Economic and Financial Determinants of Credit Risk
Premiums in the Sovereign CDS Market

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Abstract

We specify and estimate no-arbitrage models that value sovereign CDS contracts by assuming that the country’s default intensity depends on observable economic and financial indicators. We estimate these models using a sample of twenty-eight countries, three CDS maturities, and over a decade of daily data. The models provide a good fit. The impact of the economic and financial variables on spreads varies substantially across countries and over time, but is consistent with economic intuition. Spreads increase as a function of stock market and exchange rate volatility, but decrease as a function of interest rates and stock market returns. Estimated risk premiums are highly time-varying and peak during the 2008 financial crisis for nearly all countries. For European countries the risk premiums are also high during the Eurozone debt crisis. In periods of market stress and high CDS spreads, the increase in market risk aversion is even larger than the increase in default probabilities. The cross-sectional variation in risk premiums across countries is high, also in non-crisis periods.

JEL Classification: G12

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1 Introduction

For several decades, the relevance of sovereign risk seemed limited to emerging economies in Latin America and Asia. But following the U.S. debt downgrade in August 2011 and the Eurozone debt crisis, the study of sovereign risk has suddenly taken center stage. Meanwhile, the rapid development of the sovereign and corporate credit default swap (CDS) markets, and the associated increased importance of credit as an asset class, have focused attention even more on the determinants of sovereign credit spreads and the sources of the differences in spread levels between countries.

Following the increased availability of reliable CDS data over the last few years, the academic literature has seen rapid growth in the empirical literature on corporate CDS spreads.\footnote{See for instance Bai and Wu (2011), Berndt, Douglas, Duffie, Ferguson, and Schranz (2008), Blanco, Brennan, and Marsh (2005), Bongaerts, de Jong, and Driessen (2011), Cao, Yu, and Zhong (2010), Chen, Cheng, Fabozzi, Liu (2008), Ericsson, Jacobs, and Oviedo (2009), Houweling and Vorst (2005), Longstaff, Mithal, and Neis (2005), and Zhang, Zhou, and Zhu (2009).} The literature on sovereign CDS spreads has also developed but not as rapidly.\footnote{See for instance Pan and Singleton (2008), Longstaff, Pan, Pedersen and Singleton (2011), Ang and Longstaff (2013), Augustin (2012), Benzoni, Collin-Dufresne, Goldstein, and Helwege (2011), and Dieckmann and Plank (2012) for recent studies of sovereign CDS. See also Duffie, Pedersen, and Singleton (2003), and Hilscher and Nosbusch (2010) for recent studies of sovereign debt.} From an analytical perspective, there is an important difference between sovereign and corporate CDS markets. Whereas there is consensus that variables such as interest rates, asset or equity volatility, and leverage should matter for corporate CDS spreads, following the logic of structural models such as Merton (1974), no such simple encompassing theory is available for sovereign CDS. The economics literature of course has a rich history of highlighting macroeconomic factors that are likely to influence sovereign default and sovereign credit risk, such as debt-to-GDP ratios and the terms of trade, but these are largely empirical discussions, and identifying parsimonious sets of variables that are prime candidates for explaining sovereign CDS spreads is not straightforward.

This paper contributes to the expanding literature on sovereign credit risk, and sovereign CDS in particular. The recent literature contains two very different approaches to analyze sovereign CDS. On the one hand is the use of so-called reduced-form models of credit risk, as in Pan and Singleton (2008) and Longstaff, Pan, Pedersen and Singleton (2011), for example. These models originate in the term-structure literature and start by specifying a default intensity that depends on a number of latent factors or state variables. Given the specification of the default intensity, the CDS spread can be obtained as a function of the same latent factors. The advantage of this approach is that one can increase the number of factors and choose the appropriate statistical specification to achieve a good fit. These models are typically estimated using different CDS
maturities, and because the model starts from basics, pricing consistency across maturities is ensured. Another advantage is that by specifying the price of risk, one can obtain estimates of the prices of risk and the risk premiums as a by-product of the estimation. Credit risk premiums are indeed a central objective of the analysis in Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2011).

Several other studies analyze sovereign CDS spreads by regressing the spreads on (macro) economic and financial determinants of credit spreads. The advantage of this approach compared to reduced form models with latent factors is that it provides more intuition on the economic determinants of sovereign default. The disadvantage of the regression approach is that it does not provide as good a fit as the reduced-form latent models, and the regressions are estimated for each maturity separately so that there is no pricing consistency across maturities. Longstaff, Pan, Pedersen, and Singleton (2011) use linear regression to determine the relative importance of global and local factors in sovereign credit spreads. Dieckmann and Plank (2012) provide an exhaustive analysis of potential determinants of sovereign CDS spreads using linear regression.

This paper combines the advantages of both approaches. We use the framework of Doshi, Ericsson, Jacobs, and Turnbull (2013), who value corporate CDS in a reduced-form framework with intensities that are functions of observable covariates. This combines the advantages of linear regressions on observable covariates and the reduced-form approach. It readily provides economic intuition, but additionally the pricing is consistent across maturities and risk premiums are readily obtained as a by-product of the estimation. Moreover, we specify the country’s default intensity as a quadratic function of observable economic and financial indicators, guaranteeing positive default intensities at all times.

Just as in the case of linear regressions, the selection of observable covariates is not straightforward. There is no consensus theory to guide the specification search, and economic intuition suggests a large number of variables that ought to influence sovereign default probabilities. However, parsimony ought to be a guiding principle, because for this type of model, the numerical optimization becomes more time-consuming and less reliable when the number of parameters increases. We select a parsimonious benchmark model with four covariates based on the explanatory power of the observable variables. We confirm the findings of Longstaff, Pan, Pedersen and Singleton (2011), who argue that a substantial part of the variation in CDS spread can be explained by global factors such as the VIX, and therefore we use global factors as well as country-specific factors.

Our preferred benchmark model contains four determinants of the countries’ default intensities: the U.S. interest rate, the VIX stock market volatility index, the one-year trailing return on the country’s stock market index, and the implied exchange rate volatility for the country’s
currency. We estimate this model using a sample of twenty-eight countries. For each country we have over a decade’s worth of daily data, and we use the 1-year, 5-year, and 10-year tenors in estimation. The benchmark model provides a satisfactory fit.

The impact of the economic and financial variables on spreads varies substantially across countries and over time, but is consistent with economic intuition. In the benchmark model, spreads increase as a function of stock market and exchange rate volatility, but decrease as a function of interest rates and stock market returns. Estimated risk premiums are highly time-varying and peak during the 2008 financial crisis for nearly all countries. For European countries the risk premiums are also high during the Eurozone debt crisis. This means that in periods of market stress and high CDS spreads, the increase in market risk aversion is even larger than the increase in default probabilities. Outside of the financial crisis, the variation in risk premium across countries is also very large. Some of this variation is driven by regional factors, and some of it is country-specific. We document an interesting relation between the term-structure slopes in the CDS spreads and the credit risk premium. In the 2008 crisis these slopes are clearly inversely related, but this is not the case pre- and post-crisis.

We also report on two more richly specified models, which include the one year local swap rate and the terms of trade. These models improve the fit but not dramatically so. Importantly, they provide similar economic intuition regarding the size and time variation in risk premiums and the sign of the deltas of spreads with respect to the observable covariates.

