Sovereign Credit Risk: Consumption Strikes Again*

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Abstract

This paper examines the ability of a consumption-based asset pricing model to reproduce stylized facts of sovereign credit risk. For this purpose, we develop a general equilibrium framework for credit default swap spreads and empirically study their common factors and strong co-movement, both across countries and the term structure. This allows us to link sovereign credit risk premia to consumption growth forecasts and macroeconomic uncertainty, as well as investor preferences. We find evidence that shocks to U.S. consumption are a common source of time varying risk premia in the global sovereign debt market. Furthermore, spreads are mainly driven by compensation for losses in bad states, pointing to the fact that sovereign CDS spreads are similar in nature to catastrophe bonds. A principal component analysis suggests that three factors are sufficient to explain on average 95% of commonality. We interpret the first and second principal components as the level and the slope of the term structure of CDS prices. Regression analysis reveals that expected consumption growth and consumption volatility explain about 75% of these two components, and a similar fraction of the actual level, slope and curvature of the CDS term structure. Furthermore, our model provides a joint framework for pricing stocks and credit default swaps, suggesting that both markets are integrated.

Keywords: Credit Default Swap Spreads, Default Risk, Equilibrium Asset Pricing, Generalized Disappointment aversion, Markov Chain, Sovereign Debt, Term structure

JEL Classification: C1, C5, C68, G12, G13, G15, F34

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1 Introduction

The emerging market sovereign debt crisis in the nineties, and particularly the recent sovereign debt crisis in Europe with three international bailouts in less than a year, have revived interest in sovereign credit risk. The real economic consequences of sovereign default, such as inflation, exchange rate crashes, banking crises, and currency debasements, and the accompanied social costs over and above financial losses, justify the need to understand the drivers of sovereign default risk. Yet, the academic literature fails to agree on its determinants.

There is substantial evidence that global factors have strong explanatory power for the price of sovereign credit risk (in particular at lower frequencies), above and beyond that of country-specific fundamentals. Some examples are Eichengreen and Mody (1998b), Kamin and von Kleist (1999), Mauro et al. (2002), McGuire and Schrijvers (2003), Kaminsky et al. (2003), Geyer et al. (2004), Baek et al. (2005), Garca-Herrero and Ortiz (2005), Weigel and Gemmill (2006), Pan and Singleton (2008), Remolona et al. (2008), Gonzlez-Rozada and Yeyati (2008), Ciarlone et al. (2009), Longstaff et al. (2010) and Ang and Longstaff (2011). In addition, there is a large strand of literature emphasizing the role of shocks to the U.S. propagating to the rest of the world or documenting a link between sovereign credit risk and the U.S. Among these papers are for instance Roll (1988), Eichengreen and Mody (1998a), Arora and Cerisola (2001), Goetzmann et al. (2005), Uribe and Yue (2006), Reinhart and Rogoff (2008), Pan and Singleton (2008), Obstfeld and Rogoff (2009), Borri and Verdelhan (2009) and Longstaff et al. (2010).

This paper follows up on the literature and studies the nature of sovereign credit risk embbeded in credit default swaps (CDS) from a novel perspective. In contrast to regression-based analysis, we develop a general equilibrium consumption-based pricing model yielding closed-form solutions for CDS spreads and their moments. Calibrating the pricing kernel to U.S. consumption data, we implicitly attempt to explain variation in the global sovereign CDS market through macroeconomic shocks in the United States. Our goal is thus to identify the common factor(s) of sovereign credit risk. In addition, we empirically study the strong co-movement of global sovereign CDS spreads across countries and the term structure using a data set spanning the global sovereign CDS market[1].

The rational investor of our endowment economy, where both the conditional mean and volatil-

[1] See Figure 1.

ity are stochastic, is risk averse and exhibits generalized disappointment aversion of Routledge and Zin (2010). Moreover, the equilibrium framework embeds a reduced-form default process linked to consumption risk factors. In this setting, spreads are not only tractable, but can be interpreted through their link with the preferences of a representative agent and their interaction with consumption forecasts and macroeconomic uncertainty.

From the theoretical model derive several empirical implications. Calibrating the pricing kernel to the moments of historical U.S. consumption estimates, we manage to match both the historically observed cumulative default probabilities and the first moment of the term structure at aggregate levels, but we perform less well in explaining CDS volatility at shorter maturities for the rating categories BB and B[2]. Moreover, the model produces ratios of risk-neutral to physical default probabilities consistent with the literature (Huang and Huang (2003), Berndt et al. (2007)). These results suggest that two factors, macroeconomic forecasts and uncertainty, are sufficient to explain a large fraction of the variation in the global sovereign CDS market. These findings also support the view that the price of global sovereign credit risk is more likely to be driven by investors' aversion towards risk, rather than by country-specific assessments of economic fundamentals[3], which is consistent with earlier work. In contrast to the literature emphasizing the importance of American financial market variables in the variation of sovereign risk premia (Pan and Singleton (2008) and Longstaff et al. (2010)), measures of investors' risk appetite (Remolona et al. (2008)) or the correlation with the U.S. business cycle (Borri and Verdelhan (2009))[4], we add to the debate on the source of common variation in credit risk by suggesting a different channel, namely macroeconomic shocks to the United States (level and volatility of consumption growth). This finding obviously raises the question about the cross-country correlation of consumption growth. We rule out such a concern due to the existing results on the consumption correlation puzzle (See Backus and Smith (1993), Backus et al. (1992) and Obstfeld and Rogoff (2000)).

[2]Testable implications at a country level pose a challenge, given that country-specific physical default intensities are unobservable. In order to obtain prices for CDS contracts, we need to calibrate our exogenous default process to historical estimates of forward looking cumulative default probabilities, which are only available at aggregate level. This is a limitation to our approach, which makes it more difficult to explain cross-sectional country variations in the sovereign CDS term structure.

[3]See Pan and Singleton (2008) for this point.

[4]Duffie et al. (2003) cites the price of Brent oil and the total level of currency reserves for the case of Russian debt. Carr and Wu (2007) document that CDS spreads of Mexico and Brazil show strong positive contemporaneous correlations with both the currency option implied volatility and the slope of the implied volatility curve in moneyness, but point to additional systematic movements in the credit spreads that their model fails to capture.

Given that we restrict ourselves to parameter scenarios which have been successful in explaining the equity premium puzzle and in reproducing equity valuation ratios and return predictability consistent with historical data (Bonomo et al. (2011)), we manage to simultaneously price the equity and fixed income derivative market. This finding suggests that the equity and sovereign CDS markets are integrated.

In addition, the model-implied state-dependent spreads highlight the systemic nature of sovereign credit risk and the interpretation of sovereign CDS spreads as disaster insurance, characterized by low probability of high impact events. Furthermore, the model generates mean upward sloping term structures, with reversals in states of low expected consumption growth, which is consistent with the observed stylized facts.

Empirically, we find evidence of strong commonality in the sovereign CDS term structure. A principal Component Analysis performed on all maturities of the 38 countries taken together reveals that the first three principal components explain on average 95% of the variation of the global sovereign CDS market. The first two factors can be identified as the level and the slope of the term structure of CDS spreads. We further corroborate our findings of U.S. consumption risk as a priced global factor by investigating its role with the commonality of the CDS term structure. We regress the factors from the Principal Component Analysis on the monthly consumption growth dynamics to show that the latter have strong explanatory power in terms of R^2 for the first two principal components (75%), but are unrelated to the third (0%). Hence we are not only able to identify common factors of sovereign CDS spreads, but we can also link them to the strong commonality observed in the term structure. We rule out endogeneity concerns that consumption patterns may adapt to financial market activity by proving that the Variance Risk Premium is endogenous in our model. Moreover, we show empirically that the latter has no explanatory power in explaining the first two principal components after controlling for macroeconomic shocks. We further support our hypothesis by running a Vector Autoregression (VAR) between consumption growth and the VIX and show that the expected consumption risk is not driven by the VIX, while results for the link between implied option volatility and consumption volatility are inconclusive and point to mere correlation.

We contribute to the pricing literature by providing an analytical formula for the credit default swap spread in a setting where the market is naturally in zero excess supply. In addition, we add to the debate in the literature on the source of common variation in sovereign credit risk through a general equilibrium analysis, thereby specifically replying to Collin-Dufresne and Solnik (2001), who call for the application of general equilibrium models embedding default risk to further investigate the determinants of credit spread (changes)[5]. Restricting the set of parameter values to scenarios, which produce reasonable estimates for stock valuation ratios, we provide a unified framework to price the synthetic credit and the equity markets [6].

Finally, and most importantly, we provide evidence that U.S. consumption risk is priced in the global sovereign CDS market and is a strong driver of common variation in sovereign CDS risk premia. This risk factor has previously not been used to investigate sovereign CDS spreads. Surprisingly, Pan and Singleton (2008) address the importance of consumption risk in their discussion, yet don't include it directly in their analysis[7].

Although there has been a growing body of literature analyzing corporate spreads[8], sovereign CDS prices are explored only to a lesser extent. Some featured articles are Zhang (2003), Carr and Wu (2007), Remolona et al. (2008), Pan and Singleton (2008), Longstaff et al. (2010) and Ang and Longstaff (2011). While we are conceptually closely aligned with this strand of literature, we significantly depart however from these papers by our methodology, which borrows from Bonomo et al. (2011), who reproduce asset moments of the Bansal and Yaron (2004) long-run risk economy using a general equilibrium consumption based asset pricing model where the representative agent is risk averse and exhibits disappointment aversion. We also differ by our data set. The former authors either study the full term structure for a selection of individual countries, or restrict themselves to one maturity of the CDS contract in a specified region. Our study embraces a rich dataset including the full term structure for 38 sovereign countries[9], spanning a geographical region and

[5]Existant literature on the determinants of sovereign credit risk remains largely regression-based or fails to match observed stylized facts.

[6]Two recent papers addressing the equity and cash credit spread puzzle in a unified consumption-based framework are Bhamra et al. (2010) and Chen et al. (2009)

[7]Using regression-based analysis, Tsuji (2005) shows that the covariance between historical consumption and bond yields, a proxy for the business cycle, increases the adjusted R^2 of the regressions to 75%, when added to a large set of theoretical determinants, which have little explanatory power in explaining corporate bond spreads in Japan.

[8]See among others Fama and French (1989), Fama and French (1993), Duffee (1998), Collin-Dufresne and Goldstein (2001), Elton et al. (2001), Duffie et al. (2003), Campbell and Taksler (2003) for bonds and Hull et al. (2004), Berndt et al. (2007), Blanco et al. (2005), Longstaff et al. (2005), Fabozzi et al. (2007), Cao and Yu (2007), Ericsson et al. (2009), Cremers et al. (2008), Yibin Zhang et al. (2009), Carr and Wu (2010), Wang et al. (2010) for CDS.

[9]The authors would like to thank Markit for providing the data.

maturity spectrum representative of the global sovereign CDS market. The sample period runs from May 2003 through July 2010 and thus allows us to split the sample into two equal sub-periods referring to the pre- and post-crisis period. With a few exceptions, academic papers have focused their analysis on individual countries (Pan and Singleton (2008)) or, if a larger sample is used, they have restricted themselves to the most liquid five year contract rather than the whole term structure (Longstaff et al. (2010)), and mainly to emerging markets (Remolona et al. (2008)). In addition, studies including the recent financial crisis, a period of increased financial integration due to the "originate-and-distribute" framework, are also limited.

We further differ from these studies by studying sovereign CDS spreads at a daily frequency as opposed to monthly (Remolona et al. (2008), Pan and Singleton (2008)), by deriving a two-factor framework in contrast to a one-factor set-up (Pan and Singleton (2008), Longstaff et al. (2010)) and by studying the total spread premium instead of disentangling the risk premium from the expected loss componenent (Remolona et al. (2008), Pan and Singleton (2008), Longstaff et al. (2010)). Finally, macroeconomic shocks as a channel of contagion contrast with financial market variables (Pan and Singleton (2008), Longstaff et al. (2010)) and investors' risk appetite (Remolona et al. (2008)).

Another paper closely associated with ours is Borri and Verdelhan (2009), who apply the general equilibrium set-up of Campbell and Cochrane (1999) to price sovereign bonds and establish a link between emerging markets sovereign risk premia and the U.S. business cycle (over a longer horizon than our study). Yet, they investigate one-period bonds which are not matched in magnitude and neglect any term structure effects, whereas we match the first moment of the term structure closely. In addition, their set-up doesn't allow to obtain closed-form solutions for bond prices, whereas we obtain tractable analytic solutions for non-linear CDS payoffs. Finally, their objective is closer to the extensive literature on the sovereign incentives to default (See among others Eaton and Gersovitz (1981), Grossman and Huyck (1988), Bulow and Rogoff (1989b,a), Atkeson (1991), Cantor and Packer (1996), Cole and Kehoe (2000), Aguiar and Gopinath (2006), Arellano (2008), Hatchondo and Martinez (2009) and Yue (2010)).

The rest of the paper proceeds as follows. Section 2 reviews the pricing of Credit default swap spreads. In section 3, we present the general equilibrium set-up. The empirical application is discussed in section 4, featuring summary statistics, the model calibration and a discussion of the results. Section 5 studies the commonality of sovereign CDS spreads and responds to endogeneity concerns. Finally, in section 6 we conclude. An external appendix contains additional robustness results.

2 Credit Default Swap Valuation

A Credit Default Swap is a fixed income derivative instrument, which allows a protection buyer to purchase insurance against a contingent credit event on a Reference Entity (as defined by the International Swaps and Derivatives Association (ISDA) 2003 Credit Derivatives Definition) by paying an annuity premium to the protection seller, generally referred to as the Credit Default Swap spread. The credit event triggers a payment by the protection seller to the insuree equal to the difference between the notional principal and the mid-market value of the underlying reference obligation, obtained through a dealer poll. Settlement can occur either through physical delivery or a cash exchange. In general, the occurrence of a credit event must be documented by public notice and notified to the investor by the protection buyer. Qualifying ISDA credit events are Bankruptcy, Failure to pay, Obligation default or acceleration, Repudiation or moratorium (for sovereign entities) and Restructuring, and represent thus a broader definition of distress than the more general form of Chapter 7 or Chapter 11 bankruptcy.

In order to derive our General-Equilibrium valuation of closed-form solutions to credit default swaps, we rely on a discretization of the continuous framework in Duffie (1999), Hull and White (2000a) and Lando (2004), albeit adapting the explicit modeling of the hazard and recovery rate. In practice, risky bonds are priced relative to a “risk-free” benchmark rate such as the yield on a Treasury bond. Pure default spreads are thus hard to disentangle due to implicit liquidity components, as the yield on a T-year Treasury bond is not a pure default-free rate due to repurchase agreement specials and tax advantages (“moneyness”). Credit default swap spreads however, can be regarded as pure default spreads. We thus adopt the assumption in Longstaff et al. (2005), who hypothesize that default swap spreads only contain a default component[10].

[10] Longstaff et al. (2005) assume that CDS spreads are a pure measure of credit risk and trade them off against bond yields in order to derive the liquidity component implicit in corporate yield spreads.

We write the model at a daily frequency in order to agree with daily quotations in the CDS market. We assume that there are J trading days in a coupon period[11] and that the period n contains the trading days $(n-1)J + j,\ j = 1, \ldots, J$. Every coupon period has thus J trading days and a K-period credit default swap has KJ trading days. Credit default swaps can be priced similar to interest rate swaps, that is net present values of cash flows for both legs (protection buyer and protection seller) must equalize at inception. Suppose you want to price a K-period CDS on an underlying reference obligation. The protection premium, π_t^{pb} to be paid by the protection buyer is equal to

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

where $CDS_t(K)$ is the constant premium defined at day t and to be paid until the earlier of either maturity (day $t + KJ$), or a credit event occurring at day τ. The process $M_{t,T},\ T > t$ denotes the stochastic discount factor that values at day t, any financial payoff to be claimed at a future day T. Notice that $\lfloor \cdot \rfloor$ denotes the floor function that maps a real number to the largest previous integer, and $I(\cdot)$ is an indicator function that takes the value 1 if the condition is met and 0 otherwise. The expression in equation (1) contains two parts. The first relates to the premium payments made by the protection buyer conditional on survival. The second part defines the accrual payments in case the reference entity defaults in between two payment dates.

The protection seller on the other hand must cover any losses incurred by the protection buyer in the presence of a credit event affecting the underlying reference obligation. The net present value of the protection seller's leg must thus equal

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

where the process R_τ represents the post-default recovery rate, which can be random in the general

[11] In the calibration exercise, we 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 directly be translated into annualized spreads. However, the model can easily accommodate bi-annual and quarterly payment frequencies.

setting and possibly contain claimed accruals from the defaulted reference obligation.

Equating the two legs, such that the net present value of the difference is zero at inception, we can write the price of the CDS as

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

Applying the Law of Iterated Expectations to both the numerator and the denominator, we obtain

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

where the process $S_t \equiv Prob(\tau > t \mid \mathcal{I}_t) \equiv Prob_t(\tau > t)$ denotes the conditional survival probability, that is the conditional probability that the credit event did not occur at day t, and where $\mathcal{I}_t$ denotes the information up to and including day t. In the above, we assume that $Prob(\tau = t \mid \mathcal{I}_T) = Prob\left(\tau = t \mid \mathcal{I}_{\min(t,T)}\right)$ for all integers t and T. Thus, the conditional survival probability S_t is defined as

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

where the process $h_t \equiv Prob(\tau = t \mid \tau \geq t; \mathcal{I}_t) \equiv Prob_t(\tau = t \mid \tau \geq t)$ denotes the conditional instantaneous default probability of a given reference entity at day t, i.e. the hazard rate. Generally, reduced-form credit risk models assume an exogenous default intensity whose probability law governs the default process. We innovate by defining a hazard rate whose default intensity is determined by its sensitivity to macroeconomic fundamentals. Moreover, R_t defines the recovery rate at date t as a fraction of face value and $L_t = (1 - R_t)$ determines the Loss Given Default (Loss Rate)[12]. The above definition illustrates that the derivation of a closed-form solution for the valuation of a CDS spread requires an exogenous process governing the stochastic discount factor $M_{t,t+1}$, the default intensity h_{t+1} and the recovery rate R_{t+1}. These processes are described more explicitly in

[12] In what follows, we will interchange freely between the notions of Loss Given Default and Loss Rate.

the following section.

