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Understanding sovereign rating movements in euro area countries

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Abstract

This paper investigates the link between sovereign ratings and macroeconomic fundamentals for a group of euro area countries which recorded rating downgrades amid the euro area sovereign debt crisis. We apply an elaborated econometric estimation technique, based on a Bayesian ordered probit model, to understand how the decisions of rating agencies can be explained by economic developments. The estimated model re-produces historical ratings by using a small number of economic and institutional variables, which seem to effectively summarize the large number of criteria used by Moody's, Standard & Poor's and Fitch in their assignment of sovereign ratings. Our results suggest that the size of the downgrades observed since the start of the sovereign crisis has been broadly in line with the deterioration of economic fundamentals for most countries.

JEL Codes: C25; G24; H63; H68.

Keywords: Sovereign debt, sovereign rating, euro area crisis, panel probit model.

Non-technical summary

This paper investigates the link between sovereign ratings and macroeconomic fundamentals for a group of euro area countries which recorded rating downgrades amid the euro area sovereign debt crisis. Some of these countries experienced significant financial market stress (Greece, Ireland, Spain, Portugal, and Italy), while others were relatively shielded by the crisis (Belgium, France). Compared to the existing empirical work on rating behaviour determinants, this paper introduces two key novelties.

The first novelty relates to the country-coverage – in contrast to the bulk of the literature our sample includes only a subgroup of euro area countries. The lower heterogeneity of our sample implies that the paper is free from criticisms related to the finding by Bissoondoyal-Bheenick (2005) according to which the weights assigned by ratings agencies to economic and political indicators differ depending on a country's economic development and institutional track record. The sample period starts in 1995 and thus covers enough observations to have a robust assessment of the rating behaviour and allows us to analyse the impact of the euro area sovereign debt crisis. The event study analysis suggests that in the pre-crisis sovereign ratings did not serve as a leading indicator of rising government debt or deteriorating growth prospects. By contrast, the aftermath of rating changes is rather uneventful with economic growth and public debt remaining unaffected by the rating changes. This suggests that rating changes in the euro area countries are typically following economic developments rather than serving as a leading indicator for future developments.

The second key novelty relates to the estimation method. We estimate a parsimonious ordered probit panel model using Bayesian techniques. Given the limited number of observations below investment grade in our sample, the Bayesian approach helps with the model's statistical identification by imposing restrictions on the prior distribution of the model. Contrary to other approaches, the model does not include country-fixed effects and long-run differences in countries' ratings are explained by institutional variables.

The empirical model reproduces historical ratings by using only a small number of economic and institutional variables (the government debt ratio and its change, GDP per capita, the unemployment rate and government effectiveness) which effectively summarize the large number of criteria used by Moody's, Standard & Poor's and Fitch in their assignment of sovereign ratings. We find some evidence for a structural break in rating agencies' assessment around the start of the sovereign debt crisis. Since the beginning of 2010, i.e. shortly after the revision of Greek fiscal data in October 2009, rating agencies seem to have been putting more weight on economic fundamentals and there has been somewhat lower inertia in rating behaviour. In contrast to the findings by Ferri et al. (1999) in the context of the Asian crisis, we would, however, be cautious to conclude that the current ratings are 'excessively conservative'. The downgrades of a number of euro area sovereigns since 2010 may, to a certain extent, be explained by the correction of excessive optimism in the pre-crisis period, when the default of a euro area country was treated as a very low probability event. This implies that the current ratings may better reflect the significant vulnerabilities and risks of several euro area countries. While in the pre-sovereign crisis period buoyancy was masking latent vulnerabilities, there appear to have been some learning process by rating agencies since 2010, leading to a swifter adjustment of rating agencies to a move in fundamentals.

1. Introduction

This paper investigates the link between sovereign ratings and macroeconomic fundamentals in a group of euro area countries which recorded rating downgrades amid the euro area sovereign debt crisis. Empirical work on the determinants and the effects of sovereign ratings is considerable and often related to crises situations. For example, Ferri et al. (1999) argue that rating agencies first failed to predict the East Asian crisis and then overreacted by decreasing the ratings of East Asian countries more than the economic situation would have suggested. This increased the cost of borrowing and worsened the crisis. Similarly, Kaminsky and Schmukler (2002) find that rating changes were lagging indicators of financial collapse in emerging economies and exacerbated boom-bust phases through their effects on bond spreads and stock prices. More recently, Gaillard (2014), focusing on EU countries, finds similar results for the period of the financial turmoil 2009-2012 demonstrating that rating agencies were late to adjust ratings.

In this study we ask similar questions, but approach them in a new manner, by using a parsimonious ordered probit panel estimation allowing for cross-country effects and explaining long-term effects via institutional variables. First, we investigate whether changes in sovereign ratings of euro area economies lead or lag changes in macroeconomic fundamentals. Our results support the finding of 'rating stickiness', i.e. rating agencies failed to adequately forewarn investors of European sovereign securities of changes to credit risks. In particular, sovereign ratings did not serve as a leading indicator of rising government debt or deteriorating growth prospects. By contrast, the event study shows that the aftermath of rating changes is rather uneventful with the debt ratio and economic growth remaining unaffected by rating changes.

Second, we estimate the determinants of sovereign ratings in an ordered probit model using Bayesian techniques. Our empirical model reproduces historical ratings by using only a small number of economic and institutional variables which effectively summarize the large number of criteria used by Moody's, Standard & Poor (S&P) and Fitch in their assignment of sovereign ratings. Our studies does not find evidence that rating agencies exacerbated the crisis, i.e. the size of the downgrades of euro area sovereigns was in line with the worsening in these countries' economic fundamentals.

Third, we find some evidence for a change in rating agencies' assessment around the start of the sovereign debt crisis. Since the beginning of 2010, i.e. shortly after the revision of Greek fiscal data in October 2009, rating agencies seem to have put more weight on economic fundamentals and there has been lower inertia in ratings. In difference to the conclusion by Ferri et al. (1999) for the Asian crisis, we would however be cautious to conclude that the current ratings are 'excessively conservative'. While current ratings are below the ones suggested by our model in some cases, this may be related to an overly optimistic pre-crisis metric rather than due to procyclical behaviour.

