A Structural Approach to Estimate Market-Assessed Sovereign Credit Risk

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Abstract

This paper explores the economic determinants of market-assessed sovereign risk of members of the European monetary union. The empirical work is innovative in its specification of appropriate inputs. The Merton structural model provides a theoretical background for the empirical investigation of sovereign risks. We make use of publicly available government financial statistics as well as national stock market volatility estimated by EGARCH, implied from traded options and by fitting a generalized Pareto distribution. We show a high degree of association between our modelled spreads and credit default swap spreads using volatility estimates based on option implied and generalized Pareto distribution. Model performance holds in out-of-sample prediction and the non-linear model derived from structural theory is shown to outperform a benchmark linear regression model. These results provide policy makers and regulators with a set of insights into the factors which influence credit market activity enabling them to take an informed approach to policy and regulatory settings which will be subject to market appraisal.

JEL classification: G01; G10

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1 Introduction

Following the banking crisis in September 2008, the yields on many Eurozone sovereign bonds began to widen sharply, challenging the perception that advanced economies are immune to default. Subsequent emergency multi-national bailouts have highlighted the severity of the crisis and underscored the importance of timely and accurate estimation of sovereign credit risk.

Sovereign crisis are not a new phenomenon. Frank and Cline (1971) exemplifies a field of work that search for the determinants of developing country debt defaults among a wide range of macroeconomic variables. Macroeconomic variables are symptoms of a debt crisis (Berg and Sachs, 1988), since they are reported infrequently and are backward-looking. Subsequent studies have benefited from market data and sought to explain sovereign credit risk measured by credit spreads. For example, Boehmer and Megginson (1990), Min (1998) and Hilscher and Nosbusch (2010), have searched for the determinants of sovereign bond yield spreads and Ejsing and Lemke (2009) and Dieckmann and Plank (2011) among others, have investigated the determinants of Eurozone sovereign default swap spreads. However these studies have used a regression framework that cannot capture the non-linearity between spreads and determinants. Closer to our study are the studies that apply a structural framework to the analysis of sovereign credit risk. Nevertheless, these existing studies have examined emerging markets only and there is a wide disagreement in the parameterisation.

This study makes the three following contributions to the existing literature; Firstly, sovereign credit risk studies commonly consider debt servicing capacity of a country rather than the government. Since governments are the ultimate underwriters of sovereign debt, we develop a generic public sector balance sheet to gauge government fundamentals. Secondly, we use the non-linear functional form of the Merton model to assess the ability of the structural framework to explain the market-assessed credit risk of sovereigns who are members of a monetary union, expressed in terms of risk-neutral credit spread. To our best knowledge, we are the first to apply this framework to members of an economic and monetary union (EMU).

Lastly, we examine the problem of approximating unobserved sovereign asset volatility. We look at the performance of three asset volatility proxies; national stock index volatility based on EGARCH, a market tail risk measure based on Generalized Pareto (GP) distribution and stock index option implied volatility. Our approach of using private sector information to approximate sovereign characteristics is consistent with Altman and Rijken (2011), who proposed companies as a leading indicator of sovereign crisis, and Acharya, Drechsler and Schnabl (2011) and Mody's (2009) who show public-private sectoral risk transfers.

A credit spread is a market-assessed level of credit risk in the sense that it incorporates investor risk aversion (Amato, 2005). Market-assessed measures of sovereign credit risk are important as observed changes in the market's attitude can indicate the imminent propagation of a crisis from one country to another as the market reinterprets the status quo. Baek, Bandopadhyaya and Du (2005) refer to this type of contagion as "pure contagion", which is supported by empirical evidence using corporate bonds (Collin-Dufresne, Goldstein and Martin, 2001), in emerging market Brady bonds (Weigel and Gemmill, 2006) and recently in Eurozone CDSs (Dieckmann and Plank, 2011). The results of this study may also be of use to government regulators charged with assessing the robustness of government debt positions to private sector shocks, as it establishes a link between sovereign debt positions and the financial health of the private sector.

We evaluate our model estimates against credit default swap (CDS) spreads. CDS spreads are seen a cleaner indicator of cross-sectional and time-series credit quality information, as they do not depend on the choice of a risk-free rate and are unaffected by taxation (Longstaff, Mithal and Neis (2005) and Ericsson, Jacobs and Oviedo (2009)).

Our results show that using sovereign balance sheet information and national equity market volatility as inputs in the Merton model which explains market assessed sovereign credit risk measured by sovereign CDS well, with an average R^2 of 0.74 and average Spearman correlation of 87 percent for 12 Eurozone countries. We also find that long-dated index option implied volatility and the Pareto distribution tail risk measure offer similar proxies for sovereign asset volatility. However, in the absence of traded options, we show that the tail risk volatility measure outperforms an EGARCH based volatility estimate. Finally, the out-of-sample forecast results indicate that the structural model is superior to a linear regression model, particularly with volatile sovereigns with the result holding across all volatility specifications.

The remainder of the paper is organised as follows. Section 2 summarises prior attempts of modelling emerging market sovereign credit risk using the structural framework and discusses their limitations. Section 3 introduces the model and demonstrates an approach that is both economically intuitive and implementable. Section 4 describes the data. Section 5 explains the evaluation procedure and presents the results, while section 6 concludes.

2 Studies of Sovereign Credit Risk Using a Structural Framework

The strong economic underpinning of the structural model has spawned a growing field of literature which uses the model to estimate the sovereign credit risk of emerging nations.

Derived from the national income identity, Clark (1991) shows that the 'market value' of a country can be measured as the sum of a country's discounted future net exports. Subsequent studies including Clark and Kassimatis (2004) and Karmann and Maltritz (2002) use this valuation of a countries assets within a structural model to estimate the default risk of Latin American sovereign nations and Russia. While this approach may be suited to developing countries it is problematic in large advanced economies such as the US, Germany and UK. Focusing only on cross-border inflows and outflows requires strong assumptions that exclude taxation cash flows and government spending.

Currie and Velandia (2002) depart from Clark's (1991) framework and propose a conceptual government balance sheet, where sovereign assets consist of the present value of fiscal revenue, foreign reserves and marketable securities. In this framework liabilities consist of the present value of fiscal expenditures, public debt and contingent liabilities. However, forecasting future fiscal revenue and expenditure entails numerous assumptions including the appropriate discount rates for revenue and expenditure. Moreover, contingent liabilities like those which arise when financial institutions require government guarantees or bailouts, are difficult to estimate.

A number of authors have steered away from direct estimation of sovereign asset value and resorted to implied estimates using the option pricing framework of

Black and Scholes (1973). This method has been the standard approach in the corporate literature where company debt and equity are characterised as put and call options written on company assets respectively. Oshiro and Saruwatari (2005) use a country's stock index as a proxy for sovereign 'equity'. They use sovereign debt and the option pricing technique to solve for implied sovereign asset value. However, the notion of sovereign equity is ambiguous and it can be argued that the link between corporate sector equity valuation and public sector equity is tenuous.

More recently the proprietary Macro-financial Risk model, jointly developed by Moody's and MfRisk Inc., and introduced in 2001 by Gray, Merton and Bodie (2007) proposes a sovereign capital structure based on implied debt seniority. The authors argue that foreign-currency debt can be viewed as a senior claim, as governments prefer not to default on their foreign-currency debt, and governments have the flexibility to issue, repurchase or dilute local currency debt. Gapen, Gray, Lim and Xiao (2005) empirically test Gray et al.'s (2007) model by evaluating modelled spreads against market CDS and EMBI+ from January 2003 to August 2004. Although they report a strong correlation between the market and modelled spreads they find that without parameter calibration, the model underestimates market spreads. This is a problem that has consistently plagued structural models since the early work of Jones, Mason, and Rosenfeld (1984).

