Real Economic Shocks and Sovereign Credit Risk*

Forthcoming, Journal of Financial and Quantitative Analysis

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Abstract

We provide new empirical evidence that U.S. expected growth and consumption volatility are closely related to the strong co-movement in sovereign spreads. We rationalize these findings in an equilibrium model with recursive utility for CDS spreads. The framework nests a reduced-form default process with country-specific sensitivity to expected growth and macroeconomic uncertainty. Exploiting the high-frequency information in the CDS term structure across 38 countries, we estimate the model and find parameters consistent with preference for early resolution of uncertainty. Our results confirm the existence of time-varying risk premia in sovereign spreads as compensation for exposure to common U.S. macroeconomic risk.

Keywords: CDS, Generalized Disappointment Aversion, Sovereign Risk, Term Structure
JEL Classification: C5, E44, F30, G12, G15

*The authors would like to thank the Managing Editor Stephen J. Brown and an anonymous referee for their valuable inputs to this draft of the paper. We would also like to thank David Backus, Steven Baker, Nina Boyarchenko, Tobias Broer, Anna Cieslak, Mike Chernov, Magnus Dahlquist, René Garcia, Jørgen Haug, Kris Jacobs, David Lando, Belen Nieto, Stijn Van Nieuwerburgh, Paoloa Zerilli, Stanley Zin and seminar participants at the Stockholm School of Economics, the London School of Economics AIRC, the IRMC Amsterdam, the Nordic Finance Network, the EDHEC Business School, the Bank of Spain/Bank of Canada Workshop on Advances in Fixed Income Modeling, the New York Fed, the NYU Stern Macro-Finance Workshop, the Queen Mary University London, the 2012 Meeting of the Econometric Society, the 2012 Financial Econometrics Conference in Toulouse, the European Economic Association 2012 Malaga, the 3rd International Conference of the Financial Engineering and Banking Society in Paris and the 2013 Northern Finance Association for helpful comments. The present project has been supported by the National Research Fund Luxembourg, the Nasdaq-OMX Nordic Foundation, the Jan Wallander and Tom Hedelius Foundation, as well as the Bank Research Institute in Stockholm.

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I Introduction

Sovereign credit spreads co-move significantly over time. In light of this fact, there is substantial evidence that global factors have strong explanatory power for sovereign credit risk (in particular at higher frequencies), above and beyond that of country-specific fundamentals. The recent literature has emphasized the United States (U.S.) financial channel as a global source of risk (Pan and Singleton (2008), Longstaff, Pan, Pedersen, and Singleton (2010)). Whether the ultimate source is financial or macroeconomic in nature is nevertheless a debate (Ang and Longstaff (2013)).[1] We emphasize the macroeconomic channel through new empirical evidence on a tight relationship of expected U.S. consumption growth and consumption volatility with sovereign credit risk. We rationalize this evidence by embedding a reduced-form default process driven by expected growth and consumption volatility into an equilibrium model for credit default swap (CDS) spreads. The model's ability to match several dimensions of the sovereign CDS market corroborates the existence of time-varying risk premia as compensation for exposure to (common) U.S. macroeconomic risk.

We empirically document a strong association between sovereign and global macroeconomic risk, which cannot be accounted for by global financial risk. To demonstrate our results, we exploit the homogenous contract specification and daily variation in CDS spreads.[2] Our sample contains information on the full term structure for a geographically dispersed panel of 38 countries. The motivation for our analysis is based on the fact that sovereign defaults tend to cluster at business cycle frequencies (Reinhart and Rogoff (2008)). First, we show that the average level of spreads has a surprisingly high correlation of respectively -65% and 85% with expected growth rates and economic uncertainty in the U.S. Second, the same two risk factors in turn can account for approximately 75% of the variation in the first two common factors embedded in the term structure across all 38 countries. We believe the two

[1]Ang and Longstaff (2013) focus on systemic sovereign risk.

[2]CDS spreads are better comparable across countries than sovereign bonds, as they are not plagued by differences in covenants, issuer country legislation or declining spread maturities.

factors to be a level and a slope factor. Importantly, this association is robust against a battery of financial market variables, such as the CBOE S&P 500 volatility index, the variance risk premium, the U.S. excess equity return, the price-earnings ratio as well as the high-yield and investment-grade bond spreads. While some of these factors have individually statistical explanatory power for the level factor, none of them accounts for the variation in the slope factor. Third, we document that our results are qualitatively and quantitatively maintained for country-specific regressions, where we test for the level and slope of the CDS term structure as regressands. The empirical evidence survives several robustness tests, among which one suggests that expected growth and consumption volatility contemporaneously predict the Reinhart and Rogoff sovereign distress indicator over the past 50 years.

These new empirical findings suggest that consumption risks are priced factors in the term structure of sovereign CDS spreads and that time-variation in expected growth and consumption volatility are strongly related to the significant co-movement in spreads. We rationalize this result through a general equilibrium framework for CDS spreads that embeds a reduced-form default process driven by aggregate consumption risk factors. Our rational investor is risk averse and exhibits Epstein and Zin (1989) (EZ) recursive preferences. We also extend the model to accommodate generalized disappointment averse (GDA) preferences as in Routledge and Zin (2010). The conditional mean and volatility of aggregate consumption growth, the two state variables of our endowment economy, drive the default process, while countries differ cross-sectionally through their sensitivity to the systematic risk factors. As the model yields closed-form solutions for CDS spreads and their moments, we are able to estimate the structural parameters of the model. In addition, country spreads can be interpreted based on preferences and exposures to macroeconomic risk factors.

To investigate the asset pricing implications, we exploit the high-frequency information in CDS spreads from May 2003 through August 2010 and estimate both preference parameters and the cross-sectional default sensitivities to expected growth rates and consumption volatility. We quantitatively match the unconditional mean, volatility, skewness and persistence of the term structure, the decreasing pattern of the kurtosis with asset maturity as well as historically observed cumulative default probabilities. A two-factor model for the default process is necessary to account for these stylized facts, as a specification based only on expected consumption growth consistently produces a term structure, which is too steep, while it is too low if macroeconomic uncertainty is the only source of risk. Adding country-specific shocks to the model only marginally improves the fit. In addition to average upward sloping term structures, the model qualitatively matches the conditional slope reversals for distressed sovereign borrowers in states of bad macroeconomic fundamentals. Both the EZ and GDA scenarios produce comparable unconditional results. However, a model with downside risk aversion endogenously generates relatively higher risk aversion in states of bad macroeconomic fundamentals, which yields a stronger term structure inversion in the worst economic state that is quantitatively consistent with empirically observed magnitudes. A likelihood ratio test favors asymmetric preferences over symmetric gambles. State-dependent prices in bad states further reflect the tail risk embedded in CDS spreads. Moreover, the model produces ratios of risk-neutral to physical default probabilities consistent with the literature.

Regarding the preference parameters in the EZ (GDA) case, we estimate an elasticity of intertemporal substitution of 1.58 (1.49) and a coefficient of relative risk aversion of 8.27 (4.91), consistent with preference for early resolution of uncertainty. In the GDA case, we estimate a disappointment aversion parameter of 0.25 and a disappointment threshold at 85% of the certainty equivalent. We continue to match first and second moments of the stock market and risk-free rate. We thus provide a joint framework for pricing equity and fixed income derivatives, consistent with evidence of information flow between both markets.[3]

The results suggest that a simple two-factor model including expected growth and macroeconomic uncertainty is sufficient to explain a large fraction of the common time-variation in the global sovereign CDS market. While the previous literature has emphasized the im-

[3]Two recent papers addressing the equity and cash credit spread puzzle in a unified consumption-based framework are Bhamra, Kuehn, and Strebulaev (2010) and Chen, Collin-Dufresne, and Goldstein (2009).

portance of U.S. financial market variables for the common variation in spreads (Pan and Singleton (2008), Longstaff, Pan, Pedersen, and Singleton (2010), Ang and Longstaff (2013)), we focus on a different channel: shocks to the expected level and volatility of U.S. consumption growth. We explain our findings in a tractable two-state model.[4] Surprisingly, Pan and Singleton (2008) address the importance of consumption risk in their discussion, yet don't include it directly in their analysis. Other evidence on the role of global factors in explaining the co-movement in sovereign spreads points to links through U.S. interest rates (Uribe and Yue (2006)), investors' risk appetite (Baek, Bandopadhyaya and Du (2005), Remolona, Scatigna, and Wu (2008), González-Rozada and Yeyati (2008)), investor sentiment (Weigel and Gemmill (2006)), aggregate credit risk (Geyer, Kossmeier, and Pichler (2004)) or contagion (Benzoni, Collin-Dufresne, Goldstein, and Helwege (2012)).

Benzoni, Collin-Dufresne, Goldstein, and Helwege (2012) develop an equilibrium model for CDSs with fragile beliefs as in Hansen (2007) and Hansen and Sargent (2010). The co-movement in spreads arises through a hidden contagion factor that affects the posterior default distribution of all countries after a shock to one individual country. They focus on fitting the dynamics of the level of spreads, while we show that a simple two-factor model matches higher order moments of the term structure. Our model is conceptually also close to Borri and Verdelhan (2009), who apply the Campbell and Cochrane (1999) external habit framework to show that emerging market bonds reflect a risk premium for exposure to the U.S. market returns. Their objective is closer to the extensive literature on the sovereign incentives to default and they fail to match the level of spreads. We focus on the pricing of spreads and match the moments of the term structure up to the fourth order closely. Moreover, we derive analytic solutions for non-linear CDS payoffs, allowing us to estimate the default and preference parameters in the model.

We believe our results to be useful in better understanding the determinants of the

[4]The consumption correlation puzzle of Backus, Kehoe, and Kydland (1992) illustrates that consumption growth is only weakly correlated across countries.

term structure of sovereign credit risk. Improving this understanding is warranted in light of the developments in the emerging markets in the nineties, and particularly the recent sovereign debt crisis in Europe with six international bailouts in approximately three years. Understanding the relationship between higher frequency variation in sovereign spreads and global risk factors is also relevant for the diversification benefits of international investors and the efficiency of government intervention aimed at reducing sovereign borrowing costs.

The rest of the paper proceeds as follows. Section 2 provides new empirical evidence on a tight link between sovereign credit and aggregate macroeconomic risk. Section 3 presents the general equilibrium framework for CDS spreads. The model estimation is explained in section 4, followed by a discussion of the results in section 5. We conclude in section 6.

II U.S. Consumption Risk and Sovereign CDS Spreads

Reinhart and Rogoff (2008) document over a 200-year period that sovereign defaults tend to cluster at business-cycle frequencies. This motivates us to investigate more closely the link between sovereign credit risk, for which we exploit the daily information on sovereign distress embedded in CDS spreads, and global macroeconomic risk, proxied through the conditional mean and volatility of aggregate U.S. consumption growth. The next paragraph describes our CDS dataset, followed by a deeper study of its link with global macroeconomic risk.

A CDS Data and Summary Statistics

A CDS is a fixed income derivative, which allows a protection buyer to purchase insurance from the protection seller against a contingent credit event on a reference entity by paying a premium, referred to as the CDS spread.[5] CDSs are particularly useful to study sovereign credit risk across countries as the contract specification is identical for each sovereign. Public bonds are usually characterized through differences in covenants and are often issued in

[5]Pan and Singleton (2008) describe the structure and institutional details of the sovereign CDS market.

different legal jurisdictions. In addition, CDSs are constant-maturity products with price information available at daily frequencies. This makes them suitable for studying the common variation in sovereign spreads, which is particularly pronounced at higher frequencies.

Our data set consists of daily mid composite USD denominated CDS prices for 38 sovereign countries 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.[6,7] All contracts contain the full restructuring clause. The sample is representative of the global sovereign CDS market as it spans 4 major geographical regions and 17 rating categories. The list of 38 countries is provided in Table 1. Keeping track of rating changes over time, there are on average 4 countries in rating category AAA, 6 in AA, 9 in A, 11 in BBB, 6 in BB and 2 in rating group B.[8]

Our working data set thus contains 1900 observations for 38 countries and 6 maturities, amounting to a total of 433,200 observations. We aggregate countries by rating categories and present summary statistics in Table 2.[9] The dataset exhibits a considerable amount of heterogeneity both across time and across countries. For instance, the mean 5-year spread for AAA rated countries is 22 basis points and 558 basis points for B rated sovereigns. The mean term structure is always upward sloping, increasing monotonically with the deterioration of credit quality from 11 (AAA) to 177 basis points (B). The sample features great time-series variation, with standard deviations for the 5-year series ranging from 31 (AAA) to 287 basis points (B). All time series are highly persistent, with an average daily autocorrelation coefficient for 5-year spreads as high as 0.9965.

[6]We fill gaps with CDS information from CMA Datastream and interpolate if no information is available.

[7]While trading in corporate CDS is highly concentrated around the 5-year maturity, Pan and Singleton (2008) document that trading volume in sovereign CDS is more balanced across maturities.

[8]Venezuela is excluded for the 31 first days of the sample period when it was rated CCC+.

[9]We map ratings into a numerical scheme ranging from 1 (AAA) to 21 (C). The daily rating-specific spread is the equally weighted mean spread of countries in a rating group.

B The Role of Macroeconomic Risk

As a first exercise to investigate the relationship between sovereign and global macroeconomic risk, we test how strongly U.S. consumption risk factors are related to the common factors in the sovereign CDS term structure. A principal component analysis (PCA) on the level of spreads yields that the first two factors account for approximately 91% of the common variation. This is rather strong, given the wide spectrum of contract maturities and reference entities we consider. The magnitude is consistent with Pan and Singleton (2008), who find that the first principal component explains on average 96% of the (daily) common variation for Korea, Turkey and Mexico, and Longstaff, Pan, Pedersen, and Singleton (2010), who document an average explained (monthly) variation by the first factor of 64% for 26 countries, increasing to 75% during the financial crisis. Table 3 illustrates the proportion of the variance explained by the first six principal components. The magnitudes remain similar for subsamples of the term structure. The importance of the first factor decreases nevertheless relative to the second factor as we move towards longer maturities.

To summarize the information from the PCA, we average the country factor loadings across maturities. Figure 1 shows that the average factor loadings on the first principal component have roughly equal magnitudes, whereas those on the second factor increase monotonically with maturity. We therefore interpret the first and second factors as a level and slope factor in the CDS term structure.

If U.S. consumption risk is priced in the sovereign CDS market, then it ought to be linked to the factors extracted from this PCA. As insurance premia on contingent future default events may be linked to expectations about future growth rates, we investigate both channels of time-varying expected consumption growth and macroeconomic uncertainty. More specifically, we use monthly real per capita consumption data from January 1959 until August

2010, available at the Federal Reserve Bank of St.Louis, to estimate the system of equations

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

where g_t, x_t and σ_t reflect the dynamics for, respectively, aggregate consumption growth, its conditional mean and volatility, and all error terms are standard normal. In addition to the short-run consumption shocks $\epsilon_{g,t+1}$, consumption growth is fed with long-run shocks $\epsilon_{x,t+1}$, whose persistence is defined through the parameter ϕ_x. The unconditional mean growth-rate is given by μ_x and ν_x denotes the sensitivity of expected growth to long-run shocks. The parameters ϕ_σ and ν_σ define the persistence of and sensitivity to shocks $\epsilon_{\sigma,t+1}$ to macroeconomic uncertainty, which is fluctuating around its long-run mean μ_σ. We define macroeconomic uncertainty as a GARCH-like stochastic volatility process that has been used in Heston and Nandi (2000), henceforth HN, to price options. Such dynamics have recently been applied in Tédongap (2014) to illustrate the relationship between consumption volatility and the cross-section of stock returns.[10] We note that the volatility shocks are directly related to the realized consumption shocks, but this does not drive our empirical results, as we later discuss. The results are also robust to other volatility filters, which we describe in the internet appendix because of space limitations.

