# Real Economic Shocks and Sovereign Credit Risk*

Patrick Augustin† Roméo Tédongap‡
*McGill University* *Stockholm School of Economics*

This version: August 2013
First version: December 2010

**Abstract**

We provide new empirical evidence that unspanned global macroeconomic risk bears some responsibility for the strong co-movement in sovereign spreads. To rationalize these findings, we embed a reduced-form default process into an equilibrium model with downside risk for CDS spreads. Countries differ through their sensitivity to global macroeconomic forecasts and 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 a compensation for exposure to common U.S. business cycle risk.

**Keywords:** CDS, Generalized Disappointment Aversion, Sovereign Risk, Term Structure

**JEL Classification:** C5, E44, F30, G12, G15

---

*The authors would like to thank David Backus, Nina Boyarchenko, Tobias Broer, Anna Cieslak, Mike Chernov, Magnus Dahlquist, René Garcia, Jørgen Haug, David Lando, Belen Nieto, Stijn Van Nieuwerburgh, 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, 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 and the 3rd International Conference of the Financial Engineering and Banking Society in Paris 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.

†McGill University - Desautels Faculty of Management, 1001 Sherbrooke St. West, Montreal, Quebec H3A 1G5, Canada. Email: Patrick.Augustin@mcgill.ca.

‡Swedish House of Finance and Stockholm School of Economics, Drottninggatan 98, SE-111 60 Stockholm, Sweden. Email: Romeo.Tedongap@hhs.se.

# 1 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 the price of sovereign credit risk (in particular at higher frequencies), above and beyond that of country-specific fundamentals. The recent literature has emphasized the U.S. financial channel as a major source of risk (Pan and Singleton 2008, Longstaff et al. 2010). Whether the ultimate source is financial or macroeconomic in nature is nevertheless a debate, as outlined in Ang and Longstaff (2011).[1] We emphasize the macroeconomic channel by providing new empirical evidence on a tight link between U.S. consumption and sovereign credit risk. We rationalize our results by embedding a reduced-form default process animated through expected growth rates 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 a compensation for exposure to (common) U.S. business cycle 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 high-frequency variation in CDS spreads. Our sample contains information on the full term structure for a geographically dispersed panel of 38 countries. The motivation for our analysis comes from the observation that the number of countries in distress, as measured by the sovereign crisis tally indicator of Reinhart and Rogoff (2011), tends to peak during or around NBER recessions. 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 United States. Secondly, 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 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 can account for the variation in the slope factor. Interestingly, these results contrast sharply

[1] Ang and Longstaff (2011) focus on systemic sovereign risk.

with the $R^2$-statistic of 0% from a regression of the third common factor on the same series. Thirdly, we document that our results are qualitatively and quantitatively maintained for country-specific regressions, where we test for the level, slope and curvature of the CDS term structure as regressands. To further support the macroeconomic channel as the primary source of risk, we run a Vector Autoregression (VAR) between consumption growth and the VIX index and show that expected consumption growth is not driven by the VIX, while results for the link between implied option volatility and consumption volatility are inconclusive and point to mere correlation.

These new empirical findings suggest that consumption risk is a priced factor in the term structure of sovereign CDS spreads and that time-variation in the consumption stream of the marginal investor may bear some responsibility for the significant co-movement in spreads. To rationalize this result, we embed a reduced-form default process animated by aggregate consumption risk factors into a general equilibrium framework for CDS spreads. Our rational investor is risk averse and exhibits generalized disappointment aversion of Routledge and Zin (2010). Such preferences are a natural playground for assets with concave payoff functions, yet they allow for straightforward comparison with the nested recursive expected utility set up. The conditional mean and volatility of aggregate consumption growth, the two state variables of our endowmment economy, animate 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 all 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 conditionally matches the magnitude of the slope reversal for distressed sovereign borrowers in states of bad macroeconomic fundamentals only if an investor is averse to downside risk. 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 (Driessen 2005, Berndt et al. 2007). Regarding the preference parameters, we estimate an elasticity of intertemporal substitution of 1.49 and a coefficient of relative risk aversion of 4.91, consistent with preference for early resolution of uncertainty. We fix the subjective discount factor at 0.9989. Together with a disappointment aversion parameter of 0.25 and a disappointment threshold estimated 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 the equity and fixed income derivative markets, consistent with existing results on information flow between the two markets.[2]

We also test our benchmark model against the classical expected utility framework without generalized disappointment aversion. Although both set ups produce comparable unconditional results, a model without downside risk cannot generate conditional slope reversals consistent with empirically observed magnitudes. This is because generalized disappointment aversion yields relatively higher risk aversion in states of bad macroeconomic fundamentals. A likelihood ratio test favors asymmetric preferences over symmetric gambles.

The results suggest that a simple two-factor model including macroeconomic forecasts and 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 importance of American financial market variables for the common variation in spreads (Pan and Singleton 2008 and Longstaff et al. 2010, Ang and Longstaff 2011), we focus on a different channel, namely aggregate macroeconomic shocks to the United States (level and volatility of consumption growth), and we explain our findings in a tractable two-state model.[3] 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 soverein spreads points to links through U.S. interest rates (Uribe and Yue (2006)), investors' risk appetite (Baek et al. (2005), Remolona et al. (2008), González-Rozada and Yeyati (2008)), investor sentiment (Weigel and Gemmill (2006)) aggregate credit risk (Geyer et al. (2004)) or contagion (Benzoni et al. (2012).)

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

[3]This finding raises the question about the cross-country correlation of consumption growth. We rule out such concerns due to the existing results on the consumption correlation puzzle (See for example Backus et al. 1992).

Benzoni et al. (2012) develop an equilibrium model for CDSs with fragile beliefs where the co-movement in spreads arises through their updates on the posterior probability of a hidden state. As the hidden state affects all countries, this channel is defined as contagion risk. They focus on fitting the dynamics of the level of spreads. We show that a simple non-linear dependence on two systematic risk factors can account for several stylized facts of the term structure, as long as the agent asymmetrically values losses versus gains. Our model is conceptually also close to Borri and Verdelhan (2009), who apply the Campbell and Cochrane (1999) framework to price emerging market bonds, establishing a link between sovereign risk premia and the U.S. business cycle. Their objective is closer to the extensive literature on the sovereign incentives to default, whereas we focus on the pricing. In contrast to their bond results, we derive analytic solutions for non-linear CDS payoffs, allowing us to estimate the full model. Finally, they quantitatively fail to match the level of spreads, whereas we match the moments of the term structure up to the fourth order closely.

Evidence based on sovereign CDS is less explored, but growing. We exploit the homogenuous CDS pricing information as it is better comparable across countries. It is not plagued by differences in covenants, issuer country legislations or declining spread maturities. It is important to point out that the literature tends to focus the analysis on the term structure of individudal countries or on one specific spread maturity in the cross-section, and mostly covers emerging markets. Our study embraces a rich dataset including the full term structure of spreads for 38 countries, spanning a geographical region and maturity spectrum representative of the global sovereign CDS market.

We believe our results to be useful in better understanding the drivers 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. Sovereign default has real economic consequences above financial losses, such as inflation, exchange rate crashes, banking crises, currency debasements, and accompanied social costs. Understanding the relationship between high frequency variation in spreads and global risk factors is also relevant for the diversification benefits of international investors and the efficieny 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. Finally, we conclude in section 6.

# 2 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. A naive plot of annual U.S. consumption growth against the sovereign crisis tally indicator from the authors' database in Figure 1 shows that the number of distressed countries peaks during or around NBER recession dates.[4] This motivates us to investigate more closely the link between U.S. consumption growth and sovereign credit risk, for which we exploit the high-frequency information on sovereign distress embedded in CDS spreads. The next paragraph describes our dataset, followed by a deeper study of its link with global macroeconomic risk.

## 2.1 Data and summary statistics

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.[5,6] All contracts contain the full restructuring clause. The sample spans 4 major geographical regions and 17 rating categories, and is thus representative of the entire sovereign CDS market. The list of 38 countries is provided in Table 1. Gaps in the Markit database are filled with CDS information from CMA, available in Datastream. If no information is available, we fill missing data using the nearest-neighbor method, i.e. we replace missing values with a weighted mean of the 2 nearest-neighbor observations. We set the weights inversely proportional to the distances from the neighboring observations to be consistent with persistent CDS prices. Nevertheless, we emphasize that less than 1% of all observations at any maturity are affected by this procedure, and approximately 0.01% at the 5-year horizon.[7] 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 reference countries and 6 maturities,

[4]We are grateful to Carmen Reinhart for making the crisis indicator publicly available on her website. The count variable accounts for currency crises, inflation crises, stock market crashes, domestic and external sovereign debt crises as well as banking crises. We also thank an anonymous referee for suggesting this graph.

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

[6]While liquidity in corporate CDS is known to be highly concentrated around the 5-year maturity, Pan and Singleton (2008) document that trading volume in sovereign CDS is more balanced across the maturity sprectrum.

[7]We have relegated the detailed table with statistics from the replacement algorithm to an external appendix.

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

amounting to a total of 433,200 observations. We aggregate countries by rating categories and present summary statistics in Table 2.[9] Our data set is most similar to those studies in Pan and Singleton (2008), Remolona et al. (2008) and Longstaff et al. (2010). The first paper, however, studies only three emerging countries, the second 24 emerging countries and is restricted to 5-year CDS quotes. Likewise, the third paper only uses 5-year CDS spreads and looks at 26 countries[10], although at a slightly longer horizon from October 2000 to January 2010. Our data source Markit coincides with Remolona et al. (2008). 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 172 basis points (B). The sample features large time-series variation, with standard deviations for the 5-year series ranging from 22 (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.

## 2.2 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 three factors account for approximately 95% of the common variation.[11] This is rather strong, given the wide spectrum of contract maturities and reference entities we consider.[12] 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 et al. (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.

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

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

[11] We note that results are insensitive, if not stronger, if we do a PCA on spread changes or on standardized spreads.

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

To summarize the information from the PCA, we average the country factor loadings across maturities. Interestingly, Figure 2 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. The average country loadings on the third component decrease from maturities one to three and subsequently stabilize. While we suspect a U-shape pattern, we would need data on longer-dated maturities to conclude with certainty in favor of a curvature factor.

If U.S. consumption risk is priced in the sovereign CDS market, then it ought to be strongly linked to the factors extracted from this principal component analysis. As insurance premia on contingent future default events may be linked to expectations about future growth rates, we investigate the channels of both time-varying expected consumption growth and macroeconomic uncertainty. We estimate both series as described in model (1) with a traditional Kalman Filter (Hamilton (1994)) using monthly real per capita consumption data from January 1959 until August 2010, downloaded from the FRED database of the Federal Reserve Bank of St.Louis,

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

where $\sigma^2_{t+1}$ is a GARCH-like stochastic volatility with $\epsilon_{\sigma,t+1} = \left(\epsilon^2_{g,t+1} - 1\right)/\sqrt{2}$ such that it has zero mean and unit variance. Thus, we get a filtered time series for the conditional expected consumption growth $\hat{x}_{t|t}$, where $x_{t|t}$ denotes the expectation conditional on the information set $\mathcal{I}_t$, and the conditional consumption volatility $\hat{\sigma}_t$.[13] Parameter estimates are provided in Table 4 and are comparable to those used in standard calibration exercises of long-run risk frameworks. As the highest available frequency for consumption information is monthly, we need to take month-end averages of the factor scores and regress the first three factors $F_{i,t}$ onto conditional expected consumption growth and conditional 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 $i = 1, 2, 3$ and $t$ is the month index. Regression results based on 88 monthly observations with block-bootstrapped standard errors are reported in columns one to three of Table 5.[14]

[13] Note that we don't smooth the filtered series, so that we don't suffer from a look-ahead bias.

[14] All results are qualitatively similar if we do the analysis based directly on monthly, rather than daily spreads.

