,t} = E_t\left[M_{t,t+j}\frac{S_{t+j}}{S_t}\right], \\ \tilde{\Psi}_{j,t}^* &= E_t\left[M_{t,t+j}\left(1-R_{t+j}\right)\frac{S_{t+j-1}}{S_t}\right] \quad \text{and} \quad \tilde{\Psi}_{j,t} = E_t\left[M_{t,t+j}\left(1-R_{t+j}\right)\frac{S_{t+j}}{S_t}\right], \end{aligned} \tag{27}$$

using standard recursion techniques after dividing the numerator and the denonimator of equation 4 by the survival probability S_t. I conjecture that all four terms are exponentially affine in the state vector $X_t = (x_t, \sigma_t^2, \lambda_t)$ and therefore fully characterized by their moment-generating function. The expressions jointly yield the solution for the CDS spread, defined in proposition 2.1.

Proposition 2.1. *A K-period credit default swap spread is defined as*

$$CDS_t(K) = \frac{\sum_{j=1}^{KJ} \left[\Psi^*_{j,t} - \tilde{\Psi}^*_{j,t} - \Psi_{j,t} + \tilde{\Psi}_{j,t} \right]}{\sum_{k=1}^{K} \Psi_{kJ,t} + \sum_{j=1}^{KJ} \left(\frac{j}{J} - \left\lfloor \frac{j}{J} \right\rfloor \right) \left[\Psi^*_{j,t} - \Psi_{j,t} \right]}, \tag{28}$$

where the sequences $\{\Psi^*_{j,t}\}$, $\{\Psi_{j,t}\}$, $\left\{\tilde{\Psi}^*_{j,t}\right\}$ *and* $\left\{\tilde{\Psi}_{j,t}\right\}$ *are solved recursively with detailed expressions and initial conditions provided in appendix A.*

Spreads contain two components. The expected loss EL_t compensates investors for expected losses. The risk premium RP_t rewards investors for unpredictable variation in future default rates. EL_t, described in proposition 2.2, is derived by discounting expected cash-flows at the risk-free rate.

Proposition 2.2. *The expected loss component of a K-period CDS spread is defined as*

$$EL_t(K) = \frac{\sum_{j=1}^{KJ} B_t(j) \left[\Psi^{*EL}_{j,t} - \tilde{\Psi}^{*EL}_{j,t} - \Psi^{EL}_{j,t} + \tilde{\Psi}^{EL}_{j,t} \right]}{\sum_{k=1}^{K} B_t(kJ)\, \Psi^{EL}_{kJ,t} + \sum_{j=1}^{KJ} B_t(j) \left(\frac{j}{J} - \left\lfloor \frac{j}{J} \right\rfloor \right) \left[\Psi^{*EL}_{j,t} - \Psi^{EL}_{j,t} \right]}, \tag{29}$$

where $B_t(j) = E_t[M_{t,t+j}]$ is the time-t price of a zero-coupon bond that matures at time $t+j$ and delivers one unit of the consumption good, and where the sequences $\left\{\Psi^{*EL}_{j,t}\right\}$, $\left\{\Psi^{EL}_{j,t}\right\}$, $\left\{\tilde{\Psi}^{*EL}_{j,t}\right\}$, *and* $\left\{\tilde{\Psi}^{EL}_{j,t}\right\}$ *are solved recursively, with expressions and initial conditions provided in appendix B.*

Following Pan and Singleton (2008), among many others, I define the risk premium in proposition 2.3 as the simple difference between the observed CDS spread and the expected loss.

Proposition 2.3. *The risk premium component of a K-period CDS spread is defined as*

$$RP_t(K) = CDS_t(K) - EL_t(K), \tag{30}$$

where the K-period CDS and EL are defined in propositions 2.1 and 2.2 respectively.

I also map the default process into cumulative default probabilities, which are directly comparable to numbers reported by credit rating agencies or implied by market prices. The term structure of time-t conditional cumulative default probabilities from time $t+1$ to T is given by

$$Prob_t\left(t < \tau < T \mid \tau > t\right) = 1 - \Psi^{PD}_{T-t,t}, \tag{31}$$

where τ determines the random default time. Finally, the term structure of expected recovery rates can be written as

$$\Psi^{R}_{j,t} = E_t\left[e^{-\eta_{t+j}}\right]. \tag{32}$$

Closed form expressions for the scalars $\Psi^{R}_{j,t}$ and $\Psi^{PD}_{T-t,t}$ are provided in appendix C.

3 Asset Pricing Implications

This section starts with a description of the data. I then explain the calibration of the model, for which I need to estimate time-series of expected growth rates and consumption volatility as inputs to price CDS spreads. Finally, I discuss the model dynamics and explain the results.

3.1 Data

To study the term structure of sovereign CDS spreads, I use information on daily spreads from Markit for maturities of 1, 2, 3, 5, 7 and 10 years. All contracts are denominated in USD, apply to senior foreign debt and embed the full restructuring credit event clause. As I work with monthly spreads, I use the last available observation in each month. The slope of the term structure is defined as the difference between the 10 and 1-year spreads. With 44 countries from Europe/Eastern Europe, Asia, Latin America and the Middle East/Africa, the panel spans a broad geographical region and exhibits significant time-series and cross-sectional heterogeneity. Compared to the 26 countries in Longstaff et al. (2010), the panel is larger and contains many distressed countries.[24] As a consequence, the data exhibit richer dynamics for the slope. Table 1 presents summary statistics. The earliest starting period is January 2001 and all observations end in February 2012, covering a large part of the ongoing European debt crisis. In contrast to the findings in Pan and Singleton (2008), the average term structure is not always upward-sloping. Instead it is negative for four countries. The mean slope can be as negative as -382 basis points as in the case of Greece, and Colombia has the largest positive slope of 234 basis points. The average 5-year spread ranges from 13 basis points for Finland to 868 basis points for Venezuela. The last column displays the number of months for which the term structure was inverted. Six countries had an inverted term structure for at least one year. Additional summary statistics are relegated to the external appendix due to space limitations.

3.2 Parameter calibration

The calibration process proceeds in three steps. First, I define the parameters for preferences and the endowment economy. Second, I estimate a time-series of expected growth and macroeconomic uncertainty. Third, I use these ingredients to identify the structural parameters of the default process. The decision interval is monthly.

The parameters for preferences and aggregate consumption growth are summarized in Table 2. The subjective discount factor δ is set to 0.9987, while the EIS ψ and the coefficient of relative risk aversion γ are 1.7 and 10 respectively. In line with Bansal et al. (2009), consumption dynamics are calibrated to have an annualized growth rate of 1.8% and a volatility of 2.5%. The mean of expected consumption growth μ_x is 0.0015. The process has a persistence ϕ_x of 0.975 and a volatility leverage coefficient ν_x equal to 0.034. The level of stochastic volatiliy $\sqrt{\mu_\sigma}$ is calibrated to 0.00725, with the unconditional volatility of volatility

[24] While the sample contains no countries with outright default, it does include Hungary, which received a first IMF bailout in November 2008, Mexico, which suffered economic distress in connection with the cartel drug war, and Venezuela, which the markets expected to default in 2010.

$\sqrt{\omega_\sigma}$ given by 2.8035e-005. Shocks to consumption volatility are persistent, with the value of ϕ_σ set at 0.9945. Table 2 also shows that the dynamics reproduce the moments in the data well, both in-population and out-of-sample. The calibrated values are taken as given for the subsequent analysis. To convince the reader that these numbers are reasonable, I show in the external appendix that the model provides reasonable results for the first and second moments of the equity premium, the risk-free rate, the real and nominal term structures of interest rates, the variance risk premium, and the wealth-consumption and price-dividend ratios.

To pin down the structural parameters of the default process, I need time-series information on expected consumption growth and consumption volatility. As these state variables are unobserved, I estimate them using a traditional Kalman Filter (Hamilton 1994). Using monthly real per capita consumption data from January 1959 to February 2012, downloaded from the FRED database of the Federal Reserve Bank of St. Louis, I estimate the system of equations

$$\begin{aligned} \Delta c_{t+1} &= x_t + \sigma_t \epsilon_{c,t+1} \\ x_{t+1} &= (1-\phi_x)\,\mu_x + \phi_x x_t + \nu_x \sigma_t \epsilon_{x,t+1} \\ \sigma^2_{t+1} &= (1-\phi_\sigma)\,\mu_\sigma + \phi_\sigma \sigma^2_t + \nu_\sigma \epsilon_{\sigma,t+1}, \end{aligned} \tag{33}$$

where the errors of time-varying volatility σ^2_{t+1} are standardized to have zero mean and unit variance and are thus defined as $\epsilon_{\sigma,t+1} = \left(\epsilon^2_{c,t+1} - 1\right)/\sqrt{2}$. The filtered time-series for conditional expected consumption growth ($\hat{x}_{t|t}$) and consumption volatility ($\hat{\sigma}_t$) are plotted in Figure 1 against NBER recessions (grey shaded areas), together with their structural estimates and standard errors. The graph illustrates the cyclicality and long-term declining trend of consumption volatility, while expected consumption growth exhibits a large drop during the Great Recession.

With the previous ingredients, I can pin down the structural parameters of the default process. The recovery rate is kept constant at 25%, consistent with industry practice and the results in Pan and Singleton (2008). I define the vector of default parameters by $\Theta = [\phi_{\lambda\sigma}, \phi_{\lambda}, \nu_{\lambda}, c_{\lambda}]^{\top}$ and note that the CDS spread is a function of expected consumption growth x_t, macroeconomic uncertainty σ_t^2 and the latent default process λ_t, that is $CDS = f\left(x_t, \sigma_t^2, \lambda_t\left(\Theta\right)\right)$. Like Longstaff et al. (2010), I assume that the 5-year CDS spread is perfectly priced. Conditional on a set of starting values for Θ, I can then back out $\hat{\lambda}_t$, which becomes a function of the observed 5-year CDS spread $CDS_t^o\left(5\right)$ and the filtered estimates $\hat{x}_{t|t}$ and $\hat{\sigma}_t^2$, i.e. $\hat{\lambda}_t = f\left(CDS_t^o\left(5\right), \hat{x}_{t|t}, \hat{\sigma}_t^2, \Theta\right)$. The estimated time-series of hazard rates $\{\hat{\lambda}_t\}_{t=1}^{T}$ can be injected back into the pricing equation to generate the term structure of the credit spreads. This two-step iterative procedure is repeated until the distance between the implied and observed sample moments is minimized. To ensure that a global minimum to the optimization is found, the problem is solved over a large grid of starting values. Such an estimation procedure has previously been used in the option literature by Christoffersen et al. (2009), for example.

The calibration outcomes are reported in Table 3. The parameter $\phi_{\lambda\sigma}$ modulates the sensitivity of the default process to global shocks. On the other hand, ϕ_{λ} determines the persistence of the process. Recalling that the default process is defined as

$$\lambda_{t+1} = \mu_{\lambda} + \phi_{\lambda\sigma}\left(\sigma_t^2 - \mu_{\sigma}\right) + \phi_{\lambda}\left(\lambda_t - \mu_{\lambda}\right) + \sqrt{\omega_{\lambda_t}}\eta_{\lambda,t+1}, \tag{34}$$

it becomes clear that, when the global leverage factor $\phi_{\lambda\sigma}$ is small and the persistence ϕ_{λ} is large, the process is mainly driven by contemporaneous and past country-specific shocks. Vice versa, if $\phi_{\lambda\sigma}$ is large, global shocks dominate the behavior of the default process. In addition, the higher its value, the higher is the correlation with the stochastic discount factor. Common dependence on the global factor also introduces the co-movement of spreads across countries. The results indicate that there is a systematic difference in the parameter values for countries, that have positive or respectively negative slopes, on average, in the sample. For the former group, the leverage coefficient on the global factor $\phi_{\lambda\sigma}$ is large and mostly above 1, ranging between a minimum value of 2.30 for Finland and a maximum of 191 for Venezuela.[25] At the same time, the persistence of the default process ϕ_λ tends to be small, mostly below 0.10. For the latter group, on the other hand, the global leverage factor is below one and close to zero, while the persistence is rather large. Examples are Portugal, Uruguay and Greece, which all display leverage factors very close to zero, but have persistence parameters of 0.99, 0.98 and 0.95 respectively. ν_λ and c_λ determine the density of the default process but are not worth discussing in more in detail. Countries in the sample with a negative slope on average are the most distressed. The calibration results are thus a first indication that the default probabilities of sovereigns with financial difficulties are driven relatively more by idiosyncratic shocks than by global risk factors.[26]

3.3 Performance of the model

The model is simulated for a time-series of 120,000 months to obtain reliable population values. Columns 6 to 11 in Table 3 report the mean spreads of the term structure in basis points. Column 12 summarizes the average slope. The model does a good job in reproducing the 5-year spread and the long end of the curve, but it has a tendency to overestimate short-term spreads.

In particular, the 5-year CDS spreads are close to the data. Quantitatively, the performance is judged by the relative squared distance between the observed and model-implied moments of the term structure. Relative root-mean-square errors (RRMSE) are reported in the column labeled *Fit-RRMSE*. These values are generally quite low, indicating that the model outcomes are quite satisfactory. Austria yields the best result, with a RRMSE of 2%. The worst of the satisfactory results is 26%, for Ireland. Only Greece and Portugal show less pleasing results. RRMSEs calculated over the long end of the curve are close to those

[25] Note that Germany is the exception, with a value of 0.91 for $\phi_{\lambda\sigma}$.

[26] I emphasize that the calibration exercise should not be evaluated on the ability of fitting sample moments, as a 10-year sample ultimately reflects conditional moments. Rather, the exercise should be seen as a way to learn about the model and the tendency of the structural parameters in relation to the shape of the term structure.

measured on the 5-year spread only. The satisfactory values range from 3% for Austria to 35% for Venezuela. Again, the model fails for Greece and Portugal. Part of the difference between the theoretical and observed spreads can be explained through the long-run properties of the term structure. The model generates a positive slope on average.[27] This result mirrors the findings in Donaldson et al. (1990) for an application of a consumption-based model with CRRA preferences to the term structure of interest rates. These discrepancies are, however, not entirely disappointing. In contrast, it would be rather worrisome if the outcome predicted Greece to be constantly in distress and to have a negative slope on average. On the other hand, conditional moments obtained from snapshots of the simulated time-series can mirror the in-sample observations.

The slope of the term structure tends to be underestimated, with the most severe errors at the short end of the curve. This is illustrated through the relatively higher RRMSEs calculated over all six maturities. Such a difficulty in matching short-term spreads mirrors the results of Pan and Singleton (2008), who face a similar challenge. Based on discussions with practitioners, those authors note that the 1-year spread may be driven by an idiosyncratic liquidity factor, as large institutional money management firms often use the short-dated CDS contract as a primary trading vehicle for expressing views on sovereign bonds. As pointed out in the modeling section, accounting for a liquidity factor may improve the fit at the expense of making the model more cumbersome. This is, however, unlikely to significantly affect the dynamics of the term structure inversion.