We adopt a Kalman Filter as in Hamilton (1994) to filter a (unsmoothed) time series for the conditional expected consumption growth $\hat{x}_{t|t}$, where $x_{t|t}$ denotes the expectation conditional on observed consumption growth up to time t, and the conditional consumption volatility $\hat{\sigma}_t$. The parameter estimates reported in Panel A of Table 4 are comparable to those used in standard calibration exercises of long-run risk frameworks. As the highest

[10]Note that in contrast to Heston and Nandi (2000), we restrict the leverage parameter to zero. In addition, the volatility process is strictly positive as long as $(1-\phi_\sigma)\,\mu_\sigma - \nu_\sigma/\sqrt{2} \geq 0$. The residuals are normalized to have zero mean and unit variance, i.e. $\epsilon_{\sigma,t+1} = \left(\epsilon^2_{g,t+1} - 1\right)/\sqrt{2}$.

available frequency for consumption information is monthly, we regress monthly averages of the first two factor scores $F_{i,t}$ onto conditional expected growth and consumption volatility

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

where $i = 1, 2$ and t is the month index. Results based on 88 monthly observations with block-bootstrapped standard errors are reported in columns (1) to (2) of Table 5.

Both coefficients on the explanatory variables are statistically significant at the 1% significance level for regressions (1) and (2). In addition, the adjusted R^2 from the first two regressions is 75% and 74%, respectively. On a stand-alone basis, U.S. consumption risk seems strongly associated with the first two common components in the CDS term structure, which themselves explain on average almost 91% of the time-variation in sovereign spreads. We will discuss the signs of the individual regression coefficients in relation to the model-implied results on the assumption that the first two principal components reflect a level and a slope factor. An exact interpretation of the economic magnitudes of the latent factor loadings in relation to the common factors is, however, more difficult.

Our results support the view that expected U.S. consumption growth and volatility are two risk factors in the term structure of sovereign credit spreads.[11] Macroeconomic shocks channel through to the level and the slope of the term structure. A back-of-the-envelope calculation yields that shocks to expected U.S. consumption growth and volatility manage to explain roughly 68.25% of the common variation in sovereign CDS premia.[12] Our conclusion is visually emphasized by plotting the filtered series of conditional expected consumption growth and consumption volatility against the average monthly 5-year CDS spread of all 38 countries in Figure 2. There is a strong negative correlation (-65%) between the average

[11] We acknowledge an error-in-variables problem in the factor regressions, but a simultaneous estimation of the regression coefficients and the risk factors is unlikely to undo our strong results.

[12] This back-of-the-envelope calculation is based on the filtered consumption series, which explains 75% of the first two principal components, which themselves account for 91% of the variation in spreads.

sovereign spread and conditional expected consumption growth. Moreover, the conditional consumption volatility tracks the mean 5-year CDS spread closely with a staggering correlation of 85%.

In order to obtain further empirical support for the relationship between sovereign credit risk and both expected growth and consumption volatility over a longer horizon than the CDS data availability, we exploit the crisis tally indicator of Reinhart and Rogoff (2008).[13] The crisis tally is a count indicator accounting for currency crises, inflation crises, stock market crashes, domestic and external sovereign debt crises, and banking crises. It is available for the entire period where we have monthly consumption growth data and for 29 countries in our sample. Therefore we fit a probit model to test whether the two US macroeconomic risk factors explain the outcome of the crisis tally indicator.[14] More specifically, we fit the model

$$Pr\left(Crisis = 1\right) = \Phi\left(a_0 + a_1 \hat{x}_{t|t} + a_2 \hat{\sigma}_t\right), \tag{3}$$

and report the results using block-bootstrapped standard errors in column (15) of Table 5. Both coefficients for the conditional mean and volatility of consumption growth are significant at the 1% level. Evaluating all explanatory variables at their median value, the coefficients of -0.22 and 0.45 correspond to marginal effects of -0.09 and 0.18, respectively. This implies that, if all values are at their median, a one percentage point increase in expected consumption growth decreases the likelihood of a crisis by 0.09, ceteris paribus. Likewise, a one percentage point rise in consumption volatility increases the probability of a crisis by 0.18. In particular the marginal effect of consumption volatility is economically meaningful.

[13] We are grateful to Carmen Reinhart for making the crisis indicator publicly available on her website.

[14] Note that the crisis tally indicator is a yearly count variable. Thus we assume that if a country is in a crisis in a given year, it is in crisis during all the months of that same year.

C Macroeconomic vs. Financial Risk

The previous empirical findings highlight the possibility that expected growth and macroeconomic uncertainty may explain the co-movement of sovereign CDS spreads. Previous papers have identified a link between sovereign risk premia and financial market variables such as the variance risk premium (Wang, Zhou, and Zhou (2010)) or the CBOE S&P500 volatility index (Pan and Singleton (2008), Longstaff, Pan, Pedersen, and Singleton (2010)). An alternative explanation to our story would be that, as financial volatility increases, risk-averse investors adjust their consumption patterns to account for future macroeconomic uncertainty. We explore this hypothesis in three ways.

First, we rerun the factor regressions of equation (2) by projecting the first two factors from the PCA on several global financial market variables such as the variance risk premium (VRP), the CBOE S&P500 volatility index (VIX), the monthly excess value-weighted return on all NYSE, AMEX, and NASDAQ stocks from CRSP (USret), the US price-earnings ratio (PE), as well the difference between the Bank of America/Merrill Lynch BBB and AAA effective yield (IG) and the difference between the BB and BBB effective yield (HY).[15] We then run a horse race with the global macroeconomic risk factors and test the robustness of the probit specification in equation (3) against the inclusion of financial market variables.

The univariate regressions are reported in columns (3) to (14) of Table 5. Only the coefficients for VIX, PE, IG and HY are statistically significant on their own for the first common factor and, assuming it reflects a level factor, have economically plausible signs. None of the coefficients are statistically significant for the second principal component.[16] Moreover, for the first factor regression, the adjusted R^2 of the VIX is with 55% significantly smaller than the 75% obtained with the macroeconomic risk factors and the PE, IG and HY have adjusted R^2s in the same ballpark region. Most importantly though, for the second

[15]The data for the VRP is taken from Hao Zhou's webpage, the USret from Kenneth French's website, the PE from Robert Shiller's website, and the VIX, AAA_BBB and BBB_BB from the FRED H15 report

[16]Only PE is borderline significant at the 5% level.

factor regression, the maximum adjusted R^2 of 9% is obtained for PE (4% for IG and 2% for HY), compared to 74% for the conditional mean and volatility of US consumption growth.

A horse race between macroeconomic and financial risk confirms the former's importance for the common factors in the term structure of sovereign CDS spreads. Columns (1) to (12) of Table 6 show that none of the financial market variables drives out the statistical significance of expected growth and macroeconomic uncertainty. Again, only the PE, IG and HY remain statistically significant for the first factor and none of them has statistical significance for the second factor. Importantly, the sign of consumption volatility is always preserved and changes little in magnitude. Comparing all variables in columns (13) and (14), only the high-yield spread keeps its statistical significance at the 5% level for the level factor, while the consumption risk factors remain highly statistically significant for both the level and slope factors.[17] Thus, our results suggest that only the high-yield bond spread (HY) contains additional information besides the macroeconomic risk factors for the level factor in the term structure of sovereign CDS spreads, while global financial risk has no additional explanatory power beyond the conditional mean and volatility of consumption growth for the slope factor. Finally, we include in column (16) of Table 5 the USret and PE into the probit regressions as they are available since 1959. The results are qualitatively and quantitatively maintained. In column (17), we use all financial market variables over a shorter time period starting in 1996 and we include all countries from the Reinhart & Rogoff database. Over the shorter time period, the coefficient of consumption volatility of 0.99 corresponds to a marginal effect of 0.38, implying that a one percentage point rise in consumption volatility increases the probability of a crisis by 0.38. Overall, these results corroborate our hypothesis of U.S. macroeconomic fundamentals being a source of common sovereign credit risk.

[17]The coefficient on expected growth flips sign, which is due to multicollinearity issues with the PE ratio and the investment-grade and high-yield bond spreads. We have tested that the part of expected consumption growth orthogonal to the other variables remains statistically significant in the horse race regressions with a negative sign on the level factor. The power and economic sign for the level factor of this orthogonalized component is on its own interesting, but is not central to our message.

To close the loop of our analysis, we regress in Table 7, for each country, empirical measures of the level and slope of the CDS term structure on the same macroeconomic and financial risk factors.[18] The level of the term structure at any day t is defined as the average spread over all maturities, the slope is the difference between the 10-year and the 1-year spread.[19] Our previous conclusions hardly change. The power of the VRP fades out once we include the consumption risk factors. At least 58% 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 54% for the slope regressions up to 70% for the level regressions. The signs of the coefficients are consistent with the evidence of countercyclical spreads and default probabilities. A rise in expected growth decreases the level of spreads for 68% of all countries, whereas a rise in macroeconomic uncertainty raises the level of spreads for 97% of all countries. On the other hand, the term structure loads positively on expected growth for more than half of all countries, and positively on macroeconomic uncertainty for 74% of all countries in the univariate regressions. A concern is that the level and slope measures are highly correlated. To the contrary, the correlation between the level and slope is a weak 12%.

To summarize, our results show that global macroeconomic risk contains information unaccounted for by financial market variables for the first two common factors in the sovereign CDS term structure. These new findings motivate us to develop a parsimonious preference-based model for sovereign CDSs using only two state variables, time-varying expected growth and consumption volatility.

[18]We report and discuss only results for the VRP.

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

D Robustness of the Empirical Results

In order to strengthen the empirical evidence of a relationship between global macroeconomic and sovereign credit risk, we conduct several robustness tests.[20] First, we run the regressions in first differences rather than in levels. Second, we discuss the use of industrial production growth data as an alternative to consumption growth. Third, we check alternative specifications of the endowment dynamics. Fourth, we check whether our results are robust to the inclusion of realized consumption growth. Finally, we test the relationship between macroeconomic and financial risk in a VAR specification.

We emphasize that our analysis focuses on spread levels rather than differences, which is consistent with Doshi, Ericsson, Jacobs, and Turnbull (2013) and references therein.[21] As the authors point out, there is no consensus in the literature, but economic intuition suggests that spreads are mean-reverting and stationary, as opposed to trending stock prices. In addition, first differencing comes at the cost of less efficient statistical estimates, and measurement errors may reduce the signal-to-noise ratio more for difference regressions. We therefore advocate the use of levels. Irrespectively of our motivation though, a concern may be that the results are spurious because of high persistence in spreads, expected growth and consumption volatility. Therefore, we have reported results using difference regressions in section A-V of the internet appendix. Consistent with the literature, R^2 statistics are significantly smaller for the difference regressions, ranging around 9%. But we maintain statistical significance, in particular for the regressions with the slope factor. Importantly, we run a Dickey-Fuller test on the residuals of the regressions in levels and we strictly reject the presence of a unit root (see last row in Tables 5 and 6). Regressions are thus not spurious. Even if the factors and consumption variables were integrated of order one, these results would suggest that there exists a cointegrating relationship. We don't pursue such tests as they are not the

[20]We thank an anonymous referee for suggesting several of these robustness checks.

[21]Campbell and Taksler (2003) use spread levels, and Benzoni, Collin-Dufresne, Goldstein, and Helwege (2012) advocate regressions in levels.

focus of our study. However, if we were to find evidence in favor of a long-run equilibrium relationship, this would still not undo our message that there exists a strong relationship between the common information in the term structure of spreads and macroeconomic risk.

Next, we verify our results using monthly industrial production growth data instead of monthly consumption growth, similar to Bansal, Kiku, Shaliastovich, and Yaron (2013), Joslin, Le, and Singleton (2013) and Lustig, Roussanov, and Verdelhan (2013). Industrial production growth data has the advantage of being available since 1919 and correlates substantially with consumption growth at lower frequencies. Unreported results suggest that we get statistically significant estimates in the regression analysis with heteroscedasticity-robust, but not with block-bootstrapped standard errors. We believe that this may be due to the fact that industrial production, which accounts for inputs and outputs of both non-durables and durables, is an imperfect proxy for the non-durable component of consumption growth. At the monthly horizon from 1959 to 2010, the correlation coefficient between the two time series is only 19.88%.

We further test whether our base regression results are affected by the functional form specification of consumption volatility. We adopt other GARCH models commonly adopted in the financial literature: the standard GARCH(1,1) model (Bollerslev (1986)), the EGARCH model (Nelson (1991)) and the GJR GARCH model (Glosten, Jagannathan, and Runkle (1993)). The dynamics and parameter estimates of the different GARCH specifications are reported in Panel B of Table 4. These alternative specifications are comparatively more persistent, with estimates for ϕ_σ ranging from 0.9779 for the GARCH(1,1,) specification to 0.9907 for the EGARCH specification. Replications of the benchmark regression results, using these different volatility specifications, are reported in section A-VI of the external internet appendix because of space restrictions. Both the univariate and the multivariate tests illustrate that a different functional form of the volatility process does not alter our conclusion of a strong relationship between the first two principal components and expected consumption growth and volatility.

GARCH models inherit contemporaneous correlation between realized consumption growth and consumption volatility. Hence there is a possibility that large moves in realized consumption growth mechanically lead to large increases in volatility. Therefore we test whether the significance of the macroeconomic risk factors survives once we control for variation in realized consumption growth. Unreported results suggest that the statistical relationship between consumption volatility and the common information in the term structure of CDS spreads is not merely due to jumps in realized consumption growth. The regression coefficient on realized consumption growth is insignificant and neither the statistical significance nor the magnitude of the coefficient on expected growth and consumption volatility changes.

Finally, we investigate the relationship between the macroeconomic risk factors and the VIX index in a VAR specification. Unreported results show no evidence that financial market volatility Granger causes expected growth. Moreover, results between consumption volatility and the VIX are inconclusive and point to mere correlation.

III A Macroeconomic Model for Sovereign CDS

Our empirical exercise highlights that expected U.S. consumption growth and macroeconomic uncertainty accounts for a large fraction of the co-movement in sovereign CDS spreads. We show that an equilibrium model for CDS spreads with only two state variables can rationalize these facts. Our ingredients are an endowment economy with time-varying expected growth and consumption volatility, recursive Epstein and Zin (1989) preferences, and an embedded reduced-form default process driven by the two state variables of the economy.