Interestingly, both coefficients on the explanatory variables are statistically significant at the 1% significance level for regressions (1) and (2), but statistically insignificant for regression (3). In addition, the adjusted $R^2$ from the first two regressions is 75% and 74% respectively, but drops close to zero in the third regression. 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. All loadings on the first principal component are maturity-invariant and uniformly positive across reference entities. A negative coefficient on $\hat{a}_1$ then 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 (macroeconomic uncertainty) increases sovereign insurance premia. These results are economically intuitive. Beyond statistical significance, interpretation of the economic magnitudes of the latent factor loadings is more difficult.

In the second regression, both coefficients are statistically significant at the 1% significance level with a positive sign. A positive coefficient on expected consumption growth implies that the slope of the CDS term structure is increasing as the perception of future economic conditions improve. As shocks to expected consumption growth are persistent, positive shocks increase interest rates, which depresses bond prices and increases yields. Yields on longer dated bonds increase proportionally more, thereby steepening the slope. The positive regression coefficient on macroeconomic uncertainty is a result of two offsetting effects. If expected consumption growth is low, higher macroeconomic uncertainty will lower interest rates as investors' willingness to save increases. Thus, bond prices increase and yields drop, again more so for longer maturities. However, conditional on high expected consumption growth, investors still want to borrow from future consumption following higher conditional consumption volatility. This steepens the term structure. We later show that such a feature can be rationalized in a model when the unconditional probability of being in a state of high expected consumption growth is larger than the probability of being in a state of low macroeconomic forecasts. In that case, the latter effect dominates and the net result is a steeper slope. We confirm this interpretation by running an additional (unreported) regression where we include an interaction term of conditional consumption volatility and an indicator variable equal to one if expected consumption growth is high. Finally, the $R^2$ is close to zero for the third regression, and the regression coefficients are statistically insignificant.

Our results support the view that expected U.S. consumption growth and volatility are two major risk factors in the term structure of sovereign credit spreads.[15] Their shocks channel through primarily to the level and the slope of the term structure. To quantify the results, 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.[16] Our conclusion is visually emphasized by plotting the filtered series of conditional consumption forecasts and volatility against the monthly average 5-year CDS spread of all 38 countries in Figure 3. There is a strong negative correlation (-65%) between the aggregated prices for sovereign credit risk and conditional expected consumption growth. Moreover, the conditional consumption volatility tracks the mean 5-year CDS spread closely with a staggering correlation of 85%.

We emphasize that our analysis focuses on spread levels rather than differences, which is consistent with Doshi et al. (2013) and references therein.[17] As the authors point out, there is no consensus in the literature, but economic intution suggests that spreads are mean-reverting and stationary, as opposed to a trending stock price series. 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 persistency in spreads, expected growth and consumption volatility. Therefore, we have reported results using difference regressions in the external 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. Finally, we run a Dickey-Fuller test on the residuals of the regressions and we strictly reject the presence of a unit root. Regressions are hence 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 focus of our study. However, if we were to find evidence in favor of a long-run equilibrium relationship, this would still not undue our message that there exists a strong relationship between the common information in the term structure of spreads and macroeconomic risk.

[15] While we are aware of an error-in-variables problem as we use estimates of expected consumption growth and volatility in the factor regressions, a simultaneous estimation of the regression coefficients and the risk factors is unlikely to undo our strong results.

[16] 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.

[17] Also Campbell and Taksler (2003) use spread levels as opposed to changes, likewise Benzoni et al. (2012) advocate regressions in levels.

## 2.3 Macroeconomic vs. financial risk

The previous empirical findings highlight the possibility that time-variation in the consumption stream of the marginal investor may be responsible for 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 et al. 2010) or the CBOE S&P500 volatility index (Pan and Singleton 2008 and Longstaff et al. 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 two 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).[18] We then run a horse race with the global macroeconomic risk factors.

The univariate regressions are reported in columns (4) to (15) of Table 5.[19] Only the coefficients for VIX, PE, IG and HY are statistically significant on their own for the first common factor and have economically plausible signs, and none of them displays statistical significance for the second principal component. Moreover, for the first factor regression, the adjusted $R^2$ of the VIX with 55% is significantly smaller than the 75% obtained with the macroeconomic risk factors and the PE, IG and HY have adjusted $R^2$s in the same ballpark region. Most importantly though, for the second factor regression, the maximum adjusted $R^2$ is obtained with the PE of 9% (4% for IG and 2% for HY), compared to 74% for the conditional mean and variance 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 rates and macroeconmic 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.

[18]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

[19]Results using difference regressions are available in section C of the external appendix.

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 remains its statistical significance at the 5% level for the level factor, and at the 10% level for the slope factor, while the consumption risk factors remain highly statistically significant for both. The coefficient on expected growth rates 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 positive sign on the level factor. The power and economic sign for the level factor of this orthogonalized component is on its own interesting, but as it it is not central to our message, we leave it for future research. 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 consumption forecasts and volatility for the slope factor. This corroborates our hypothesis of U.S. macroeconomic fundamentals being a source of common sovereign credit risk.

As a robustness check, we investigated the relationship between macroeconomic and financial risk factors in a VAR specification to test for Granger causality. The unreported results show no evidence that expected consumption growth is driven by financial market volatility. Moreover, results between consumption volatility and the VIX are inconclusive and point to mere correlation.

To close the loop of our analysis, we regress in Table 7 for each country empirical measures of the level, slope and curvature of the CDS term structure on the same macroeconomic and financial risk factors.[20] The level of the term structure at any day $t$ is defined as the average spread over all maturities[21], the slope is the difference between the 10-year and the 1-year spread and the curvature is computed as twice the 5-year spread minus the sum of the 10-year and 1-year CDS spreads. Our previous conclusions hardly change. The power of the VRP fades out once we include the consumption risk factors. At least 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 $R^2$s are high, ranging from 54% for the slope regressions up to 70% for the level regressions. Looking ahead to our model-implied results in population, this

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

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

compares to theoretically implied $R^2$s of 75% and 97%. Moreover, the model predicts a negative and positive coefficient respectively on expected growth and volatility of consumption for the level and curvature regressions, and positive slope estimates on both regressors for the slope regressions. Likewise in the data, most of the coefficients have the predicted sign, and more than half of the regression coefficients for the slope are positive.[22] The same feature is reflected in the positive slope coefficient from the regression of the second principal component on expected consumption growth reported in regressions (2) and (8) of Table 5.

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

To summarize, our results show that global macroeconomic risk contains information unspanned 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 rates and consumption volatility.

# 3 A Macroeconomic Model for Sovereign Credit Default Swaps

Our empirical exercise highlights that expected U.S. consumption growth and macroeconomic uncertainty can account for a large fraction of the co-movement in sovereign CDS spreads. Time-variation in the consumption stream of a marginal investor matters as credit spreads are partly driven by expected returns. 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 utility with generalized disappointment averse preferences to account for downside risk in concave CDS payoff functions, and an embedded reduced-form default process animated by the two state variables of the economy.

[22] 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.

### 3.1 Credit Default Swaps

A CDS is a fixed income derivative instrument, which allows a protection buyer to purchase insurance against a contingent credit event on a Reference Entity by paying an annuity premium to the protection seller, generally referred to as the credit default swap spread. The credit event triggers a payment by the protection seller to the insuree equal to the difference between the notional principal and the mid-market value of the underlying reference obligation, obtained through a dealer poll. Settlement can occur either through physical delivery or a cash exchange. In general, the occurrence of a credit event must be documented by public notice and notified to the investor by the protection buyer. Qualifying credit events for sovereign reference entities are Failure to pay, Obligation default or acceleration, Repudiation or moratorium and Restructuring.[23] Longstaff et al. (2010) point out that Bankruptcy does not figure among the spectrum of credit events for sovereign contracts. This is due to the inexistence of a formal international bankruptcy court for sovereign borrowers. Such an institutional detail is crucial, as it guides our focus on distress risk and leads us to abstract from the "jump-at-default" risk existing in the literature.[24] This form of credit risk is however not less relevant for financial assets, as it guides the daily variation in prices. Moreover, as a government's default decision is mostly strategic, we cannot model an explicit default threshold as in a structural default risk model and choose to embed a reduced-form credit risk model into an equilibrium set up. This differentiates our study from Bhamra et al. (2010), who embed a structural model of credit risk inside a long run risk framework for a *corporate* firm.

To derive the valuation of CDS spreads in closed-form, we discretizate 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.[25] A $K$-period credit default swap thus has $KJ$ trading days. CDSs are priced similar to interest rate swaps, that is net present values of cash flows for both legs (protection buyer and protection seller) must equalize at inception. For a

[23]The legal and institutional details of CDS contracts are defined and governed by the International Swaps and Derivatives Association (ISDA) 2003 Credit Derivatives Definition.

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

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

$K$-period CDS, the protection premium, $\pi_t^{pb}$ to be paid by the protection buyer is equal to

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

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 $\tau$. 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 (3) 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 on the other hand must cover any losses incurred by the protection buyer in case of a credit event. The net present value of the protection seller's leg is thus equal to

$$\pi_t^{ps} = E_t\left[M_{t,\tau}\left(1 - R_\tau\right) I\left(\tau \leq t + KJ\right)\right], \quad (4)$$

where the process $R_\tau$ represents the post-default recovery rate, which can be random and possibly contain claimed accruals from the defaulted reference obligation.

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

$$CDS_t\left(K\right) = \frac{E_t\left[M_{t,\tau}\left(1 - R_\tau\right) I\left(\tau \leq t + KJ\right)\right]}{\sum_{k=1}^{K} E_t\left[M_{t,t+kJ} I\left(\tau > t + kJ\right)\right] + E_t\left[M_{t,\tau}\left(\frac{\tau - t}{J} - \left\lfloor \frac{\tau - t}{J} \right\rfloor\right) I\left(\tau \leq t + KJ\right)\right]}. \quad (5)$$

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

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

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 $t$.[26] The conditional survival probability $S_t$ is defined as

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

where the process hazard rate $h_t \equiv Prob\,(\tau = t \mid \tau \geq t; \mathcal{I}_t)$ denotes the conditional instantaneous default probability of a given reference entity at day $t$. Generally, reduced-form credit risk models assume an exogenous default intensity whose probability law governs the default process. We innovate by defining a hazard rate whose default intensity is determined by its sensitivity to macroeconomic fundamentals. Moreover, $R_t$ defines the recovery rate at date $t$ as a fraction of face value and $L_t = (1 - R_t)$ determines the Loss Given Default (Loss Rate).[27] To derive analytic solutions to the CDS spread, we need to specify dynamics for the stochastic discount factor $M_{t,t+1}$, the default intensity $h_{t+1}$ and the recovery rate $R_{t+1}$. These processes are determined by the two state variables of the economy, which are described more explicitly in the following section.

### 3.2 A Markov-switching model for consumption growth

In section 2, 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 consumption growth and macroeconomic uncertainty. For the purpose of our model, we do however approximate the continous-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 (Garcia et al. 2008, Timmermann 2000). More importantly, without the discrete-state approximation, we are not able to obtain analytical formulas for spreads 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 et al. (2011), we thus assume that both the mean and variance of consumption growth $g_{t+1}$ ($g_{t+1} = \ln G_{t+1}$, where $G_{t+1} = (C_{t+1}/C_t)$ and $C_t$ defines the level of consumption in period $t$.) fluctuate according to a Markov variable $s_t$, which can take a different value in each of the $N$ states of the economy. The stochastic sequence $s_t$ evolves according to a transition probability

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

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

matrix $P$

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

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 $j$th 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 forecast and the volatility of consumption growth respectively. The vectors $\mu_g$ and $\omega_g$ 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 simplicitly and without loss of generality, 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 of the world ($LL$, $LH$, $HL$ and $HH$) if the factors are linearly independent.