3 Model Setup

Consumption-based asset pricing models follow the insight that investors care mostly about consumption and that macroeconomic fundamentals, defined in our case by the forecast and volatility of consumption growth, should hence entail predictive power for asset prices[13]. Thus, a representative agent should require higher risk premia when expected consumption growth is low and volatility is high. While this economic insight has justified the use of consumption-based models to price basic assets such as stocks and to a lesser extent bonds, the intuition should hold for CDS spreads. This is strongly confirmed when we plot the iTraxx EU on-the-run series, an index representing the 125 most traded corporate credit default swaps against consumption growth in the United States[14]. The picture clearly shows a negative correlation between expected consumption growth and an aggregate index of credit spreads. This observation crucially motivates our attempt to link CDS spreads to macroeconomic fundamentals in a general equilibrium model.

3.1 A markov-switching model for consumption growth

Following Bonomo et al. (2011), we assume that both mean and variance of consumption growth g_{t+1} ($g_{t+1} = \ln G_{t+1}$, where $G_{t+1} = (C_{t+1}/C_t)$ and C_t defines the level of consumption in period t.) fluctuate according to a Markov variable s_t, which can take a different value in each of the N states of the economy. The stochastic sequence s_t evolves according to a transition probability matrix P defined as:

$$P^{\top} = [p_{ij}]_{1 \leq i,j \leq N}\,, \quad p_{ij} = Prob\,(s_{t+1} = j \mid s_t = i)\,. \tag{6}$$

As in Hamilton (1994), let $\zeta_t = e_{s_t}$, where e_j is the $N \times 1$ vector with all components equal to zero but the jth component equals one. Formally, consumption growth can be written as follows:

$$g_{t+1} = x_t + \sigma_t \varepsilon_{g,t+1}, \tag{7}$$

[13]See Campbell (2003) for an excellent survey of consumption-based asset pricing.

[14]The Figure is reported in the External Appendix due to space limitations.

where $x_t = \mu_g^\top \zeta_t$ and $\sigma_t = \sqrt{\omega_g^\top \zeta_t}$ are the forecast and the volatility of consumption growth respectively. The vectors μ_g and ω_g contain the values of expected consumption growth and consumption volatility respectively in each state of the economy, and the component j refers to the value in state $s_t = j$.

3.2 Preferences and stochastic discount factor

We study the valuation of credit default swaps in the context of a representative agent consumption-based general equilibrium model. We assume that the representative investor has generalized disappointment aversion (GDA) preferences of Routledge and Zin (2010). Following Epstein and Zin (1989) and Weil (1989), such an investor derives utility from consumption recursively as follows:

$$\begin{aligned} V_t &= \left\{ (1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left[\mathcal{R}_t \left(V_{t+1} \right) \right]^{1-\frac{1}{\psi}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \quad \text{if } \psi \neq 1 \\ &= C_t^{1-\delta} \left[\mathcal{R}_t \left(V_{t+1} \right) \right]^{\delta} \quad \text{if } \psi = 1. \end{aligned} \tag{8}$$

The current period lifetime utility V_t is a combination of current consumption C_t, and $\mathcal{R}_t \left(V_{t+1} \right)$, a certainty equivalent of next period lifetime utility. The parameter ψ defines the elasticity of intertemporal substitution (EIS), which can be disentangled from the coefficient of relative risk aversion γ through this form of utility. With GDA preferences the risk-adjustment function $\mathcal{R}\left(.\right)$ is implicity defined by:

$$\frac{\mathcal{R}^{1-\gamma} - 1}{1-\gamma} = \int_{-\infty}^{\infty} \frac{V^{1-\gamma} - 1}{1-\gamma} dF\left(V\right) - \left(\frac{1}{\alpha} - 1 \right) \int_{-\infty}^{\kappa \mathcal{R}} \left(\frac{\left(\kappa \mathcal{R}\right)^{1-\gamma} - 1}{1-\gamma} - \frac{V^{1-\gamma} - 1}{1-\gamma} \right) dF\left(V\right), \tag{9}$$

where $0 < \alpha \leq 1$ and $0 < \kappa \leq 1$. When α is equal to one, the certainty equivalent function $\mathcal{R}$ reduces to the Kreps and Porteus's (Kreps and Porteus (1978), henceforth KP) preferences, while V_t represents Epstein and Zin (1989) recursive utility. When $\alpha < 1$, the certainty equivalent decreases as outcomes below the threshold $\kappa\mathcal{R}$ receive an additional weight $(1/\alpha - 1)$. Thus, the parameter α characterizes disappointment aversion, while the parameter κ reflects the fraction of the certainty equivalent $\mathcal{R}$ below which outcomes become disappointing[15]. Formula (9) emphasizes

[15]The certainty equivalent is decreasing in γ, increasing in α (for $0 < \alpha \leq 1$) and decreasing in κ (for $0 < \kappa \leq 1$). Thus, α and κ characterize also measures of risk aversion, but they are of a different nature than γ.

the fact that, when disappointment kicks in, state-probabilities are redistributed. Moreover, the threshold of disappointment is time-varying.

Hansen et al. (2008) derive the stochastic discount factor in terms of the continuation value of utility of consumption when preferences are KP as follows:

$$M^*_{t,t+1} = \delta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left(\frac{V_{t+1}}{\mathcal{R}_t \left(V_{t+1} \right)} \right)^{\frac{1}{\psi}-\gamma} \tag{10}$$

If $\gamma = 1/\psi$, equation (10) corresponds to the stochastic discount factor of an investor with time-separable utility and constant relative risk aversion. Alternatively, if $\gamma > 1/\psi$, Bansal and Yaron (2004) and Hansen et al. (2008) show that a premium for long-run consumption risk is added by the ratio of future utility V_{t+1} to its certainty equivalent $\mathcal{R}_t \left(V_{t+1} \right)$. For GDA preferences, down-side consumption risks enter through an additional term capturing disappointment aversion as follows:

$$M_{t,t+1} = M^*_{t,t+1} \left(\frac{1 + (1/\alpha - 1)\, I \left(Z_{t+1} < \kappa \right)}{1 + (1/\alpha - 1)\, \kappa^{1-\gamma} E_t \left[I \left(Z_{t+1} < \kappa \right) \right]} \right). \tag{11}$$

Hence, disappointing outcomes in the economy will obtain a relatively higher importance and require higher risk premia accordingly.

Based on the dynamics (7) and using the Euler condition for the claim to aggregate consumption, we show in Appendix (A) that the stochastic discount factor (11) may be expressed as follows:

$$M_{t,t+1} = \exp \left(\zeta_t^\top A \zeta_{t+1} - \gamma g_{t+1} \right) \left[1 + \left(\frac{1}{\alpha} - 1 \right) I \left(g_{t+1} < -\zeta_t^\top B \zeta_{t+1} + \ln \kappa \right) \right], \tag{12}$$

where the components of the $N \times N$ matrices A and B are described in Appendix (A) and we refer to Bonomo et al. (2011) for formal proofs.

3.3 Hazard rate and recovery rate

Modeling the instantaneous conditional default probability or hazard rate in discrete time is challenging when the final goal is tractability of closed-form solutions for CDS prices. The range of the hazard rate process must be bounded and take values in the interval $[0, 1]$. In addition, it should be a persistent process such that the default propensity tends to be higher following a high default intensity and vice-versa. Given our intention to link the hazard rate to macroeconomic fundamentals, we assume that the conditional instantaneous default probability process h_t and the associated default intensity λ_t are given by:

$$h_t = 1 - \exp\left(-\lambda_t\right) \quad \text{where} \quad \lambda_t = \exp\left(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda \sigma} \sigma_t\right) = \lambda^{\top} \zeta_t. \tag{13}$$

This set-up guarantees that the hazard rate is well defined and belongs to the interval $[0, 1]$. In addition, this form of the hazard rate ensures that the marginal propensity to default is persistent, given that consumption growth forecasts and volatility are themselves persistent processes. While the model-specific investor preferences are needed to generate sufficiently large countercyclical risk aversion necessary to match the levels of CDS spreads, a persistent default intensity is essential to generate a term risk premium. We also invite the reader to note that the hazard rate is country-heterogenous and that we omit a superscript for ease of readability (In essence, $\beta_{\lambda 0}$, $\beta_{\lambda x}$ and $\beta_{\lambda \sigma}$ can be defined for each country and/or rating cohort). From an economic point of view, we expect the parameters $\beta_{\lambda x}$ and $\beta_{\lambda \sigma}$ to be non-positive and non-negative respectively. The default intensity should increase when forecasts of macroeconomic growth are low and/or macroeconomic uncertainty is high. Furthermore, the parameters also have an economic interpretation in the sense that

$$\begin{aligned} \frac{\partial\left(1-h_t\right)/\left(1-h_t\right)}{\partial x_t / x_t} &= -\beta_{\lambda x} \times \lambda_t \times x_t \\ \frac{\partial\left(1-h_t\right)/\left(1-h_t\right)}{\partial \sigma_t / \sigma_t} &= -\beta_{\lambda \sigma} \times \lambda_t \times \sigma_t \end{aligned} \tag{14}$$

represent the elasticities of the "marginal propensity to survive" to a marginal change in macroeconomic forecasts and volatility respectively[16].

Similar to the hazard rate, the dynamics of the recovery rate process are also governed by macroeconomic fundamentals. We assume that the loss rate L_t (defined as $L_t = (1 - R_t)$) and the

[16] As a numerical illustration, for an instantaneous default probability of 1 basis point and an expected consumption growth of 1%, a 1% relative increase in expected consumption growth would raise the marginal propensity to survive of a BBB-rated entity by 0.125% relative to its current level, and a 1% relative increase in consumption volatility would decrease it by 0.0015% for a level of consumption volatility equal to 1%.

associated severity of loss η_t are given by:

$$L_t = 1 - \exp(-\eta_t) \quad \text{where} \quad \eta_t = \exp(\beta_{\eta 0} + \beta_{\eta x} x_t + \beta_{\eta\sigma}\sigma_t) = \eta^\top \zeta_t, \tag{15}$$

where

$$\begin{aligned} \frac{\partial(1-L_t)/(1-L_t)}{\partial x_t / x_t} &= -\beta_{\eta x} \times \eta_t \times x_t \\ \frac{\partial(1-L_t)/(1-L_t)}{\partial \sigma_t / \sigma_t} &= -\beta_{\eta\sigma} \times \eta_t \times \sigma_t \end{aligned} \tag{16}$$

can be interpreted as the elasticities of the recovery rate to small changes in macroeconomic fundamentals. Likewise, the coefficients $\beta_{\eta x}$ and $\beta_{\eta\sigma}$ are expected to be non-positive and non-negative respectively, so that loss rates are higher in times of negative macroeconomic forecasts and high macroeconomic uncertainty. The recovery rate is thus state dependent and consistent with previous findings of procyclical recovery rates (see Altman and Kishore (1996) among others).

Finally, the conditional cumulative default probability over a $(T-t)$-year horizon can be defined as

$$Prob_t(t < \tau \leq T \mid \tau > t). \tag{17}$$

Using our pricing framework, we show in Appendix (B) that the conditional and unconditional cumulative default probabilities can be expressed as:

$$\begin{aligned} Prob_t(t < \tau \leq T \mid \tau > t) &= 1 - \left(\tilde{\Psi}_{T-t}^\top \zeta_t\right) \\ Prob(t < \tau \leq T \mid \tau > t) &= 1 - \left(\tilde{\Psi}_{T-t}^\top \Pi\right), \end{aligned} \tag{18}$$

where the maturity-dependent vector sequence $\left\{\tilde{\Psi}_j\right\}$ satisfies the recursion (B.3) with initial conditions (B.4). In contrast to the historical or real-world cumulative default probabilities, we also derive a closed-form solution of the cumulative default rate under the risk-neutral measure in Appendix (C)[17].

[17]Henceforth, dynamics under the risk-neutral ($\mathbb{Q}$) measure will be represented with a $\mathbb{Q}$ subscript.

3.4 Credit default swap spread

The challenge remains to derive a closed-form solution for the CDS spread and its moments. The Markov property of the model is crucial for deriving the corresponding analytical formula. The development of equation (4) leads to the following simplified characterization of a K- period CDS spread at day t:

$$CDS_t(K) = \zeta_t^\top \lambda_{1s}(K), \tag{19}$$

where the components of the vectors $\lambda_{1s}(K)$ are functions of the consumption dynamics, the default and recovery process and of the recursive utility function defined above. Its components are given by:

$$\lambda_{i,1s}(K) = \frac{\sum_{j=1}^{KJ}\left[\Psi_{i,j}^{*}(L) - \Psi_{i,j}(L)\right]}{\sum_{k=1}^{K}\Psi_{i,kJ}(e) + \sum_{j=1}^{KJ}\left(\frac{j}{J} - \left\lfloor\frac{j}{J}\right\rfloor\right)\left[\Psi_{i,j}^{*}(e) - \Psi_{i,j}(e)\right]}, \tag{20}$$

where e is the vector with all components equal to one, and $L = 1 - \exp(-\eta)$ is the vector of conditional loss rates, and where the sequences $\left\{\Psi_j^{*}(\cdot)\right\}$ and $\{\Psi_j(\cdot)\}$ are given by the recursion (D.12), with initial conditions (D.11). In this form, also all unconditional moments of CDS spreads exist in closed form.

4 Empirical Application

In the empirical application, we start by giving an overview of the summary statistics. We then proceed by explaining the calibration methodology and finally present and discuss the results.

4.1 Data and summary statistics

Our data set consists of daily mid composite USD denominated CDS prices for 38 sovereign countries taken from Markit over the sample period May 9th, 2003 until August 19th, 2010, and covers prices for the full term structure, including 1, 2, 3, 5, 7 and 10-year contracts[18]. All contracts contain the

[18] Our initial data set covers 84 countries from January 2, 2001 until August 19, 2010. Omitting non-rated countries or contracts with too many stale data points, we remain with the reduced data set as our purpose is to study the entire term structure. This faces a selection bias, but the characterization through ratings and the resulting sample which is representative of the rating distribution in the market should mitigate concerns.

full restructuring clause. We thus study a very heterogenous data set spanning the entire sovereign CDS market, both across geographical regions and rating categories. The list of the 38 countries is provided in Table 1. The biggest group with 11 countries is rating category BBB, while the smallest with 2 entities is rating bucket B. The number of sovereigns for the remaining categories are 4 (AAA), 6 (AA and BB) and 9 (A). We face some gaps in observations, which we fill using the following algorithm. For every missing number, we check whether the corresponding price exists in the Datastream database. If the missing price can be found, we use it to replace the missing observation in the Markit database. If the data point is missing in both databases, we fill missing data using the nearest-neighbor method, i.e. we replace missing values with a weighted mean of the 2 nearest-neighbor observations. The weights are inversely proportional to the distances from the neighboring observations. This methodology is consistent with persistent CDS prices.

[Table 1 here]

Our working data set thus contains 1900 observations for 38 reference countries and 6 maturities, amounting to a total of 433,200 observations[19]. For the purpose of our study, we group the countries in buckets corresponding to their individual rating categories[20] and present summary statistics in Table 2. Our data set is most similar to those studies in Pan and Singleton (2008), Remolona et al. (2008) and Longstaff et al. (2010). The first paper, however, studies only three emerging countries, the second 24 emerging countries and is restricted to 5-year CDS quotes. Likewise, the third paper only uses 5-year CDS spreads and looks at 26 countries[21], although at a slightly longer horizon from October 2000 to January 2010. Our data source Markit coincides with Remolona et al. (2008). Additional country-specific summary statistics may be found in the external Appendix. The dataset exhibits a considerable amount of heterogeneity both across time and across entities. For instance, the mean 5-year spread for AAA rated countries is 23 basis points, and 564 basis points for B rated sovereigns. The mean term structure is always upward sloping, with the maximum slope as high as

[19] In order to provide an overview of the data handling, the number of missing observations for each step of the algorithm is reported in the external Appendix.

[20] The countries are grouped according to a Rating classification, which is achieved by assigning an integer value ranging from 1 (AAA) to 21 (C) at each date to each country. The equally weighted historical average is then rounded to the nearest integer, which is used as the final rating categorization.

[21] Our sample covers all three countries of Pan and Singleton (2008), and the overlap in countries is 20 for the study of Remolona et al. (2008) and 22 for that of Longstaff et al. (2010).

195 basis points for the BB group. The sample features large time-series variation, with standard deviations for the 5-year series ranging from 34 (AAA) to 328 basis points (B). All time series are highly persistent, with an average daily autocorrelation coefficients for 5-year spreads as high as 0.9965.

[Table 2 here]

4.2 Model calibration

The exogenous processes in our model are the endowment process, the hazard rate as well as the loss rate. We will describe the calibration for each of these processes as well as the choice of preference parameters in what follows.

4.2.1 Consumption, equity and dividend growth dynamics

Our calibration of consumption and equity dividend growths dynamics is as follows. We first consider the dynamics of these processes as postulated by Bansal and Yaron (2004) and written at a monthly decision interval, but allow for contemporaneous correlation of consumption and dividend schocks as in Bansal et al. (2009).

Next, we assume that the dynamics of consumption and equity dividend growth at a daily decision interval are identical and simply adjust model parameters accordingly. We find the corresponding daily parameters so that aggregate daily processes at the monthly frequency have the same population first and second moments as the monthly processes, assuming twenty-two trading/decision days in a month. For the purpose of illustration, if Bansal and Yaron (2004) use a value of $\mu_x = 0.0015$ at a monthly decision interval for the mean consumption growth, then the corresponding value at a daily decision interval would be equal to $\mu_x^{daily} = \Delta\mu_x$, where $\Delta = 1/22$. Similarly, a value of $\phi_x = 0.975$ for the persistence of the predictable component of consumption growth is translated into a daily value equal to $\phi_x^{daily} = \phi_x^{\Delta}$.

Finally, we characterize the Markov-switching model at the daily decision interval, using the same procedure as described in Garcia et al. (2008) for the monthly endowment dynamics. Calibration results for the consumption and dividend growth dynamics are reported in Table 3, where we obtain values for all four states of nature defined by the combinations of low (indexed by the letter L) and high (indexed by the letter H) conditional means and variances of consumption growth.