Figure 2 shows that in-sample 5-year spreads (solid red lines) also match the observed spreads (dotted black lines) well. The left column provides examples for Malaysia, Finland, Uruguay and Ireland. The corresponding graphs in the right column plot the difference between the conditional 10-year and 1-year spreads against the data. The model partly fails to regenerate the observed dynamics of the slope for countries that kept an upward-sloping term structure throughout the crisis (Malaysia and Finland). The cause is the structural

[27] Ireland and Uruguay exhibit negative slopes of -7 and -6 basis points respectively. This is close to flat. On the other hand, it may be that 120,000 are insufficient to generate population values for these countries.

break at the start of the financial crisis. Spreads jumped, for example from 10 to 300 basis points in the case of Malaysia. To account for this jump, the volatility of default risk has to increase sharply in the model. High uncertainty of default causes the term structure to invert. On the other hand, the conditional slope tracks the observed series if spreads rise sharply and the term structure inverts (Uruguay and Ireland).

The fit of the model is very reasonable given that the structural parameters are held constant across the whole sample period. I have also implemented the methodology of Collin-Dufresne et al. (2012), who dynamically recalibrate the structural paramters of a default process to price CDO tranches of corporate debt. These (unreported) results yield a close fit of both the level and the slope of the term structure for most countries. The time series of structural parameters implied by the dynamic calibration also illustrates that the sensitivity to the volatility of aggregate consumption growth decreases and the sensitivity to domestic shocks increases when the term structure inverts.

3.4 Decomposing CDS spreads into local and global spreads

The structure of the model allows for three different pieces of analysis. First, I decompose CDS spreads into their expected loss and risk premium components. Risk premia reflect a compensation for unpredictable variation in future default rates. Second, all dynamics are directly specified under the physical probability distribution. It is therefore possible to infer cumulative default probabilities that are comparable to the estimates reported by credit rating agencies. Third, I decompose spreads into their local and global components, which is a novel contribution of this analysis.

Table 4 reports the decomposition of model-implied spreads into risk premia and expected losses for each of the 44 countries. The term structure of the risk premia is upward-sloping. Their magnitude hovers around 3% for short maturities up to approximately 10% for 5-year spreads and 18% at the 10-year maturity. These numbers may appear small relative to the model-implied estimates of Longstaff et al. (2010), who report average risk premia of 30%

for 5-year spreads. As previously pointed out, however, those authors allow for a different stochastic discount factor for each country, while I impose the restriction of a unique pricing kernel. A second explanation for the relatively smaller risk compensation is the specification of consumption volatility. The autoregressive gamma process implies smaller volatility premia compared to Gaussian dynamics. The reason is that the practice of assigning positive outcomes to negative realizations of the variance increases the correlation with the pricing kernel. The difference in risk premia can become important when consumption volatility is highly persistent. Arguably, the level of the risk premium is also linked to the marginal investor's attitude towards risk, defined by the values of the subjective discount factor δ, the EIS ψ and the coefficient of relative risk aversion γ. However, as all results are preconditioned to match an extensive series of asset classes, I see these values as forming a reasonable benchmark.[28] Another pattern is that risk premia are proportionally smaller for countries that load weakly on the global factor.[29] This is due to two reasons: Lower values for $\phi_{\lambda\sigma}$ imply lower correlations with the stochastic discount factor. In addition, distressed countries are marked by higher expected losses, which rise more quickly than risk premia. While it may seem counter-intuitive that riskier countries command lower risk premia, it is rational from the perspective of a global investor, who can diversify away idiosyncratic country risk. Only aggregate risk is priced. When the dependence on the global factor is low, default risk becomes mainly country-specific. At those times, speculators who bet on default are only compensated for expected losses.[30]

Table 4 also reports cumulative expected default probabilities for 1-year, 5-year and 10-year horizons. These numbers can be compared to historical and implied estimates of sovereign default probabilities, which sometimes diverge dramatically. Sovereign defaults are rare events, making the reported statistics sensitive to the time period and methodology

[28] A scenario analysis shows that the levels of risk premia increase with risk aversion and decrease for higher values of the EIS and the subjective discount factor.

[29] Note that, although the percentage risk premium is, on average, smaller, the risk premium spread may be large.

[30] I note that the implications of higher risk premia in the level of spreads for safer countries seems also consistent with a more severe credit spread puzzle for highly rated companies in the corporate literature.

applied. Moreover, although statistical models are more flexible in modeling risk-adjusted (as opposed to physical) default probabilities, they lack a tangible economic interpretation. To illustrate this more clearly, take the example of Greece. On 14 January 2011, Fitch downgraded Greece's credit rating to Ba1, which made its financial assessment comparable to that of Moody's and Standard & Poor's. Both backed a rating of BB+ on that date. Their respective statistical estimates of historical one-year cumulative sovereign default probabilities were 0.00%, 2.13% and 0.77%.[31] Moreover, risk-neutral estimates implied by market prices indicate a one-year default probability of 13.47% if we assume a constant recovery rate of 25%, and 16.84% if we assume that 40 cents in the dollar are recovered upon default.[32] Another benefit of the model is that default probabilities may be inferred in real time. Ex post, we know that Greece did eventually default on 9 March 2012.[33] The question of how likely Greece was to default on any date prior to its failure remains unanswered.

I also decompose model-implied spreads into their local and global components. I call them local and global spreads, denoted CDS^L and CDS^G. The yellow bars in the upper graph of Figure 3 depict the average 5-year CDS^L as a fraction of the model-implied 5-year CDS spread. The bars are sorted in ascending order and their magnitude is reported on the left scale. The relative local spreads are compared to the number of months for which the term structure was inverted on the right axis. Although the relationship is not perfect, the model captures the fact that spreads of more distressed countries are more local than global. A clear outlier is Venezuela. Its local spread represents only 0.49% of the total spread, but the slope was negative during 26 months of the data. Finally, the bottom plot produces a similar conclusion based on a variance decomposition of spreads. Again, the model suggests that a larger fraction of the CDS comes from the variation in local spreads as the slope is

[31] More precisely, these numbers represent sovereign foreign-currency cumulative average default rates with rating modifiers from 1975 to 2010 for Standard&Poor's, issuer-weighted sovereign cumulative default rates from 1983 to 2010 for Moody's, and sovereign average issuer cumulative default rates from 1995 to 2011 for Fitch. All numbers are taken from publicly available reports on the respective web sites.

[32] The implied default probabilities assume a flat term structure and constant recovery rates. A more precise estimate would not change the message of very large divergences in default probability estimates.

[33] The ISDA Determinations Committee concluded that 9 March 2012 constitutes the date of the Restructuring Credit Event with respect to The Hellenic Republic.

inverted for a longer period of time. As before, Venezuela does not fit the pattern.

3.5 Time variation in the term structure of CDS spreads

The model generates time variation in the slope of the term structure. Such dynamics arise through the joint evolution of risk premia and expected losses. In normal times, the term structure of expected losses is flat or slightly decreasing. Risk aversion introduces a risk premium and raises the level of spreads. However, the increase is higher for longer maturities as the Epstein-Zin agent prefers early resolution of uncertainty. Following a series of negative shocks, expectations about future default rates become more uncertain and more volatile. As a consequence, expected losses increase dramatically around short maturities. Because of mean reversion in prices, the term structure of expected losses becomes steeply downward-sloping. Yet, a flat or increasing term structure of risk premia is insufficient to offset the strongly inverted shape of expected losses. The net outcome is a negative term structure of spreads. Thus, the joint dynamics of global and local shocks together with investor preferences are responsible for time variation in the term structure. Global shocks are the dominant force underlying spread variation when the slope is positive. An inverted term structure nevertheless indicates that domestic shocks are more important. These dynamics are in addition modulated by the sensitivity of countries to each risk factor.

Figure 4 illustrates the mechanism graphically for a simulated sample path of 600 months.[34] The graph in the north-west corner plots the evolution of the 1-year (dash-dotted blue line) and 10-year (solid green line) spreads. While on average the long-maturity spread is higher, it occasionally falls below the short spread. The box in the north-east corner plots the slope (solid black line, left scale) against the volatility of the default process (dash-dotted red line, right scale). It is straightforward to see that the term structure inverts when uncertainty about default rises sharply. In these situations, expected losses rise more quickly than risk premia, as is shown for the 5-year spread in the south-west corner. Finally, the graph in the

[34] The default parameters for the simulated path are the calibrated values for Uruguay, that is $\phi_{\lambda\sigma} = 1.84$, $\phi_{\lambda} = 0.9871$, $\nu_{\lambda} = 1.60e\text{-}03$ and $c_{\lambda} = 1.59e\text{-}04$.

south-east corner illustrates that risk premia (dash-dotted blue line, right scale) are strongly correlated with global macroeconomic uncertainty (solid green line, left scale). Also note that risk premia are only weakly correlated with the country-specific default process (solid red line with bullet markers, right scale).

A scenario analysis in Figure 5 provides deeper insights into the mechanics of the model. I plot the difference between the model-implied 10-year and 1-year CDS spreads for perturbed values of $\phi_{\lambda\sigma}$ and ϕ_{λ}, keeping the mean and volatility of default risk constant at 0.005 and 5e-04 respectively.[35] The upper left graph shows that, for small values of $\phi_{\lambda\sigma}$, the slope becomes more negative as the default process becomes more persistent. The upper right panel, on the other hand, shows that, for high values of $\phi_{\lambda\sigma}$, raising the persistence has a positive effect on the slope. Thus, everything else being equal, the slope tends to be more negative for low loadings on the global factor and a high persistence of past idiosyncratic shocks. The lower graph analyzes the effect of default volatility on the slope for a constant mean default rate of 0.0039. The outcome is reproduced for various combinations of $\phi_{\lambda\sigma}$ and ϕ_{λ}. Overall, volatility decreases the slope of the term structure. If the slope is very negative though, raising volatility increases the slope. This reflects an option-type feature in the term structure of spreads. A severely distressed country has a strongly downward-sloping curve. If the country is close to default, the protection seller's position behaves like a deep out-of-the money put. Raising volatility increases the likelihood of a positive payoff and increases the slope.

3.6 Empirical predictions

The model describes how the joint dynamics of global and country-specific risk factors generate time variation in the slope of the CDS term structure. Local shocks are the main determinant when the slope is negative, while global shocks dominate when it is positive. The mechanism suggests three testable empirical predictions. Firstly, during the sovereign

[35] Note that keeping the mean and volatility constant requires an adjustment to $\nu_{\lambda} > 0$ and $c_{\lambda} > 0$. The lines are plotted only for values remaining in their respective domains.

debt crisis, correlations should decrease and the first principal component should explain less common variation in spread changes. Secondly, country-specific factors are expected to explain relatively more of the spread variation of distressed countries. I use an inverted term structure as an observable proxy for distress. Thirdly, there should be a positive relationship between the duration of distress and how much spread variation the country-specific factors explain. To test these predictions, I extend the dataset of Longstaff et al. (2010) from 26 to 44 countries. All results are discussed in the following section.

4 Empirical Investigations

I evaluate the model using three empirical tests. I first perform a principal component analysis on CDS spread changes. This is followed by an updated regression analysis of the results presented in Longstaff et al. (2010). The final part of this section investigates the relationship between how much spread variation the local factors explain and the number of months for which the term structure is inverted.

4.1 Principal component analysis

The first hypothesis suggests that correlations between spreads should decrease during a *sovereign* crisis. Consequently, the first principal component is predicted to explain relatively less of the variation in spread changes at such times. Table 5 reports the results of the factor analysis for the whole sample period, as well as for the pre-crisis period of 2003-2006, for the *financial* crisis of 2007-2010, and for the *sovereign* debt crisis of 2010-2012.[36] Over the whole sample period, the first principal component explains, on average, 57% of the variation in monthly 5-year spread changes (panel A). In line with the earlier literature, this number varies from 43% in the pre-crisis period (with sovereign defaults) to 75% during the financial meltdown (with no sovereign defaults). These results are not new. During the sovereign debt

[36] To perform the principal component analysis, I need a balanced panel dataset, which is why the starting year of the analysis is 2003. The analysis is carried out for standardized spread changes.

crisis, one might expect spreads to co-move even more. However, the fraction explained by the first factor falls back to the long-run average of 58%. Such a result is not found if I limit the sample to the countries used in Longstaff et al. (2010).[37] I should point out that, apart from Hungary and Venezuela, no country in their database defaulted, received a financial bailout, or was expected to default over the last decade.[38] This suggests that the drop in correlation is entirely driven by the countries in distress. Similar results are found for a principal component analysis performed on pooled spreads of all maturities. These results are reported in panel B.[39] Interestingly, panel C shows that the first principal component has relatively little explanatory power for the slope of the term structure. On average, the first factor explains 22% of the variation. Conditional values change from 24% to 38 % and back to 31% over the three time periods.

I plot the country coefficients for the first two principal components in Figure 6. Longstaff et al. (2010) interpret the first component as a parallel shift factor, as most sovereigns have more or less an equal weighting on it. The second component is interpreted as a spread between Latin-American and other countries. The updated sample, which includes richer slope dynamics, shows that these interpretations are no longer entirely correct. Sorting the countries on the size of the first factor emphasizes an upward trend, which contrasts with the interpretation of a level factor. The red bars relating to the right axis show the observed number of months with a negative slope. Although the relationship is not monotonic, the most distressed countries cluster on the left side of the graph and are associated with the lowest weightings on the first principal component. Examples are Uruguay (which defaulted in 2003), Portugal, Cyprus, Ireland, Greece and Spain.[40]

[37] These results are reported in the external appendix.

[38] Hungary received an IMF bailout in November 2008. The markets expected Venezuela to default on its external debt in 2010, when a series of press articles circulated, citing the unsustainability of Venezuela's outstanding debt. The sample of Longstaff et al. (2010) also contains Mexico, which suffered economic consequences as a result of the cartel drug war.

[39] The requirement of a balanced panel for the full term structure reduces the sample to 30 countries.

[40] The same tendency is visible in the Longstaff et al. (2010) dataset, but the insufficient number of observations and a sample period characterized by a financially more benign period for sovereigns make it difficult to detect this pattern.

Moreover, the interpretation of the second principal component is contested as negative factor loadings are not restricted to Latin American countries, but rather to developing countries in general. In fact, all positive loadings are associated with members of the European Union, except for Croatia, a member candidate, and Japan, whose loading is close to zero. Thus, the second factor is rather interpreted as a spread between EU and non-EU countries, or as a spread between emerging and non-emerging markets. I now turn to the regression analysis.

4.2 Regression analysis

The second prediction suggests that domestic risk factors explain relatively more spread variation than global factors for distressed countries. An inverted term structure serves as an observable proxy for distress, available at high frequencies. To test this hypothesis, I extend the dataset of Longstaff et al. (2010) from 26 to 44 countries and run the same regressions as in their paper.