We restrict our analysis to euro area countries as our model could not capture the high degree of heterogeneity across different regions in the world. Bissoondoyal-Bheenick (2005) finds, e.g., that the weight assigned by rating agencies to different economic indicators depends on the level of economic development and the institutional track record. For example, critical debt thresholds may be different for euro area countries than for emerging market economies and there may be interaction effects between the level of economic development and credit risk which are difficult to capture in an econometric setting since it is not enough to simply control for the level of economic development. Furthermore, the disclosure of new private information through rating actions may play a less important role for European economies than for emerging economies where problems of asymmetric information and transparency are more severe.

While we explore a large data set encompassing a wide array of economic, financial and institutional factors, our preferred model is relatively parsimonious. Just five variables (the government debt ratio and its change, GDP per capita, the unemployment rate and a measure of government effectiveness) explain the rating assessment by Moody's, S&P and Fitch. Our specification provides a very good fit by capturing the dynamics of ratings both before and during the sovereign crisis period. Our results are thus in line with the seminal paper by Cantor and Packer (1996) who also explain a country's rating by a small number of variables as well as Polito and Wickens (2013), whose model-based measure of sovereign credit ratings is based purely on a country's fiscal position.

The finding that only five variables capture the dynamics in euro area sovereign ratings does not imply that rating agencies ignore further variables. In fact, our robustness tests show that some additional variables can also enter our regression in a statistically significant way, though without improving the overall model fit. However, many of these additional potential determinants of ratings co-move and our variables of relevance thus possibly summarise a larger space of structural and macroeconomic indicators. Furthermore, some variables may exert an influence on rating assignments in a less systematic way, e.g. only during certain periods. Finally, our model is based on indicators which have a lower frequency (quarterly) than that normally used in empirical models. The key implication of this is that some of the low frequency indicators are a good summary statistical measure of the information included in higher frequency data, which, however, are very important indicators in real time.

The rest of this paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 describes the data used in our analysis and performs an event study to analyse the dynamics of macroeconomic variables around the time of rating changes. In Section 4, we present our econometric rating model and provide some forecast performance statistics. Section 5 concludes. The appendices contain additional materials.

2. Related literature

Sovereign ratings indicate a sovereign's ability and willingness to service financial obligations in time and in full. This implies that ratings are affected by both economic ('ability to pay') and political ('willingness to pay') factors. It is generally acknowledged that rating decisions play a useful role in providing investors with information about the credit risk associated with a financial investment (Kräussl, 2005). At the same time, however, rating agencies have been confronted with multiple accusations, ranging from pro-cyclical behaviour (resulting from rating agencies joining prevailing consensus rather than providing own contributions) to a skewed incentive bias resulting from excessive reliance on issuer fees (Mathis et al., 2009). In the context of financial crises, rating agencies are typically blamed for 'stickiness', i.e. rating changes tend to happen after some anticipation took place already in the market with regard to changes in the issuer's credit quality (Ferri et al., 1999). Equally, the ratings agencies are often accused for excessive downgrades during downturns and for a failure to upgrade sovereigns adequately in the recovery following the crisis.

Most of the literature on sovereign ratings has analysed the short-term impact of rating decisions on financial returns. These studies typically use daily or weekly data in an emerging market context. Using event study methodology, Granger causality analysis and VAR modelling, the key finding from these studies is that rating agencies lag rather than lead financial markets and fail to predict sudden changes in credit risk within countries. Nevertheless, rating agencies convey new information to the market and some authors find that rating changes exert an important influence on government bond yield spreads (Reisen and von Maltzan, 1999; Afonso et al., 2012), CDS spreads (Norden and Weber, 2004), stock prices (Hill et al., 2010; Kaminsky and Schmukler, 2002) and financial stability (Kräussl, 2005). These results are generally more pronounced in cases of sovereign downgrades than in the case of positive rating adjustments and in cases of downgrades or upgrades (in or) out of investment grade categories (Kiff et al., 2012).

Only a few studies have analysed the link between rating decisions and macroeconomic fundamentals. Chen et al. (2013) find that sovereign rating changes exert a temporary influence on real private investment through their impact on the cost of capital. Upgrades are followed by increases in private investment growth while downgrades lead to declines in private investment growth.

Another branch of the literature aims to identify the determinants of sovereign ratings. Credit rating agencies do not publish their models but provide some information on their methodology (Fitch 2012, Moody's 2013, S&P's 2011). While there are differences across rating agencies in terms of methodological approaches, the assignment of a sovereign rating starts in all cases with a quantitative analysis which is either scorecard-based or econometric model-based. The analysis encompasses several broad areas of economic performance, including economic structure, fiscal strength, external sector, monetary stability, financial aspects, political environment, and institutional framework. Both forward and backward looking indicators are taken into account. The outcome of the quantitative analysis is however not binding. The final rating decision is influenced significantly by judgement based on country-specific expert information (see also Gaillard, 2011, 2014, for more details how ratings are designed).

Since the seminal study by Cantor and Packer (1996), who analyse the ratings of 49 countries at a particular point of time, a number of studies have tried to reproduce sovereign ratings (see e.g. Mora, 2006; Bissoondoyal-Bheenick, 2005; Afonso et al., 2009, 2011; Gaillard, 2014). These studies have identified GDP growth, inflation, external and public debt, external reserves, level of economic development, and country's default history as most important variables. Other indicators, while relevant during certain periods, do not seem to have the same importance.

Only in the context of the current crisis attention has turned to default risk in euro area sovereign debt. De Vries and de Haan (2014) identify a divergence of sovereign credit ratings and yield spreads for stressed euro area countries after 2012, with spreads gradually returning to pre-crisis levels, while credit ratings remaining low. D'Agostino and Lennkh (2016) study the sovereign ratings of euro area countries by disentangling the rating drivers into a 'fundamental' and 'subjective' component using Moody's Methodology.

