Assigning Eurozone sovereign credit ratings using CDS spreads

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Abstract

Purpose – The credit ratings issued by the Big 3 ratings agencies are inaccurate and slow to respond to market changes. This paper aims to develop a rigorous, transparent and robust credit assessment and rating scheme for sovereigns.

Design/methodology/approach – This paper develops a regression-based model using credit default swap (CDS) data, and data on financial and macroeconomic variables to estimate sovereign CDS spreads. Using these spreads, the default probabilities of sovereigns can be estimated. The new ratings scheme is then used in conjunction with these default probabilities to assign credit ratings to sovereigns.

Findings – The developed model accurately estimates CDS spreads (based on RMSE values). Credit ratings issued retrospectively using the new scheme reflect reality better.

Research limitations/implications – This paper reveals that both macroeconomic and financial factors affect both systemic and idiosyncratic risks for sovereigns.

Practical implications – The developed credit assessment and ratings scheme can be used to evaluate the creditworthiness of sovereigns and subsequently assign robust credit ratings.

Social implications – The transparency and rigor of the new scheme will result in better and trustworthy indications of a sovereign's financial health. Investors and monetary authorities can make better informed decisions. The episodes that occurred during the debt crisis could be avoided.

Originality/value – This paper uses both financial and macroeconomic data to estimate CDS spreads and demonstrates that both financial and macroeconomic factors affect sovereign systemic and idiosyncratic risk. The proposed credit assessment and ratings schemes could supplement or potentially replace the credit ratings issued by the Big 3 ratings agencies.

Keywords Forecasting, Credit ratings, Big three, CDS spread, Sovereign credit risk

Paper type Research paper

1. Introduction

It became evident during the credit crisis of 2008 that there were several major issues with sovereign credit ratings issued by the Big 3 (S&P, Moody's and Fitch). The main issues were a misuse of their position, as they control 95 per cent of the market (Klein, 2004; Eijffinger, 2012; Taylor *et al.*, 2011), a conflict of interest (EC, 2013; Larosiere *et al.*, 2009; Ozturk *et al.*, 2016), not being transparent about the rating procedure (Iyengar, 2010; Katz *et al.*, 2009; Benmelech and Duglosz, 2009) and a slow response to market changes (Eijffinger, 2012; Ozturk *et al.*, 2016). Due to these issues, the sovereign credit ratings that were issued did not reflect the true credit risk faced by a sovereign adequately.

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Take Iceland for example – prior to September 29, 2008 – was considered to be relatively credit worthy, as evidenced by the credit ratings issued by the Big 3 (Table I). According to these ratings, Iceland should have had enough liquidity to withstand a mild to severe crisis. However, within just three days, the three major banks of Iceland defaulted on $62bn dollars of external debt and were nationalized by the government (Amadeo, 2015). It is remarkable that the credit ratings for Iceland were positive just the day before the crisis started, as the external debt of Iceland in June 2008 was seven times the GDP of 2007 (Iceland Statistics, 2008). As a comparison, the ratio of debt (both internal and external) to GDP in the USA in 2013 was 1.045 (IMF, 2014). At that time, the USA was rated AAA by Moody's (2013), which was just one step above the rating that was assigned by Moody's for Iceland before the crisis. As a result of the chaos that occurred, the Króna lost 50 per cent of its value against the US dollar in just one week (Central Bank of Iceland, 2008), the stock market fell 95 per cent (Amadeo, 2015) and many businesses went bankrupt (Anderson, 2015). After nationalization, the credit ratings agencies had to downgrade Iceland to keep up with the current situation (as can be seen in the second column in Table I). This revision, however, came too late. This example highlights the relevance of sovereign credit ratings and the need for these to be issued in a rigorous manner.

In this paper, we propose a novel framework that uses credit default swap (CDS) spreads to estimate the probability that a sovereign will default. A CDS is essentially an insurance contract that the buyer of a bond (sovereign or corporate) purchases. The seller of the CDS agrees to pay to the buyer a portion of the bond's face value in the event that the sovereign or corporate experiences a default event. In exchange for this insurance, the buyer makes a sequence of payments to the seller. This payment or premium is termed as the CDS spread and is usually expressed in basis points with reference to the nominal amount of the swap. The CDS market is a highly liquid market (Ang and Longstaff, 2013). Changes in the CDS spreads can therefore quickly signal changes in the creditworthiness of the corporate or sovereign underlying the bond.

Our framework uses the multi-factor affine model developed by Ang and Longstaff (2013) to study sovereign credit risk of Eurozone countries using CDS spreads. This model allows for both systemic and sovereign-specific credit shocks but is not forward looking and can only be used in a retrospective study. To be able to investigate the current situation, financial and macroeconomic data can serve as proxies for the current health of a sovereign's economy and be used as indicators of future performance. As mentioned by Ang and Longstaff (2013), there is a certain relationship between sovereign credit risk and macro-economic and financial variables, which has to be explored. This is further explored in this paper. Our framework therefore retains the focus on systemic and sovereign-specific credit shocks of the Ang and Longstaff (2013) model and extends it by incorporating a regression model on indicative financial and macroeconomic variables. We calibrate the framework using data from 2007 to 2010 and test it during the peak of the sovereign debt crisis (2010 to 2013). Our framework results in a better estimation of the default risk as compared to the model by Ang and Longstaff (2013), as seen in Table IV. With the framework, we can estimate the probability that a sovereign will default on its debt. These default probabilities

Agency	September 29, 08	October 10, 08
Fitch	A+	BBB
Moody's	Aa1	A1
S&P	A	BBB

Table I. Credit ratings of Iceland

can then be used to assign credit ratings to sovereigns. We illustrate the framework on eight Eurozone countries and show that the ratings assigned by our framework are both accurate and responsive to market changes. In comparison to the ratings assigned by the Big 3 (Section 5), our framework is able to provide an early warning on the change in the creditworthiness of a sovereign, whereas the Big 3 are slow to respond to the market. Further-more, by using default probabilities to assign sovereign credit ratings, our framework provides transparency (in contrast to the ratings assigned by the Big 3). We emphasize that while the framework is presented in the context of the eight Eurozone countries, the framework itself is generic and can be easily applied to data from other countries with minor modifications. The accuracy and responsiveness of our framework further imply that when assessing the systemic and idiosyncratic risks of sovereigns, both macroeconomic and financial factors must be considered.

The paper continues with a brief literature review in Section 2. We provide an explanation of the data used in Section 3 and the model description in Section 4. The alternative ratings procedure and the comparison with the ratings issued by the Big 3 are explained in Chapter 5 and the paper concludes in Section 6.

2. Literature review

Our work is primarily related to the literature on assessing sovereign credit risk. More specifically, we contribute to the literature on assessing sovereign credit risk using CDS spreads.

To address the shortcomings of the ratings issued by the Big 3, several models have been developed to assess sovereign credit risk. Much of the recent literature works on assessing sovereign credit risk have focused on European sovereigns, given the euro debt crisis which started in 2009, when Greece became the first European sovereign to face financial problems (Gibson *et al.*, 2014). Other countries followed, such as Ireland, Portugal, Spain and Italy; these countries are collectively known as the PIIGS countries. The Eurozone continues to be volatile given recent political and economic conditions. As such, assessing the sovereign credit risk of countries in the Eurozone remains a priority. One approach to assessing sovereign credit risk is the development of a statistical model using historical default data to build an empirical distribution of the probability of default. Given the limited number of sovereign defaults in Europe to date (Reinhart and Rogoff, 2008) and differences between the definitions of default in each case, the potential of a statistical model using historical default data to assess sovereign credit risk is rather restricted.

Gibson *et al.* (2014) stated that there are two main alternatives that one can use to assess sovereign credit risk. The first alternative is the use of sovereign bond yields. If the yield increases, one would assume that the level of sovereign credit risk increases. The second alternative is to use the CDS spread, which reflects the implied market perception of sovereign credit risk. The CDS market is more liquid than the sovereign bond market (Pan and Singleton, 2008). Furthermore, the CDS spread is a direct measure of implied sovereign credit risk, whereas bond spreads are also subject to interest rate risk (Ang and Longstaff, 2013) and liquidity risk (Longstaff *et al.*, 2005). Consequently, the usage of the CDS spreads to assess sovereign credit risk would better reflect the true credit risk of a sovereign. Kiesel and Spohnholtz (2017) also argued that CDS spreads are better indicators of credit risk and demonstrated the use of CDS data on corporate bonds to issue credit ratings for corporations.

Within the work so far conducted on using CDS models to assess sovereign credit risk, there is a classification into two different types of models. The first category consists of models that split the CDS spread into a default and risk premium part. The default part is the share of the spread that represents the implied default probability, whereas the risk premium part can be seen as the implied market value. The advantage of this model is that it is capable of deriving a clear implied sovereign credit risk default value, but not what the factors are that change this value. Examples of such models can be found in articles by Pan and Singleton (2008), Longstaff *et al.* (2011) and Duffie and Singleton (2003). The second category consists of models that split the CDS spread into a systemic risk part, which affects each borrower, and an idiosyncratic risk part, which is sovereign specific. This type of model provides a more in-depth analysis of what drives sovereign credit risk and more specifically, to what extent it is dependent on the status of other sovereigns. There are a limited number of articles available in this category, but an example of such a model can be found in Ang and Longstaff's study (2013). As there is a lot of debate going on in Europe whether sovereign credit risk is mainly affected by other sovereigns and the second type of model is capable of splitting the implied sovereign credit risk into a systemic and idiosyncratic risk part, the second type of model is preferred to be used in the current economic condition.

The model that was tested by Ang and Longstaff (2013) (henceforth: AL-CDS model) is quite accurate when one looks back over the period till the euro debt crisis. The AL-CDS model has a backward looking design, and its performance for future prediction is not clear. It would be interesting to measure its performance on the data of the euro debt crisis. The model is solely based upon the CDS spread and does not take into account financial and/or macroeconomic data for the calculation. However, the authors investigate the relationship between systemic risk and financial factors, finding that there is a significant relationship. They also mention that more attention has to be paid to this relationship, since they test a limited set of financial variables and other financial variables could provide more insight. Furthermore, several researchers point out that one should include macroeconomic variables if one investigates the euro debt crisis (Gibson *et al.*, 2014; Afonso *et al.*, 2014; Bernoth *et al.*, 2012; Hagen *et al.*, 2011). As the model is retrospective in nature and does not include financial and/or macroeconomic data for the calculation, the question arises whether the model is accurate for future predictions and specifically when one tries to model the euro debt crisis. To provide an answer to this question, this research tries to identify whether the AL-CDS model can be used for future predictions and whether incorporating financial and/or macroeconomic date results into a more accurate model for future predictions. Based upon this model, a sovereign credit risk rating scale can be designed which can replace the current rating procedure used by the Big 3.

3. Data

Our investigation covers the period from April 2007 to April 2013. We collect the CDS spreads, and financial and macroeconomic data over this time period for eight countries in the Eurozone. We split the six-year time span in to a calibration period and a testing period. The calibration period is set to 3.5 years, from April 2007 to September 2010. The model parameters obtained from the calibration are tested on the remaining 2.5 years of data. Below we discuss some characteristics of the collected data.

3.1 Credit default swap data

We collect the one- and three-year CDS spreads of eight sovereigns in the Eurozone from Bloomberg. The eight countries are Germany, Netherlands, France, Belgium, Italy, Spain, Ireland and Portugal. This choice allows us to perform an in-depth analysis in the Eurozone, as we cover sovereigns having less fluctuation in their CDS spread (such as Germany) and those that have a high fluctuation in their CDS spread (such as Portugal). We are also able to analyze the dependency of a sovereign's credit risk on its own performance and macroeconomic variables, as well as other sovereigns. Greece has not been included in our data set as the CDS spread of both the three-year and five-year maturity is extremely high (over 30,000 basis points). The three-year maturity CDS spread for the calibration period can be seen in Figure 1 and for the testing period in Figure 2.

We would like to note certain observations regarding the data. There is no data available on Ireland's CDS spreads before the first of January 2008, when they started to issue CDS contracts. Ireland has the highest CDS values for the calibration period (a mean of 143 basis points and a maximum of 470 basis points), whereas Portugal has the highest values for the testing period (a mean of 807 basis points and a maximum of 1,711 basis points). A high CDS value reflects a high level of sovereign credit risk. For all the European sovereigns, we see an increase in the CDS spread from 2010, which marks the start of the euro debt crisis. We also remark that among the eight countries under consideration, Portugal has the highest standard deviation due to the high fluctuation in its CDS spread. It is of interest to note that for both Portugal and Ireland, the 3-years CDS spread is higher than the 5-years CDS spread for about a third of the time span. This is why we do not include the 5-year spread in our calibration and testing.