The paper proceeds as follows. Section 2 outlines the model. Section 3 briefly summarizes the data and the estimation method. Section 4 discusses the empirical results, with particular attention for risk premiums and common trends across the countries in the sample. Section 5 provides more detailed evidence on individual countries. Section 6 discusses alternative model specifications, and Section 7 concludes.

2 The Model

In this section, we describe the model used for CDS valuation. We work in discrete time and assume that the observable macroeconomic and financial factors are described by autoregressive processes. We also specify the market prices of risk.

2.1 Credit Default Swap Valuation

We use the quadratic framework of Doshi, Ericsson, Jacobs, and Turnbull (2013), who value corporate CDS based on the dynamics of observable covariates. The resulting models are easier
to estimate than models with latent dynamics because there is no need to filter latent state variables from CDS prices.\(^3\) A stopping time has an intensity process \(\lambda(t)\). Given no default up to time \(t\), the probability of no default over the next interval is \(\exp(-\lambda(t))\). The probability for an obligor surviving until at least time \(h\) is given by

\[
P_t[\tau > t + h] = E_t \left[ \exp \left( - \sum_{j=0}^{h-1} \lambda_{t+j} \right) \right],
\]

where \(\tau\) denotes the time of default. The default intensity of each country is assumed to be a quadratic function of common factors that affect all countries, denoted by \(X_{w,k,t}\), and country-specific factors denoted by \(X_{c,k,t}\)

\[
\lambda_t = \left( \alpha_0 + \sum_{k=1}^{n} \alpha_k^w X_{w,k,t} + \sum_{k=1}^{m} \alpha_k^c X_{c,k,t} \right)^2,
\]

where \(n\) is the number of common factors and \(m\) the number of country-specific covariates. The advantage of a quadratic specification over a Gaussian specification is that the intensity function is strictly positive. Defining \(q = n + m\) and stacking \(X_{w,t}^w\) and \(X_{c,t}^c\) in the \(q\) by 1 vector \(X_t\), we can write

\[
\lambda_t = \gamma_0 + \gamma_t' X_t + X_{t+j}^t \Omega X_t,
\]

We assume that the covariates \(X_t\) are described by the following dynamics under the risk-neutral measure,

\[
X_t = \mu + \rho X_{t-1} + \Sigma e_t,
\]

where \(e_t \sim N(0, I)\), \(\mu\) is a \((q,1)\) vector, and \(\rho\) and \(\Sigma\) are \((q,q)\) matrices that we assume to be diagonal for simplicity.

Consider the payments by the CDS protection buyer, who typically makes an initial payment and a series of quarterly payments. In our CDS sample, we are provided with the spread and the initial payment is zero, so we ignore it in the pricing. Let \(S\) denote the CDS spread. The protection buyer promises to make payments \(S\Delta\) each quarter, conditional on no default by the reference obligor, where \(\Delta\) is the time between payment dates. If a credit event occurs, the protection buyer receives a payment from the protection seller and the contract terminates. The

present value of the payments by the protection buyer is

\[ PB_t = E_t \left[ S \Delta \sum_{j=1}^{h} 1_{(r > t + j)} B(t, t + j) \right], \] (2.5)

where 1 denotes the indicator function and \( B(t, t + j) \) is the riskless discount rate, which is assumed to be deterministic. Doshi, Ericsson, Jacobs, and Turnbull (2013) show that

\[ B(t, t + j) E_t[1_{(r > t + j)}] = B(t, t + j) \times \exp(F_j + G_j X_t + X_t^t H_j X_t), \] (2.6)

where the coefficients \( F_j, G_j, \) and \( H_j \) are derived recursively. The protection seller will make a payment of \((1 - R)\) per dollar of notional, where \( R \) is the recovery rate, if a default event occurs. We assume that if a default event occurs during the interval \((t + j - 1, t + j)\), payment by the protection seller is made at the end of the interval. The present value of the promised payment by the protection seller is

\[ PS_t = E_t \left[ (1 - R) \sum_{j=1}^{h} 1_{(t + j - 1 < r \leq t + j)} B(t, t + j) \right]. \]

Assuming that the recovery rate is known and constant,\(^4\) this gives

\[ PS_t = (1 - R) \left( E_t \left[ \sum_{j=1}^{h} 1_{(r > t + j - 1)} B(t, t + j) \right] - E_t \left[ \sum_{j=1}^{h} 1_{(r > t + j)} B(t, t + j) \right] \right). \] (2.7)

where both expectations on the right side are of the form (2.6). The spread of the CDS is set such that

\[ PB_t = PS_t. \] (2.8)

### 2.2 The Market Prices of Risk

Section 2.1 introduces the pricing model under the risk-neutral measure \( Q \). We now specify the market prices of risk. To change from the risk-neutral measure to the physical measure, we

\(^4\)The assumption of a constant recovery rate can be relaxed. We experimented with stochastic recovery rates but found that the resulting model is subject to serious econometric identification issues, confirming the findings of Pan and Singleton (2008).
specify the Radon–Nikodym derivative to take the form

\[ \frac{\Delta P}{\Delta Q} = \frac{\exp (-\Lambda'_t e_{t+1})}{E_t[\exp (-\Lambda'_t e_{t+1})]} \]  

(2.9)

where \( \Lambda_t \) is an \( q \times 1 \) vector, with \( q \) the number of factors that are priced. Given this assumption and the risk-neutral dynamic (2.4), the dynamics of the state variables \( X_t \) under the physical measure are given by

\[ X_{t+1} = \mu + \rho X_t + \Sigma e_{t+1} - \Sigma \Lambda_t. \]  

(2.10)

We assume time-varying prices of risk that are a linear function of the state variables:

\[ \Lambda_t = \lambda_0 + \lambda_1 X_t, \]  

(2.11)

where \( \lambda_0 \) is an \( N \times 1 \) vector and \( \lambda_1 \) is an \( N \times N \) matrix. The dynamics of the state variables under the physical measure can therefore be written as

\[ X_{t+1} = \mu^P + \rho^P X_t + \Sigma e_{t+1}, \]  

(2.12)

where \( \mu^P \) and \( \rho^P \) are given by

\[ \mu^P = \mu - \Sigma \lambda_0 \]  

(2.13)

\[ \rho^P = \rho - \Sigma \lambda_1. \]

### 3 Data and Estimation Method

#### 3.1 Data

The data consists of daily sovereign CDS spreads for a set of twenty-eight countries for the period January 2, 2001 to June 29, 2012, and is obtained from Markit. We use 1-, 5-, and 10-year tenors in estimation.

We estimate the model for each country separately, but in order to save space we report some results that are averaged within regions. We report on three regions. The Latin American region in our sample consists of five countries: Brazil, Chile, Colombia, Mexico, and Peru. The Eurozone region includes ten countries: Austria, Belgium, Finland, France, Germany, Ireland, 

\[ \text{See Ang and Piazzesi (2003), Ang et al. (2011), and Dai, Le, and Singleton (2010) for other studies that make this assumption.} \]
Italy, Portugal, Slovenia, and Spain. The Asian region includes six countries: Hong Kong, Japan, Malaysia, Philippines, South Korea, and Thailand. There are seven countries in our sample that are not part of any of these three regions: the Czech Republic, Israel, Poland, Russia, South Africa, Turkey, and the United Kingdom.