### 3.3 Preferences and stochastic discount factor

We study the valuation of CDSs in the context of a representative agent general equilibrium model. As sovereign default insurance is essentially a protection against downside risk, we assume that the representative investor has generalized disappointment aversion (GDA) preferences of Routledge and Zin (2010), which allows for a comparison with the nested symmetric recursive preferences of Epstein and Zin (1989). Such an investor derives utility $V_t$ from consumption recursively

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

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

$$U\left(\mathcal{R}\right) = E\left[U\left(V\right)\right] - \left(\frac{1}{\alpha} - 1\right) E\left[\left(U\left(\kappa\mathcal{R}\right) - U\left(V\right)\right) I\left(V < \kappa\mathcal{R}\right)\right], \tag{11}$$

where $0 < \alpha \leq 1$ and $0 < \kappa \leq 1$. When $\alpha$ is equal to one, the certainty equivalent function $\mathcal{R}$ reduces to the Kreps and Porteus's (Kreps and Porteus 1978, henceforth KP) preferences where the investor cares only about systematic risk, while $V_t$ represents Epstein and Zin (1989) recursive utility. When $\alpha < 1$, the agent values downside risk and the certainty equivalent decreases as outcomes below the threshold $\kappa\mathcal{R}$ receive an additional weight. Thus, $\alpha$ characterizes disappointment aversion, while $\kappa$ reflects the fraction of the certainty equivalent $\mathcal{R}$ below which outcomes become disappointing.[28] Formula (11) emphasizes that state-probabilities are redistributed when disappointment kicks in, the threshold of disappointment being endogenously time-varying.

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

$$M^*_{t,t+1} = \delta \left( \frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left( \frac{V_{t+1}}{\mathcal{R}_t \left( V_{t+1} \right)} \right)^{\frac{1}{\psi} - \gamma} . \tag{12}$$

If $\gamma = 1/\psi$, equation (12) 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 $\mathcal{R}_t \left( V_{t+1} \right)$. For GDA preferences, downside consumption risks enter through an additional term capturing disappointment aversion

$$M_{t,t+1} = M^*_{t,t+1} \left( \frac{1 + (1/\alpha - 1) \, I \left( Z_{t+1} < \kappa \right)}{1 + (1/\alpha - 1) \, \kappa^{1-\gamma} E_t \left[ I \left( Z_{t+1} < \kappa \right) \right]} \right) . \tag{13}$$

Hence, disappointing outcomes obtain relatively higher importance and require higher risk premia.

Based on the dynamics (9) and the recursion (10), we show in Appendix (A) that the stochastic discount factor (13) may be expressed as

$$M_{t,t+1} = \exp \left( \zeta_t^\top A \zeta_{t+1} - \gamma g_{t+1} \right) \left[ 1 + \left( \frac{1}{\alpha} - 1 \right) I \left( g_{t+1} < -\zeta_t^\top B \zeta_{t+1} + \ln \kappa \right) \right] , \tag{14}$$

where the components of the $N \times N$ matrices $A$ and $B$ are described in equation (A.10).

Note that we assume that our representative agent is based in the United States 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

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

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.

### 3.4 Hazard rate and recovery rate

Modeling the instantaneous conditional default probability or hazard rate in discrete time is challenging when the final goal is tractability of closed-form solutions for CDS prices. The range of the hazard rate process must be bounded and take values in the interval $[0, 1]$. In addition, it should be a persistent process such that the default propensity tends to be higher following a high default intensity and vice-versa. Given our intention to link the default process to global macroeconomic risk, we assume that the country-specific hazard rate $h_t^i$ follows a logistic distribution[29]

$$h_t^i = \frac{\lambda_t^i}{1+\lambda_t^i} \quad \text{where} \quad \lambda_t^i = \exp\left(\beta_{\lambda 0}^i + \beta_{\lambda x}^i x_t + \beta_{\lambda\sigma}^i \sigma_t\right), \tag{15}$$

where we subsequently drop the $i$ superscript for ease of readability.[30] 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 consumption growth forecasts and volatility are themselves persistent processes. While the model-specific investor preferences are needed to generate sufficiently large countercyclical risk aversion necessary to match the levels of CDS spreads, a persistent and time-varying default intensity, coupled with a preference for early resolution of uncertainty, is essential to generate a term risk premium.

Economically, we expect $\beta_{\lambda x}$ and $\beta_{\lambda\sigma}$ to be non-positive and non-negative respectively. The default intensity should increase when forecasts of macroeconomic growth are low and/or macroeconomic uncertainty is high. We emphasize that our goal is to show how a simple equilibrium model with only two macroeconomic state variables can rationalize many 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 however remain important for the variation in spread levels.[31] We therefore also derive solutions where the hazard rate contains additional country-specific shocks. While the results improve only marginally, the number of states increases to eight even if we allow

[29]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 robuts to a Weibull-type hazard rate, specified as $h_t = 1 - \exp(-\lambda_t)$ where $\lambda_t = \exp(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda\sigma}\sigma_t)$.

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

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

only for two contingent states of the idiosyncratic Markov chain. This renders the interpretation of the state-dependent results cumbersome. We therefore focus here on the aggregate risk factors only and provide the additional formulas and results in the external appendix.

We fix the dynamics of the recovery rate process at a constant level, consistent with industry standards for CDS pricing. This is also in line with standard assumptions in the CDS pricing literature such as Pan and Singleton (2008) or Longstaff et al. (2010). We leave the analysis of time-varying recovery rates for further research.[32]

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

$$\begin{aligned} Prob_t\left(t<\tau\leq T\mid\tau>t\right) &= 1-\left(\tilde{\Psi}_{T-t}^{\top}\zeta_t\right) \\ Prob\left(t<\tau\leq T\mid\tau>t\right) &= 1-\left(\tilde{\Psi}_{T-t}^{\top}\Pi\right), \end{aligned} \tag{16}$$

where the maturity-dependent vector sequence $\left\{\tilde{\Psi}_j\right\}$ satisfies the recursion (B.3) with initial condition $\tilde{\Psi}_0=e$, and where $\Pi$ denotes the vector of unconditional state probabilities. To complement the historical cumulative default probabilities, we also derive a closed-form solution of the cumulative default rate under the risk-neutral ($\mathbb{Q}$) measure in Appendix (C).

### 3.5 Credit default swap spread

The Markov property of the model is crucial for deriving analytical solutions for CDS spreads and their moments. We develop equation (6) in Appendix (D) to characterize a $K$- period CDS as

$$CDS_t\left(K\right)=\zeta_t^{\top}\lambda_s\left(K\right), \tag{17}$$

where the components of the vectors $\lambda_{1s}\left(K\right)$ are non-linear functions of the consumption dynamics, the default and recovery process and of the recursive utility function. Its components are given by

$$\lambda_{i,s}\left(K\right)=\frac{\sum\limits_{j=1}^{KJ}L\left[\Psi_{i,j}^{*}-\Psi_{i,j}\right]}{\sum\limits_{k=1}^{K}\Psi_{i,kJ}+\sum\limits_{j=1}^{KJ}\left(\frac{j}{J}-\left\lfloor\frac{j}{J}\right\rfloor\right)\left[\Psi_{i,j}^{*}-\Psi_{i,j}\right]}, \tag{18}$$

where $e$ is the vector with all components equal to one, $L$ is the vector of conditional loss rates, and where the sequences $\left\{\Psi_j^{*}\right\}$ and $\left\{\Psi_j\right\}$ are given by the recursion (D.9), with initial conditions (D.8).

[32] We did explore the possibility of deterministic procyclical and state-dependent recovery rates, while keeping the unconditional recovery rate fixed at 25%. Our results are not very sensitive to such a variation.

All unconditional moments of CDS spreads exist in closed form, which is particularly useful for a full estimation of the structural model parameters given the highly non-linear pay-off function.

# 4 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.

## 4.1 Consumption growth dynamics

We calibrate the parameters of the consumption growth dynamics at a monthly frequency as in Bansal et al. (2012) to match observed annual growth rates from 1930 to 2008. The calibrated parameters are quite close to the Kalman Filter estimates obtained in the empirical section. We nevertheless require higher persistence of of macroeconomic growth forecasts and uncertainty. The mean expected consumption growth $\mu_x$ is 0.0015 with a sensitivity to long-run risk shocks $\nu_x$ set to 0.038. These shocks are persistent with a value $\phi_x$ equal to 0.975. Consumption volatility has a mean $\sqrt{\mu_\sigma}$ of 0.0072, a persistence $\phi_\sigma$ of 0.999 and a sensitivity to shocks $\nu_\sigma$ of $2.80 \times 10^{-6}$. 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 also Table 8).

The mapping from the continuous daily endowment process into a discrete Markov-switching model follows the procedure described in Garcia et al. (2008). 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.

## 4.2 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 23 parameters, i.e. 5 preference parameters and 3 default parameters for each of the 6 rating groups.[33] 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 et al. (2010).

Estimation results with Newey-West standard errors are reported in Table 9. We fix the 1-period subjective discount factor $\delta$ at a monthly frequency at 0.9989 and estimate all other preference parameters. All coefficients turn out to be statistically significant at the 1% significance level. Using spread levels (changes) for the estimation, we obtain a coefficient of relative risk aversion $\gamma$ of 4.9081 (5.0614) and an elasticity of intertemporal substitution (EIS) $\psi$ equal to 1.4874 (1.2473). The CDS market thus implies values consistent with preference for early resolution of uncertainty. The parameter of disappointment aversion $\alpha$ 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%).[34] The parameter $\kappa$, 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. The high-frequency information in CDS spreads provides additional support for a value of EIS above 1 and preference for early resolution of uncertainty.

Regarding the default parameters, all signs of the coefficients are consistent with economic

[33] A detailed description of the estimation steps is provided in Appendix E.

[34] A value of $\alpha$ equal to 0.25 maps into a loss aversion parameter $\ell = (1/\alpha - 1)$ of 3, a well accepted measure in the literature for loss aversion.

intuition.[35] A rise in expected consumption growth lowers the marginal propensity to default. Moreover, in times of high macroeconomic uncertainty, sovereign debt becomes riskier and the likelihood of default increases. Thus, asset markets dislike macroeconomic uncertainty (Bansal et al. 2005). Also, the average default intensity is inversely related to credit-worthiness, that is the constant coefficient $\beta_{\lambda 0}$ increases from negative 15.44 to negative 9.21 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.

# 5 Asset pricing implications and discussion

We start by studying the model implications for unconditional CDS moments and default probabilities and then move on to asset pricing results for the conditional CDS term structure. A more detailed analysis of the model structure follows in the subsequent sections.

## 5.1 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)

$$RMSE = \sqrt{\frac{1}{K}\sum_{j=1}^{K}(\hat{x}_j - x_j)^2}, \tag{19}$$

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

[35] For the estimation results using spread changes, we have limited the reporting to the estimated preference parameters. Full estimation results are available upon request.

and Korea reported by Pan and Singleton (2008).[36] RMSEs for the term structure of spreads are approximately 1 basis point for investment grade reference entities, and range from 2 to 10 basis points for high-yield categories. To give an example, for single A rated countries, the one-year (ten-year) spread is 35 (72) 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 10 basis points for high-yield countries. Only for the B group, the RMSE is 28 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. This result arises mainly because of the kink in utility around the disappointment threshold, which leads to higher kurtosis at the short end of the term structure.

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.

## 5.2 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.[37] Inspection of these numbers warrants several explanations at the outset of our discussion. Both physical and risk-neutral default probabilities are unobserved

[36] 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.

[37] We also benchmarked the results against the cumulative default rates reported by Moody's. The RMSEs are very similar and the tables are available from the authors upon request.

and a proper comparison is thus close to impossible. In particular, no country rated A or higher has defaulted within the last 40 years.[38] 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 0.86% and 9.82% for BBB and B rated countries respectively. The cumulative default probabilities line up in the cross-section, with the default probability at the 5-year horizon ranging from 0.70% to 21.40% for the AAA and B rated entities. Moreover, cumulative default probabilities rise with the asset horizon, which is consistent with increasing cumulative default probabilities over time. Results are slightly better at longer horizons than at short horizons. It is also interesting to compare metrics under the physical and risk-neutral measure. The ratios of risk-neutral to physical default probabilities, also called risk-adjustments in the literature, are monotonically increasing with maturity, reflecting the term premium required by investors who offer credit risk insurance by selling CDS contracts. 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 physcial probabilities range between 1.15 and 5.06, while the average is 2.72.