During the testing period, the CDS spread is much higher compared to the calibration period for all sovereigns. Portugal and Ireland still show the reverse behavior with the three- and five-year maturity CDS spread. Germany continues to have the lowest CDS spreads and is thus perceived to have the lowest level of implied sovereign credit risk. We see that for all the countries, the highest CDS spread was in 2011 which marks the peak of the euro debt crisis. From 2012, a downward trend in the CDS spreads is observed for all the sovereigns, implying that the level of sovereign credit risk starts to diminish.

3.2 Explanatory variables for systemic risk

The systemic risk component of the sovereign risk is calibrated with many financial factors. Many articles show, as well as point, the need to establish this relationship, such as those of Wegener *et al.* (2016), Rösch (2003), Ang and Longstaff (2013), Jakubík (2006), Hamerle and Liebig (2003), Koopman *et al.* (2012) and Virolainen (2004). These articles provide us a comprehensive list of financial variables to use. In addition, we use corporate financial data as they are highly correlated with the performance of the country and also because limited information is available on the factors for sovereigns. The following variables were collected from Bloomberg:

- FX rates (Euro-Dollar ratio, Euro-Pound ratio, Euro-Yen ratio, Euro-RMB ratio);
- Stock indices (NASDAQ index, S&P500 index, Eurostoxx index);
- VIX indix (EU VIX Eurostoxx);
- Commodities (Brent Oil price per barrel in Euro, Gold price per ounce in Euro);
- Bond prices (one-, three- and five-year Euro-bond bid prices);
- Swap rates (one-, three- and five-year swap rates); and
- Interest rates (one-, three- and six-month Euribor, ECB interest rate, Euro-Dollar deposit interest rate, TED Spread, LIBOR-OIS spread).

The FX rates are the ones used in the IMF basket of the Special Drawing Rights valuation. The US stock indices are included as the USA is the biggest economy in the world and the biggest trading partner of the European Union (Directorate General for Trade, 2016). The VIX index has been included as it is a strong indicator for systemic risk, as mentioned by

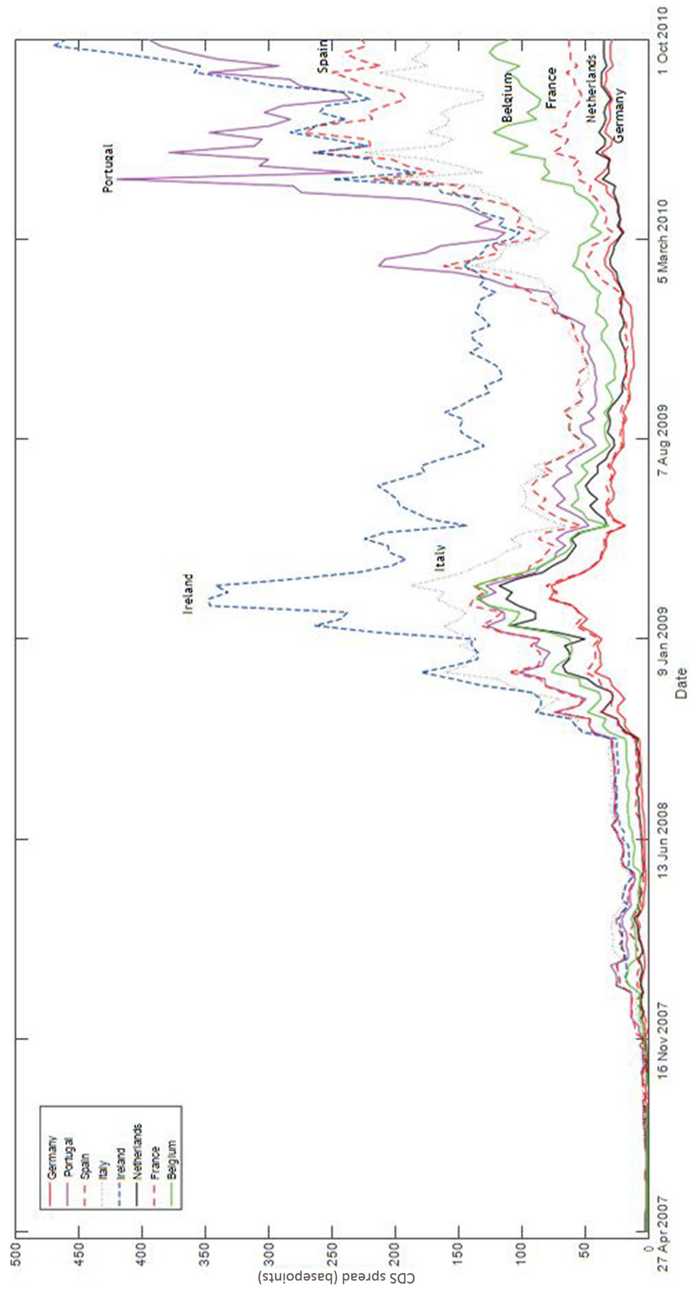


Figure 1.
Three-year CDS
spreads during the
calibration period

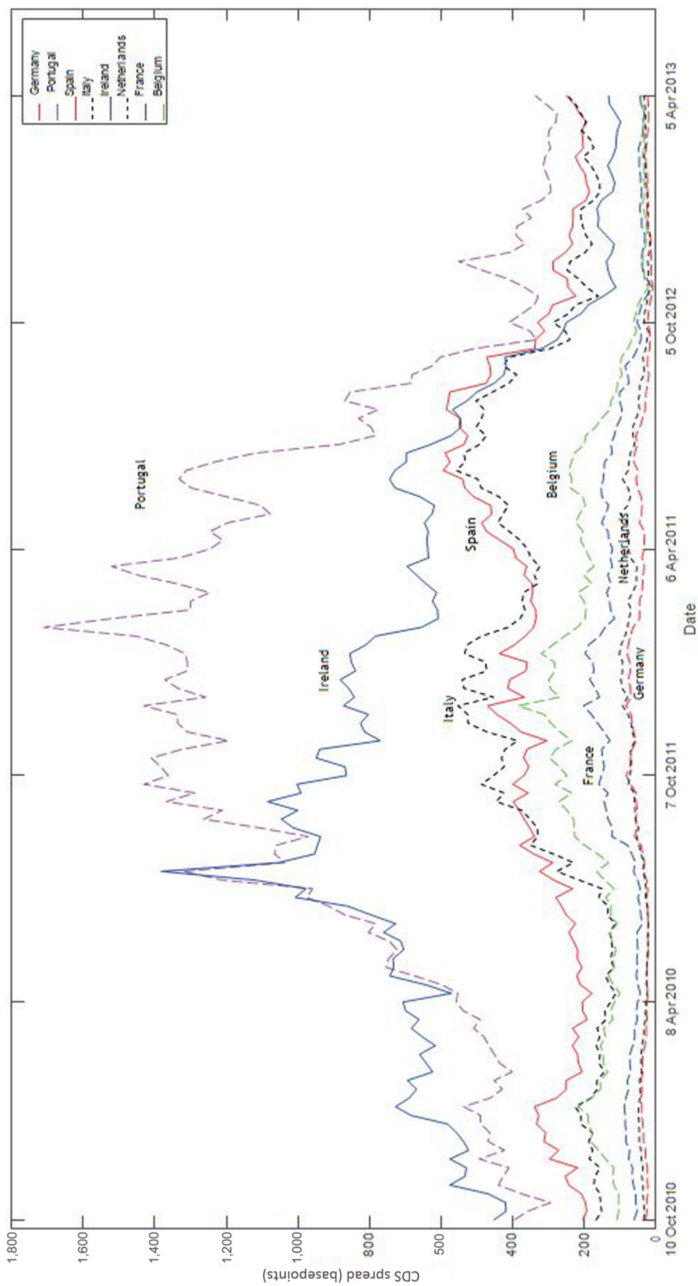


Figure 2.
Three-year CDS spreads during the testing period

Ang and Longstaff (2013). The oil price has been included since it has been shown by Wegener *et al.* (2016) that positive oil price shocks lead to lower sovereign CDS spreads. The bond prices, swap rates and interest rates have been selected using a combination of several frameworks (Rösch, 2003; Ang and Longstaff, 2013; Jakubík, 2006; Hamerle and Liebig, 2003; Koopman *et al.*, 2012; Virolainen, 2004).

3.3 Explanatory variables for idiosyncratic risk

A selection of 14 financial and macroeconomic variables has been made to assess the idiosyncratic (or non-systemic) sovereign credit risk. We chose these variables as they are valid indicators of idiosyncratic risk for sovereigns, as well as corporate institutions, as mentioned by Koopman *et al.* (2012), Rösch (2005), Jakubík (2006) Hilscher and Nosbusch (2010) and Gestel *et al.* (2006). The data are collected from Bloomberg, ECB and Eurostat at a sovereign level. The variables collected are:

- finance (10-year treasury bond bid price, stock index, interest rate on deposits, long-term interest rate, inflation ratio);
- unemployment ratios (total unemployment, unemployment over 25 years, unemployment under 25 years);
- industry indices (production index construction, manufacturing turnover index); and
- balances (real effective exchange rate, international trade ratio, index of deflated turnover), economic indices (Generic economic situation over the next year of customers, financial situation over the last year of customers).

No data are available for the production index construction for both Ireland and Spain.

4. Framework

In this section, we first explain the backward looking model developed by Ang and Longstaff (2013), which forms the base of our framework and model. We calibrate it using data from 2007 to 2010 and test its performance on data from 2010 to 2013. Seeing the deficiencies in the AL-CDS model's performance, we develop an alternative model, explained in Section 4.2.

4.1 Ang and Longstaff-credit default swap model and calibration

The AL-CDS model is based on the classical framework presented by Duffie and Singleton (2003)[1]. The model assumes two kinds of shocks – a systemic shock that affects every sovereign and a non-systemic shock (or idiosyncratic shock) that only affects the default probability of an individual sovereign. The systemic and non-systemic shocks are assumed to be independent of each other. The idiosyncratic shock is the same as the underlying standard reduced-form credit models used by (Pan and Singleton, 2008; Duffie and Singleton, 1999). In the AL-CDS model, the idiosyncratic default is triggered by "the first jump of a sovereign-specific Poisson process" (Ang and Longstaff, 2013). This intensity process follows a standard square-root process for sovereign i:

$$d\zeta_{i,t} = \left(a_i - b_i\zeta_{i,t}\right)dt + c_i\sqrt{\zeta_{i,t}}dZ_{i,t} \tag{1}$$

where a_i, b_i and c_i are constants and $Z_{i,t}$ is a standard Brownian motion, all sovereign specific. The constants a_i, b_i and c_i denote the slope and curvature of the idiosyncratic part of the CDS term structure (or a_i represents the mean, b_i the rate of adjustment towards the mean and c_i the volatility), whereas the values of $\zeta_{i,t}$ reflect the idiosyncratic risk level of the CDS spread of a sovereign. This setting allows for mean reversion and conditional heteroskedasticity in the intensity process and guarantees that the intensity process never becomes negative. It has to be noted that there is no restriction placed on the correlation between the Brownian motions across sovereigns, as this is partially taken into account by the systemic risk intensity process (except for Germany, which we assume has no idiosyncratic risk).

Systemic risk affects every sovereign, but each sovereign experiences its impact differently. This impact is modeled by the parameter γ_i which is sovereign specific and is assumed to be constant. The intensity process for systemic risk is also modeled as a Poisson intensity process, which follows a standard square-root process:

$$d\lambda_t = (a - \beta\lambda_t)dt + \sigma\sqrt{\lambda_t}dZ_{\lambda,t} \tag{2}$$

where α, β and σ are constants and $Z_{\lambda,t}$ is the Brownian motion of the systemic risk intensity process in equation (2). The constants α, β and σ denote the slope and curvature of the systemic risk part of the CDS term structure (or α represents the mean, β the rate of adjustment toward the mean and σ the volatility), whereas the value of λ_t reflects the systemic risk level. The Brownian motion for systemic risk and the Brownian motions driving the idiosyncratic risk are uncorrelated. Similar to the idiosyncratic risk intensity process, the systemic risk intensity process can never become negative. The probability that there is no default of sovereign i by time t can be expressed as follows:

$$P(\text{no default by time } \tau) = \exp\left(-\int_0^\tau \left(\gamma_i\lambda_t + \zeta_{i,t}\right) dt\right). \tag{3}$$

The total default intensity is the sum of the idiosyncratic shock intensity $\zeta_{i,t}$ and the systemic risk intensity λ_t multiplied by the exposure (or impact) γ_i. Sovereign credit risk thus depends on the two intensity processes and the exposure. These values can be derived from the CDS spread ($s_{i,t,\tau}$) of sovereign i and maturity τ using the following formula:

$$s_{i,t,\tau} = \frac{\omega \int_t^\tau D(t,\tau)\big(A(\lambda,t)C(\zeta_i,t) + \gamma_i B(\zeta_i,t)F(\lambda,t)\big)dt}{\int_t^\tau \big(D(t,\tau)A(\lambda,t)B(\zeta_i,t)\big)dt} \tag{4}$$

where ω is the recovery rate and $D(t, \tau)$ is the value of a risk-free zero-coupon bond with maturity τ at time t. The formulas for $A(\lambda, t)$, $B(\zeta_i, t)$, $C(\zeta_i, t)$, $F(\lambda, t)$ can be found in the appendix and have been derived by Ang and Longstaff (2013). The value of ω has been set at 50 per cent, which is in line with Duffie and Singleton (2003) and Ang and Longstaff (2013). The recovery rates are usually in the range of 30 to 75 per cent, as shown in Sturzenegger and Zettelmeyer's study (2008). The value of ω will have little effect on the estimates of the systemic and idiosyncratic components since it is applied to both legs of the

CDS contract in the estimation process. If this rate varies over time, it can have an impact on the spreads without a big movement in the systemic risk component. Therefore we also assume here that the recovery rates are constant over the time period in consideration[2].