We used linear regression to select covariates with high incremental explanatory power for CDS spreads. Based on this specification search, we chose a benchmark model with four covariates. Two covariates are common across the entire set of countries, and two covariates are specific to each country. For the common or global covariates we use the 10-year U.S. Treasury bond yield and the VIX index. For the country-specific or local covariates we use the 1-year trailing return of the Morgan Stanley Composite Index (MSCI), and the 3-month foreign exchange implied volatility. We also estimated two extensions to the benchmark model: these models include the 1-year local denominated interest rate swap and the Citi terms of trade index. Note that for Eurozone countries, the foreign exchange implied volatility, the 1-year interest rate swap, and the terms of trade index are identical. All covariates data is obtained from Bloomberg.

Our set of twenty-eight countries is determined by data availability. Our sample period has 2999 business days. We require at least 75% of the 2999 observations on the CDS data and the covariates to be available for a country to be included.

Panel A of Figure 2 contains the time path of the 5-year CDS spreads (black line) averaged over all twenty-eight countries. Panels B, C, and D present the average time path of CDS spreads for three regions. Whereas in Panel A there is clear peak around the credit crisis in 2008, this is not the case for all regions. In the Eurozone countries in Panel B, spreads decreased in 2009, just as in the other regions, but then they increased again fueled by concerns regarding the fiscal solvency of Greece, Italy, Ireland, Portugal and Spain. The Latin American countries experience a period of major uncertainty between 2003 and 2005, when Brazil elected a new president and doubts developed about monetary policy and increasing inflation. Asian countries also experienced substantial uncertainty in 2003, but spreads did not reach the levels of the 2008 financial crisis.

Figure 1 shows the time-series evolution of the covariates. We report the cross-sectional average for the entire set of twenty-eight countries. The 2008 financial crisis is clearly visible with peaks in the VIX and the average exchange rate volatility in 2008. The drop in stock markets in that period is also clearly visible, and the crisis also shows up in the time series for the average terms of trade. The 2008 crisis is less visible in the fixed-income variables. U.S. interest rates in Panel A clearly drop in 2008-2009, but they continue their decline through the

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6We compute the averages only if there are at least four countries in a given region with available data. Therefore, the averages for Latin American and Asian countries start later.
end of the sample.

Another event that emerges from Figure 1 is the period following the bursting of the internet stock market bubble at the beginning of our sample. The corresponding decline in worldwide stock markets and the increase in the VIX are clearly visible from Panels C and B respectively.

In summary, based on Figures 1 and Panel A of Figure 2, we anticipate a positive relationship between spreads and the VIX, as well as between the spreads and exchange rate volatility. We anticipate a negative relationship between spreads and stock market returns, as well as between the terms of trade variable and spreads. For the U.S. ten-year yield, Figure 1 suggests a negative relationship with overall average spreads in Panel A of Figure 2 which is more low-frequency in nature than the relationship between volatility and spreads. However, comparing the U.S. ten-year yield in Panel A of Figure 1 with the spreads in different regions in Panels B, C, and D of Figure 2, it is already clear that the strength of the overall negative relation will differ across regions.

Because of space constraints we do not report time paths of spreads and covariates for individual countries. Table 1 reports sample averages and standard deviations for each country. Columns 2 and 3 report the descriptive statistics on the CDS spreads for five year maturity for each country, columns 4 to 11 report the descriptive statistics on the country specific covariates. There are substantial cross-sectional differences in the first and second moments of spreads and covariates.

3.2 Estimation Method

We estimate the models for each country separately. Because we observe the time-series of covariates, we first estimate the dynamics of the covariates under the physical measure in a first step. The observable macroeconomic and financial variables are described by the AR(1) process in (2.12). Based on the normality assumption for the AR(1) innovation, it is straightforward to write the resulting likelihood function in order to estimate the physical dynamics.

Subsequently, in a second step we estimate the dynamics of the covariates under the risk-neutral measure and the loadings on the covariates using the term-structure of credit default swap spreads. Given the assumptions on the prices of risk, the standard deviations of the innovations are identical under the physical and risk-neutral measures. In the second estimation step, we therefore fix them to the estimates obtained in the first step. Following market convention and existing studies on sovereign CDS (see for example Pan and Singleton (2008)), we assume a constant recovery rate of 25% in estimation.
4 Empirical Results

In this section, we estimate the no-arbitrage model for all countries in our sample using a parsimonious specification, with four covariates: the level of U.S. interest rates measured using the 10 year Treasury yield, the S&P 500 volatility index (VIX), the one-year trailing returns on the MSCI country index, and foreign exchange implied volatility. We refer to this parsimonious specification as the benchmark specification.

We chose the benchmark model after an extensive specification analysis using linear regressions. We selected variables that provided substantial incremental explanatory power. Our specification search favored a parsimonious model, in the sense that other variables are available that are relevant in a univariate context, but they do not increase explanatory power much when the benchmark covariates are included. Our search also yielded results that are consistent with the recent literature that convincingly demonstrates a substantial global component to sovereign credit risk (see Longstaff, Pan, Pedersen and Singleton (2011)). Our benchmark specification includes two country-specific variables and two variables that are common to all countries. We report on other (richer) specifications of the covariates in Section 6, and compare the implications of those models with the benchmark model.

The top four panels of Figure 1 show the time paths for the four covariates in the benchmark model. Panel A contains the U.S. 10-year Treasury yield, which steadily decreased over the sample period. Panel B shows the VIX, which substantial varies over the sample and peaks during the financial crisis. Panels C and D contain averages of country-specific variables. Note that the average stock market return in Panel C is clearly highly negatively correlated with the VIX in Panel B, presumably because it is highly positively correlated with the S&P500. This illustrates that in our sample we also have a substantial systemic component to sovereign risk that is present in the country-specific covariates. Panel D shows that average exchange rate volatility is also highly related to the VIX and the stock market index. Of course there is substantial country-specific variation in both variables which is not apparent from Figure 1.

4.1 Parameter Estimates and Model Fit

Table 2 presents the distribution of the parameter estimates across all countries. For each parameter, the table provides information about the mean, median, standard deviations and percentiles ranging from 2.5% to 97.5%. Panel A presents the distribution of the covariate loadings. The loadings on the level of US interest rates and the MSCI index are mostly negative. The loadings on the VIX and exchange rate volatility are mostly positive. Since the default intensity is a quadratic function of the covariates, it is difficult to interpret the impact of the
covariates based on the sign of the loadings. Later in this section, we compute the numerical
deltas of the CDS spreads with respect to each covariate to provide more intuition for the impact
of the covariates on the term structure of CDS spreads.

Panels B to F present the distribution of the parameters characterizing the covariate dynamics
under the risk-neutral and physical measures. Remember that the off-diagonal elements of $\rho$ and
$\Sigma$ in (2.4) are assumed to be zero. All covariates are highly persistent under both the risk-neutral
and physical measures. The risk-neutral dynamic for the level of the US Treasury yield is mostly
explosive. For all covariates, the range of the persistence parameter $\rho$ is relatively tighter under
the physical measure compared to the risk-neutral measure. This suggests that the market price
of risk associated with this parameter varies a lot across countries. The distribution of the
intercept of the autoregressive process $\mu$ also differs substantially under the risk-neutral and
physical measure suggesting that these covariates carry large risk premiums. For example, for
the exchange rate volatility, the percentile range under the physical measure is between 0.0316
and 0.232, while it is between -0.688 and 0.13 under the risk-neutral measure. Note that these
comparisons are only suggestive. The overall risk premium associated with each of the covariates
is jointly driven by the persistence parameters and the intercepts. We discuss the estimates of
the overall risk premiums in greater detail in Section 4.3.