We compare these results with some of the metrics reported in the literature on corporate CDS. Berndt et al. (2007) find strongly time-varying ratios of implied risk neutral default probabilities to Moody's KMV Expected Default Frequencies (EDF) in three sectors, Broadcasting&Entertainment, Healthcare and Oil&Gas. Their conditional ratios range on average between 1 and 3 for short horizons, but go as high up as 10 in 2002. Similarly, Driessen (2005) reported an average ratio of risk-neutral to actual default intensities of 1.89 using corporate bonds over the time period 1991 to 2000. Huang and Huang (2003) find ratios between 1.11 and 1.75. Our implied risk-adjustments are thus qualitatively close to existing estimates from the corporate credit risk literature.

[38] While no A rated country had an outright default, it may be argued that countries are downgraded prior to default, which could be characterized through an approach based on rating migrations. As we have previously noted, we pursue this different approach in a companion paper.

### 5.3 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 4, 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.[39] Note that the slope of the term structure inverts in times of low macroeconomic forecasts and high macroeconomic uncertainty. Thus, an investor who cares about downside risk becomes much more risk averse in bad economic times and requires a significant increase in 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 prices 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 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. 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 (dashed line) and the average slope across reversal dates is 195 basis points. This is close to the inverted spread curve of 169 basis points generated by the model in the worst state. In addition, Portugal (solid line), 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 close to the conditionally inverted slope of 47 basis points. Moreover, the highest (mean) slope reversal for Spain (dotted line), which was downgraded to AA+ in 2010, was 56 (29) basis points, which again matches the model result of a negative slope of 26 basis points quite closely. Although the slope of Italy (dash-dotted line) didn't decrease as much during our sample period, it continued to decrease as the sovereign debt crisis intensified. In sum, the conditional moments of our model quantitatively match the magnitude of the slope reversal of distressed sovereign borrowers in states of bad macroeconomic fundamentals.

Furthermore, the level of CDS spreads in states of low expected consumption growth and high macroeconomic uncertainty reflects the tail risk embedded in CDS spreads, which are by nature a protection against downside risk and should reflect the asymmetric nature of credit markets. Consider for instance the 1-year contract for the BBB rating category. Although the mean CDS

[39]We report graphs for the rating categories AA, A and B, but results are similar for all the rating categories.

spread is 83 basis points, there is a huge price discrepancy between 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 macroeconomic forecasts and uncertainty. Taking into account that the unconditional probability of being in the worst state is low (2.3%), this discrepancy of spreads among regimes explicitly reflects the embedded nature of tail risk, which confirms the "picking up pennies in front of a steamroller" interpretation during the financial crisis, where the selling of credit protection was perceived as piling up significant quantities of tail risk in compensation for small, but consistent returns. Conceptually, this result resembles also 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.

### 5.4 An analysis of the hazard rate

To provide further intuition about how the effects of the systematic risk factors on the term structure, we plot in Figure 5 the results of our benchmark model against different specifications of the hazard process from equation 15. 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 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 business cycle 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 et al. (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.

### 5.5 Discussion

Our results suggest that U.S. expected consumption growth and consumption volatility are major drivers of the common variation in sovereign CDS spreads and that a two-factor model does a good job in fitting the sample estimates. Expected consumption growth and macroeconomic uncertainty feed both into the pricing kernel and the default process and, coupled with preference for early resolution of uncertainty, generate time-varying risk and term premia. While there has been previous evidence that sovereign credit markets are priced globally rather than locally, we emphasize the global macroeconomic channel as a primary source of risk. This is consistent with for example Pan and Singleton (2008) and Longstaff et al. (2010) among others, who identify a strong link between the co-movement of CDS spreads and the VIX and argue that their evidence is "consistent with premium for credit risk in sovereign markets being influenced by spillovers of real economic growth in the United States to economic growth in other regions of the world". In contrast to the previous authors, we explore the link between the total spread and U.S. consumption data, while these papers decompose the spread into an expected loss and a risk premium component.

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

To conclude, we highlight that our estimated preference parameters based on sovereign CDS spreads remain consistent with the stock market, as we generate 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). We thus 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.[40]

## 5.6 A benchmark comparison

We compare our benchmark scenario with a downside risk averse investor against that of a risk averse investor without disappointment aversion and a Kreps-Porteus (KP) certainty equivalent as in the long-run risk economy of Bansal and Yaron (2004). The comparison is straightforward as the KP scenario is nested by shutting down disappointment aversion with a value of $\alpha$ equal to 1. As shown in Table 9, although the model is not rejected, the $J-Test$ statistic is less satisfactory with

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

a value of 45.73. More importantly, a likelihood ratio test rejects the model against the alternative with generalized disappointment averse preferences.[41] Fixing the subjective discount factor again at 0.9989, we estimate a coefficient of relative risk aversion of 8.2692 (7.1713) using spread levels (changes). This is significantly less than the value of 20.90 estimated in Bansal and Shaliastovich (2012). The elasticity of intertemporal substitution is 1.5774 (1.5953), still implying preference for early resolution of uncertainty.

Unconditional results for the CDS term structure are reported in Table 12. A first observation is that the KP scenario manages to match the unconditional moments of the CDS term structure quite well. The model performs slightly less well for the mean term structure, with RMSEs ranging between 0.97 and 27.20 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 less kurtosis at the short end of the curve for the asset distributions. Staring at these unconditional results, the reader may wonder why the downside risk battery is necessary.

Glancing at the conditional moments for the term structure in Figure 6 on the other hand illustrates, that the symmetric recursive preferences fail to account for a reversal of the term structure in states of low expected consumption growth and high macroeconomic uncertainty, which is observed in the data. An investor, who only cares about systematic risk, does jack up the price of credit protection in "bad" regimes, but the mean reversion is marginal, and the term structure is close to flat. For instance, for a AAA rated country, the 1-year CDS spread in the "low-high" state is 122 basis points, vs. 113 basis points at the long end of the curve. Although the effect becomes stronger for lower-rated countries, a maximum negative slope of 92 basis points for BB rated countries is insufficient to reproduce the magnitudes of slope reversals for distressed economies during the sovereign debt crisis. The magnitude of the slope reversal in the bad state is consistently about half the value obtained with asymmetric preferences. We thus find that both the KP and the GDA economies manage to match the unconditional moments of the CDS term structure quite 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.

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

# 6 Conclusion

This paper provides new empirical evidence that global macroeconomic shocks may bear some responsibility for the strong co-movement in sovereign credit spreads in a large panel of 38 emerging and developed countries. We show that expected growth rates 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 with generalized disappointment averse preferences. The two state variables of the economy, time-varying expected growth rates 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. Strong 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. Sensitivity to downside risk is needed to match 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 all preference parameters of the model. The evidence is consistent with preference for early resolution of uncertainty.

Our results emphasize the global macroeconomic risk channel as a source of common variation in the levels of sovereign spreads, beyond the well-documented financial risk channel. We find it useful to pursue this route in future ressearch to understand the dynamics of the term structure.

# References

Acharya, V. V. and Johnson, T. C. (2007). Insider trading in credit derivatives, *Journal of Financial Economics* **84**(1): 110–141.

Ang, A. and Longstaff, F. A. (2011). Systemic sovereign credit risk: Lessons from the u.s. and europe, *Working Paper 16982*, National Bureau of Economic Research.

Backus, D. K., Kehoe, P. J. and Kydland, F. E. (1992). International real business cycles, *The Journal of Political Economy* **100**(4): pp. 745–775.

Baek, I.-M., Bandopadhyaya, A. and Du, C. (2005). Determinants of market-assessed sovereign risk: Economic fundamentals or market risk appetite?, *Journal of International Money and Finance* **24**(4): 533 – 548.

Bansal, R., Khatchatrian, V. and Yaron, A. (2005). Interpretable asset markets?, *European Economic Review* **49**(3): 531 – 560.

Bansal, R., Kiku, D. and Yaron, A. (2012). An empirical evaluation of the long-run risks model for asset prices, *Critical Finance Review* **1**: 183–221.

Bansal, R. and Shaliastovich, I. (2012). A long-run risks explanation of predictability puzzles in bond and currency markets, *Review of Financial Studies* .

Bansal, R. and Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles, *The Journal of Finance* **59**(4): 1481–1509.

Benzoni, L., Collin-Dufresne, P., Goldstein, R. S. and Helwege, J. (2012). Modeling credit contagion via the updating of fragile beliefs, *Working Paper 2012-04 Federal Reserve Bank of Chicago* .

Berndt, A., Jarrow, R. A. and Kang, C. (2007). Restructuring risk in credit default swaps: An empirical analysis, *Stochastic Processes and their Applications* **117**(11): 1724–1749.

Berndt, A. and Obreja, I. (2010). Decomposing european cds returns, *Review of Finance* **14, 2**: 189–233.

Bhamra, H. S., Kuehn, L.-A. and Strebulaev, I. A. (2010). The levered equity risk premium and credit spreads: A unified framework, *Review of Financial Studies* **23**(2): 645–703.

Bonomo, M., Garcia, R., Meddahi, N. and Tédongap, R. (2011). Generalized disappointment aversion, long-run volatility risk, and asset prices, *Review of Financial Studies* **24**(1): 82–122.

Borri, N. and Verdelhan, A. (2009). Sovereign risk premia, *SSRN eLibrary* .

Campbell, J. Y. and Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior, *The Journal of Political Economy* **107**(2): pp. 205–251.

Campbell, J. Y. and Taksler, G. B. (2003). Equity volatility and corporate bond yields, *The Journal of Finance* **58**(6): pp. 2321–2349.

Chen, L., Collin-Dufresne, P. and Goldstein, R. S. (2009). On the relation between the credit spread puzzle and the equity premium puzzle, *The Review of Financial Studies* **22**(9): 3367–3409.

Doshi, H., Ericsson, J., Jacobs, K. and Turnbull, S. M. (2013). Pricing credit default swaps with observable covariates, *Review of Financial Studies* **26**(8): 2049–2094.

Driessen, J. (2005). Is default event risk priced in corporate bonds?, *The Review of Financial Studies* **18**(1): pp. 165–195.

Duffie, D. (1999). Credit swap valuation, *Financial Analysts Journal* **55**(1): 73–87.

Epstein, L. G. and Zin, S. E. (1989). Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* **57**(4): 937–969.

Garcia, R., Meddahi, N. and Tédongap, R. (2008). An analytical framework for assessing asset pricing models and predictability, *SSRN eLibrary* .

Geyer, A., Kossmeier, S. and Pichler, S. (2004). Measuring systematic risk in emu government yield spreads, *Review of Finance* **8**(2): 171–197.

González-Rozada, M. and Yeyati, E. L. (2008). Global factors and emerging market spreads*, *The Economic Journal* **118**(533): 1917–1936.

Hamilton, J. D. (1994). *Time Series Analysis*, Princeton University Press, New Jersey.

Hansen, L. P., Heaton, J. C. and Li, N. (2008). Consumption strikes back? measuring long-run risk, *The Journal of Political Economy* **116**(2): pp. 260–302.

Huang, J.-Z. J. and Huang, M. (2003). How much of corporate-treasury yield spread is due to credit risk?: A new calibration approach, *SSRN eLibrary* .

Kreps, D. M. and Porteus, E. L. (1978). Temporal resolution of uncertainty and dynamic choice theory, *Econometrica* **46**(1): pp. 185–200.

Longstaff, F. A., Pan, J., Pedersen, L. H. and Singleton, K. J. (2010). How sovereign is sovereign credit risk?, *American Economic Journal: Macroeconomics* (13658).

Pan, J. and Singleton, K. J. (2008). Default and recovery implicit in the term structure of sovereign cds spreads, *The Journal of Finance* **63**(5): 2345–2384.

Reinhart, C. M. and Rogoff, K. S. (2008). This time is different: A panoramic view of eight centuries of financial crises, *NBER Working Papers 13882*, National Bureau of Economic Research, Inc.

Reinhart, C. M. and Rogoff, K. S. (2011). From financial crash to debt crisis., *American Economic Review* **101**(5): 1676 – 1706.