A sovereign default event is assumed to occur upon the first arrival of either of the two Poisson processes, but in reality a default is triggered by credit events described in the CDS contracts. The precise legal definition of a sovereign default is thus not fully captured by the model. We work with the risk-neutral measure, since there are almost no historical cases of sovereign defaults. We take the country with the lowest CDS spread to be the comparison country - and its default depends only on systemic risk. In this paper, Germany is set as the comparison country since it has the lowest CDS spread, in addition to being the biggest economy in the Eurozone.

4.1.1 Calibration. The constants and the intensity processes have been estimated using the one- and three-year CDS spread over the calibration period. We chose to exclude the five-year CDS spreads as there were many instances when the five-year spread was lower than the three-year spread. The values for the zero coupon bonds $D(t)$ have been bootstrapped using the one-, three- and six-month Euribor rates and the one-, three and five-year swap rates, collected from Bloomberg. The cubic spline interpolation algorithm (Longstaff *et al.*, 2005) has been used to calculate these values. The recovery rate is set to $\omega = 0.5$, which is in line with Ang and Longstaff (2013) and Lando (1998). The parameters are estimated using the nonlinear least squares method:

$$\min_{\lambda,\zeta_1,\ldots,\zeta_N,\theta} \sum_i \sum_t \sum_\tau \left(s_{i,t,\tau} - \hat{s}_{i,t,\tau}\right)^2 \tag{5}$$

where $s_{i,t,\tau}$ denotes the CDS spread of issuer i of maturity τ at time t, and $\hat{s}_{i,t,\tau}$ is the estimated CDS spread calculated using equation (4) where $\lambda,\ \zeta_1,\ \ldots\zeta_N$ represent the systemic and idiosyncratic risk intensities and θ represents the vector of the estimated parameters $\alpha,\ \beta,\ \sigma,\ a_i,\ b_i,\ c_i$ and γ_i.

As Germany is the country that represents systemic risk in the Eurozone, the systemic risk constants $\alpha,\ \beta,\ \sigma$ and the systemic risk intensity values λ_t have been estimated first, over data of Germany. Note that $\gamma_{Germany} = 1$ as Germany is the base for systemic risk. The second step is to estimate the constants $a_i,\ b_i,\ c_i,\ \gamma_i$ and the idiosyncratic risk intensity process $\zeta_{i,t}$ for each of the seven sovereigns. Further details of the calibration steps can be seen in Ang and Longstaff's study (2013). The outcome of the calibration of the parameters can be found in Table II, in which the standard error is listed within brackets and the RMSE is denoted in basis points. As can be seen, the model has a good fit to the term structure of

Table II.
Parameter estimates

Systemic risk	α	β	σ		RMSE (in bp)
Germany	0.0622 (0.0073)	−0.0219 (0.0.0015)	0.0146 (0.0086)		4.4965
Idiosyncratic risk	a	b	c	γ	RMSE (in bp)
Portugal	−0.9267 (0.0428)	1.9328 (0.0421)	0.0.1233 (0.0037)	2.2520 (0.0001)	11.0307
Spain	−0.9789 (0.0082)	1.0953 (0.0414)	0.0955 (00.0026)	2.6460 (0.0001)	14.0276
Italy	−1.4098 (0.0020)	0.0103 (0.0024)	0.0143 (0.0011)	2.5916 (0.0001)	12.1977
Ireland	−2.3348 (0.0595)	1.5549 (0.1113)	0.1762 (0.0104)	4.5194 (0.0001)	20.2708
The Netherlands	−0.7996 (0.0059)	1.1922 (0.0187)	0.0907 (0.0020)	0.9368 (0.0002)	5.5004
France	−0.7993 (0.0028)	0.3291 (0.0066)	0.0477 (0.0010)	1.0238 (0.0002)	6.0192
Belgium	−0.9967 (0.0012)	0.0872 (0.0014)	0.1706 (0.0018)	1.1147 (0.0002)	8.8933

the CDS spreads. The RMSE values for each country are between 6 and 21 basis points, a small percentage of their absolute CDS spreads. To illustrate the fit, the outcome of the calibration for France for the one-year maturity in shown in Figure 3.

4.2 Alternative model

The AL-CDS model was designed for backward calculation and does not perform well for future prediction (see Section 4.3). It needs to be re-calibrated every time the default probability needs to be calculated. To improve on the predictive power, we present a regression-based model – referred to as Reg-model hereafter. A reliable estimation for λ and ζ is important since they are the key components to calculate the survival probability, as can be seen in equation (3). Based upon these two intensity process values, the default probability can be estimated for each sovereign. Given the intensity process values λ and ζ, a regression analysis of the relevant financial and macroeconomic variables has taken place to reveal the relationship. Given that there are a high number of explanatory variables, a factor analysis has been executed to identify which variables are independent and able to explain the major share of the variance. These variables are used as input for the regression model. The model's performance is observed over the testing period and the results can be seen in Section 4.3. Note that the number of independent variables, n and m, in the regression outcome may vary by sovereign:

$$\lambda_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_n x_{nt} \tag{6}$$

$$\zeta_{i,t} = \beta_0 + \beta_1 x^i_{1t} + \ldots + \beta_m x^i_{mt} \tag{7}$$

4.2.1 Regression outcome. For each of the sovereigns, we conduct a factor analysis using an orthogonal rotation technique (Varimax). A factor analysis reveals what factors explain the major share of the variance, while keeping in mind that the factors are not correlated to eliminate multicollinearity. The outcome of the factor analysis is reported in the Appendix and reveals what variables can be used as input for a regression analysis. Based upon the

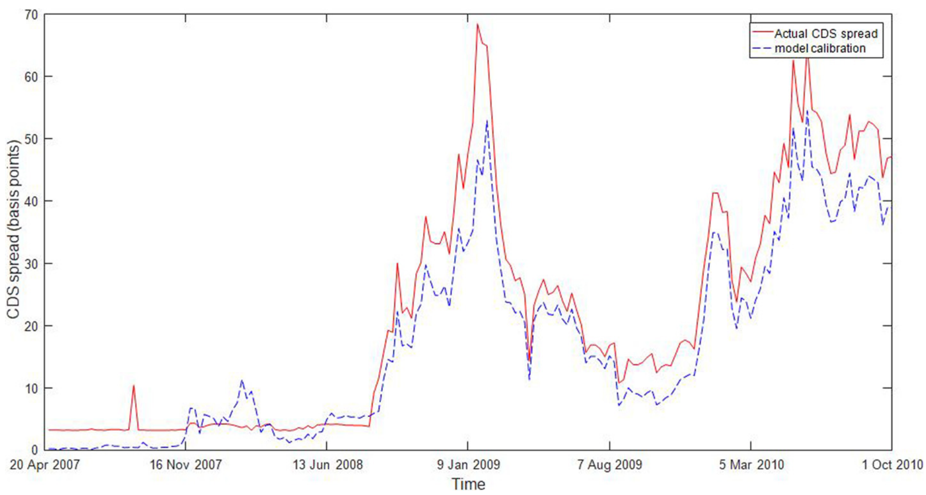


Figure 3.
Calibration outcome for the one-year maturity CDS spread of France

several explanatory variables that are independent, different models for each country have been tested using lagged time series. The model with the highest R-square value has been selected as the final model for each sovereign. Note that each sovereign has a different model, given that the Reg-model allows a differentiation on sovereign level. A summary of the outcome can be seen in Table III, whereas more detailed information is reported in the Appendix (with lags, t-stats, etc.).

As can be seen, the R-squared values are between 0.662 and 0.845, which indicates that a significant portion of both the systemic risk and the idiosyncratic risk intensity process can be explained by financial and macroeconomic data. More information about the outcome of the regression analysis can be found in the Appendix (such as the lag on a variable, t-statistics, etc.), in which is also shown that all variables are significant at a 99 per cent level. Based upon the estimate for each explanatory variable, the values of λ and ζ can be estimated for the testing period. These estimated values are used as input for the default probability calculation.

4.3 Model comparison

Based upon the settings for the AL-CDS model and the Reg-model, the CDS spreads of both the one-year and three-year maturity have been simulated for the testing time period. Note that the actual data of the macroeconomic variables over the testing period have been used, in which the estimated λ and ζ values are used as input for the CDS spread calculation. The RMSE between the actual and the estimated CDS spread from the models is shown in Table IV. We can conclude that the Reg-model does better than the AL-CDS model (it has a lower RMSE), as it incorporates the financial and macroeconomic data. The smallest RMSE values can be found for the country with the lowest CDS values, which is Germany with a RMSE value of 14 basis points. The highest RMSE values are for Portugal and Ireland, the countries with the highest

Country	Variables	R^2
Germany	ECB interest rate Oil price Euro vs RMB	0.845
Portugal	Industrial confidence indicator Unemployment ratio - Pop > 25 years stock index Production industrial construction	0.689
Spain	Manufacturing turnover index Production prices in industry, domestic market Real effective exchange rate - 42 trading partners	0.753
Italy	Unemployment ratio - Pop. > 25 years General economic situation Production prices in industry, domestic market Manufacturing, production index	0.721
Ireland	Inflation ratio General economic situation	0.696
France	General economic situation LT interest rate Production prices in industry, domestic market	0.720
Belgium	Treasury bond (10 years) Unemployment ratio - Pop. > 25 years Interest rate deposits Stock index	0.662
The Netherlands	Unemployment ratio - Pop. > 25 years Industry confidence indicator Consumer confidence indicator	0.737

Table III. Summary regression outcome

CDS spread. Thus, the Reg-model can be used for forecasting, which is necessary to assign a credit rating for a sovereign.

The outcome for two different countries for the one-year maturity is shown in Figures 4 and 5. As can be seen in these figures, the Reg-model yields an accurate fit for the first two years, while it does not incorporate the decrease of the CDS values in the last half year. This is due to the fact that there is no significant change in the macroeconomic data for the last half year, whereas the macroeconomic data do incorporate the changes for the first two years.

It is important to note here that our testing period is quite long (2.5 years). In practice, models are usually re-calibrated every six months to a year. The purpose of our test is to showcase that it is possible to predict the CDS spread for a short amount of time in the future with good accuracy. This enables us to quantify the future default probability and adapt the rating of the sovereign bonds. This process is outlined in the next section. Since the start of the crisis, stress testing is required by the financial authorities (BBC, 2009) and reveals the impact of a negative scenario on the outcome of the model. One of the types of stress testing that can be applied is to test the vulnerability of a sovereign to a macroeconomic shock (Wong *et al.*, 2008). The Reg-model is capable of including the possibility of a macro economic shock. The stress tests can be done by using either stressed macroeconomic forecasts or standard forecast and then multiplying the constants λ and ζ by a stress factor.