As regards estimation techniques, some studies relied on linear model regression (either single-country OLS or linear panel data models if applied to multiple countries) assuming that the rating scale can be divided into equally spaced intervals (Cantor and Packer, 1996). It is however inappropriate to argue that the risk intervals between two ratings convey the same information across the full rating scale. More recent studies therefore apply ordered response models. One feature of both linear and non-linear (ordered response) panel models is that the fixed effects which are included in the regression capture the country's average rating and therefore implicitly measure long-term characterizations of countries, such as the financial history or the quality of institutions. The remaining variables will only capture movements in the ratings across time (see Bissoondoyal-Bheenick, 2005; Afonso et al., 2011). In this paper, we use an ordered probit panel model estimated by Bayesian techniques. The Bayesian approach helps with the statistical identification of the model that may arise due to the low number of observations with sub-investment grade ratings. In contrast to the previous literature, we do not include country fixed effects but explain long-run differences in country's ratings by institutional variables.

3. Data analysis

3.1 Data description

The analysis uses quarterly data for the seven euro area countries Belgium, Ireland, Greece, Spain, France, Italy and Portugal as published by Eurostat, over the period from 1995Q1 to 2014Q2.[1] All countries experienced downgrades in the course of the euro area sovereign debt crisis. As regards our dependent variable, we use a sovereign's issuer rating for foreign currency denominated debt as published by Moody's, S&P's and Fitch. Our sample includes 18 upgrades and 27 downgrades by Moody's, 25 upgrades and 36 downgrades by S&P and 26 upgrades and 26 downgrades by Fitch. The majority of rating changes occurred after the onset of the debt crisis with ten upgrades by Moody's and S&P and five by Fitch as well as 27 downgrades by Moody's and 32 (23) by S&P (Fitch).

Building on the existing literature, we use a number of macroeconomic and institutional variables that may determine sovereign ratings. In terms of macroeconomic fundamentals, we use a country's quarterly real growth rate and the government debt-to-GDP ratio. To adjust for revisions, real time data as available at the end of a given quarter are used for the real output growth. To capture institutional factors, we employ the annual average of the World Bank's Worldwide Governance Indicators (WGI), covering the following four sub-indicators: voice and accountability, political stability and no violence, government effectiveness, regulatory quality rule of law and control of corruption.

3.2 Event study

Before constructing the econometric model, this section associates changes in ratings with real growth and government debt by means of an event study analysis. We first look at the development of real GDP growth before and after rating changes. The focus is on a 13-quarter window centred on the date of the rating change for every rating change in our sample. Figure 1 shows the mean, median, and the interquartile range of GDP growth in the six quarters before and after a rating change with quarter 0

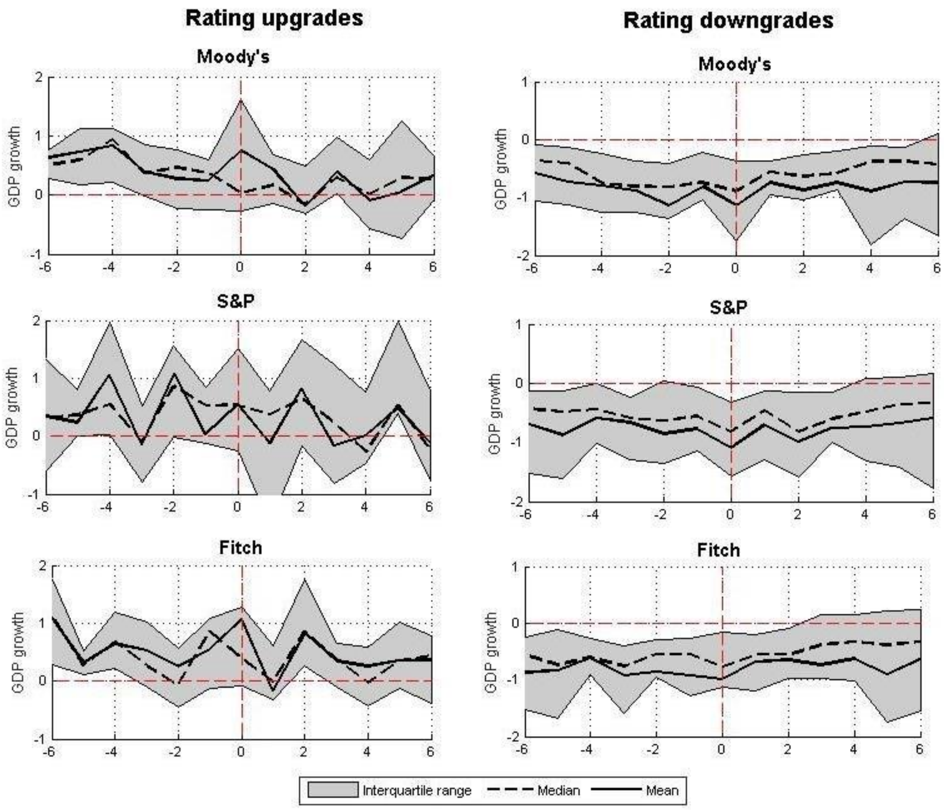
[1] For some countries data start as early as 1991 (Italy, France and Germany), while for Greece only data since 2000Q1 are available.

corresponding to the quarter of the rating change. We record the results for all three rating agencies and distinguish between upgrades (charts on the left) and downgrades (charts on the right). The growth path before a rating event is in line with expectations as GDP increases before rating upgrades and falls before rating downgrades. The visual inspection however, does not provide evidence that rating changes impact or predict future growth developments. In the aftermath of rating changes there is neither a further improvement in the growth performance for countries that were assigned a higher rating nor is there a worsening in growth for countries affected by a downgrade.