Recognising the difficulty of structural model implementation, Hui and Lo (2002) abandon the Merton approach in favour of the hybrid approach of Cathcart and El-Jahel (1998). In this approach the relationship between assets and debt is replaced by the proximity of an exogenous signalling process to a predefined threshold. The authors choose the foreign exchange rate as the signalling process but show that it alone may not adequately capture all the changes in the credit spreads of sovereign bonds. In a similar study, Moreira and Rocha (2004) employ three alternative default triggering processes based on accounting ratios involving debt, reserves, exports and industrial output. The major drawback of the hybrid approach is the loss of valuable insight into the relationship between fundamentals, market factors and credit risk.

Generally, structural models designed for emerging markets do not apply to developed nations or nations within an EMU, and there is wide disagreement in the parameterisation of the models. The following section presents a generic implementation of the structural model that directly captures government debt positions with weekly evolution in modelled spreads driven by changes in stock market volatility.

3 Model Description and Parameter Setting

3.1 Structural Credit Risk Model

Merton (1974) pioneered the basic structural approach to assessing credit risk by directly applying the theory of European option pricing developed by Black and Scholes (1973). The model relates credit risk to the capital structure of a firm to produce a forecast of the firm's probability of default at a given point in time. It assumes the total value of the firm's assets, A, follow a geometric Brownian process:

$$dA = \mu A dt + \sigma A dW \tag{1}$$

where μ is the asset drift, σ is the asset volatility, and dW is a standard Weiner process. The underlying assumption is that debt, B, is a zero-coupon bond with maturity at time T, and default occurs when the asset value falls below the bond's principal value at maturity. In this specification, equity essentially represents a European call option on the assets of the firm with the same maturity as the bond and a strike price equal to the face value of the debt, *D*. Although a firm's limited liability feature does not feature in the sovereign context, expected default loss characterised by a put option is similar for both corporate and sovereign creditors. The value of firm's defaultable debt is equal to the value of a default-free discount bond minus the value of a put option written on the asset value, with a strike price equal to the face value of debt and a time-to-maturity of *T*. The value of defaultable debt, *B*, at time *t* can be expressed as:

$$B_t = De^{-rt} - [De^{-rt}N(-d_2) - AN(-d_1)] \quad (2)$$

where *r* is the instantaneous risk-free rate, $N(\cdot)$ is the cumulative standard normal distribution function, and d_1 and d_2 are given by:

$$d_1 = \left[\log\left(\frac{A}{D}\right) + \left(r + \frac{1}{2}\sigma^2\right)T\right]/\sigma\sqrt{T} \quad (3)$$

$$d_2 = d_1 - \sigma\sqrt{T} \quad (4)$$

The credit spread, *s*, between the two zero-coupon bonds is given by.

$$s = -\frac{1}{T}log\left(\frac{B_t}{De^{-rt}}\right) \quad (5)$$

By substituting equation 2 into equation 5 and rearranging, the credit spread implied from Merton's model is given by

$$s = -\frac{1}{T}log\left[N(d_2) + \frac{A}{De^{-rt}}N(-d_1)\right], \quad (6)$$

which shows that credit spread is effectively driven by the asset value, asset volatility and the level of debt. The level of government debt can be easily obtained from publicly available information, sovereign asset value and volatility dynamics need to be estimated. The implementation is discussed in the next two sections. For parsimony in model parameters, we implement the basic Merton model over a large body of variants.

3.2 Adapting the Structural Model to Sovereigns

In the corporate context, the Merton framework utilises the market value of firm assets, debt and asset volatility to estimate default probability of a firm. One may argue that a firm's ability to service debt as it falls due is based on its ability to generate free cash flows. However, from a valuation perspective, the market value of a corporation is the present value of all expected future free cash flows. Similarly, the market value equivalent of a sovereign should be the expected taxation and spending cash flows. Further justification for the use of a stock rather than a flow measure is that it considers asset liquidation. The Greek government for example, has committed to privatising €50 billion worth of assets, which is still less than a fifth of all the assets that Greece could privatise (Hetzner, Framke and Taylor, 2011).

The question of how to estimate the market value equivalent of sovereign assets still remains. As explained in section 2, for a corporation with a simple balance sheet comprising of debt (put option + risk free debt) and equity with limited liability (call option), unobservable asset value can be inferred from these claims on company assets using the Blank and Scholes option pricing model. Since stock prices capture the current expectation of future cash flows, they imply asset value. Sovereigns however, do not have traded equity. Merton's (1974) insights show us that asset value, asset volatility and debt value determine the risk-neutral probability of default under a set of assumptions. It follows that the market price of default risk under risk-neutral valuation must also contain information about the value of assets. Therefore, we can solve for 'market-implied' sovereign asset value using market credit spreads from CDS contracts.[1]

It has been recognised that governments are exposed to substantial contingent liabilities stemming from the financial sector. In this paper, we do not explicitly model government contingent guarantees, such as deposit insurance, due to the added complexity and the variability of guarantee value (See, for example, Lucas and McDonald (2010)). Instead, we account for contingent liabilities in our modelling of volatility. The value of government contingent liabilities is likely to be correlated with the financial health (or tail risk) of the private sector due to the provision of bailout funds. If contingent liabilities bring sovereign issuer closer to the default barrier, the same can be achieved by extending government asset's lower tail closer to the default boundary though increased volatility.

3.3 Estimating Asset Value

Since a high proportion of Eurozone government's debt is denominated in Euros we do not consider the capital structure proposed by Gray et al. (2007). Furthermore, Vasishtha (2010) and Roubini and Setser (2004) claim that inferring seniority structure from the ownership of debt is difficult, as the decision to default on external or domestic debt is largely political.[2] We also do not believe that equity index valuation can provide a good approximation of the sovereign's net worth.

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[1] This is the intuition behind our model calibration process in section 5.

[2] Usually, external debt refers to debt held by non-resident while domestic debt is held by resident. Other definitions include the legal definition of "governing law" see Roubini and Setser (2004).

Our approach is more straightforward. We model the value of the asset directly using the Government Finance Statistics (GFS) database published quarterly by Eurostat (See Appendix A).[3] The advantage of the Eurostat database is that it adopts a common, legally binding accounting method known as the European System of National Accounts (ESA95), which is consistent with the System of National Accounts (SNA 1993).[4] Government assets comprise financial and non-financial assets. Financial assets include currency and deposits, shares and other securities such as derivatives and loans. While the value of financial assets and liabilities are observable and hence recorded, government non-financial assets are harder to value. The schematic diagram below shows the classification of government non-financial assets according to ESA95.

Produced assets

- Fixed assets
  - Tangible: Buildings; other structures; cultivated assets; machinery & equipment
  - Intangible: Mineral exploration; software
- Inventory: Material and supplies
- Valuables: Precious metal & stones not for production

Non-produced assets

- Tangible: Assets form by nature such as land
- Intangible: Patents; goodwill

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[3] Eurostat is a Directorate-General of the European Commission, whose main role is to consolidate and publish comparable statistical information submitted by the Member States.

[4] ESA 95 also plays an administrative role in the EU such as the Growth and Stability Pact. ESA 95 is based on accrual accounting, consistent with the general accounting principles in the private sector. (Eurostat, 2011)

We simplify the above balance sheet and focus on fixed assets as they constitute a large part of the non-financial assets, exhibit the most variability and thus have the largest impact on the changes in non-financial asset value. Moreover, we have accurate measures of changes in fixed assets. Our quarterly update of the government total asset is therefore given by:

$$Total\ Assets_t = Financial\ Assets_t + Fixed\ Assets_t + Other\ Assets_0$$

Each quarter, we measure the net additions to fixed assets.

$$Fixed\ Asset_t = Fixed\ Asset_{t-1} + Net\ Capital\ Formation_t$$

where:

$$Net\ Capital\ Formation_t = Gross\ Fixed\ Capital\ Formation_t - Consumption_t$$

Gross fixed capital formation is a measure of a government's investments less disposals in fixed assets in a given period, while consumption measures the decline in the fixed assets value. Note that government privatisations would be reflected in changes of financial assets and gross fixed capital formation.