Table IV.
AL-CDS model vs the Reg-model (RMSE denoted in basis points) over the testing period

	Germany	Portugal	Spain	Italy	Ireland	The Netherlands	Belgium	France
AL-CDS model	16	600	150	177	363	26	84	47
Reg-model	14	392	71	121	303	15	65	34

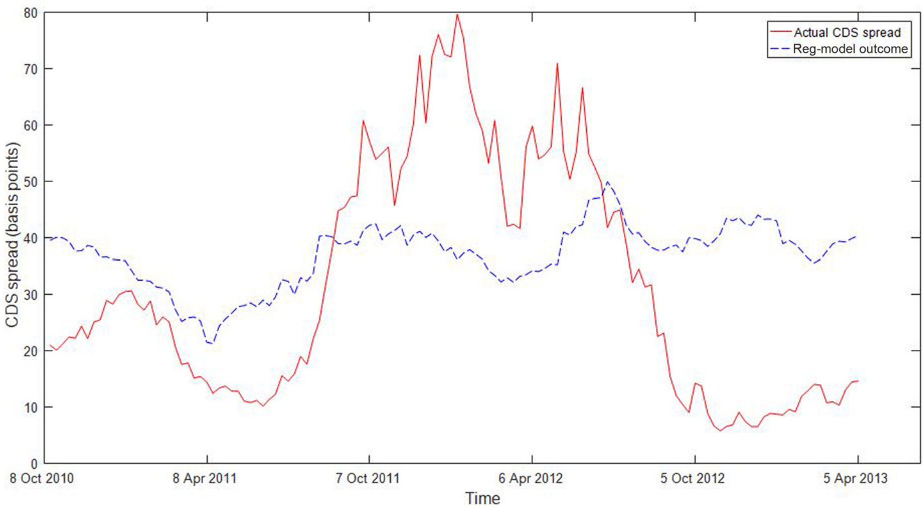


Figure 4.
Reg-model vs CDS spreads for The Netherlands (one-year maturity)

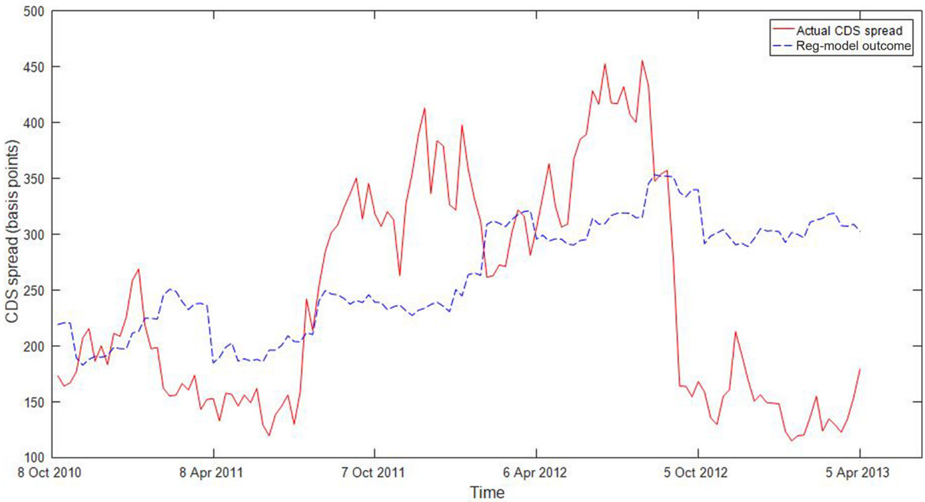


Figure 5.
Reg-model vs CDS spreads for Spain (one-year maturity)

5. New rating scheme and comparison with the Big 3

To be able to compare the outcome of the forecasting model with the ratings assigned by the Big 3, a classification scale has to be designed to assign a rating based upon the estimated default probability. However, there are a couple of issues to notice. First, the Big 3 do not release information regarding what default probability is assigned to a credit rating. There is a qualitative definition for each rating, but no quantitative expression in terms of default rates or default probability over time. As the rating procedures used by the Big 3 are different, different ratings are issued for the same sovereign. Furthermore, data from S&P [Standard & Poor's (S&P), 2012] and Moody's (Moody's, 2008) show a discrepancy between the sovereign credit rating assigned by a credit rating agency and the default rate that is observed over time by the credit rating agency. One would assume that a higher rating would result into a lower default rate, but the opposite situation can be seen. These observations show that is it not clear what the quantitative impact is of a rating in terms of the observed default rate.

To be able to compare the ratings, we first calculate the estimated default probability using the Reg- model, as shown in Section 5.1. Based upon the default probabilities, a rating scheme is developed shown in Section 5.2. A comparison of the ratings assigned by the Reg-model and the ratings assigned by the Big 3 is shown in Section 5.3. As an extra benchmark, the sovereign one-year bond yields are also included in the comparison.

5.1 Default probability forecast

To be able to calculate the default probability, one needs to have the values of lambda, zeta and gamma. As these values are known for the calibration time period, the default probability for the eight countries can be calculated. There are two main approaches to calculate the default probability (BCBS, 2005). The first is the Through The Cycle approach, which can be used in case one considers the stressed default probability. In this situation, the probability of default is not heavily affected by the economic circumstances, such as an economic downturn or a global crisis. The second approach is the Point In Time approach, in which the unstressed default probability is calculated. In this approach, the default probability the impact of macroeconomic changes is taken into account. The second approach is used by the Big 3 and should also be used for the Reg-model, as the impact of macroeconomic changes is taken into account. Therefore, the Point In Time approach will be applied to calculate the default probability, which is calculated as:

$$P(\text{Default within one year from time } t) = 1 - \exp\left(-\int_{t}^{t+1} (\gamma_i \lambda_t + \zeta_{i,t})dt\right) \tag{8}$$

The time span has been set to one year, as assets are commonly valued on a yearly basis. The lambda and zeta values are known on a weekly basis during the testing period (2.5 years), but one-year data are needed to calculate the default probability. Thus, the default probabilities values within one year from time t have been calculated per week for 1.5 years, which include the peak of the euro debt crisis. The default probabilities can be found in Figure 6.

As can be seen in Figure 6, the default probabilities are the highest for Portugal and Spain which matches with their high CDS spread. Thus, the model reflects the implied sovereign credit risk in an adequate manner. The default probability for Portugal decreases from the beginning of 2012, which points out that Portugal is perceived by the market to take adequate steps to lower its credit risk. The default probability for Ireland is decreasing from the start of 2011, which shows that Ireland is quicker to deal with the crisis that appeared than Portugal. Germany has the lowest default probability, closely followed by The Netherlands; they can be classified as stable and safe sovereigns since their default probability values are low and stable. Belgium and France follow a similar pattern in which their values are between the relatively stable sovereigns and the more risky sovereigns. Thus, they can be classified as low risk sovereigns.

5.2 New rating scheme

To be able to understand the relationship between the ratings assigned by the Big 3 and the market perception by the sovereign one-year maturity yield, a scatter plot has been made

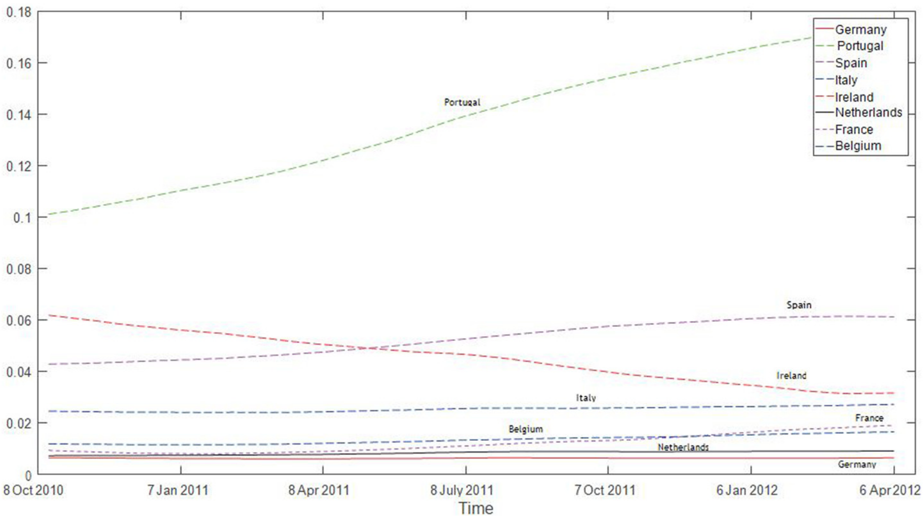
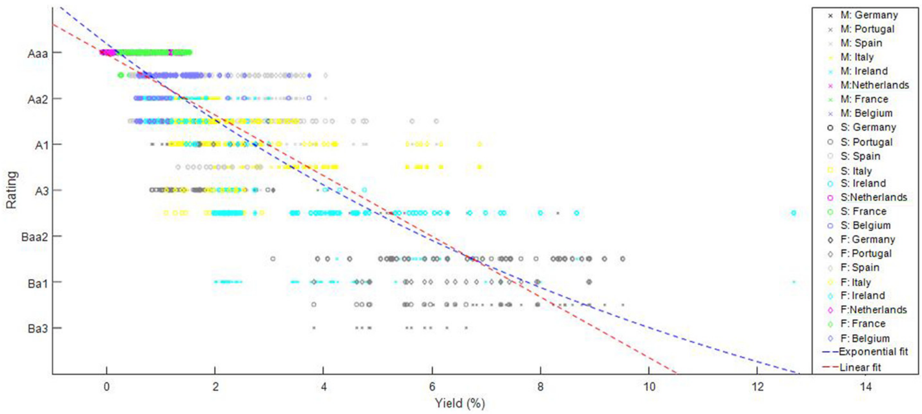


Figure 6.
The estimated default probabilities within one year of time t, over the testing period

which can be seen in Figure 7. As there are no data available for the sovereign one-year maturity bond of Portugal and The Netherlands, the one-year yield has been calculated from the corresponding two-year maturity bond. Both a linear and exponential fit have been applied, in which the exponential fit is a closer fit compared to the linear fit. However, as we see in the plot, there is a wide range for the yield for ratings below Aa2; especially for Ba2 where yields range from 2 to 10 per cent. This shows that while the market perceives a higher level of risk, the sovereigns have the same credit rating. Hence, using bond yields alone would not be sufficient to set up a rating scheme. To complement a bond yield-based rating scheme, we can make use of our model and the default probabilities we obtain. This allows a more reliable comparison of sovereigns, since there is a quantitative metric which applies to each sovereign. We have a total of 22 buckets, each one representing a rating, which is developed as follows. As Germany is the sovereign which is used as comparison and its implied default probability is low, it is assigned the highest credit rating which is Aaa. The probability of default of the highest rating bucket is set to be maximum default probability value of Germany. When a sovereign defaults, the default probability value should have a value of 1 and it should have the lowest possible rating. We use just one rating for default, similar to Moody's and S&P and unlike Fitch which includes three different default categories. An exponential scale has been applied to the remaining buckets. The bucket range increases as we go toward the last bucket that has the highest default probability, with 1.267 being the range multiplier ensuring that the last bucket ends with default probability of 1. The first bucket includes sovereigns with a default probability between 0 and 0.0066 per cent, and the second bucket contains sovereigns with a default probability between 0.0067 and 0.0084 per cent and so on. A nomenclature similar to Moody's has been used for this rating scheme. The buckets can be seen in Table V.

5.3 Comparison against the Big 3

The ratings assigned by the Reg-model are compared with the ratings assigned by the Big 3, which can be seen in Figures 8-10. The sovereign one-year bond yield is also included as a benchmark. One could categorize the eight countries in three groups based upon the ratings issued by the forecasting model. The first group consists of Germany and The Netherlands, which have a low level of sovereign credit risk. The second group consists of Belgium,



Notes: M: Moody's; S: S&P; F: Fitch

Figure 7.
Ratings vs one-year sovereign bond yields

Big 3 Moody's	S&P	Fitch	Reg-model PD (default)	Bucket	Label
Aaa	AAA	AAA	0.0000-0.0066	1	Aaa
Aa1	Aa+	Aa+	0.0067-0.0084	2	Aa1
Aa2	Aa	AA	0.0085-0.0107	3	Aa2
Aa3	Aa–	AA–	0.0108-0.0136	4	Aa3
A1	A+	A+	0.0137-0.0172	5	A1
A2	A	A	0.0173-0.0219	6	A2
A3	A–	A–	0.0220-0.0278	7	A3
Baa1	BBB+	BBB+	0.0279-0.0353	8	Baa1
Baa2	BBB+	BBB+	0.0354-0.0448	9	Baa2
Baa3	BBB-	BBB-	0.0449-0.0569	10	Baa3
Ba1	BB+	BB+	0.0570-0.0722	11	Ba1
Ba2	BB	BB	0.0723-0.0917	12	Ba2
Ba3	Bb–	Bb–	0.0918-0.1164	13	Ba3
B1	B+	B+	0.1165-0.1479	14	B1
B2	B	B	0.1480-0.1878	15	B2
B3	B–	B–	0.1879-0.2384	16	B3
Caa1	CCC+	CCC	0.2385-0.3028	17	Caa1
Caa2	CCC	CCC	0.3029-0.3845	18	Caa2
Caa3	CCC–	CCC	0.3846-0.4883	19	Caa3
Ca	CC	CCC	0.4884-0.6201	20	Ca1
Ca	C	CCC	0.6202-0.7875	21	Ca2
C	D	DDD	0.7876-1.0000	22	D
		DD		23	
		D		24	