We then link the timing of rating changes to the level of government debt (Figure 2). As can be seen, rating actions downgrades typically occurred when the debt ratio had already deteriorated significantly. This is was particularly evident during the recent crisis period. For example, Moody's started to downgrade Greece only in October 2009, Portugal in July 2010, Spain in September 2010 and Italy in 2011, i.e. long after the debt ratio of these countries had started to rise significantly.

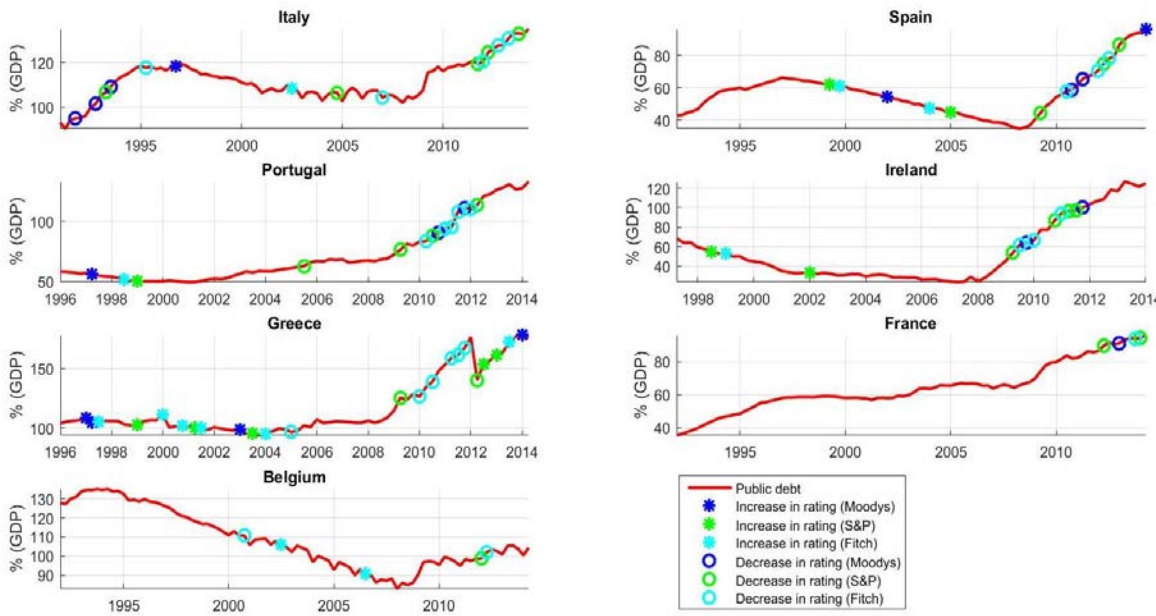
Overall, the graphical analysis therefore suggests that rating actions follow (rather than lead) the adjustment of the main macroeconomic flow and stock variables. Hence, in line with the results by Ferri et al. (1999), rating changes tend to confirm the current trend rather than warning investors about the risks of default or expected losses.

Figure 1: GDP growth and changes in sovereign ratings



Note: Charts show real GDP growth in 13-quarters window around rating changes. Quarter 0 is quarter of change in rating. Quarters -6 to -1 denote period prior to rating change, quarters 1 to 6 denote period after rating change.

Figure 2: Government debt to GDP ratio and changes in sovereign ratings



4. Estimation design and results

4.1 Rating equation

In our econometric analysis, we use an ordered response model as suggested by e.g. Afonso et al. (2009). We introduce, however, two innovations. First, although we estimate the model jointly for the seven countries in our sample, we do not include fixed or random effects or countries dummies. Instead we capture the low frequency component of ratings by institutional factors. Second, we opt for the Bayesian approach. Since our sample does not include a large number of sub-investment grade ratings, the model would be poorly identified and the maximum likelihood or other frequentist technique would be infeasible. In the Bayesian framework, the restrictions on the prior distribution help to estimate the model.[2] Moreover, the Bayesian approach does not require the maximization of a highly non-linear function and the posterior distribution can be found by a globally converging stochastic algorithm.

Our model is formulated in the latent variable framework. Given that ratings are ordered categorial values the natural approach is the ordered probit model. The model can be represented as follows:

(4.1) $$y_{it} = k \Leftrightarrow y_{it}^{*} \in [c_{k-1} c_k)$$

where y_{it} is the rating of country *i* at time *t*, y_{it}^{*} is the corresponding numerical latent variable, and $c = \{c_0 \dots c_n\}$ are cut-off values. In other words, a country i has rating k in year t if the latent variable y_{it}^{*} falls into the interval $[c_{k-1} c_k)$.

The latent variable is assumed to follow the autoregressive linear model:

[2] Note that the linear scaling implicitly assumed in studies using the OLS or linear panel data models is more restrictive than our relatively uninformative prior.

$$(4.2) \qquad y_{it}^* = X_{it}\beta + \beta_0 + \phi y_{it-1}^* + \varepsilon_{it}$$

where X_{it} are observed macroeconomic and institutional variables, β is the vector of unknown regressors, $\phi \in (-1\ 1)$ is the autoregressive parameter that models the persistence in rating[3], and ε_{it} are random disturbances distributed as an i.i.d. N(0, 1) sequence.[4]

Intuitively, the latent (unobserved) numerical values y_{it}^* are transformed to the actual (observed) ordered categorial ratings y_{it} (such as AAA, etc.) using Equation (4.1). The latent variables are then assumed to follow the ARX process described in (4.2). The coefficients β correspond to the regression coefficients of the latent variables on fundamentals X_{it}, while cut-offs c_k determine how the latent variables are transformed to the observed ratings.

We estimate the model using Bayesian techniques via a slight modification of Müller and Czado's (2005) algorithm (see Appendix A). We also consider a simpler approach of transforming the rating into numerical scale, both using linear interpolation and non-linear interpolation (following Ferri et al., 1999) and then applying pooled OLS regression. The implications of the estimation results of the two approaches are very similar. In the following, we present the results for the Bayesian estimation. The results of the pooled OLS estimation are available in Appendix B.