[Table 3 here]

4.2.2 Choice of preference parameters

Asset pricing implications are analyzed for an investor who exhibits generalized disappointment aversion as in Routledge and Zin (2010). This warrants the choice of relevant preference parameters, which are adopted from Bonomo et al. (2011). The latter authors were able to match stylized facts of the equity market. We decide to restrict ourselves to their choice of parameters, as we want to see how our model fares in the credit market, conditional on matching moments for basic assets. The constant coefficient of relative risk aversion is set to 2.5. The parameter of disappointment aversion α is equal to 0.3, implying that the ratio of investor's marginal utility of wealth for non-disappointing to disappointing outcomes is 30%. In addition, κ, which defines the fraction of the certainty equivalent below which disappointment kicks in, is equal to 0.994. Bonomo et al. (2011) use a level of κ equal to 0.989 to match the stylized fact of asset prices. However, their decision interval is monthly. In order to remain consistent with the calibration results at a daily decision interval, we need to adjust this parameter. The elasticity of intertemporal substitution (EIS) ψ is equal to 1.50, implying that the investor prefers early resolution of uncertainty. The 1-period subjective discount factor is kept constant at 0.9989 for a monthly frequency.

4.2.3 Default dynamics

We recall that the hazard rate and the loss processes are given by

$$h_t = 1 - \exp(-\lambda_t) \quad \text{where} \quad \lambda_t = \exp(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda \sigma} \sigma_t).$$

and

$$L_t = 1 - \exp(-\eta_t) \quad \text{where} \quad \eta_t = \exp(\beta_{\eta 0} + \beta_{\eta x} x_t + \beta_{\eta \sigma} \sigma_t).$$

We calibrate the parameters of the default intensity process by minimizing the Root Mean-squared-error (RMSE) between the observed and model-implied cumulative sovereign default rates.

Historical sovereign default rates by Moody's and Standard&Poor's are provided in Table 4. Inspection of these numbers warrants several explanations. First, while cumulative default probabilities are to a large extent similar in magnitude for the two rating agencies, considerable differences arise because of differences in the considered time horizon and calculation methodologies (For example, the 10-year cumulative default probability for a BB-rated sovereign is almost 21% for Moody's, but only close to 14% for Standard&Poor's.). In addition, no country rated A or higher has defaulted within the last 40 years. This makes it impossible to calibrate default parameters for the latter rating categories. As a consequence, we take rating categories BBB to B as our benchmark. Model implications for other rating groups are not studied in this paper. Moreover, physical default probabilities are unobservable, especially so for countries, which have never defaulted. Thus, the calculation of historical cumulative default probabilities is not entirely representative of physical default probabilities. Finally, the sample of countries in Table 4 is not identical to the sample of countries in our study. While we acknowledge that our approach is open to critique, we believe that calibrating our exogenous default process to these observations and studying the implications for the term structure of CDS spreads of sovereign countries is the best we can do.

[Table 4 here]

We start by shutting off the loadings on expected consumption growth and volatility in the hazard rate process, that is $\beta_{\lambda x}$ and $\beta_{\lambda \sigma}$ are set to zero in equation (13). This implies that the default process is constant over time. We then calibrate the value of $\beta_{\lambda 0}$ to match the historical cumulative default probabilities by both Moody's and Standard&Poor's for all ten maturities. In fact, it turns out that a constant default intensity is sufficient to match the term structure of observed cumulative default probabilities well, as is demonstrated by rather low RMSEs. Calibration results for the default parameters and the RMSE for the term structure of default parameters are provided in Table 5.

4.2.4 Loss dynamics

In order to avoid over-fitting, we keep the recovery rate initially constant at 37.5%. A common practice in the industry is to define a constant exogenous recovery rate of 25% for sovereign entities.

Yet, this should be under the risk-neutral measure and actual recovery rates for defaulted countries generally turn out to be higher. We acknowledge the countercyclical nature of the loss rate as has been studied by Altman and Kishore (1996) among others. However, the main objective of this paper is not to study the Recovery rate as such. We hence decide to start with a constant loss rate of 62.5%. A more in depth analysis of implications for recovery rates is left out for further research.

4.3 Asset pricing implications and discussion

As we don't observe any historical cumulative defaults for countries with a credit standing A or higher, we are forced to restrict the analysis to the rating categories BBB, BB and B. We start by considering the case of a constant default process where the sensitivities to expected consumption growth and macroeconomic uncertainty are shut off. We then move on to analyze the case of a time-varying default process linked to macroeconomic fundamentals.

4.3.1 Constant default process

Model-implied and observed statistics for cumulative physical default probabilities are provided in Table 5. RMSEs are generally low. It is highest for the Ba rating category of Moody's (1.60%) and lowest for the Baa rating category by Moody's (0.49%). The fit is slightly better at maturities five and higher, while the model performs worse for maturities less than three years. For this scenario, interpretation of the default probabilities under the risk-neutral measure becomes redundant, as there is no risk premium for a constant default parameter. Thus, the ratios of risk-neutral to physical default probabilities are all equal to one[22].

[Table 5 here]

Given the calibration of our three exogenous processes (endowment, default and loss dynamics), we check how the model fares in reproducing the term structure. While one parameter is enough to match the default probabilities, it is clearly insufficient to match the level or the term premium of the CDS term structure, both for the first and second moments. Model results are reported in Table 5. This was expected, given the constant ratio of risk-neutral to physical default probabilities

[22] As the cumulative default probabilities under the risk-neutral measure are equal to those under the physical measure, we don't report the ratio of risk-neutral to physical default probabilities here.

of one. Levels are far too low, and there is no term premium. Moreover, the volatilities are close to zero. A constant default process is thus insufficient to provide a solution to the credit spread puzzle, and we need a time-varying hazard rate process to generate a term premium. This scenario will be studied in the following section.

4.3.2 Time-varying default process

In order to match both the historical cumulative default probabilities and the term structure of CDS prices, it is imperative to augment the hazard rate process by incorporating expected consumption growth and volatility. Thus we run the risk of overfitting our model as we depart from the most parsimonious outcome possible for the default probabilities. We reactivate the parameters $\beta_{\lambda x}$ and $\beta_{\lambda\sigma}$ of the default process (13), which were shut off in the previous analysis. As a consequence, the hazard rate becomes time-varying and state-dependent and is now sensitive to shocks to macroeconomic forecasts and consumption volatility.

We recalibrate the loss process by minimizing the RMSE between the observed and model-implied cumulative default probabilities, means and standard deviations of the term structure, but we put most weight on matching the observed default patterns. This will likely reduce our fit of the historical default probabilities, but we reemphasize the fact that these reported numbers depend heavily on the time horizon and the methodology, that the actual physical default intensities are unobserved, and that the sample of the reported Moody's and Standard&Poor's default statistics is not entirely representative of the countries in our sample. More formally, we minimize the following RMSE:

$$RMSE^{*} = \sqrt{w_p \frac{1}{K}\sum_{j=1}^{K}\left(\hat{p}_j - p_j\right)^2 + w_\mu \frac{1}{K}\sum_{j=1}^{K}\left(\hat{\mu}_j - \mu_j\right)^2 + \left(1 - w_p - w_\mu\right)\frac{1}{K}\sum_{j=1}^{K}\left(\hat{\sigma}_j - \sigma_j\right)^2} \quad (21)$$

where $1 \geq w_p \geq w_\mu \geq (1 - w_p - w_\mu) \geq 0$ are the weights attributed to the RMSE of each of the statistics, $w_p = 100 \times w_\mu$, $w_\mu = 100 \times (1 - w_p - w_\mu)$ and K represents the maturity of the contract, and

$$p_j = E\left[Prob\left(t < \tau \leq t + j \mid \tau > t\right)\right], \quad \mu_j = E\left[CDS_t\left(j\right)\right], \quad \sigma_j = \sigma\left[CDS_t\left(j\right)\right] \quad (22)$$

are the unconditional cumulative default probabilities, first and second moments of the term structure implied by the model and the homologue with a *hat* superscript refers to the observed counterpart.

In Table 6, we report the calibration results for the parameters of the hazard rate process as well as the associated RMSEs (in absolute %). $RMSE^*$ refers to the RMSE as defined in equation (21), while $RMSE_p$, $RMSE_\mu$ and $RMSE_\sigma$ refer to the RMSEs of the default probabilities, the mean and standard deviation of CDS prices respectively for maturities 1, 2, 3, 5, 7 and 10. The low numbers for $RMSE_p$ indicate that we keep doing a good job in matching the cumulative default probabilities. Furthermore, $RMSE_\mu$ shows only slight deviations from the actual mean of term structure. Hence, linking the hazard rate process to macroeconomic fundamentals improves the fit of the term structure and suggests that such a specification is necessary to match both default probabilities and mean CDS spreads at the same time. However, the large numbers reported for $RMSE_\sigma$ suggest that we face a challenge in matching CDS volatilities[23]. Turning to the parameters of the hazard rate process, it is interesting to note that all signs are consistent with economic intuition. Negative values for $\beta_{\lambda 0}$ imply that the tendency to default increases when expected consumption growth decreases. Similarly, positive values for $\beta_{\lambda\sigma}$ suggest that defaults are more likely in times of higher macroeconomic uncertainty.

[Table 6 here]

Model-results for cumulative default probabilities under the physical and risk-neutral measure, as well as their ratios, are reported in Table 7. As expected, given the low RMSEs, the model-implied default probabilities are close to their observed counterparts. Results are better at longer horizons than at short horizons. In contrast to the constant hazard rate case, it becomes now interesting to compare metrics under the physical and risk-neutral measure. The ratios of risk-neutral to physical default probabilities are monotonically increasing with time, reflecting the term premium required by investors who offer credit risk insurance by selling CDS contracts. Results for Moody's also indicate that the term premium is systematically higher for Baa rated entities than for those in the B rating category, while the ratio of the latter is always higher than that for Ba rated countries. When we use the Standard&Poor's statistics, the term premium is still consistently

[23]The volatility fit could easily be improved be reshuffling the weights in the calibration process.

higher for BBB rated entities. But the pattern for BB vs B inverts for maturities five and higher. All $\frac{\mathbb{Q}}{\mathbb{P}}$ ratios range between 1.24 and 4.04, while the average is 2.36. We would like to compare these results with some of the metrics reported in the financial literature. Berndt et al. (2007) find strongly time-varying ratios of CDS implied risk neutral default probabilities to Moody's KMV Expected Default Frequencies (EDF) in three sectors, Broadcasting&Entertainment, Healthcare and Oil&Gas. Their ratios range on average between 1 and 3 for short horizons, but go as high up as 10 in 2002. Similarly, Driessen (2005) reported an average ratio of risk-neutral to actual default intensities of 1.89 using corporate bonds over the time period 1991 to 2000. In addition, Huang and Huang (2003) find ratios between 1.11 and 1.75 for corporate bonds. It is thus comforting to find model-implied results of "default risk premia", which are in line with the literature.

[Table 7 and 8 here]

Turning to first and second moments of the CDS term structure, we face satisfactory results for the former, but not entirely for the latter. Results are reported in Table 8. For the mean spread of the term structure, the best model-implied results are found for the rating categories Baa/BBB and B, while entities rated Ba/BB perform slightly less good. This is seen by the RMSEs, which are respectively 2.32% and 8.02% for BBB and B, but 22.27% for BB (Panel B: Standard&Poor's). For the former two categories, we slightly underestimate at the low end of the curve. Thus, considering again Panel B, the one-year model-implied CDS spread is for instance 75 basis points for the BBB rating category, while the observed spread is 77 basis points. Likewise for the B entities, the model-implied spread of 417 (590) opposes that empirical spread of 433 (599) basis points at the one-year (ten-year) horizon. On the other hand, we slightly overestimate spreads in the data at the long end for rating category BBB, generating slightly steeper slopes. The model-implied spread of 159 basis points is unsignificantly higher than 155 basis points in the data. For the BB category, this pattern is inversed, as there is overestimation for short maturities, and a slight underestimation at longer maturities, leading to flatter curves. Hence, the three-year (ten-year) spread is for example 205 (263) basis points against the empirical 196 (281) basis points.

The worst performance is to be found at maturities 1 and 2 for the rating category Ba/B. We link this finding to that of Pan and Singleton (2008), who analyze the CDS term structure of

Mexico, Turkey and Korea. Turkey also belongs to our Ba/B rating category. Their one-factor model performs worst at the 1-year maturity. They conclude, following discussions with traders, that the 1-year contract is extensively used by large institutional money management firms often as a primary trading vehicle for expressing views on sovereign bonds. They argue that there is an idiosyncratic liquidity factor arising from significant demand and supply pressures in the short end of the curve. Given that we first calibrate our exogenous process to match observed default probabilities, we are more likely to overestimate short maturities for these given countries (whereas Pan and Singleton (2008) underestimate). Overall, we produce upward sloping term structures for all rating categories, consistent with the sample data[24]. Several structural models find upward sloping term structures for high grade corporate debt, hump-shaped curves for intermediate credit quality and even downward sloping curves for low quality names[25]. These papers usually focus on corporate debt though, whereas our focus lies on sovereign CDS spreads. Pan and Singleton (2008) also find persistent upward sloping term structures for three emerging countries. However, the behavior of the sovereign CDS curves remains to a large extent unexplained.

Model results for standard deviations are less satisfactory, except for the rating category BBB/Baa. They are on average twice as high as observed values at short maturities, but converge to empirical observations at longer maturities. Volatilities are upward sloping for the rating category Ba/BB, flat for Baa/BBB and downward sloping for B/B, whereas model-implied volatilities are consistently downward sloping.

4.3.3 Discussion

With these results in mind, we want to emphasize that (to our knowledge), this is the first consumption-based general equilibrium pricing framework for credit default swaps. Within this setting, all our dynamics are expressed in real-life dynamics. Moreover, the exogenous processes are calibrated to historical data. This is in contrast to reduced-form risk-neutral pricing frameworks, such as in Pan and Singleton (2008). The latter authors model the mean risk-neutral arrival rate of a credit event according to a one-factor log-normal process. Using the assumption that

[24]Summary statistics are only provided at the aggregate level. Nevertheless, the term structure is persistently upward sloping for every country over our sample period.

[25]See for example Lando and Mortensen (2005).

the five-year CDS contract is perfectly priced, they back out the dynamics of the default process and price the other maturities relative to the five-year benchmark. However, they cannot check consistency with the unobserved default rates of the countries in their study. Apart from the conceptual pricing framework, our results significantly differ from this methodology by the fact that we price CDS contracts at an aggregate level, whereas Pan and Singleton (2008) price CDS contracts for individual countries. Our theoretical framework is not restricted to aggregate levels. Empirically however, we face the challenge that the physical default intensities are unobservable. As a consequence, we need to calibrate the default process to historical estimates of forward-looking unconditional default probabilities of a given rating category (as provided by rating agencies) to back out the parameters of the default process.

Comparing our model with the previous literature, we focus on U.S. consumption dynamics (expected consumption growth and consumption volatility) as being a major channel through which shocks to a U.S. based international investor spread through the sovereign credit risk market. We thus revert to a two-factor model rather than a one-factor model. While an additional factor might improve the fit, we don't take a stand on the other factors and conclude, similar to Pan and Singleton (2008), that there might be an idiosyncratic liquidity factor, which contributes to the variation in sovereign CDS spreads. To our interest is also that the authors conclude that a one-factor model is acceptable, but that a two-factor model may be desirable.

Our results suggest that U.S. expected consumption growth and consumption volatility are major drivers of the common variation in sovereign CDS spreads and that a two-factor model does a good job in fitting the sample estimates. While there has been previous evidence that sovereign credit markets are priced globally, rather than locally, and that required risk premia are largely driven by investors' appetite for risk or investor sentiment[26], we offer an alternative explanation and explore a new channel (macroeconomic uncertainty) where changes in risk aversion may originate. This is consistent with for example Pan and Singleton (2008) and Longstaff et al. (2010) among others, who identify a strong link between the co-movement of CDS spreads and the VIX and argue that their evidence is "consistent with premium for credit risk in sovereign markets being influenced by spillovers of real economic growth in the United States to economic growth in other regions of

[26] See Eichengreen and Mody (1998b), Kamin and von Kleist (1999) and McGuire and Schrijvers (2003) among others.

the world"[27]. In contrast to Longstaff et al. (2010), Pan and Singleton (2008) and Remolona et al. (2008), we explore the link between the total spread and U.S. consumption data, while these papers decompose the spread into an expected loss component and a risk premium component.

The economic intuition that sovereign credit risk is priced globally is valid for several reasons. Technological developments, as well as financial innovation leading to a spreading of the "originate-to-distribute" model have resulted in increased financial integration. Globalization, increasing liberalization, tighter trade networks and the European integration have led to a better level playing field, where shocks to the economy spread easier from one part of the globe to the other. Such an interpretation may help to explain why sovereign spreads had persistent downward trends during an economically benign period with low interest rates, where consumption was high and investors were chasing for yield with increasing risk appetite. Subsequently, the credit crunch in the U.S. reversed this trend with a regime shift in risk aversion and a repricing of global asset markets.

The valuation of other asset ratios or welfare ratios has so far not been part of our discussion. It is important to point out however, that we have restricted ourselves to preference parameter scenarios, which have proved to be effective in resolving the equity premium, the risk-free rate, the volatility and the return predictability puzzles[28]. Hence, we show that there is a strong overlap in the stochastic discount factor for pricing both the U.S. equity market and the global sovereign CDS market, suggesting that both are integrated. This is an important finding. As this is not the main emphasis of our paper though and because of space limitations, we report the results without further discussion in the external appendix for investor with and without generalized disappointment aversion.

4.3.4 A disaster explanation of sovereign CDS

The regime-switching set-up of the model allows us to get a better insight into the CDS prices and default probabilities in different regimes. In Tables 9 and 10, we report state-dependent spreads and probabilities for the four states of nature determined by expected growth and volatility of consumption, as well as their means. It is interesting to note that spreads are mainly driven by

[27]Similar conclusions about the U.S. acting as the epicentre for the transmission of economic shocks are drawn by Roll (1988) and Goetzmann et al. (2005) among others.

[28]See Bansal and Yaron (2004) for Kreps-Porteus and Bonomo et al. (2011) for Generalized Disappointment Aversion preferences.

the low probability states (low expected consumption growth and high macroeconomic uncertainty, and low expected consumption growth and low macroeconomic uncertainty). For the purpose of illustration, consider for instance the 1-year contract in Table 9 for the Baa rating category by Moody's (Panel A). It can be seen that the mean CDS spread is 68 basis points. There is however a huge price discrepancy between states. The "low-high" state for example has a spread of 1373 basis points, but spreads for the other three states are very low. In comparison, this spread is higher than the maximum observed spread for the 1-year contract in this rating category, but differences are smaller at other maturities. Taking into account that the probability of being in the worst state is very low in the long run (2.3%), we compare the nature of sovereign CDS spreads to that of catastrophe bonds, or disaster insurance[29]. This result is very intuitive, as CDS are basically an insurance against downside risk and should hence reflect the asymmetric nature of the credit markets. This pattern is observed throughout our results. The model thus generates a disaster interpretation similar in spirit to that of Rietz (1988) and Barro (2006), and confirms the "picking up pennies in front of a steamroller" interpretation during the financial crisis, where the selling of credit protection was perceived as piling up significant quantities of tail risk in compensation for small, but consistent returns. Empirically, a similar result is found for European corporate CDS. Berndt and Obreja (2010) find that a factor mimicking economic catastrophe risk explains a large fraction of CDS returns.