Table V.
Ratings assigned by the Big 3 and used in the Reg-model

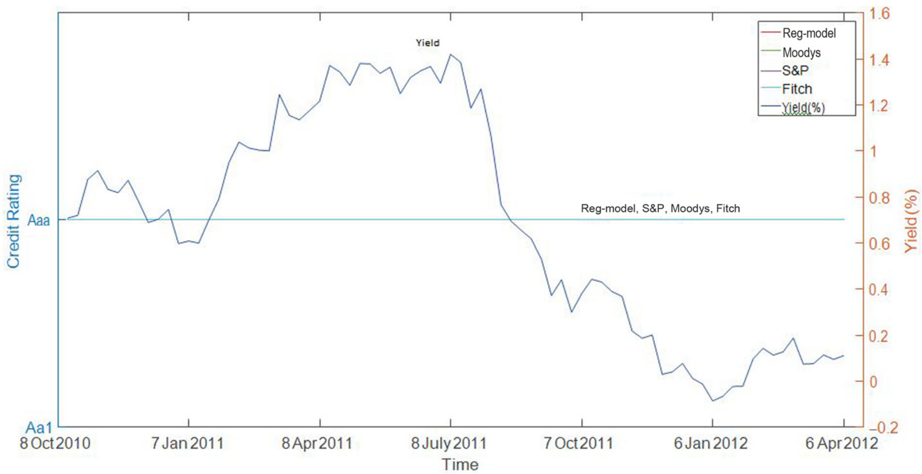


Figure 8.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for Germany

France and Italy, which have a small level of sovereign credit risk. The third group consists of Portugal, Spain and Ireland, which have a serious level of sovereign credit risk. The Reg-model gives Germany the highest possible rating, similar to the Big 3. Germany's bond yields are low and have a low fluctuation which indicates that there is less implied sovereign

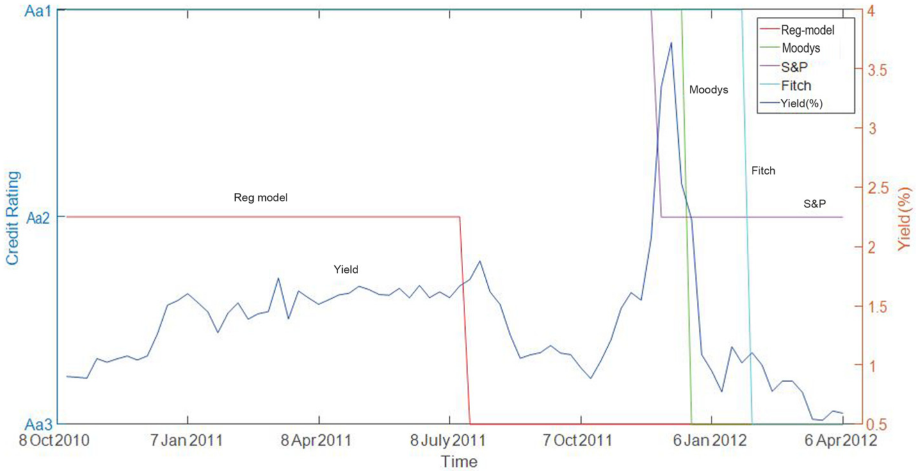


Figure 9.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for Belgium

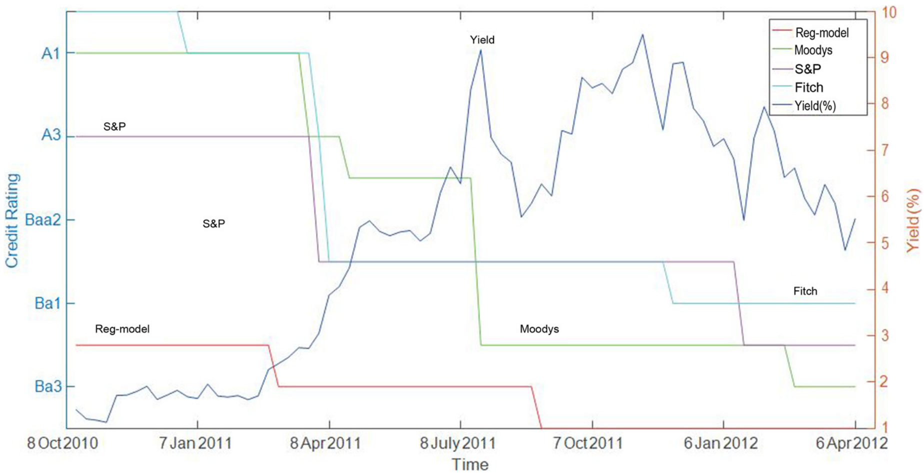


Figure 10.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for Portugal

credit risk. A similar situation can be found for The Netherlands but note that the Reg-model downgraded The Netherlands during the peak of the crisis (see Figure 11 in the Appendix).

For Belgium (Figure 9), the credit ratings issued by the Big 3 show a lag, since they start to downgrade Belgium from the start of 2012. The yield values indicate a rise in the implied sovereign credit risk midway 2011. The CDS spread indicates that there is an increase in the implied sovereign credit risk from the start of 2011. This market behavior is captured by the Reg-model and not by the credit ratings issued by Big 3. Thus, it can be concluded that the ratings issued by the Reg-model provide better insights than the ratings issued by the Big 3. The same situation applies to Italy and France (Figure 10).

For Portugal, the credit rating issued by the Reg-model follows a decreasing trend. Portugal is rated Ba3 from the beginning of 2011, indicating a serious level of sovereign credit risk. This can easily be inferred by looking at the yield values, which increase over time. The Big 3 also downgrade Portugal over time, a sharp decrease in March 2011 and again at the end of 2011. However, the CDS spread and the yield were already an early indication of high level of sovereign risk – which the Big 3 were slow to respond to. Their update at the end of 2011 was late since the yield was already quite high before. This is another example why the rating issued by the Reg-model provides better insight and faster market response compared to the Big 3. A similar situation in which Big 3 are slow to respond can also be found for Ireland and Spain.

It can be concluded that the ratings issued by the Big 3 tend to be slow to respond to market changes. The ratings are not downgraded at the moment when both the CDS spread and the sovereign bond yield increase. This is in contrast with the ratings issued by the Reg-model, which respond quicker to changes in the markets. Second, our rating scheme is a quantitative measure based on the Reg-model, allowing for a more reliable comparison between the sovereigns. This is in contrast with the rating procedure used by the Big 3, which is qualitative in nature and allows for different ratings for the same sovereign. Thus, this new procedure can be used to replace the current sovereign credit risk assessment procedure.

6. Conclusion

The credit ratings assigned to sovereigns play a crucial role in indicating the financial health of these sovereigns. The inadequacies of the ratings assigned by the Big 3 (S &P, Moody's and Fitch) became apparent during the financial crisis of 2008. The manner in which these firms assign their ratings lacks transparency. Furthermore, the fact that these firms receive payments from the sovereigns they assess and assign ratings to leads to significant conflicts of interest issues. More crucially, as was evidenced during the financial crisis, the ratings assigned by the Big 3 are slow to respond to market changes. The current financial climate is one in which many sovereigns are vulnerable to shifts in the geopolitical landscape. Given the vital role played by sovereign credit ratings, there is an urgent need for a transparent and rigorous model that can assess the creditworthiness of a sovereign and assign ratings that are accurate and respond quickly to market changes. In this paper, we develop a framework using the CDS spreads of a sovereign to assess its creditworthiness and assign a credit rating. The framework is centered on a regression-based model to estimate the CDS spreads of sovereigns. The model adopts the notion that sovereign credit risk is composed of both systemic and idiosyncratic risk and uses historical CDS data and data on other financial and macroeconomic variables to estimate the CDS spreads of sovereigns. With these estimates, the values of the systemic and idiosyncratic risk intensity processes can be calculated. These values in turn yield estimates of the default probability of a sovereign. A ratings scale based on these estimated default probabilities is then used to assign credit ratings to the sovereigns. We tested our framework on data from eight Eurozone countries during the peak of the financial crisis. Our results show that our framework provides good estimates of CDS spreads. Furthermore, the credit ratings assigned to sovereigns using our framework and ratings scheme reflect reality better, as opposed to the credit ratings issued by the Big 3. The proposed framework is generic and readily allows for modifications in the input data. Users can adjust factors and/or add new information easily. Due to the modular nature of the framework, users can use more sophisticated models to estimate default intensities and default probabilities. For example, a non-linear regression model might be used. A dynamic factor model, with parameter estimates obtained using a Kalman Filter, in conjunction with simulation could also be used. The framework is also demonstrably accurate and responsive. The framework is also transparent in the assessment of sovereign creditworthiness and assignment of credit ratings. Furthermore, the model also allows for stress testing to be performed, a key requirement for financial models in current economic conditions.

Notes

1. See Section 10.7 of Duffie and Singleton, pp. 247-249
2. We are grateful to the referee for this observation.
3. Regression outcomes of rejected variable combinations can be made available on request.

References

Afonso, A., Gomes, P. and Taamouti, A. (2014), "Sovereign credit ratings market volatility, and financial gains", *Computational Statistics and Data Analysis*, Vol. 76, pp. 20-33.

Amadeo, K. (2015), "Iceland: financial crisis, bankruptcy, and economy".

Anderson, J. (2015), "How Iceland emerged from its deep freeze".

Ang, A. and Longstaff, F.A. (2013), "Systemic sovereign credit risk: lessons from the US and Europe", *Journal of Monetary Economics*, Vol. 60 No. 5, pp. 493-510.

BBC (2009), "NorthernRock in trouble".

BCBS (2005), "Studies on the validation of internal rating systems", Technical Report 14, BCBS.

Benmelech, E. and Duglosz, J. (2009), "The credit ratings crisis", *NBER Macroeconomics Annual*, Vol. 24 No. 1, pp. 161-207.

Bernoth, K., Hagen, J.V. and Schuknecht, L. (2012), "Sovereign risk premiums in the European", *Journal of International Money and Finance*, Vol. 31 No. 5, pp. 975-995.

Central Bank of Iceland (2008), "Exchange rate".

Directorate General for Trade (2016), "Client and Suppllier countries of the EU28 in Marchandise trade", Technical report, European Commission.

Duffie, D. and Singleton, K.J. (1999), "Modeling term structures of defaultable bonds", *Review of Financial Studies*, Vol. 12 No. 4, pp. 687-720.

Duffie, D. and Singleton, K.J. (2003), *Credit Risk*, 1st ed., Princeton University Press, Princeton.

EC (2013), "New rules on credit rating agencies (CRAs): frequently asked questions", Technical report, EC.

Eijffinger, S.C.W. (2012), "Rating agencies: role and influence of their sovereign credit risk assessment in the eurozone", *Journal of Common Market Studies*, Vol. 50 No. 6, pp. 912-921.

Gestel, T.V., Baesens, B., Dijcke, P.V., Garcia, J., Suykens, J.A.K. and Vanthienen, J. (2006), "A process model to develop an internal rating system: sovereign credit ratings", *Decision Support Systems*, Vol. 42 No. 2, pp. 1131-1151.

Gibson, H.D., Hall, S.G. and Tavlas, G.S. (2014), "Fundamentally wrong: market pricing of sovereigns and the greek financial crisis", *Journal of Macroeconomics*, Vol. 39, pp. 405-419.

Hagen, J.V., Schuknecht, L. and Wolswijk, G. (2011), "European journal of political economy government bond risk premiums in the EU revisited: the impact of the financial crisis", *European Journal of Political Economy*, Vol. 27 No. 1, pp. 36-43.

Hamerle, A. and Liebig, T. (2003), "Benchmarking asset correlations", *Risk*, Vol. 16 No. 11, pp. 77-81.

Hilscher, J. and Nosbusch, Y. (2010), "Determinants of sovereign risk: macroeconomic fundamentals and the pricing of sovereign debt âĹŮ", *Review of Finance*, Vol. 14 No. 2, pp. 235-262.

Iceland Statistics (2008), "News and announcements".

IMF (2014), "World economic outlook database", April 2014.

Iyengar, S. (2010), "Are sovereign credit ratings objective and transparent?", *The IUP Journal of Financial Economics*, Vol. 8 No. 3, pp. 7-22.

Jakubík, P. (2006), "Does credit risk vary with economic cycles?", The Case of Finland.

Katz, J., Salinas, E. and Stephanou, C. (2009), "Credit rating agencies – no easy Solutions", Technical Report 8, The World Bank, WA.

Kiesel, F. and Spohnholtz, J. (2017), "Cds spreads as an independent measure of credit risk", *The Journal of Risk Finance*, Vol. 18 No. 2, pp. 122-144.