To initialise the model, an initial combined estimate for fixed and other assets ($Fixed\ Asset_0 + Other\ Assets_0$) is required. We obtain this by calibrating the starting asset value A_0 to observable CDS spreads. Subsequently, fixed assets evolve by quarterly changes in the net capital formation. We assume that inventory, valuables and non-produced assets ($Other\ Assets_0$) remain constant.

3.4 Estimating Sovereign Asset Volatility

Sovereign asset volatility is generally measured by changes in macroeconomic variables, foreign exchange or equity markets. Catão and Sutton (2002) find significant explanatory power when macroeconomic variable variances are regressed on sovereign default measures. They maintain that countries with higher income volatility may produce insufficient output to service debt. We do not consider macroeconomic data due to their infrequent updates.

Foreign exchange volatility proposed by Gray et al. (2007) and Hui and Lo (2002) cannot be used to explain differences between CDS spreads as our sample countries are a subset of an EMU. Using Altman and Rijken's (2011) conjecture that the fundamental source of national wealth and of the financial health of sovereigns is the economic output and productivity of their companies, we use three types of equity volatility estimates. This is consistent with Ang and Longstaff (2011) who show that stock index return can significantly explain systemic credit risk in the Eurozone.

Our first volatility estimate is based on an asymmetric EGARCH (1,1) model. This model allows for volatility clustering as well as greater volatility induced by negative returns, a common characteristic of financial market returns especially during financial turbulence. The conditional mean and variance of the model are given respectively by,

$$r_t = a_0 + \varepsilon_t, \tag{7}$$

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2}\right| + \omega \frac{\varepsilon_{t-1}}{\hbar_{t-1}} + \beta \ln\,(\sigma_{t-1}^2), \tag{8}$$

where σ_t^2 is the variance on week t, and a_0, $\alpha 0$, $\alpha 1$, ω are constants. β determines the smoothness of the estimated volatility. To capture fat tails in the returns, we assume a Student-t distribution for the conditional distribution of the error, ε. The parameters are estimated using maximum likelihood. For each stock index, volatility is estimated using annualised 5-year rolling window of weekly data.

The second volatility estimate is obtained from equity index or futures options. This is motivated by Cao, Yu and Zhong (2010) who find that the performance of the structural model is improved significantly by using option implied volatility rather than historical volatility. Since volatility estimates based on short-maturity option contracts are likely to be too volatile to represent government asset volatility, we select options of longer-dated maturities to match our horizon. However, traded option contracts are not always available.

Existing literature provides strong evidence that the distribution of stock changes is significantly non-Gaussian. Our third volatility estimate is based on Kelly's (2009) tail risk measure. It is motivated by governments' exposure to the tail risk of their private sector (contingent liabilities). To calculate volatility based on tail risk, we fit a generalized Pareto distribution to a cross-section of stock returns over a 95 percent threshold, consistent with the literature, and extract the scale parameter. The stocks are constituents of their respective national broad stock index, and therefore unlike option implied volatility, volatility based on generalized Pareto is available for all countries. The probability density function of a generalized Pareto distribution is given by:

$$\left(\frac{1}{\sigma}\right)\left(1+k\,\frac{x-\mu}{\sigma}\right)^{-1-\frac{1}{k}} \tag{10}$$

where k is the shape parameter that determines the behaviour of the tail, σ is the scale parameter and μ is the threshold parameter. We use a rolling window of 20 trading days of cross-sectional daily stock returns to estimate the parameters by maximum likelihood. Because daily returns produce a scale parameter that is quite volatile, an

Exponentially Weighted Moving Average (EWMA) filter is further applied to smooth the series.[5] Figure 1 presents a fitted generalized Pareto distribution to a panel of daily stock returns (20 trading days and stock index constituents) exceeding the 95 percent threshold. Finally, the calculated volatility is annualised by a factor of $\sqrt{250}$.

[Insert Figure 1]

In order to derive unobserved asset volatility from equity volatility, the final step is to adjust the equity volatility proxy by a constant parameter δ. Therefore, our sovereign asset volatility is given by $\sigma_A = \delta\sigma_S$, where delta is similar to the gearing ratio used in the CreditGrades model, $\sigma = \sigma_S \frac{S}{S+\overline{L}D}$ (See, for example in Cao et al. (2010)). We find that our estimated parameter δ, has an average correlation of 0.94 across all countries and volatility specifications with the gearing ratio, which in our case is $1 - D/A$. δ is estimated simultaneously with the initial asset value A_0.

3.5 Willingness-to-pay

While corporations are bounded by national bankruptcy laws, the strategic decision of a government to default can be both economic and political. Duffie, Pedersen and Singleton (2003) maintain that without a formal bankruptcy framework a government will default when it is optimal to do so by weighing up the benefits and the costs, namely, the loss of reputation (Eaton and Gersovitz, 1981), trade blockages, and future inability to borrow (Grossman and Huyck, 1989). The problem, also known as the willingness-to-pay is difficult to account for in econometric models.

In the theoretical framework postulated by Eaton and Gersovitz (1981), higher national income volatility increases the cost of defaulting, implying a negative

[5] We assume that $Y_1=\sigma_1$ and $Y_t=0.9*Y_{t-1}+0.1*\sigma_t$

relationship between volatility and the willingness to default. However, the authors show that introducing uncertainty into the borrower's future income actually increases the willingness to default.

The issue of willingness-to-pay has less relevance for our study for two reasons. Firstly, we focus on advanced Eurozone economies. Historically, defaults due to unwillingness-to-pay have been more prevalent during revolts and violent transition of Governments, for example, China in 1949 and Cuba in 1960. Further, Karmann and Maltritz (2002) argue that due to closer integration of economies, willingness-to-pay has become less relevant. The increased the threat of international punishment reinforces the duty of governments to meet debt obligations. Recently, Borensztein and Panizza (2009) show the cost of sovereign default on its own financial sector.

4 Data

The data covers a period from 4 July 2007 to 28 December 2011, a total of 235 weekly observations. The start of the sample coincides with increasing liquidity of Eurozone sovereign CDS contracts partly due to the first decline in value of high grade mortgage backed securities in the US. Concern raised over the valuation of these products subsequently led to widespread market panic by August 2007 (Brunnermeier, 2009).

Although the euro was utilised by 16 countries at the start of the sample, we exclude Vatican City, San Marino, Luxembourg, and Monaco from the sample due to their small economies and unavailability of CDS spreads. Our sample consists of Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Slovenia and Spain. Despite a remarkable growth of single-name CDS contracts over the past decade, the sovereign CDS market is substantially smaller than the corporate CDS market, consisting of fewer obligors and representing only 18% of the total notional amount of CDS contracts outstanding as of June 2011.[6] Consistent with Ericsson et al. (2009), we focus on 5-year contracts as they offer the highest level of liquidity. All spreads are obtained from DataStream.

Table I shows the properties of CDS spreads and credit ratings for 12 Eurozone sovereigns over four sub-periods. The first sub-period from July 2007 to June 2008 is the pre-sovereign crisis period, characterised by low CDS spread levels and variability across countries. The second period from July 2008 to June 2009 extends over the peak of the financial crisis marked by Lehman failure. The market recovered briefly at the start of the third period from July 2009 to June 2010 and worsened again when Greece was bailed out. The final period from July 2010 to December 2012 covers deteriorating economic conditions in the Eurozone market when Ireland followed by Portugal was also bailed out. Greece restructured its debt soon after the end of our sample.