[Table 9 and 10 here]

Interestingly, except for the Baa rating category of the Moody's calibration results, we also observe reversals of the term structure in the low probability states where expected consumption growth is low.

4.3.5 A model without disappointment aversion: The kreps-porteus certainty equivalent

In what follows, we compare two scenarios: that of a disappointment averse investor, whose required compensation for bearing systematic risk is higher below a certain threshold as in Bonomo et al.

[29] See Coval et al. (2009) for a discussion on catastrophe bonds.

(2011), and that of a risk averse investor without disappointment aversion and a Kreps-Porteus[30] (KP) certainty equivalent as in the Long-run-risk economy of Bansal and Yaron (2004). The comparison of these two scenarios is well suited for several reasons. First of all, the comparison is straightforward as the Kreps-Porteus scenario is easily obtained by shutting down disappointment aversion if α is equal to 1. In addition, Bonomo et al. (2011) showed that asset valuation ratios for an investor in the long-run-risk economy with a coefficient of risk aversion γ equal to 10 and the elasticity of substitution ψ equal to 1.5 can be reproduced in an economy with generalized disappointment aversion, where γ reduces to 2.5 in combination with a weight attributed to disappointment aversion (α) equal to 0.30 and a disappointment threshold level set at κ equal to 0.989. Their results are also less sensitive to the value of the EIS ψ, which is crucial for the results of Bansal and Yaron (2004). In both cases the 1-period discount factor is kept constant at 0.9989. Model results can be found in the external appendix.

A first observation is that the calibrated parameters of the default process have no more economic interpretation and are counterintuitive. Four values of $\beta_{\lambda\sigma}$ are negative, implying that default should decrease in times of higher macroeconomic uncertainty. This is in contrast to the results of the GDA economy, where all values for $\beta_{\lambda\sigma}$ line up positively. While this creates obstacles to infer a meaningful interpretation, we note that, conditional on these parameters, the KP manages to match default probabilities and the first moment of the spread curve quite well. Moreover, the KP scenario does a much better job in matching volatilities, except for the B rating category, albeit the latter RMSE is much smaller than for the GDA economy. These results warrant however some care for interpretation. The starting point of our analysis was to restrict ourselves to preference parameter scenarios, which manage to match equity valuation ratios. Bonomo et al. (2011) have shown that the results of Bansal and Yaron (2004) are heavily dependent on a value of the EIS equal to 1.5, as well as on the high persistence of expected consumption growth. Similarly, results for the term structure break down once these values are disturbed. We thus find that both the KP and the GDA economies manage to match both the default probabilities and the first moment of the term structure quite well. However, given the counterintuitive meaning of the default parameters (negative values for $\beta_{\lambda\sigma}$) and the strong sensitivity to the values of ϕ_x and ψ, we decide to use the

[30]See Kreps and Porteus (1978).

GDA economy as our benchmark for further sensitivity analysis and omit the KP scenario in what follows.

4.4 Parameter sensitivity analysis - disturbing α, κ, ψ and γ

In order to get a better insight of the sensitivity of the model results to the choice of our preference parameters, we have conducted an extensive sensitivity analysis to the results derived by calibrating the exogenous default process to the historical cumulative default probabilities provided by Standard&Poor's. More specifically, we have studies perturbations to the parameters α, κ, ψ and γ. Because of space limitations, these are reported in the external appendix. To summarize, we find that model-implied CDS spreads prove rather insensitive to perturbations in κ and robust to changes in ψ, but sensitive to perturbations in α. Finally, as expected, a rational investor systematically requires higher compensation for bearing systematic risk when the value of γ increases.

5 U.S. Consumption and the Co-Movement of Sovereign CDS Spreads

5.1 A principal component analysis

We have postulated that expected U.S. consumption growth and volatility are common factors and a driving force of sovereign CDS risk premia. Merely fitting the moments of the data using the means of a consumption-based stochastic discount factor is likely not convincing enough to support the view that shocks to the consumption patterns of global investors based in the U.S. affect their risk appetite, thereby affecting risk premia required for unpredictable variation in future default intensities. We therefore proceed with a deeper study (disconnected from the model) of the link between the strong co-movement of the CDS term structure with U.S. consumption data. For this purpose, we perform a Principal Component Analysis on the spread levels of our data set over the full sample horizon May 9, 2003 until August 19, 2010, for the 38 countries in our sample[31]. The algorithm displays that the first three factors account for approximately 95% of the variation in the spread levels, which is rather strong, given the wide spectrum of contract maturities and reference entities[32]. This is consistent with Pan and Singleton (2008), who find that the first principal component explains on average 96% of the (daily) common variation in a set of three geographically dispersed countries[33], and Longstaff et al. (2010), who document an average explained (monthly) variation by the first factor of 64% for a set of 26 countries, increasing to 75% during the financial crisis. Table 11 illustrates the proportion of the variance explained by the first six principal components. Applying the PCA to subsamples of the term structure doesn't change the results. As we move towards longer maturities, the importance of the first factor decreases nevertheless relative to the second factor.

[Table 11 here]

The most straightforward way to summarize the information from the factor loadings obtained from the PCA is by grouping the country loadings in maturity buckets and taking averages. Therefore, we plot averages of the factor loadings for the first three factors against the contract maturity in Figure 2. Interestingly, the loadings for the first factor are invariant of maturity, whereas those on the second factor are a monotonically increasing function thereof. We thus feel safe to interpret the first and second factors as a level and slope of the CDS term structure. For the third factor, we observe a decreasing pattern at maturities one to three, and a subsequent stabilization. We suspect a U-shape pattern, but can't conclude with certainty as ten years is the longest maturity in our sample. In such a case, the third factor could be interpreted as a curvature effect.

[Figure 2 here]

If U.S. consumption is a priced factor in the sovereign CDS market, then it ought to be strongly linked to the factors extracted from this Principal Component Analysis. Hence, we first estimate the

[31] We note that results are insensitive or even stronger if the PCA analysis is performed on the changes in spreads, on standardized spreads by the sample mean and sample standard deviation or on the correlation matrix of the spreads.

[32] We perform a PCA on the spread levels as opposed to Longstaff et al. (2010), who perform a PCA on swap spread changes, and Pan and Singleton (2008), who do a country- and maturity-based PCA using the model-implied risk-premia.

[33] Korea, Turkey and Mexico.

conditional monthly expected consumption growth and conditional consumption volatility using a Kalman Filter method with time-varying coefficients. The estimation procedure follows Hamilton (1994) and we estimate the model (23) using monthly real per capita consumption data from January 1959 until August 2010, downloaded from the FRED database of the Federal Reserve Bank of St.Louis[34],

$$\begin{aligned} g_{t+1} &= x_t + \sigma_t \epsilon_{g,t+1} \\ x_{t+1} &= (1-\phi_x)\,\mu_x + \phi_x x_t + \nu_x \sigma_t \epsilon_{x,t+1} \end{aligned} \tag{23}$$

with

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

and where $x_{t|T}$ denotes the conditional expectation $E\left[x_t \mid g_T, g_{T-1}, \ldots\right]$. Thus, we get a filtered time series for the conditional expected consumption growth ($\hat{x}_{t|t}$) and the conditional consumption volatility ($\hat{\sigma}_t$). Parameter estimates, which are comparable to those used in the calibration exercise described in section 4.2.1, are provided in Table 12. We then take month-end averages of the factor scores and regress the first three factors onto conditional expected consumption growth and conditional consumption volatility, that is we run the base regressions (24). For each regression, we have 88 monthly observations.

$$F_{i,t} = a_{0,i} + a_{1,i} \times \hat{x}_{t|t} + a_{2,i} \times \hat{\sigma}_t + \epsilon_t \tag{24}$$

where $i = 1, 2, 3$ and t is the month index. Regression results are reported in columns one to three of Table 13.

[Table 12 and 13 here]

It is interesting to observe that both coefficients on the explanatory variables are statistically significant at the 1% significance level for regressions (1) and (2), but statistically insignificant

[34]The model set-up features a parsimonious discrete-time state approximation of expected consumption growth and volatility, which is useful to provide economic insights and necessary to derive closed-form solutions to asset prices. In reality, however, these variables are continous, which justifies our approach of estimating a continous autoregressive process of order 1 in the empirical exercise.

for regression (3). In addition, the adjusted R^2 from the first two regressions is 76% and 74% respectively, but drops close to zero in the third regression. Hence at this stage, we can already dare to promote U.S. consumption data as an influental determinant of the first two factors, which themselves explain on average almost 91% of the variation in sovereign credit risk premia. Figure 2 illustrates that loadings on the first Principal Component are maturity-invariant and uniformly positive across reference entities. The interpretation of the coefficients then implies that, as $\hat{a}_1$ is negative, the level of sovereign CDS spreads is lower in states of high conditional expected consumption growth. Moreover, a positive $\hat{a}_2$ implies that increased consumption volatility (macroeconomic uncertainty) leads to an increase in sovereign risk premia. These results are in line with economic intuition. Beyond statistical significance, it is more difficult to come up with with an economic interpretation of the latent factor loadings.

For the second regression, both coefficients are statistically significant at the 1% significance level. In this case, however, both coefficients are positive. The interpretation of the regression coefficients requires some care. A positive coefficient on expected consumption growth implies that the slope of the CDS term structure is increasing as the perception of economic conditions improve. As shocks to expected consumption growth are persistent, positive shocks increase interest rates, which depresses bond prices and increases yields. Yields on longer dated bonds increase proportionally more, thereby steepening the slope. The positive regression coefficient on macroeconomic uncertainty is a result of two offsetting effects. If expected consumption growth is low, higher macroeconomic uncertainty will lower interest rates as investors' willingness to save increases. Thus, bond prices increase and yields drop, again more so for longer maturities. However, conditional on high expected consumption growth, investors still want to borrow from future consumption following higher conditional consumption volatility. This leads to a steepening of the term structure. As the unconditional probability of being in a state of high expected consumption growth is approximately four times as high the probability of being in a state of low macroeconomic forecasts, the latter effect dominates and the net result is a steeper term slope. The model replicates this feature as can be seen in Table 9 and we confirm this interpretation by running an additional regression where we include an interaction term of conditional consumption volatility and an indicator variable equal to one if expected consumption growth is high. These results are not reported because of space limitations.

Finally, the R^2 is close to zero for the third regression, and the regression coefficients are statistically insignificant. The regression results support our view that expected U.S. consumption growth and volatility are two major drivers of the commonality observed in sovereign credit risk premia. Their shocks channel through primarily to the level and the slope of the CDS term structure. Nevertheless, they are not sufficient for explaining the residual variance, which in addition should help to explain risk premia. Although this remains mere speculation at this point, we believe the remaining factor to be a local liquidity factor, influenced by the forces of supply and demand, following the discussion by Pan and Singleton (2008) for the 1-year contract of sovereign CDS. To put the results of our PCA into numbers, we conclude that shocks to expected U.S. consumption growth and volatility manage to explain on average 91% of the common variation in sovereign CDS premia. An additional factor, likely more local in nature, should manage to explain an additional 4%. We conclude by raising the awarness of an error-in-variables (EIV) problem in our robustness test, as we first estimate expected consumption growth and volatility and use the estimates in the factor regressions. This problem could be solved by proceeding to a simultaneous estimation of the conditional consumption time series and the regression coefficients, but would not allow us to use the long consumption data series for the estimation of conditional expected consumption growth and volatility. This is a trade-off and we currently decide to live with the EIV problem.

In order to provide the reader with a visual overview of the previous results, we plot the filtered series of conditional consumption forecasts and conditional volatility at a monthly horizon against the monthly mean 5-year CDS spread of all 38 countries in our sample in Figure 3. Our previous intuition that consumption risk is not only a priced factor in basic assets is clearly confirmed. There is a strong negative correlation (-65%) between the aggregated prices for sovereign credit risk and conditional expected consumption growth. Moreover, the conditional consumption volatility tracks the mean 5-year CDS spread closely with a staggering correlation of 85%.

[Figure 3 here]

A major concern is that our results are mainly driven by the crisis period. Ang and Bekaert (2002) discuss the fact that correlations in financial markets tend to increase during turbulent times. Subdividing our sample into two sub-periods of equal length, one for the pre-crisis regime and one for the crisis episode, we observe that the first three PC still account for approximately 96% of the variation in CDS spread levels. In addition, the explanatory power of the first PC becomes even stronger (See Table 11). This suggests that the results are not merely an artifact of the crisis.

5.2 The variance risk premium and the VIX

We argue that U.S. consumption data is a major driver of the co-movement of sovereign CDS spreads. Previous papers have identified a strong link between sovereign risk premia and the VIX[35]. An alternative explanation to our story would be that, as financial volatility increases, investors who become more risk averse, adjust their consumption patterns to account for future macroeconomic uncertainty. We explore this hypothesis and answer to the above findings in three ways. First, we show that (in our model) the Variance Risk Premium (VRP) is endogenous and itself a function of the exogenous macroeconomic fundamentals. In addition, we rerun the regressions of the first two factors extracted from the PCA on the estimates of consumption forecasts and macroeconomic uncertainty and add the VRP in the regressions. Finally, we run a VAR (Vector autoregression) between our estimates of U.S. consumption, i.e. expected consumption growth and consumption volatility, and the CBOE VIX index.

The first attempt to corroborate our hypothesis that U.S. macroeconomic fundamentals are a source of common risk is to show that the VRP is itself endogenous and a function of expected consumption growth and volatility. We show in Appendix (E) that the VRP in closed form is equal to:

$$VRP_t = \zeta_t^\top \upsilon^* \tag{25}$$

where the explicit expression of the vector υ^* is given by equation (E.12).

The model-implied VRP is thus itself endogenous and driven by the exogenous endowment dynamics. Yet, we want to investigate how this result fares empirically. Wang et al. (2010) investigate corporate CDS and argue that the firm-level VRP contains explanatory power even after controlling for the market wide VRP and other firm-specific and macroeconomic variables. In addition, they

[35]See Pan and Singleton (2008), Longstaff et al. (2010), Remolona et al. (2008) and Hilscher and Nosbusch (2010) among others.

show that the market VRP Granger causes option-implied and expected variance. Results for the firm-level VRP don't show any causality pattern. Taking these findings into account, we rerun the factor regressions (24) and include the VRP[36]. Regression results are reported in columns four to nine of Table 13.

Regressions (4) and (5) are the same as in columns (1) and (2)[37]. The adjusted R^2s are 76% and 66% respectively and all coefficients remain significant at the 1% level. The univariate regressions (6) and (7) include only the market VRP. Although the coefficient a_3 on the VRP is statistically significant at the 5% level for the regression with the first Principal Component, the adjusted R^2 is considerably lower at 7%. For the second Principal Component, the coefficients are statistically insignificant, and the adjusted R^2 is negative. Regressions (8) and (9) contain all three variables. It is interesting to see that the coefficients $\hat{a}_1$ and $\hat{a}_2$ hardly change once the VRP is included in the regressions and all signs remain the same. Also the adjusted R^2 remains at the same magnitude. In addition, the coefficient $\hat{a}_3$ on the VRP loses its statistical significance. These results suggest that the market VRP provides no additional explanatory power beyond the macroeconomic fundamentals (conditional consumption forecasts and volatility) for the first two Principal Components, thereby corroborating our hypothesis of U.S. macroeconomic fundamentals being a source of common risk in the sovereign CDS market[38].

Finally, we also investigate the relationship between our estimates of U.S. consumption, i.e. expected consumption growth and consumption volatility, and the CBOE VIX index. This is done by running tests for Granger causality following the specified regression:

$$Y_t = \phi + \theta Y_{t-1} + \epsilon_t, \tag{26}$$

where $Y_t = [VIX_t \quad \hat{x}_{t|t} \quad \hat{\sigma}_t]'$. The results are not reported here. There is no evidence that expected consumption growth is driven by the financial market volatility. Moreover, Granger

[36]The data for the VRP is taken from Hao Zhou's webpage. As this data series stops in January 2010, we have to cut the seven last monthly observations from the consumption series.

[37]The reader should note that the results are almost identical, but that the coefficients change slightly, as we have seven observations less.

[38]We redid the same analysis using the CBOE S&P 500 VIX index instead of the VRP, and we find that the R^2 in column (6) increases to 55%, still much lower than the 76% for the consumption regression. These results can be found in the external appendix.

causality between consumption volatility and the VIX goes in both directions. Our findings are thus inconclusive and point to mere correlation.

Having examined the relationship between the latent principal components, the consumption risk factors and the VRP, a natural question to ask is how the observed CDS spreads relate to these risk factors. To close the loop, we thus construct measures for the level, slope and curvature of the CDS term structure and regress these for each country on expected consumption growth, consumption volatility and the VRP. These results are summarized in Table 14. The level of the term structure at any day t is defined as the average spread over all maturities[39], the slope is the difference between the 10-year and the 1-year spread and the curvature is computed as twice the 5-year spread minus the sum of the 10-year and 1-year CDS spreads. Our previous conclusions hardly change. The power of the VRP fades out once we include the consumption risk factors. At least 66% of the coefficients on $\hat{x}_{t|t}$ and $\hat{\sigma}_t$ are statistically significant, while this is the case for maximally 21% of the coefficients on the VRP. Moreover, the median adjusted R^2s are high, ranging from 60% for the slope regressions up to 72% for the level regressions.

Again, a concern is that the measures for the level, slope and curvature are highly correlated. To the contrary, the correlation between the level and slope series is a weak 12%, and that between the level and curvature is only 42%. On the other hand, the correlation between the slope and the curvature is 78%. Given that the curvature regressions have very high adjusted R^2s, similar to the slope and level regressions and that a large fraction of the regression coefficients are statistically significant, we can rule out that the third principal component is a curvature factor, but we can conjecture that the second principal component may be a linear combination of both the slope and curvature of the CDS term structure.