Klein, A. (2004), "Credit rates' power leads to abuses some borrowers say".

Koopman, S.J., Lucas, Á. and Schwaab, B. (2012), "Dynamic factor models with macro, frailty, and industry effects for US default counts: the credit crisis of 2008", *Journal of Business & Economic Statistics*, Vol. 30 No. 4, pp. 521-532.

Lando, D. (1998), "On cox processes and credit risky securities", *Review of Derivatives Research*, Vol. 2, pp. 99-120.

Larosiere, J.D., Balcerowicz, L., Issing, O., Masera, R., Carthy, C.M., Nyberg, L. and Ruding, O. (2009), "The high-level group of financial supervision in the EU", Group, pp. 1-85.

Longstaff, B.F.A., Pan, J., Pedersen, L.H. and Singleton, K.J. (2011), "How sovereign is sovereign credit risk?", *American Economic Journal*, Vol. 3 No. 2, pp. 75-103.

Longstaff, F., Sanjay, M. and Neis, E. (2005), "Corporate yield spreads default risk or liquidity", *The Journal of Finance*, Vol. 60 No. 5, pp. 2213-2253.

Moody's (2008), "Sovereign default and recovery rates, 1983-2007", Technical report, Moody's.

Moody's (2013), "Moody's changes outlook on US Aaa sovereign rating to stable from negative; rating affirmed".

Ozturk, H., Namli, E. and Erdal, H.I. (2016), "Modelling sovereign credit ratings: the accuracy of models in a heterogeneous sample", *Economic Modelling*, Vol. 54, pp. 469-478.

Pan, J. and Singleton, K.J. (2008), "Default and recovery implicit in the term structure of sovereign CDS spreads", *The Journal of Finance*, Vol. 63 No. 5, pp. 2345-2384.

Reinhart, C.M. and Rogoff, K.S. (2008), "The forgotten history of domestic debt".

Rösch, D. (2003), "Correlations and business cycles of credit risk: evidence from bankruptcies in Germany", *Financial Markets and Portfolio Management*, Vol. 17 No. 3, pp. 309-331.

Rösch, D. (2005), "An empirical comparison of default risk forecasts from alternative credit rating philosophies", *International Journal of Forecasting*, Vol. 21 No. 1, pp. 37-51.

Standard & Poor's (S&P) (2012), "Annual global corporate default study and rating transitions", Technical report, Standard & Poor's (S&P).

Sturzenegger, F. and Zettelmeyer, J. (2008), "Haircuts: estimating investor losses in sovereign debt restructurings, 1998-2005", *Journal of International Money and Finance*, Vol. 27 No. 5, pp. 780-805.

Taylor, A.M., Jordá, Ó. and Schularick, M.H. (2011), "When credit bites back: leverage, business cycles, and crises".

Virolainen, K. (2004), "Macro stress testing with a macroeconomic credit risk model for Finland".

Wegener, C., Basse, T. and Kunze, F. (2016), "Oil prices and sovereign credit risk of oil producing countries: an empirical investigation", *Quantitative Finance*, Vol. 16 No. 12, pp. 1961-1968.

Wong, J., Choi, K.-F. and Fong, T.P.-W. (2008), *A Framework for Stress Testing Banks' Credit Risk*, Palgrave Macmillan UK, London, pp 240-260.

Appendix

Formulas

Please note that for reasons of simplicity, the subscript i on ξ_i, a_i, b_i, c_i, and γ_i is suppressed in this appendix. There are three layers of equations for equation (8). The first layer is as follows:

$$\begin{aligned} A(\lambda,t) &= A_1(t)\exp(A_2(t)\lambda), \\ B(\xi,t) &= B_1(t)\exp(B_2(t)\xi), \\ C(\xi,t) &= (C_1(t)+C_2(t)\xi)\exp(B_2(t)\xi), \\ F(\lambda,t) &= (F_1(t)+F_2(t)\lambda)\exp\big(A_2(t)\lambda, \end{aligned} \tag{9}$$

The second layer of formulas is as follows:

$$\begin{aligned} A_1(t) &= \exp\left(\frac{\alpha(\beta+\psi)t}{\sigma^2}\right)\left(\frac{1-\nu}{1-\nu e^{\psi t}}\right)^{2\alpha/\sigma^2}, \\ A_2(t) &= \frac{\beta-\psi}{\sigma^2}+\frac{2\psi}{\sigma^2(1-\nu e^{\psi t})}, \\ B_1(t) &= \exp\left(\frac{a(b+\phi)t}{c^2}\right)\left(\frac{1-\theta}{1-\theta e^{\phi t}}\right)^{2a/c^2}, \\ B_2(t) &= \frac{b-\phi}{c^2}+\frac{2\phi}{c^2(1-\theta e^{\phi t})}, \\ C_1(t) &= \frac{a}{\phi}(e^{\phi t}-1)\exp\left(\frac{a(b+\phi)t}{c^2}\right)\left(\frac{1-\theta}{1-\theta e^{\phi t}}\right)^{2a/c^2+1}, \\ C_2(t) &= \exp\left(\frac{a(b+\phi)t}{c^2}+\phi t\right)\left(\frac{1-\theta}{1-\theta e^{\theta t}}\right)^{2a/(c^2+2)}, \\ F_1(t) &= \frac{\alpha}{\psi}(e^{\psi t}-1)\exp\left(\frac{\alpha(\beta+\psi)t}{\sigma^2}\right)\left(\frac{1-\nu}{1-\nu e^{\nu t}}\right)^{2\alpha/(\sigma^2+1)}, \\ F_2(t) &= \exp\left(\frac{\alpha(\beta+\psi)t}{\sigma^2}+\psi t\right)\left(\frac{1-\nu}{1-\nu e^{\nu t}}\right)^{2\alpha/(\sigma^2+2)}, \end{aligned} \tag{10}$$

The third and last layers are as follows:

$$\begin{aligned} \psi &= \sqrt{\beta^2+2\gamma\sigma^2}, \\ \nu &= \frac{\beta+\psi}{\beta-\psi}, \\ \phi &= \sqrt{b^2+2c^2}, \\ \theta &= \frac{b+\phi}{b-\phi}. \end{aligned} \tag{11}$$

Summary statistics credit default swap data

The summary statistics of the CDS data that has been used are provided, which include the minimum, maximum, mean, median value and the standard deviation for each country for both maturities for both time periods.

Table AI.
1 Year maturity – calibration period

	Portugal	Spain	Germany	France	Belgium	The Netherlands	Italy	Ireland
Minimum	0.06	0.5	0.05	0.1	0.1	0.1	0.3	9.19
Maximum	418.95	290.54	56.4	54.47	104.62	91.66	221.15	450
Mean	75.44089	60.84469	11.94123	16.4426	28.13712	17.28903	55.46489	120.1494
SD	105.7686	70.1786	11.54708	14.68932	26.26394	19.61382	53.67102	98.45314
Median	33.65	38.99	8.8	11.8	21.7	10.64	34.37	106.19

Table AII.
1 Year maturity – testing period

	Portugal	Spain	Germany	France	Belgium	The Netherlands	Italy	Ireland
Minimum	141.41	115.37	1	1	5.92	5.88	39.11	38
maximum	2111.86	455.23	64.97	155.61	280.63	79.75	575.65	1399.15
Mean	752.5288	244.4679	19.0874	53.03504	99.41443	31.43687	216.6076	549.5824
SD	494.9929	98.20741	14.56084	39.78464	70.83529	20.66263	146.4079	320.8312
Median	671.18	213.99	12.29	43.1	89.45	25.18	141	586.54

Table AIII.
3 Year maturity – calibration period

	Portugal	Spain	Germany	France	Belgium	The Netherlands	Italy	Ireland
Minimum	0.42	0.13	0.1	0.04	0.13	0.33	1	13.22
Maximum	420.19	271.66	77.9	80.4	135.77	117.55	224.58	470
Mean	84.85927	72.48218	18.16034	25.2104	40.63486	25.45829	70.92361	142.8992
SD	100.7825	69.21517	16.47848	21.66183	36.49449	25.11502	59.6018	103.161
Median	46.57	54.25	15.33	20.1	33.16	21.72	57.285	134.74

Table AIV.
3 Year maturity – testing period

	Portugal	Spain	Germany	France	Belgium	The Netherlands	Italy	Ireland
Minimum	276	177.97	6.53	11.32	20.33	16.14	110.84	97.83
Maximum	1710.53	593.34	82.47	201.17	384.91	101.36	557.06	1382.59
Mean	806.9045	325.6863	35.54603	88.11168	150.5534	46.65962	293.5842	587.3289
SD	415.7854	111.3329	18.20514	47.13585	84.00408	22.94473	138.7676	285.95
Median	744.84	310.36	28.2	72.42	141.99	40.02	239.46	637.13

Outcome factor analyses

Factor analyses have been conducted for each country, using the Varimax technique (which is an orthogonal rotation). This type of rotation reveals what factors are independent and are able to explain the major share of the variance. If the absolute value for a variable in a column is close to 1, then this variable can be used as a factor. These values have been shown italic font. For each country, the factor analysis has been run for four factors, but in case there is no relevant fourth factor (only low values for every variable), only the outcome of the three relevant factors is shown. Note that to determine the number of factors to be included, the Eigen values are used. If there are three variables with an Eigen value above 1, then the output includes three variables. The Eigen value explains to what extent the variable explains the variance in the data set.

The outcome of this step is then used in the regression. Only the independent factors are used in the regression analysis, and the results are shown in Tables AXIII-AXX.

Explanatory variable	Factor 1	Factor 2	Factor 3
EuroPound	0.616558	0.664497	−0.15381
EuroYen	−0.75481	0.320791	0.098007
EuroDollar	0.010489	*0.949263*	0.139646
EuroRMB	0.206015	*0.91886*	0.026854
NASDAQ	0.302189	0.775275	−0.03774
SP500	0.975376	0.049568	0.20786
Eurostoxx	0.988254	0.0406	0.135817
USA_VIX	0.994707	0.078487	−0.01599
EU_VIX	0.952373	−0.07788	*0.287881*
Gold	0.973755	−0.06975	0.208045
Oil	*0.99564*	−0.0657	0.01584
Euribor_1month	0.883354	−0.01508	0.013808
Euribor_3months	0.97448	0.152782	−0.10934
Euribor_6months1	0.980075	0.180285	−0.07062
ECB	0.977938	0.18527	*−0.08245*
EuroDollardepositrate	0.979791	0.168192	−0.0901
Eurobond_1year	0.482125	−0.25135	−0.09044
Eurobond_3years	−0.73993	−0.17037	*−0.27834*
Eurobond_5years	−0.21686	0.885383	−0.14034
Swap_1year	−0.15034	0.910437	−0.13428
Swap_3years	0.799695	−0.52619	−0.01897
Swap_5years	0.74942	−0.59888	−0.08096
1MLibor_OIS	0.510381	−0.74401	−0.09702
3MLibor_OIS	0.748547	−0.3858	0.220502
6MLIBOR_OIS	0.267364	−0.13413	0.170986
Treasury10Y_3M	0.75121	−0.2163	0.23993
TEDspread	−0.82051	0.296817	0.109306

Table AV. Germany – factor analysis outcome

Belgium	Factor 1	Factor 2	Factor 3	Factor 4
10-year treasury bond	0.08572	*0.912353*	−0.07611	−0.02078
Stock indices	0.777766	0.48697	−0.34358	0.061598
Interest rates deposit	0.169828	0.95443	0.129339	0.005102
Long-term interest rates	0.082906	*0.931921*	−0.08043	−0.02098
Unemployment ratio - I (total)	−0.03431	−0.83469	−0.05151	−0.20913
Unemployment ratio - II (under 25 year)	−0.14108	−0.69746	−0.10846	−0.20605
Unemployment ratio - III (over 25 years)	−0.01915	*−0.85833*	−0.01793	−0.16749
Production index construction	0.046551	0.107344	0.025976	*0.990313*
Real effective exchange rate – 42 trading partners	−0.55202	0.234547	0.265417	0.171959
Manufacturing, turnover index unadjusted	0.662155	0.349613	0.423345	0.382035
Manufacturing, turnover index adjusted	0.74914	0.38848	0.493763	0.058326
Manufacturing, production index	0.748514	0.300985	0.472548	−0.01545
International trade ratio	−0.0652	−0.73614	−0.05981	0.022743
Inflation ratio (HCIP)	−0.23977	−0.54562	0.732864	0.180602
Production development observed over the past 3 months	0.927417	−0.17674	−0.03281	−0.03264
Employment expectation over the next 3 months	0.978112	−0.01356	0.02216	0.013338
Industrial confidence indicator	*0.983275*	0.146347	−0.04515	0.01533
Economic sentiment indicator	*0.989793*	0.096555	−0.06965	0.037629
Consumer confidence indicator	0.912342	0.019564	−0.24795	0.096708
Volume index of production – buildings	0.027346	0.162747	0.001996	0.959992
Expectation of the demand over the next 3 months	0.960049	0.189253	−0.01361	0.105161
Savings over the next 12 months	0.46137	−0.28268	−0.63119	0.105843
General economic situation over the next 1 year of customers	0.31164	−0.77329	−0.42176	0.008392
Financial situation over the last 12 months	0.664327	−0.10341	−0.66251	0.067165
Index of deflated turnover	−0.25031	−0.08477	0.198608	0.114365
Producer prices in industry, domestic market	0.20202	0.15645	*0.950781*	0.007368