The next to last column in Table 1 presents the root mean squared error (RMSE) in basis
points for the five year maturity contract for each country in our sample. We also report the
averages based on different geographical regions. For comparison, the last column also reports
the goodness of fit measure for the linear regression

$$S_t = \gamma + \beta_w X_t^w + \beta_c X_t^c + \varepsilon_t,$$ (4.1)

where $X_t^w$ denotes the factors that are common to all countries and $X_t^c$ denotes the factors
that are country specific. The RMSEs for the five-year contract are similar for the no-arbitrage
model and the simple regression model.\footnote{Note that the regression model is estimated one maturity at a time, whereas the no-arbitrage model is
estimated using the entire term structure of CDS spreads.} The no-arbitrage model performs well in capturing the
variation in spreads for the Latin American and Asian countries. Table 1 indicates that the ratio
of the average RMSE to average spreads for Latin American countries is 49%; for the Asian
countries it is 37%. The model has more difficulty to capture the variation in the spreads of the
Eurozone countries. The ratio of average RMSE to average spreads for Eurozone countries is
almost 100%. However, there is clearly a lot of variation within regions. For instance, the ratio
is around 50% for Finland, while for Portugal the fit is very poor. The table does not report
RMSEs for other maturities, but the conclusions are similar.

Panel A of Figure 2 provides additional perspective on model fit by presenting the time-series average of the spreads across all countries for the no-arbitrage model and the regression model, together with the average market spreads, again using the 5-year tenor. The no-arbitrage model generally performs well in capturing the level and the variation in spreads except between 2005 and 2007, when its prediction is too high. The linear regression model performs better between 2005 and 2007, but predicts negative spreads in 2001. Panel B of Figure 2 presents the same information for the Eurozone countries. For these countries, the no-arbitrage model is unable to capture the level of spreads before the financial crisis of 2008. The linear regression model on the other hand generates large negative fitted spreads before the financial crisis. The fit of the no-arbitrage model and the linear regression model during and after the financial crisis is similar and fairly good. Note that these model deficiencies are due to the nature of the data. The large increase in Eurozone spreads after 2008 represents a structural break, but we are trying to fit the data using a single set of parameters for the entire time period.

Panels C and D of Figure 2 present the graph of the average model and market spreads for Latin American and Asian countries respectively. For both regions, the no-arbitrage model is able to capture the substantial rise in spreads during the 2008 financial crisis. While the fit is good throughout the sample of Asian countries, for the Latin American countries the model tends to underestimate spreads in 2003 and 2004. This time period coincides with the Argentinian debt crisis and uncertainty in Brazil.

Overall, the fit of the no-arbitrage model across all countries is reasonable for our purpose. Our main objective with the benchmark model is to provide economic intuition by studying the impact of the covariates on the term structure of spreads and the associated risk premiums. In Section 6, we consider alternative covariate specifications that provide better fit, and we compare estimated risk premiums from different specifications.

4.2 Economic Determinants of Credit Spreads

We now turn to a detailed study of the quantitative impact of covariates on CDS spreads. Note that the loadings $\alpha$ in equation (2.2) are not directly interpretable because the default intensity is quadratic in the state variables. We therefore focus on the numerical derivatives (deltas) of the credit spreads with respect to changes in the covariates. These deltas also make it easier to compare the results of the no-arbitrage specification and the regression approach, because in the no-arbitrage specification it is the default intensity (2.2) that is specified as a function of the covariates, whereas for the regression (4.1) it is the credit spread.
4.2.1 Cross-Sectional Variation

Columns 12 to 15 of Table 1 report the average sensitivities or deltas of the five year maturity spreads with respect to all four covariates. The delta of the spreads with respect to U.S. Treasury yield is mostly negative, which is confirmed by the time paths in Figures 1 and 2, and is consistent with economic intuition. In bad economic times, when credit spreads are high, the Federal Reserve generally maintains a low interest rate environment in order to spur growth. On average, a one percentage point increase in yields results in a 19 basis points decrease in spreads. The sensitivity to the U.S. interest rate environment is lowest for Portugal and Ireland, two countries which experienced substantial distress during our sample and may have a large country-specific component in their spreads. The sensitivity is positive for several emerging economies: Brazil, Colombia, Mexico, Peru, Philippines, and Turkey. One potential explanation for the positive sign for these countries is as follows. A decrease in US Treasury rates may result in investors looking for yield elsewhere, which may increase the demand for bonds of developing countries and hence, result in reduction in spreads for these countries. Note that the often-cited flight-to-quality effect predicts the opposite: when there is turmoil in emerging markets, characterized by falling stock markets and higher sovereign CDS spreads, additional capital flows to the U.S., and U.S. Treasury market in particular, leading to lower yields.

We expect an increase in spreads when U.S. stock market volatility, as measured by VIX, increases. There is no formal theory to support this prior. However, the Merton (1974) model predicts a positive relation between stock market volatility and corporate credit spreads, and it is not unreasonable to expect this to carry over to sovereign spreads. Consistent with our intuition, the average sensitivity of the spreads with respect to VIX is positive for all countries except Brazil, Portugal, and Spain. On average, a one unit increase in VIX results in a 0.38 basis points increase in spreads. Colombia has the largest sensitivity with respect to the VIX, followed by Mexico, and Latin American countries have on average higher sensitivity to VIX.

For the country-specific covariates, we expect an increase in spreads when the stock market in a given country performs poorly, and an increase in spreads when the exchange rate is more volatile. Columns 14 and 15 of Table 1 show that the impact of the MSCI returns is indeed mostly negative. On average, a one percentage point decrease in yearly returns results in a 0.41 basis points increase in spreads. Local stock market conditions have the largest negative impact on the spreads of Asian countries and the least impact on the spreads of European countries. Finally, consistent with our intuition, spreads increase by 2 basis points on average with a one unit increase in exchange rate volatility. The impact of the exchange rate volatility is mostly positive across all countries. Brazil and Ireland have among the largest deltas to exchange rate
volatility. Interestingly, European countries have larger exchange rate volatility deltas than Asian countries.

4.2.2 Time-Series Variation

Figures 3 and 4 report the average time-path of the deltas for different covariates. The figures present the overall average time-path and the average time-path for different geographical regions for the five-year contract. For comparison, each panel also presents the average estimated delta from the linear regression model, indicated by the horizontal line in grey. Panels A to D of Figure 3 present the average delta of spreads with respect to the U.S. yield level across all countries and for different geographical regions. The linear regression model estimates the average delta with respect to U.S. interest rates at approximately -48 basis points, whereas the estimate from the no-arbitrage model is substantially smaller on average. More importantly, the no-arbitrage model allows for substantial time-variation in interest rate deltas. The deltas drop during the 2008 financial crisis as well as during the Eurozone debt crisis from mid-2011 to mid-2012. We obtain similar time-series patterns in deltas for the European and Asian countries. For Asian countries, the interest rate delta is positive on average at the beginning of the sample. For Latin American countries, the interest rate delta is positive throughout our sample. It increases in the later part of 2008 and drifts downward from then on. This result is partly driven by Brazil, which has a large positive delta with respect to US interest rates in our sample.

Panels E to H report the deltas with respect to the VIX for different geographical regions, as well as the overall average. The time-series pattern of the deltas is largely similar across Latin America and Asia. For the Eurozone countries the deltas decrease towards the end of the sample. The negative average delta for Eurozone countries is partly driven by Portugal and Spain which have large negative deltas with respect to VIX. The overall delta is 0.35 on average, similar to the delta obtained from the linear regression model.