Remolona, E., Scatigna, M. and Wu, E. (2008). The dynamic pricing of sovereign risk in emerging markets: Fundamentals and risk aversion, *Journal of Fixed Income* **17**(4): 57 – 71.

Routledge, B. R. and Zin, S. E. (2010). Generalized disappointment aversion and asset prices., *Journal of Finance* **65**(4): 1303 – 1332.

Timmermann, A. (2000). Moments of markov switching models, *Journal of Econometrics* **96**(1): 75 – 111.

Uribe, M. and Yue, V. Z. (2006). Country spreads and emerging countries: Who drives whom?, *Journal of International Economics* **69**(1): 6 – 36. Emerging Markets - Emerging Markets and macroeconomic volatility: Lessons from a decade of financial debacles a symposium for the Journal of International Economics.

Wang, H., Zhou, H. and Zhou, Y. (2010). Credit default swap spreads and variance risk premia, *SSRN eLibrary* .

Weigel, D. D. and Gemmill, G. (2006). What drives credit risk in emerging markets? the roles of country fundamentals and market co-movements, *Journal of International Money and Finance* **25**(3): 476 – 502. Emerging Markets Finance.

# A Asset Prices and the Stochastic Discount Factor

The Markov chain $s_t$ or $\zeta_t$ is stationary with ergodic distribution and moments given by

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

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

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

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

Solving these ratios amounts to characterizing the vectors $\lambda_z$, $\lambda_v$, $\lambda_c$ and $\lambda_{1f}$ as functions of the parameters of the consumption dynamics and of the recursive utility function defined above. We here provide expressions for these ratios and refer to Bonomo et al. (2011) for formal proofs.

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

$$\frac{\mathcal{R}_t\left(V_{t+1}\right)}{C_t} = \lambda_z^\top \zeta_t \text{ and } \frac{V_t}{C_t} = \lambda_v^\top \zeta_t$$

*respectively the ratio of the certainty equivalent of future lifetime utility to current consumption and the ratio of lifetime utility to consumption. The components of the vectors $\lambda_z$ and $\lambda_v$ are given by*

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

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

*where the components of the matrix $P^{*\top} = \left[p_{ij}^*\right]_{1\leq i,j\leq N}$ in (A.3) and (A.4) are given by*

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

*where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution function and where the expression for the components $q_{ij}$ is given in equation (A.11).*

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

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

*the price-consumption ratio and the risk-free rate. The components of the vectors $\lambda_c$ and $\lambda_{1f}$ are given by*

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

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

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

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

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

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

**Proposition A.3** ***Characterization of the Stochastic Discount Factor.*** *Based on the dynamics (9) and using the Euler condition for the claim to aggregate consumption, it can be shown that the stochastic discount factor (13) may be expressed as follows:*

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

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

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

*respectively, and where*

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

*Observe that the vectors $\lambda_z$ and $\lambda_v$ characterize the welfare valuation ratios, for which explicit expressions are provided in equations (A.3) and (A.4).*

# B Cumulative Default Probabilities

The time $t$ probability of defaulting between time $t+1$ and $T$ conditional on not having defaulted prior to $t+1$, formally $Prob_t\,(t < \tau \leq T \mid \tau > t)$, is given by

$$Prob_t\,(t < \tau \leq T \mid \tau > t) = \frac{Prob_t\,(t < \tau \leq T)}{Prob_t\,(\tau > t)} = 1 - E_t\left[\frac{S_T}{S_t}\right]. \tag{B.1}$$

Given the conjecture

$$E_t\left[\frac{S_{t+j}}{S_t}\right] = \tilde{\Psi}_j^\top \zeta_t, \tag{B.2}$$

it can be shown that the solution sequence $\left\{\tilde{\Psi}_j\right\}$ satisfies the recursion

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

with the initial condition $\tilde{\Psi}_0 = e$, and it follows that

$$\tilde{\Psi}_j = P^\top \left(\tilde{\Psi}_{j-1} \odot \frac{1}{1+\lambda}\right). \tag{B.4}$$

The conditional and unconditional cumulative default probabilities are thus given by

$$Prob_t\,(t < \tau \leq T \mid \tau > t) = 1 - \left(\tilde{\Psi}_{T-t}^\top \zeta_t\right) \quad \text{and} \quad Prob\,(t < \tau \leq T \mid \tau > t) = 1 - \left(\tilde{\Psi}_{T-t}^\top \Pi\right), \tag{B.5}$$

where the latter simplifies in case of a constant default process to

$$Prob\,(t < \tau \leq T \mid \tau > t) = 1 - \exp\left(-\lambda\,(T-t)\right) \quad \text{where} \quad \lambda = \exp\left(\beta_{\lambda 0}\right). \tag{B.6}$$

# C Risk-Neutral Cumulative Default Probabilities

We denote probabilities taken under the risk-neutral measure with the $\mathbb{Q}$ subscript. The $T$-year conditional cumulative default probability under the risk-neutral measure is defined by

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

and can be rewritten as

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

Given the conjecture

$$E_t\left[Z_{t,t+j}\frac{S_{t+j}}{S_t}\right] = \left(\tilde{\Psi}_j^{\mathbb{Q}}\right)^\top \zeta_t, \tag{C.1}$$

it turns out the sequence $\left\{\tilde{\Psi}_j^{\mathbb{Q}}\right\}$ satisfies the recursion

$$\left(\tilde{\Psi}_j^{\mathbb{Q}}\right)^\top \zeta_t = E_t\left[Z_{t,t+1}\left(1-h_{t+1}\right)\left(\left(\tilde{\Psi}_{j-1}^{\mathbb{Q}}\right)^\top \zeta_{t+1}\right)\right] \tag{C.2}$$

with the initial condition $\tilde{\Psi}_0^{\mathbb{Q}} = e$, and it follows that

$$\tilde{\Psi}_j^{\mathbb{Q}} = \text{ diagonal of } \left(\tilde{M} \odot \left(\lambda_{2f}\left(\left(\tilde{\Psi}_{j-1}^{\mathbb{Q}}\right) \odot \frac{1}{1+\lambda}\right)^\top\right)\right) P. \tag{C.3}$$

Thus the $(T-t)$-year horizon conditional and unconditional cumulative default probability are

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

# D Credit Default Swap Spreads

**Lemma D.1** *Let $\Phi_\rho(\cdot,\cdot)$ be the bivariate normal cumulative distribution function with correlation parameter $\rho$. Then, if*

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

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

Recall that the hazard rate $h_t$ and the associated default intensity $\lambda_t$ are given by

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

and that the loss rate $L_t$ is constant over time. Dividing both the numerator and the denonimator of the expression in equation (6) by $S_t$, computing the CDS spread is equivalent to deriving the individual expressions

$$E_t\left[M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] \quad \text{and} \quad E_t\left[M_{t,t+j}\frac{S_{t+j}}{S_t}\right]. \tag{D.2}$$

To compute these expressions, we conjecture that

$$E_t\left[M_{t,t+j}\frac{S_{t+j-1}}{S_t}\right] = \left(\Psi_j^*\right)^\top \zeta_t \quad \text{and} \quad E_t\left[M_{t,t+j}\frac{S_{t+j}}{S_t}\right] = \left(\Psi_j\right)^\top \zeta_t. \tag{D.3}$$

Given our conjecture, both sequences $\left\{\Psi_j^*\right\}$ and $\{\Psi_j\}$ satisfy the same recursion

$$\begin{aligned}\left(\Psi_j^*\right)^\top \zeta_t &= E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\left(\left(\Psi_{j-1}^*\right)^\top \zeta_{t+1}\right)\right] \\ \left(\Psi_j\right)^\top \zeta_t &= E_t\left[M_{t,t+1}\left(1-h_{t+1}\right)\left(\left(\Psi_{j-1}\right)^\top \zeta_{t+1}\right)\right]\end{aligned} \tag{D.4}$$

but with different initial conditions given by

$$\left(\Psi_1^*\right)^\top \zeta_t = E_t\left[M_{t,t+1}\right] \quad \text{and} \quad \left(\Psi_0\right)^\top \zeta_t = 1. \tag{D.5}$$

Using Lemma D.1, it can be shown that

$$E_t\left[M_{t,t+1} \mid \zeta_m, m \in \mathbb{Z}\right] = \zeta_t^\top \tilde{M} \zeta_{t+1}, \tag{D.6}$$

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

$$\tilde{m}_{ij} = \exp\left(a_{ij} - \gamma\mu_{g,i} + \frac{1}{2}\gamma^2\omega_{g,i}\right)\left[1 + \left(\frac{1}{\alpha} - 1\right)\Phi\left(q_{ij} + \gamma\sqrt{\omega_{g,i}}\right)\right]. \tag{D.7}$$

It follows that the initial conditions in D.5 are determined by

$$\Psi_1^* = \lambda_{1f} \quad \text{and} \quad \Psi_0 = e, \tag{D.8}$$

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

The solution for the recursion (D.4) satisfied by the solution sequences $\left\{\Psi_j^*\right\}$ and $\{\Psi_j\}$ is

$$\begin{aligned}\Psi_j^* &= \text{ diagonal of } \left(\tilde{M} \odot \left(e\left(\Psi_{j-1}^* \odot \frac{1}{1+\lambda}\right)^\top\right)\right) P \\ \Psi_j &= \text{ diagonal of } \left(\tilde{M} \odot \left(e\left(\Psi_{j-1} \odot \frac{1}{1+\lambda}\right)^\top\right)\right) P.\end{aligned} \tag{D.9}$$

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

$$CDS_t\left(K\right) = \lambda_s\left(K\right)^\top \zeta_t \tag{D.10}$$

*The components of the vectors $\lambda_s(K)$ are functions of the consumption dynamics and of the recursive utility function defined above, and its components are given by*

$$\lambda_{i,s}\left(K\right) = \frac{\sum_{j=1}^{KJ} L\left[\Psi_{i,j}^* - \Psi_{i,j}\right]}{\sum_{k=1}^{K} \Psi_{i,kJ} + \sum_{j=1}^{KJ}\left(\frac{j}{J} - \left\lfloor\frac{j}{J}\right\rfloor\right)\left[\Psi_{i,j}^* - \Psi_{i,j}\right]}, \tag{D.11}$$

*where $e$ is the vector with all components equal to one, $L$ the vector of conditional loss rates, and where the sequences $\left\{\Psi_j^*\right\}$ and $\{\Psi_j\}$ are given by the recursion (D.9), with initial conditions (D.8).*

## E Estimation Procedure

We obtain analytical moments of the form

$$\mu_{CDS^j}(K,n) = E\left[\left(CDS_t^j(K)\right)^n\right],$$

$n \in \{1,2\}$, $K \in \{1Y, 2Y, 3Y, 5Y, 7Y, 10Y\}$, $j \in \{AAA, AA, A, BBB, BB, B\}$. All moments are functions of the parameter vector $\theta$, which contains the preference parameters and the default parameters of the six rating groups. We thus have 72 moments to estimate 23 parameters. Let

$$g_t(\theta) = \left[\left(CDS_t^j(K)\right)^n - \mu_{CDS^j}(K,n)\right]_{j,K,n}$$

denote the $72 \times 1$ vectors of the chosen moments. We have $E[g_t(\theta)] = 0$ and we define the sample counterpart of this moment condition as

$$\widehat{g}(\theta) = \widehat{E}\left[\left[\left(CDS_t^j(K)\right)^n - \mu_{CDS^j}(K,n)\right]_{j,K,n}\right]. \tag{E.1}$$

Given the $72 \times 72$ matrix $\widehat{W}$ used to weight the moments, the GMM estimator $\widehat{\theta}$ of the parameter vector is given by

$$\widehat{\theta} = \arg\min_{\theta} \; T\left(\widehat{g}(\theta)^\top \widehat{W} \widehat{g}(\theta)\right), \tag{E.2}$$

where $T$ is the sample size. The heteroskedasticity and autocorrelation (HAC) estimator of the variance-covariance matrix of $g_t(\theta)$ is simply that of the variance-covariance matrix of

$$\left[\left(CDS_t^j(K)\right)^n\right]_{j,K,n},$$

which does not depend on the vector of parameters $\theta$. This is an advantage, since with a nonparametric empirical variance-covariance matrix of moment conditions, the optimal GMM procedure can be implemented in one step. It is important to note that two different preference models can be estimated via the same moment conditions and weighting matrix. Only the model-implied moments

$$\left[\mu_{CDS^j}(K,n)\right]_{j,K,n}$$

differ from one preference model to another in this estimation procedure. In this case, the minimum value of the GMM objective function itself is a criterion for comparison of the alternative preference models, since it represents the distance between the model-implied and actual moments. Moments are weighted using the inverse of the diagonal of their long-run variance-covariance matrix

$$\widehat{W} = \left\{Diag\left(\widehat{Var}[g_t]\right)\right\}^{-1}.$$

This matrix is nonparametric and puts more weight on moments with low magnitude. If the number of moments to match is large, as in our case, then inverting the long-run variance-covariance matrix of moments will be numerically unstable. Using the inverse of the diagonal instead of the inverse of the long-run variance-covariance matrix itself allows for numerical stability if the number of moments to match is large, as inverting a diagonal matrix is equivalent to taking the diagonal of the inverse of its diagonal elements. The distance to minimize reduces to

$$\sum_j \sum_K \sum_n \left( \frac{\widehat{E}\left[\left(CDS_t^j\left(K\right)\right)^n\right] - E\left[\left(CDS_t^j\left(K\right)\right)^n\right]}{\widehat{\sigma}\left[\left(CDS_t^j\left(K\right)\right)^n\right]/\sqrt{T}} \right)^2, \tag{E.3}$$

where observed moments are denoted with a hat and the model-implied theoretical moment without.