The Bayesian approach also helps to deal with the obvious inertia in ratings. The problem of inertia is manifested in the autoregressive parameter ϕ that is very close to 1. From the statistical point of view, this complicates the inference as the dynamics of ratings tend to be explained mainly by its lagged values. We solve this by putting the proper prior on ϕ which is the truncated normal distribution with mean zero and the variance 1/10; the distribution is truncated to the interval (−1, 1) to ensure stationarity (see Appendix A.1 for an explanation how this is reflected in the Gibbs sampler). The prior on the coefficient of the institutional variable WGI is proper and centred around 0.2, which puts the prior probability mass to the positive values. The reason for this choice is to ensure that the posterior mean of this coefficient will be positive. The prior on the rest of the parameters β is improper: normal with zero means and infinite variances. The prior on cut-off values is improper uniform on the real axis with the natural restrictionc_k<c_(k+1).

To assess the model properties, we consider the maximum aposterior probable predictive rating $\text{Rating}_{it}^{MAP1}$, i.e. the most probable rating given current macroeconomic fundamentals and the past rating. The construction of this statistics is described in Appendix A.2.

4.2 Estimation results

We investigate the inclusion of a large number of potential variables, such as real GDP growth, various fiscal variables, current account, various measures of country's size, private debts. Based on the predictive properties of the model, the following five variables were identified as variables with the highest explanatory power: (i) the government debt-to-GDP ratio (henceforth *government debt*), (ii) the change in the Hodrick-Prescott trend of the government debt-to-GDP ratio (henceforth *government debt change*), (iii) real GDP per capita, (iv) the unemployment rate, and (v) the average of the World Bank worldwide governance indicators (henceforth *WGI*). In economic terms, the debt-to-GDP ratio

[3] The constraint $\phi \in (-1\ 1)$ is imposed to ensure stationarity of the model.
[4] The assumption of unitary variance of ε_{it} is the usual identification assumption, see e.g. Müller and Czaldo (2005).

and the change in the trend debt ratio capture fiscal sustainability risks, the governance indicator relate to a country's growth potential, resilience to economic and political shocks and risks of over-borrowing, the unemployment rate summarizes structural rigidities and cyclical developments, while per capita GDP reflects the government's ability to repay outstanding obligations and captures long-term structural and institutional features of an economy which may be relevant even in a more homogenous sample since they have proven challenging in EMU to be adjusted (Masuch et al., 2016).

The estimation results for our preferred specification are given in Tables 1-3. We report the posterior mean and the 95% Bayesian credible interval. To address a possible change in the coefficients around the beginning of the sovereign debt crisis, we re-estimated the model on the subsamples prior and post 2010. Overall, the results are similar across the three rating agencies. All our coefficients have the expected sign and are statistically significant at the 5% level except the unemployment rate and the WGI indicator in the Fitch specification which are, however, both significant at the 10% level. As regards the results for the two sub-periods, the sensitivity of ratings to changes in the government debt ratio increases in the post-2010 period, suggesting that over the last years rating agencies have attached a higher emphasis on risks stemming from the fiscal dynamics. On the other hand, the level of economic development seemed to have played a stronger role in the pre-crisis period. The inertia in ratings tends to decrease in the post-2010 period for S&P and Fitch, but increases for Moody's. Taken together, this provides some tentative evidence that rating agencies reacted more sensitive to institutional factors and economic fundamentals after the outbreak of the sovereign debt crisis compared to the pre-crisis period.

The choice of a relatively small number of explanatory variables in our benchmark specification does not imply that rating agencies look exclusively at these five variables. In fact, it is well-known that the assignment of a rating is the result of a multi-dimensional process that encompasses many different categories. Our findings that only five variables provide a very good fit of the actual rating provide, however, some evidence that the *additional* explanatory power of further variables is relatively limited either because of high correlation with other variables or because some variables became relevant only during certain periods. For example, the vulnerabilities stemming from large intra-euro area current account imbalances were long underestimated by many observers and became only fully visible after 2008. Similarly, Target 2 balances were largely ignored before 2011 and only became relevant as a summary indicator for a country's balance-of-payment difficulties afterwards. Nevertheless, we will report more extended versions of our model in the following section.

Table 1: Estimation of the rating equation – Moody's

	Full sample			**Prior 2010**			**Post 2010**		
	l.c.i.	*pst.m.*	*u.c.i.*	*l.c.i.*	*pst.m.*	*u.c.i.*	*l.c.i.*	*pst.m.*	*u.c.i.*
Institutional quality (WGI)	0.030	0.099	0.229	0.048	0.179	0.314	0.005	0.140	0.272
Government debt	-2.438	-1.842	-1.273	-4.203	-3.388	-2.581	-3.478	-2.249	-1.076
Government debt change	-0.230	-0.168	-0.105	-0.132	-0.054	0.024	-0.616	-0.397	-0.185
GDP per capita	0.763	1.229	1.725	2.685	3.579	4.510	-0.189	0.639	1.426
Unemployment rate	-0.043	-0.020	0.004	-0.042	-0.004	0.033	-0.066	-0.017	0.033
Constant	0.808	1.672	2.467	0.208	1.114	2.003	0.927	3.624	6.248
Lagged rating	0.733	0.798	0.856	0.484	0.576	0.660	0.681	0.753	0.828

Note: pst.m. = posterior mean; l.c.i. = the lower (2.5%) quantile of the Bayesian 95% credible interval; u.c.i.= the upper (97.5%) quantile of the Bayesian 95% credible interval. Full sample refers to 1995Q1-2014Q2, prior 2010 is 1995Q1 to 2009Q4 and post 2010 is 2010Q1-2014Q2.