A Credit Default Swaps

To derive the valuation of CDS spreads in closed-form, we discretize the continuous framework in Duffie (1999), albeit adapting the explicit modeling of the hazard and recovery rate. We write the model at a daily frequency in order to agree with daily quotations in the CDS market. We assume that each coupon period n contains J trading days.[22] A K-period CDS thus has KJ trading days. CDSs are priced similar to interest rate swaps, that is expected net present values of cash flows for both legs (protection buyer and protection seller) must equalize at inception. For a K-period CDS, the expected net present value of the protection leg, π_t^{pb}, to be paid by the protection buyer is equal to

(4)

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

where $CDS_t\left(K\right)$ is the constant premium agreed at day t and to be paid until the earlier of maturity (day $t + KJ$), or a credit event occurring at a random day τ. For $t' > t$, $M_{t,t'}$ denotes the stochastic discount factor valuing any financial payoff to be claimed at a future day t'. The floor function $\lfloor\cdot\rfloor$ rounds a real number to the largest previous integer, and $I\left(\cdot\right)$ is an indicator function taking the value 1 if the condition is met and 0 otherwise. The first part in equation (4) defines the net present value of payments made by the protection buyer conditional on survival. The second part defines the accrual payments if the reference entity defaults between two payment dates.

The protection seller must cover any losses incurred by the protection buyer in case of a credit event. The expected net present value of the protection seller's leg, π_t^{ps}, is equal to

$$\pi_t^{ps} = E_t\left[M_{t,\tau}\left(1 - R\right) I\left(\tau \leq t + KJ\right)\right], \tag{5}$$

where R represents the constant post-default recovery rate as a fraction of face value, and we define the constant Loss Given Default $L = \left(1 - R\right)$.[23] We fix the dynamics of the recovery rate process at a constant level, consistent with industry standards for CDS pricing. This

[22]Note that the period n contains the trading days $\left(n-1\right)J + j,\ j = 1, \ldots, J$. 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.

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

is also in line with standard assumptions in the CDS pricing literature such as Pan and Singleton (2008) or Longstaff, Pan, Pedersen, and Singleton (2010). We leave the analysis of time-varying recovery rates for further research.[24]

Equating the two legs, as the expected net present values are zero at inception, and applying the Law of Iterated Expectations, we can write the CDS spread as

$$CDS_t\left(K\right) = \frac{\sum_{j=1}^{KJ} E_t\left[M_{t,t+j}\left(1-R\right)\left(S_{t+j-1}-S_{t+j}\right)\right]}{\sum_{k=1}^{K} E_t\left[M_{t,t+kJ}S_{t+kJ}\right] + \sum_{j=1}^{KJ}\left(\frac{j}{J}-\lfloor\frac{j}{J}\rfloor\right)E_t\left[M_{t,t+j}\left(S_{t+j-1}-S_{t+j}\right)\right]}, \tag{6}$$

where the survival probability $S_t \equiv Prob\left(\tau > t \mid \mathcal{I}_t\right)$ denotes the conditional probability that the credit event did not occur at day t, and where $\mathcal{I}_t$ denotes the information set up to and including day t.[25] The conditional survival probability S_t is defined as

$$S_t = S_0 \prod_{j=1}^{t}\left(1-h_j\right), \quad t \geq 1, \tag{7}$$

where the hazard rate process $h_t \equiv Prob\left(\tau = t \mid \tau \geq t; \mathcal{I}_t\right)$ denotes the conditional instantaneous default probability of a given reference entity at day t.

To derive analytic solutions to the CDS, we need to specify dynamics for the stochastic discount factor $M_{t,t+1}$ and the default intensity h_{t+1}. These processes are determined by the two state variables of the economy, which are described in the following section.

B A Markov-switching Model for Consumption Growth

In section II, we estimate the dynamics of consumption growth using a continuous-state space model because a discrete approximation with regimes does not provide a sufficiently good approximation in small samples for highly persistent processes such as expected con-

[24]We did explore the possibility of deterministic procyclical and state-dependent recovery rates, while keeping the unconditional recovery rate fixed. Our results are not very sensitive to such a variation.

[25]Note that we assume $Prob\left(\tau = t \mid \mathcal{I}_{t'}\right) = Prob\left(\tau = t \mid \mathcal{I}_{\min(t,t')}\right)$ for all integers t and t'.

sumption growth and macroeconomic uncertainty. For the purpose of our model, we do however approximate the continuous-state dynamics with a discrete regime-switching framework as it is well known that Markov switching models provide excellent approximations of continuous processes in population (Timmermann (2000), Bonomo, Garcia, Meddahi, and Tédongap (2011)). More importantly, without the discrete-state approximation, we are not able to obtain analytical formulas for spread moments in our preference framework, which is particularly useful for computational efficiency when we want to estimate the preference parameters. In addition, if we limit us to two regimes for each state variable, the closed-form formulas enhance the understanding and interpretation of the mechanisms underlying the empirical results.

Following Bonomo, Garcia, Meddahi, and Tédongap (2011), we assume that both the mean and variance of consumption growth g_{t+1} 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

$$P^{\top} = [p_{ij}]_{1 \leq i,j \leq N}\,, \quad p_{ij} = Prob\,(s_{t+1} = j \mid s_t = i)\,. \tag{8}$$

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

$$g_{t+1} = x_t + \sigma_t \varepsilon_{g,t+1}, \tag{9}$$

where $x_t = \mu_g^{\top} \zeta_t$ and $\sigma_t = \sqrt{\omega_g^{\top} \zeta_t}$ are the expected mean 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 $s_t = j$. For simplicity, we limit the number of states to two for each risk factor, indexed by the letters L for the low state and H for the high states. This amounts to a total of four states (LL, LH, HL and HH) if the factors are linearly independent.

C Preferences and Stochastic Discount Factor

We study the valuation of CDSs in the context of a representative agent general equilibrium model. We assume that the representative investor has Epstein and Zin (1989) preferences. Such an investor derives lifetime utility V_t recursively from the combination of the current level of consumption C_t and $\mathcal{R}_t(V_{t+1})$, a certainty equivalent of next period lifetime utility

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

where $\mathcal{R}_t(V_{t+1}) = \left(E_t\left[V_{t+1}^{1-\gamma}\right]\right)^{\frac{1}{1-\gamma}}$ and where δ represents the subjective discount factor. 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.

Hansen, Heaton, and Li (2008) derive the stochastic discount factor $M_{t,t+1}$ in terms of the continuation value of utility of consumption as

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

If $\gamma = 1/\psi$, equation (11) 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), for instance, show that a premium for long-run consumption risk is added by the ratio of future utility V_{t+1} to its certainty equivalent $\mathcal{R}_t(V_{t+1})$.

Based on the dynamics (9) and the recursion (10), we show in the internet appendix section (A-II.A) that the stochastic discount factor (11) may be expressed as

$$
(12) \qquad M_{t,t+1} = \exp\left(\zeta_t^{\top} A \zeta_{t+1} - \gamma g_{t+1}\right),
$$

where the components of the $N \times N$ matrix A are described in equation (A-9) of the appendix.

We assume that the representative agent is based in the U.S. and that he values his international investment opportunity set using the domestic pricing kernel. This assumption is merely for simplicity and is in no way restrictive. Borri and Verdelhan (2009) theoretically prove that as long as markets are complete and assets are USD denominated, all results carry through for non-U.S. investors who use their foreign currency denominated discount factor. The same results apply to our set up as we are pricing only USD denominated CDS.

D Hazard Rate

Given our intention to link the default process to global macroeconomic risk, we assume that the hazard rate h_t^i for each country i follows a logistic distribution[26]

$$h_t^i = \frac{\lambda_t^i}{1+\lambda_t^i} \quad \text{where} \quad \lambda_t^i = \exp\left(\beta_{\lambda 0}^i + \beta_{\lambda x}^i x_t + \beta_{\lambda \sigma}^i \sigma_t\right), \tag{13}$$

where the default intensity λ_t^i is impacted by expected growth and consumption volatility. Heterogeneous exposures to the macroeconomic risk factors are determined through the parameters $\beta_{\lambda x}^i$ and $\beta_{\lambda \sigma}^i$, and $\beta_{\lambda 0}^i$ is a country-specific constant. We will drop the i superscript for ease of readability.[27] This set up guarantees that the hazard rate is well defined and belongs to the interval $(0, 1)$. In addition, it ensures that the marginal propensity to default is persistent, given that expected consumption growth 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 and time-varying default intensity, coupled with a preference for early resolution of uncertainty, is essential to generate a term risk premium.

Sovereign default risk is modeled as a reduced-form process, where the latent default intensity depends on the global macroeconomic risk factors exogenously specified in the

[26] This functional form of the hazard rate is not essential to derive closed-form expression for CDS spreads, nor for our quantitative results. Our results are robust to a Weibull-type hazard rate, specified as $h_t = 1 - \exp(-\lambda_t)$, where $\lambda_t = \exp(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda \sigma} \sigma_t)$.

[27] An alternative to this approach is to define a representative country and model its rating transition probability matrix. We pursue this methodology in parallel work, but it is not the focus of our analysis here.

endowment economy. This is similar in spirit to models that link the default intensity to observable covariates, such as in Duffie, Saita, and Wang (2007) for default prediction and in Doshi, Ericsson, Jacobs, and Turnbull (2013) to model the dynamics of CDS spreads. We choose to embed a reduced-form credit risk model into an equilibrium set up for two reasons. First, a CDS payout is triggered through a credit event. Longstaff, Pan, Pedersen, and Singleton (2010) point out that *Bankruptcy* does not figure among the spectrum of credit events for sovereign contracts. This is due to the nonexistence of a formal international bankruptcy court for sovereign borrowers. As we focus on the pricing of CDS spreads prior to default, we are less interested in the default decision as such, but rather in sovereign distress risk (abstracting from the "jump-at-default" risk in the literature).[28] Our set up thus differs from the endogenous default literature starting with Eaton and Gersovitz (1981), which typically imposes exogenous default costs, which are also necessary to justify optimal default decisions in bad states (Arellano (2008)). Recent work by Mendoza and Yue (2012) provides a foundation to justify these exogenous default costs and highlights the stylized fact of countercyclicality in credit spreads (and thus default probabilities) in a business cycle model with endogenous default.

Second, a government's default decision is mostly strategic. Modeling an explicit default threshold in a structural default risk model for a *sovereign* requires therefore additional assumptions (such as ad-hoc exogenous default costs, for instance). Structural default models for *corporate* default have successfully been integrated into equilibrium models by Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010) and Bhamra, Kuehn, and Strebulaev (2010). The success of these models relies crucially on the ability to generate countercyclical default probabilities. This property is obtained in our reduced-form framework if the default intensity increases when expected growth is low and/or macroeconomic uncertainty is high. This is guaranteed as long as $\beta_{\lambda x}$ and $\beta_{\lambda\sigma}$ are non-positive and non-negative respectively.

We emphasize that our goal is to show how a simple equilibrium model with only two

[28]For the rest of the paper, we will refer more generally to the term default risk.

macroeconomic state variables can rationalize several stylized facts of the sovereign CDS market. We are aware that our specification implies that heterogeneity in the level of spreads arises only because of differential sensitivity to aggregate risk. While idiosyncratic shocks may play no role in CDS returns, they may be important for the variation in spread levels.[29] We therefore derive solutions where the hazard rate contains additional country-specific shocks. The results improve only marginally, but the number of states increases to eight, even if we allow only for two states of the idiosyncratic Markov chain. This renders the interpretation of the state-dependent results cumbersome. We therefore focus on the aggregate risk factors only and provide the additional formulas and results in the internet appendix.

Using our pricing framework and specification of the default process, we derive in internet appendix section (A-II.B) the conditional and unconditional cumulative default probabilities over a $(T-t)$-year horizon

$$\begin{aligned} Prob_t\left(t<\tau\leq T \mid \tau>t\right) &= 1-\left(\tilde{\Psi}_{T-t}^{\top}\zeta_t\right) \\ Prob\left(t<\tau\leq T \mid \tau>t\right) &= 1-\left(\tilde{\Psi}_{T-t}^{\top}\Pi\right), \end{aligned} \tag{14}$$

where the maturity-dependent vector sequence $\left\{\tilde{\Psi}_j\right\}$ satisfies the internet appendix recursion (A-12) with initial condition $\tilde{\Psi}_0 = e$, where e is the vector with all components equal to one, and where Π denotes the vector of unconditional state probabilities. We complement the historical cumulative default probabilities with closed-form solutions of the cumulative default rate under the risk-neutral ($\mathbb{Q}$) measure in internet appendix section (A-II.C).

E Credit Default Swap Spread

Markov chains are crucial for deriving analytical solutions for CDS spreads and their moments. We develop equation (6) in appendix (A-II.D) to characterize a K- period CDS

$$CDS_t\left(K\right) = \zeta_t^{\top}\lambda_s\left(K\right), \tag{15}$$

[29] We thank an anonymous referee for pointing this out.

where the components of the vectors $\lambda_s(K)$ are non-linear functions of the consumption dynamics, the default process, the recovery rate and of the recursive utility function. Its components are given by

$$\lambda_{i,s}(K) = \frac{\sum_{j=1}^{KJ} L\left[\Psi^*_{i,j} - \Psi_{i,j}\right]}{\sum_{k=1}^{K} \Psi_{i,kJ} + \sum_{j=1}^{KJ}\left(\frac{j}{J} - \left\lfloor\frac{j}{J}\right\rfloor\right)\left[\Psi^*_{i,j} - \Psi_{i,j}\right]}, \tag{16}$$

where L is the vector of loss rates, and where the sequences $\left\{\Psi^*_j\right\}$ and $\left\{\Psi_j\right\}$ are given by the internet appendix recursion (A-30), with initial conditions (A-29). All moments of CDS spreads exist in closed form, which is particularly useful for the estimation of the default and preference parameters, given the highly non-linear pay-off function of CDS spreads.

IV Model Estimation

We first describe the calibration for the dynamics of aggregate consumption growth, which is the only exogenous process in the model. We then explain how we estimate the structural preference parameters and the cross-sectional sensitivities of the default process to aggregate risk factors by exploiting the high-frequency information in daily CDS spreads.

A Consumption Growth Dynamics

We calibrate the consumption growth dynamics at a monthly frequency as in Bansal, Kiku, and Yaron (2012) to match observed annual growth rates from 1930 to 2008, because we target a longer sample of consumption data than the monthly post-war data available only since 1959.[30]

[30]The calibrated parameters differ slightly from the Kalman Filter estimates obtained in the empirical section. Nevertheless, all calibrated parameters for expected growth remain within the tight bound of one standard deviation away from the estimates. Moreover, the persistence of consumption volatility is within two standard deviations of the GARCH, EGARCH and GJR-GARCH volatility estimates.

The mean expected consumption growth μ_x is 0.0015 with a sensitivity to long-run risk shocks ν_x set to 0.038. These shocks are persistent with a value ϕ_x equal to 0.975. Consumption volatility has a mean $\sqrt{\mu_\sigma}$ of 0.0072, a persistence ϕ_σ of 0.999 and a sensitivity to shocks ν_σ of 2.80×10^{-6}. As we want to exploit the rich information in the daily dynamics of CDS spreads to estimate the structural default and preference parameters, we choose to map the monthly calibrated values into a daily frequency, assuming twenty-two trading days in a month. More specifically, we translate the monthly dynamics of consumption growth into a daily system such that the time-averaged first and second moments of annual consumption growth are preserved in population. For the purpose of illustration, a value of $\mu_x = 0.0015$ at a monthly decision interval for the mean consumption growth corresponds to a value at a daily decision interval 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 $\phi_x^{daily} = \phi_x^{\Delta}$ (see Table 8 for further details).