As a quick reminder of their results, the authors regress changes in monthly 5-year sovereign CDS spreads on three local factors and three groups of global factors. The punchline is that both observed spreads and model-based expected losses are related primarily to global determinants, in particular U.S. equity returns, volatility, and bond market risk premia. The three local variables are the domestic excess stock market return in local currency, the exchange rate relative to the USD, and foreign currency reserves. The first set of global variables are financial market indicators from the Unites States: the U.S. excess stock market return, changes in the 5-year constant maturity Treasury yield, and changes in the spreads of US investment-grade and high-yield bond indices. The second set of global variables comprises proxies for international risk premia, based on the intuition that risk premia should correlate across asset classes. The equity risk premium is proxied by changes in the earnings-price ratio of the S&P index. Changes in the spread between implied and realized volatility of index options are used for the volatility premium and changes in the expected excess returns on five-year Treasury bonds approximate the term premium. To capture valuation effects based on international capital-flows, the authors add net new global flows into equity and bond mutual funds. Finally, to account for any residual economic sources of risk, the predictor variables include a regional and a global sovereign spread. The regional spread is computed as the mean spread of all other countries in the same region, whereas the global spread is measured as the mean spread of the countries in all other regions, but excluding the specific region being analyzed. Only the residual part orthogonal to all other regressors is used in the regressions. I stay as close as possible to the data sources in Longstaff et al. (2010), conditional on accessibility constraints. Data sources and variable descriptions are explained in appendix D. To summarize, I run the regression

$$\Delta CDS_t^i = \alpha_i + \beta_i^\top \Delta L_t^i + \gamma_i^\top \Delta G_t + \varepsilon_{t+1}^i \qquad \varepsilon_{t+1}^i \sim \mathcal{N}(0,1), \tag{35}$$

where L_t^i denotes a vector of domestic variables and G_t refers to the vector of global factors. Regression results and statistical significance based on White robust standard errors are reported in Table 6.[41] The results are consistent with the analysis of Longstaff et al. (2010). Signs are as expected, adjusted R^2 statistics are high, ranging up to 78%, and global factors matter relatively more than domestic factors. Repeating their comments would be a stretch for the reader. However, it is worth emphasizing a pattern found here that is absent from their results. For fiscally distressed countries with inverted term structures, most of the global variables (if not all of them) are statistically insignificant, while the domestic variables are usually statistically significant. Examples are Greece, Cyprus, Spain, Turkey and Uruguay. These countries had inverted term structures for respectively 26, 10, 4, 8 and 18 months. Moreover, this tendency becomes stronger for countries that had a negative slope for a longer time. The last three rows indicate the fraction of statistically significant t-statistics at the

[41] Arguably, the well-documented persistence of CDS spreads may justify the computation of standard errors corrected for time-series correlation. In order to remain as close as possible to the analysis in Longstaff et al. (2010), I report statistical significance based on White standard errors. Having said this, the results hold if I correct for time-series correlation.

10% level, overall, as well as for the countries with less ($Group^o$) and more ($Group^{++}$) than 5 months with a negative slope. This fraction tends to be lower for local and higher for global variables for $Group^o$, whereas the opposite is true for $Group^{++}$.

Domestic factors dominate if I use monthly changes in the slope of the term structure as the dependent variable in regression 35. However, statistical significance occurs less often overall. These results are available in the external appendix. The local stock market return, the exchange rate and foreign currency reserves are statistically significant at the 10% level for respectively 45%, 34% and 32% of the countries. The only global variable that beats the domestic risk factors is net inflows into bond mutual funds, which is statistically significance for 50% of the countries. More importantly, distressed countries with inverted term structures generally have a positive slope coefficient on the domestic stock market return. This indicates that good news in the stock market raises the slope and improves the outlook. Two exceptions are Bulgaria and Korea. However, Bulgaria responds positively to foreign currency reserves, showing that more robust government finances decrease the market's perception of the likelihood of default. Korea has a negative and statistically significant coefficient on the exchange rate. Thus, a depreciation in Korea's currency can lead to a worse perception of the country's short-term default risk. The net effects for these two countries may still go in the right direction.

To summarize, global factors explain relatively more spread variation for countries with a persistent upward-sloping term structure, in particular U.S. stock returns, the U.S. equity premium and global and regional spreads. Domestic factors dominate for countries that had inverted term structures for an extended period of time. This tendency becomes stronger as the number of months with a negative slope increases. In addition, country-specific risk factors explain relatively more variation in the slope of the CDS term structure, especially the domestic stock market return.

4.3 Ranked local ratios

The third hypothesis predicts a positive relationship between the number of months for which the slope was inverted and how much spread variation the domestic factors explain. To proxy for the explanatory power of local risk, I compute the local ratio statistic (LR) suggested by Longstaff et al. (2010). LR is the ratio of the adjusted R^2s from a restricted and an unrestricted regression. The restricted regression projects spread changes onto domestic variables only, while the unrestricted regression includes all variables. The metric thus reflects the importance of country-specific factors.[42] I first separate all countries into two groups: those that never had an inverted slope (G1) vs. those which had an inverted slope during at least one month (G2). Table 7 reports the mean and median LR for both groups, which are highly statistically different.[43,44] The mean LRs for the two groups are 40% and 61%, while the median LRs are 38% and 63%. The set of indiviual country LRs contains several outliers. In G1, the LR for Venezuela is roughly 5%. The country arguably plays a special role, given its importance for global oil production. In G2, two countries with a high LR never had an inverted term structure but went through significant financial or political trouble. Mexico faced an economic downward trend in connection with the cartel drug war, while Egypt suffered as a result of the Arab revolution. Their LRs are respectively 77% and 65%. Excluding the outliers, the difference in the mean and median LRs between the two groups widens further, both the mean and median LRs being 36% for G1 and 64% for G2. LRs for Portugal, Greece and Ireland are 109%, 76% and 100%.

[42] As pointed out by the authors of that paper, the correlation between the domestic and global factors is non-zero, and this ratio may overstate the importance of the country-specific influence.

[43] Inference is obtained by block-bootstrapping 10,000 times a sample size of 36 months for each country. A one-sided t-test on the equality of means assuming paired data against the alternative that G1 has a smaller mean is rejected at the 1% significance level. The Wilcoxon matched-pairs signed-rank test rejects the null hypothesis that both distributions are the same, while the one-sided sign test rejects the equality of the medians against the alternative that the median of G1 is lower.

[44] Note that this inference assumes that the correlation between local and global factors is the same for each country. Adjusting for this correlation would lower the LR statistic. Unless the local economies of distressed countries are more highly correlated with global factors than are those with non-distressed countries, the results would be even stronger. It is, however, more likely that distressed economies are less highly correlated with the global economy.

In line with the hypothesis, the LR is monotonically increasing with the number of months for which the term structure was inverted. The relationship between the distress duration and how much variation the domestic factors explain is plotted in Figure 7 (excluding the special case of Venezuela). A linear regression fitted to the scatter plot yields a solid R^2 statistic of 33%, with a statistically significant t-statistic of 3.11. Overall, these empirical findings support the view that both global and local risk factors matter. They are simply relevant at different points in time. Local risk dominates when a country is in distress, and distress is observable based on the shape of the term structure.

5 Conclusion

I show that both global and country-specific risk factors are important for explaining the dynamics of sovereign credit risk. They simply matter in different periods. Global shocks are the primary source of spread variation in normal times, when the term structure is upward-sloping. In contrast, spreads are mainly influenced by domestic shocks when countries are close to distress and the term structure is downward-sloping. Sovereign distress is inherently difficult to observe. As the slope of the CDS term structure is a direct proxy, available at high frequencies, it can aid the detection of sovereign distress. The bottom line is that the term structure of spreads conveys useful information with which to pinpoint the relative importance of global and domestic risk. My conclusions are based on two pieces of analysis.

I develop a recursive preference-based model with long-run risk for CDS spreads, where the underlying default process depends both on aggregate macroeconomic uncertainty and domestic risk. The joint dynamics of global and country-specific shocks combined with investor preferences economically explain time variation in the slope of the term structure. Several empirical tests support the model's implications. In particular, I establish a relationship between the duration of inverted term structure and how much spread variation is explained by domestic risk factors. Thus, local shocks become relatively more important than global factors as countries become more distressed. Overall, these findings reconcile previous opposing views in the literature favoring either local or global risk as a determinant of sovereign credit risk.

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A Analytical Solutions to the CDS Spread

The pricing equation for the CDS spread is obtained in closed form by deriving analytical expressions for the individual components in equation 27. To compute these expressions, I conjecture that each element is exponentially affine in the state vector $X_t = (x_t, \sigma_t^2, \lambda_t)$,

$$\Psi_{j,t}^* = e^{A_j^* + \left(B_j^*\right)^\top X_t}, \ \Psi_{j,t} = e^{A_j + B_j^\top X_t}, \ \tilde{\Psi}_{j,t}^* = e^{\tilde{A}_j * + \left(\tilde{B}_j^*\right)^\top X_t}, \ \tilde{\Psi}_{j,t} = e^{\tilde{A}_j + \tilde{B}_j^\top X_t}, \tag{A.1}$$

and therefore fully characterized by its cumulant-generating function. Given this conjecture, it can be shown that the four solution sequences $\left\{\Psi_{j,t}^*\right\}$, $\left\{\Psi_{j,t}\right\}$, $\left\{\tilde{\Psi}_{j,t}^*\right\}$ and $\left\{\tilde{\Psi}_{j,t}\right\}$ satisfy similar recursions,[45]

$$\begin{aligned} \Psi_{j,t}^* &= E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\Psi_{j-1,t+1}^*\right], & \Psi_{j,t} &= E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\Psi_{j-1,t+1}\right], \\ \tilde{\Psi}_{j,t}^* &= E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\tilde{\Psi}_{j-1,t+1}^*\right], & \tilde{\Psi}_{j,t} &= E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\tilde{\Psi}_{j-1,t+1}\right], \end{aligned} \tag{A.2}$$

but have different initial conditions given by

$$\Psi_{1,t}^* = E_t\left[M_{t,t+1}\right], \ \Psi_{0,t} = E_t\left[1\right], \ \tilde{\Psi}_{1,t}^* = E_t\left[M_{t,t+1}e^{-\eta_{t+1}}\right], \ \tilde{\Psi}_{0,t} = E_t\left[e^{-\eta_t}\right], \tag{A.3}$$

where the solutions to the initial conditions in equation A.3 are obtained by the method of undetermined coefficients. It can be shown that, for $j = n$, we have that

$$\Psi_{n,t}^* = e^{A_n^* + B_n^{*\top} X_t}, \tag{A.4}$$

where the scalar A_n^* and components of the column vector B_n^* are given by

$$\begin{aligned} A_n^* &= A_{n-1}^* + \bar{m} + \left(\left(1-\phi_x\right)B_{x,n-1}^* + \lambda_c - \lambda_x\left(\kappa_1^c - \phi_x\right)\right)\mu_x - \lambda_\sigma\left(\kappa_1^c - 1\right)\mu_\sigma \\ &\quad - \nu_\sigma \log\left(1 - \left(B_{\sigma,n-1}^* - \lambda_\sigma\right)c_\sigma\right) - \nu_\lambda \log\left(1 - \left(B_{\lambda,n-1}^* - 1\right)c_\lambda\right) \\ B_{x,n}^* &= \phi_x B_{x,n-1}^* - \lambda_c + \lambda_x\left(\kappa_1^c - \phi_x\right) \\ B_{\sigma,n}^* &= \frac{1}{2}\left[\lambda_c^2 + \left(B_{x,n-1}^* - \lambda_x\right)^2\nu_x^2\right] + \lambda_\sigma\kappa_1^c + \frac{\left(B_{\sigma,n-1}^* - \lambda_\sigma\right)\phi_{\sigma\sigma}}{1 - \left(B_{\sigma,n-1}^* - \lambda_\sigma\right)c_\sigma} + \frac{\left(B_{\lambda,n-1}^* - 1\right)\phi_{\lambda\sigma}}{1 - \left(B_{\lambda,n-1}^* - 1\right)c_\lambda} \\ B_{\lambda,n}^* &= \frac{\left(B_{\lambda,n-1}^* - 1\right)\phi_{\lambda\lambda}}{1 - \left(B_{\lambda,n-1}^* - 1\right)c_\lambda}, \end{aligned} \tag{A.5}$$

[45] Note that $\Psi_{j,t}^* = E_t\left[M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] = E_t\left[M_{t,t+1}\frac{S_{t+1}}{S_t}E_{t+1}\left[M_{t+1,t+j}\frac{S_{t+j-1}}{S_{t+1}}\right]\right] = E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)E_{t+1}\left[M_{t+1,t+j}\frac{S_{t+j-1}}{S_{t+1}}\right]\right] = E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\Psi_{j-1,t+1}^*\right]$.

and that the recursions for the other equations are identical. It is sufficient to replace the scalars $A^*_\bullet$ by $A_\bullet$, $\tilde{A}^*_\bullet$ and $\tilde{A}_\bullet$ respectively, while the vectors $B^*_\bullet$ have to be substituted by the vectors $B_\bullet$, $\tilde{B}^*_\bullet$ and $\tilde{B}_\bullet$.
The first initial condition for the recursions in equations A.3 is given by

$$E_t\left[M_{t,t+1}\right] = e^{A^*_1 + \left(B^*_1\right)^\top X_t}, \tag{A.6}$$

where the scalar A^*_1 and components of the column vector B^*_1 are given by

$$\begin{aligned} A^*_1 &= \bar{m} + \left(\lambda_c - \lambda_x\left(\kappa^c_1 - \phi_x\right)\right)\mu_x - \lambda_\sigma\left(\kappa^c_1 - 1\right)\mu_\sigma - \nu_\sigma \log\left(1 + \lambda_\sigma c_\sigma\right), \\ B^*_{x,1} &= \lambda_x\left(\kappa^c_1 - \phi_x\right) - \lambda_c, \quad B^*_{\sigma,1} = \frac{1}{2}\left(\lambda_c^2 + \lambda_x^2\nu_x^2\right) + \lambda_\sigma\kappa^c_1 - \frac{\lambda_\sigma\phi_{\sigma\sigma}}{1+\lambda_\sigma c_\sigma}, \quad B^*_{\lambda,1} = 0. \end{aligned} \tag{A.7}$$

The second initial condition in equation A.3 is given by

$$E_t\left[1\right] = e^{A_0 + B_0^\top X_t}, \tag{A.8}$$

where the scalar A_0 and components of the column vector B_0 are given by

$$A_0 = 0, \quad B_{x,0} = 0, \quad B_{\sigma,0} = 0, \quad B_{\lambda,0} = 0. \tag{A.9}$$