In 2007, all governments in the sample were rated as investment grade with seven of them rated as AAA. By the end of December 2012 only five AAA-rated sovereigns remained. In line with Baek et al. (2005), we observe little consistency between credit ratings and CDS spreads. Greece experienced a downgrade to BBB+ when its CDS spread exceeded 150 basis points, yet France and Austria were yet to lose their AAA rating with their spreads at the same level. Baek et al. (2005) argues that the divergence is caused by market sentiment not being reflected in credit ratings.

[Insert Table I]

[6] Data sourced from DTCC Trade Information Warehouse Reports, which can be accessed from: www.dtcc.com/products/derivserv/data/index.php

Turning to the construction of volatility proxy, the national stock exchange in each country usually calculates multiple stock indices, therefore for consistency we use the Morgan Stanley Capital International (MSCI) Country Equity index obtained from DataStream. Implied volatilities calculated from 12 month at-the-money options written on national equity indices - ATX, BEL20, DAX, FTASE, IDK2 (index futures for Spain), CAC, FTSEMBI, HEX25 and AEX are obtained from Bloomberg. Where 12 month maturities are not available, we use shorter dated options of no less than 3 months. Three countries, Ireland, Portugal and Slovenia do not have traded options on their stock index. For the fitting of the generalized Pareto distribution, we collect daily adjusted stock prices of constituents from large indices: Weiner Boerse Index (79 stocks), Brussels all shares (123 stocks), HDAX (110 stocks), ISEQ (48 stocks), FTSE/Athex (82 stocks), Madrid SE General (115 stocks), SBF (120 stocks), FTSEIta (229 stocks), PSI Gen (52 stocks), OMXH (129 stocks) and ASE all shares (114 stocks). Since the Slovenian index SBITOP only contains seven stocks, we manually collect 272 stocks listed on the Ljubljana Stock Exchange. Except for index constituents, all market data is based on Wednesday-to-Wednesday weekly observations with Tuesday's price substituted for non-trading Wednesdays.

Government balance sheet items including financial assets, general government debt, gross capital formation and consumption of fixed capital are collected from the GFS database each quarter. As the model inputs are released at different frequencies, balance sheet data released at lower frequencies is set to the most recent reported value. Finally, we take the AAA rated Eurozone long-term Government bond obtained from DataStream as our proxy for the risk-free rate.

5 Evaluation Procedure and Results

The ability of structural determinants and the Merton model to explain market assessed sovereign credit risk is best judged by its ability to produce good in-sample fit and out-of-sample prediction of sovereign CDS spreads. In the in-sample experiment, we evaluate our model performance using the parametric coefficient of determination (R^2), non-parametric Spearman rank correlation test[7], a standard root mean squared error (RMSE) and a mean absolute percentage error (MAPE). We also compare three asset volatility proxies using a prediction comparison statistic proposed by Diebold and Mariano (2002)[8].

We slice our sample into the four segments in Table I. For robustness, we repeat the in-sample fitting experiment across the first three segments covering the period prior to, and following the onset of the sovereign crisis. The last 18 months are held out for out-of-sample prediction.

In the out-of-sample experiment, the performance of the non-linear Merton structural model is compared to a naïve linear regression using the same variables. Again we report the RMSE and MAPE statistics and evaluate the models using the Diebold and Mariano (2002) test.

To calibrate the Merton model in-sample, we estimate A_0 and δ by minimising the RMSE for each time period. For out-of-sample static prediction, only the first 10

[7] The Spearman coefficient rho is $\rho = 1 - (6 \sum d^2 / (n^3 - n))$ where $d = rank_{1n} - rank_{2n}$. For $n < 10$, test statistic is calculated by the exact distribution. For $n \geq 10$, test statistic of Spearman is approximated by the Student-t distribution.

[8] The null hypothesis for Diebold and Mariano (2002) is equal forecast accuracy. The test statistic is $\mathrm{S} = \bar{\mathrm{d}} / \sqrt{\mathrm{Var}(\bar{\mathrm{d}})}$, where $\bar{\mathrm{d}}$ is the mean of $\mathrm{d} = \mathrm{g}(\mathrm{e}_1) - \mathrm{g}(\mathrm{e}_2)$ and $\mathrm{g}(.)$ can be any economic loss function. The authors show that the test statistic, S, converges in distribution to standard normal.

weeks worth of data is used to estimate the parameters. The objective function for each country is given by:

$$\min_{A_0,\delta} \sqrt{\frac{\sum_{t=1}^{T}(\hat{S}_t - CDS_t)^2}{N}}, \tag{11}$$

where $\hat{S}$ is the estimated spread from the Merton model, T denotes total number of weeks, A_0 is the initial asset value and δ is the volatility adjustment factor.

The linear regression benchmark is given by:

$$CDS_t = \beta_0 + \beta_1 L_t + \beta_2 Vol_t + \varepsilon_t, \tag{12}$$

where L is the ratio of financial assets to total liabilities and Vol is the volatility proxy. Regression parameters are estimated using all data prior to 7 July 2010.

5.1 In-sample fitting

Figures 2, 3 and 4 are scatter plots showing the relationship between of CDS spread and in-sample fitted spread using EGARCH, option implied (Opt-Imp) and generalized Pareto (GP) as the volatility estimate respectively. Three periods are initially pooled but then examined separately. A diagonal line depicts the line of best fit.

The reported R^2 measure across the three volatility estimates ranges from 0.37 to 0.81 for EGARCH, 0.51 to 0.89 for Opt-Imp and 0.68 to 0.92 for GP. This indicates that for Opt-Imp and GP, the model has produced good fit overall. In relative terms, Opt-Imp and GP are superior to EGARCH, while Opt-Imp is only marginally better than GP. The result is evident in the scatter plots.

Comparing between countries, the R^2 measure for Finland and Slovenia is lowest in all three volatility specifications, suggesting poorer fit. Conversely, countries perceived as risky by the market such as Ireland, Greece, Italy and Portugal all displayed outstanding fit. This relationship between volatile entities and better model fit has been documented by Cao et al. (2010) in the corporate environment, and it appears that the same effect can be observed with sovereigns. For sovereign issuers, this effect could be attributed to increased correlation between public and private sectoral asset returns in the wake of financial distress.

[Insert Figures 2, 3, 4]

Next, following Hull, Nelken and White (2004), Table II presents test results using the non-parametric Spearman rank correlation test for each country to address potential non-linearity between modelled and market spreads. In line with previous results, Opt-Imp and GP are better than EGARCH, and Finland and Slovenia yielded the lowest correlation. Overall, the rankings are high. By excluding Finland and Slovenia, the rankings across all three specifications range from 0.77 to 0.95.

[Insert Table II]

Finally, we evaluate each sub-period separately. We observe from Table III that our model is robust across all three periods covering different regimes. Although the RMSE has increased from July 2008 to June 2009 due to the collapse of Lehman Brothers and the spreading panic, the percentage errors are on average lower than the first sub-sample. Note that the error measures have reduced substantially in the third sample period. This is consistent with the results of Acharya et al. (2011), who find significant co-movement between banking sector credit risk and sovereign credit risk during the post-bailout period from fourth quarter of 2008 to first quarter of 2011.

Such inter-connectedness of private and public sector credit risk supports our inclusion of stock market information in the estimation of sovereign credit risk.

In the last three columns of Table III, we show with statistical confidence that Opt-Imp and GP yielded lower error measures than EGARCH. The result holds over all three periods.

[Insert Table III]

5.2 Out-of-sample static prediction

In-sample fit indicates that the structural model and its inputs can explain the dynamic of market assessed CDS spread. However, it is important to test whether out-of-sample performance is maintained and whether a sophisticated non-linear model can outperform a naïve regression model. The out-of-sample prediction comparison is conducted from July 2010 to December 2011.