The mapping from the continuous daily endowment process into a discrete Markov-switching model follows the procedure described in Bonomo, Garcia, Meddahi, and Tédongap (2011). Calibration results for the consumption growth dynamics are reported in Panel A of Table 8, 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. Panel B reports annualized (time-averaged) descriptive statistics for aggregate consumption growth, which are compared against the observed values. The mean, volatility and persistence for consumption growth of 1.8%, 2.53% and 0.46 are consistent with the estimates of 1.92%, 2.12% and 0.46 found in the data.

B Estimation of Preference and Default Parameters

We exploit the high-frequency information in daily sovereign CDS spreads to estimate the preference parameters as well as the cross-sectional sensitivities of the default process to the two systematic risk factors via the Generalized Method of Moments (GMM). The weighting matrix is the inverse of the diagonal of the spectral density matrix, and the moments are the expectations of CDS spreads and their squares. We thus have 72 moments for 36 spread series (6 maturities for each rating category) to estimate in total 21 parameters, i.e. 3 preference parameters and 3 default parameters for each of the 6 rating groups.[31] The recovery rate is fixed at 25%, which is the standard recovery rate for sovereigns and also consistent with Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2010).

Estimation results with Newey-West standard errors are reported in Table 9. We fix the subjective discount factor δ at a monthly frequency at 0.9989 and estimate the other preference parameters. All coefficients turn out to be statistically significant at the 1% level. Using spread levels (changes) for the estimation, we obtain a coefficient of relative risk aversion γ of 8.2692 (7.1713). This is significantly less than the value of 20.90 estimated in Bansal and Shaliastovich (2013), who estimate a value of 1.81 for the EIS ψ at a quarterly model frequency. Part of the discrepancy could be due to a different decision interval, as time-aggregation can lead to higher estimates of risk aversion. We estimate a value of the EIS equal to 1.5774 (1.5953). The daily information in CDS spreads provides additional support for a value of the EIS above 1 and preference for early resolution of uncertainty.

Regarding the default parameters, all signs of the coefficients are consistent with economic intuition and imply countercyclical default probabilities.[32] This feature is essential for asset pricing implications as emphasized in Bhamra, Kuehn, and Strebulaev (2010), among others, and helps us generate countercyclical credit spreads. Negative values for $\beta_{\lambda x}$ suggest that a rise in expected consumption growth lowers the marginal propensity to default. Moreover, positive values for $\beta_{\lambda \sigma}$ indicate that in times of high macroeconomic uncertainty, sovereign debt becomes riskier and the likelihood of default increases. Thus, asset markets dislike macroeconomic uncertainty (Bansal, Khatchatrian, and Yaron (2005)). Also, the average default intensity is inversely related to credit-worthiness, that is the constant coefficient $\beta_{\lambda 0}$

[31] A detailed description of the estimation steps is provided in internet appendix section (A-II.E).

[32] Default parameter estimates using spread changes are available upon request.

increases from negative 15.37 to negative 9.15 for the AAA and B rating category respectively. Furthermore, highly rated countries are more sensitive to macroeconomic uncertainty and the pattern is monotonically decreasing, while there is no clear pattern for the sensitivity to expected consumption growth. The last panel reports the J-statistic for the test of overidentifying restrictions and the corresponding p-value. The model is not rejected at the 1% significance level.

V Asset Pricing Implications and Discussion

We first study the model implications for unconditional CDS moments and default probabilities. Then, we investigate asset pricing results for the conditional CDS term structure. A more detailed analysis of the hazard rate is followed by an extension of the model to preferences that incorporate generalized disappointment aversion.

A Unconditional CDS Moments

All results for the unconditional moments of the CDS term structure are summarized in Table 10 in the left panel. We evaluate the outcome against empirical moments in the data reported in the right panel based on the root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{1}{K}\sum_{j=1}^{K}(\hat{x}_j - x_j)^2}, \tag{17}$$

where K represents the CDS contract maturity, x_j is the unconditional model-implied moment and $\hat{x}_j$ refers to the empirical counterpart.

The model does a particularly good job in reproducing the unconditional mean, standard deviation, skewness and first-order autocorrelation coefficients of the CDS term structure. We generate consistently a mean upward sloping term structure for all rating categories, in line with the data. This is consistent with the finding of persistent upward sloping term structures for Mexico, Turkey and Korea reported by Pan and Singleton (2008).[33] RMSEs for the term structure of spreads are approximately 1 basis point for investment grade reference entities, and range from 4 to 14 basis points for high-yield categories. To give an example, for single A rated countries, the one-year (ten-year) spread is 37 (73) basis points against 35 (71) in the data. We also fit the upward sloping term structure of volatility for groups AAA to A, and the downward sloping volatility pattern of groups BBB to B. RMSEs range from 1 to 2 basis points for investment-grade countries, and are less than 12 basis points for high-yield countries. Only for the B group, the RMSE is 27 basis points, implying an average error of roughly 10% for the 5-year B volatility. In addition, the model is highly satisfactory in reproducing the right-skewed distribution of CDS spreads and the first-order autocorrelation coefficients of the observed spreads, which are highly persistent. While the model generates excessive leptokurtic distributions at short maturity contracts, it reproduces the pattern of decreasing fat tails with asset horizon and converges to the observed results at longer maturities. We also note that the average level of spreads is higher for less-creditworthy countries, which is consistent with the monotonic pattern in the coefficient estimates of $\beta_{\lambda 0}$.

In our model, time-varying global macroeconomic risk feeds into the default process. Negative shocks to expected consumption growth and macroeconomic uncertainty are persistent and create uncertainty about future default rates, which is priced. In addition to a level risk premium, preference for early resolution of uncertainty helps to generate a term premium, which rises with the asset horizon. In sum, with only two macroeconomic state variables, we are able to match closely the term structure of spreads, volatility, skewness and kurtosis, as well as the persistence of CDS spreads across 6 broad rating categories.

Before analyzing the conditional asset pricing implications and default probabilities, we highlight that, given the calibrated endowment dynamics and estimated preference parameters based on sovereign CDS spreads, we remain consistent with the stock market. The

[33] Every country in our sample has an upward sloping term structure on average. Because of space limitations, we have only reported summary statistics for the aggregated series in Table 2.

model generates a sizable equity premium of 5.52%, equity volatility of 17.48%, a risk-free rate of 1.01% with a volatility of 0.80% (see Table 8). Thus, we provide a joint framework to price stocks and CDS. A strong overlap in the stochastic discount factor for pricing both the U.S. equity market and the global sovereign CDS market suggests that both are integrated and reflects previous evidence of information flow between the two asset markets.[34]

B Default Probabilities

Model-results for cumulative default probabilities under the physical and risk-neutral measure, as well as their ratios, are reported in Table 11. We benchmark the model outcomes against the historical sovereign foreign-currency cumulative average default rates reported by Standard&Poor's over the time period 1975 to 2009.[35] Inspection of these numbers warrants several explanations at the outset of our discussion. Both physical and risk-neutral default probabilities are unobserved and a proper comparison is thus close to impossible. In particular, no country rated A or higher has defaulted within the last 40 years.[36] Although arguably very small, the default probability of a AAA rated country is unlikely zero. This is particularly true for the CDS market, where a technical default could trigger a payout. Therefore, we use cumulative historical default probabilities from the cash market as a first best benchmark for comparison, but we remain critical about their use.

Given the low RMSEs, the model-implied default probabilities for CDS under the physical measure are close to their observed counterparts from the cash market. The lowest and highest RMSEs are 0.97% and 11.11% for AAA and B rated countries respectively. Cumulative default probabilities line up cross-sectionally, with the 5-year default probability ranging from 0.79% to 22.60% for the AAA and B rated entities. Moreover, cumulative default prob-

[34]See Acharya and Johnson (2007) among others.

[35]The results benchmarked against the cumulative default rates reported by Moody's are very similar.

[36]While no A rated country had an outright default, countries may be downgraded prior to default. We study rating migrations in parallel work.

abilities rise with the asset horizon, which is consistent with increasing cumulative default probabilities over time. Results are slightly better at longer than at shorter horizons.

The ratios of risk-neutral to physical default probabilities are monotonically increasing with maturity, reflecting the term premium required for selling CDS insurance. Similar for the physical default probabilities, the risk-neutral values are cross-sectionally increasing for less credit-worthy countries. All ratios of risk-neutral to physical probabilities range between 1.09 and 3.98, while the average is 2.15. These values are consistent with Berndt, Jarrow, and Kang (2007), who find strongly time-varying ratios of implied risk neutral default probabilities to Moody's KMV Expected Default Frequencies between 1 and 3 for short horizons, but going as high up as 10 in 2002. For corporate bonds, Driessen (2005) and Huang and Huang (2012) who find average ratios of, respectively, 1.89 and 1.11 to 1.75.

C Conditional CDS Moments

The regime-switching set up of the model allows for a better understanding of the relationship between macroeconomic risk factors and asset prices. In Figure 3, we report state-dependent spreads for the four states of nature determined by expected growth and volatility of consumption, as well as the unconditional moments.

We first note that, ceteris paribus, an increase in expected consumption growth shifts the entire term structure downwards. These shifts are visible, for instance, when moving from the solid to the dashed line, and from the dotted to the dash-dotted line. In contrast, a rise in consumption volatility has the opposite effect on the level of spreads. Higher macroeconomic uncertainty raises the level of spreads. This model-implied result is consistent with the empirical regression results. More specifically, the projection of the first principal component, extracted from the term structure of spreads across all countries, on the two macroeconomic risk factors yields, respectively, a negative and positive loading on expected growth and consumption volatility. In addition, we remind that the average country loadings on the first principal component are maturity-invariant and uniformly positive across reference entities.

Thus if we believe that the first principal component is a level factor in the term structure of spreads, then a negative coefficient $\hat{a}_1$ on expected growth in equation 2 implies that the level of sovereign CDS spreads is lower in states of high conditional expected consumption growth. Moreover, a positive coefficient on $\hat{a}_2$ implies that higher volatility of aggregate consumption growth increases sovereign spreads. These results are economically intuitive and consistent with a countercyclical level of spreads. We add that this relationship between the level of spreads and the two macroeconomic risk factors is also obtained in the country regressions reported in Table 7, where we use the actual level of spreads as the regressand. Replicating these regressions inside the model, we find that the model-implied results in population predict a negative and positive coefficient, respectively, on expected growth and consumption volatility for the level of spreads.[37] The theoretical R^2 of 97% of that regression compares favorably to the empirical value of 75%.

While global macroeconomic risk affects the level of spreads, this effect is asymmetric across maturities and thereby affects the slope of spreads. Irrespectively of whether consumption volatility is high or low, a positive growth outlook steepens the CDS term structure. This is because a positive contemporaneous shock to expected consumption growth will decrease default probabilities, given the negative estimates of $\beta_{\lambda x}$. The improved likelihood of default is particularly pronounced at shorter horizons, since at longer horizons, there is greater uncertainty and a higher probability of negative shocks to expected growth (and therefore higher default probabilities). Given preference for early resolution of uncertainty, this commands a term premium, which increases the slope of the term structure. This model-implied feature is also reflected in the positive slope coefficient $\hat{a}_1$ from the regression of the second principal component on expected consumption growth reported in regression (2) of Table 5, if we are to interpret the second principal component as a slope factor. It is likewise

[37]Observe that in the model, the Variance Risk Premium is perfectly collinear with expected consumption growth and volatility. Comparing the model predictions for the slope coefficients and R^2 to the empirical observations when all factors are included in the specification is thus not possible.

consistent with the country regressions, where more than half of the regression coefficients for the slope are positive. Columns (10) to (12) of Table 7 show that, in the model, expected growth positively predicts the slope in population with a R^2 of 75%, which squares well with a value of 74% and a positive regression coefficient in the second factor regression.

The relationship between consumption volatility and the slope depends on the perception of future economic conditions. If expected consumption growth is low, higher macroeconomic uncertainty will decrease the slope of the term structure. However, conditional on high expected consumption growth, the term structure steepens following a positive shock to macroeconomic uncertainty. The positively estimated hazard rate coefficients $\beta_{\lambda\sigma}$ indicate that a rise in uncertainty increases default probabilities and therefore raises spreads. In times of high expected growth, if the agent expects more volatility in the future, with preference for early resolution of uncertainty, he will command a term premium because of the aversion towards uncertainty shocks. This increases the slope. However, if expected growth is low, a positive volatility shock pushes the marginal investor into the worst economic state and induces a strong deterioration of conditional default probabilities. Conditional on survival, default probabilities are expected to be lower at longer horizons and this effect dominates over a term risk premium. Unconditionally, we expect the positive relationship between uncertainty and the slope of spreads to dominate as in our model the unconditional probability of being in a state of high expected consumption growth (≈89%) is larger than the probability of being in a state of low expected growth (≈11%). Indeed, this outcome is predicted by the model-implied replication of the country regressions in columns (10) to (12) of Table 7. This explanation also rationalizes the positive regression coefficient $\hat{a}_2$ in column (2) of Table 5 if we believe the second principal component to be a slope factor.

Figure 3 further emphasizes that the slope of the term structure inverts in times of low expected growth and high macroeconomic uncertainty. The economic magnitude of the inversion ranges from 9 to 93 basis points, in absolute value, for the AAA and B rating categories respectively. Thus, an investor becomes much more risk averse in bad economic times and requires higher compensation to offer protection on sovereign default. This jacks up the price of CDS at short horizons. The possibility of reverting back to sound economic fundamentals introduces mean reversion and spreads converge back to lower levels at longer horizons. But as shocks are persistent, the average level remains elevated.

For the purpose of comparison, we plot in Figure 4 the historical difference between the 10 and 1-year CDS spread of four European distressed economies during the sovereign debt crisis in the north-east corner of the figure.[38] In the year prior to default, Greece was rated B. Within our sample, the slope of its CDS term structure inverted by a maximum of 525 basis points and the average slope across reversal dates is 195 basis points. This is about twice as large as the inverted spread curve of 93 basis points generated by the model in the worst state. In addition, Portugal, which was rated A in 2010, had a maximum reversal of approximately 150 basis points and an average inverted slope of 68 points, which is also a bit more than twice the conditionally inverted slope of 26 basis points. Moreover, the mean (highest) slope reversal for Spain, which was downgraded to AA+ in 2010, was 29 (56) basis points, which again is twice the negative slope of 14 basis points. The slope of Italy didn't decrease as much during our sample period, but it continued to decrease as the sovereign debt crisis intensified. In sum, the conditional moments of our model qualitatively match the slope reversal of distressed sovereign borrowers in states of bad macroeconomic fundamentals. We quantitatively underestimate the inversion by about 50%.

D An Analysis of the Hazard Rate

To provide further intuition about how the effects of the systematic risk factors affect the term structure, we plot in Figure 5 the results of our benchmark model against different specifications of the hazard process from equation 13. The solid bullet points are the unconditional moments from the data and the dashed-dotted line represents the unconditional moments when both expected consumption growth and volatility are active. With a constant

[38] Graphs for other rating categories than AA, A and B look very similar and are available upon request.

default process (dashed line), the term structure is flat. This is not surprising, as default intensities become deterministic, and we expect no term premium. On the other hand, a specification with only expected consumption growth (dotted line) creates a term structure, which is way too steep, while the opposite is true, when consumption volatility is the only risk driver. Thus, the first and second moments of aggregate macroeconomic risk have offsetting effects on the term structure, and a two-factor model is necessary to reproduce stylized facts observed in the data. This compares with Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2010) for example, who use a one-factor model. However, the authors argue that a one-factor model is acceptable, but that a two-factor model may be desirable.