Figure 1: U.S. Consumption Growth, NBER Recessions and Sovereign Crises

This graph plots annual real per capita consumption growth in the United States (solid blue line, left axis) against the crisis tally indicator (dash-dotted black line, right axis) of Reinhart and Rogoff (2011) over the time period 1929 to 2010. The grey shaded areas indicate NBER recessions. 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. Source: Bureau of Economic Analysis and the website of Carmen Reinhart (http://www.carmenreinhart.com/).

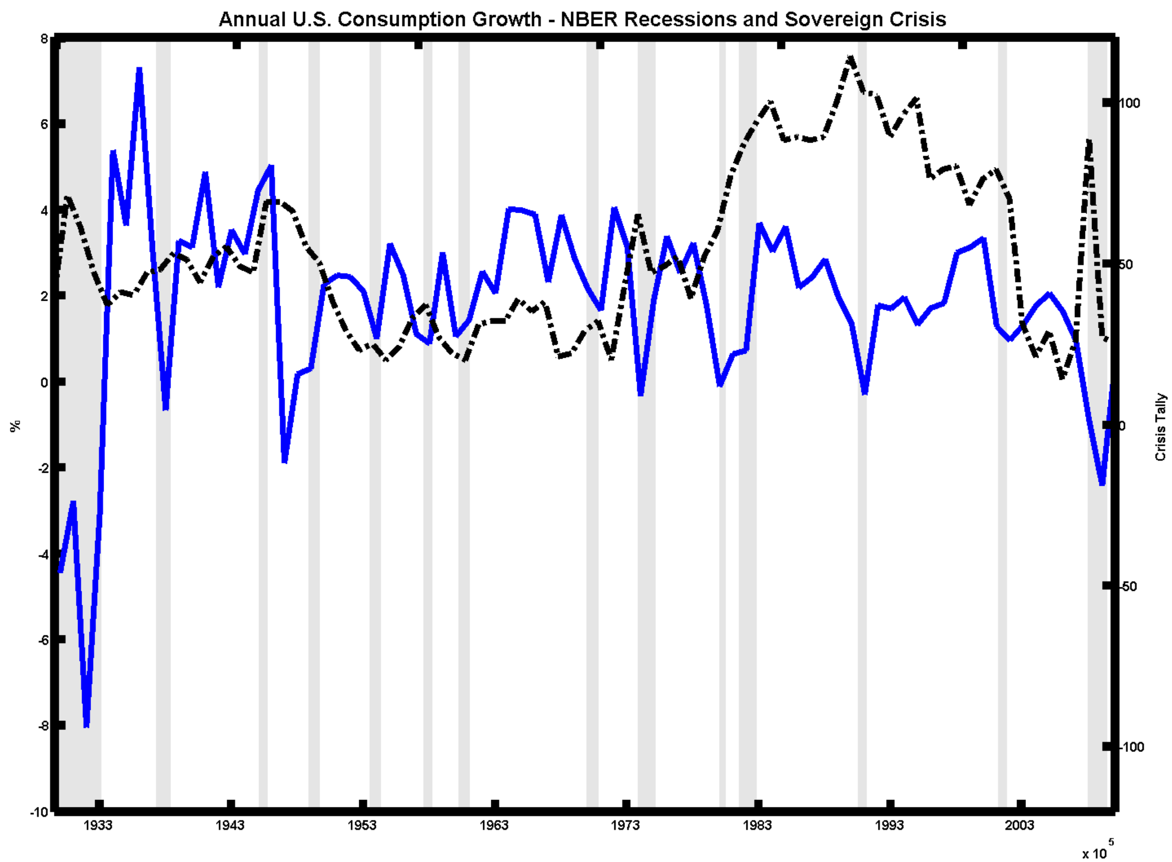


Figure 2: Principal Component Analysis - Factor Loadings

Each bar in the first (second, third) panel represents the equally-weighted average factor loading across the 38 countries in the sample and by CDS contract maturity on the first (second, third) principal component extracted from a principal component on the spread levels from May 2003 until August 2010. Source: Markit

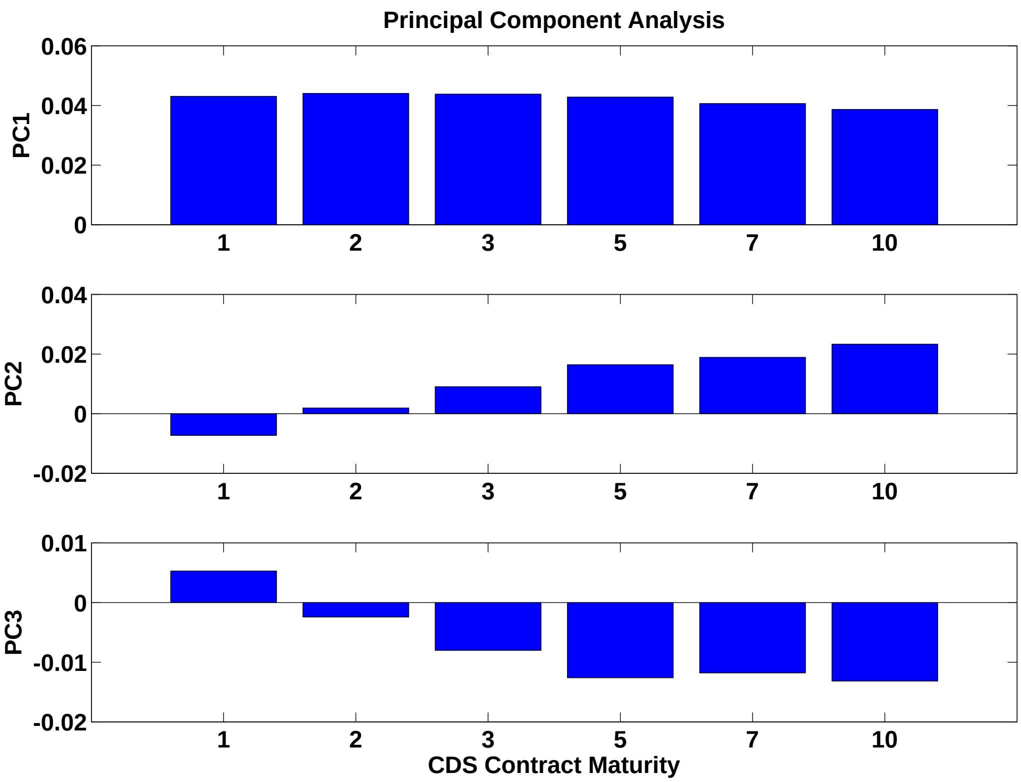
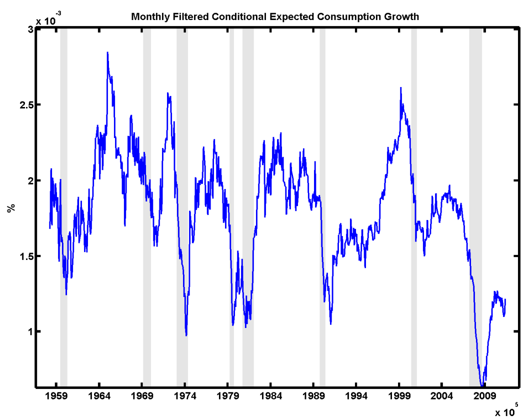


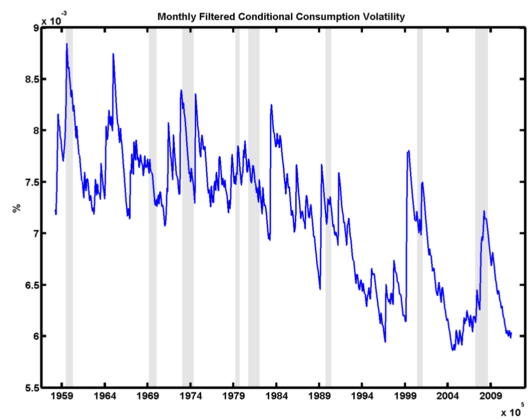
Figure 3: Expected Consumption Growth and Consumption Volatility vs. 5-year Mean CDS Spread

Graph (3a) plots the entire estimated series of monthly filtered conditional expected consumption growth from 1959 to 2010 and figure (3b) traces the entire estimated series of conditional expected consumption volatility. Both series are annulaized for illustration. Grey shaded areas indicate NBER recessions. Graph (3c) 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 (3d) 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 traditonal Kalman Filter as described in equation (1). The CDS data are obtained from Markit.

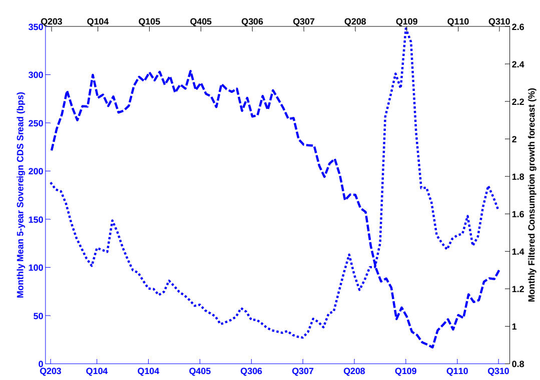
(a)




(b)




(c)




(d)

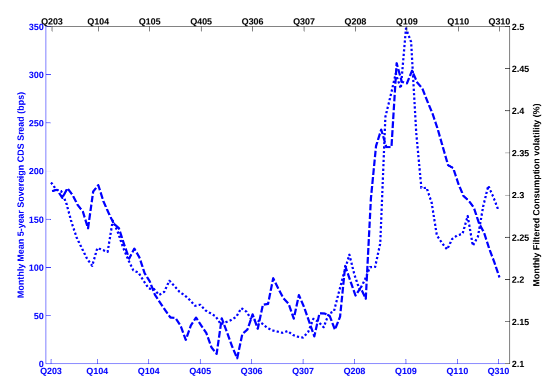


Figure 4: Reversal of the CDS Term Structure

This figure 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 for a time-varying hazard rate process defined as:

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

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 Generalized Disappointment Aversion. The conditional states are defined by the combinations of low ($\mu^L$, $\sigma^L$) and high ($\mu^H$, $\sigma^H$) expected consumption growth and volatility. The dots reflect the unconditional mean.