Table 2: Estimation of the rating equation – S & P

	Full sample			Prior 2010			Post 2010		
	l.c.i.	*pst.m.*	*u.c.i.*	*l.c.i.*	*pst.m.*	*u.c.i.*	*l.c.i.*	*pst.m.*	*u.c.i.*
Institutional quality (WGI)	0.024	0.144	0.278	0.055	0.179	0.310	0.020	0.154	0.287
Government debt	-1.291	-0.860	-0.429	-1.753	-1.204	-0.688	-3.127	-1.937	-0.689
Government debt change	-0.186	-0.130	-0.071	-0.137	-0.080	-0.020	-0.665	-0.439	-0.212
GDP per capita	0.188	0.613	1.051	0.768	1.385	2.023	0.036	0.905	1.701
Unemployment rate	-0.031	-0.007	0.016	0.000	0.036	0.071	-0.041	0.005	0.051
Constant	-0.049	0.756	1.580	-0.757	0.093	0.879	0.232	2.518	4.894
Lagged rating	0.828	0.886	0.929	0.752	0.818	0.879	0.703	0.771	0.845

Note: See Table 1.

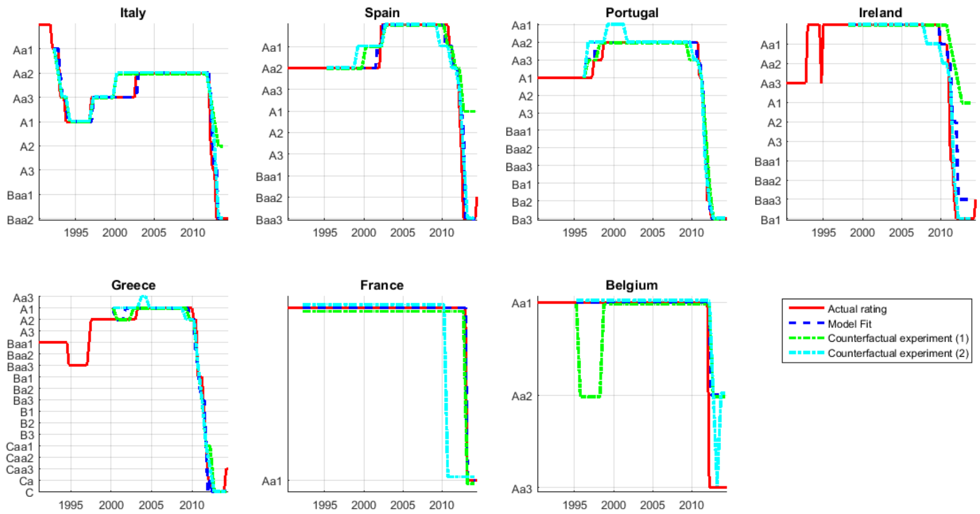
Table 3: Estimation of the rating equation – Fitch

	Full sample			Prior 2010			Post 2010		
	l.c.i.	*pst.m.*	*u.c.i.*	*l.c.i.*	*pst.m.*	*u.c.i.*	*l.c.i.*	*pst.m.*	*u.c.i.*
Institutional quality (WGI)	-0.025	0.108	0.235	0.024	0.153	0.289	0.016	0.144	0.273
Government debt	-2.442	-1.862	-1.289	-3.508	-2.673	-1.853	-4.869	-3.384	-1.870
Government debt change	-0.234	-0.176	-0.118	-0.147	-0.081	-0.012	-0.797	-0.560	-0.318
GDP per capita	0.594	1.069	1.554	1.370	2.144	2.933	0.604	1.433	2.262
Unemployment rate	-0.042	-0.018	0.006	-0.017	0.020	0.056	-0.062	-0.016	0.030
Constant	1.443	2.539	3.763	1.640	2.725	3.799	2.467	5.662	8.681
Lagged rating	0.749	0.822	0.881	0.629	0.713	0.792	0.607	0.702	0.795

Note: See Table 1.

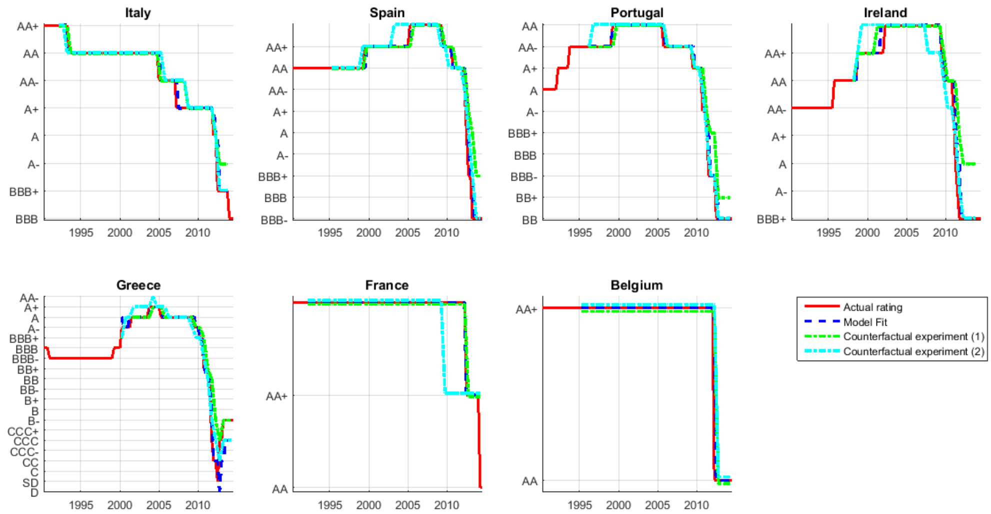
A common criticism is that rating agencies aggravated the euro area crisis by becoming overly conservative and downgrading euro area sovereigns beyond what would have been justified by economic fundamentals. Figures 3 to 5 show however that the actual ratings during the crisis period have been close to the model predicted rating for most countries. For Greece the ratings by Moody's S&P and Fitch at the end of the sample period are even above the model generated ratings. This finding is broadly corroborated by two counterfactual experiments. First, we extrapolate the pre-crisis model on the post-2010 period. Second, we extrapolate the sovereign-crisis specification (post 2010) on the pre-crisis period. While for most countries and rating agencies, the two counterfactuals are closely aligned, for Ireland, Spain and to some extent Italy, the pre-2010 model predicts a rating significantly above the actual rating after 2010. Rather than related to an overly conservative post-crisis stance, this could, however, also be related to an overly optimistic pre-crisis assessment. Hence, we find no strong evidence that rating agencies played a procyclical role during the crisis.