The third initial condition in equation A.3 is shown to be equal to

$$E_t\left[M_{t,t+1}e^{-\eta_{t+1}}\right] = e^{\tilde{A}^*_1 + \left(\tilde{B}^*_1\right)^\top X_t}, \tag{A.10}$$

where the scalar $\tilde{A}^*_1$ and components of the column vector $\tilde{B}^*_1$ are given by

$$\begin{aligned} \tilde{A}^*_1 &= \bar{m} - \left(\mu_\eta - \phi_{\eta\sigma}\mu_\sigma - \phi_{\eta\lambda}\mu_\lambda\right) + \left(\lambda_c - \lambda_x\left(\kappa^c_1 - \phi_x\right)\right)\mu_x - \lambda_\sigma\left(\kappa^c_1 - 1\right)\mu_\sigma \\ &\quad - \nu_\sigma\log\left(1 + \left(\phi_{\eta\sigma} + \lambda_\sigma\right)c_\sigma\right) - \nu_\lambda\log\left(1 + \phi_{\eta\lambda}c_\lambda\right), \\ \tilde{B}^*_{x,1} &= \lambda_x\left(\kappa^c_1 - \phi_x\right) - \lambda_c, \quad \tilde{B}^*_{\sigma,1} = \frac{1}{2}\left(\lambda_c^2 + \lambda_x^2\nu_x^2\right) + \lambda_\sigma\kappa^c_1 - \frac{\left(\phi_{\eta\sigma} + \lambda_\sigma\right)\phi_{\sigma\sigma}}{1 + \left(\phi_{\eta\sigma} + \lambda_\sigma\right)c_\sigma} - \frac{\phi_{\eta\lambda}\phi_{\lambda\sigma}}{1 + \phi_{\eta\lambda}c_\lambda}, \\ \tilde{B}^*_{\lambda,1} &= -\frac{\phi_{\eta\lambda}\phi_{\lambda\lambda}}{1 + \phi_{\eta\lambda}c_\lambda}\;. \end{aligned} \tag{A.11}$$

The final initial condition in equation A.3 is characterized by

$$E_t\left[e^{-\eta_t}\right] = e^{\tilde{A}_0 + \tilde{B}_0^\top X_t}, \tag{A.12}$$

where the scalar $\tilde{A}_0$ and components of the column vector $\tilde{B}_0$ are given by

$$\tilde{A}_0 = -\left(\mu_\eta - \phi_{\eta\sigma}\mu_\sigma - \phi_{\eta\lambda}\mu_\lambda\right), \quad \tilde{B}_{x,0} = 0, \quad \tilde{B}^*_{\sigma,0} = -\phi_{\eta\sigma}, \quad \tilde{B}_{\lambda,0} = -\phi_{\eta\lambda}. \tag{A.13}$$

B Decomposing the CDS Spread

Computing the expected loss is equivalent to computing the expressions

$$\begin{aligned}
\Psi^{*EL}_{j,t} &= E_t\left[\frac{S_{t+j-1}}{S_t}\right], \quad \Psi^{EL}_{j,t} = E_t\left[\frac{S_{t+j}}{S_t}\right], \\
\tilde{\Psi}^{*EL}_{j,t} &= E_t\left[\left(1 - R_{t+j}\right)\frac{S_{t+j-1}}{S_t}\right], \quad \tilde{\Psi}^{EL}_{j,t} = E_t\left[\left(1 - R_{t+j}\right)\frac{S_{t+j}}{S_t}\right],
\end{aligned} \tag{B.1}$$

which are conjectured to be exponentially affine in the state vector $X_t = (x_t, \sigma_t^2, \lambda_t)$. More specifically, it can be shown that

$$\begin{aligned}
\Psi^{*EL}_{j,t} &= E_t\left[\left(1 - h_{t+1}\right)\Psi^{*EL}_{j-1,t+1}\right] = e^{A^{*EL}_j + B^{*EL\top}_j X_t}, \\
\Psi^{EL}_{j,t} &= E_t\left[\left(1 - h_{t+1}\right)\Psi^{EL}_{j-1,t+1}\right] = e^{A^{EL}_j + B^{EL\top}_j X_t}, \\
\tilde{\Psi}^{*EL}_{j,t} &= E_t\left[\left(1 - h_{t+1}\right)\tilde{\Psi}^{*EL}_{j-1,t+1}\right] = e^{\tilde{A}^{*EL}_j + \tilde{B}^{*EL\top}_j X_t}, \\
\tilde{\Psi}^{EL}_{j,t} &= E_t\left[\left(1 - h_{t+1}\right)\tilde{\Psi}^{EL}_{j-1,t+1}\right] = e^{\tilde{A}^{EL}_j + \tilde{B}^{EL\top}_j X_t},
\end{aligned} \tag{B.2}$$

where the closed-form expressions of the scalars $A^{*EL}_j, A^{EL}_j, \tilde{A}^{*EL}_j, \tilde{A}^{EL}_j$ and of the column vectors $B^{*EL}_j, B^{EL}_j, \tilde{B}^{*EL}_j, \tilde{B}^{EL}_j$ follow the same recursions given by

$$\begin{aligned}
A_n &= A_{n-1} + B_{x,n-1}\left(1 - \phi_x\right)\mu_x - \nu_\sigma \log\left(1 - B_{\sigma,n-1}c_\sigma\right) - \nu_\lambda \log\left(1 - \left(B_{\lambda,n-1} - 1\right)c_\lambda\right), \\
B_{x,n} &= B_{x,n-1}\phi_x, \quad B_{\sigma,n} = \frac{1}{2}\left(B_{x,n-1}\right)^2 \nu_x^2 + \frac{B_{\sigma,n-1}\phi_{\sigma\sigma}}{1 - B_{\sigma,n-1}c_\sigma} + \frac{\left(B_{\lambda,n-1} - 1\right)\phi_{\lambda\sigma}}{1 - \left(B_{\lambda,n-1} - 1\right)c_\lambda}, \\
B_{\lambda,n} &= \frac{\left(B_{\lambda,n-1} - 1\right)\phi_{\lambda\lambda}}{1 - \left(B_{\lambda,n-1} - 1\right)c_\lambda},
\end{aligned} \tag{B.3}$$

but with different initial conditions

$$\begin{aligned}
\Psi^{*EL}_{1,t} &= E_t\left[1\right] = e^{A^{*EL}_1 + B^{*EL\top}_1 X_t}, \quad \Psi^{EL}_{0,t} = E_t\left[1\right] = e^{A^{EL}_0 + B^{EL\top}_0 X_t}, \\
\tilde{\Psi}^{*EL}_{1,t} &= E_t\left[e^{-\eta_{t+1}}\right] = e^{\tilde{A}^{*EL}_1 + \tilde{B}^{*EL\top}_1 X_t}, \quad \tilde{\Psi}^{EL}_{0,t} = E_t\left[e^{-\eta_t}\right] = e^{\tilde{A}^{EL}_0 + \tilde{B}^{EL\top}_0 X_t},
\end{aligned} \tag{B.4}$$

where

$$
\begin{aligned}
&A_1^{*EL} = 0, \qquad A_0^{EL} = 0, \qquad \tilde{A}_0^{EL} = -\left(\mu_\eta - \phi_{\eta\sigma}\mu_\sigma - \phi_{\eta\lambda}\mu_\lambda\right), \\
&\tilde{A}_1^{*EL} = -\left(\mu_\eta - \phi_{\eta\sigma}\mu_\sigma - \phi_{\eta\lambda}\mu_\lambda\right) - \nu_\sigma \log\left(1 + \phi_{\eta\sigma}c_\sigma\right) - \nu_\lambda \log\left(1 + \phi_{\eta\lambda}c_\lambda\right), \\
&B_1^{*EL} = [0,0,0]^\top, \qquad B_0^{EL} = [0,0,0]^\top, \qquad \tilde{B}_0^{EL} = [0, -\phi_{\eta\sigma}, -\phi_{\eta\lambda}]^\top, \\
&\tilde{B}_1^{*EL} = \left[0, -\frac{\phi_{\eta\sigma}\phi_{\sigma\sigma}}{1+\phi_{\eta\sigma}c_\sigma} - \frac{\phi_{\eta\lambda}\phi_{\lambda\sigma}}{1+\phi_{\eta\lambda}c_\lambda}, -\frac{\phi_{\eta\lambda}\phi_{\lambda\lambda}}{1+\phi_{\eta\lambda}c_\lambda}\right]^\top.
\end{aligned} \tag{B.5}
$$

C Default Probabilities and Recovery Rates

Given the definition of survival probabilities in equation 5, the cumulative probability of default between time $t+1$ and T, conditional on no default prior to $t+1$ and described in equation 31, is equal to

$$
Prob_t\left(t < \tau < T \mid \tau > t\right) = 1 - E_t\left[\frac{S_T}{S_t}\right] = 1 - E_t\left[\prod_{k=1}^{T-t}\left(1 - h_{t+k}\right)\right]. \tag{C.1}
$$

Conjecturing that the second part of equation C.1 is exponentially affine in the state vector $X_t = (x_t, \sigma_t^2, \lambda_t)$,

$$
\Psi_{j,t}^{PD} = E_t\left[\prod_{k=1}^{T-t}\left(1 - h_{t+k}\right)\right] = e^{A_j^{PD} + \left(B_j^{PD}\right)^\top X_t}, \tag{C.2}
$$

it can be shown that the sequence $\{\Psi_j^{PD}\}$ follows the recursion

$$
\Psi_{j,t}^{PD} = E_t\left[\left(1 - h_{t+1}\right)\Psi_{j-1,t+1}^{PD}\right] = e^{A_j^{PD} + \left(B_j^{PD}\right)^\top X_t}, \tag{C.3}
$$

where the recursions of the scalar A_j^{PD} and the vector $\left(B_j^{PD}\right)^\top$ are given by

$$
\begin{aligned}
&A_n^{PD} = A_{n-1}^{PD} + B_{x,n-1}^{PD}\left(1 - \phi_x\right)\mu_x - \nu_\sigma \log\left(1 - B_{\sigma,n-1}^{PD}c_\sigma\right) - \nu_\lambda \log\left(1 - \left(B_{\lambda,n-1}^{PD} - 1\right)c_\lambda\right), \\
&B_{x,n}^{PD} = B_{x,n-1}^{PD}\phi_x, \qquad B_{\sigma,n}^{PD} = \frac{1}{2}\left(B_{x,n-1}^{PD}\right)^2\nu_x^2 + \frac{B_{\sigma,n-1}^{PD}\phi_{\sigma\sigma}}{1 - B_{\sigma,n-1}^{PD}c_\sigma} + \frac{\left(B_{\lambda,n-1}^{PD} - 1\right)\phi_{\lambda\sigma}}{1 - \left(B_{\lambda,n-1}^{PD} - 1\right)c_\lambda}, \\
&B_{\lambda,n}^{PD} = \frac{\left(B_{\lambda,n-1}^{PD} - 1\right)\phi_{\lambda\lambda}}{1 - \left(B_{\lambda,n-1}^{PD} - 1\right)c_\lambda},
\end{aligned} \tag{C.4}
$$

with initial condition

$$
A_0^{PD} = 0 \quad \text{and} \quad B_0^{PD} = [0,0,0]^\top. \tag{C.5}
$$

Similarly, the term structure of expected recovery rates is assumed to be exponentially affine in the state vector $X_t = (x_t, \sigma_t^2, \lambda_t)$,

$$\Psi_{j,t}^R = E_t\left[e^{-\eta_{t+j}}\right] = e^{A_j^R + \left(B_j^R\right)^\top X_t}, \tag{C.6}$$

where the scalar A_j^R and the vector B_j^R can be solved through the recursion

$$\Psi_{j,t}^R = E_t\left[\Psi_{j-1,t+1}^R\right], \tag{C.7}$$

and are thus given by

$$\begin{aligned}
A_n^R &= A_{n-1}^R + B_{x,n-1}^R\left(1-\phi_x\right)\mu_x - \nu_\sigma \log\left(1 - B_{\sigma,n-1}^R c_\sigma\right) - \nu_\lambda \log\left(1 - B_{\lambda,n-1}^R c_\lambda\right), \\
B_{x,n}^R &= B_{x,n-1}^R \phi_x, \qquad B_{\sigma,n}^R = \frac{1}{2}\left(B_{x,n-1}^R\right)^2 \nu_x^2 + \frac{B_{\sigma,n-1}^R \phi_{\sigma\sigma}}{1 - B_{\sigma,n-1}^R c_\sigma} + \frac{B_{\lambda,n-1}^R \phi_{\lambda\sigma}}{1 - B_{\lambda,n-1}^R c_\lambda}, \\
B_{\lambda,n}^R &= \frac{B_{\lambda,n-1}^R \phi_{\lambda\lambda}}{1 - B_{\lambda,n-1}^R c_\lambda},
\end{aligned} \tag{C.8}$$

with initial conditions

$$A_0^R = -\left(\mu_\eta - \phi_{\eta\sigma}\mu_\sigma - \phi_{\eta\lambda}\mu_\lambda\right) \quad \text{and} \quad B_0^R = \left[0, -\phi_{\eta\sigma}, -\phi_{\eta\lambda}\right]^\top. \tag{C.9}$$

D Data Description

This appendix describes in detail the data sources and definitions used for the empirical regression analysis.

1. **Sovereign CDS Spreads**

   Sovereign CDS spreads for all maturities are purchased from Markit, unlike Longstaff et al. (2010), who use CMA data extracted from Bloomberg. These spreads are mid-market quotes, based on the inputs of contributing parties. All contracts are denominated in USD, apply to senior foreign government debt and embed the full restructuring credit event clause. The original spreads are obtained at a daily frequency. To study monthly spreads, I use the last available observation in each month.

2. **Local Stock Market Returns**

   Local stock market returns are monthly total returns including dividends in local currency. To compute returns, I use the Morgan Stanley Capital International (MSCI) total return indices extracted from IHS Global for 37 countries. For those countries for which the MSCI index is not available, I need to find another source of information for the local stock market. I use the Datastream Total Market All Shares total return index for Cyprus, Romania and Slovenia, and the OMX All Share total return index for Lithuania. For Panama, I rely on the Panama SE BVS Price Index, and for Slovakia on the SAX16 Price Index. For Uruguay, I use the Barclays International Bond Index, as I could not find any domestic stock market information for this country.

3. **Exchange Rates**

   The main database for exchange rates is the H10 Report from the Federal Reserve. Non-covered exchange rates are taken from the WM Reuters database and extracted through Datastream. All exchange rates are expressed in units of USD and the regressions use monthly percentage changes. The exchange rate is excluded for Panama, as the country uses the USD.

4. **Foreign Currency Reserves**

   Foreign currency reserves refer to monthly sovereign foreign currency reserves in units of million USD and are based on the International Monetary Fund International Financial Statistics. The data are accessed through IHS Global Insight. The regressions are based on monthly percentage changes.

5. **U.S. Stock Market Returns**

The U.S. stock market return is the monthly value-weighted return on all NYSE, AMEX and NASDAQ stocks from CRSP in excess of the one-month Treasury-bill return from Ibbotson Associates. I am grateful to Kenneth French for making these data publicly available
(http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

6. **Treasury Yields**

Monthly changes in the 5-year constant-maturity Treasury yield are based on the H.15 Report from the Federal Reserve.

7. **Corporate Yield Spreads**

Monthly changes in investment-grade yield spreads are monthly changes in the basis-point yield spread between the Bank of America/Merrill Lynch US Corporate BBB and AAA Effective Yield. Monthly changes in high-yield spreads are monthly changes in the basis-point yield spread between the Bank of America/Merrill Lynch US High Yield BB and Corporate BBB Effective Yield. The data are obtained from the Federal Reserve Bank of St. Louis. In comparison, Longstaff et al. (2010) use the fair market curves for AAA, BBB and BB indices in Bloomberg.