6 Conclusion

This paper develops a consumption-based generalized equilibrium pricing framework for CDS in closed form, linking credit spreads to the preferences of a representative investor who is risk averse and exhibits generalized disappointment aversion. Strong countercyclical risk aversion and a persistent time-varying default process are necessary to match both cumulative historical default prob-

[39] Alternatively, we tried the 5-year CDS spread as a measure of the level. Results hardly change.

abilities and the first and second moments of the CDS term structure at aggregate levels. Calibrating the pricing kernel to U.S. consumption growth and linking the default process economically to macroeconomic shocks, we provide evidence that a two-factor model captures a large fraction of the variation in global sovereign credit risk and is sufficient to reproduce many stylized facts of the equity and CDS markets. Hence we add to the open debate on the determinants of sovereign credit risk by providing evidence that the level and volatility of American consumption growth are priced common factors in the sovereign CDS term structure. To our knowledge, this is the first paper modeling CDS spreads in a consumption-based general equilibrium setting and hence believe this to be an important contribution. In addition, the model delivers a disaster interpretation of sovereign CDS and provides a unified framework to simultaneously price the equity and derivative fixed income market.

We also study the strong co-movement of sovereign CDS across countries and the term structure and find that three principal components explain on average 95% of the common variation. The first two components, which we interpret as a level and slope effect, as well as the actual level, slope and curvature of the term structure, are strongly linked to U.S. macroeconomic forecasts and uncertainty, but not to the Variance risk premium. These findings further corroborate the view that macroeconomic shocks to the U.S. matter to the pricing of financial assets across the globe. Similar to other studies on sovereign CDS, it is important to point out the caveat of a relatively poor history of financial time series on sovereign CDS data. In particular, our sample period only covers one single business cycle.

Our findings have important implications for risk managers, international investors and policy makers alike. First, they point to the fact that the VIX index might not be the only "fear gauge" in the financial markets, and that U.S. consumption risk might be another risk index, whose shocks spread to sovereign credit markets around the world. Second, the common dependence on a limited set of global factors may affect the ability to diversify the risk of global debt portfolios[40]. Third, understanding the underlying source of sovereign credit risk is valuable information for policy makers, who significantly intervened in the sovereign debt and CDS market during the recent European sovereign debt crisis. This study raises awareness as to what might be a source of

[40]See Longstaff et al. (2010).

commonality in sovereign debt markets. Further research is nevertheless desirable to understand the residual deviations from the "average aggregate term structure".

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A Deriving Closed-Form Formulas for Asset Prices and Stochastic Discount Factor

The Markov chain s_t or ζ_t is stationary with ergodic distribution and moments given by:

$$E[\zeta_t] = \Pi \in \mathbb{R}_+^N, \quad E\left[\zeta_t \zeta_t^\top\right] = Diag(\Pi_1, .., \Pi_N) \text{ and } Var[\zeta_t] = E\left[\zeta_t \zeta_t^\top\right] - \Pi\Pi^\top, \tag{A.1}$$

where $Diag(u_1, .., u_N)$ is the $N \times N$ diagonal matrix whose diagonal elements are u_1,..,u_N.

In this model, we can solve for asset prices analytically, for example the price-consumption ratio $P_{c,t}/C_t$ (where $P_{c,t}$ is the price of the unobservable portfolio that pays off consumption) and the risk-free return $R_{f,t+1}$. To obtain asset prices, we need expressions for $\mathcal{R}_t(V_{t+1})/C_t$, the ratio of the certainty equivalent of future lifetime utility to current consumption, and for V_t/C_t, the ratio of lifetime utility to current consumption. The Markov property of the model is crucial for deriving analytical formulas for these expressions and we adopt the following notations:

$$\frac{\mathcal{R}_t(V_{t+1})}{C_t} = \lambda_{1z}^\top \zeta_t, \quad \frac{V_t}{C_t} = \lambda_{1v}^\top \zeta_t, \quad \frac{P_{c,t}}{C_t} = \lambda_{1c}^\top \zeta_t \text{ and } R_{f,t+1} = \frac{1}{\lambda_{1f}^\top \zeta_t}. \tag{A.2}$$

Solving these ratios amounts to characterize the vectors λ_{1z}, λ_{1v}, λ_{1c} and λ_{1f} as functions of the parameters of the consumption dynamics and of the recursive utility function defined above. In this appendix, we provide expressions for these ratios and we refer to Bonomo et al. (2011) for formal proofs.

Proposition A.1 ***Characterization of the Ratios of Utility to Consumption.*** *Let*

$$\frac{\mathcal{R}_t(V_{t+1})}{C_t} = \lambda_{1z}^\top \zeta_t \text{ and } \frac{V_t}{C_t} = \lambda_{1v}^\top \zeta_t$$

respectively denote the ratio of the certainty equivalent of future lifetime utility to current consumption and the ratio of lifetime utility to consumption. The components of the vectors λ_{1z} and λ_{1v} are given by:

$$\lambda_{1z,i} = \exp\left(\mu_{g,i} + \frac{1-\gamma}{2}\omega_{g,i}\right)\left(\sum_{j=1}^N p_{ij}^* \lambda_{1v,j}^{1-\gamma}\right)^{\frac{1}{1-\gamma}} \tag{A.3}$$

$$\lambda_{1v,i} = \left\{(1-\delta) + \delta \lambda_{1z,i}^{1-\frac{1}{\psi}}\right\}^{\frac{1}{1-\frac{1}{\psi}}} \text{ if } \psi \neq 1 \text{ and } \lambda_{1v,i} = \lambda_{1z,i}^\delta \text{ if } \psi = 1, \tag{A.4}$$

where the components of the matrix $P^{*\top} = \left[p^*_{ij}\right]_{1\leq i,j\leq N}$ *in (A.3) and (A.6) are given by:*

$$p^*_{ij} = p_{ij} \frac{1 + \left(\frac{1}{\alpha} - 1\right) \Phi\left(q_{ij} - (1-\gamma)\sqrt{\omega_{g,i}}\right)}{1 + \left(\frac{1}{\alpha} - 1\right) \kappa^{1-\gamma} \sum\limits_{j=1}^{N} p_{ij} \Phi\left(q_{ij}\right)}, \tag{A.5}$$

and where $\Phi(\cdot)$ *denotes the cumulative distribution function of the standard normal.*

Proposition A.2 ***Characterization of Basic Asset Prices.*** *Let*

$$\frac{P_{c,t}}{C_t} = \lambda_{1c}^{\top} \zeta_t \quad \text{and} \quad R_{f,t+1} = \frac{1}{\lambda_{1f}^{\top} \zeta_t}$$

respectively denote the price-consumption ratio and the risk-free rate. The components of the vectors λ_{1c} *and* λ_{1f} *are given by:*

$$\lambda_{1c,i} = \delta \left(\frac{1}{\lambda_{1z,i}}\right)^{\frac{1}{\psi}-\gamma} \exp\left(\mu_{gg,i} + \frac{\omega_{gg,i}}{2}\right) \left(\lambda_{1v}^{\frac{1}{\psi}-\gamma}\right)^{\top} P^* \left(Id - \delta A^*\left(\mu_{gg} + \frac{\omega_{gg}}{2}\right)\right)^{-1} e_i \tag{A.6}$$

$$\lambda_{1f,i} = \frac{1}{\lambda_{2f,i}} = \delta \exp\left(-\gamma \mu_{g,i} + \frac{\gamma^2}{2} \omega_{g,i}\right) \sum_{j=1}^{N} \tilde{p}^*_{ij} \left(\frac{\lambda_{1v,j}}{\lambda_{1z,i}}\right)^{\frac{1}{\psi}-\gamma} \tag{A.7}$$

where $\mu_{gg} = (1-\gamma)\mu_g$, $\omega_{gg} = (1-\gamma)^2 \omega_g$, *where the matrix function* $A^*(u)$ *in (A.6) is defined by:*

$$A^*(u) = Diag\left(\left(\frac{\lambda_{1v,1}}{\lambda_{1z,1}}\right)^{\frac{1}{\psi}-\gamma} \exp(u_1), ..., \left(\frac{\lambda_{1v,N}}{\lambda_{1z,N}}\right)^{\frac{1}{\psi}-\gamma} \exp(u_N)\right) P^*, \tag{A.8}$$

and where the components of the matrix $\tilde{P}^{*\top} = \left[\tilde{p}^*_{ij}\right]_{1\leq i,j\leq N}$ *in (A.7) are given by:*

$$\tilde{p}^*_{ij} = p_{ij} \frac{1 + \left(\frac{1}{\alpha} - 1\right) \Phi\left(q_{ij} + \gamma\sqrt{\omega_{g,i}}\right)}{1 + \left(\frac{1}{\alpha} - 1\right) \kappa^{1-\gamma} \sum\limits_{j=1}^{N} p_{ij} \Phi\left(q_{ij}\right)}.$$

Proposition A.3 ***Characterization of the Stochastic Discount Factor.*** *Based on the dynamics (7) and using the Euler condition for the claim to aggregate consumption, it can be shown that the stochastic discount factor (11) may be expressed as follows:*

$$M_{t,t+1} = \exp\left(\zeta_t^{\top} A \zeta_{t+1} - \gamma g_{t+1}\right) \left[1 + \left(\frac{1}{\alpha} - 1\right) I\left(g_{t+1} < -\zeta_t^{\top} B \zeta_{t+1} + \ln \kappa\right)\right], \tag{A.9}$$

where the components of the $N \times N$ matrices A and B are given by:

$$
\begin{aligned}
a_{ij} &= \ln \delta + \left(\frac{1}{\psi} - \gamma\right) b_{ij} - \ln \left[1 + \left(\frac{1}{\alpha} - 1\right) \kappa^{1-\gamma} \sum_{j=1}^{N} p_{ij} \Phi\left(q_{ij}\right)\right] \\
b_{ij} &= \ln \left(\frac{\lambda_{1v,j}}{\lambda_{1z,i}}\right),
\end{aligned} \tag{A.10}
$$

respectively, and where

$$
q_{ij} = \frac{-b_{ij} + \ln \kappa - \mu_{g,i}}{\sqrt{\omega_{g,i}}}. \tag{A.11}
$$

Observe that the vectors λ_{1z} and λ_{1v} characterize the welfare valuation ratios, for which explicit expressions are provided in equations (A.3) and (A.4).

B Deriving the Closed-Form Formula for the Cumulative Default Probability

An important number that often appears when discussing sovereign default is the probability that the sovereign will default in the upcoming period, usually one year or five years. We now compute the probability at time t that the entity will default between $t+1$ and T, given that it did not default before $t+1$. Formally, we aim at computing $Prob_t\left(t < \tau \leq T \mid \tau > t\right)$. We have:

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

We conjecture that:

$$
E_t\left[\prod_{k=1}^{j} \left(1 - h_{t+k}\right)\right] = \tilde{\Psi}_j^{\top} \zeta_t \tag{B.2}
$$

and we show that the solution sequence $\left\{\tilde{\Psi}_j\right\}$ satisfies the recursion

$$
\tilde{\Psi}_j^{\top} \zeta_t = E_t\left[\left(1 - h_{t+1}\right)\left(\tilde{\Psi}_{j-1}^{\top} \zeta_{t+1}\right)\right] \tag{B.3}
$$

with the initial condition

$$
\tilde{\Psi}_0 = e. \tag{B.4}
$$

It follows that

$$\tilde{\Psi}_j = P^{\top}\left(\tilde{\Psi}_{j-1} \odot \exp\left(-\lambda\right)\right). \tag{B.5}$$

Finally, we have

$$\begin{aligned} Prob_t\left(t < \tau \leq T \mid \tau > t\right) &= 1 - \left(\tilde{\Psi}_{T-t}^{\top}\zeta_t\right) \\ Prob\left(t < \tau \leq T \mid \tau > t\right) &= 1 - \left(\tilde{\Psi}_{T-t}^{\top}\Pi\right). \end{aligned} \tag{B.6}$$

In case of a constant default intensity process, the unconditional cumulative default probability between $t+1$ and T simplifies to

$$Prob\left(t < \tau \leq T \mid \tau > t\right) = 1 - \exp\left(-\lambda\left(T-t\right)\right) \quad \text{where} \quad \lambda = \exp\left(\beta_{\lambda 0}\right). \tag{B.7}$$

C Deriving the Closed-Form Formula for the Default Probability under the Risk-Neutral Measure

So far, we expressed all dynamics under the physical measure. Thus, the cumulative default probability is a historical or real-world metric. For tractability reasons however, we also need a closed-form solution of the cumulative default probability under the risk-neutral measure. Henceforth, dynamics under the risk-neutral ($\mathbb{Q}$) measure will be represented with $\mathbb{Q}$ subscript. We show that the T-year cumulative default probability under the risk-neutral measure, defined by

$$Prob_t^{\mathbb{Q}}\left[t < \tau \leq T \mid \tau > t\right]$$

can be rewritten as

$$\begin{aligned} Prob_t^{\mathbb{Q}}\left[t < \tau \leq T \mid \tau > t\right] &= \frac{Prob_t^{\mathbb{Q}}\left(\tau > t\right) - Prob_t^{\mathbb{Q}}\left(\tau > T\right)}{Prob_t^{\mathbb{Q}}\left(\tau > t\right)} \\ &= 1 - \frac{Prob_t^{\mathbb{Q}}\left(\tau > T\right)}{Prob_t^{\mathbb{Q}}\left(\tau > t\right)} \\ &= 1 - E_t^{\mathbb{Q}}\left[\frac{S_T^{\mathbb{Q}}}{S_t^{\mathbb{Q}}}\right], \end{aligned}$$

where

$$Prob_t^{\mathbb{Q}}\left(\tau > t\right) = E_t^{\mathbb{Q}}\left[I\left(\tau > t\right)\right] = S_t^{\mathbb{Q}}, \tag{C.1}$$

The derivation of the risk-neutral cumulative default probability thus involves the computation of the risk-neutral survival probability. We show that $S_t^{\mathbb{Q}} = S_t$ so that

$$Prob_t^{\mathbb{Q}}\left[t < \tau \leq T \mid \tau > t\right] = 1 - E_t^{\mathbb{Q}}\left[\frac{S_T}{S_t}\right]$$
$$= 1 - E_t\left[Z_{t,T}\frac{S_T}{S_t}\right].$$

We conjecture that

$$E_t\left[Z_{t,t+j}\frac{S_{t+j}}{S_t}\right] = \left(\tilde{\Psi}_j^{\mathbb{Q}}\right)^{\top}\zeta_t \tag{C.2}$$

Given our conjecture, it turns out the sequence $\left\{\tilde{\Psi}_j^{\mathbb{Q}}\right\}$ satisfies the recursion:

$$\left(\tilde{\Psi}_j^{\mathbb{Q}}\right)^{\top}\zeta_t = E_t\left[Z_{t,t+1}\left(1 - h_{t+1}\right)\left(\left(\tilde{\Psi}_{j-1}^{\mathbb{Q}}\right)^{\top}\zeta_{t+1}\right)\right] \tag{C.3}$$

with the initial condition:

$$\tilde{\Psi}_0^{\mathbb{Q}} = e. \tag{C.4}$$

It follows that:

$$\tilde{\Psi}_j^{\mathbb{Q}} = \text{ diagonal of } \left(\tilde{M}\odot\left(\lambda_{2f}\left(\left(\tilde{\Psi}_{j-1}^{\mathbb{Q}}\right)\odot\exp\left(-\lambda\right)\right)^{\top}\right)\right)P. \tag{C.5}$$

Using this result, we can write the cumulative probability of default over a $(T-t)$-year horizon as follows:

$$Prob_t^{Q}\left[t < \tau \leq T \mid \tau > t\right] = 1 - \left(\left(\tilde{\Psi}_{T-t}^{\mathbb{Q}}\right)^{\top}\zeta_t\right)$$
$$Prob^{Q}\left[t < \tau \leq T \mid \tau > t\right] = 1 - \left(\left(\tilde{\Psi}_{T-t}^{\mathbb{Q}}\right)^{\top}\Pi\right).$$

D Deriving the Closed-Form Formula for the CDS Spread

We have the following lemma.

Lemma D.1 *If*

$$\begin{pmatrix}\varepsilon_1\\ \varepsilon_2\end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right), \tag{D.1}$$

then

$$
\begin{aligned}
&E\left[\exp\left(\sigma_1\varepsilon_1\right) I\left(\varepsilon_1 < q_1\right) \times \exp\left(\sigma_2\varepsilon_2\right) I\left(\varepsilon_2 < q_2\right)\right] \\
&\quad = \exp\left(\frac{1}{2}\left(\sigma_1^2 + 2\rho\sigma_1\sigma_2 + \sigma_2^2\right)\right) \Phi_\rho\left(q_1 - \sigma_1 - \rho\sigma_2, q_2 - \sigma_2 - \rho\sigma_1\right),
\end{aligned}
$$

where $\Phi_\rho(\cdot,\cdot)$ *is the bivariate normal cumulative distribution function with correlation* ρ*.*

We assume that the hazard rate h_t and the associated default intensity λ_t are given by:

$$
h_t = 1 - \exp\left(-\lambda_t\right) \quad \text{where} \quad \lambda_t = \exp\left(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda\sigma}\sigma_t\right) = \lambda^\top \zeta_t. \tag{D.2}
$$

We also assume that the loss rate L_t and the associated severity of loss η_t are given by:

$$
L_t = 1 - \exp\left(-\eta_t\right) \quad \text{where} \quad \eta_t = \exp\left(\beta_{\eta 0} + \beta_{\eta x} x_t + \beta_{\eta\sigma}\sigma_t\right) = \eta^\top \zeta_t. \tag{D.3}
$$

The coefficients $\beta_{\lambda x}$ and $\beta_{\eta x}$ are nonpositive, and the coefficients $\beta_{\lambda\sigma}$ and $\beta_{\eta\sigma}$ are nonnegative, so that default and loss tend to increase when forecasts of macroeconomic growth are negative or when macroeconomic uncertainty increases.

Dividing both the numerator and the denonimator of the expression in equation (4) by S_t, we show that computing the price of the CDS is equivalent to computing expressions of the following forms:

$$
\begin{aligned}
&E_t\left[M_{t,t+j}\left(1 - R_{t+j}\right)\frac{S_{t+j-1}}{S_t}\right] \quad \text{and} \quad E_t\left[M_{t,t+j}\left(1 - R_{t+j}\right)\frac{S_{t+j}}{S_t}\right] \\
&E_t\left[M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] \quad \text{and} \quad E_t\left[M_{t,t+j}\frac{S_{t+j}}{S_t}\right],
\end{aligned} \tag{D.4}
$$

and computing the above expressions is equivalent to computing expressions of the following forms:

$$
E_t\left[\left(U^\top \zeta_{t+j}\right) M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] \quad \text{and} \quad E_t\left[\left(U^\top \zeta_{t+j}\right) M_{t,t+j}\frac{S_{t+j}}{S_t}\right] \tag{D.5}
$$

for a given $N \times 1$ vector U.