E An Extension to Preferences with Downside Risk Aversion

Our model is successful in matching the unconditional moments of the term structure, but we quantitatively underestimate the inversion of the term structure in the worst economic state. We try to improve upon this dimension by extending our benchmark scenario with symmetric recursive preferences and a Kreps and Porteus (1978) (KP) certainty equivalent to that of a risk averse investor with generalized disappointment averse (GDA) preferences of Routledge and Zin (2010).[39] This framework is well suited as GDA preferences endogenously generate higher risk aversion in the worst economic state. The extended model derivations are relegated to the external appendix. Beside the subjective discount factor δ, the coefficient of relative risk aversion γ and the elasticity of intertemporal substitution ψ, GDA preferences are characterized through two additional preference parameters. The coefficient of disappointment aversion, α, defines the weight attributed to disappointing outcomes. A state-contingent outcome is only disappointing if it falls below a fraction κ of the certainty equivalent. We first discuss the estimation results, then the asset pricing implications.

Table 9 shows that the additional degree of freedom slightly improves the fit of the

[39] In fact, the GDA preferences of Routledge and Zin (2010) nest those of Epstein and Zin (1989).

model. The model is not rejected and the J-Test statistic is a bit lower than in the KP case with a value of 14.65. A likelihood ratio test rejects the benchmark model against the alternative with generalized disappointment averse preferences.[40] Fixing the subjective discount factor at 0.9989, we find that all coefficients are statistically significant at the 1% level. Using spread levels (changes), we estimate a coefficient of relative risk aversion γ of 4.9081 (5.0614) and an EIS ψ equal to 1.4874 (1.2473). Similar to the benchmark case, this implies a value for the EIS above 1 and preference for early resolution of uncertainty. The parameter of disappointment aversion α is equal to 0.2486 (0.4819), implying that the ratio of investor's marginal utility of wealth for non-disappointing to disappointing outcomes is 25% (48%).[41] The parameter κ, which measures the fraction of the certainty equivalent below which disappointment kicks in, is estimated to be 0.8470 (0.9549). Estimation of the generalized disappointment averse preference parameters using derivative pricing information in the fixed income market is a novel result in the literature.

Table 12 illustrates that the performance of the KP and GDA scenarios are similar for the unconditional moments of the CDS term structure. The GDA model performs slightly better for the mean term structure, with RMSEs ranging between 0.52 and 9.60 basis points respectively. On the other hand, the model generates comparable results for the volatility, skewness and persistence of CDS spreads. In addition, it introduces slightly higher kurtosis at the short end of the curve for the asset distributions.

Figure 3 further illustrates that the downside risk aversion steepens the inversion of the term structure in states of low expected consumption growth and high macroeconomic uncertainty. Asymmetric preferences thus improve the fit in the worst economic state if we compare the model-implied results against the average term structure inversion of rating-equivalent countries in distress during the sovereign debt crisis, as we do in Figure 3 for the

[40] For the estimation using spread changes, we also reject the KP model in favor of GDA preferences.

[41] A value of α equal to 0.25 maps into a loss aversion parameter of 3, a well accepted measure in the literature for loss aversion.

benchmark case. An investor who cares about downside risk jacks up the price of credit protection much more in the worst economic state. The magnitude of the slope reversal in the bad state is consistently about twice the value obtained with symmetric preferences. The 10 minus 1 year slope decreases from -17 basis points for AAA countries, to a minimum of -169 basis points for the worst rating category B. We thus find that both the KP and the GDA economies manage to match the unconditional moments of the CDS term structure well. However, a model with downside risk performs better in capturing conditional stylized facts because it allows for higher risk aversion in states of bad macroeconomic fundamentals.

Finally, we highlight that the high levels of CDS spreads in states of low expected consumption growth and high macroeconomic uncertainty, which on average occur only 2.3% of the time, implicitly reflect the tail risk embedded in CDS spreads. For instance, the average 1-year BBB CDS spread is 83 basis points, but there is a huge price discrepancy across states. The "low-high" state for example has a spread of 552 basis points, but spreads for the other three states are very low, with a maximum of 187 basis points for times of low expected growth and macroeconomic uncertainty. Conceptually, this result resembles Berndt and Obreja (2010), who empirically show that a large fraction of European corporate CDS returns are explained by a factor mimicking economic catastrophe risk.

VI Conclusion

We show that expected growth and consumption volatility in the U.S. contain information to account for 75% of the variation of the first two principal components in the term structure of CDS spreads, which we believe to be a level and slope factor. This information is not accounted for by a battery of financial market variables such as the VIX index, the VRP, the excess return on the U.S. stock market, the price-earnings ratio or the investment-grade and high-yield bond spreads. While some of these variables have individually explanatory power for the level factor, none of them can account for the variation in the slope factor.

To rationalize these empirical findings, we show that a simple equilibrium model with only two state variables can account for many stylized facts of the sovereign CDS market. We essentially embed a reduced-form credit risk model into a recursive utility framework. Time-varying expected growth and macroeconomic uncertainty drive variation in both the pricing kernel and the default process. Countries differ cross-sectionally by their sensitivities to aggregate risk. Our model yields tractable closed-form solutions. Countercyclical risk aversion and a persistent time-varying default process are necessary to match unconditional moments up to the fourth order and persistence of the CDS term structure, as well as cumulative historical default probabilities at aggregate levels. We extend the model to preferences with generalized disappointment aversion and show that downside risk improves the fit of observed downward sloping term structures in states of bad macroeconomic fundamentals. To the best of our knowledge, the model is the first application of the recursive utility framework to CDS spreads. We also exploit the high-frequency information in the sovereign CDS market to estimate the preference parameters of the model. The evidence is consistent with preference for early resolution of uncertainty and a value for the EIS above 1.

Our results emphasize global macroeconomic risk channels as a source of common variation in the levels of sovereign spreads, beyond the well-documented financial risk channel. It will be useful to pursue this route to understand the dynamics of the term structure in relation to both global and local risk factors, such as in Augustin (2012).

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Figure 1: Principal Component Analysis - Factor Loadings

We use principal component analysis to extract the common common factors from the CDS term structure of the 38 countries in our sample from May 2003 until August 2010. Each bar in the upper and lower panel represents the equally-weighted average factor loading across the 38 countries in the sample for each CDS contract maturity. The upper panel refers to the loadings on the first principal component. The lower panel refers to the loadings on the second principal component. Source: Markit.

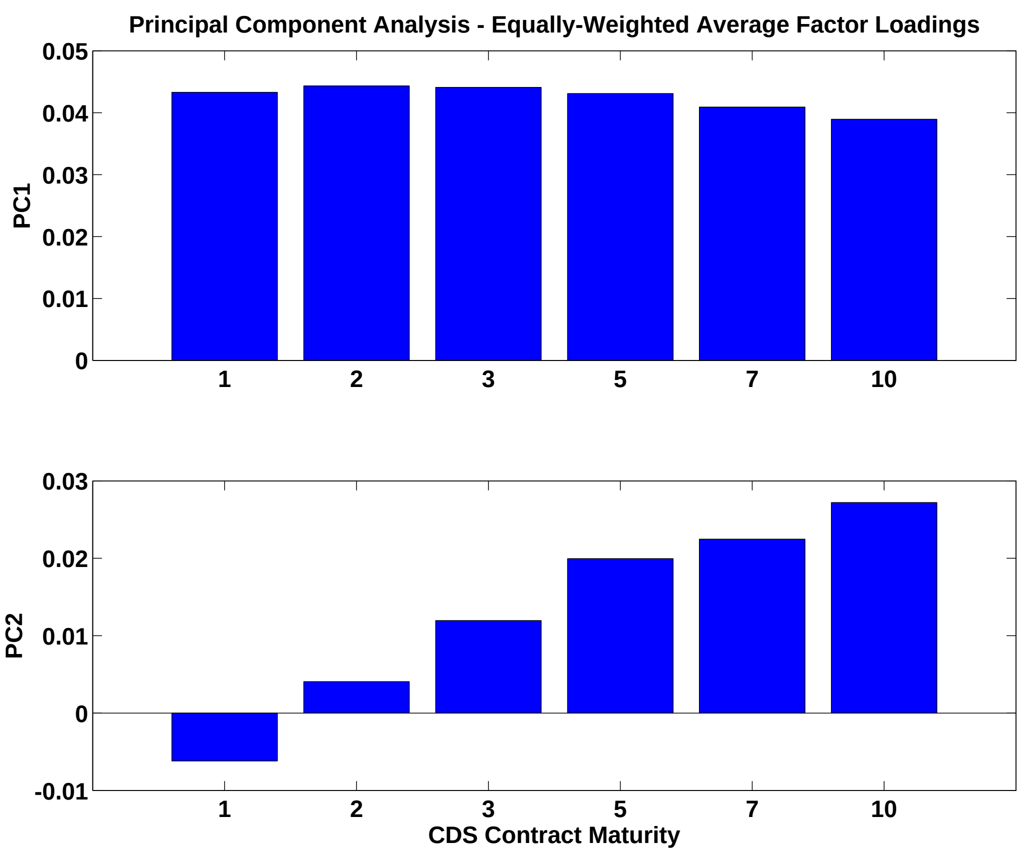
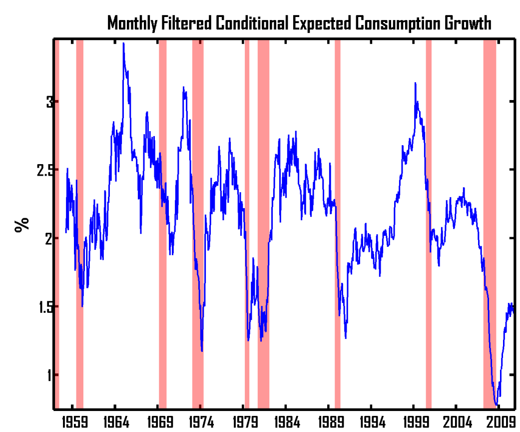


Figure 2: Expected Growth, Consumption Volatility and 5-year Mean CDS Spread

Graph (2a) plots the entire estimated series of monthly filtered conditional expected consumption growth from 1959 to 2010 and figure (2b) traces the entire estimated series of conditional expected consumption volatility. Both series are annualized for illustration. Grey shaded areas indicate NBER recessions. Graph (2c) 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 (2d) 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 consumption series are estimated with a traditional Kalman Filter as described in equation (1). The CDS data are obtained from Markit.

(a)



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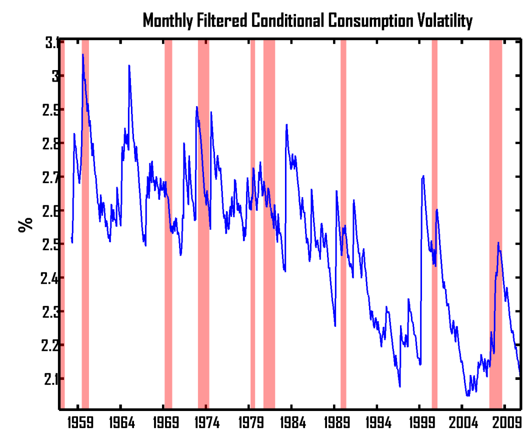
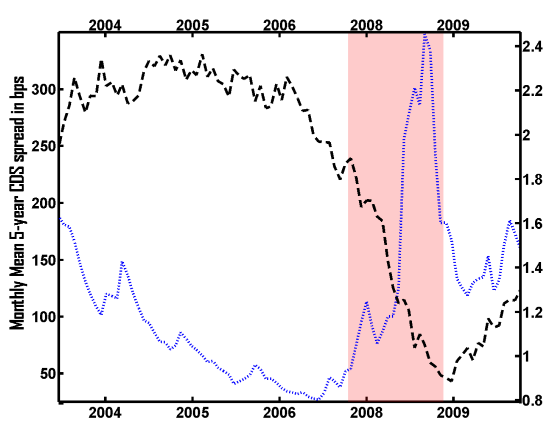


(c)



(d)

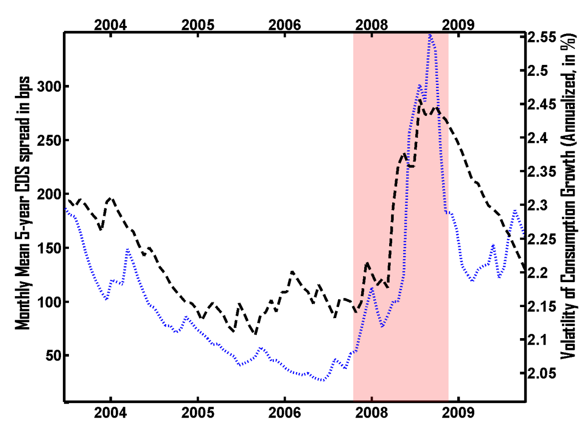


Figure 3: Model-Implied Conditional CDS Moments

Figure 3 plots the conditional and unconditional model-implied term structure of CDS Spreads for maturities 1 to 10 at the aggregated level for the rating categories AAA to B. The recovery rate is constant and exogenously set at 25%. The preference parameters are specified for an investor with a Kreps-Porteus (KP) certainty equivalent. The conditional states are defined by the combinations of low (μ^L, σ^L) and high (μ^H, σ^H) expected consumption growth and volatility. The dots reflect the unconditional moments. We also report the model-implied difference between the 10-year and 1-year CDS spreads (the Slope) in the worst economic state $\mu_L\sigma_H$. We report the model-implied results for the KP and GDA scenarios, where GDA refers to an investor with generalized disappointment averse preferences.