8. **Equity Risk Premium**

Monthly changes in equity premia are approximated by monthly changes in the cyclically adjusted S&P500 Price-Earnings Ratio. I am grateful to Robert Shiller for making these data publicly available (http://www.econ.yale.edu/ shiller/data.htm). Longstaff et al. (2010) use monthly changes in the price-earnings ratio for the S&P100 index from Bloomberg.

9. **Volatility Risk Premium**

The volatility risk premium is defined as the difference between the risk-neutral and objective expectations of realized variance, where the risk-neutral expectation of variance is measured as the end-of-month VIX-squared de-annualized ($VIX^2/12$) and the realized variance is the sum of squared 5-minute log returns of the S&P500 index over the month. I am grateful to Hao Zhou for regularly updating this series on his website (https://sites.google.com/site/haozhouspersonalhomepage/). As the information on the variance risk premium is available only up to December 2011, I replace the first two months in 2012 with the historical average. Longstaff et al. (2010) use the VIX index from Bloomberg and compute realized volatility for the S&P100 index based on the Garman-Klass (1980) open-high-low-close volatility estimator applied to the corresponding data for the S&P100 index (from the Yahoo financial web page) for the 20-day period from date t-19 to t. The authors mention that robustness checks based on Hao Zhou's data are valid.

10. Term Premium

The term premium is defined based on monthly changes in excess bond returns, which are represented as a linear combination of forward rates as in Cochrane-Piazzesi (2005). Using the CRSP Fama-Bliss data (extracted from WRDS) from January 1964 to December 2011, I update the restricted Cochrane-Piazzesi regressions to calculate five-year expected excess bond returns. For the purpose of comparison, Longstaff et al. (2010) use Fama-Bliss data up to December 2006 and five-year Treasury Strips from January 2007 until the end of their sample period. They use the estimated Cochrane-Piazzesi parameters for excess returns drawn directly from the latter publication.

11. Bond Equity Flows

Monthly global bond and equity flows are monthly net new inflows (inflows minus outflows) to long-term mutual bond and equity funds respectively. Flow estimates are derived from data collected covering more than 95 percent of industry assets, and are adjusted to represent industry totals. The information is obtained from the Investment Company Institute. It is important to point out that significant changes to the mutual fund classification have altered the historical dataset, which explains the differences from the historical series in Longstaff et al. (2010). For more details, see http://www.icifactbook.org.[46]

12. Regional and Global Sovereign Spreads

All countries in the sample are grouped into four regions: Europe, Latin America, Asia and Middle East/Africa. For each country, the regional spread is computed as the average spread of all other countries in the same region, excluding the specific country. The global spread is calculated as the mean spread of the countries in all other regions, excluding the specific region focused on. For the regression analysis, only the residual part of these spreads, unexplained by all other regressors, is used.

[46] I thank Doug Richardson from the ICI for being so forthcoming in discussing the data changes with me.

Table 1: Summary Statistics

This table presents summary statistics for sovereign CDS spreads of the 44 countries in the sample. The first four columns report respectively the country name, the geographical region, the first monthly observation in the panel and the number of observations. All series end in February 2012. Columns 5 to 10 report the sample average (in basis points) for the term structure of spreads. Columns 11 to 13 report three alternative statistics (in basis points) for the slope of the CDS curve. The final column N indicates the number of months for which the term structure was inverted. Source: Markit.

Country Information				**Mean Spread**						**Mean Slope**			**Inv. Slope**
Country	Region	Start Date	Obs	1y	2y	3y	5y	7y	10y	10y-1y	10y-3y	3y-1y	N
Austria	Europe	2001-10	125	22	26	29	37	39	41	19	12	8	0
Belgium	Europe	2001-2	133	29	34	38	44	46	47	19	9	10	0
Brazil	Lat.Amer	2001-1	134	318	406	448	498	515	530	212	82	130	7
Bulgaria	E.Eur	2001-4	131	113	145	167	203	215	233	120	66	54	5
Chile	Lat.Amer	2002-2	121	34	46	60	80	91	101	67	40	26	0
China	Asia	2001-1	134	29	36	43	58	65	75	46	32	14	0
Colombia	Lat.Amer	2001-4	131	140	220	267	329	352	374	234	107	127	0
Croatia	E.Eur	2001-2	133	107	128	141	161	171	183	76	42	34	4
Cyprus	Europe	2002-7	116	129	130	132	133	133	133	3	1	3	10
Czech Republic	E.Eur	2001-4	131	30	36	41	49	53	58	28	17	11	2
Denmark	Europe	2003-1	110	14	18	20	26	28	30	16	10	6	0
Egypt	Africa	2002-4	119	150	184	207	251	271	290	140	83	57	0
Finland	Europe	2002-9	114	9	11	13	17	19	21	12	8	4	0
France	Europe	2002-8	115	17	21	26	33	35	38	20	12	8	0
Germany	Europe	2002-10	113	9	12	15	21	23	26	17	11	6	0
Greece	Europe	2001-1	134	814	679	604	515	469	433	-382	-172	-210	26
Hungary	E.Eur	2001-2	133	99	114	122	136	142	147	48	25	23	5
Ireland	Europe	2003-1	110	162	168	167	155	148	139	-23	-27	4	22
Israel	MiddleEast	2001-11	124	47	62	73	95	104	115	68	42	26	0
Italy	Europe	2001-1	134	51	57	62	69	71	74	23	12	11	4
Japan	Asia	2001-2	133	12	17	22	32	38	45	33	22	10	0
Korea	Asia	2001-3	132	58	67	75	89	96	106	48	32	16	1
Lebanon	MiddleEast	2003-3	108	300	340	370	413	436	460	159	90	70	0
Lithuania	E.Eur	2002-9	114	125	134	141	150	153	157	32	16	16	15
Malaysia	Asia	2001-4	131	43	55	66	85	93	108	66	42	23	0
Mexico	Lat.Amer	2001-1	134	66	94	117	152	169	187	122	71	51	0
Morocco	Africa	2001-4	131	101	139	167	201	216	242	141	75	66	0
Panama	Lat.Amer	2002-7	116	77	119	159	212	236	256	179	98	81	0
Peru	Lat.Amer	2002-2	121	94	155	201	260	285	306	212	105	107	0
Philippines	Asia	2001-3	132	138	186	233	307	337	369	231	136	95	4
Poland	E.Eur	2001-1	134	44	56	64	78	85	92	48	28	20	0
Portugal	Europe	2002-2	121	170	177	173	155	147	139	-31	-34	3	22
Qatar	MiddleEast	2001-9	126	44	54	63	79	90	102	58	39	20	0
Romania	E.Eur	2002-7	116	139	169	191	218	231	239	100	48	51	6
Russia	E.Eur	2001-10	125	137	172	194	226	241	261	124	67	57	7
Slovakia	E.Eur	2001-11	124	37	45	51	63	68	74	37	23	14	1
Slovenia	E.Eur	2002-2	121	36	42	47	55	58	62	27	16	11	0
South Africa	Africa	2001-3	132	70	93	113	141	157	173	103	60	43	0
Spain	Europe	2001-7	128	55	61	66	72	72	73	18	7	11	4
Sweden	Europe	2001-5	130	11	13	15	20	21	23	13	9	4	0
Thailand	Asia	2001-5	130	47	60	71	92	101	115	68	44	24	0
Turkey	MiddleEast	2001-1	134	251	309	347	397	420	440	188	93	96	8
Uruguay	Lat.Amer	2002-4	119	790	789	771	731	707	712	-78	-59	-19	19
Venezuela	Lat.Amer	2001-2	133	695	792	832	868	868	865	170	33	137	26

Table 2: Model Parameter Calibration

The upper panel in this table reports model and preference parameter values, which are calibrated at a monthly decision interval. The middle panel reports the endogenous coefficients of the wealth-consumption ratio. The lower two panels present moments of consumption dynamics from the data and the model. The data are real, sampled at an annual frequency, and cover the period 1929 to 2011. Standard errors are Newey-West with one lag. For the model, I report percentiles of these statistics based on 10,000 simulations of 600 months, equaling 50 years of data. The column *Pop* reports population statistics based on a long simulation of 1.2 million months. All statistics are time-averaged. Data for consumption growth is taken from the Bureau of Economic Analysis National Income and Product Accounts Tables.

Preference Parameter Values		
Subjective discount factor	δ	0.9987
Intertemporal elasticity of substitution	ψ	1.7
Coefficient of relative risk aversion	γ	10

Consumption Growth Dynamics		
Mean consumption growth	μ_x	0.0015
Persistence of expected consumption growth	ϕ_x	0.975
Sensitivity to long-run risk shocks	ν_x	0.034
Persistence of volatility	$\phi_{\sigma\sigma}$	0.9945
Volatility level	$\sqrt{\mu_\sigma}$	0.00725
Volatility of volatility	$\sqrt{\omega_\sigma}$	2.8035e-005

Coefficients of the wealth-consumption ratio - Model

A_0^c	A_1^c	A_2^c
6.85	15.80	-1085.18

Consumption - Model

	Mean (%)	1%	5%	50%	95%	99%	Pop
$E[\Delta_c]$	1.79	0.40	0.83	1.78	2.77	3.20	1.80
$\sigma[\Delta_c]$	2.30	0.24	1.61	2.26	3.13	3.50	2.38
$AC1[\Delta_c]$	0.34	-0.01	0.11	0.35	0.57	0.65	0.41

Consumption - Data

	Estimate	SE
$E[\Delta_c]$ (%)	1.97	0.28
$\sigma[\Delta_c]$ (%)	2.02	0.38
$AC1[\Delta_c]$	0.48	0.12

Table 3: Calibration of Default Parameters and CDS Implications

This table reports the calibrated parameters of the default process $\Theta_\lambda = (\phi_{\lambda\sigma}, \phi_\lambda, \nu_\lambda, c_\lambda)^\top$ in columns 2 to 5 for the 44 countries in the sample. The model is simulated over a time-series of 120,000 months. The population values of the average term structure are summarized (in basis points) in columns 6 to 11. Column 12 indicates the long-run average slope (in basis points). For the purpose of comparison, column 13 reports the average 5-year spread (in basis points) observed in the data. Columns 14 to 16 denote the relative root-mean-squared error (RRMSE) in %. The RRMSE is calculated in three different ways, for the full term structure, for the 5-year spread only, and for the long end of the curve, i.e. for maturities 5, 7 and 10.

	Default Parameters Θ_λ				**Mean Spread in Population (bps)**						**Slope (bps)**	**Data**	**Fit - RRMSE (%)**		
Country	$\phi_{\lambda\sigma}$	ϕ_λ	ν_λ	c_λ	1y	2y	3y	5y	7y	10y	10y-1y	5y	All	5y	5-10y
Austria	3.76	0.4662	7.18e-004	2.41e-004	35	36	36	38	39	41	7	37	30	2	3
Belgium	9.55	0.0031	2.36e-013	5.97e-006	47	48	50	52	54	57	9	44	36	17	31
Brazil	106.69	0.0000	1.33e-004	2.37e-005	529	540	550	569	585	604	75	498	33	14	24
Bulgaria	42.70	0.0000	2.85e-008	1.46e-012	211	216	221	229	237	248	36	203	43	13	18
Chile	17.46	0.0036	1.08e-007	2.84e-002	84	86	88	92	95	100	16	80	73	15	15
China	12.77	0.0059	8.91e-008	3.02e-002	62	63	64	67	70	73	12	58	59	16	17
Colombia	133.14	0.0000	1.91e-009	9.98e-001	330	337	344	357	368	383	53	329	61	8	10
Croatia	35.01	0.0004	1.71e-003	5.81e-006	173	177	181	188	195	204	31	161	34	17	25
Cyprus	17.56	0.1441	5.71e-017	9.68e-005	101	104	106	110	114	120	19	133	17	17	24
Czech Rep.	10.20	0.0624	1.75e-008	1.56e-004	54	55	56	59	61	64	10	49	43	19	26
Denmark	5.18	0.0943	2.00e-003	9.95e-006	28	29	30	31	32	34	5	26	53	19	27
Egypt	54.78	0.0000	1.05e-003	7.97e-006	271	277	283	294	303	316	45	251	43	17	23
Finland	2.30	0.2503	2.51e-007	1.17e-002	15	15	16	16	17	18	3	17	33	5	20
France	6.77	0.0725	2.57e-002	6.71e-010	36	37	38	39	41	43	7	33	59	19	29
Germany	0.91	0.7769	2.13e-002	2.75e-015	20	20	21	22	23	24	4	21	60	4	9
Greece	0.71	0.9520	1.00e+000	7.38e-008	72	73	74	76	79	83	11	515	86	85	144
Hungary	23.70	0.0959	7.43e-004	3.29e-005	130	133	135	141	146	153	24	136	15	4	6
Ireland	0.08	0.9961	9.90e-003	5.59e-005	118	118	117	115	113	111	-7	155	26	26	40
Israel	20.12	0.0018	1.24e-007	1.56e-006	100	102	104	108	112	118	18	95	56	14	16
Italy	15.08	0.0013	1.51e-008	1.97e-007	75	76	78	81	84	89	14	69	29	18	33
Japan	5.00	0.0199	1.16e-006	3.64e-006	25	26	26	27	29	30	5	32	53	14	44
Korea	13.98	0.1973	4.79e-003	4.75e-006	86	88	90	94	97	102	16	89	25	5	6
Lebanon	92.27	0.0198	1.00e-001	1.09e-010	467	477	486	502	517	535	69	413	34	22	33
Lithuania	26.53	0.0963	8.50e-001	5.95e-005	150	154	157	163	168	176	26	150	13	8	18
Malaysia	17.72	0.0373	4.00e-004	3.63e-006	91	93	95	99	103	108	17	85	57	16	19
Mexico	62.66	0.0001	1.20e-008	9.97e-001	155	159	162	169	175	183	28	152	64	11	12
Morocco	42.50	0.0001	9.59e-001	9.71e-012	211	215	220	228	236	247	36	201	52	13	16
Panama	43.76	0.0000	2.83e-013	8.68e-004	217	221	226	235	243	254	37	212	84	11	11
Peru	52.98	0.0000	1.04e-002	3.18e-010	262	268	274	284	293	306	44	260	80	9	10
Philippines	63.61	0.0000	7.81e-008	6.91e-003	313	320	326	338	349	364	51	307	62	10	11
Poland	12.11	0.2194	4.61e-004	4.15e-006	77	78	80	83	87	91	14	78	36	7	7
Portugal	0.01	0.9943	8.19e-010	1.23e-014	5	5	5	5	5	5	0	155	97	97	167
Qatar	34.81	0.0001	5.74e-009	9.94e-001	86	88	90	94	97	103	16	79	51	19	21
Romania	55.44	0.0000	1.21e-008	1.64e-001	236	241	246	255	264	276	40	218	37	17	27
Russia	98.10	0.0000	9.03e-011	1.00e+000	243	248	253	263	272	284	41	226	40	16	23
Slovakia	21.36	0.0000	8.90e-016	5.64e-001	68	69	71	74	76	80	13	63	44	17	22
Slovenia	11.89	0.0161	1.07e-008	3.21e-008	60	61	62	65	68	71	11	55	37	18	29
Sth. Africa	59.10	0.0000	3.96e-009	9.87e-001	147	151	154	160	166	174	26	141	54	13	14
Spain	23.32	0.2212	4.26e-007	9.23e-001	65	66	67	69	72	76	11	72	8	4	5
Sweden	4.19	0.0307	7.20e-014	4.72e-005	21	22	22	23	24	26	4	20	53	16	25
Thailand	19.63	0.0021	1.29e-003	2.21e-005	97	100	102	106	110	115	18	92	55	15	17
Turkey	84.88	0.0000	4.62e-005	1.36e-005	421	430	438	454	467	484	64	397	35	14	21
Uruguay	1.84	0.9871	1.60e-003	1.59e-004	623	622	621	617	615	617	-6	731	18	16	24
Venezuela	191.41	0.0054	1.97e-003	9.75e-006	956	975	991	1018	1039	1061	105	868	24	17	35

Table 4: Asset Pricing Implications: Expected Losses, Risk Premia and Cumulative Default Probabilities

This table reports the expected loss and risk premium components of population values of CDS spreads. These are based on a simulated time-series of 120,000 months. The last three columns refer to the model-implied unconditional cumulative default probabilities.