To compute these expressions, we conjecture that

$$
\begin{aligned}
E_t\left[\left(U^\top \zeta_{t+j}\right) M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] &= \Psi_j^*\left(U\right)^\top \zeta_t \\
E_t\left[\left(U^\top \zeta_{t+j}\right) M_{t,t+j}\frac{S_{t+j}}{S_t}\right] &= \Psi_j\left(U\right)^\top \zeta_t.
\end{aligned} \tag{D.6}
$$

The goal is now to characterize the two solution sequences $\left\{\Psi_j^*(U)\right\}$ and $\{\Psi_j(U)\}$. Given our conjecture, it turns out that both sequences $\left\{\Psi_j^*(U)\right\}$ and $\{\Psi_j(U)\}$ satisfy the same recursion:

$$\begin{aligned}\Psi_j^*(U)^\top \zeta_t &= E_t\left[M_{t,t+1}(1-h_{t+1})\left(\Psi_{j-1}^*(U)^\top \zeta_{t+1}\right)\right] \\ \Psi_j(U)^\top \zeta_t &= E_t\left[M_{t,t+1}(1-h_{t+1})\left(\Psi_{j-1}(U)^\top \zeta_{t+1}\right)\right]\end{aligned} \tag{D.7}$$

but with different initial conditions:

$$\begin{aligned}\Psi_1^*(U)^\top \zeta_t &= E_t\left[\left(U^\top \zeta_{t+1}\right) M_{t,t+1}\right] \\ \Psi_0(U)^\top \zeta_t &= U^\top \zeta_t.\end{aligned} \tag{D.8}$$

To derive an explicit solution for the first initial condition in (D.8), we need to compute the expectation $E_t[M_{t,t+1} \mid \zeta_m, m \in \mathbb{Z}]$.

Using Lemma D.1, we show that:

$$E_t[M_{t,t+1} \mid \zeta_m, m \in \mathbb{Z}] = \zeta_t^\top \tilde{M} \zeta_{t+1} \tag{D.9}$$

where the components of the matrix $\tilde{M}$ are given by:

$$\tilde{m}_{ij} = \exp\left(a_{ij} - \gamma\mu_{g,i} + \frac{1}{2}\gamma^2\omega_{g,i}\right)\left[1 + \left(\frac{1}{\alpha} - 1\right)\Phi\left(q_{ij} + \gamma\sqrt{\omega_{g,i}}\right)\right]. \tag{D.10}$$

It follows that:

$$\begin{aligned}\Psi_1^*(U) &= \text{ diagonal of } \left(\tilde{M} \odot \left(eU^\top\right)\right) P \\ \Psi_0(U) &= U,\end{aligned} \tag{D.11}$$

where e denotes the $N \times 1$ vector with all components equal to one.

We now derive an explicit solution for the recursion (D.7), that is satisfied by the solution sequences $\left\{\Psi_j^*(U)\right\}$ and $\{\Psi_j(U)\}$. We show that:

$$\begin{aligned}\Psi_j^* &= \text{ diagonal of } \left(\tilde{M} \odot \left(e\left(\Psi_{j-1}^* \odot \exp(-\lambda)\right)^\top\right)\right) P \\ \Psi_j &= \text{ diagonal of } \left(\tilde{M} \odot \left(e\left(\Psi_{j-1} \odot \exp(-\lambda)\right)^\top\right)\right) P.\end{aligned} \tag{D.12}$$

Proposition D.1 ***Characterization of the Price of the CDS.***

$$CDS_t(K) = \lambda_{1s}(K)^\top \zeta_t \tag{D.13}$$

The components of the vectors $\lambda_{1s}(K)$ are functions of the consumption dynamics and of the *recursive utility function defined above, and its components are given by:*

$$\lambda_{i,1s}(K) = \frac{\sum_{j=1}^{KJ} \left[\Psi^*_{i,j}(L) - \Psi_{i,j}(L) \right]}{\sum_{k=1}^{K} \Psi_{i,kJ}(e) + \sum_{j=1}^{KJ} \left(\frac{j}{J} - \left\lfloor \frac{j}{J} \right\rfloor \right) \left[\Psi^*_{i,j}(e) - \Psi_{i,j}(e) \right]}, \tag{D.14}$$

where e is the vector with all components equal to one, and $L = 1 - \exp(-\eta)$ is the vector of conditional loss rates, and where the sequences $\left\{ \Psi^*_j(\cdot) \right\}$ and $\{\Psi_j(\cdot)\}$ are given by the recursion (D.12), with initial conditions (D.11).

E Deriving the Closed-Form Formula for the Variance Risk Premium

The return on the consumption asset can be expressed as follows:

$$R_{c,t+1} = \frac{P_{c,t+1} + C_{t+1}}{P_{c,t}}. \tag{E.1}$$

Given the endowment dynamics and the specifications of the stochastic discount factor, the log return r_{t+1}, defined as $\ln(R_{c,t+1})$, is equal to:

$$r_{t+1} = \zeta_t^\top \Lambda_c \zeta_{t+1} + \sqrt{\omega_c^\top \zeta_t} \varepsilon_{c,t+1} \qquad \textit{where} \qquad \Lambda_{c,ij} = \ln\left[\frac{\lambda_{1c,j}+1}{\lambda_{1c,i}}\right] + \mu_{c,i} \ . \tag{E.2}$$

Using the variance decomposition, we show that the variance $\sigma^2_{r,t+1} = Var_t[r_{t+1}]$ is equal to:

$$\sigma^2_{r,t+1} = \upsilon^\top \zeta_t, \tag{E.3}$$

where

$$\upsilon = \text{ diagonal of } \left((\Lambda_c \odot \Lambda_c) P + \omega_c e^\top - (\Lambda_c P) \odot (\Lambda_c P) \right). \tag{E.4}$$

The variance risk premium is defined as the difference of the implied and realized volatility, that is the difference between the variance under the risk-neutral measure and the physical measure.

$$VRP_t = E_t^{\mathbb{Q}}\left[\sigma^2_{r,t+1}\right] - E_t\left[\sigma^2_{r,t+1}\right] \tag{E.5}$$

where $\sigma^2_{r,t+1}$ is the variance and the superscript $\mathbb{Q}$ denotes the expectation taken under the risk-neutral measure. Using (E.3) and applying a change of measure, we can rewrite the above expression as follows:

$$
\begin{aligned}
VRP_t &= E_t\left[Z_{t,t+1}\sigma^2_{r,t+1}\right] - E_t\left[\sigma^2_{r,t+1}\right] && \text{(E.6)} \\
&= E_t\left[Z_{t,t+1}\upsilon^\top \zeta_{t+1}\right] - E_t\left[\upsilon^\top \zeta_{t+1}\right] && \text{(E.7)}
\end{aligned}
$$

Conditioning first on the entire Markov chain, this expression can be rewritten as:

$$
\begin{aligned}
&= E_t\left[Z_{t,t+1}\upsilon^\top \zeta_{t+1} \mid \zeta_m, m \in \mathbb{Z}\right] - E_t\left[\upsilon^\top \zeta_{t+1} \mid \zeta_m, m \in \mathbb{Z}\right] && \text{(E.8)} \\
&= E_t\left[\left(\zeta_t^\top \tilde{M}\zeta_{t+1}\right)\lambda_{2f}\left(\upsilon^\top \zeta_{t+1}\right)\right] - \left(\upsilon^\top \zeta_{t+1}\right) && \text{(E.9)} \\
&= \zeta_t^\top \left(\tilde{M} \odot \left(\lambda_{2f}\upsilon^\top\right)\right) P\zeta_t - \zeta_t^\top \left(e\upsilon^\top\right) P\zeta_t && \text{(E.10)} \\
&= \zeta_t^\top \upsilon^* && \text{(E.11)}
\end{aligned}
$$

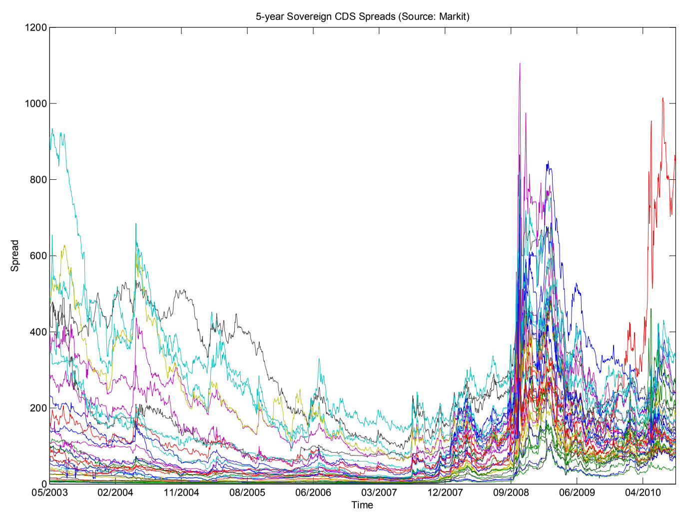
where

$$
\upsilon^* = \text{ diagonal of } \left(\tilde{M} \odot \left(\lambda_{2f}\upsilon^\top\right) P - e\upsilon^\top P\right) \qquad \text{(E.12)}
$$

Figure 1: Co-Movement of Sovereign CDS Spreads

Graph (1a) illustrates the historical 5-year CDS spread for the 38 countries in the sample over the time period May 9th, 2003 until August 19th, 2010. Graph (1b) plots the historical average 5-year CDS spread of the 38 countries in the sample over the same time period. The second plot was inspired by the illustration in Pan and Singleton (2008) Source: Markit.

(a)



(b)

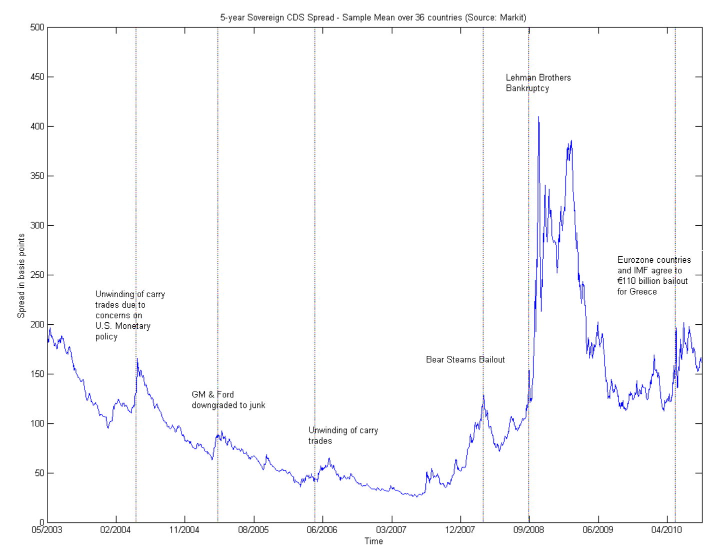


Figure 2: Factor Loadings

Average value for each contract maturity of the 38 country loadings on the First, Second and Third Principal Components extracted from a Principal Components Analysis on the levels of sovereign CDS spreads from May 2003 until August 2010. Source: Markit

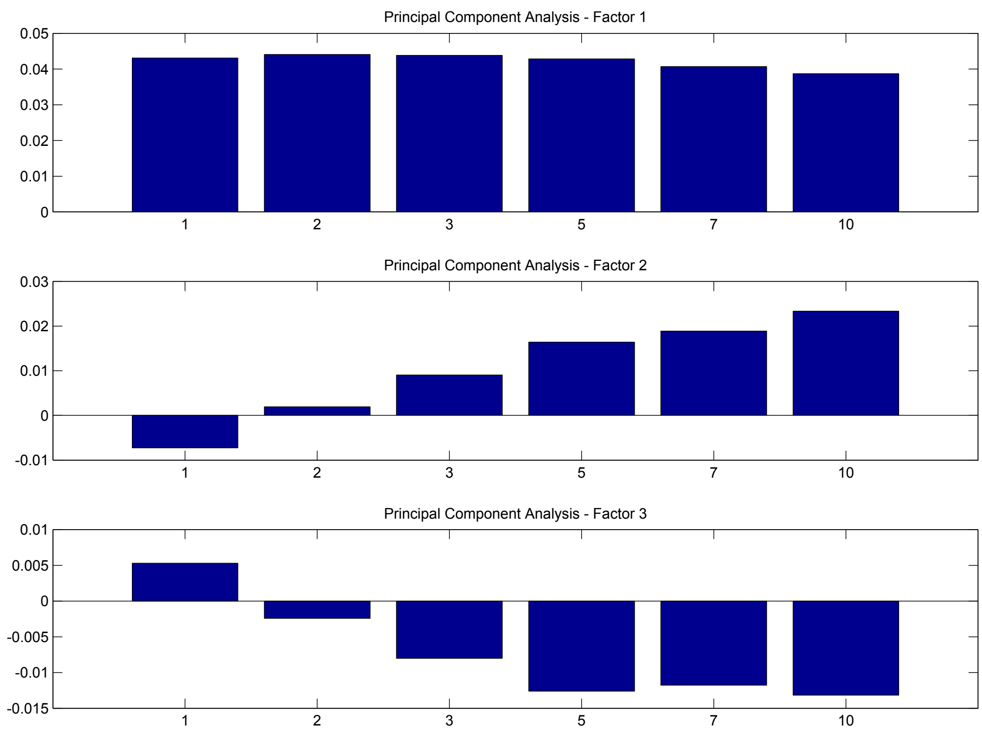
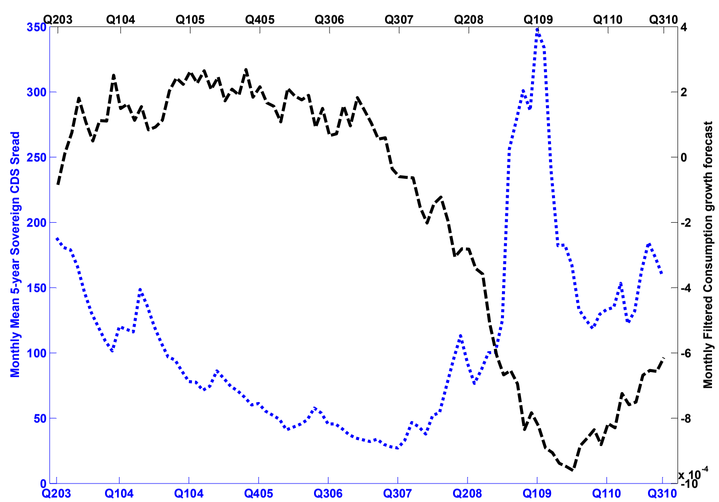


Figure 3: Expected Consumption Growth and Consumption Volatility vs. 5-year Mean CDS Spread

Graph (3a) plots the historical mean 5-year CDS spread (left scale - dotted line) of the 38 countries in the sample over the time period May 9th, 2003 until August 19th, 2010 against the filtered time series of the conditional expected consumption growth (right scale - dashed line) at a monthly horizon. Graph (3b) does the same for consumption volatility. Data for real per capita consumption is taken from the FRED database of the Federal reserve Bank of St.Louis from January 1959 until August 2010. The estimated series is obtained using a Kalman Filter method with time-varying coefficients. The CDS data is obtained from Markit.

(a)



(b)

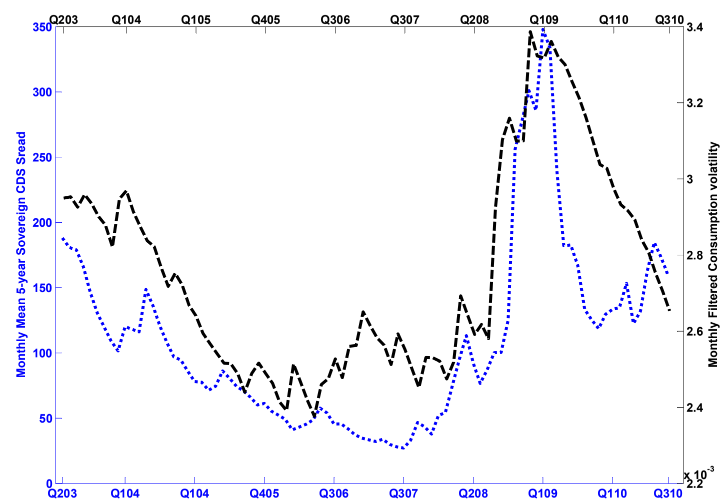


Table 1: Country List

The table presents the list of 38 countries selected for the study and the corresponding geographical region. The third column indicates the Standard&Poor's Rating in 2010. The fourth column indicates the historical rating as traced back by Fitch Ratings over the sample period, that is from May 9th, 2003 until August 19th, 2010. At each date, an integer value ranging from 1 (AAA) to 21 (C) is assigned to each country. The equally weighted historical average is then rounded to the nearest integer, which is used as the final rating categorization. Countries are then grouped into 6 rating buckets (AAA, AA, A, BBB, BB, B).