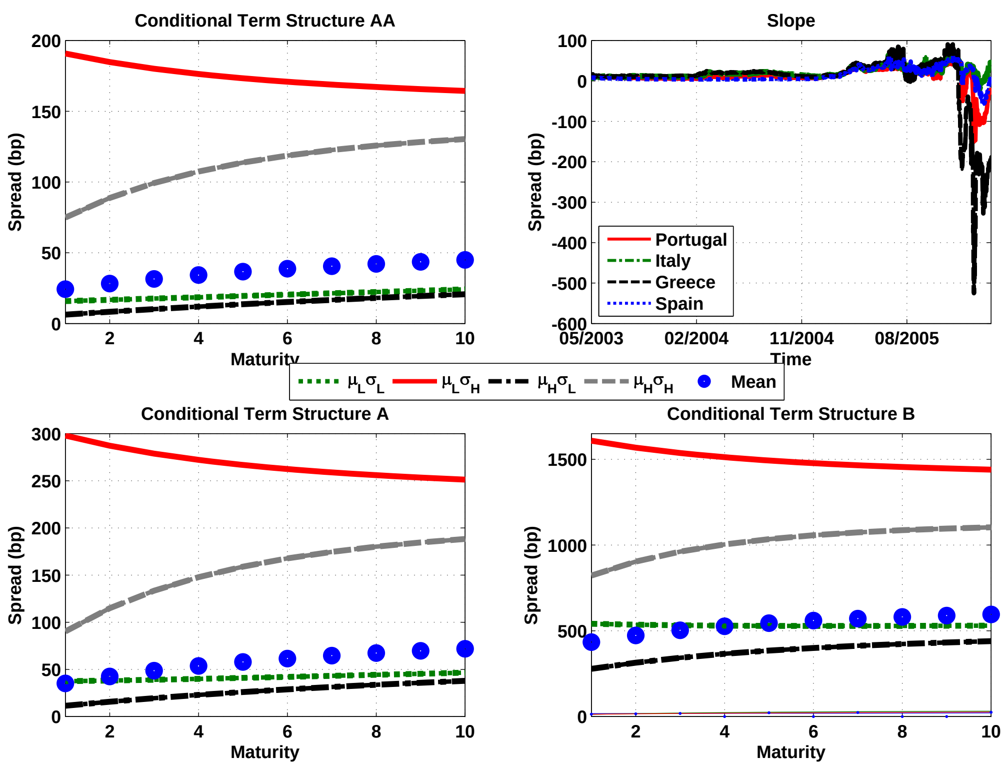


Figure 5: Hazard Rate Analysis: Downside Risk Aversion

This figure 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 process defined as

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

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 Generalized Disappointment Aversion.

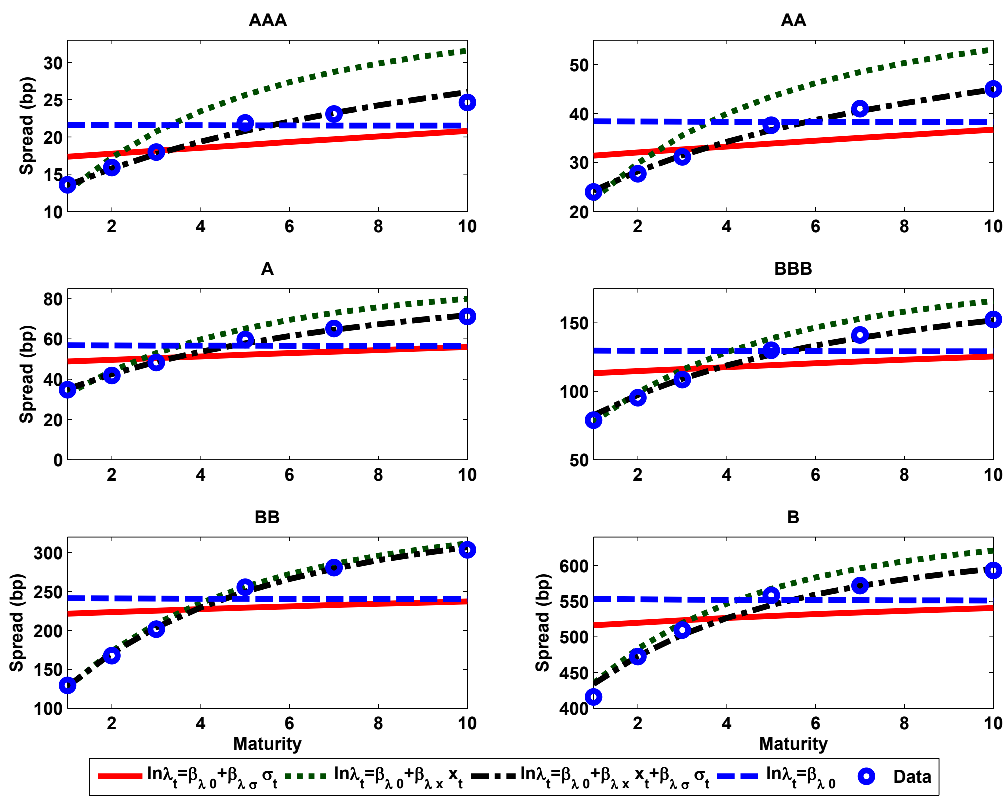


Figure 6: Term Structure Analysis: No Downside Risk Aversion

This figure 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-B for a time-varying hazard rate process defined as:

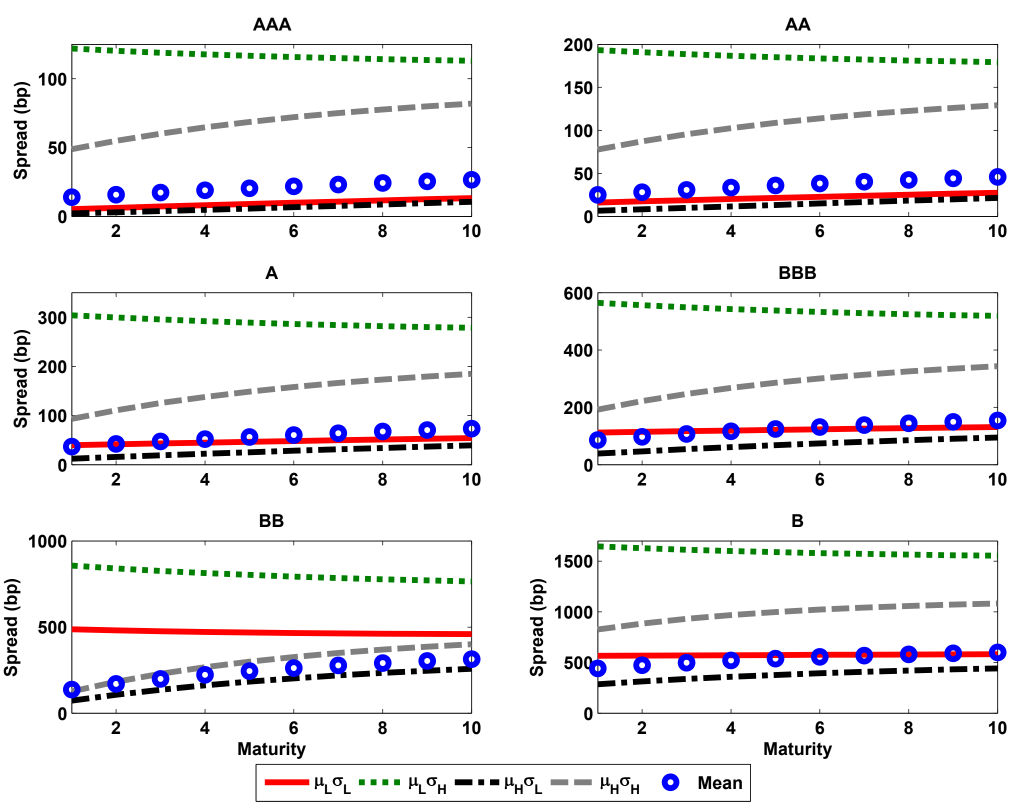
$$h_t = \frac{\lambda_t}{1+\lambda_t} \quad \text{where} \quad \lambda_t = \exp\left(\beta_{\lambda 0} + \beta_{\lambda x} x_t + \beta_{\lambda \sigma} \sigma_t\right).$$

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 ($\mu^L$, $\sigma^L$) and high ($\mu^H$, $\sigma^H$) expected consumption growth and volatility. The dots reflect the empirical observations.

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

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

| Countries | Portugal | Italy | Greece | Spain |
|---|---|---|---|---|
| Max Inversion | 150 | 19 | 525 | 56 |
| Avg. Inversion | 68 | 6 | 195 | 29 |



## Table 1: Country List

The table 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

The table reports summary statistics for the CDS term structure of 38 sovereign countries over the sample period May 9th, 2003 until August 19th, 2010. All CDS prices are mid composite quotes and USD denominated. 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. 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

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

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 |
|---|---|---|---|---|---|---|
| **All** | **77.8158** | **91.0749** | **94.7448** | **96.3491** | **97.5028** | **98.2378** |
| $1y$ | 85.9812 | 92.8245 | 95.7170 | 97.1810 | 98.2461 | 99.0540 |
| $2y$ | 83.0337 | 91.6612 | 95.5640 | 97.1889 | 98.2693 | 98.9229 |
| $3y$ | 79.7215 | 91.7345 | 95.5324 | 97.1032 | 98.1849 | 98.8207 |
| $5y$ | 75.1912 | 92.0572 | 95.2786 | 96.7295 | 97.9724 | 98.7011 |
| $7y$ | 72.8903 | 91.5746 | 94.8203 | 96.2861 | 97.4767 | 98.5779 |
| $10y$ | 70.4393 | 91.6796 | 94.6215 | 96.2402 | 97.5720 | 98.4832 |

## Table 4: Kalman Filter Estimates

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

| $\mu_x$ | $\phi_x$ | $\nu_x$ | $\mu_\sigma$ | $\phi_\sigma$ | $\nu_\sigma$ |
|---|---|---|---|---|---|
| 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) | $(1.7537e-007)$ |

# Table 5: Regression Analysis - Macroeconomic and Financial Risk

Regression results from the regression of the factors extracted from a principal component analysis onto conditional expected consumption growth, conditional consumption volatility and the Variance Risk Premium (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%, 5% and 10% respectively.

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

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 consumption forecast and $\hat{\sigma}_t$ the filtered conditional consumption volatility.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | F1 | F2 | F3 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 |
| $\hat{x}_{t\|t}$ | -128.16*** | 236.66*** | -4.03 | | | | | | | | | | | | |
| | (38.92) | (22.10) | (33.06) | | | | | | | | | | | | |
| $\hat{\sigma}_t$ | 454.81*** | 293.54*** | -13.38 | | | | | | | | | | | | |
| | (77.58) | (34.70) | (42.90) | | | | | | | | | | | | |
| VRP | | | | 23.68 | -2.28 | | | | | | | | | | |
| | | | | (22.79) | (5.25) | | | | | | | | | | |
| VIX | | | | | | 1.44*** | -0.15 | | | | | | | | |
| | | | | | | (0.37) | (0.11) | | | | | | | | |
| USret | | | | | | | | -0.46 | 0.07 | | | | | | |
| | | | | | | | | (0.91) | (0.20) | | | | | | |
| PE | | | | | | | | | | -0.04*** | 0.01** | | | | |
| | | | | | | | | | | (0.00) | (0.00) | | | | |
| AAA_BBB | | | | | | | | | | | | 17.80*** | -1.80 | | |
| | | | | | | | | | | | | (1.71) | (1.14) | | |
| BBB_BB | | | | | | | | | | | | | | 16.84*** | -1.45 |
| | | | | | | | | | | | | | | (2.05) | (1.18) |
| Constant | -1.28*** | -0.77*** | 0.04 | -0.04 | 0.00 | -0.30*** | 0.03 | 0.00 | -0.00 | 1.03*** | -0.16** | -0.25*** | 0.03 | -0.30*** | 0.03 |
| | (0.20) | (0.09) | (0.12) | (0.04) | (0.01) | (0.06) | (0.03) | (0.03) | (0.01) | (0.12) | (0.07) | (0.02) | (0.02) | (0.03) | (0.02) |
| Observations | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 |
| R-squared | 0.76 | 0.74 | 0.00 | 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 | -0.02 | 0.12 | -0.00 | 0.55 | 0.02 | 0.00 | -0.01 | 0.78 | 0.09 | 0.82 | 0.04 | 0.76 | 0.02 |
| Dickey-Fuller | R*** | R*** | A | R* | A | R*** | A | A | A | R* | A | R*** | A | R*** | A |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 6: Regression Analysis - Macroeconomic and Financial Risk

Regression results from the regression of the factors extracted from a principal component analysis onto conditional expected consumption growth, conditional consumption volatility and the Variance Risk Premium (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%, 5% and 10% respectively.