Table IV compares the prediction accuracy of Merton and regression model for all three volatility proxies. Overall, the non-linear structural specification produced a more accurate prediction than a linear model regression. Under EGARCH, the structural model significantly outperforms the linear regression in 7 out of 12 countries. With Opt-Imp, the proportion increases to 8 out of 9, while for GP, the proportion is 8 out of 12 countries. It is interesting to observe that sovereigns for which the structural model outperforms the linear regression are typically large economies with a well developed financial market. Conversely, Finland and Slovenia yielded the highest MAPE.

Focusing on the prediction for individual countries, we find that overall RMSE has increased compared to in-sample fit, suggesting a rise in the market assessed credit risk for Eurozone sovereigns during the period. However, the MAPE remained at similar level. This indicates that our structural model still performed well out-of-sample.

[Insert Table IV]

6 Conclusion

Previous studies have used high level macroeconomic variables and regressions to examine the determinants of sovereign defaults or credit spreads, but this literature has focused only on emerging markets. In this paper, we show that a simple Merton structural model can be adapted to Eurozone sovereigns and can explain a large proportion of market-assessed sovereign credit risk's dynamic using sovereign balance sheet information and national stock market information. This is confirmed by both in-sample and out-of-sample experiments. We have also shown that the structural model outperforms linear regression in out-of-sample prediction for countries with established financial market.

Moreover, consistent with corporate CDS literature, we find that long-dated option implied volatility produced the best fit as well as prediction. Where there is no option-implied volatility available a tail risk volatility measure based on generalized Pareto outperforms EGARCH. Our result is robust in all three sub-periods covering pre- and post- the onset of sovereign crisis.

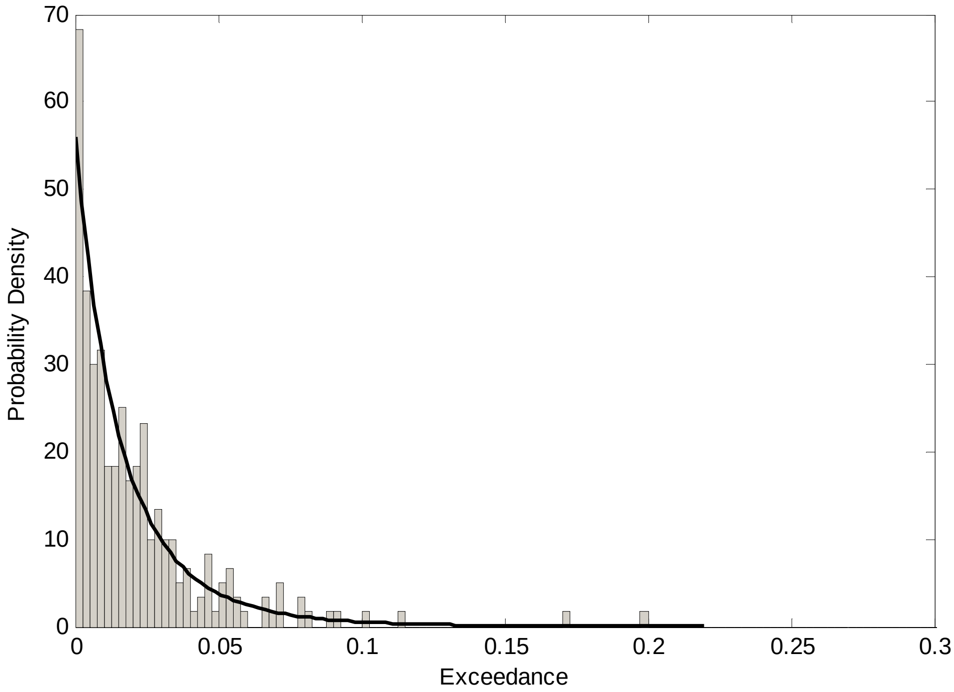

Figure 1. Fitted Generalized Pareto Distribution. This figure shows the probability density function of a generalized Pareto distribution fitted to a cross-section of daily stock returns over a 95 percent threshold. The probability density function is given by $(1/\sigma)\ (1 + k\ (x - \mu)/\sigma)$^$(-1 - 1/k)$, where the scale parameter,σ, and the shape parameter, k, are estimated by maximum likelihood. The location parameter μ is set to zero.

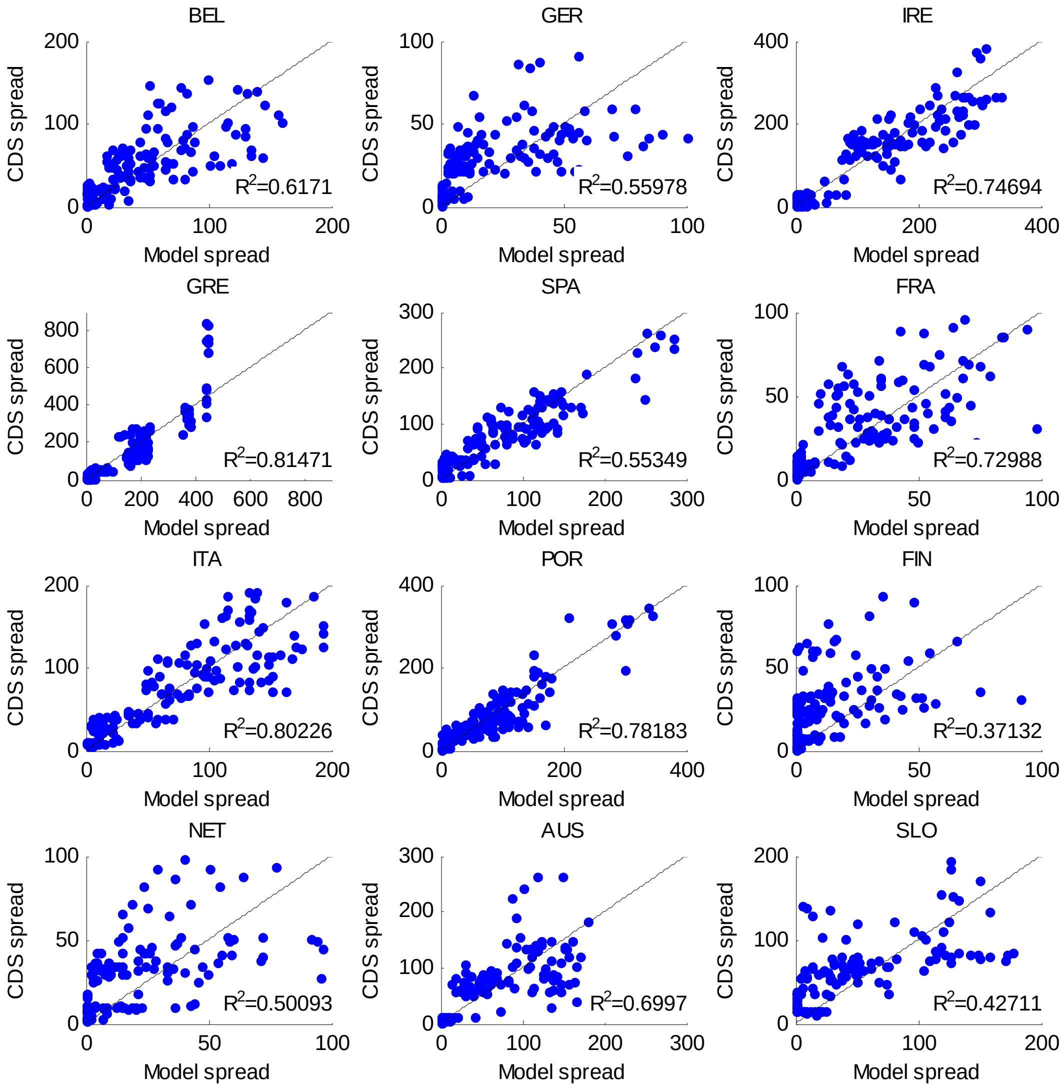

Figure 2. In-sample Fit Evaluation (EGARCH). The scatter plots show the relationship between of CDS spread and in-sample fitted spread using the Merton model from July 2007 to June 2010 for 12 Eurozone sovereigns. Asset volatility proxy is based on an EGARCH model, estimated using 5-year rolling window of weekly Morgan Stanley Capital International (MSCI) Country Equity index returns. We assume a Student-t distribution for the conditional distribution of the error, ε. The Merton model is calibrated annually in-sample to produce the best fit. A diagonal line depicts the line of best fit. The coefficients of determination, R^2, are obtained through univariate regressions.