Panels A to D of Figure 4 report the deltas with respect to the MSCI index. The overall average and the averages by region are all negative and drop substantially during the financial crisis of 2008. For the Asian countries, there is a large drop in the average delta around 2003, while in case of Europe the delta also drops substantially in the later part of the sample during the Eurozone debt crisis.

Panels E to H report the deltas with respect to exchange rate volatility. The overall average and the averages by region are positive and increase during the financial crisis of 2008. For Europe the deltas also increase in the later part of the sample between 2011 and 2012.
4.2.3 Term Structure

Panels A to D of Figure 5 report the term structure of deltas with respect to all four covariates from the no-arbitrage model together with the deltas obtained from the linear regression model. For the no-arbitrage model, we compute the time-series average of the deltas for each country and maturity and then average across countries. For the linear regression model the numbers simply represent the average across all countries. On average across countries, the term structure of deltas with respect to US treasury is upward sloping for the no-arbitrage model while it is slightly U-shaped for the linear regression model. The upward sloping pattern suggests that an increase in US interest rates results in larger decreases in short maturity spreads relative to long maturity spreads.

Panel B report the term structure of deltas with respect to VIX for the no-arbitrage and the linear regression models. The term structure of deltas is downward sloping, suggesting larger sensitivity with respect to VIX for shorter maturities.

Panel C report the term structure of deltas with respect to local stock market returns. The deltas obtained from the no-arbitrage model downward sloping, which suggests larger sensitivity with respect to country index returns at shorter horizons.

Panel D report the deltas for foreign exchange rate volatility. On average across all countries, deltas with respect to exchange rate volatility are slightly hump shaped i.e., the deltas increase up to five year maturity and decrease from then onwards.

4.2.4 Patterns in the Deltas

In summary, the deltas for all covariates have signs largely consistent with economic intuition. The term structure of deltas is upward sloping for U.S. interest rates, while it is downward sloping for the VIX and stock returns and hump shaped for exchange rate volatility. The time-variation in deltas estimated using the no-arbitrage approach is substantial, and mostly conforms to our intuition given the changes in economic conditions over the sample.

4.3 Risk Premiums

Figure 6 reports the average credit risk premium for all countries and the average across different geographical regions for the five year maturity contract. For each country in our sample, we first compute the model implied spreads under the pricing ($Q$) measure. We then change the probability measure and compute the model implied spreads under the physical measure $P$. The credit risk premium is defined as the ratio of the difference between the $Q$ and $P$ spreads over
the $P$ spreads $\left( \frac{CDS^Q - CDS^P}{CDS^P} \right)$. Our definition of the $P$ spreads follows Pan and Singleton (2008).\footnote{These estimates under the $P$ measure are not the same as estimates from historical default data. See Pan and Singleton (2008) and especially Jarrow, Lando, and Yu (2005) for a more detailed explanation.}

4.3.1 Risk Premiums

Panels A to D of Figure 6 present the average credit risk premium for all countries and for different regions. Average risk premiums are positive at each point in time for all regions. The average risk premium across all countries in Panel A varies between a minimum of 0.30 and a maximum of 2.92. Risk premiums are largest for Latin America, followed by Asia and Europe. On average over the sample, the ratio is equal to 2.25 for Latin America, 1.46 for Asia and 0.45 for Europe. The risk premium rises substantially during the financial crisis of 2008 for all geographical regions. The European risk premium also rises substantially during the Eurozone debt crisis from mid-2010 onwards. The increase in risk premiums is relatively smaller for other geographical regions during the Eurozone debt crisis. Remarkably, even following the large increase in Eurozone risk premiums following 2008, at the end of the sample the average Eurozone risk premium is still lower than the risk premium in Latin American and Asian countries.

4.3.2 Prices of Risk

Panels A to D of Figure 7 present the dynamics of the prices of risk $\lambda_0 + \lambda_1 X_t$ associated with U.S. interest rates, the VIX, the MSCI country index, and foreign exchange implied volatility. We present averages across all countries in the sample. The parameters $\lambda_0$ and $\lambda_1$ are inferred using equation (2.13) and the estimated risk-neutral and physical dynamics. A higher price of risk suggests that the price of a dollar is higher in that state of the world.

For U.S. interest rates in Panel A, the price of risk across all countries is higher in the early part of the sample and declines in the later part of the sample. It becomes slightly negative during the financial crisis of 2008 and at the very end of the sample period. This suggests that the risk premium associated with U.S. interest rates declines during the financial crisis of 2008, perhaps capturing a flight to quality effect. The price of risk associated with the VIX is high between 2002 and 2003, as well as during the 2008 financial crisis. This suggests that the risk premium associated with the VIX increased substantially during the financial crisis of 2008. The price of risk associated with the country’s stock index returns index is high between 2001 and 2003, becomes negative between 2003 and 2004, and rises from 2004 onwards. It becomes positive during the financial crisis of 2008, but then declines after the financial crisis. The increase in the price of risk associated with the negative stock returns during the financial crisis is very
pronounced, but it is dominated by the increase in the price of risk during the market decline that followed the bursting of the tech bubble in 2000. The price of risk associated with foreign exchange rate volatility is negative on average across countries and is substantially low between 2001 and 2003. It also declines during the 2008 financial crisis.

In summary, we see large increases in the (absolute value of) the price of risk for three out of the four panels during the 2008 financial crisis. The one exception is U.S. interest rates. As mentioned before, the sharp decline in the price of risk in Panel A may be a consequence of flight to quality. The increases in the price of risk during 2008 lead to sharp peaks in credit risk premiums in all geographical regions during 2008, as documented in Figure 6.

Panels E to H of Figure 7 show the ratio of risk-neutral to physical default probabilities for five year horizon for different values of the covariates. These ratios are computed for each country individually using the estimated parameters, changing each of the covariates separately while fixing other covariates at their time-series average. The graphs present the averages across all sample countries and three geographical regions. Panel E shows that on average for all countries, the ratio decreases with the U.S. yields until the yield reaches 5.6%, before increasing as a function of interest rates. The pattern for Asian and European countries is also U-shaped, but less pronounced, whereas for Latin American countries the ratio monotonically increases with interest rates. Note that the intuition for these patterns is far from obvious. As U.S. interest rates rise and business conditions improve, one expects default probabilities to decline, but these patterns are about the size of the decrease in physical default probabilities relative to the decrease in risk-neutral default probabilities.

Panel F shows that the ratio of risk-neutral to physical probabilities increases with increases in the VIX. Note that this is also the case for Europe, but the increase is very small. In general, spreads for Eurozone countries do not respond much to the VIX. The volatility index (VIX) is larger in bad states of the world. The increase in Q to P probabilities ratio with VIX suggests that risk-neutral probabilities rise more than physical probabilities as VIX increases; hence, the overall risk premium increases with VIX. Panel G presents the ratio of risk-neutral to physical probabilities as a function of stock market returns. The ratio decreases as the return on the MSCI country index rises for all geographical regions. Panel H of Figure 7 show that the ratio of Q to P probabilities increases with the increase in foreign exchange volatility for all regions. The intuition for this finding is similar to the intuition used for the pattern with respect to the VIX.
4.4 Term Structures of Spreads and Risk Premiums

Figure 8 presents the average slope for the credit risk premium for the overall sample and the three geographical regions. For comparison, we also provide the slope of the CDS spreads. The slopes are defined as the difference between the spread or credit risk premium for the 10-year maturity and the 1-year maturity. Intuitively, short-term spreads that are larger than long-term spreads suggest that the country is highly distressed. An example in our sample is the Eurozone in 2011-2012.