$Slope = CDS10y - CDS1y$: **State $\mu_L\sigma_H$ (bps)**

Model	AAA	AA	A	BBB	BB	B
KP	-9	-14	-26	-45	-92	-93
GDA	-17	-26	-47	-83	-179	-169

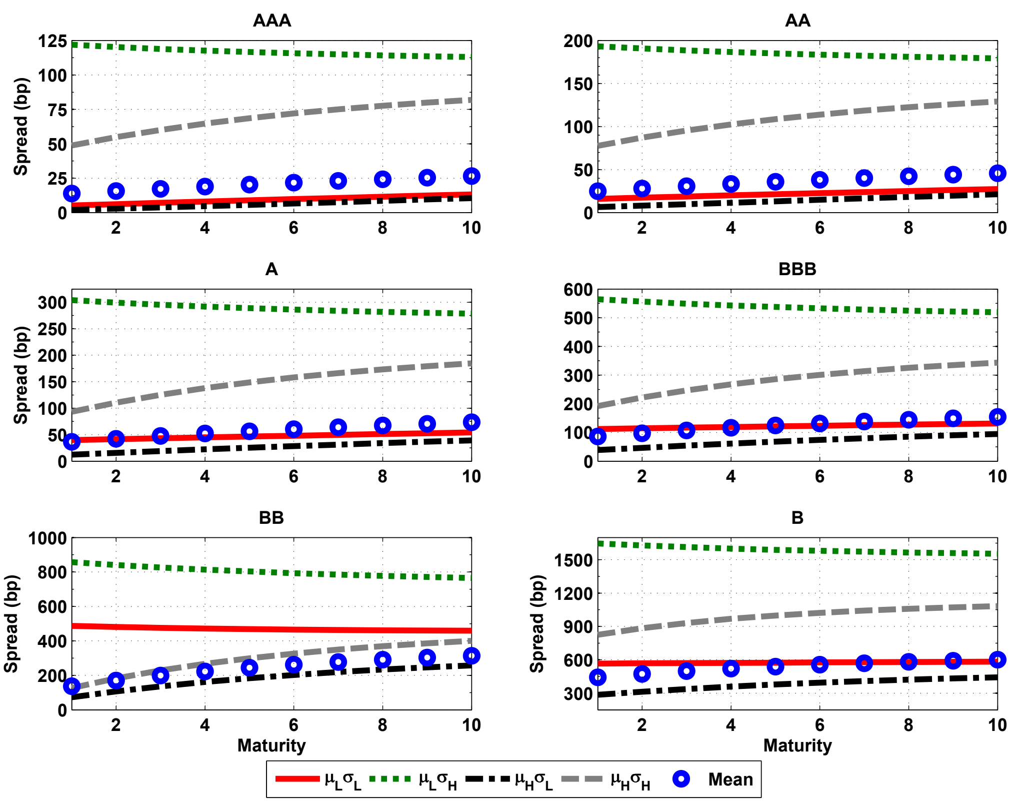


Figure 4: Reversal of the CDS Term Structure

Figure 4 plots the conditional and unconditional model-implied term structure of CDS Spreads for maturities 1 to 10 at the aggregated level for the rating categories AA, A and B, as well as the historical difference between the 10 year and 1 year CDS spread (Slope of the term structure) for Portugal, Italy, Greece and Spain. The recovery rate is constant and exogenously set at 25%. The preference parameters are specified for an investor with a Kreps Porteus certainty equivalent. The conditional states are defined by the combinations of low (μ^L, σ^L) and high (μ^H, σ^H) expected consumption growth and volatility. The dots reflect the unconditional mean.

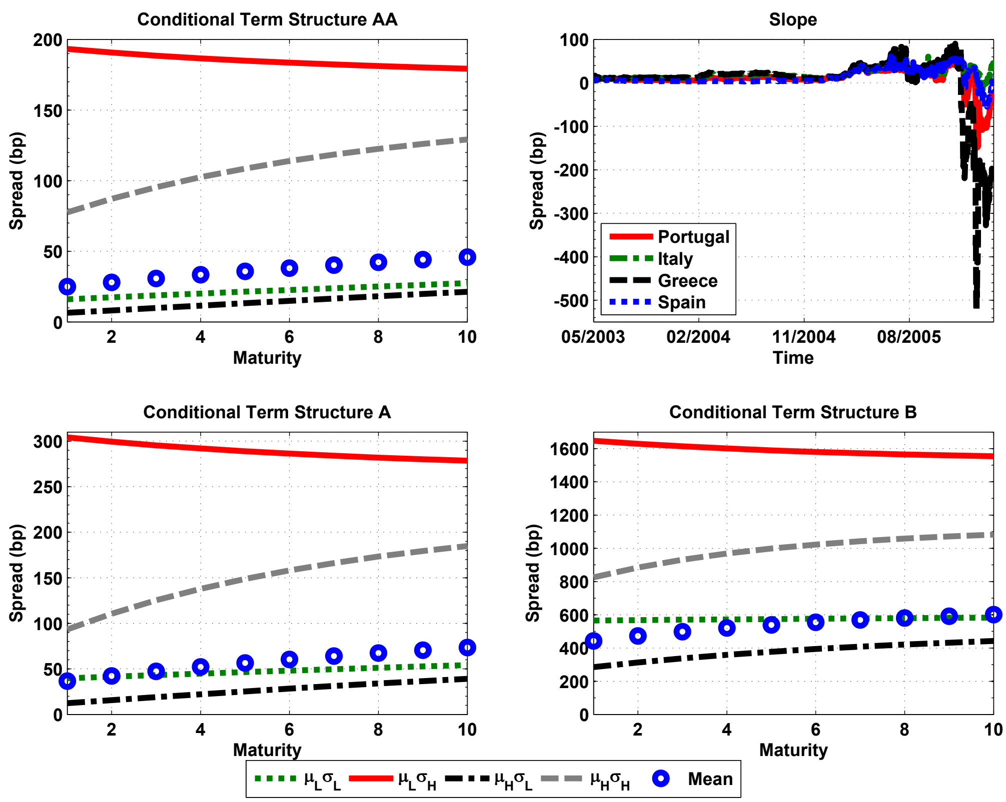


Figure 5: Hazard Rate Analysis

Figure 5 plots the unconditional observed and model-implied term structure of CDS Spreads for maturities 1 to 10 at the aggregated level for the rating categories AAA-B for various specifications of the hazard rate $h_t = \lambda_t/(1+\lambda_t)$, where $\lambda_t = \exp(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda \sigma} \sigma_t)$. The dash-dotted line represents the results using the benchmark specification of the hazard rate, the dashed line denotes the results using a constant hazard rate, whereas the dotted and solid lines feature the results for a default process specification with only expected consumption growth or macroeconomic uncertainty respectively. The empirical observations in the data are represented with the solid bullet points. The recovery rate is constant and exogenously set at 25%. The preference parameters are specified for an investor with Kreps Porteus preferences.

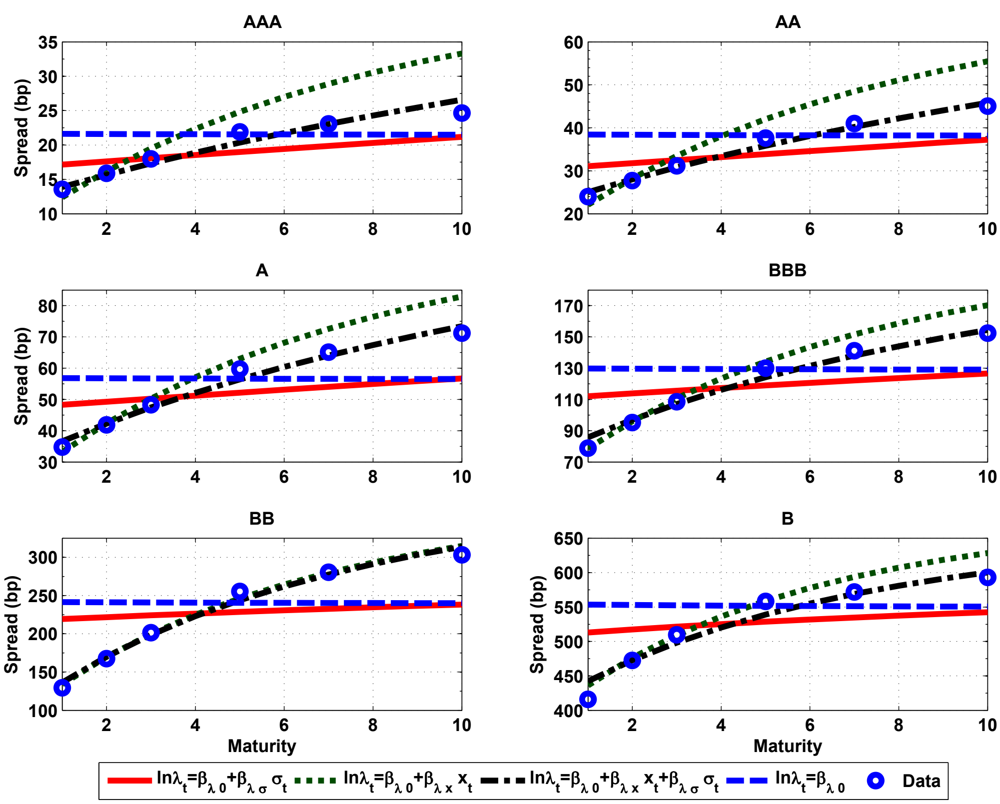


Table 1: Country List

Table 1 presents the list of 38 countries in the sample and the corresponding geographical region. We map a country's rating into a numerical scheme ranging from 1 (AAA) to 21 (C). For the analysis, countries are grouped into 6 major rating buckets (AAA, AA, A, BBB, BB, B), keeping track of rating changes over time. The third column indicates the Standard&Poor's Rating in 2010. The fourth column indicates the average historical rating as traced back by Fitch Ratings over the sample period, that is from May 9th, 2003 until August 19th, 2010. The equally weighted historical average of the numerical rating is rounded to the nearest integer to obtain the average final rating. The last two columns indicate the average number of countries in each rating group.

Country	*Region*	*S&P Rating ('10)*	*Average Rating*	*Classification*	*Average # entities*
Austria	Europe	AAA	AAA	AAA	4
France	Europe	AAA	AAA		
Germany	Europe	AAA	AAA		
Spain	Europe	AA	AAA		
Belgium	Europe	AA+	AA+	AA	6
Italy	Europe	A+	AA-		
Japan	Asia	AA	AA		
Portugal	Europe	A-	AA		
Qatar	Middle East	AA	AA		
Slovenia	E.Europe	AA	AA-		
Chile	Lat.Amer	A+	A-	A	9
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	BBB	A-		
Malaysia	Asia	A-	A-		
Slovakia	E.Eur	A+	A		
Bulgaria	E.Eur	BBB	BBB-	BBB	11
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+		
Brazil	Lat.Amer	BBB-	BB	BB	6
Colombia	Lat.Amer	BB+	BB		
Egypt	Africa	BB+	BB+		
Peru	Lat.Amer	BBB-	BB+		
Philippines	Asia	BB-	BB		
Turkey	Middle East	BB	BB-		
Lebanon	Middle East	B	B-	B	2
Venezuela	Lat.Amer	BB-	B+		

Table 2: Summary Statistics

Table 2 reports summary statistics for the CDS term structure of 38 sovereign countries over the sample period May 9, 2003 until August 19, 2010. All CDS spreads are mid composite quotes and USD denominated. Countries are aggregated based on 6 major rating categories ranging from AAA to B. At each date, all observations within a given rating category are aggregated by taking the equally-weighted average CDS spread. For the 6 aggregated spread series, the table reports the mean, median, standard deviation, minimum, maximum and the first-order autocorrelation coefficient (AC1). Source: Markit.

AAA	1y	2y	3y	5y	7y	10y	**AA**	1y	2y	3y	5y	7y	10y
Mean	14	16	18	22	23	25		24	28	31	38	41	45
Median	2	2	3	4	5	7		5	7	10	14	19	24
Stand.dev.	23	25	27	31	31	31		38	40	42	45	45	44
Minimum	0	1	1	2	2	3		1	2	3	5	6	8
Maximum	128	135	140	153	153	152		170	183	194	207	209	206
AC1	0.9930	0.9944	0.9960	0.9970	0.9970	0.9971		0.9956	0.9961	0.9965	0.9968	0.9968	0.9967
A	1y	2y	3y	5y	7y	10y	**BBB**	1y	2y	3y	5y	7y	10y
Mean	35	42	48	60	65	71		79	95	108	130	141	152
Median	14	19	24	34	41	49		29	47	66	93	110	127
Stand.dev.	51	55	58	63	62	61		106	108	107	104	101	97
Minimum	4	6	7	10	13	17		11	15	20	30	37	46
Maximum	281	294	325	351	362	370		540	568	586	608	617	628
AC1	0.9973	0.9974	0.9974	0.9978	0.9976	0.9976		0.9973	0.9973	0.9971	0.9969	0.9969	0.9967
BB	1y	2y	3y	5y	7y	10y	**B**	1y	2y	3y	5y	7y	10y
Mean	129	168	202	255	281	303		416	472	510	558	572	593
Median	91	143	182	244	274	294		346	399	440	489	516	540
Stand.dev.	141	138	133	127	122	118		320	312	302	287	265	248
Minimum	27	44	60	97	122	146		75	135	165	202	234	275
Maximum	1056	1077	1075	1063	1061	1065		2039	1984	1941	1881	1828	1800
AC1	0.9954	0.9951	0.9948	0.9943	0.9939	0.9937		0.9931	0.9933	0.9933	0.9934	0.9930	0.9924

Table 3: Principal Component Analysis

Table 3 reports the variation in CDS spreads explained by the first 6 factors PC1 to PC6 of the principal component analysis. The row *All* refers to the pooled data, where all six maturities for all 38 countries are taken together. Subsequent columns indicate results for the subsamples, taken by contract maturity (1y to 10y) each at a time. 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

Table 4: Kalman Filter Estimates

Table 4 reports the Kalman Filter estimates for the parameters of the conditional expectation of consumption growth and conditional consumption volatility for the system of equations

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

where g_t, x_t and σ_t reflect the dynamics for, respectively, aggregate consumption growth, its conditional mean and volatility, and all error terms are standard normal. In addition to the short-run consumption shocks $\epsilon_{g,t+1}$, consumption growth is fed with long-run shocks $\epsilon_{x,t+1}$, whose persistence is defined through the parameter ϕ_x. The unconditional mean growth-rate is given by μ_x and ν_x denotes the sensitivity of expected growth to long-run shocks. The parameters ϕ_σ and ν_σ define the persistence of and sensitivity to shocks $\epsilon_{\sigma,t+1}$ to macroeconomic uncertainty, which is fluctuating around its long-run mean μ_σ. Macroeconomic uncertainty is defined as a GARCH-like stochastic volatility process that has been used in Heston and Nandi (2000), henceforth HN. Panel A reports the results for this base specification. Standard errors are given in parentheses. Panel B reports the estimated coefficients and standard errors in parentheses for alternative volatility specifications: the GARCH(1,1) model of Bollerslev (1986), the EGARCH model of Nelson (1991) and the GJR GARCH model of Glosten, Jagannathan, and Runkle (1993), which have the following dynamics:

$$
\begin{aligned}
&GARCH(1,1): \sigma^2_{t+1} = (1-\phi_\sigma)\,\mu_\sigma + \phi_\sigma \sigma^2_t + \nu_\sigma \sigma^2_t \left(\epsilon^2_{c,t+1} - 1\right) \\
&EGARCH: \ln \sigma^2_{t+1} = (1-\phi_\sigma) \ln \mu_\sigma + \phi_\sigma \ln \sigma^2_t + \nu_\sigma \left(|\epsilon_{c,t+1}| - \sqrt{2/\pi}\right) + \lambda_\sigma \epsilon_{c,t+1} \\
&GJR: \sigma^2_{t+1} = (1-\phi_\sigma)\,\mu_\sigma + \phi_\sigma \sigma^2_t + \nu_\sigma \sigma^2_t \left(\epsilon^2_{c,t+1} - 1\right) + \lambda_\sigma \sigma^2_t \left(\epsilon^2_{c,t+1} I\left(\epsilon_{c,t+1} < 0\right) - \frac{1}{2}\right),
\end{aligned}
$$

where the additional leverage parameter λ_σ in the EGARCH and GJR-GARCH specifications allows for asymmetric effects of positive and negative shocks to volatility. All coefficients are estimated using data for real per capita consumption growth from the FRED database of the Federal Reserve Bank of St.Louis from January 1959 until August 2010.