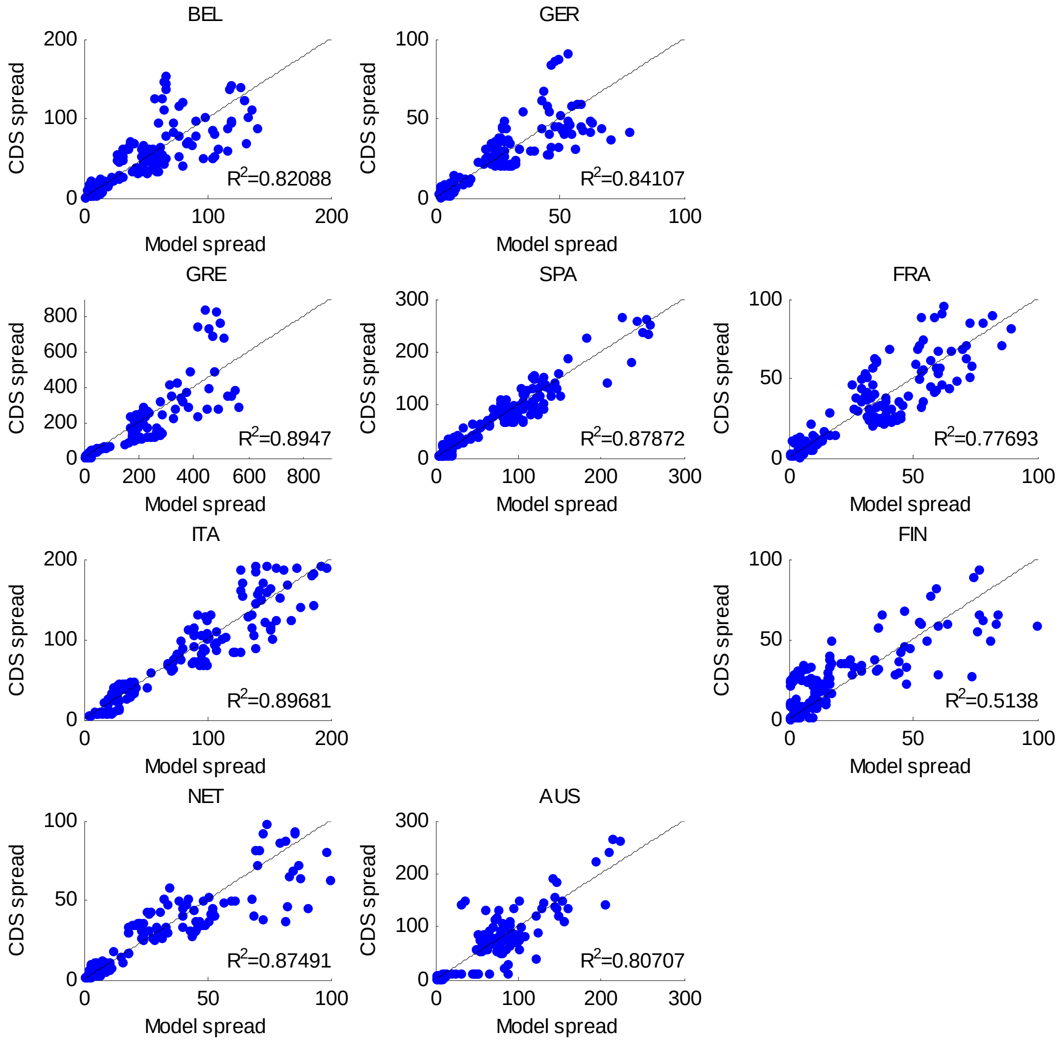

Figure 3. In-sample Fit Evaluation (Option Implied). The scatter plots show the relationship between of CDS spread and in-sample fitted spread using the Merton model from July 2007 to June 2010 for 9 Eurozone sovereigns. Asset volatility proxy is based on long-dated at-the-money options written on national equity indices - ATX, BEL20, DAX, FTASE, IDK2 (index futures for Spain), CAC, FTSEMBI, HEX25 and AEX are obtained from Bloomberg. Where 12 month maturities are not available, we use shorter dated options of no less than 3 months. Three countries, Ireland, Portugal and Slovenia do not have traded options on their stock index. The Merton model is calibrated annually in-sample to produce the best fit. A diagonal line depicts the line of best fit. The coefficients of determination, R^2, are obtained through univariate regressions.