For highly distressed entities, the ratio of Q to P probabilities is generally lower relatively to safer entities. This is consistent with the notion that the risk-premium represents a larger percentage of the spread for AAA-rated entities than for CCC-rated entities. We therefore expect that entities with high short-term spreads relative to long-term spreads have lower short-term Q to P ratios compared to the long-term Q to P ratios. In Panel A of Figure 8 we observe this pattern in the 2008 financial crisis: the slope of the credit risk premium rises when the slope of the CDS spreads drops during the financial crisis of 2008. This suggests that during these times, there is a larger increase in physical probabilities relative to risk-neutral default probabilities at the shorter horizon while there is relatively larger increase in risk-neutral probabilities compared to physical at longer horizons. We observe a similar pattern for Latin America and Asia during 2008. For the Eurozone countries, we observe this negative relation during the Eurozone debt crisis from mid-2010 onwards. We conclude that the economic intuition underlying this inverse relation applies during periods of market stress.

Panel E of Figure 8 provides additional evidence on this. We present a scatter plot of the CDS slope and credit risk premium slope. The scatter plot is generated by pooling data from all countries in our sample. The scatter plot is separated into three sample periods: before the financial crisis of 2008 (April 2001 to March 2008), during the financial crisis (April 2008 to July 2011) and post-crisis (August 2011 to June 2012). We see a very clear and interesting pattern emerging from the scatter plot. Before the financial crisis, there is no relation between the CDS slope and the credit risk premium slope. During the financial crisis, there is a negative relation between the CDS slope and credit risk premium slope, i.e., as the CDS slope declines, there is an increase in the credit risk premium consistent with the intuition mentioned earlier. After the financial crisis, the credit risk premium slope increases with the CDS slope.

These findings suggest that before the crisis, the price of a dollar in bad states of the world is similar both for short and long horizons. However, after the crisis, either the price of a dollar in bad states of world increases with the horizon, or the probability of a bad state of the world decreases with the horizon. Both arguments are intuitively plausible. Since agents just
experienced a crisis, they assign a lower probability of another crisis happening in the next 10 years, resulting in declining (implied) physical probabilities for longer horizons. Alternatively, the price of a dollar in really bad states has increased for the agents as a consequence of the crisis, even though the probability of that bad state did not change. This results in larger risk premiums and hence, larger Q probabilities at longer horizons.

5 Country-Specific Results

So far we discussed results that were averaged across all countries or across geographical regions. To provide more intuition and to illustrate the value of time-varying prices of risk and risk premiums, this section discusses detailed results for two individual countries. We also discuss credit risk premium for each country in our sample.

Figure 9 presents credit risk premiums and deltas for all covariates for Poland. Panel A presents the credit spread and the credit risk premium for the five-year contract. Poland experienced a period of uncertainty in the first half of 2003, when the final phase of the European integration referendum was at stake. This is reflected in higher credit spreads. Eventually, the referendum was approved and the country subsequently joined the European Union following the ratification of the 2003 Treaty of Accession. A very calm period followed up till the start of the credit crisis. The 2008 crisis is reflected in much higher spreads. Toward the end of the sample, the high spreads reflect the turmoil in the Eurozone countries. Even though Poland is not part of the Eurozone, it is strongly affected through the effect on its trading partners.

The credit risk premium in Panel A is highly time-varying and mostly positive. It is even more reflective of the economic reality than the spreads themselves. It is low in the early part of the sample before 2003 and peaks around March 2003. It gradually declines from mid-2003 onwards and reaches its minimum around mid-2007. It increases substantially from mid-2007 onwards with the onset of the financial crisis and reaches its peak of 4.24 in late 2008 after the defaults of Lehman Brothers and Washington Mutual. It subsequently declines until early 2010, after which it again starts rising following the Eurozone debt crisis. Overall, the conclusion from Panel A is that the estimated credit risk premium is intuitively plausible and increases in bad states of the world.

Panel B presents the slope of the credit risk premium together with the slope of the CDS spreads. As observed earlier, there is a sharp increase in the credit risk premium slope during the 2008 financial crisis. This suggests that during the financial crisis, there is a larger increase in short term physical default probabilities which results in relatively lower credit risk premiums for shorter maturity contracts.
Panel C of Figure 9 presents the sensitivity of the Polish five-year spreads with respect to the U.S. interest rates. We present the deltas for the no-arbitrage model and the linear regression model. The delta with respect to U.S. interest rates is negative throughout the sample, which is consistent with the economic intuition mentioned earlier. It is stable and around -20 basis points on average before the 2008 financial crisis. It drops to around -82 basis points during the financial crisis. It also drops substantially during the Euro zone debt crisis from mid-2010 onwards. The time-series average of the deltas is -32 basis points, which is close to the -46 basis points obtained from the linear regression model. Panel D presents the deltas with respect to the VIX for the no-arbitrage model and the linear regression model. Consistent with economic intuition, it is positive for both models. However, the sensitivity from the no-arbitrage model is low relative to the one obtained from the linear regression model. Panels E and F present the deltas with respect to the country’s stock return and exchange rate volatility respectively. Both these deltas have signs consistent with economic intuition. The average deltas for these two covariates are similar in magnitude for the no-arbitrage and linear regression models. Both deltas are substantially larger during the 2008 financial crisis.

Figure 10 presents the credit risk premium and the deltas for Mexico. The spreads in Panel A reflect Mexico’s ties to the events experienced in the Americas, especially around 2002. Mexico’s vicinity to the US makes the nation more susceptible than any other country in the sample to events occurring in the U.S. In 2001 and 2002, Mexico’s partners, both to the North and the South, experienced extreme negative events. The U.S. economy was in the aftermath of a collapsing stock market bubble, and experienced the terrorists attacks in September 2001. Argentina declared default in December 2001, and Brazil, the major country in the Latin American region, was about to elect a former union leader in 2002, and the prospects regarding monetary and fiscal policy were unclear. In addition, in 2001 the Mexican state-owned oil enterprise PEMEX, one of the main sources of income for the Mexican government, was involved in a major scandal involving illegal funding of political parties. These events are reflected in high spreads in 2002-2003. After this turbulent time, the country experienced a calm period up until the beginning of the credit crisis in early 2007.

Panel A shows that the credit risk premium for Mexico is also positive throughout the sample. It also increases in periods of turmoil, such as 2008 and 2002-2003. Panel B shows that for Mexico, we do not find strong evidence of an inverse relationship between the slope of the credit risk premium and the CDS spread slope during crisis periods. Panels C to F present the deltas with respect to all four covariates. All four deltas have economically plausible signs and have the largest impact during the financial crisis.

Overall, the results for the two countries strongly suggest that our estimated deltas and risk
premiums are consistent with economic intuition.

So far, we discussed the credit risk premium averaged across all countries and geographical regions, as depicted in Figure 6. Column 17 of Table 1 presents the time-series average of the credit risk premium for each country. The table also provides information about the average difference between the CDS spreads under Q measure and the CDS spreads under P measure for each country (see column 16). The average credit risk premium is positive for all countries in our sample except Ireland and Portugal. Table 1 shows that the average difference between the Q and P spreads is generally higher for riskier countries i.e., riskier countries have higher absolute risk premium. However, the credit risk premium defined as the ratio of Q to P spreads does not behave in the same way. We observe substantial cross-sectional variation in the credit risk premium across countries. While there is no clear cross-sectional relation between the credit risk premium and the level of credit spreads across all countries, within different geographical regions we see some sort of pattern. For example, within Eurozone countries Germany has the largest credit risk premium. This is consistent with the intuition mentioned earlier i.e., a large proportion of the spreads for highly rated countries are due to risk premium since they are likely to default in a really systematic event. On the other hand, countries with lower ratings have much higher actual default probabilities and their defaults may be idiosyncratic in nature which results in lower credit risk premium. We observe similarly larger credit risk premium for the safest countries in Latin America and Asia. For example, Chile and Japan which are the safest countries in their respective regions have the highest credit risk premium.