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

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 consumption forecast and $\hat{\sigma}_t$ the filtered conditional consumption volatility .

| 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\hat{x}_{t\|t}$ | -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 |
| R-squared | 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** |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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

Regression results from the regression of the level, slope and curvature of the monthly sovereign CDS series onto conditional expected consumption growth, conditional consumption volatility and the variance risk premium (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, and the curvature is computed as twice the 5-year minus the 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.

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

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

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

All regressions are run for each of the 38 countries. Panel B excludes the VRP, Panel C excludes the consumption predictors, and Panel D includes all explanatory variables. Columns 1 to 3 report the fraction (out of 38) of 5% statistically significant coefficient estimates, while columns 4 to 6 report the fraction (out of 38) of positive coefficient estimates. Columns 7 to 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 B | *t-stats* $\hat{x}_{t\|t}$ | *t-stats* $\hat{\sigma}_t$ | *t-stats* $VRP_t$ | $+\hat{x}_{t\|t}$ | $+\hat{\sigma}_{t,t}$ | $+VRP_t$ | *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 |
| Curvature | 0.84 | 0.68 | | 0.37 | 0.89 | | 0.55 | 0.60 | 88 | + | + | 0.82 |
| Panel C | | | | | | | | | | | | |
| Level | | | 0.95 | | | 1.00 | 0.11 | 0.12 | 88 | | | |
| Slope | | | 0.50 | | | 0.69 | 0.04 | 0.03 | 88 | | | |
| Curvature | | | 0.66 | | | 0.78 | 0.08 | 0.08 | 88 | | | |
| Panel D | | | | | | | | | | | | |
| 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 | | | |
| Curvature | 0.84 | 0.68 | 0.21 | 0.37 | 0.89 | 0.76 | 0.55 | 0.60 | 88 | | | |
| Regression | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *(9)* | *(10)* | *(11)* | *(12)* |

Table 8: Parameters of the Markov-Switching Model

The following consumption growth dynamics are calibrated at a monthly frequency as in Bansal et al. (2012) with $\mu_x = 0.0015$, $\phi_x = 0.975$, $\nu_x = 0.038$, $\sqrt{\mu_\sigma} = 0.0072$, $\phi_\sigma = 0.999$ and $\nu_\sigma = 2.80 \times 10^{-6}$.

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

where

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

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 system given by

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

where we consider $\Delta = 1/22$, meaning that there are 22 trading 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 $\nu_\sigma^{daily} = 2.7247 \times 10^{-8}$. In Panel A, we report the parameters of the four-state daily Markov-switching model in which consumption growth is predictable. The conditional mean and variance of consumption growth are $\mu_g$ and $\omega_g$ respectively. $P^\top$ is the transition matrix across different regimes and $\Pi$ is the vector of unconditional probabilities of regimes. The four states are characterized by the combinations of expected consumption growth ($\mu$) and consumption volatility ($\sigma$), 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 generalized disappointment averse preferences (GDA) and the Kreps-Porteus certainty equivalent (KP). The estimated values are sampled on an annual frequency and cover the period 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 |
| $(\omega_g^\top)^{1/2}$ | 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 (GDA) | Model (KP) | Data | |
| $E[r_m - r_f] + 0.5\sigma^2[r_m]$ | 5.52 | 6.38 | 7.84 | (1.97) |
| $\sigma[r_m]$ | 17.48 | 18.48 | 20.16 | (2.14) |
| $E[r_f]$ | 1.01 | 1.22 | 0.86 | (0.89) |
| $\sigma[r_f]$ | 0.80 | 1.05 | 1.74 | (0.33) |

Table 9: Model Estimation - Preference and Default Parameters

The table reports the estimation results for the preference parameters and the parameters of the default process for the rating categories AAA to B, as well as their standard errors (in parentheses), where the default process $h_t$ is defined as

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

$\delta$ is the subjective discount factor, $\gamma$ the coefficient of relative risk aversion, $\psi$ the elasticity of intertemporal substitution, $\alpha$ the disappointment aversion parameter and $\kappa$ denotes the fraction of the certainty equivalent below which outcomes are disppointing. $\delta$ is fixed at 0.9989. 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. Coefficient estimates are reported together with Newey-West standard errors. 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.

| | Generalized Disappointment Aversion (GDA) - Benchmark | | | | | |
|---|---|---|---|---|---|---|
| | AAA | AA | A | BBB | BB | B |
| $\beta_{\lambda_0}$ | $-15.44$ | $-13.79$ | $-12.89$ | $-11.48$ | $-10.90$ | $-9.21$ |
| (s.e.) | (0.58) | (0.24) | (0.15) | (0.10) | (0.41) | (0.05) |
| $\beta_{\lambda_x}$ | $-6,572.55$ | $-6,466.87$ | $-8,686.44$ | $-7,669.86$ | $-18,598.21$ | $-4,431.00$ |
| (s.e.) | (467.94) | (663.93) | (850.56) | (902.24) | (4,858.26) | (433.62) |
| $\beta_{\lambda_\sigma}$ | 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) |
| | **No Downside Risk Aversion (KP) - Kreps-Porteus** | | | | | |
| | AAA | AA | A | BBB | BB | B |
| $\beta_{\lambda_0}$ | $-15.37$ | $-13.71$ | $-12.71$ | $-11.34$ | $-10.07$ | $-9.15$ |
| (s.e.) | (0.66) | (0.24) | (0.14) | (0.09) | (0.09) | (0.06) |
| $\beta_{\lambda_x}$ | $-5,624.18$ | $-5,596.99$ | $-7,429.56$ | $-6,692.67$ | $-13,917.70$ | $-4,144.73$ |
| (s.e.) | (415.62) | (514.33) | (680.13) | (730.82) | (1,928.74) | (415.18) |
| $\beta_{\lambda_\sigma}$ | 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) |

| | Preference Parameters | | | |
|---|---|---|---|---|
| | Levels | | Differences | |
| Parameter | GDA | KP | GDA | KP |
| $\delta$ | 0.9989 | 0.9989 | 0.9989 | 0.9989 |
| (s.e.) | ( - ) | ( - ) | ( - ) | ( - ) |
| $\gamma$ | 4.9081 | 8.2692 | 5.0614 | 7.1713 |
| (s.e.) | ( 0.0054 ) | ( 0.0011 ) | ( 0.1294 ) | ( 0.0642 ) |
| $\psi$ | 1.4874 | 1.5774 | 1.2473 | 1.5953 |
| (s.e.) | ( 0.0018 ) | ( 0.0002 ) | ( 0.0273 ) | ( 0.0133 ) |
| $\alpha$ | 0.2486 | 1.0000 | 0.4819 | 1.0000 |
| (s.e.) | ( 0.0008 ) | ( - ) | (0.0107) | ( - ) |
| $\kappa$ | 0.8470 | - | 0.9549 | - |
| (s.e.) | ( 0.0042 ) | (- ) | ( 0.0183 ) | ( - ) |
| | **Model Statistics** | | | |
| $J-test$ | 14.65 | 45.73 | 8.32 | 19.84 |
| $p-value$ | 1.00 | 0.65 | 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: Downside Risk Aversion

This table 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 when the hazard rate is time-varying. The column labeled *RMSE* reports the root mean squared errors in basis points for the model fit. The recovery rate 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 |

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

This table reports unconditional model-implied physical and risk-neutral default probabilities for maturities 1 to 10 at the aggregated level for the rating categories AAA-B as well as their ratio when the hazard rate process is time-varying and defined as

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

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%. %hline

| | | RMSE | 1y | 2y | 3y | 4y | 5y | 6y | 7y | 8y | 9y | 10y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Physical Default Probabilities** | | | | | | | | | | | | |
| AAA | Model | 0.86 | 0.14 | 0.28 | 0.42 | 0.56 | 0.70 | 0.84 | 0.98 | 1.11 | 1.25 | 1.38 |
| | Observed | – | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| AA | Model | 1.55 | 0.26 | 0.51 | 0.77 | 1.02 | 1.27 | 1.51 | 1.76 | 2.00 | 2.24 | 2.48 |
| | Observed | – | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| A | Model | 2.05 | 0.34 | 0.68 | 1.01 | 1.35 | 1.67 | 2.00 | 2.32 | 2.64 | 2.95 | 3.27 |
| | Observed | – | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| BBB | Model | 0.86 | 0.84 | 1.66 | 2.46 | 3.25 | 4.03 | 4.79 | 5.54 | 6.28 | 7.01 | 7.73 |
| | Observed | – | 0.00 | 0.50 | 1.57 | 2.72 | 3.97 | 5.33 | 6.07 | 6.07 | 6.07 | 6.07 |
| BB | Model | 3.89 | 0.91 | 1.78 | 2.61 | 3.42 | 4.21 | 4.98 | 5.74 | 6.49 | 7.24 | 7.97 |
| | Observed | – | 0.74 | 2.36 | 3.70 | 4.70 | 6.36 | 8.24 | 10.34 | 12.72 | 13.63 | 13.63 |
| B | Model | 9.82 | 4.89 | 9.43 | 13.68 | 17.66 | 21.40 | 24.92 | 28.23 | 31.37 | 34.33 | 37.13 |
| | 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 | 0.42 | 0.70 | 1.01 | 1.35 | 1.71 | 2.09 | 2.48 | 2.88 | 3.29 |
| AA | Model | – | 0.32 | 0.74 | 1.23 | 1.78 | 2.36 | 2.97 | 3.60 | 4.25 | 4.92 | 5.59 |
| A | Model | – | 0.46 | 1.11 | 1.89 | 2.76 | 3.69 | 4.66 | 5.66 | 6.67 | 7.71 | 8.75 |
| BBB | Model | – | 1.09 | 2.53 | 4.19 | 5.99 | 7.87 | 9.79 | 11.73 | 13.67 | 15.59 | 17.49 |
| BB | Model | – | 1.67 | 4.38 | 7.68 | 11.31 | 15.07 | 18.86 | 22.60 | 26.24 | 29.77 | 33.17 |
| B | Model | – | 5.55 | 11.62 | 17.77 | 23.77 | 29.48 | 34.85 | 39.84 | 44.47 | 48.75 | 52.70 |
| **Ratio of Risk-Neutral to Physical Default Probabilities** | | | | | | | | | | | | |
| AAA | Model | – | 1.48 | 1.94 | 2.36 | 2.74 | 3.08 | 3.38 | 3.65 | 3.89 | 4.11 | 4.31 |
| AA | Model | – | 1.35 | 1.66 | 1.92 | 2.15 | 2.35 | 2.53 | 2.69 | 2.83 | 2.96 | 3.07 |
| A | Model | – | 1.50 | 1.89 | 2.20 | 2.45 | 2.65 | 2.83 | 2.98 | 3.10 | 3.22 | 3.32 |
| BBB | Model | – | 1.38 | 1.66 | 1.88 | 2.05 | 2.18 | 2.28 | 2.37 | 2.44 | 2.50 | 2.55 |
| BB | Model | – | 3.46 | 4.33 | 4.73 | 4.93 | 5.02 | 5.06 | 5.06 | 5.04 | 5.01 | 4.96 |
| B | Model | – | 1.15 | 1.26 | 1.33 | 1.38 | 1.42 | 1.44 | 1.46 | 1.46 | 1.47 | 1.46 |

Table 12: Model-Implied and Observed Term Structure of CDS Spreads AAA-B: No Downside Risk Aversion

This table 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 when the hazard rate is time-varying. The column labeled $RMSE$ reports the root mean squared errors in basis points for the model fit. The recovery rate 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 |