Panel A	μ_x	ϕ_x	ν_x	μ_σ	ϕ_σ	ν_σ
HN	0.001785	0.955642	0.058611	1.372177e-05	0.9610790	7.5528e-007
	(0.000235)	(0.033936)	(0.028885)	(1.541653e-06)	(0.013410)	(1.7537e-007)

Panel B	μ_σ	ϕ_σ	ν_σ	λ_σ
GARCH(1,1)	9.0536e-06	0.97791	0.03598	–
	(1.0199e-05)	(0.00364)	(0.00840)	(–)
EGARCH	1.5787e-05	0.99068	0.09589	0.02269
	(4.5563e-06)	(0.00460	(0.02338)	(0.00969)
GJR	1.3293e-05	0.98495	0.07086	−0.03128
	(1.6063e-05)	(0.00554)	(0.01731)	(0.01736)

Table 5: Regression Analysis - Macroeconomic and Financial Risk

Table 5 reports the results from the regression of the monthly averages of the factors extracted from a principal component analysis onto conditional expected consumption growth, conditional consumption volatility and the Variance Risk Premium (VRP), the CBOE S&P500 volatility index (VIX), the excess return on the CRSP value-weighted portfolio (USret), the US price-earnings ratio (PE), as well as the U.S. investment-grade (AAA_BBB) and high-yield (BBB_BB) bond spreads. Data for real per capita consumption is from January 1959 until August 2010 from the FRED database of the Federal Reserve Bank of St.Louis. The VRP is from Hao Zhou's webpage, the USret from Kenneth French's website, the PE from Robert Shiller's website, and the VIX, AAA_BBB and BBB_BB from the FRED H15 report.

$$F_{i,t} = a_{0,i} + a_{1,i} \times \hat{x}_{t|t} + a_{2,i} \times \hat{\sigma}_t + a_{3,i} \times VRP_t + a_{4,i} \times VIX_t + a_{5,i} \times USret_t + a_{6,i} \times PE_t + a_{7,i} \times AAA\_BBB_t + a_{8,i} \times BBB\_BB_t + \epsilon_t,$$

where $i = 1, 2$ and t is the month index. The dependent variables $F_{i,t}$ denote the principal components, $\hat{x}_{t|t}$ is the filtered expected consumption growth and $\hat{\sigma}_t$ the filtered conditional consumption volatility. The last row reports the decision rule ($A = Accept, R = Reject$) from a Dickey-Fuller test on the residuals to test for the presence of a unit root. Columns (15) to (17) report the results of the probit model that tests whether the explanatory variables can predict the Reinhart and Rogoff crisis tally indicator, which is available for 29 countries in our sample. The crisis tally is a count indicator accounting for currency crises, inflation crises, stock market crashes, domestic and external sovereign debt crises, and banking crises. More specifically, we fit the regression specification.

$$Pr\left(Crisis = 1\right) = \Phi\left(a_0 + a_1 \hat{x}_{t|t} + a_2 \hat{\sigma}_t + a_3 VRP_t + a_4 VIX_t + a_5 USret_t + a_6 PE_t + a_7 BBB\_AAA_t + a_8 BB\_BBB_t\right).$$

Block-bootstrapped standard errors are reported in brackets. $**$ and $*$ indicate significance at the 1% and 5% respectively.

VARIABLES	(1) F1	(2) F2	(3) F1	(4) F2	(5) F1	(6) F2	(7) F1	(8) F2	(9) F1	(10) F2	(11) F1	(12) F2	(13) F1	(14) F2	(15) CI	(16) CI	(17) CI
$\hat{x}_{t\|t}$	-128.16**	236.66**													-0.22**	-0.22**	-0.22
	(38.92)	(22.10)													(0.06)	(0.07)	(0.15)
$\hat{\sigma}_t$	454.81**	293.54**													0.45**	0.42*	0.99**
	(77.58)	(34.70)													(0.17)	(0.18)	(0.37)
VRP			23.68	-2.28													-0.01
			(22.79)	(5.25)													(0.00)
VIX					1.44**	-0.15											0.04**
					(0.37)	(0.11)											(0.01)
USret							-0.46	0.07								-0.01**	-0.02
							(0.91)	(0.20)								(0.00)	(0.01)
PE									-0.04**	0.01*						-0.00	0.04**
									(0.00)	(0.00)						(0.00)	(0.01)
AAA_BBB											17.80**	-1.80					0.04
											(1.71)	(1.14)					(0.14)
BBB_BB													16.84**	-1.45			-0.11
													(2.05)	(1.18)			(0.13)
Constant	-1.28**	-0.77**	-0.04	0.00	-0.30**	0.03	0.00	-0.00	1.03**	-0.16*	-0.25**	0.03	-0.30**	0.03	-0.59	-0.50	-3.58**
	(0.20)	(0.09)	(0.04)	(0.01)	(0.06)	(0.03)	(0.03)	(0.01)	(0.12)	(0.07)	(0.02)	(0.02)	(0.03)	(0.02)	(0.42)	(0.48)	(0.76)
Observations	88	88	88	88	88	88	88	88	88	88	88	88	88	88	18,096	18,096	11,830
R2	0.76	0.74	0.13	0.01	0.56	0.04	0.01	0.00	0.78	0.10	0.83	0.05	0.76	0.03			
adj.R2	0.75	0.74	0.12	-0.00	0.55	0.02	0.00	-0.01	0.78	0.09	0.82	0.04	0.76	0.02			
ps.R2															0.01	0.01	0.07
Dickey-Fuller	R**	R**	R	A	R**	A	A	A	R	A	R**	A	R**	A			

Table 6: Regression Analysis - Macroeconomic and Financial Risk

Table 6 reports the 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 (VRP), the CBOE S&P500 volatility index (VIX), the excess return on the CRSP value-weighted portfolio (USret), the US price-earnings ratio (PE), as well as the U.S. investment-grade (AAA_BBB) and high-yield (BBB_BB) bond spreads. Factor scores are first averaged at the end of each month and then projected onto the explanatory variables. 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 data for the VRP is taken from Hao Zhou's webpage, for the USret on Kenneth French's website, the PE from Robert Shiller's website, and the VIX, AAA_BBB and BBB_BB from the FRED H15 report. Block-bootstrapped standard errors are reported in brackets. $**$ and $*$ indicate significance at the 1% and 5% respectively.

$$F_{i,t} = a_{0,i} + a_{1,i} \times \hat{x}_{t|t} + a_{2,i} \times \hat{\sigma}_t + a_{3,i} \times VRP_t + a_{4,i} \times VIX_t + a_{5,i} \times USret_t + a_{6,i} \times PE_t + a_{7,i} \times AAA\_BBB_t + a_{8,i} \times BBB\_BB_t + \epsilon_t,$$

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 expected consumption growth and $\hat{\sigma}_t$ the filtered conditional consumption volatility. The last row reports the decision rule ($A = Accept, R = Reject$) from a Dickey-Fuller test on the residuals to test for the presence of a unit root.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
VARIABLES	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2
$\hat{x}_{t\|t}$	-120.99*	239.89**	-69.26	248.26**	-118.87**	238.30**	164.96*	260.42**	70.69	255.43**	29.07	266.36**	136.96*	247.91**
	(47.79)	(23.65)	(62.20)	(22.31)	(39.96)	(22.39)	(69.97)	(24.13)	(45.69)	(20.23)	(40.92)	(25.27)	(67.02)	(29.92)
$\hat{\sigma}_t$	450.18**	291.46**	401.68**	283.08**	469.60**	296.15**	286.17**	279.87**	254.52**	274.64**	348.96**	273.55**	255.53**	280.00**
	(81.73)	(36.66)	(60.58)	(38.47)	(82.80)	(34.99)	(53.98)	(39.20)	(59.90)	(43.13)	(52.07)	(33.28)	(56.98)	(47.37)
VRP	3.64	1.63											0.98	3.38
	(13.18)	(1.82)											(9.57)	(4.79)
VIX			0.48	0.09									0.06	-0.05
			(0.40)	(0.07)									(0.33)	(0.12)
USret					-0.55	-0.10							0.11	0.20
					(0.36)	(0.10)							(0.33)	(0.20)
PE							-0.04**	-0.00					-0.02	0.00
							(0.01)	(0.00)					(0.01)	(0.01)
AAA_BBB									14.75**	1.39			5.56	-0.76
									(2.73)	(1.11)			(4.42)	(2.49)
BBB_BB											11.25**	2.12*	5.94*	4.06
											(1.98)	(0.98)	(2.90)	(2.28)
Constant	-1.27**	-0.76**	-1.22**	-0.76**	-1.31**	-0.77**	0.29	-0.64**	-0.89**	-0.73**	-1.15**	-0.74**	-0.52	-0.90**
	(0.21)	(0.09)	(0.17)	(0.10)	(0.22)	(0.09)	(0.27)	(0.16)	(0.15)	(0.11)	(0.14)	(0.09)	(0.33)	(0.22)
Observations	88	88	88	88	88	88	88	88	88	88	88	88	88	88
R2	0.76	0.75	0.78	0.75	0.77	0.75	0.87	0.75	0.88	0.75	0.88	0.77	0.91	0.78
adj.R2	0.75	0.74	0.77	0.74	0.77	0.74	0.86	0.74	0.87	0.74	0.88	0.76	0.90	0.76
Dickey-Fuller	R**	R**	R**	R**	R**	R**	R**	R*	R**	R	R**	R*	R**	R*

Table 7: Country Regressions - Macroeconomic Risk and Variance Risk Premium

Table 7 reports the results from the regression of the level and slope of the monthly sovereign CDS series onto conditional expected consumption growth, conditional consumption volatility and the Variance Risk Premium (VRP). The level is defined as the average monthly CDS spread over all maturities, the slope is equal to the difference between the average monthly 10-year and 1-year CDS spread. 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 consumption series are estimated using a traditional Kalman Filter as described in equation (1). The data for the VRP are taken from Hao Zhou's webpage. We specify the regression model

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

where $Y_{i,t}$ is either the *Level* or the *Slope* of the CDS curve, i denotes the country and t is the month index. $\hat{x}_{t|t}$ is the filtered expected consumption growth, $\hat{\sigma}_t$ the filtered conditional consumption volatility and VRP_t denotes the VRP. The average correlation between the level and slope across countries is 0.12. All regressions are run for each of the 38 countries. Panel A excludes the VRP, Panel B excludes the consumption predictors, and Panel C 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 (8) report respectively the mean and median adjusted R^2 of the 38 country-pecific regressions. Column (9) indicates the number of observations for each regression. Columns (10) to (12) report the signs of $\hat{a}_1$ and $\hat{a}_2$, as well as the median R^2 from the population regressions predicted by the model.

	Data									Model		
Panel A	*t-stats* $\hat{x}_{t\|t}$	*t-stats* $\hat{\sigma}_t$	*t-stats* VRP_t	$+\hat{x}_{t\|t}$	$+\hat{\sigma}_{t,t}$	$+VRP_t$	*mean adj.* R^2	*median adj.* R^2	*# obs.*	*Sign* $\hat{a}_1$	*Sign* $\hat{a}_2$	*median* R^2
Level	0.82	0.89		0.32	0.97		0.69	0.70	88	-	+	0.97
Slope	0.84	0.61		0.55	0.74		0.46	0.54	88	+	+	0.75
Panel B												
Level			0.95			1.00	0.11	0.12	88			
Slope			0.50			0.69	0.04	0.03	88			
Panel C												
Level	0.76	0.89	0.18	0.32	0.97	1.00	0.69	0.70	88			
Slope	0.84	0.58	0.11	0.61	0.74	0.84	0.47	0.54	88			
Regression	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*

Table 8: Parameters of the Markov-Switching Model

Consumption growth dynamics are calibrated at a monthly frequency as in Bansal, Kiku, and Yaron (2012) with $\mu_x = 0.0015$, $\phi_x = 0.975$, $\nu_x = 0.038$, $\sqrt{\mu_\sigma} = 0.0072$, $\phi_\sigma = 0.999$ and $\nu_\sigma = 2.80 \times 10^{-6}$. Conditional on the information set J_t, the errors are i.i.d. normal.

$$
\begin{aligned}
g_{t+1} &= x_t + \sigma_t \epsilon_{g,t+1} \\
x_{t+1} &= (1-\phi_x)\,\mu_x + \phi_x x_t + \nu_x \sigma_t \epsilon_{x,t+1} \\
\sigma^2_{t+1} &= (1-\phi_\sigma)\,\mu_\sigma + \phi_\sigma \sigma^2_t + \nu_\sigma \epsilon_{\sigma,t+1}
\end{aligned}
\qquad
\begin{pmatrix} \epsilon_{g,t+1} \\ \epsilon_{x,t+1} \\ \epsilon_{\sigma,t+1} \end{pmatrix} \Big| \, J_t \sim \mathcal{NID}\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \right).
$$

To be consistent with the daily frequency of CDS spreads, we map the monthly parameters into daily values such that annual moments of consumption growth are preserved. We use the monthly-to-daily mapping

$$
\mu_x^{daily} = \Delta \mu_x, \quad \phi_x^{daily} = \phi_x^{\Delta}, \quad \nu_x^{daily} = \nu_x \sqrt{\left(\frac{1-\phi_x^{2\Delta}}{1-\phi_x^2}\right) \Big/ \left(1 + \frac{2\phi_x}{1-\phi_x} - \frac{2\Delta\phi_x\left(1-\phi_x^{1/\Delta}\right)}{(1-\phi_x)^2}\right)}
$$

$$
\mu_\sigma^{daily} = \Delta \mu_\sigma, \quad \phi_\sigma^{daily} = \phi_\sigma^{\Delta}, \quad \nu_\sigma^{daily} = \nu_\sigma \sqrt{\Delta} \sqrt{\left(\frac{1-\phi_\sigma^{2\Delta}}{1-\phi_\sigma^2}\right) \Big/ \left(1 + \frac{2\phi_\sigma}{1-\phi_\sigma} - \frac{2\Delta\phi_\sigma\left(1-\phi_\sigma^{1/\Delta}\right)}{(1-\phi_\sigma)^2}\right)}
$$

where we consider $\Delta = 1/22$, i.e. 22 trading days per month. The parameters at a daily frequency obtained from the mapping system are $\mu_x^{daily} = 6.8182 \times 10^{-5}$, $\phi_x^{daily} = 0.9988$, $\nu_x^{daily} = 0.0019$, $\mu_\sigma^{daily} = 2.3564 \times 10^{-6}$, $\phi_\sigma^{daily} = 0.99995$ and $\nu_\sigma^{daily} = 2.7247 \times 10^{-8}$. Panel A reports the parameters of the four-state daily Markov-switching model. The conditional mean and variance of consumption growth are μ_g and ω_g respectively. $P^\top$ 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 B and C report the (time-averaged) annualized model statistics for aggregate consumption growth, the risk premium and the volatility of the aggregate stock market, the risk-free rate and its volatility, all compared against observed values. The model-implied values are reported for both the model with the Kreps-Porteus certainty equivalent (KP) and generalized disappointment averse preferences (GDA). The estimated values are sampled on an annual frequency from 1930 to 2008. Standard errors are reported in parentheses.