Figure 3: Actual ratings by Moody's versus model predicted ratings



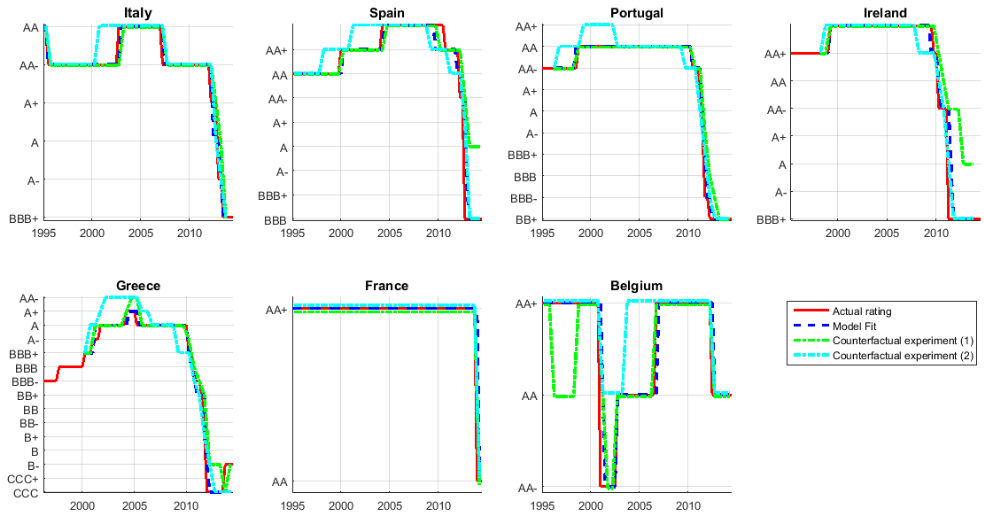
Note: Counterfactual experiment 1 is based on equation (4.1) estimated until 2009Q4 and extrapolated thereafter. Counterfactual experiment 2 is based on equation (4.1) estimated from 2010Q1 onwards and extrapolated on the pre-crisis period.

Figure 4: Actual ratings by S&P versus model predicted ratings



Note: Counterfactual experiment 1 is based on equation (4.1) estimated until 2009Q4 and extrapolated thereafter. Counterfactual experiment 2 is based on equation (4.1) estimated from 2010Q1 onwards and extrapolated on the pre-crisis period.

Figure 5: Actual ratings by Fitch versus model predicted ratings



Note: Counterfactual experiment 1 is based on equation (4.1) estimated until 2009Q4 and extrapolated thereafter. Counterfactual experiment 2 is based on equation (4.1) estimated from 2010Q1 onwards and extrapolated on the pre-crisis period.

4.3 Predictive properties of the model

In principle, the good fit of our parsimonious model could be caused by the high value of the autoregressive parameter. The visual analysis of Figures 3 to 5 illustrates however that the model predicted ratings sometimes lead the change in the actual rating. To shed more light on this issue, we report the predictive power of our model. First, Figures 6 to 8 compare the actual rating with the ex-post prediction for horizons of four and eight quarters. For these longer horizons, the stickiness of ratings loses importance and the rating dynamics are dominated by fundamental factors. Again, there is some evidence that for the crisis period rating agencies assigned ratings for Ireland, Spain and Italy below the ratings predicted by the economic fundamentals, while the actual rating for Greece has been better than suggested by the model.

Moreover, we report the root mean square error (RMSE) and the absolute mean error (AME)[5] constructed as follows. Given the maximum aposterior probable rating (see Appendix A.2 for its construction), we define the RMSE at horizon h as:

$$RMSE^h = \sqrt{\frac{1}{I}\frac{1}{T}\sum_i \sum_t \left(Rating_{it}^{MAP_h} - y_{it+h}\right)^2}$$

and the MAE:

$$MAE^h = \frac{1}{I}\frac{1}{T}\sum_i \sum_t \left|Rating_{it}^{MAP_h} - y_{it+h}\right|$$

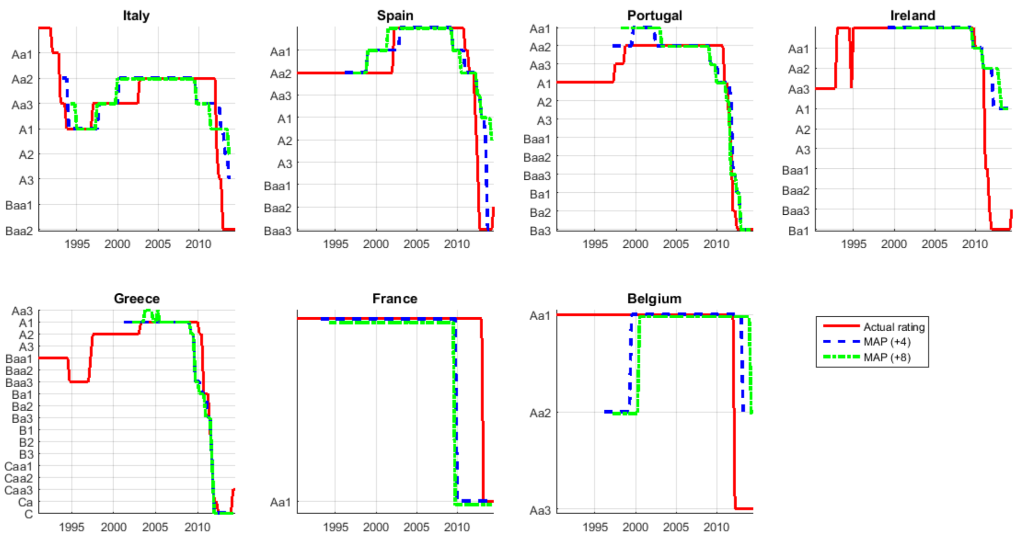
[5] The RMSE statistics is a standard measure in the statistical literature. However, given the discrete nature of data, the AME can be more transparent. The value of AME=1 means that -on average- the model misclassifies the actual rating by one category.