Table AVI.
Belgium – factor analysis outcome

Spain	Factor 1	Factor 2	Factor 3	Factor 4
10-year treasury bond	0.649684	−0.09752	0.193004	0.180192
Stock indices	0.848528	0.413421	−0.24822	−0.02068
Interest rates deposit	0.700111	−0.62342	−0.04067	−0.31948
Long term interest rates	0.71576	−0.11271	0.232035	0.194864
Unemployment ratio – I (total)	−0.97338	−0.10623	0.192209	0.04036
Unemployment ratio – II (under 25 year)	−0.97139	−0.09014	0.202565	0.012117
Unemployment ratio – III (over 25 years)	−0.97333	−0.09913	0.189693	0.054793
Real effective exchange rate – 42 trading partners	0.026498	−0.33915	−0.01708	*−0.65259*
Manufacturing, turnover index unadjusted	0.746558	0.179934	0.078503	0.07899
Manufacturing, turnover index adjusted	*0.950851*	0.269047	0.101262	0.05664
Manufacturing, production index	0.942891	0.292175	−0.10347	0.074787
International trade ratio	−0.59469	−0.08522	0.329779	−0.09792
Inflation ratio (HCIP)	−0.5336	−0.23382	0.741496	0.035247
Production development observed over the past 3 months	0.404059	0.684738	0.355232	0.408897
Employment expectation over the next 3 months	0.459069	0.678069	0.146216	0.287376
Industrial confidence indicator	0.587591	0.686784	0.034823	0.411773
Economic sentiment indicator	0.379337	0.846795	−0.09991	0.350828
Consumer confidence indicator	−0.00811	*0.973122*	−0.20693	0.053241
Volume index of production – buildings	0.758915	0.028416	−0.39139	0.050688
Expectation of the demand over the next 3 months	0.408882	0.731194	−0.26404	0.304279
Savings over the next 12 months	−0.11544	0.926941	−0.20892	−0.13276
General economic situation over the next 1 year of customers	−0.08127	*0.961434*	−0.1815	0.011013
Financial situation over the last 12 months	0.46942	0.730576	−0.35246	0.248655
Index of deflated turnover	0.892527	0.246039	−0.3506	0.053354
Producer prices in industry, domestic market	−0.03405	−0.27651	*0.948896*	0.044392

Table AVII. Spain – factor analysis outcome

France	1	2	3	4
10-year treasury bond	0.27495	*0.86611*	−0.14383	0.146342
Stock indices	0.773415	0.591731	0.132657	0.088649
Interest rates deposit	−0.03324	*0.859538*	−0.41263	0.103059
Long-term interest rates	0.274355	*0.879301*	−0.14214	0.153628
Unemployment ratio – I (total)	−0.42833	−0.63695	0.553693	−0.12334
Unemployment ratio – II (under 25 year)	−0.57667	−0.63153	0.369343	−0.03884
Unemployment ratio – III (over 25 years)	−0.34279	−0.6182	0.593826	−0.12954
Production index construction	0.059277	0.123758	0.013707	*0.987934*
Real effective exchange rate – 42 trading partners	−0.3136	0.557649	−0.03662	0.005296
Manufacturing, turnover index unadjusted	0.308547	0.165999	−0.27255	0.582454
Manufacturing, turnover index adjusted	0.666918	0.391746	−0.57766	0.135094
Manufacturing, production index	0.763847	0.58147	−0.22137	0.123352
International trade ratio	0.366199	−0.28656	−0.25354	0.027839
Inflation ratio (HCIP)	−0.30216	−0.80432	−0.38943	−0.05674
Production development observed over the past 3 months	0.789098	−0.12491	0.139439	−0.05776
Employment expectation over the next 3 months	0.952394	0.104842	−0.15599	0.136968
Industrial confidence indicator	0.983127	0.108553	−0.04878	0.104798
Economic sentiment indicator	0.988043	0.075597	0.083991	0.084463
Consumer confidence indicator	0.883582	0.204895	0.396149	0.058619
Volume index of production – buildings	−0.00055	0.105489	0.045509	0.981278
Expectation of the demand over the next 3 months	0.958445	0.176899	−0.03067	0.131568
Savings over the next 12 months	0.435244	−0.37719	0.74795	−0.05826
General economic situation over the next 1 year of customers	*0.675616*	0.093906	0.705685	0.00518
Financial situation over the last 12 months	0.478297	−0.02353	0.783853	0.040052
Index of deflated turnover	0.040829	−0.89876	−0.01972	−0.09441
Producer prices in industry, domestic market	0.262257	0.066959	*−0.88198*	0.054606

Table AVIII.
France – factor analysis outcome

Ireland	1	2	3
10-year treasury bond	0.8828	−0.0424	−0.2641
Stock indices	−0.1700	0.8087	0.4143
Interest rates deposit	−0.6113	0.1553	−0.7106
Long-term interest rates	0.8996	−0.0462	−0.2791
Unemployment ratio – I (total)	*0.9088*	−0.2860	0.2420
Unemployment ratio – II (under 25 year)	0.8737	−0.2725	0.1957
Unemployment ratio – III (over 25 years)	*0.9088*	−0.2861	0.2459
Production index construction	0.0658	−0.4377	0.5437
Real effective exchange rate – 42 trading partners	−0.3080	0.7657	−0.2904
Manufacturing, turnover index adjusted	−0.3860	0.8487	−0.2396
Manufacturing, production index	−0.7213	0.5539	−0.2162
International trade ratio	0.6727	0.0205	−0.0354
Inflation ratio (HCIP)	*0.9023*	−0.0787	−0.0194
Production development observed over the past 3 months	0.4422	0.8667	0.1556
Employment expectation over the next 3 months	−0.2666	*0.9108*	0.1444
Economic sentiment indicator	−0.4877	0.8452	0.0349
Consumer confidence indicator	−0.6929	0.2353	0.6346
Volume index of production – buildings	−0.4503	0.8334	−0.0499
Expectation of the demand over the next 3 months	−0.7666	0.0972	0.0048
General economic situation over the next 1 year of customers	−0.2001	0.0956	*0.9564*
Financial situation over the last 12 months	−0.7395	0.1295	0.3408
Index of deflated turnover	−0.7165	0.4962	−0.0413
Producer prices in industry, domestic market	0.2204	0.8553	−0.2146

Table AIX. Ireland – factor analysis outcome

Italy	Factor 1	Factor 2	Factor 3	Factor 4
10-year treasury bond	−0.63114	−0.41425	0.393333	−0.01556
Stock indices	0.766428	0.492713	−0.28333	−0.03176
Interest rates deposit	0.865474	−0.2564	0.383078	0.123555
Long-term interest rates	−0.70362	−0.33484	−0.01411	0.117043
Unemployment ratio – I (total)	−0.9907	−0.04981	−0.0575	−0.10377
Unemployment ratio – II (under 25 year)	*−0.98566*	−0.03156	0.003816	−0.14389
Unemployment ratio – III (over 25 years)	*−0.99048*	−0.0417	−0.08743	−0.07481
Real effective exchange rate – 42 trading partners	0.613883	−0.4805	0.227444	−0.44161
Manufacturing, turnover index adjusted	0.708059	−0.00587	0.205685	0.611141
Manufacturing, production index	0.124612	0.232354	0.002627	*0.718988*
International trade ratio	−0.80227	0.021208	−0.00635	−0.01443
Inflation ratio (HCIP)	0.436595	−0.50637	0.724571	−0.05819
Production development observed over the past 3 months	0.44072	0.744018	0.020358	0.306074
Consumer confidence indicator	0.190824	0.962247	−0.13007	0.126322
Savings over the next 12 months	0.580048	0.447636	−0.51872	0.128973
General economic situation over the next 1 year of customers	−0.10328	*0.954014*	−0.18393	0.090142
Financial situation over the last 1 year	0.938316	0.177644	0.013791	0.197092
Index of deflated turnover	0.917433	0.220751	−0.01216	0.219344
Producer prices in industry, domestic market	0.022723	−0.04054	*0.905368*	0.071051

Table AX. Italy – factor analysis outcome

The Netherlands	Factor 1	Factor 2	Factor 3	Factor 4
10-year treasury bond	0.818013	−0.08198	0.276189	−0.06288
Stock indices	0.674659	0.707371	−0.15913	0.086432
Interest rates deposit	*0.875897*	−0.03373	0.302919	−0.26566
Long-term interest rates	*0.849845*	−0.13567	0.278611	−0.07774
Unemployment ratio – I (total)	−0.7562	−0.2821	−0.02968	0.103451
Unemployment ratio – II (under 25 year)	−0.70923	−0.25016	−0.09078	0.063584
Unemployment ratio – III (over 25 years)	−0.80726	−0.29679	−0.01686	0.080142
Production index construction	0.387677	0.156118	0.095832	−0.02704
Real effective exchange rate – 42 trading partners	0.425893	−0.56986	−0.04683	0.392091
Manufacturing, turnover index unadjusted	0.345673	0.363459	0.238785	−0.07731
Manufacturing, turnover index adjusted	0.573001	0.663659	0.431875	−0.13631
Manufacturing, production index	0.687056	0.655087	0.244733	−0.11751
International trade ratio	0.07863	0.192546	0.426576	0.182395
Inflation ratio (HCIP)	−0.75831	−0.36755	0.367054	−0.05889
Production development observed over the past 3 months	0.184999	0.845695	0.00339	0.050557
Employment expectation over the next 3 months	0.514026	0.810818	0.197219	−0.02654
Industrial confidence indicator	0.173842	*0.967173*	0.174693	0.001887
Economic sentiment indicator	−0.0225	*0.975414*	0.093073	0.186938
Consumer confidence indicator	−0.15618	0.382088	−0.08397	*0.838995*
Expectation of the demand over the next 3 months	0.08362	0.887352	0.047225	0.231254
Savings over the next 12 months	−0.79245	−0.1623	−0.2636	0.315762
General economic situation over the next 1 year of customers	−0.41029	−0.02904	−0.12877	0.899575
Financial situation over the last 12 months	−0.51436	0.047169	−0.75588	0.220917
Index of deflated turnover	0.618507	0.660066	−0.22598	0.062572
Producer prices in industry, domestic market	0.115092	0.125572	*0.926514*	−0.30263

Table AXI. The Netherlands – factor analysis outcome

Portugal	1	2	3	4
10-year treasury bond	0.137032	0.712429	*0.579112*	0.344407
Stock indices	0.720354	0.196677	*0.613012*	0.007339
Interest rates deposit	−0.15054	0.9035	0.216507	0.2163
Long-term interest rates	0.152872	0.724988	0.58379	0.317031
Unemployment ratio – I (total)	−0.07467	*−0.98993*	−0.09056	0.049147
Unemployment ratio – II (under 25 year)	−0.20699	*−0.94505*	−0.04078	0.102197
Unemployment ratio – III (over 25 years)	−0.05096	*−0.98037*	−0.13433	0.023906
Production index construction	−0.03393	0.121706	0.060446	*0.545098*
Real effective exchange rate – 42 trading partners	−0.68589	0.187964	0.270104	0.313666
Manufacturing, turnover index unadjusted	0.741113	0.42498	0.049666	0.259512
Manufacturing, turnover index adjusted	0.731527	0.593219	−0.11134	0.226621
Manufacturing, production index	0.933255	0.213873	0.145225	0.153845
International trade ratio	0.286229	−0.00923	0.040459	−0.26551
Inflation ratio (HCIP)	−0.36343	−0.40799	−0.61245	0.133084
Production development observed over the past 3 months	*0.949384*	0.047179	0.192085	0.020457
Employment expectation over the next 3 months	*0.935026*	0.244056	0.188554	0.062906
Industrial confidence indicator	*0.960799*	0.129351	0.224922	0.07225
Economic sentiment indicator	*0.950316*	0.022033	0.304628	0.00961
Consumer confidence indicator	0.836621	−0.06972	0.517452	−0.12734
Expectation of the demand over the next 3 months	0.93917	0.038524	0.26149	−0.02568
Savings over the next 12 months	0.264744	0.230049	0.296232	0.156182
General economic situation over the next 1 year of customers	0.373727	−0.6553	0.53589	−0.32084
Financial situation over the last 12 months	0.324291	0.437538	0.49023	−0.0016
Index of deflated turnover	0.447594	0.776976	0.215063	0.109921
Producer prices in industry, domestic market	0.195984	−0.04014	−0.02902	0.345657

Table AXII. Portugal – factor analysis outcome

Outcome regression analyses

For each country, a regression analysis has been conducted which uses variables chosen from the factor analysis, shown in Tables AV-AXII. These variables are chosen as they can best represent the variability in the data. We also test different lagged time series to obtain the best regression outcome. We report the following: Estimate, Standard Error, *t*-Statistic, Rejection value (1 *p*-value), the lag and the R-squared value. As can be seen, all variables have a rejection value under 1 per cent (*p*-value over 99 per cent) which shows that every variable is significant at a 99 per cent level. Given that there are several variables as outcome from the factor analysis, different models have been tested. The model with the highest R-square value has been reported. Note, an explanatory variable which has a high value in the factor analysis might not directly be incorporated into the final regression model.