Panel A	$\mu_L\sigma_L$	$\mu_L\sigma_H$	$\mu_H\sigma_L$	$\mu_H\sigma_H$
$\mu_g^\top$	-0.00011	-0.00011	0.00009	0.00009
$\left(\omega_g^\top\right)^{1/2}$	0.00094	0.00281	0.00094	0.00281
		$P^\top$		
$\mu_L\sigma_L$	0.99897	0.00001	0.00102	0.00000
$\mu_L\sigma_H$	0.00004	0.99894	0.00000	0.00102
$\mu_H\sigma_L$	0.00013	0.00000	0.99986	0.00001
$\mu_H\sigma_H$	0.00000	0.00013	0.00004	0.99984
$\Pi^\top$	0.08600	0.02304	0.70268	0.18828
Panel B	Model		Data	
$E[\Delta g]$	1.80		1.92	(0.33)
$\sigma[\Delta g]$	2.53		2.12	(0.52)
$AC1[\Delta g]$	0.46		0.46	(0.15)
Panel C	Model (KP)	Model (GDA)	Data	
$E[r_m - r_f] + 0.5\sigma^2[r_m]$	6.38	5.52	7.84	(1.97)
$\sigma[r_m]$	18.48	17.48	20.16	(2.14)
$E[r_f]$	1.22	1.01	0.86	(0.89)
$\sigma[r_f]$	1.05	0.80	1.74	(0.33)

Table 9: Model Estimation - Preference and Default Parameters

Table 9 reports estimation results (with with Newey-West standard errors in parentheses) for preference parameters and the parameters of the default process for the rating categories AAA to B, where the default process h_t is defined as $h_t = \lambda_t / (1 + \lambda_t)$, where $\lambda_t = \exp(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda \sigma} \sigma_t)$. The subjective discount factor δ is fixed at 0.9989. γ is the coefficient of relative risk aversion, ψ the elasticity of intertemporal substitution, α the disappointment aversion parameter and κ denotes the fraction of the certainty equivalent below which outcomes are disappointing. The estimation is carried out via the Generalized Method of Moments using the historical observed time series of credit default swap spreads over the sample period 9 May 2003 through 19 August 2010. We do the estimation using both spread levels and changes. The moments in the estimation are the expectations of the CDS spreads (respectively spread changes) and their squared values. The weighting matrix is the inverse of the diagonal of the spectral density matrix. The last panel reports the J statistic for the test of overidentifying restrictions and the corresponding p-value, as well as the likelihood-ratio test (LR) where the null hypothesis is that the true preferences are Kreps-Porteus against the alternative that they are generalized disappointment averse.

	Kreps-Porteus (KP)					
	AAA	AA	A	BBB	BB	B
β_{λ_0}	-15.37	-13.71	-12.71	-11.34	-10.07	-9.15
(*s.e.*)	(0.66)	(0.24)	(0.14)	(0.09)	(0.09)	(0.06)
β_{λ_x}	$-5,624.18$	$-5,596.99$	$-7,429.56$	$-6,692.67$	$-13,917.70$	$-4,144.73$
(*s.e.*)	(415.62)	(514.33)	(680.13)	(730.82)	(1,928.74)	(415.18)
β_{λ_σ}	1,818.66	1,390.45	1,125.74	886.99	309.57	583.87
(*s.e.*)	(228.44)	(80.70)	(68.55)	(46.44)	(131.77)	(40.24)
	Generalized Disappointment Aversion (GDA)					
	AAA	AA	A	BBB	BB	B
β_{λ_0}	-15.44	-13.79	-12.89	-11.48	-10.90	-9.21
(*s.e.*)	(0.58)	(0.24)	(0.15)	(0.10)	(0.41)	(0.05)
β_{λ_x}	$-6,572.55$	$-6,466.87$	$-8,686.44$	$-7,669.86$	$-18,598.21$	$-4,431.00$
(*s.e.*)	(467.94)	(663.93)	(850.56)	(902.24)	(4,858.26)	(433.62)
β_{λ_σ}	1,812.21	1,388.35	1,143.98	901.76	467.94	593.74
(*s.e.*)	(198.52)	(75.36)	(64.03)	(42.32)	(73.04)	(37.71)

	Preference Parameters			
	Levels		Differences	
Parameter	KP	GDA	KP	GDA
δ	0.9989	0.9989	0.9989	0.9989
(*s.e.*)	(-)	(-)	(-)	(-)
γ	8.2692	4.9081	7.1713	5.0614
(*s.e.*)	(0.0011)	(0.0054)	(0.0642)	(0.1294)
ψ	1.5774	1.4874	1.5953	1.2473
(*s.e.*)	(0.0002)	(0.0018)	(0.0133)	(0.0273)
α	1.0000	0.2486	1.0000	0.4819
(*s.e.*)	(-)	(0.0008)	(-)	(0.0107)
κ	-	0.8470	-	0.9549
(*s.e.*)	(-)	(0.0042)	(-)	(0.0183)
	Model Statistics			
$J-test$	45.73	14.65	19.84	8.32
$p-value$	0.65	1.00	1.00	1.00
$LR-test$	31.08		11.52	
$p-value$	<0.01		<0.01	

Table 10: Model-Implied and Observed Term Structure of CDS Spreads AAA-B

Table 10 reports observed and model-implied unconditional means, standard deviations (in basis points), skewness, kurtosis and first-order autocorrelation coefficients for CDS spreads for maturities 1 to 10 for the rating categories AAA to B. The column labeled *RMSE* reports the root mean squared errors in basis points for the model fit. The recovery rate has a constant value of 25%. Preference parameters are those of an investor with a Kreps-Porteus certainty equivalent.

	MODEL							**DATA**					
AAA	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	14	16	17	20	23	27	1.06	14	16	18	22	23	25
Volatility	25	26	27	29	30	31	1.50	23	25	27	31	31	31
Skewness	2	2	2	2	2	2	0.15	2	2	2	2	2	2
Kurtosis	9	7	6	5	4	3	1.12	7	7	6	5	5	4
AC1	0.9997	0.9998	0.9998	0.9999	0.9999	0.9999	0.0044	0.9930	0.9944	0.9960	0.9970	0.9970	0.9971
AA	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	25	28	31	36	40	46	0.97	24	28	31	38	41	45
Volatility	38	39	41	43	45	47	1.28	38	40	42	45	45	44
Skewness	2	2	2	2	2	2	0.21	2	2	2	2	2	2
Kurtosis	10	8	6	5	4	4	1.74	6	6	5	5	4	4
AC1	0.9997	0.9998	0.9998	0.9999	0.9999	0.9999	0.0034	0.9956	0.9961	0.9965	0.9968	0.9968	0.9967
A	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	37	42	47	56	64	73	1.89	35	42	48	60	65	71
Volatility	52	54	56	59	62	64	2.14	51	55	58	63	62	61
Skewness	3	3	2	2	2	2	0.35	3	2	2	2	2	2
Kurtosis	17	13	10	7	5	4	3.41	10	9	8	7	7	7
AC1	0.9995	0.9996	0.9997	0.9998	0.9999	0.9999	0.0022	0.9973	0.9974	0.9974	0.9978	0.9976	0.9976
BBB	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	86	97	107	124	138	154	4.11	79	95	108	130	141	152
Volatility	95	98	101	105	108	111	9.33	106	108	107	104	101	97
Skewness	3	3	2	2	2	2	0.48	2	2	2	2	2	2
Kurtosis	15	12	9	7	5	4	4.04	7	7	7	6	6	7
AC1	0.9995	0.9996	0.9997	0.9998	0.9998	0.9999	0.0027	0.9973	0.9973	0.9971	0.9969	0.9969	0.9967
BB	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	136	170	199	244	278	314	7.23	129	168	202	255	281	303
Volatility	159	146	136	121	111	100	11.89	141	138	133	127	122	118
Skewness	3	3	3	3	3	2	0.33	3	3	3	2	2	2
Kurtosis	12	12	12	12	11	10	1.85	15	14	13	11	11	10
AC1	0.9989	0.9989	0.9990	0.9991	0.9992	0.9993	0.0046	0.9954	0.9951	0.9948	0.9943	0.9939	0.9937
B	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	442	473	498	539	569	600	14.34	416	472	510	558	572	593
Volatility	282	285	287	289	289	287	27.20	320	312	302	287	265	248
Skewness	2	2	2	2	2	2	0.35	2	2	2	2	2	2
Kurtosis	8	7	6	5	5	4	3.33	10	9	9	8	9	9
AC1	0.9997	0.9997	0.9998	0.9998	0.9998	0.9999	0.0067	0.9931	0.9933	0.9933	0.9934	0.9930	0.9924

Table 11: Model-Implied Term Structure of Default Probabilities AAA-B

Table 11 reports unconditional model-implied physical and risk-neutral default probabilities for maturities 1 to 10 at the aggregated level for the rating categories AAA to B as well as their ratio. The column labeled RMSE reports the root mean squared errors in % points for the model fit. Model results are compared against the observed Standard&Poor's sovereign foreign-currency cumulative average default rates over the time frame 1975 to 2009 for the physical default probabilities. The recovery rate has a constant value of 25%.

		RMSE	1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Physical Default Probabilities												
AAA	Model	0.97	0.16	0.32	0.48	0.63	0.79	0.94	1.10	1.25	1.40	1.55
	Observed	–	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	Model	1.73	0.29	0.57	0.86	1.14	1.41	1.69	1.96	2.23	2.50	2.77
	Observed	–	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	Model	2.40	0.40	0.80	1.19	1.58	1.96	2.34	2.72	3.09	3.46	3.83
	Observed	–	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBB	Model	1.37	0.96	1.90	2.82	3.73	4.62	5.49	6.34	7.19	8.01	8.83
	Observed	–	0.00	0.50	1.57	2.72	3.97	5.33	6.07	6.07	6.07	6.07
BB	Model	2.02	1.25	2.45	3.61	4.74	5.84	6.92	7.99	9.03	10.06	11.08
	Observed	–	0.74	2.36	3.70	4.70	6.36	8.24	10.34	12.72	13.63	13.63
B	Model	11.11	5.19	10.00	14.49	18.68	22.60	26.28	29.75	33.00	36.08	38.98
	Observed	–	2.13	5.03	6.71	9.32	11.67	13.54	15.85	20.06	21.87	24.57
Risk-Neutral Default Probabilities												
AAA	Model	–	0.18	0.41	0.68	0.98	1.32	1.68	2.06	2.47	2.89	3.34
AA	Model	–	0.33	0.74	1.21	1.73	2.30	2.91	3.56	4.24	4.94	5.66
A	Model	–	0.48	1.11	1.84	2.68	3.59	4.56	5.58	6.65	7.75	8.87
BBB	Model	–	1.13	2.52	4.10	5.84	7.69	9.62	11.60	13.62	15.65	17.69
BB	Model	–	1.78	4.35	7.46	10.95	14.67	18.50	22.39	26.25	30.05	33.76
B	Model	–	5.65	11.59	17.58	23.47	29.15	34.56	39.66	44.44	48.88	53.01
Ratio of Risk-Neutral to Physical Default Probabilities												
AAA	Model	–	1.34	1.69	2.03	2.36	2.68	2.98	3.26	3.52	3.76	3.98
AA	Model	–	1.22	1.44	1.65	1.84	2.03	2.21	2.37	2.53	2.67	2.80
A	Model	–	1.27	1.51	1.72	1.92	2.11	2.27	2.43	2.57	2.70	2.82
BBB	Model	–	1.21	1.38	1.54	1.68	1.80	1.91	2.00	2.09	2.16	2.22
BB	Model	–	1.75	2.22	2.53	2.76	2.93	3.06	3.16	3.23	3.28	3.32
B	Model	–	1.09	1.17	1.23	1.28	1.32	1.35	1.37	1.38	1.39	1.40

Table 12: Model-Implied and Observed Term Structure of CDS Spreads AAA-B: Downside Risk Aversion

Table 12 reports observed and model-implied unconditional means, standard deviations (in basis points), skewness, kurtosis and first-order autocorrelation coefficients for CDS spreads for maturities 1 to 10 for the rating categories AAA-B. The column labeled $RMSE$ reports the root mean squared errors in basis points for the model fit. The recovery rate has a constant value of 25%. Preference parameters are those of an investor with Generalized Disappointment Aversion.

	MODEL							**DATA**					
AAA	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	13	16	18	21	23	26	0.73	14	16	18	22	23	25
Volatility	24	26	27	29	30	31	1.13	23	25	27	31	31	31
Skewness	3	2	2	2	1	1	0.18	2	2	2	2	2	2
Kurtosis	10	7	5	4	3	3	1.49	7	7	6	5	5	4
AC1	0.9997	0.9998	0.9999	0.9999	0.9999	0.9999	0.0044	0.9930	0.9944	0.9960	0.9970	0.9970	0.9971
AA	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	24	28	31	37	41	45	0.52	24	28	31	38	41	45
Volatility	37	39	41	44	46	46	1.17	38	40	42	45	45	44
Skewness	3	2	2	2	2	1	0.21	2	2	2	2	2	2
Kurtosis	10	7	5	4	3	3	1.84	6	6	5	5	4	4
AC1	0.9997	0.9998	0.9999	0.9999	0.9999	0.9999	0.0034	0.9956	0.9961	0.9965	0.9968	0.9968	0.9967
A	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	35	43	49	58	65	72	0.90	35	42	48	60	65	71
Volatility	51	54	56	61	63	64	1.91	51	55	58	63	62	61
Skewness	3	3	2	2	2	1	0.42	3	2	2	2	2	2
Kurtosis	17	11	7	5	4	3	3.65	10	9	8	7	7	7
AC1	0.9995	0.9997	0.9998	0.9999	0.9999	0.9999	0.0023	0.9973	0.9974	0.9974	0.9978	0.9976	0.9976
BBB	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	83	97	109	127	139	152	2.35	79	95	108	130	141	152
Volatility	93	97	101	106	109	111	9.99	106	108	107	104	101	97
Skewness	3	2	2	2	2	2	0.45	2	2	2	2	2	2
Kurtosis	15	10	7	5	4	4	3.89	7	7	7	6	6	7
AC1	0.9996	0.9997	0.9998	0.9999	0.9999	0.9999	0.0028	0.9973	0.9973	0.9971	0.9969	0.9969	0.9967
BB	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	128	171	204	250	279	307	3.32	129	168	202	255	281	303
Volatility	155	140	131	122	118	115	6.39	141	138	133	127	122	118
Skewness	4	3	3	2	2	2	0.25	3	3	3	2	2	2
Kurtosis	18	17	15	11	8	6	2.31	15	14	13	11	11	10
AC1	0.9990	0.9991	0.9993	0.9995	0.9996	0.9997	0.0049	0.9954	0.9951	0.9948	0.9943	0.9939	0.9937
B	1	2	3	5	7	10	**RMSE**	1	2	3	5	7	10
Mean	434	473	503	545	571	596	9.60	416	472	510	558	572	593
Volatility	279	284	287	290	289	287	28.31	320	312	302	287	265	248
Skewness	2	2	2	2	2	2	0.46	2	2	2	2	2	2
Kurtosis	8	6	5	4	4	4	4.16	10	9	9	8	9	9
AC1	0.9997	0.9998	0.9998	0.9999	0.9999	0.9999	0.0068	0.9931	0.9933	0.9933	0.9934	0.9930	0.9924