Figure 11 presents the credit risk premium for all countries in our sample. For most countries in our sample, the credit risk premium is positive throughout the sample. One important conclusion is that there is a substantial time-series variation in credit risk premium for all countries. A second important conclusion is that there is a large amount of cross-sectional variation in the credit risk premium at a given point in time, consistent with the averages reported in Table 1. Further, while the correlation between credit risk premiums across countries is modest, one common pattern that emerges for almost all countries is the large increase in credit risk premiums during the 2008 financial crisis.

6 Alternative Specifications

All empirical results discussed so far are based on the benchmark specification with four covariates: U.S. interest rates, the VIX, the MSCI country index return, and exchange rate volatility. In this section, we compare the credit risk premiums obtained from the benchmark covariate specification with alternative covariate specifications. We also compare the credit risk risk premium
from the benchmark model with the credit risk premium obtained from a fully latent model.

Figure 12 presents the comparison of the credit risk premium from the benchmark model with two alternative, more richly parameterized, covariate specifications. Specification 2 augments the benchmark covariates with the one year local swap rate. Specification 3 includes the covariates from the benchmark specification, the one year local swap rate and the terms of trade. We decided on these two covariates based on the results of an extensive specification search using linear regression.

We estimate these two richer specifications for each country in our sample. Panel A shows the comparison of the average credit risk premium across all countries obtained from each of the specifications. The key observation from the figure is that the level and the dynamics of the credit risk premium are similar across all three specifications. Panels B to D show the comparison of the credit risk premium for all three specifications for different geographical regions. These graphs also show that the dynamics and level are fairly similar across the three specifications for all regions. There are of course differences in the levels of the credit risk premiums, but the time-series correlation of the paths is very high.

These findings suggest that our estimated credit risk premiums are relatively robust to the choice of covariate specification. To put the robustness of our findings in perspective, we now compare the credit risk premium obtained from our benchmark covariate specification with the one obtained from a fully latent model. Fully latent models of credit risk are very popular for a good reason, because they provide a better fit than models with observables. It is well-understood that this represents a trade-off, because models with observables are capable of providing more economic intuition.

We estimate a two-factor latent model using the unscented Kalman filter. It is instructive to focus on individual countries rather than averages, and therefore Figure 13 provides evidence for four countries in our sample: Mexico, Poland, South Africa, and South Korea. Note that we choose four countries from different continents. Figure 13 compares the risk premium obtained from the benchmark covariate model with that from the latent factor model for all four countries. The risk premiums estimated from the latent models differ from those estimated from the models with observables, but of course we do not know the true risk premium.

Figure 13 contains three different risk premium estimates for the latent model. These are risk premiums corresponding to three local optima which provide essentially identical model fit (within two basis points). Despite the very similar fit, the credit risk premiums are substantially different. For example, for Mexico, the latent parameter set 2 generates large credit risk premiums between 2001 and 2003 while other parameter sets (latent 1 and latent 3) generate much smaller credit risk premiums for the same time period. We observe similar differences in credit risk
premiums for different parameters for all four countries. In addition, the credit risk premiums obtained from the latent models are quite noisy and often tend to be negative. The credit risk premium obtained from the observable model is more stable and mostly positive.

To establish the ability of models with latents and observables to identify risk premiums, a detailed Monte Carlo analysis is needed, and the appropriate choice of data generating mechanism for such an analysis is not straightforward. Figure 13 merely suggests that the advantages of no-arbitrage models with observable covariates may go beyond providing more economic intuition, and that risk premiums computed using models with observables deserve further study. In our opinion there is good econometric intuition for these results. For a latent model, the fit under the pricing measure will be superior, but ratios of the Q and P dynamics may be less reliable. In a model with observable covariates, the P dynamics can be directly obtained from the time-series data of the covariates, whereas the latent model has to infer all information on the Q and P dynamics from the CDS prices. As a result, the P-estimates may not be well anchored, and ratios of P and Q dynamics may not always be well identified.

7 Conclusion

We specify no-arbitrage models for the valuation of sovereign CDS contracts. The country’s default intensity is assumed to be a quadratic function of observable economic and financial indicators, guaranteeing positive default intensities at all times. We select a parsimonious benchmark model based on the explanatory power of the observable variables. This model contains four determinants of the countries’ default intensities: the U.S. interest rate, the VIX stock market volatility index, the one-year trailing return on the country’s stock market index, and the implied exchange rate volatility for the country’s currency.

We estimate this model using a sample of twenty-eight countries. For each country we have over a decade’s worth of daily data, and we use the 1-year, 5-year, and 10-year tenors in estimation. The benchmark model provides a satisfactory fit. We also report on two more richly specified models, which include the one year local swap rate and the terms of trade. These models have similar implications regarding the size of risk premiums and their time-variation, and the sign of the deltas of spreads with respect to the observable covariates.

The impact of the economic and financial variables on spreads varies substantially across countries and over time, but is consistent with economic intuition. In the benchmark model, spreads increase as a function of stock market and exchange rate volatility, but decrease as a function of interest rates and stock market returns. Estimated risk premiums are highly time-varying and peak during the 2008 financial crisis for nearly all countries. For European countries
the risk premiums are also high during the Eurozone debt crisis. It seems that during periods of market stress, market risk aversion increases by more than default probabilities. The variation in risk premium across countries is very large, also outside of crisis periods, and some of this variation is driven by regional factors. We document an interesting relation between the term-structure slopes in the CDS spreads and the credit risk premium. In the 2008 crisis these slopes are clearly inversely related, but this is not the case pre- and post-crisis.

Our work can be extended in a number of ways. It is possible to further improve in-sample fit by adding economic and financial variables, but in our opinion this is not a priority. Reduced-form models with latent factors are much better suited for this task. Instead, the model has much more promise for investigating the effects of specific economic and financial variables. In this paper we have limited ourselves to economic and financial data that are available daily, partly to avoid econometric complications. Combining low-frequency macroeconomic variables such as inflation and GDP growth with daily CDS data might provide interesting additional insights. Allowing for stochastic recovery rates could be an interesting extension, but this substantially complicates the resulting estimation problem. Finally, a more in depth investigation of the relative strengths and weaknesses of models with latents and observables, for instance in identifying risk premia, would also be interesting.
References


Figure 1: Global and Local Covariates

Panel A. U.S. Interest Rates
Panel B. VIX
Panel C. Stock Returns
Panel D. Exchange Rate Volatility
Panel E. Local Swap Rate
Panel F. Terms of Trade

Notes to Figure: We plot the time series of the ten-year US Treasury bond yield (UST), the VIX index, the average of the MSCI one-year trailing returns across all twenty-eight countries, the average of the three-month foreign exchange implied volatility, the average of the one-year constant maturity local swap (SWA), and the average of the terms of trade index (TOT). The first two covariates are common to all countries. The remaining covariates are specific to each country, but for Eurozone countries, FXIV, SWA, and TOT are identical.
Figure 2: Model and Market Spreads