	Expected Loss (%)			**Risk Premium (%)**			**Cumulative PD (%)**		
Country	1y	5y	10y	1y	5y	10y	1y	5y	10y
Austria	97.38	89.44	81.53	2.62	10.56	18.47	0.45	2.22	4.37
Belgium	97.10	89.19	81.37	2.90	10.81	18.63	0.61	3.01	5.90
Brazil	97.12	89.76	83.55	2.88	10.24	16.45	6.55	27.96	46.99
Bulgaria	97.11	89.39	82.15	2.89	10.61	17.85	2.69	12.58	23.26
Chile	97.11	89.23	81.55	2.89	10.77	18.45	1.08	5.27	10.19
China	97.11	89.21	81.44	2.89	10.79	18.56	0.80	3.89	7.59
Colombia	97.11	89.53	82.70	2.89	10.47	17.30	4.16	18.77	33.42
Croatia	97.11	89.34	81.98	2.89	10.66	18.02	2.21	10.47	19.61
Cyprus	97.16	89.30	81.67	2.84	10.70	18.33	1.30	6.30	12.11
Czech Rep.	97.13	89.22	81.42	2.87	10.78	18.58	0.69	3.40	6.66
Denmark	97.14	89.20	81.30	2.86	10.80	18.70	0.37	1.81	3.58
Egypt	97.11	89.46	82.43	2.89	10.54	17.57	3.44	15.77	28.61
Finland	97.19	89.23	81.28	2.81	10.77	18.72	0.19	0.96	1.90
France	97.13	89.20	81.33	2.87	10.80	18.67	0.47	2.30	4.53
Germany	97.97	90.15	82.05	2.03	9.85	17.95	0.26	1.30	2.57
Greece	98.85	93.50	85.67	1.15	6.50	14.33	0.95	4.62	8.97
Hungary	97.14	89.32	81.79	2.86	10.68	18.21	1.66	7.97	15.16
Ireland	98.60	95.31	90.55	1.40	4.69	9.45	1.43	5.52	9.11
Israel	97.11	89.25	81.62	2.89	10.75	18.38	1.28	6.20	11.92
Italy	97.11	89.22	81.50	2.89	10.78	18.50	0.96	4.69	9.10
Japan	97.11	89.17	81.26	2.89	10.83	18.74	0.33	1.62	3.19
Korea	97.19	89.31	81.62	2.81	10.69	18.38	1.11	5.38	10.41
Lebanon	97.12	89.70	83.30	2.88	10.30	16.70	5.81	25.22	43.13
Lithuania	97.24	89.72	82.46	2.76	10.28	17.54	1.93	9.17	17.34
Malaysia	97.12	89.25	81.59	2.88	10.75	18.41	1.17	5.68	10.96
Mexico	97.11	89.32	81.89	2.89	10.68	18.11	1.99	9.44	17.80
Morocco	97.11	89.39	82.15	2.89	10.61	17.85	2.68	12.52	23.17
Panama	97.11	89.39	82.18	2.89	10.61	17.82	2.75	12.85	23.73
Peru	97.11	89.45	82.39	2.89	10.55	17.61	3.33	15.31	27.84
Philippines	97.11	89.51	82.62	2.89	10.49	17.38	3.95	17.91	32.05
Poland	97.20	89.31	81.58	2.80	10.69	18.42	0.99	4.81	9.33
Portugal	99.20	98.16	95.12	0.80	1.84	4.88	0.06	0.32	0.63
Qatar	97.11	89.24	81.56	2.89	10.76	18.44	1.11	5.40	10.43
Romania	97.11	89.42	82.27	2.89	10.58	17.73	3.00	13.90	25.50
Russia	97.11	89.42	82.30	2.89	10.58	17.70	3.08	14.27	26.13
Slovakia	97.10	89.21	81.47	2.90	10.79	18.53	0.87	4.25	8.28
Slovenia	97.11	89.21	81.43	2.89	10.79	18.57	0.77	3.77	7.36
Sth. Africa	97.11	89.31	81.85	2.89	10.69	18.15	1.88	8.98	16.98
Spain	97.12	89.23	81.47	2.88	10.77	18.53	0.83	4.02	7.82
Sweden	97.11	89.17	81.25	2.89	10.83	18.75	0.28	1.37	2.71
Thailand	97.11	89.25	81.61	2.89	10.75	18.39	1.25	6.06	11.65
Turkey	97.12	89.64	83.09	2.88	10.36	16.91	5.26	23.12	40.07
Uruguay	98.86	95.47	90.26	1.14	4.53	9.74	7.35	27.83	44.81
Venezuela	97.14	90.25	85.19	2.86	9.75	14.81	11.44	43.66	66.29

Table 5: Principal Component Analysis

These tables report the fraction of variation in CDS spread changes explained by the first three principal components. Panel A is for 5-year CDS spreads only, panel B applies the principal componenent analysis to the full term structure of spreads, including the 1, 2, 3, 5, 7 and 10-year spreads, while panel C uses changes in the slope of the term structure. The slope is defined as the difference between the 10-year and 1-year spread. The column *Full Sample* is for the entire sample period from January 2003 to February 2012. The subperiods refer to the time before the financial crisis (Jan2003-Dec2006), the financial crisis (Jan2007-Dec2010) and the sovereign debt crisis (Jan2011-Feb2012).

	Full Sample		2003-2006		2007-2010		2011-2012	
A: 44 countries - 5-year spreads								
	%	Cumulative	%	Cumulative	%	Cumulative	%	Cumulative
PC1	56.52	56.52	42.63	42.63	75.36	75.36	57.96	57.96
PC2	8.14	64.66	15.25	57.88	6.05	81.41	13.33	71.29
PC3	4.44	69.10	11.95	69.83	4.74	86.15	7.56	78.85
B: 30 countries - Term structure of spreads								
	%	Cumulative	%	Cumulative	%	Cumulative	%	Cumulative
PC1	54.59	54.59	54.60	54.60	75.84	75.84	62.70	62.70
PC2	10.04	64.63	12.74	67.34	5.71	81.55	12.82	75.52
PC3	5.03	69.66	7.43	74.77	3.70	85.26	9.26	84.78
C: 30 countries - Slope of spreads								
	%	Cumulative	%	Cumulative	%	Cumulative	%	Cumulative
PC1	21.79	21.79	24.20	24.20	38.00	38.00	31.30	31.30
PC2	9.26	31.06	16.35	40.55	12.85	50.85	18.32	49.62
PC3	7.92	38.98	10.38	50.93	10.22	61.07	12.43	62.05

Table 6: Country Regressions - CDS

T-statistics and regression results from the projection of monthly changes in 5-year sovereign CDS spreads onto local and global variables. T-statistics are calculated using White robust standard errors. N denotes the number of monthly observations. *, ** and *** denote significance at the 1, 5 and 10 % levels respectively. LR denotes the ratio of the adjusted R^2 statistic from the restricted regression including only domestic variables to that of the unrestricted regression. The +, ++ and + + + superscripts mark countries that had an inverted term structure for 1 to 5, 6 to 15 and 17 to 26 months respectively during the sample period. Rows are sorted on the number of inverted term structure months. The last three rows report the fraction of countries for which statistical significance is obtained at the 10% level. $Group^{o}$ and $Group^{++}$ denote all countries that had less than 6, respectively more than 5, months with an inverted term structure. For the columns headed R^2_{adj}, LR and N, the values are sample averages.

Country	Local Variables			Global Financial Market Variables				Global Risk Premia			Capital Flows		Sovereign Spreads		R^2_{adj}	LR	N
	Stock return	Exchg Rate	Currncy Resrv	Stock Market	Trsy Yield	Invst Grade	High Yield	Equity Prem	Vol Prem	Term Prem	Stock Flows	Bond Flows	Global Sprd	Region Sprd			
Austria	-3.18***	2.23**	0.47	-2.89***	1.04	0.89	0.23	3.53***	1.69**	-0.38	-0.69	-1.21	-0.64	6.44***	0.68	0.58	124
Belgium	0.53	2.49***	0.30	-3.18***	0.07	-1.03	0.77	3.11***	0.16	-0.51	-2.35***	-1.81**	-1.89**	3.49***	0.33	0.35	132
Chile	-1.63*	2.70***	-0.57	-4.85***	-0.54	0.10	-0.25	0.80	-1.79**	-2.91***	-1.09	-0.23	5.61***	1.14	0.64	0.55	120
China	-4.58***	-1.24	-3.71***	-3.78***	-2.27**	0.18	2.19**	2.82***	1.97**	-3.33***	1.27	-2.22**	3.85***	2.09**	0.71	0.53	133
Colombia	-0.34	2.86***	0.56	-4.12***	1.41*	2.02**	-2.20**	-1.23	-0.82	-2.77***	0.45	2.96***	-1.52*	3.55***	0.61	0.33	130
Denmark	-1.91**	1.53*	-1.22	-1.51*	-0.50	1.18	2.38***	2.73***	3.70***	-0.40	-1.49*	-2.13**	0.13	3.91***	0.70	0.33	109
Egypt	-4.12***	-3.54***	0.15	-3.27***	-2.25**	0.30	-0.93	2.39***	-1.91**	0.17	-0.69	-1.64*	1.04	2.50***	0.50	0.65	118
Finland	-0.22	1.48*	-0.74	-3.18***	-0.96	-0.31	0.79	2.62***	0.98	-0.81	-1.51*	-1.93**	0.85	5.44***	0.67	0.36	113
France	-1.77**	2.66***	-1.76**	-1.19	-0.24	-0.40	1.36*	2.26**	0.41	0.04	-1.37*	-1.36*	-2.03**	5.66***	0.61	0.54	114
Germany	-2.04**	2.21**	-1.17	-4.13***	-0.22	0.05	0.15	3.03***	3.65***	-0.48	-1.21	-1.76**	1.85**	6.13***	0.74	0.38	112
Israel	0.41	0.00	-2.45***	-5.23***	1.38*	0.38	-0.46	2.41***	-1.72**	-2.60***	-1.33*	0.37	1.72**	1.53*	0.36	0.25	123
Japan	-2.35***	1.63*	0.55	-3.19***	0.48	2.02**	0.05	2.50***	1.69**	-1.24	0.06	0.56	3.03***	2.09**	0.45	0.35	132
Lebanon	-1.88**	0.63	-4.29***	-2.30**	1.74**	-0.66	-0.01	-0.46	-2.70***	-0.92	-1.73**	0.74	-0.18	4.15***	0.44	0.40	107
Malaysia	-1.26	2.77***	2.36***	-4.66***	0.52	-0.34	3.32***	0.67	0.59	-0.94	-0.24	1.23	3.03***	3.04***	0.70	0.38	130
Mexico	-4.24***	3.23***	-0.14	-4.70***	-0.04	0.97	-0.20	0.70	-1.46*	-2.44***	0.80	1.02	4.45***	5.35***	0.76	0.77	133
Morocco	1.12	-0.31	-1.08	-0.91	-0.46	1.43*	1.58*	-0.60	1.19	-0.20	-2.28**	-0.45	1.71**	-0.14	0.37	0.10	130
Panama	2.32**		0.62	-4.56***	3.08***	-0.13	-0.51	-1.87**	0.98	-2.90***	-2.85***	0.31	1.74**	3.35***	0.71	-0.02	96
Peru	-3.89***	2.84***	2.11**	-3.42***	0.18	1.00	-0.98	-0.85	-1.40*	-2.30**	0.48	2.44***	0.02	2.91***	0.59	0.41	120
Poland	-4.08***	1.10	-2.36***	-4.26***	-0.90	1.02	2.68***	3.24***	0.88	-2.44***	-0.24	-1.54*	0.18	7.33***	0.78	0.49	133
Qatar	-2.74***	-0.57	1.28	-5.43***	-0.83	0.24	-0.92	2.25**	-0.39	-1.18	-2.48***	-2.90***	0.67	3.66***	0.61	0.16	125
Slovenia	-0.55	4.91***	-2.57***	-2.18**	-1.70**	-0.56	1.09	1.39*	1.46*	-2.41***	-1.56*	-2.05**	-0.31	4.04***	0.68	0.30	120
SouthAfrica	-1.03	6.19***	0.54	-4.06***	1.08	0.25	3.38***	2.34***	-0.58	-2.37***	-0.75	-0.98	3.39***	1.08	0.68	0.64	131
Sweden	2.23**	0.40	-0.40	-3.22***	0.37	0.92	2.03**	5.32***	0.11	-0.75	-2.74***	-2.35***	-0.33	2.61***	0.57	0.34	129
Thailand	-2.69***	3.20***	-0.71	-4.36***	-0.01	1.44*	4.35***	3.17***	1.55*	-1.10	1.16	1.21	1.75**	2.98***	0.68	0.40	129
Korea^{+}	-2.43***	4.94***	-2.01**	-5.00***	0.65	-0.89	2.54***	2.45***	-2.34***	-1.71**	1.60*	0.53	3.21***	4.16***	0.77	0.68	131
Slovakia^{+}	0.74	4.32***	-0.14	-3.79***	-1.57*	-0.06	1.04	2.03**	0.31	-3.23***	-1.67**	-1.19	1.66**	6.82***	0.75	0.19	123
CzechRep.$^{+}$	-4.65***	4.28***	0.45	-3.91***	-0.40	-0.39	0.04	2.02**	-0.24	-2.59***	0.26	-2.18**	0.11	6.81***	0.74	0.54	130
Croatia^{+}	-1.78**	0.55	-1.64*	-5.30***	0.36	1.19	2.14**	4.10***	0.08	-0.91	-1.91**	-1.64*	-0.16	6.68***	0.71	0.36	132
Italy^{+}	-2.81***	2.68***	-2.02**	-0.37	-0.51	1.63*	2.55***	3.15***	1.69**	-1.45*	-1.39*	-0.68	-1.98**	3.85***	0.47	0.57	133
Philippines^{+}	-4.10***	2.81***	0.21	-4.41***	0.21	0.69	0.31	1.18	-1.21	-0.62	-0.43	1.01	1.96**	3.90***	0.55	0.64	131
Spain^{+}	-2.31**	3.10***	1.29*	-0.06	-0.73	0.26	2.38***	3.45***	0.96	-0.73	-0.25	0.00	-2.02**	3.43***	0.41	0.64	127
Bulgaria^{+}	-0.82	1.79**	1.01	-6.02***	2.49***	3.29***	1.66**	3.58***	2.00**	-1.18	-2.82***	-1.14	2.94***	6.53***	0.67	0.25	130
Hungary^{+}	-4.08***	3.39***	0.11	-2.60***	0.61	3.42***	1.48*	4.15***	0.78	-0.25	-1.61*	-1.67**	-2.88***	3.78***	0.70	0.76	132
Romania^{++}	-1.10	0.85	0.05	-4.53***	0.26	1.10	0.66	1.71**	1.17	-1.48*	-0.12	0.11	2.46***	3.37***	0.63	0.34	115
Brazil^{++}	-2.67***	2.20**	1.32*	-0.91	0.53	1.14	-2.16**	-1.86**	0.47	-1.43*	1.89**	3.65***	-1.46*	4.58***	0.56	0.41	133
Russian^{++}	-4.63***	0.06	-1.35*	-5.50***	-0.55	0.44	1.53*	3.14***	-0.80	-2.70***	0.13	-1.64*	3.90***	3.44***	0.76	0.63	124
Turkey^{++}	-3.25***	2.52***	-0.53	-1.16	-0.01	0.42	-0.43	-0.76	-0.09	-1.23	1.37*	2.92***	2.79***	0.65	0.45	0.94	132
Cyprus^{++}	-1.54*	0.94	0.39	-0.20	-1.18	-1.24	0.31	0.06	-1.07	-1.02	-0.58	-1.28	-1.01	0.72	0.17	0.93	115
Lithuania^{++}	-2.37***	0.25	0.97	-4.38***	0.37	1.64*	-0.65	3.43***	-0.38	-2.37***	-1.75**	-1.48*	0.99	3.60***	0.69	0.40	113
Uruguay^{+++}	-4.19***	-0.55	-2.13**	-1.23	-1.84**	-1.10	-0.02	1.71**	-0.88	-0.66	-0.78	0.56	-1.60*	0.76	0.41	1.00	118
Ireland^{+++}	-0.80	0.22	-2.35***	-1.46*	0.25	-1.10	0.32	1.58*	0.27	-0.74	-1.80**	-0.67	-0.46	0.14	0.11	1.00	109
Portugal^{+++}	-1.88**	1.75**	-1.69**	0.32	-0.94	0.29	2.00**	2.30**	1.08	-0.13	0.13	0.52	0.25	-0.28	0.07	1.08	120
Greece^{+++}	-1.56*	-0.06	1.47*	-0.09	-0.17	1.50*	1.04	1.08	1.36*	1.68**	0.12	1.01	0.41	1.47*	0.19	0.76	133
Venezuela^{+++}	-0.81	0.82	0.84	-4.35***	-0.87	1.98**	-0.12	2.51***	-2.96***	-2.42***	-0.79	-1.27	2.06**	1.73**	0.46	0.05	132
All	0.70	0.61	0.41	0.77	0.23	0.23	0.43	0.75	0.41	0.45	0.48	0.45	0.61	0.82	0.60	0.49	124
Group^{o}	0.70	0.73	0.36	0.88	0.27	0.21	0.48	0.76	0.48	0.42	0.52	0.48	0.64	0.91	0.60	0.43	125
Group^{++}	0.73	0.27	0.55	0.45	0.09	0.27	0.27	0.73	0.18	0.55	0.36	0.36	0.55	0.55	0.40	0.69	122