Classification	*# entities*	*Country*	*Region*	*S&P Rating ('10)*	*Average S&P Rating*
AAA	4	Austria	Europe	AAA	AAA
		France	Europe	AAA	AAA
		Germany	Europe	AAA	AAA
		Spain	Europe	AA	AAA
AA	6	Belgium	Europe	AA+	AA+
		Italy	Europe	A+	AA-
		Japan	Asia	AA	AA
		Portugal	Europe	A-	AA
		Qatar	Middle East	AA	AA
		Slovenia	E.Europe	AA	AA-
A	9	Chile	Lat.Amer	A+	A-
		China	Asia	A+	A
		Czech Republic	E.Europe	A	A
		Greece	Europe	BB+	A
		Israel	Middle East	A	A-
		Korea (Republic of)	Asia	A	A+
		Lithuania	E.Europe	AAA	A-
		Malaysia	Asia	A-	A-
		Slovakia	E.Eur	A+	A
BBB	11	Bulgaria	E.Eur	BBB	BBB-
		Croatia	E.Europe	BBB	BBB-
		Hungary	E.Europe	BBB-	BBB+
		Mexico	Lat.Amer	BBB	BBB+
		Morocco	Africa	BBB-	BBB-
		Panama	Lat.Amer	BBB-	BBB-
		Poland	E.Europe	A-	BBB+
		Romania	E.Europe	BB+	BBB-
		Russian Federation	E.Europe	BBB	BBB+
		South Africa	Africa	BBB+	BBB+
		Thailand	Asia	BBB+	BBB+
BB	6	Brazil	Lat.Amer	BBB-	BB
		Colombia	Lat.Amer	BB+	BB
		Egypt	Africa	BB+	BB+
		Peru	Lat.Amer	BBB-	BB+
		Philippines	Asia	BB-	BB
		Turkey	Middle East	BB	BB-
B	2	Lebanon	Middle East	B	B-
		Venezuela	Lat.Amer	BB-	B+

Table 2: Summary Statistics

The table reports summary statistics for the CDS term structure of 38 sovereign countries over the sample period May 9th, 2003 until August 19th, 2010. All CDS prices are mid composite quotes and USD denominated. Rating classification is achieved by assigning an integer value ranging from 1 (AAA) to 21 (C) at each date to each country. The equally weighted historical average is then rounded to the nearest integer, which is used as the final rating categorization. The Mean (Median) spread is calculated as the historical mean (median) spread, where at each date, all observations within a given rating category are aggregated by taking the mean. Similarly, the standard deviation (Skewness, Kurtosis) is calculated as the standard deviation (skewness, kurtosis) of the data series aggregated at each date within a given rating category. AC1 and AC2 are the first-order and second-order autocorrelation coefficients respectively. Source: Markit

AAA	1y	2y	3y	5y	7y	10y	**AA**	1y	2y	3y	5y	7y	10y
Mean	15	17	19	23	24	26		24	27	31	38	41	45
Median	2	2	3	4	5	7		3	4	5	8	12	16
Stand.dev.	26	28	30	34	34	33		36	38	40	44	44	43
Minimum	0	0	1	1	2	2		0	1	1	2	2	3
Maximum	304	301	293	274	270	266		557	536	499	461	433	410
AC1	0.9940	0.9949	0.9970	0.9975	0.9975	0.9974		0.9969	0.9972	0.9975	0.9978	0.9978	0.9977
A	1y	2y	3y	5y	7y	10y	**BBB**	1y	2y	3y	5y	7y	10y
Mean	49	55	61	71	76	81		77	95	109	132	143	155
Median	12	18	24	34	41	49		33	54	74	106	123	139
Stand.dev.	69	72	74	77	75	73		105	106	105	103	99	96
Minimum	1	2	3	5	5	6		3	3	5	8	11	14
Maximum	1235	1172	1127	1015	952	893		1190	1100	1110	1106	1096	1081
AC1	0.9967	0.9970	0.9971	0.9974	0.9973	0.9972		0.9976	0.9974	0.9970	0.9967	0.9966	0.9964
BB	1y	2y	3y	5y	7y	10y	**B**	1y	2y	3y	5y	7y	10y
Mean	110	157	196	255	281	305		433	484	517	564	574	599
Median	78	115	146	197	225	250		328	403	455	517	538	562
Stand.dev.	92	111	125	138	138	138		371	362	350	328	303	286
Minimum	15	7	1	1	74	72		19	34	55	117	140	186
Maximum	822	845	903	1032	1036	1039		3654	3504	3400	3234	3111	3053
AC1	0.9979	0.9977	0.9976	0.9974	0.9972	0.9971		0.9901	0.9916	0.9926	0.9927	0.9889	0.9928

Table 3: Parameters of the Markov-Switching Models.

The following Bansal and Yaron (2004) model at the monthly frequency is calibrated as in Bonomo et al. (2011) with $\mu_x = 0.0015$, $\phi_d = 2$, $\nu_d = 6.5075$, $\phi_x = 0.975$, $\nu_x = 0.038$, $\sqrt{\mu_\sigma} = 0.0072$, $\phi_\sigma = 0.995$, $\nu_\sigma = 6.2547 \times 10^{-6}$ and $\rho_1 = 0.4018$.

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

where

$$\begin{pmatrix} \epsilon_{c,t+1} \\ \epsilon_{d,t+1} \\ \epsilon_{x,t+1} \\ \epsilon_{\sigma,t+1} \end{pmatrix} \mid J_t \sim \mathcal{NID}\left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_1 & 0 & 0 \\ \rho_1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \right).$$

Parameters of the model with predictable consumption growth at the daily frequency are obtained from the monthly-to-daily mapping system as described below:

$$\begin{aligned}
&\mu_x^{daily} = \Delta\mu_x, \quad \mu_\sigma^{daily} = \Delta\mu_\sigma, \quad \phi_d^{daily} = \phi_d, \quad \nu_d^{daily} = \nu_d, \quad \rho_1^{daily} = \rho_1, \\
&\phi_x^{daily} = \phi_x^{\Delta}, \quad \nu_x^{daily} = \nu_x \sqrt{\left(\frac{1-\phi_x^{2\Delta}}{1-\phi_x^2}\right) \Big/ \left(1 + \frac{2\phi_x}{1-\phi_x} - \frac{2\Delta\phi_x\left(1-\phi_x^{1/\Delta}\right)}{(1-\phi_x)^2}\right)} \\
&\phi_\sigma^{daily} = \phi_\sigma^{\Delta}, \quad \nu_\sigma^{daily} = \nu_\sigma \sqrt{\Delta} \sqrt{\left(\frac{1-\phi_\sigma^{2\Delta}}{1-\phi_\sigma^2}\right) \Big/ \left(1 + \frac{2\phi_\sigma}{1-\phi_\sigma} - \frac{2\Delta\phi_\sigma\left(1-\phi_\sigma^{1/\Delta}\right)}{(1-\phi_\sigma)^2}\right)}
\end{aligned}$$

where we consider $\Delta = 1/22$, meaning that there are 22 trading/decision days per month. The parameters at a daily frequency obtained from the mapping system are $\mu_x^{daily} = 6.8182 \times 10^{-5}$, $\phi_d^{daily} = 2$, $\nu_d^{daily} = 6.5075$, $\phi_x^{daily} = 0.9988$, $\nu_x^{daily} = 0.0019$, $\mu_\sigma^{daily} = 2.3564 \times 10^{-6}$, $\phi_\sigma^{daily} = 0.9998$, $\nu_\sigma^{daily} = 6.1873 \times 10^{-8}$ and $\rho_1^{daily} = 0.4018$. In Panel A, we report the parameters of the four-state daily Markov-switching model in which consumption growth is predictable. μ_c and μ_d are conditional means of consumption and dividend growths, ω_c and ω_d are conditional variances of consumption and dividend growths and ρ is the conditional correlation between consumption and dividend growths. $P^\top$ is the transition matrix across different regimes and Π is the vector of unconditional probabilities of regimes. The four states are characterized by the combinations of expected consumption growth (μ) and consumption volatility (σ), which can be high (H) and low (L).

Panel A	$\mu_L\sigma_L$	$\mu_L\sigma_H$	$\mu_H\sigma_L$	$\mu_H\sigma_H$
$\mu_c^\top$	-0.0001048	-0.0001048	0.0000898	0.0000898
$\mu_d^\top$	-0.0002778	-0.0002778	0.0001114	0.0001114
$(\omega_c^\top)^{1/2}$	0.0009251	0.0028207	0.0009251	0.0028207
$(\omega_d^\top)^{1/2}$	0.0060201	0.0183558	0.0060201	0.0183558
$\rho^\top$	0.4017868	0.4017868	0.4017868	0.4017868
		$P^\top$		
$\mu_L\sigma_L$	0.9989295	0.0000481	0.0010224	0.0000000
$\mu_L\sigma_H$	0.0001795	0.9987981	0.0000002	0.0010223
$\mu_H\sigma_L$	0.0001277	0.0000000	0.9998242	0.0000481
$\mu_H\sigma_H$	0.0000000	0.0001277	0.0001797	0.9996926
$\Pi^\top$	0.0875685	0.0234639	0.7011066	0.1878610

Table 4: Moody's and Standard&Poor's Historical Sovereign Default Rates.

Panel A reports Moody's Historical sovereign Issuer-Weighted cumulative default probabilities over the time period 1983 to 2008. Panel B reports Standard&Poor's Sovereign Foreign-Currency Cumulative Average Default Rates Without Rating Modifiers over the time frame 1975 to 2009. Default rates are conditional on survival. Implied senior debt ratings through 1995, sovereign credit ratings thereafter. Source: Moody's and Standard&Poor's

Moody's Default Rates (1983-2008)

Panel A	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Aaa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Aa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Baa	0.00	0.55	1.17	1.87	2.68	3.53	3.53	3.53	3.53	3.53
Ba	0.90	2.04	4.02	6.27	8.75	10.58	13.10	15.96	18.35	20.83
B	2.83	6.18	7.45	9.54	11.59	14.11	16.30	18.25	20.91	24.72
Caa	22.64	27.22	33.33	33.33	33.33	33.33	33.33	33.33	33.33	33.33

Standard&Poor's Default Rates (1975-2009)

Panel B	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
AAA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBB	0.00	0.50	1.57	2.72	3.97	5.33	6.07	6.07	6.07	6.07
BB	0.74	2.36	3.70	4.70	6.36	8.24	10.34	12.72	13.63	13.63
B	2.13	5.03	6.71	9.32	11.67	13.54	15.85	20.06	21.87	24.57
CCC	36.84	48.33	59.81	65.55	72.44	81.63	90.81	–	–	–

Table 5: Model-Results: Constant Hazard Rate

This table reports model-implied and observed physical default probabilities, mean CDS spreads and volatilities in basis points for maturities 1 to 10 at the aggregated level for the rating categories BBB-B when the hazard rate process is constant. The recovery rate is constant and exogenously set at 37.5%. Preference parameters are as indicated below. The column labeled $\beta_{\lambda 0}$ indicates the calibrated constant hazard rate parameter and the column labeled $RMSE$ reports the Root Mean Squared Errors (in % points for the default probabilities and in basis points for the spreads and volatilities) for the model fit. Panel A reports the results using the Moody's statistics to match the cumulative historical default probabilities, while Panel B reports the results using the Standard&Poor's information to calibrate the cumulative historical default probabilities.

	δ	γ	ψ	α	κ
GDA	0.9989	2.5	1.5	0.3	0.994

		$\beta_{\lambda 0}$	RMSE	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Physical Default Probabilities													
Panel A: Moody's													
Baa	Observed	−11.0000	–	0.00	0.55	1.17	–	2.68	–	3.53	–	–	3.53
	Model		0.49	0.44	0.88	1.31	1.75	2.18	2.61	3.04	3.47	3.89	4.31
Ba	Observed	−9.7680	–	0.90	2.04	4.02	–	8.75	–	13.10	–	–	20.83
	Model		1.60	2.06	4.07	6.04	7.98	9.87	11.72	13.54	15.32	17.06	18.76
B	Observed	−9.2076	–	2.83	6.18	7.45	–	11.59	–	16.30	–	–	24.72
	Model		0.88	2.59	5.11	7.56	9.96	12.29	14.56	16.77	18.92	21.02	23.06
Panel B: Standard&Poor's													
BBB	Observed	−10.4891	–	0.00	0.50	1.57	–	3.97	–	6.07	–	–	6.07
	Model		0.83	0.73	1.46	2.18	2.90	3.61	4.31	5.01	5.71	6.40	7.09
BB	Observed	−9.7680	–	0.74	2.36	3.70	–	6.36	–	10.34	–	–	13.63
	Model		0.66	1.50	2.98	4.43	5.87	7.28	8.67	10.04	11.39	12.72	14.03
B	Observed	−9.2076	–	2.13	5.03	6.71	–	11.67	–	15.85	–	–	24.57
	Model		0.86	2.61	5.16	7.63	10.05	12.40	14.69	16.91	19.09	21.20	23.26
Mean CDS Spread													
Panel A: Moody's													
Baa	Observed		–	77	95	109	–	132	–	143	–	–	155
	Model		95.01	28	28	28	28	28	28	27	27	27	27
Ba	Observed		–	110	157	196	–	255	–	281	–	–	305
	Model		111.70	130	130	130	130	130	130	130	129	129	129
B	Observed		–	433	484	517	–	564	–	574	–	–	599
	Model		369.30	164	164	164	164	164	164	163	163	163	163
Panel B: Standard&Poor's													
BBB	Observed		–	77	95	109	–	132	–	143	–	–	155
	Model		77.63	46	46	46	46	46	46	46	46	46	46
BB	Observed		–	110	157	196	–	255	–	281	–	–	305
	Model		141.12	95	95	95	94	94	94	94	94	94	94
B	Observed		–	433	484	517	–	564	–	574	–	–	599
	Model		367.74	166	166	166	165	165	165	165	165	165	165
CDS Volatility													
Panel A: Moody's													
Baa	Observed		–	105	106	105	–	103	–	99	–	–	96
	Model		102.05	0	0	0	0	0	0	0	0	0	0
Ba	Observed		–	92	111	125	–	138	–	138	–	–	138
	Model		123.34	2	2	2	2	1	1	1	1	1	1
B	Observed		–	371	362	350	–	328	–	303	–	–	286
	Model		332.86	2	2	2	2	2	2	2	2	2	1
Panel B: Standard&Poor's													
BBB	Observed		–	105	106	105	–	103	–	99	–	–	96
	Model		101.84	1	1	1	1	1	0	0	0	0	0
BB	Observed		–	92	111	125	–	138	–	138	–	–	138
	Model		123.73	1	1	1	1	1	1	1	1	1	1
B	Observed		–	371	362	350	–	328	–	303	–	–	286
	Model		332.84	2	2	2	2	2	2	2	2	2	1

Table 6: Calibration Results - Time-Varying Hazard Rate

The table reports the calibration results for the parameters of the default process for the rating categories Baa to B for Moody's (Panel A) and BBB to B for Standard&Poor's (Panel B) as well as the associated RMSE (in absolute %) defined by equation 21. The last three rows refer to the RMSEs for the default probabilities (in absolute %), the mean and standard deviation of CDS spreads (in basis points) respectively. The calibration results are derived by matching the observed data at the 1, 2, 3, 5, 7 and 10 year horizon.

Panel A: Moody's							
	$\beta_{\lambda 0}$	$\beta_{\lambda x}$	$\beta_{\lambda \sigma}$	$RMSE^{*}$	$RMSE_{p}$	$RMSE_{\mu}$	$RMSE_{\sigma}$
Baa	−24.1051	−124788.9872	1447.2255	1.2791	0.7832	7.8985	64.4408
Ba	−10.0420	−11836.1966	635.1939	3.5419	1.9686	29.0345	60.5523
B	−9.5113	−27883.1286	128.9387	2.7151	1.7329	7.7210	196.1384

Panel B: Standard&Poor's							
	$\beta_{\lambda 0}$	$\beta_{\lambda x}$	$\beta_{\lambda \sigma}$	$RMSE^{*}$	$RMSE_{p}$	$RMSE_{\mu}$	$RMSE_{\sigma}$
BBB	−22.0475	−128796.5374	278.5633	0.9223	0.8508	2.3217	28.5383
BB	−10.6147	−21499.5930	538.9388	2.5525	0.8734	22.2712	92.6357
B	−9.7539	−30137.1928	138.6164	3.0052	2.1053	8.0244	201.1532

Table 7: Model-Implied Term Structure of Default Probabilities BBB-B

This table reports model-implied physical and risk-neutral default probabilities for maturities 1 to 10 at the aggregated level for the rating categories BBB-B as well as their ratio when the hazard rate process is time-varying. The column labeled *RMSE* reports the Root Mean Squared Errors in % points for the model fit. The recovery rate is constant and exogenously set at 37.5%. Preference parameters are as indicated below. Panel A reports the results using the Moody's statistics to match the cumulative historical default probabilities, while Panel B reports the results using the Standard&Poor's information to calibrate the cumulative historical default probabilities.

	δ	γ	ψ	α	κ
GDA	0.9989	2.5	1.5	0.3	0.994

		RMSE	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Physical Default Probabilities												
Panel A: Moody's												
Baa	Observed	–	0.00	0.55	1.17	–	2.68	–	3.53	–	–	3.53
	Model	0.78	0.68	1.26	1.80	2.30	2.78	3.25	3.70	4.15	4.60	5.04
Ba	Observed	–	0.90	2.04	4.02	–	8.75	–	13.10	–	–	20.83
	Model	1.97	2.05	3.97	5.79	7.53	9.22	10.86	12.46	14.02	15.54	17.03
B	Observed	–	2.83	6.18	7.45	–	11.59	–	16.30	–	–	24.72
	Model	1.73	4.14	7.18	9.68	11.89	13.94	15.88	17.75	19.57	21.34	23.07
Panel B: Standard&Poor's												
BBB	Observed	–	0.00	0.50	1.57	–	3.97	–	6.07	–	–	6.07
	Model	0.85	0.81	1.58	2.31	3.02	3.71	4.38	5.05	5.70	6.35	6.99
BB	Observed	–	0.74	2.36	3.70	–	6.36	–	10.34	–	–	13.63
	Model	0.87	1.62	3.07	4.41	5.67	6.88	8.06	9.21	10.33	11.43	12.52
B	Observed	–	2.13	5.03	6.71	–	11.67	–	15.85	–	–	24.57
	Model	2.11	4.10	7.10	9.55	11.71	13.70	15.60	17.43	19.21	20.94	22.63
Risk-Neutral Default Probabilities												
Panel A: Moody's												
Baa	Model	–	1.03	2.52	4.34	6.40	8.60	10.90	13.25	15.62	17.99	20.35
Ba	Model	–	2.53	5.66	9.14	12.81	16.55	20.29	23.98	27.58	31.07	34.44
B	Model	–	5.90	12.72	19.68	26.40	32.72	38.57	43.96	48.91	53.43	57.56
Panel B: Standard&Poor's												
BBB	Model	–	1.17	2.84	4.84	7.04	9.36	11.74	14.15	16.55	18.94	21.28
BB	Model	–	2.27	5.32	8.82	12.56	16.39	20.22	23.99	27.67	31.23	34.66
B	Model	–	5.88	12.68	19.63	26.33	32.64	38.49	43.88	48.81	53.33	57.46
Ratio of Risk-Neutral to Physical Default Probabilities												
Panel A: Moody's												
Baa	Model	–	1.52	1.99	2.42	2.78	3.10	3.36	3.58	3.76	3.91	4.04
Ba	Model	–	1.24	1.43	1.58	1.70	1.80	1.87	1.93	1.97	2.00	2.02
B	Model	–	1.43	1.77	2.03	2.22	2.35	2.43	2.48	2.50	2.50	2.49
Panel B: Standard&Poor's												
BBB	Model	–	1.44	1.80	2.09	2.33	2.52	2.68	2.80	2.90	2.98	3.05
BB	Model	–	1.40	1.73	2.00	2.21	2.38	2.51	2.61	2.68	2.73	2.77
B	Model	–	1.43	1.79	2.06	2.25	2.38	2.47	2.52	2.54	2.55	2.54

Table 8: Model-Implied and Observed Term Structure of CDS Spreads BBB-B

This table reports observed and model-implied means and standard deviations for CDS spreads (in basis points) for maturities 1 to 10 at the aggregated level for the rating categories BBB-B when the hazard rate is time-varying. The column labeled *RMSE* reports the Root Mean Squared Errors in basis points for the model fit. The recovery rate is constant and exogenously set at 37.5%. Preference parameters are as indicated below. Panel A reports the results using the Moody's statistics to match the cumulative historical default probabilities, while Panel B reoprts the results using the Standard&Poor's information to calibrate the cumulative historical default probabilities.