Belgium	Estimate	SE	*t*-stat	Rejection value	Lag
Constant	121.72	51.992	2.3411	0.020354	
10-year treasury bond	−60.076	7.4132	−8.1039	8.84E-14	5 weeks
Unemployment ratio III - pop > 25 years	21.225	5.6796	3.7371	2.52E-04	–
Interest rate deposit	21.719	4.7057	4.6155	7.56E-06	5 weeks
Stock index	−0.01636	0.002022	−8.0869	9.78E-14	–
R-squared value	0.662				

Table AXIII. Belgium – regression outcome

For example, in the case of Germany, we note the independent factors to be the Oil price, the ECB interest rate, the 3-year eurobond and the EUR-RMB exchange rate from Table AV. These variables are tested with different lags and the best regression outcome is chosen, as shown in Table AXVII[3]. With multiple independent factors, we test the regression on multiple combinations of the factors and choose the best outcome.

Table AXIV. Spain – regression outcome

Spain	Estimate	SE	*t*-stat	Rejection value	Lag
Constant	2642	246.1	10.736	5.62E-21	–
Manufacturing turnover index (adjusted)	−3.2754	0.24306	−13.476	7.48E-29	5 weeks
Producer prices in industry, domestic market	16.704	1.3905	12.013	1.25E-24	1 week
Real effective exchange rate – 42 trading partners	−36.953	2.0902	−17.679	8.71E-41	4 weeks
R-squared value	0.753				

Table AXV. France – regression outcome

France	Estimate	SE	*t*-stat	Rejection value	Lag
Constant	−217.79	35.665	−6.1064	6.40E-09	–
General economic situation over the next 1 year	0.60865	0.066156	9.2002	1.06E-16	–
Long-term interest rates	−35.189	1.6686	−21.089	6.28E-50	2 weeks
Producer prices in industry, domestic market	3.8541	0.38975	9.8886	1.35E-18	–
R-squared value	0.720				

Table AXVI. Italy – regression outcome

Italy	Estimate	SE	*t*-stat	Rejection value	Lag
Constant	−640.4	112.73	−5.6806	5.50E-08	–
Unemployment ratio – III (over 25 years)	14.617	0.7557	19.343	2.54E-45	–
General economic situation over the next 1 year	1.2931	0.17421	7.4228	4.80E-12	5 weeks
Producer prices in industry, domestic market	3.6681	1.0176	3.6046	0.000407	5 weeks
Manufacturing, production index	2.6689	0.54775	4.8725	2.46E-06	–
R-squared value	0.721				

Table AXVII. Germany – regression outcome

Germany	Estimate	SE	*t*-stat	Rejection value	Lag
Constant	126	12.794	9.8482	2.39E-18	–
ECB_interestrate	21.562	0.77017	27.997	3.61E-65	5 weeks
Oil_price	−0.54303	0.049259	−11.024	1.31E-21	no
Euro-RMB	−9.4096	1.5593	−6.0345	9.89E-09	2 weeks
R-squared value	0.845				

Ireland	Estimate	SE	t-stat	Rejection value	Lag
Constant	12275	718.82	17.077	4.82E-36	–
Inflation ratio	−112.42	6.6732	−16.847	1.74E-35	–
General economic situation	4.8012	0.4734	10.142	1.84E-18	–
R-squared value	0.696				

Table AXVIII.
Ireland – regression outcome

The Netherlands	Estimate	SE	t-stat	Rejection value	Lag
(Intercept)	44.785	7.5233	5.9529	1.44E-08	–
Unemployment ratio III - > 25 years	−7.3676	1.3022	−5.6576	6.29E-08	–
Industry confidence indicator	−1.6201	0.09481	−17.088	6.57E-39	–
R-squared value	0.630				

Table AXIX.
The Netherlands – regression outcome

Portugal	Estimate	SE	t-stat	Rejection value	Lag
Constant	461.56	106.34	4.3403	2.40E-05	–
Industrial confidence indicator	16.385	1.2996	12.608	2.41E-26	–
Unemployment ratio – III (over 25 years)	176.37	16.218	10.875	2.26E-21	1 week
Stock indices	−0.17191	0.014587	−11.785	5.65E-24	–
Production index construction	−0.8305	0.35345	−2.3497	0.019904	3 weeks
R-squared value	0.689				

Table AXX.
Portugal – regression outcome

Comparison of the ratings

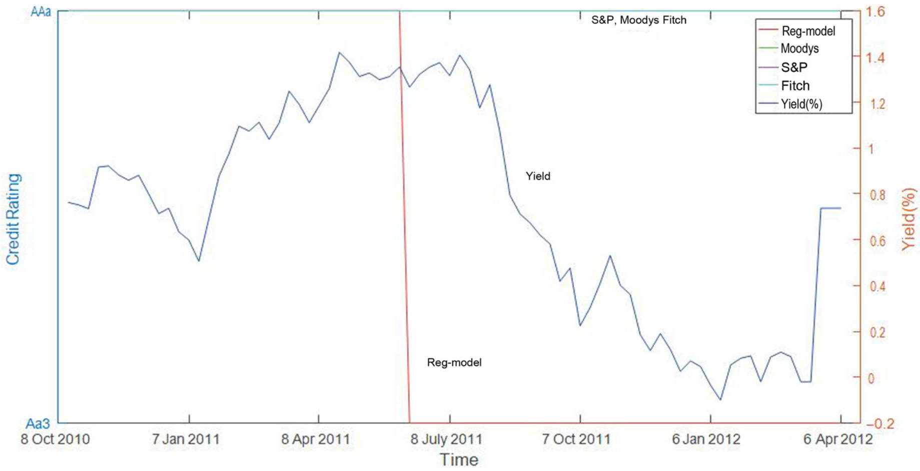


Figure A1.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for The Netherlands

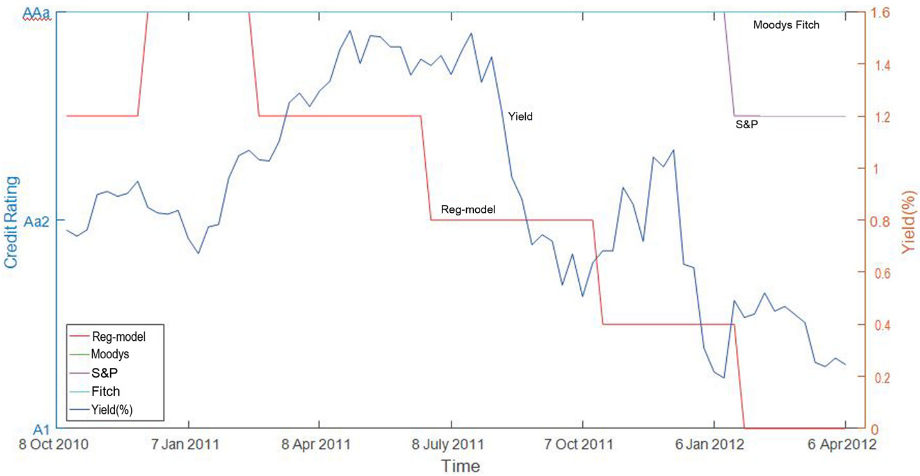


Figure A2.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for France

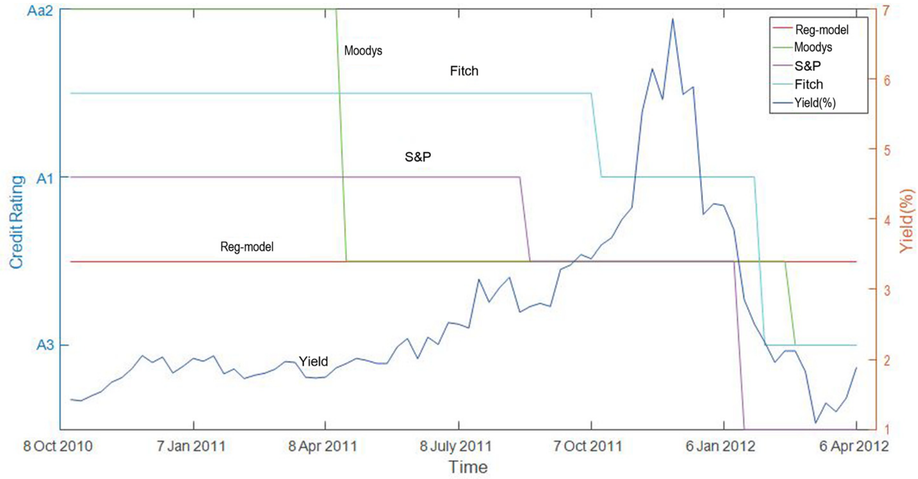


Figure A3.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for Italy

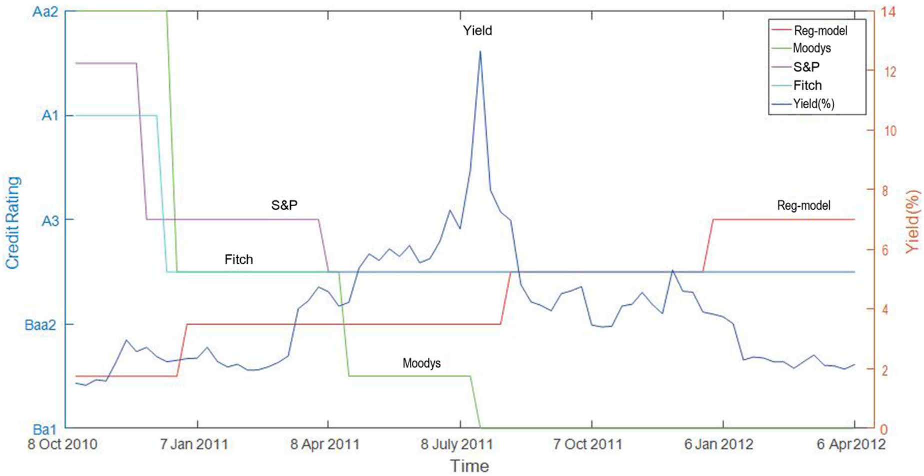


Figure A4.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for Ireland

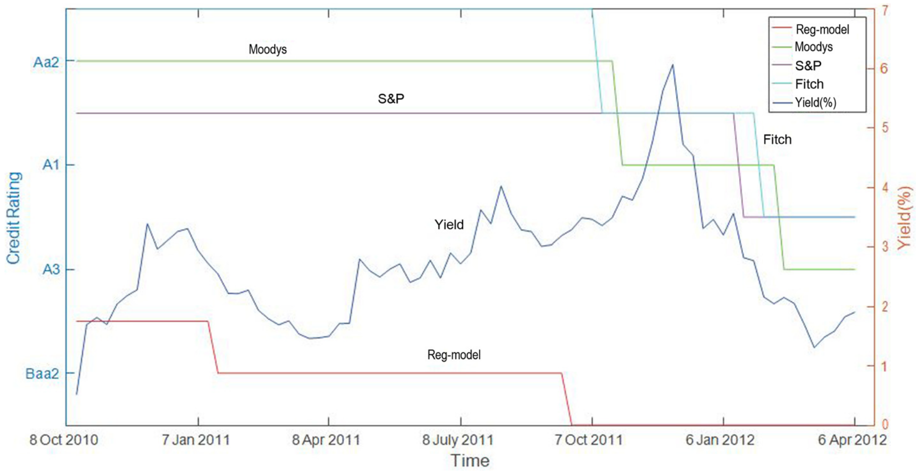


Figure A5.
Ratings assigned by the Big 3 and the Reg-model with the one-year sovereign bond yield for Spain

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