Table 7: Local Ratios

The local ratio (LR) denotes the ratio of the adjusted R^2 from the restricted regression of changes in 5-year CDS spreads on local variables only to that from the unrestricted regression on local and global variables. Countries are grouped into two categories. G1 contains all countries that never had an inverted slope. G2 contains all countries with at least one month of inverted slope. The restricted sample excludes outliers. Venezuela had inverted slopes, but the adjusted R^2-statistic from the restricted regression is close to zero. Given its significance for global oil production, it is arguably a special case. Egypt and Mexico never had inverted CDS slopes. However, Mexico faced a significant economic downward trend in connection with the cartel drug war, while Egypt went through the Arab revolution. Inferences are obtained by block-bootstrapping 10,000 times a sample size of 36 months for each country. A one-sided t-test on the equality of means, assuming paired data, against the alternative that G1 has a smaller mean, is rejected at the 1% significance level. The Wilcoxon matched-pairs signed-rank test rejects the null hypothesis that both distributions are the same, while the one-sided sign test rejects equality of medians against the alternative that the median of G1 is lower.

	Full Sample (44 countries)		**Restricted Sample (41 countries)**	
	Mean LR (%)	Median LR (%)	Mean LR (%)	Median LR (%)
Group 1: Slope was never inverted	40	38	36	36
Group 2: Slope was inverted	61	63	64	64
t-test	$p < 0.01$		$p < 0.01$	
Sign test		$p < 0.01$		$p < 0.01$
Wilcoxon signed-rank test	$p < 0.01$		$p < 0.01$	

Figure 1: Expected Consumption Growth and Consumption Volatility

These two figures plot the filtered time series of the conditional expected consumption growth and consumption volatility over the time period January 1959 through March 2012. Grey shaded areas indicate NBER recessions. Data for real per capita consumption are taken from the FRED database of the Federal Reserve Bank of St.Louis. The estimated series is obtained using a Kalman Filter method with time-varying coefficients. The parameters are based on the model

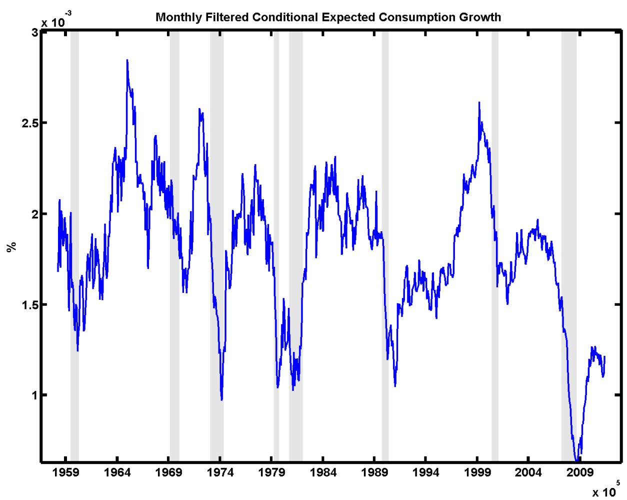
$$\begin{aligned}\Delta c_{t+1} &= x_t + \sigma_t \epsilon_{c,t+1} \\ x_{t+1} &= (1-\phi_x)\,\mu_x + \phi_x x_t + \nu_x \sigma_t \epsilon_{x,t+1},\end{aligned}$$

with time-varying volatility

$$\sigma_{t+1}^2 = (1-\phi_\sigma)\,\mu_\sigma + \phi_\sigma \sigma_t^2 + \frac{\nu_\sigma}{\sqrt{2}}\left(\left(\frac{\Delta c_{t+1} - x_{t|t}}{\sigma_t}\right)^2 - 1\right),$$

and the standard errors are given in parentheses. The parameter ν_σ is constrained to $\nu_\sigma = \sqrt{2}\,(1-\phi_\sigma)\,\mu_\sigma$. A Likelihood-Ratio test failed to reject the constrained version over the unconstrained model.

Parameter	μ_x	ϕ_x	ν_x	μ_σ	ϕ_σ
Estimate	0.001680	0.963716	0.059194	1.307831e-005	0.950917
s.e.	(0.000245)	(0.026166)	(0.028746)	(1.447318e-006)	(0.015701)
t-stat	6.87	36.83	2.06	9.04	60.56



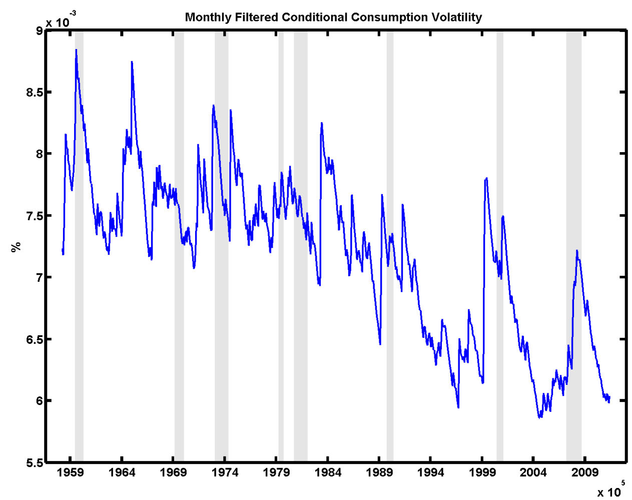


Figure 2: Model-implied 5-year CDS Spreads and Slope vs. DATA

These figures plot the model-implied 5-year conditional CDS spread (left column) and the conditional slope (right column) against the observed series in the data for Malaysia, Finland, Uruguay and Ireland. The red solid line is the model-implied spread, while the dotted black line with bullet points is the observed spread in the data.

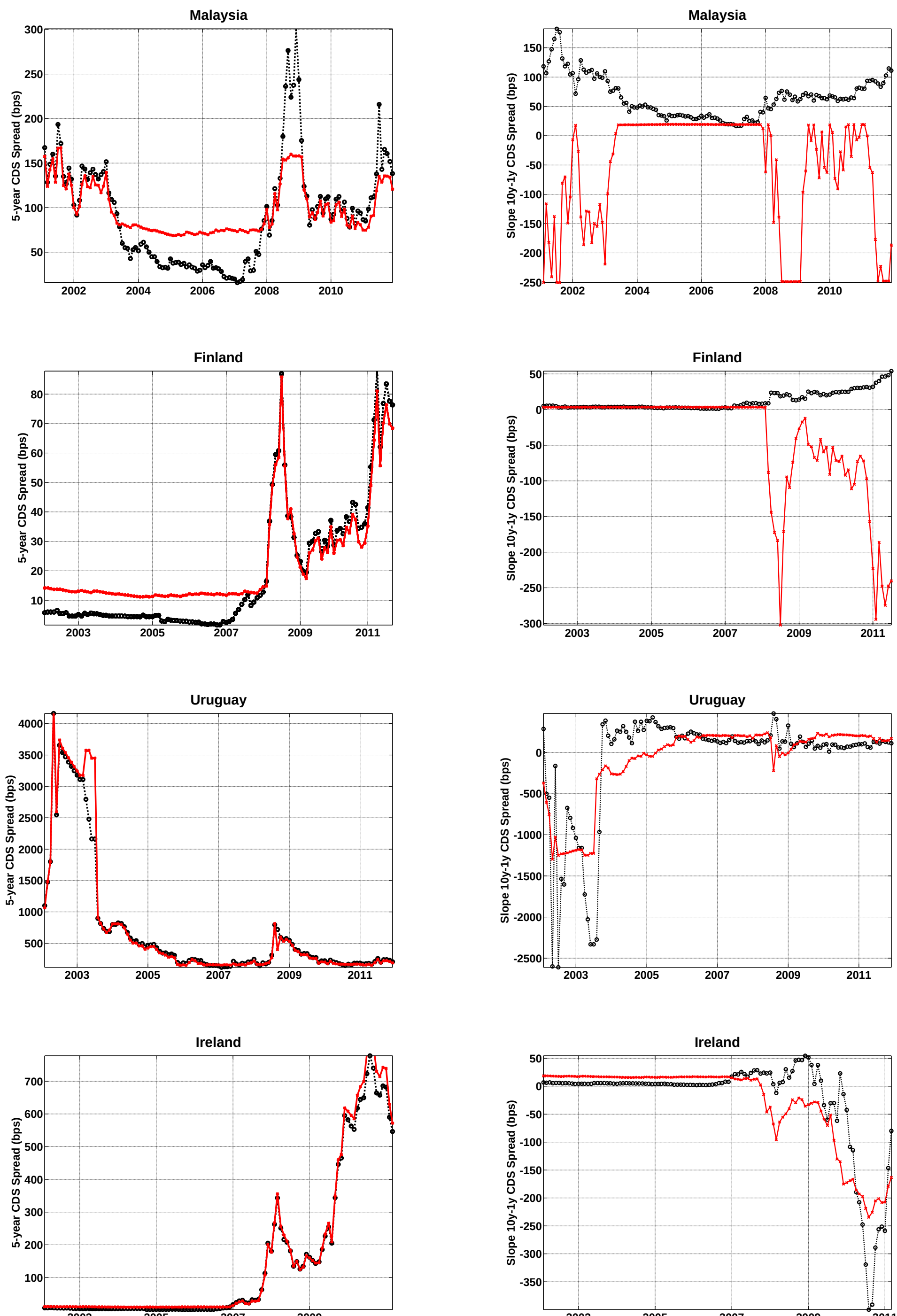
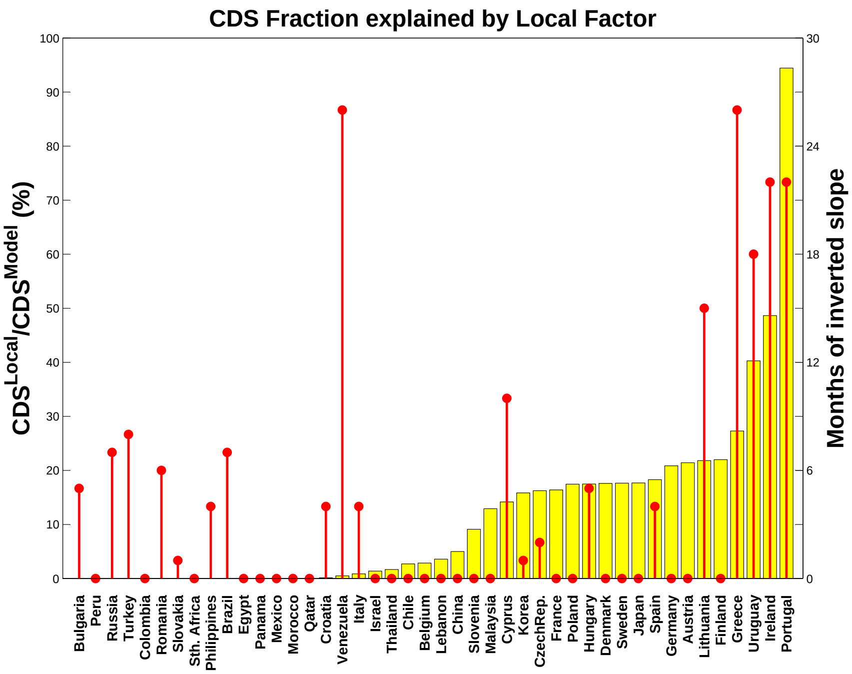


Figure 3: Local CDS Spreads and Variance Decomposition

The upper graph plots the average local CDS spread as a fraction of the model-implied spread (yellow bars, left scale). The lower graph reports the fraction of the CDS variance explained by the global CDS spread (yellow bars, left scale). In both figures, the red lines refer to the number of months for which the CDS term structure was inverted in the data (right scale). The slope of the term structure is defined as the difference between the 10-year and 1-year spreads.