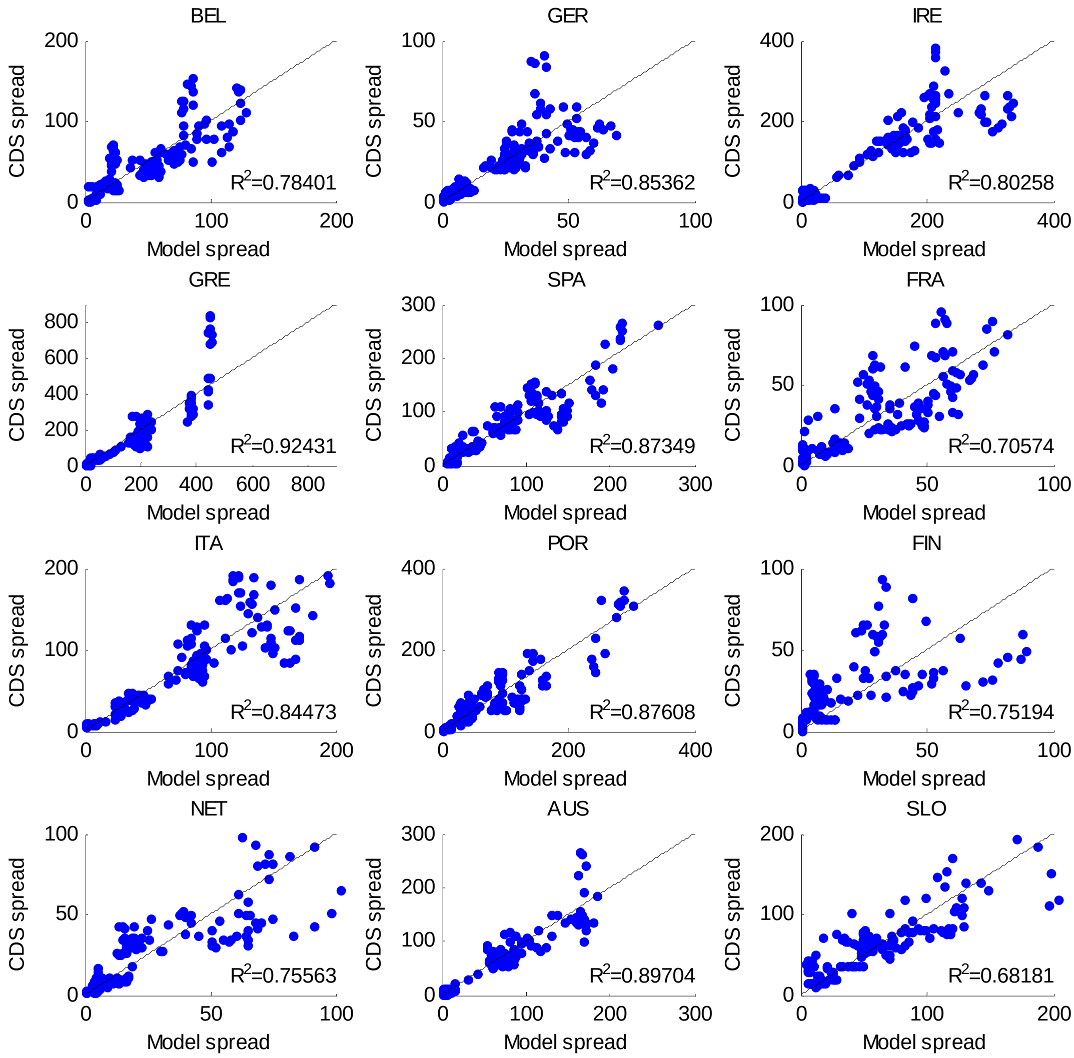

Figure 4. In-sample Fit Evaluation (Generalized Pareto). The scatter plots show the relationship between of CDS spread and in-sample fitted spread using the Merton model from July 2007 to June 2010 for 9 Eurozone sovereigns. Asset volatility proxy is based on the tail risk measure of Kelly (2009). A generalized Pareto distribution is fitted to daily constituent stock returns of the following national stock indices over a 95 percent threshold: Weiner Boerse Index (79 stocks), Brussels all shares (123 stocks), HDAX (110 stocks), ISEQ (48 stocks), FTSE/Athex (82 stocks), Madrid SE General (115 stocks), SBF (120 stocks), FTSEIta (229 stocks), PSI Gen (52 stocks), OMXH (129 stocks) and ASE all shares (114 stocks). Since the Slovenian index SBITOP only contains seven stocks, we manually collect 272 stocks listed on the Ljubljana Stock Exchange. The Merton model is calibrated annually in-sample to produce the best fit. A diagonal line depicts the line of best fit. The coefficients of determination, R^2, are obtained through univariate regressions.

Table I
Descriptive Statistics: CDS Spread and Credit Rating

This table summarises 5-year CDS spread levels for 12 Eurozone countries from July 2007 to December 2011 split in four sub-periods. CDS data is obtained from DataStream. Credit rating data presented in the table is the Standard & Poor's Foreign Currency Long-Term credit rating at the end of each sub-period.

Period		AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SLO	SPA
Jul 07 ~ Jun 08													
	Max	14	29	12	17	14	65	31	48	18	48	37	46
	Min	1	2	1	1	1	4	2	6	2	4	10	4
	Average	6	13	6	7	6	28	15	23	7	21	23	20
	Credit Rating	AAA	AA+	AAA	AAA	AAA	A	AAA	A+	AAA	AA-	AA	AAA
Jul 08 ~ Jun 09													
	Max	265	155	94	96	91	288	383	192	126	148	234	159
	Min	11	19	9	10	5	50	28	39	9	37	31	36
	Average	99	67	40	42	36	152	166	110	56	80	100	87
	Credit Rating	AAA	AA+	AAA	AAA	AAA	A-	AA+	A+	AAA	A+	AA	AA+
Jul 09 ~ Jun 10													
	Max	108	143	36	90	54	929	267	233	52	422	92	265
	Min	50	31	17	21	20	105	116	62	25	46	47	58
	Average	73	60	26	43	31	328	167	110	36	137	66	119
	Credit Rating	AAA	AA+	AAA	AAA	AAA	BB+	AA	A+	AAA	A-	AA	AA
Jul 10 ~ Dec 11													
	Max	230	381	83	250	110	10063	1060	577	133	1141	450	491
	Min	50	96	24	61	32	677	205	130	29	221	64	183
	Average	101	190	43	113	58	2274	612	264	61	664	141	294
	Credit Rating	AAA	AA	AAA	AAA	AAA	CC	BBB+	A	AAA	BBB-	AA-	AA-

Table II
Spearman Rank Correlation Between Modelled and CDS Spread

This table shows the Spearman rank correlation between CDS spread and modelled spread for each country from July 2007 to July 2010. The three columns refer to asset volatility proxies based on EGARCH, option implied, and generalized Pareto respectively. Ireland, Portugal and Slovenia do not have traded options on their main stock index. Average is calculated as the arithmetic average of all countries for each volatility specification. All Spearman rank coefficients are statistically significant at 1 percent level.

	EGARCH	OPT-IMP	GP
BEL	0.84	0.90	0.89
GER	0.83	0.88	0.91
IRE	0.90		0.90
GRE	0.92	0.94	0.95
SPA	0.90	0.95	0.92
FRA	0.83	0.87	0.84
ITA	0.89	0.95	0.92
POR	0.89		0.89
FIN	0.65	0.76	0.74
NET	0.77	0.92	0.90
AUS	0.86	0.86	0.90
SLO	0.80		0.87
Average	0.84	0.89	0.89

Table III
In-sample Fitting Accuracy

This table reports the RMSE in basis points and MAPE of modelled spread and market CDS spread for three annual sub-periods. The Merton model is calibrated annually in-sample to produce the best fit. Three asset volatility proxies based on EGARCH, option implied and generalized Pareto are also compared. Volatility estimated with EGARCH uses 5-year rolling window of weekly Morgan Stanley Capital International (MSCI) Country Equity index returns. Implied volatility is calculated from long-dated at-the-money options written on national stock indices. GP is obtained by fitting a generalized Pareto distribution to daily stock returns of national stock index constituents over the 95 percent threshold. The last three columns show the difference in RMSE between two volatility specifications as indicated by the headers. * denotes significance at 5 percent level using a two-tailed Diebold and Mariano (2002) prediction comparison test. (See footnote 8)

7/07-6/08	**EGARCH**		**OPT-IMP**		**GP**		**OPT−EGARCH (bps)**	**OPT−GP (bps)**	**GP−EGARCH (bps)**
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE			
BEL	13.37	0.88	4.56	0.42	4.91	0.34	-8.81*	-0.34	-8.47*
GER	5.78	0.92	2.37	0.42	2.35	0.39	-3.41*	0.03	-3.44*
IRE	16.39	1.01	-	-	13.80	0.81	-	-	-2.60*
GRE	17.71	0.73	7.95	0.39	9.83	0.37	-9.76*	-1.89	-7.88*
SPA	19.50	0.80	7.66	0.40	7.40	0.33	-11.84*	0.25	-12.10*
FRA	6.68	0.83	2.40	0.35	3.56	0.49	-4.28*	-1.15*	-3.13*
ITA	12.95	0.50	8.55	0.42	6.31	0.30	-4.39*	2.25*	-6.64*
POR	15.32	0.52	-	-	6.67	0.33	-	-	-8.65*
FIN	5.09	0.79	2.86	0.60	4.69	0.80	-2.23*	-1.83*	-0.40
NET	7.20	0.90	2.81	0.38	4.26	0.51	-4.38*	-1.44*	-2.94*
AUS	6.00	0.83	3.30	0.50	2.93	0.43	-2.70*	0.36	-3.07*
SLO	22.96	0.83	-	-	6.69	0.26	-	-	-16.28*