Notes to Figure: Panel A plots the CDS spreads (black line), the fitted OLS spreads (grey line), and the no-arbitrage (NA) model spreads (dashed line) averaged over the entire set of twenty-eight countries. Panel B uses only the countries in the Eurozone. Panel C only uses the Latin American countries, and Panel D only uses the Asian countries. For all regions, the average is computed only if we have at least four countries with available data.
Figure 3: Model Spread Sensitivity to U.S. Interest Rates and VIX

Notes to Figure: We plot the sensitivity or delta (in basis points) of the credit spreads to a change in the ten-year U.S. Treasury bond yield (UST) and the VIX. Panels A, B, C, and D plot the UST delta for the entire set of countries, the Eurozone, Latin American, and Asian countries respectively. Panels E, F, G, and H plot the VIX delta for the same sets of countries.
Figure 4: Model Spread Sensitivity to Stock Returns and Exchange Rate Volatility

Notes to Figure: We plot the sensitivity or delta (in basis points) of the credit spreads to a change in the country’s one-year trailing stock return index (MSCI) and the three-month foreign exchange implied volatility (FXIV). Panels A, B, C, and D plot the MSCI delta for the entire set of countries, the Eurozone, Latin American, and Asian countries respectively. Panels E, F, G, and H plot the FVIX delta for the same sets of countries.
Figure 5: Term Structure of Deltas

Notes to Figure: For the entire set of twenty-eight countries, panels A, B, C, and D plot the term structure of deltas for the ten-year U.S. Treasury bond yield (UST), the VIX, the country’s one-year trailing stock return index (MSCI), and the three-month foreign exchange implied volatility (FXIV) respectively.
Notes to Figure: We plot the credit risk premium (CRP) defined as $\frac{CDS^Q}{CDS^P} - 1$. Panels A, B, C, and D plot the credit risk premium for the entire set of twenty-eight countries, the Eurozone, the Latin American, and Asian countries respectively.
Figure 7: Prices of Risk and Ratios of Risk-Neutral to Physical Default Probabilities

Notes to Figure: For the entire set of twenty-eight countries, panels A, B, C, and D plot the prices of risk for the ten-year U.S. Treasury bond yield (UST), the VIX, the one-year trailing stock return index (MSCI), and the three-month foreign exchange implied volatility (FXIV) respectively. For different groups of countries, panels E, F, G, and H plot the sensitivity of the ratio of the risk-neutral (Q) and physical (P) default probabilities to changes in UST, VIX, MSCI, and FXIV respectively. The default probabilities under both measures are computed for five year horizon.
Figure 8: Credit Risk Premium Slopes and CDS Spread Slopes

Notes to Figure: We plot the difference between the ten-year and one-year credit risk premium (CRP), and between the ten-year and one-year CDS spreads for the entire set of countries (Panel A), the Eurozone countries (Panel B), the Latin American countries (Panel C), and the Asian countries (Panel D). The left axis refers to CRP slopes, in black. The right axis refers to CDS spread slopes, in grey (in basis points). Panel E plots the CRP and the CDS slopes’ cross-country average. Each circle denotes one day. Different colors refer to different periods. The first period, indicated by white circles, starts in April 2001 and ends in March 2008. The second period starts in April 2008 and ends in July 2011, and is indicated by grey circles. The third period starts in August 2011 and ends in June 2012, and is indicated by black circles. The vertical axis measures the CRP slope, and the horizontal axis measures the CDS spread slope (in basis points).
Notes to Figure: We plot information on deltas and credit risk premiums for Poland. Panel A shows the credit risk premium and the CDS spread. Panel B shows the credit risk premium and CDS slopes, defined by the difference between the ten-year and one-year maturities. Panels C, D, E, and F plot the deltas of model spreads with respect to changes in the ten-year U.S. Treasury bond yield (UST), the VIX, the one-year trailing stock return index (MSCI), and the three-month foreign exchange implied volatility (FXIV).
Notes to Figure: We plot information on deltas and credit risk premiums for Mexico. Panel A shows the credit risk premium and the CDS spread. Panel B shows the credit risk premium and CDS slopes, defined by the difference between the ten-year and one-year maturities. Panels C, D, E, and F plot the deltas of model spreads with respect to changes in the ten-year U.S. Treasury bond yield (UST), the VIX, the one-year trailing stock return index (MSCI), and the three-month foreign exchange implied volatility (FXIV).
Figure 11: Credit Risk Premiums by Country

Notes to Figure: We plot the credit risk premium for individual countries, for the entire set of twenty-eight countries.
Figure 11 (continued): Credit Risk Premiums by Country

Notes to Figure: We plot the credit risk premium for individual countries, for the entire set of twenty-eight countries.
Figure 12: Credit Risk Premiums for Different Model Specifications

Notes to Figure: The solid black line shows the credit risk premium obtained from the benchmark model specification, which includes the following covariates: the ten-year U.S. Treasury bond yield (UST), the VIX, the one-year trailing stock return index (MSCI), and the three-month foreign exchange implied volatility (FXIV). The thin grey line shows the credit risk premium obtained from model 2, which includes the same covariates as the benchmark model, as well as the one-year constant maturity local swap (SWA). The light grey line shows the credit risk premium obtained from model 3, which includes the covariates from model 2, as well as the terms of trade (TOT). Panels A, B, C, and D report on the entire set of twenty-eight countries, the Eurozone countries, the Latin American countries, and the Asian countries respectively.
Figure 13: Credit Risk Premiums for the Model with Observables and the Latent Model

Notes to Figure: We plot credit risk premiums for the benchmark model and for different parameterizations of the latent model, for four countries.
Table 1: Descriptive Statistics and Results

| Country     | CDS Avg | SD | MSCI Avg | SD | FXIV Avg | SD | SWA Avg | SD | TOT Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD 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| SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | Delta Avg | SD | DeltaAvg | "Notes to Table: For each country, we report descriptive statistics for five-year CDS spreads and local covariates. MSCI refers to the one-year trailing stock return index, FXIV refers to the three-month foreign exchange implied volatility, SWA refers to the one-year constant maturity local swap, and TOT refers to the terms of trade (columns 2 to 11). We report the deltas (scaled by 10000) to the four covariates in the benchmark model, along with the average of the credit risk premium, \(CDS^Q - CDS^P\) (in basis points), the RMSE of the no-arbitrage model and the OLS regression (columns 12 to 19)."
<table>
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<th>Panel A. Intensity Loadings (x100)</th>
<th>Panel B. Standard Deviation (x100)</th>
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<th>Panel C. Persistence, Q-Dynamics</th>
<th>Panel D. Intercept, Q-Dynamics (x100)</th>
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<tbody>
<tr>
<td>$\rho_{UST}$</td>
<td>$\rho_{VIX}$</td>
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<td>Average</td>
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<th>Panel F. Intercept, P-Dynamics (x100)</th>
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<td>Std.Dev.</td>
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Notes to Figure: We report the distribution of the model parameters for the four covariates: the ten-year U.S. Treasury bond yield (UST), the VIX index, the country’s one-year trailing stock return index (MSCI), and the three-month foreign exchange implied volatility (FXIV). Panel A reports the intensity loadings. Panel B reports the standard deviation. Panel C reports the persistence under the Q measure. Panel D reports the intercept under the Q measure. Panel E reports the persistence under the P measure. Panel F reports the intercept under the P measure.