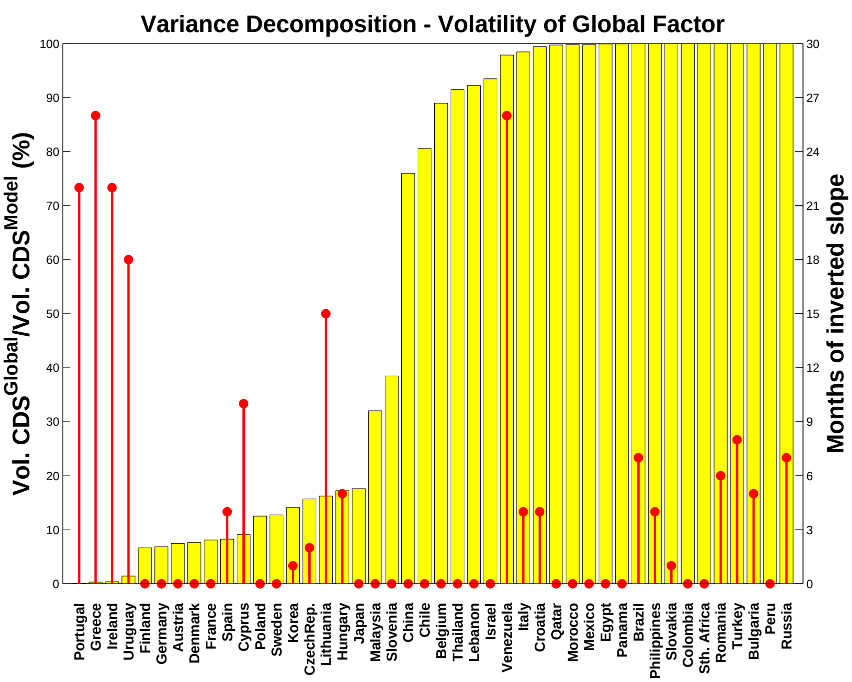


Figure 4: Time Variation in the Term Structure

These graphs plot model-implied metrics for a simulated sample path of 600 months. The default parameters used for the simulation are the calibrated values for Uruguay, that is $\phi_{\lambda\sigma} = 1.84$, $\phi_{\lambda} = 0.9871$, $\nu_{\lambda} = 1.60e\text{-}03$ and $c_{\lambda} = 1.59e\text{-}04$. The north-west graph plots the evolution of the 1-year (dash-dotted blue line) and 10-year (solid green line) CDS spreads in basis points. The north-east graph illustrates the slope of the CDS curve in basis points (solid black line, left scale) vs. the conditional volatility of the default process (dash-dotted red line, right scale). The south-west corner shows the simulated time-series for the risk premium (solid red line, right axis) and expected loss (dash-dotted black line, left axis) in basis points. The south-east corner plots the evolution of aggregate macroeconomic uncertainty (solid green line, left axis), annualized and in %, against the risk premium in basis points (dash-dotted blue line, right axis), and the default process λ_t (solid red line with dotted markers, right axis). The default process is multiplied by 1,000 for better visualization.

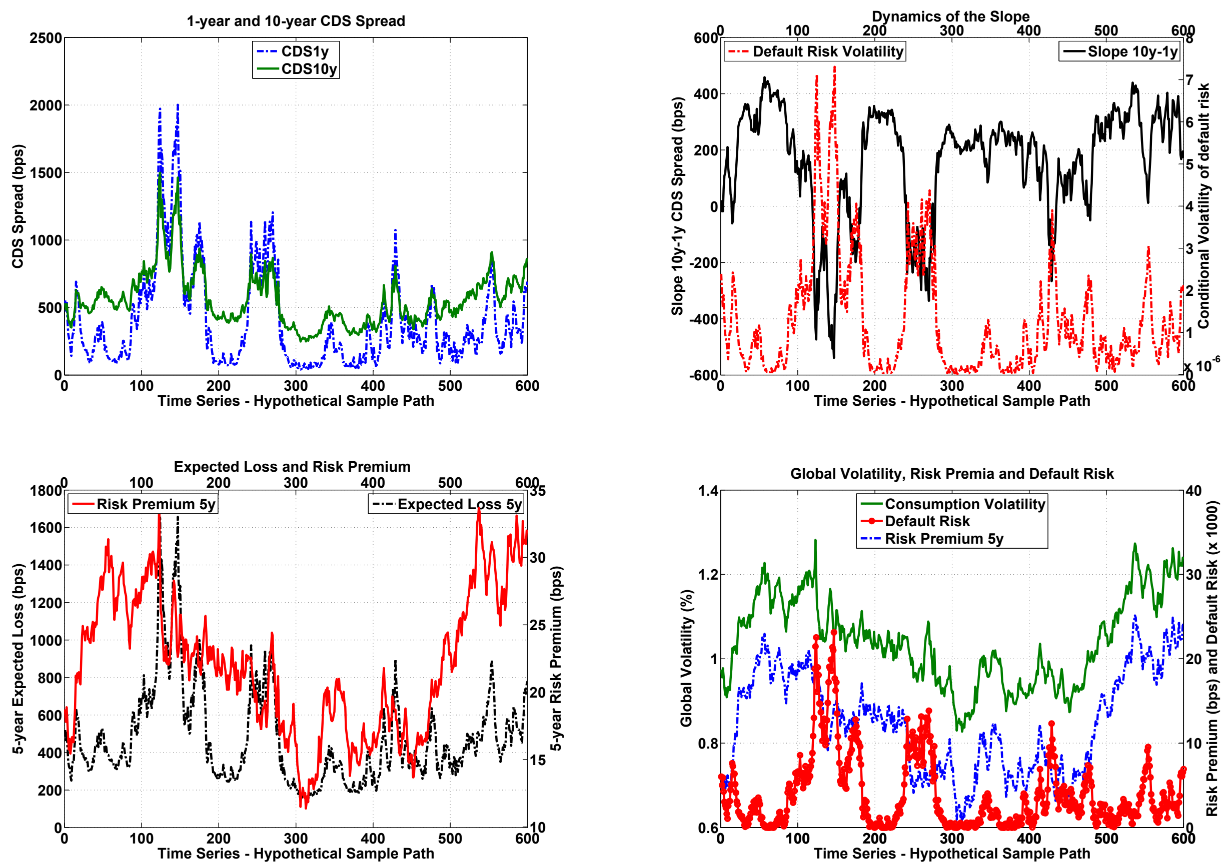


Figure 5: Analyzing the CDS Term Structure

The two upper graphs illustrate the sensitivity of the slope of the CDS term structure (in basis points) when ϕ_λ and $\phi_{\lambda\sigma}$ are perturbed, keeping the mean μ_λ and volatility of default ω_λ constant at 0.005 and 5e-04 respectively. The north-west figure perturbs ϕ_λ for different values of $\phi_{\lambda\sigma}$ equal to 1 (dotted red line), 2.6 (solid black line), 42 (dash-dotted blue line) and 66 (dashed green line). The north-east figure perturbs $\phi_{\lambda\sigma}$ for different values of ϕ_λ equal to 0.1 (dotted red line), 0.25 (dash-dotted blue line), 0.5 (dashed green line) and 0.75 (solid black line). Keeping the mean and volatility constant requires an adjustment to $\nu_\lambda > 0$ and $c_\lambda > 0$. The lines are plotted for values remaining in their respective domains. The bottom graph illustrates a similar analysis for the slope of the CDS term structure by perturbing the volatility of the default process ω_λ and keeping the mean default rate μ_λ constant at 0.0039. The outcome is reproduced for different combinations of ϕ_λ and $\phi_{\lambda\sigma}$, that is 0.90 and 7.5 (dotted red line), 0.50 and 37.5 (dashed-dotted blue line line), 0.20 and 60 (dashed green line), 0.01 and 74.25 (solid black line).

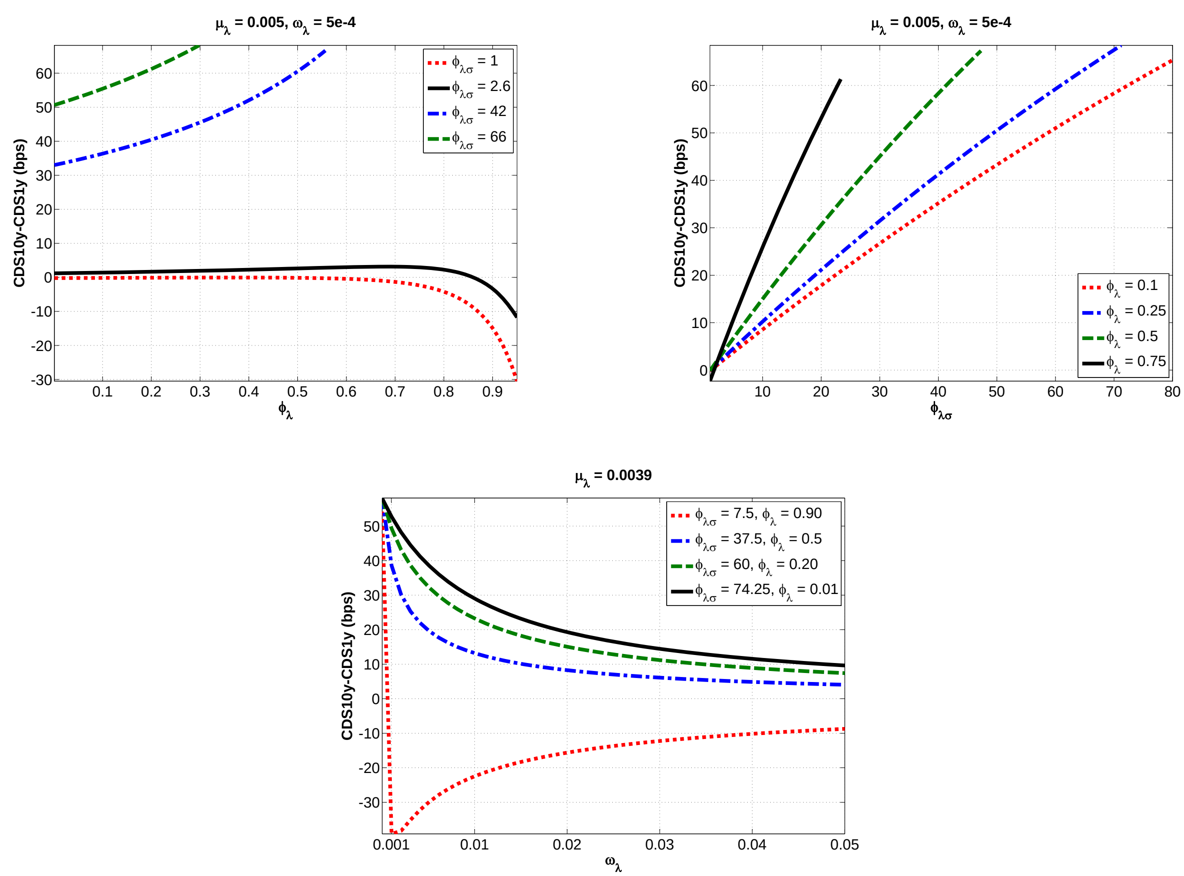


Figure 6: Principal Components

These figures plot the loadings of the individual countries on the first (upper graph) and second (lower graph) principal component, PC1 and PC2 respectively. The value of the loadings is indicated on the left axis. The red lines in the top graph indicate the number of months for which the term structure was inverted and are related to the right axis. The graphs are sorted on the size of their loadings.

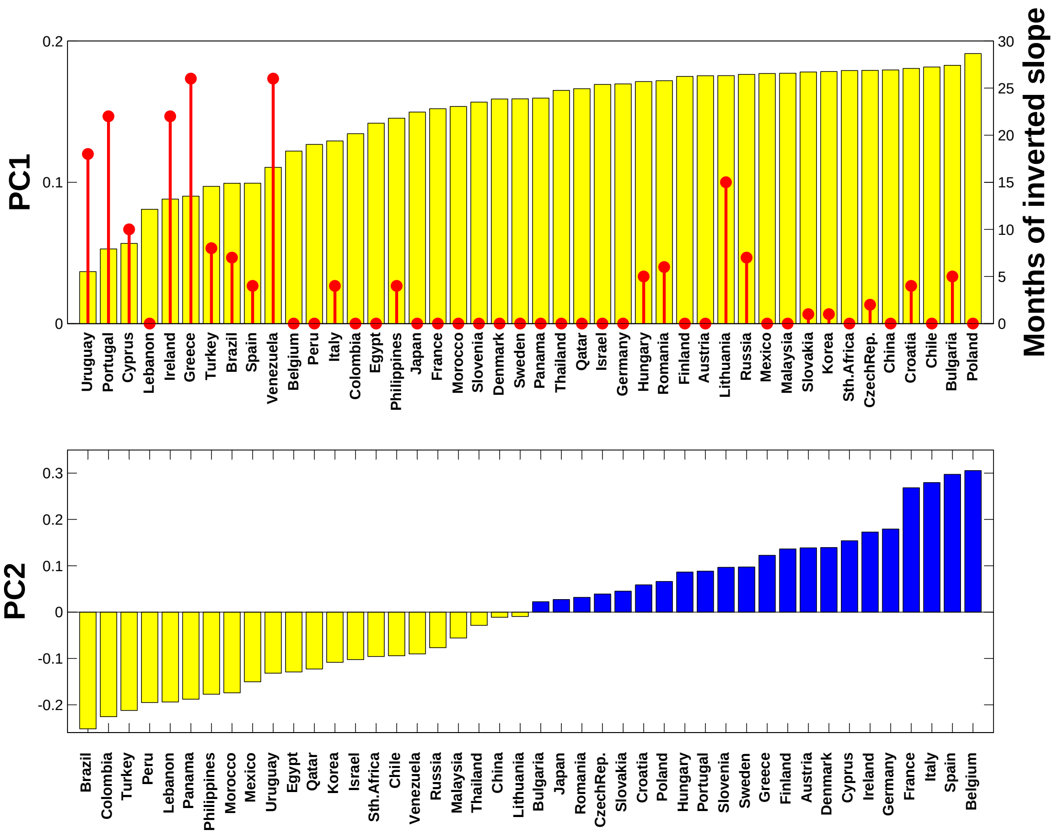


Figure 7: The Slope of the CDS Term Structure and Local Ratios

The local ratio (LR) denotes the ratio of the adjusted R^2 from the restricted regression of changes in 5-year CDS spreads on local variables only to that from the unrestricted regression on local and global variables. This figure plots the LRs for the countries which have had inverted term structures against the number of months for which the term structure was inverted. The severe outlier Venezuela is excluded from the graph. It has a LR of 0.05 and its term structure was inverted for 26 months.