7/08-6/09	**EGARCH**		**OPT-IMP**		**GP**		**OPT−EGARCH (bps)**	**OPT−GP (bps)**	**GP−EGARCH (bps)**
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE			
BEL	41.04	0.52	36.09	0.39	28.11	0.38	-4.95	7.98*	-12.93*
GER	23.86	0.61	15.93	0.38	18.62	0.42	-7.94*	-2.70*	-5.24*
IRE	48.71	0.39	-	-	69.63	0.41	-	-	20.92*
GRE	52.89	0.36	37.14	0.23	34.91	0.21	-15.74*	2.24	-17.98*
SPA	25.43	0.29	20.10	0.26	31.28	0.35	-5.33*	-11.18*	5.84*
FRA	21.44	0.54	14.07	0.39	16.50	0.47	-7.37*	-2.42*	-4.94*
ITA	40.72	0.38	27.19	0.23	40.58	0.28	-13.53*	-13.39*	-0.13
POR	33.35	0.43	-	-	34.73	0.36	-	-	1.38
FIN	35.73	0.79	15.55	0.44	26.81	0.52	-20.18*	-11.25*	-8.92*
NET	48.26	0.90	20.20	0.39	26.39	0.35	-28.06*	-6.19*	-21.86*
AUS	55.73	0.60	43.91	1.07	31.77	0.32	-11.82	12.15	-23.97*
SLO	63.74	0.62	-	-	41.87	0.46	-	-	-21.88*

Table III – *Continued*

7/09-6/10	**EGARCH**		**OPT-IMP**		**GP**		**OPT− EGARCH (bps)**	**OPT− GP (bps)**	**GP− EGARCH (bps)**
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE			
BEL	25.68	0.38	17.68	0.27	21.83	0.34	-8.00*	-4.14*	-3.86
GER	22.52	0.65	10.01	0.25	7.70	0.18	-12.51*	2.31*	-14.82*
IRE	43.77	0.23	-	-	28.20	0.13	-	-	-15.58*
GRE	155.25	0.30	175.67	0.52	155.37	0.34	20.42*	20.30*	0.12
SPA	32.57	0.26	21.39	0.15	27.36	0.17	-11.18*	-5.97*	-5.20
FRA	22.88	0.46	15.37	0.35	19.82	0.43	-7.51*	-4.45*	-3.06
ITA	28.82	0.23	18.62	0.14	20.60	0.16	-10.21*	-1.98	-8.22*
POR	38.23	0.26	-	-	42.11	0.31	-	-	3.88
FIN	20.81	0.72	19.01	0.63	19.93	0.69	-1.80	-0.92	-0.88
NET	22.44	0.57	10.44	0.25	18.11	0.47	-11.99*	-7.67*	-4.33*
AUS	40.67	0.48	15.96	0.18	15.89	0.18	-24.71*	0.07	-24.79*
SLO	36.54	0.48	-	-	17.65	0.20	-	-	-18.89*

Table IV
Comparison of Out-of-sample Merton and Linear Regression Model Prediction Accuracy

This table compares the RMSE is basis points and MAPE of out-of-sample predictions made by Merton model to predictions made from a benchmark linear regression model. We calibrate Merton model parameters using the first 10 week of data from 7/7/2010 to 8/9/2010, which are excluded from evaluation. The regression equation is $CDS_t = \beta_0 + \beta_1 L_t + \beta_2 Vol_t + \varepsilon_t$, where L is the ratio of financial assets to total liabilities and Vol is the asset volatility proxy using EGARCH, option implied and fitted generalized Pareto distribution respectively. Regression equations are estimated using all data prior to 7 July 2010. We use a two-tailed Diebold and Mariano (2002) prediction comparison test to compare the performance of Merton model to the linear regression model. * indicates, for each asset volatility proxy, which of the two competing models has a lower RMSE significant at a 5 percent level.

	EGARCH				OPT-IMP				GP			
9/10-12/11	Merton		Regression		Merton		Regression		Merton		Regression	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
BEL	88.79*	0.40	152.87	0.69	82.29*	0.35	164.19	0.74	86.14*	0.38	171.65	0.77
GER	33.63	0.53	21.98*	0.27	19.70*	0.31	27.23	0.36	16.78*	0.26	28.83	0.35
IRE	137.79*	0.16	468.48	0.67					137.54*	0.16	473.30	0.68
GRE	2782.15*	0.43	3107.82	0.77	2732.26*	0.38	3111.86	0.77	2769.21*	0.37	3093.98	0.73
SPA	105.71*	0.32	133.98	0.39	91.62*	0.28	117.84	0.33	146.41	0.47	120.35*	0.34
FRA	51.03*	0.37	77.57	0.51	33.39*	0.25	85.66	0.58	37.86*	0.28	84.18	0.55
ITA	110.80*	0.30	163.13	0.37	106.44*	0.27	168.15	0.40	107.82*	0.28	165.77	0.39
POR	455.30*	0.51	708.22	0.85					419.52*	0.44	725.88	0.86
FIN	38.45	0.84	13.03*	0.20	32.68	0.76	15.39*	0.28	28.22	0.52	18.92*	0.28
NET	37.70	0.48	39.40	0.42	20.88*	0.30	50.53	0.70	61.73	0.87	40.28*	0.51
AUS	56.38	0.50	40.44*	0.25	29.70*	0.23	72.23	0.75	21.65*	0.17	49.91	0.33
SLO	156.61	0.76	125.41*	0.31					116.64	0.47	114.64	0.32

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Appendix A

Government Finance Statistics - Summary page

Consolidated general government

in million national currency

Table A - Summary table

	Government balance sheet	1996	2000	2007	2008	2009	2010
41=42+43	**Total assets**	:	:	:	:	:	:
42	**Non-financial assets**	:	:	:	:	:	:
43=44+..+48	**Financial assets**	**37,823**	**40,844**	**49,725**	**67,063**	**69,024**	**70,615**
44	Currency and deposits	5,383	5,762	6,636	12,632	9,395	10,678
45	Securities other than shares	158	196	456	462	641	673
46	Loans	6,971	6,476	1,523	1,485	1,666	2,355
47	Shares and other equity	14,622	14,844	25,225	36,425	41,477	40,770
48	Other financial assets	10,690	13,566	15,885	16,059	15,846	16,140
49=50+..+53	**Liabilities**	**281,577**	**286,857**	**295,267**	**321,312**	**340,409**	**355,000**
50	Currency and deposits	543	597	1,116	1,176	1,279	1,393
51	Securities other than shares	233,415	242,064	249,613	275,292	291,158	303,521
52	Loans	34,464	29,525	31,377	32,722	33,881	35,824
53	Other liabilities	13,155	14,671	13,161	12,120	14,090	14,261
54=43-49	**Financial assets net of liabilities**	**-243,754**	**-246,014**	**-245,541**	**-254,249**	**-271,384**	**-284,385**
55=41-49	**Net worth**	:	:	:	:	:	:
19	*of which, Gross fixed capital formation*	*3,700*	*4,934*	*5,312*	*5,510*	*5,756*	*5,840*
73	*Consumption of fixed capital*	*3,637*	*4,086*	*5,657*	*5,930*	*5,656*	*5,902*

Source: Eurostat Government Statistical Books 2011

On the assets side, financial assets include government holdings of currency and deposits, securities other than shares (e.g. private sector bonds), loans, and shares (e.g. public ownership in corporations). International reserves (monetary gold and SDR) are grouped under other financial assets. General government debt is made up of currency and deposits (notes and coins in circulation plus deposits) and securities other than shares and loans. According to the ESA95 manual, valuation of financial assets and liabilities are based on their market values.

ESA 95 defines five sectors in an economy, namely, general government, non-financial corporations, financial corporations, households and non-profit institutions. The general government sector comprises of central government, state and local governments, and social security funds. The data presented above is the consolidated general government sector.

Full definition of ESA95 accounting categories can be obtained from
http://circa.europa.eu/irc/dsis/nfaccount/info/data/esa95/en/esa95en.htm