	δ	γ	ψ	α	κ
GDA	0.9989	2.5	1.5	0.3	0.994

Mean CDS Spread												
		RMSE	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Panel A: Moody's												
Baa	Observed	–	77	95	109	–	132	–	143	–	–	155
	Model	7.90	67	85	101	114	126	136	145	152	159	165
Ba	Observed	–	110	157	196	–	255	–	281	–	–	305
	Model	29.03	163	188	208	225	239	250	260	269	276	283
B	Observed	–	433	484	517	–	564	–	574	–	–	599
	Model	7.72	418	482	520	544	560	570	578	583	587	590
Panel B: Standard&Poor's												
BBB	Observed	–	77	95	109	–	132	–	143	–	–	155
	Model	2.32	75	93	107	119	129	137	144	149	154	159
BB	Observed	–	110	157	196	–	255	–	281	–	–	305
	Model	22.27	149	180	205	224	240	252	263	272	280	286
B	Observed	–	433	484	517	–	564	–	574	–	–	599
	Model	8.02	417	481	520	544	560	570	577	583	587	590
CDS Volatility												
		RMSE	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Panel A: Moody's												
Baa	Observed	–	105	106	105	–	103	–	99	–	–	96
	Model	64.44	207	187	172	159	149	140	132	125	119	114
Ba	Observed	–	92	111	125	–	138	–	138	–	–	138
	Model	60.55	207	187	170	157	146	136	128	121	115	110
B	Observed	–	371	362	350	–	328	–	303	–	–	286
	Model	196.14	714	615	537	477	429	391	361	336	317	300
Panel B: Standard&Poor's												
BBB	Observed	–	105	106	105	–	103	–	99	–	–	96
	Model	28.54	129	112	98	86	77	69	63	58	53	49
BB	Observed	–	92	111	125	–	138	–	138	–	–	138
	Model	92.64	263	231	205	184	167	152	141	131	122	115
B	Observed	–	371	362	350	–	328	–	303	–	–	286
	Model	201.15	722	622	543	482	433	395	365	340	320	303

Table 9: Disaster - CDS

This table reports model-implied state-dependent and mean CDS spreads (in basis points) for maturities 1 to 10 at the aggregated level for the rating categories BBB/Baa-B/B when the hazard rate is time-varying. The column labeled *State* reports the state of the economy, Low-Low (Low-High, High-Low, High-High) referring to low (low, high, high) expected consumption growth and low (high, low, high) consumption volatility. The recovery rate is constant and exogenously set at 37.5%. Preference parameters and unconditional probabilities of regimes are as indicated below. Panel A reports the results using the Moody's statistics to match the cumulative historical default probabilities, while Panel B reports the results using the Standard&Poor's information to calibrate the cumulative historical default probabilities.

	δ	γ	ψ	α	κ
GDA	0.9989	2.5	1.5	0.3	0.994

	$\mu_L\sigma_L$	$\mu_L\sigma_H$	$\mu_H\sigma_L$	$\mu_H\sigma_H$
$\Pi^\top$	0.0875685	0.0234639	0.7011066	0.1878610

	State	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
CDS Spreads											
Panel A: Moody's											
Baa	Low-Low	125	138	146	152	156	159	162	164	167	169
	Low-High	1373	1237	1124	1031	955	892	839	795	758	727
	High-Low	10	22	35	49	61	73	83	93	102	110
	High-High	91	153	197	228	250	267	279	288	295	300
	Mean	67	85	101	114	126	136	145	152	159	165
Ba	Low-Low	431	417	405	395	386	380	374	370	367	365
	Low-High	1303	1194	1104	1030	970	920	879	844	815	790
	High-Low	76	102	126	146	163	178	192	203	214	223
	High-High	222	275	313	340	360	375	387	395	402	407
	Mean	163	188	208	225	239	250	260	269	276	283
B	Low-Low	2317	2116	1948	1812	1702	1614	1542	1484	1436	1397
	Low-High	2845	2575	2347	2159	2007	1884	1784	1702	1635	1578
	High-Low	161	257	322	367	400	424	442	456	467	476
	High-High	189	296	365	412	444	468	485	498	509	517
	Mean	418	482	520	544	560	570	578	583	587	590
Panel B: Standard&Poor's											
BBB	Low-Low	381	355	334	317	303	292	283	275	269	264
	Low-High	612	559	516	480	451	426	406	388	374	361
	High-Low	27	49	67	82	94	105	114	121	128	134
	High-High	42	75	100	119	135	147	157	165	172	178
	Mean	75	93	107	119	129	137	144	149	154	159
BB	Low-Low	599	568	541	518	499	483	470	459	451	443
	Low-High	1530	1387	1269	1172	1092	1026	972	927	889	856
	High-Low	52	88	117	142	162	180	195	207	218	228
	High-High	125	193	241	275	300	319	334	345	353	360
	Mean	149	180	205	224	240	252	263	272	280	286
B	Low-Low	2324	2123	1954	1817	1707	1618	1546	1487	1439	1400
	Low-High	2904	2626	2392	2199	2043	1917	1814	1730	1661	1604
	High-Low	158	254	320	365	398	422	440	454	465	474
	High-High	188	296	366	412	445	468	485	498	509	517
	Mean	417	481	520	544	560	570	577	583	587	590

Table 10: Disaster - Default

This table reports model-implied state-dependent and mean cumulative default probabilities (in %) for maturities 1 to 10 at the aggregated level for the rating categories BBB/Baa-B/B when the hazard rate is time-varying. The column labeld *State* reports the state of nature, Low-Low (Low-High, High-Low, High-High) referring to low (low, high, high) expected consumption growth and low (high, low, high) consumption volatility. The recovery rate is constant and exogenously set at 37.5%. Preference parameters and unconditional probabilities of regimes are as indicated below. Panel A reports the results using the Moody's statistics to match the cumulative historical default probabilities, while Panel B reports the results using the Standard&Poor's information to calibrate the cumulative historical default probabilities.

	δ	γ	ψ	α	κ
GDA	0.9989	2.5	1.5	0.3	0.994

	$\mu_L\sigma_L$	$\mu_L\sigma_H$	$\mu_H\sigma_L$	$\mu_H\sigma_H$
$\Pi^\top$	0.0875685	0.0234639	0.7011066	0.1878610

Default Probabilities											
	State	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Panel A: Moody's											
	Low-Low	1.54	2.86	3.96	4.86	5.61	6.24	6.77	7.24	7.67	8.06
	Low-High	19.47	30.64	37.17	41.11	43.60	45.26	46.45	47.36	48.10	48.74
Baa	High-Low	0.03	0.11	0.24	0.41	0.61	0.84	1.09	1.36	1.65	1.95
	High-High	0.35	1.16	2.19	3.31	4.45	5.58	6.67	7.73	8.74	9.71
	Mean	0.68	1.26	1.80	2.30	2.78	3.25	3.70	4.15	4.60	5.04
	Low-Low	6.23	10.96	14.62	17.52	19.87	21.85	23.56	25.08	26.47	27.76
	Low-High	18.70	30.19	37.54	42.47	45.97	48.62	50.74	52.53	54.08	55.48
Ba	High-Low	0.82	1.81	2.92	4.12	5.37	6.66	7.98	9.31	10.65	11.99
	High-High	2.61	5.47	8.39	11.26	14.03	16.69	19.21	21.60	23.87	26.02
	Mean	2.05	3.97	5.79	7.53	9.22	10.86	12.46	14.02	15.54	17.03
	Low-Low	29.79	45.15	53.26	57.72	60.36	62.08	63.33	64.34	65.22	66.02
	Low-High	36.01	52.48	60.28	64.21	66.40	67.79	68.82	69.67	70.43	71.13
B	High-Low	0.73	2.16	3.91	5.81	7.76	9.71	11.64	13.55	15.42	17.25
	High-High	0.90	2.59	4.58	6.68	8.79	10.88	12.93	14.93	16.88	18.79
	Mean	4.14	7.18	9.68	11.89	13.94	15.88	17.75	19.57	21.34	23.07
Panel B: Standard&Poor's											
	Low-Low	5.66	9.78	12.81	15.09	16.83	18.19	19.30	20.22	21.01	21.72
	Low-High	9.28	15.56	19.89	22.95	25.16	26.82	28.11	29.15	30.03	30.79
BBB	High-Low	0.10	0.36	0.73	1.18	1.68	2.21	2.78	3.36	3.95	4.55
	High-High	0.16	0.57	1.13	1.79	2.49	3.23	3.99	4.74	5.50	6.25
	Mean	0.81	1.58	2.31	3.02	3.71	4.38	5.05	5.70	6.35	6.99
	Low-Low	8.60	14.72	19.13	22.36	24.79	26.68	28.20	29.47	30.56	31.55
	Low-High	21.47	33.74	40.95	45.35	48.20	50.17	51.64	52.81	53.80	54.68
BB	High-Low	0.31	0.85	1.56	2.38	3.27	4.22	5.19	6.18	7.19	8.20
	High-High	0.80	2.09	3.61	5.22	6.85	8.46	10.04	11.58	13.07	14.52
	Mean	1.62	3.07	4.41	5.67	6.88	8.06	9.21	10.33	11.43	12.52
	Low-Low	29.86	45.22	53.31	57.75	60.36	62.06	63.28	64.27	65.13	65.92
	Low-High	36.58	53.11	60.84	64.69	66.82	68.16	69.15	69.97	70.70	71.38
B	High-Low	0.67	2.04	3.74	5.59	7.48	9.39	11.27	13.13	14.96	16.76
	High-High	0.84	2.47	4.41	6.46	8.53	10.57	12.57	14.53	16.44	18.30
	Mean	4.10	7.10	9.55	11.71	13.70	15.60	17.43	19.21	20.94	22.63

Table 11: Principal Component Analysis

Variation of CDS spreads (levels) explained by the first 6 factors of the Principal Component Analysis. The row *All* refers to the pooled data, where all maturities for all countries are taken together. Subsequent columns indicate results for the subsamples, taken by contract maturity each at a time. Rows labeled Pre-crisis and Crisis refer to the sample periods 09.05.2003-29.12.2006 and 01.01.2007-19.08.2010 applied to all maturities. Source: Markit

	PC1	PC2	PC3	PC4	PC5	PC6
All	**77.8158**	**91.0749**	**94.7448**	**96.3491**	**97.5028**	**98.2378**
$1y$	85.9812	92.8245	95.7170	97.1810	98.2461	99.0540
$2y$	83.0337	91.6612	95.5640	97.1889	98.2693	98.9229
$3y$	79.7215	91.7345	95.5324	97.1032	98.1849	98.8207
$5y$	75.1912	92.0572	95.2786	96.7295	97.9724	98.7011
$7y$	72.8903	91.5746	94.8203	96.2861	97.4767	98.5779
$10y$	70.4393	91.6796	94.6215	96.2402	97.5720	98.4832
$Pre-crisis$	88.2523	93.8364	95.9182	97.1180	97.9096	98.3989
$Crisis$	86.9193	94.8430	96.7877	98.2607	98.7504	99.0409

Table 12: Kalman Filter Estimates

Kalman Filter estimates for the parameters of the conditional expectation of consumption growth and conditional consumption volatility. Standard errors are given in parentheses.

μ_x	ϕ_x	ν_x	μ_σ	ϕ_σ
0.001785	0.955642	0.058611	$1.372177e-05$	0.9610790
(0.000235)	(0.033936)	(0.028885)	$(1.541653e-06)$	(0.013410)

Table 13: Regression Analysis - Consumption Data and Variance Risk Premium

Regression results from the regression of the factors extracted from a Principal Component Analysis onto conditional expected consumption growth, conditional consumption volatility and the Variance Risk Premium. Bootstrapped errors are reported in parentheses. Factor scores are first averaged at the end of each month and the aggregated factors are then regressed against the monthly series of filtered consumption forecasts, conditional consumption volatility and the Variance Risk Premium. Data for real per capita consumption is taken from the FRED database of the Federal reserve Bank of St.Louis from January 1959 until August 2010. The estimated series are obtained using a Kalman Filter method with time-varying coefficients. The data for the VRP is taken from Hao Zhou's webpage. Bootstrapped standard errors are reported in brackets. $***$, $**$ and $*$ indicate significance at the 1%, 5% and 10% respectively.

$$F_{i,t} = a_{0,i} + a_{1,i} \times \hat{x}_{t|t} + a_{2,i} \times \hat{\sigma}_t + a_{3,i} \times VRP_t + \epsilon_t,$$

where $i = 1, 2, 3$ and t is the month index. The dependent variables $F_{i,t}$ denote the principal components, $\hat{x}_{t|t}$ is the filtered consumption forecast, $\hat{\sigma}_t$ the filtered conditional consumption volatility and VRP_t denotes the Variance Risk Premium.

	F1	*F2*	*F3*	*F1*	*F2*	*F1*	*F2*	*F1*	*F2*
$\hat{a}_0$	−1.2753***	−0.7674***	−0.0369	−1.3872***	−0.7262***	−0.0422*	0.0130	−1.3845***	−0.7246***
(*s.e.*)	(0.1480)	(0.0602)	(0.0640)	(0.1505)	(0.0680)	(0.0245)	(0.0094)	(0.1499)	(0.0683)
$\hat{a}_1$	−128.1614***	236.6641***	4.0282	−95.6389**	222.6566***			−92.3956**	224.6693**
(*s.e.*)	(34.8215)	(14.7612)	(15.8554)	(39.1151)	(17.4100)			(37.9882)	(17.7275)
$\hat{a}_2$	454.8142***	293.5407***	13.3784	495.5985***	278.6042***			493.5822***	277.353***
(*s.e.*)	(55.1858)	(22.5358)	(23.9283)	(55.9620)	(25.2232)			(55.9370)	(25.4428)
$\hat{a}_3$						0.0019**	−0.0000	0.0002	0.0001
(*s.e.*)						(0.0008)	(0.0003)	(0.0004)	(0.0002)
$adj.R^2$	0.76	0.74	0.00	0.76	0.66	0.069	−0.01	0.76	0.66
Obs.	88	88	88	81	81	81	81	81	81
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*

Table 14: Country Regressions - Consumption Data and Variance Risk Premium

Regression results from the regression of the level, slope and curvature of the monthly sovereign CDS series onto conditional expected consumption growth, conditional consumption volatility and the Variance Risk Premium. The level is defined as the average monthly CDS spread over all maturities, the slope is equal to difference between the average monthly 10-year and 1-year CDS spread, and the curvature is computed as twice the 5-year minus the 10-year and 1-year CDS spread. The regressors are the monthly series of filtered consumption growth forecasts, conditional consumption volatility and the Variance Risk Premium. Data for real per capita consumption is taken from the FRED database of the Federal reserve Bank of St.Louis from January 1959 until August 2010. The estimated series are obtained using a Kalman Filter method with time-varying coefficients. The data for the VRP is taken from Hao Zhou's webpage.

$$Y_{i,t} = a_{0,i} + a_{1,i} \times \hat{x}_{t|t} + a_{2,i} \times \hat{\sigma}_t + a_{3,i} \times VRP_t + \epsilon_t$$

where $Y_{i,t}$ is either the *Level*, *Slope* or *Curvature* of the CDS curve, i denotes the country and t is the month index. The dependent variables denote the level, slope and curvature, $\hat{x}_{t|t}$ is the filtered consumption forecast, $\hat{\sigma}_t$ the filtered conditional consumption volatility and VRP_t denotes the Variance Risk Premium. The correlation between the dependent variables is reported in Panel A.

Panel A	*Corr(Y_i,Y_j)*
Level/Slope	0.12
Level/Curvature	0.42
Slope/Curvature	0.78

All regressions are run for each of the 38 countries. Panel B excludes the Variance Risk Premium, Panel C excludes the consumption predictors, and Panel D includes all explanatory variables. Columns 1 to 3 report the fraction (out of 38) of 5% statistically significant coefficient estimates, while columns 4 to 6 report the fraction (out of 38) of positive coefficient estimates. Columns 7 to 10 report respectively the minimium, maximum, mean and median adjusted R^2 of the 38 country-pecific regressions. Column 11 indicates the number of observations for each regression.

Panel B	*t-stats* $\hat{x}_{t\|t}$	*t-stats* $\hat{\sigma}_t$	*t-stats* VRP_t	+$\hat{x}_{t\|t}$	+$\hat{\sigma}_{t,t}$	+VRP_t	*min adj.*R^2	*max adj.*R^2	*mean adj.*R^2	*median adj.*R^2	*# obs.*
Level	0.82	0.89		0.32	0.97		0.54	0.75	0.69	0.70	88
Slope	0.84	0.61		0.55	0.74		-0.01	0.77	0.46	0.54	88
Curvature	0.84	0.68		0.34	0.89		-0.02	0.90	0.55	0.60	88
Panel C											
Level			1.00			0.89	0.01	0.14	0.07	0.07	81
Slope			0.45			0.71	-0.01	0.18	0.04	0.02	81
Curvature			0.61			0.82	-0.01	0.17	0.06	0.07	81
Panel D											
Level	0.66	1.00	0.05	0.29	1.00	1.00	0.54	0.82	0.72	0.72	81
Slope	0.87	0.76	0.16	0.56	0.79	0.84	0.05	0.90	0.52	0.60	81
Curvature	0.87	0.74	0.21	0.37	0.95	0.74	-0.02	0.90	0.59	0.64	81
Regression	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*