We compare both statistics for our model (BMPS) with the 'random-walk' model (which simply sets $Rating_{it}^{MAP_h} = Rating_{it-h}$), the autoregressive model and two more extended models. The latter specifications follow Afonso et al. (2011) and add the current account-to-GDP ratio, the inflation rate, real GDP growth, and the Target 2 balance (as a substitute for the foreign exchange reserve ratio which is typically used in the literature for non-euro area countries as a measure for risks resulting from sudden capital outflows) to the variables in the BMPS model. In line with Afonso et al (2011), we use for each variable either the actual value (extended model I) or long-run averages (extended model II).

The results are given in Appendix C for the full sample (Table 5), the pre-crisis model extrapolated on the full sample (Table 6) and the post-crisis model extrapolated on the full sample (Table 7). All Tables include the absolute RMSE and MAE for all models as well as the relative RMSE and MAE of the BMPS model compared to the alternative models. As regards the relative model comparison, values above (below) one indicate a better (worse) model performance of the BMPS model compared to the respective comparison model.

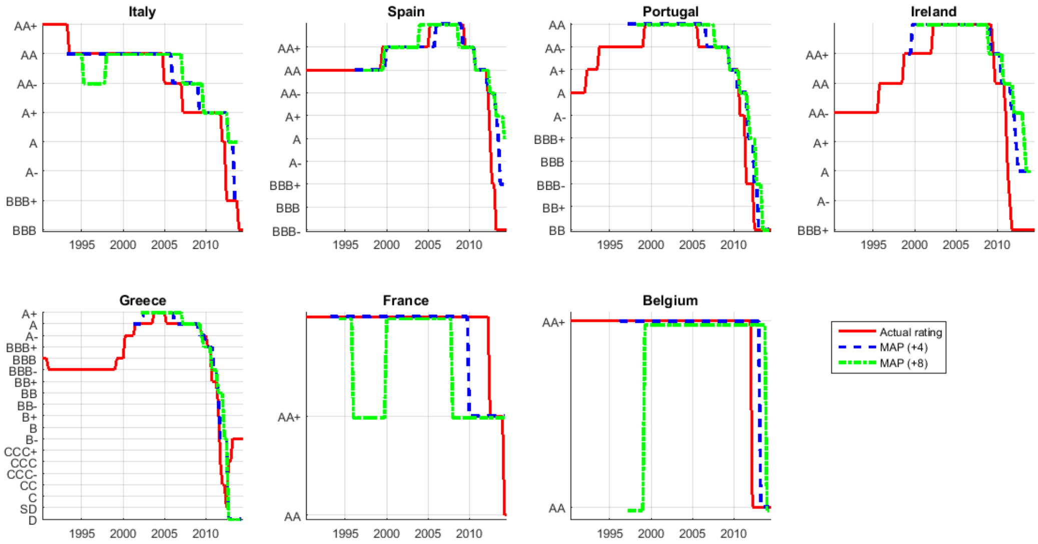
Over the short term, the random walk model and the BMPS model tend to outperform the remaining models. Over longer horizons, the BMPS model and the extended model I display the best forecast performance. The BMPS model performs also relatively favourable over both estimation periods. The relative performance of the random walk model is, however, better in the pre-2010 specification, while the extended models perform worse in this setting. This is another indication of the high inertia in ratings and the less systematic reaction of rating agencies to macroeconomic and institutional factors before 2010. Overall, these exercises confirm the good forecasting properties of the relatively parsimonious BMPS model, in particular over longer horizons.

Figure 6: Actual ratings by Moody's versus model predicted ratings



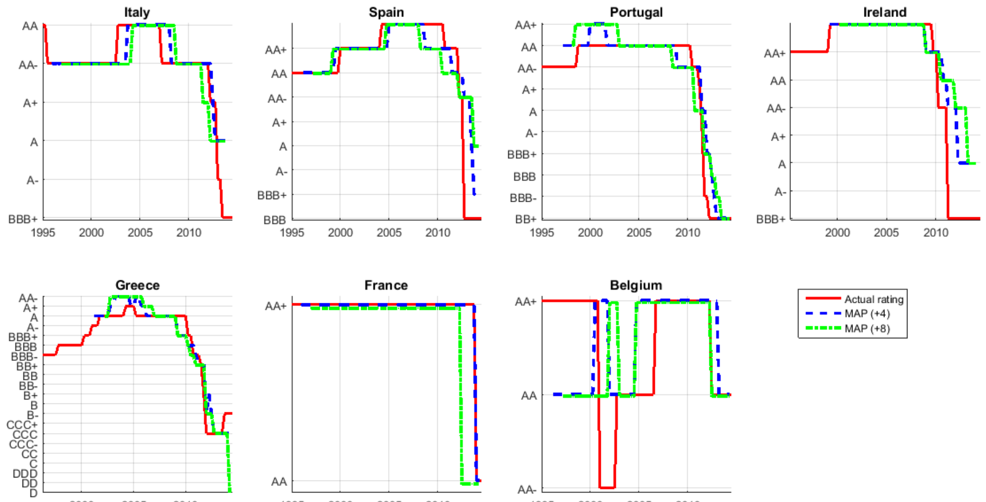
Note: Chart compares actual Moody's rating with 4- and 8- quarter ahead model predicted ratings.

Figure 7: Actual ratings by S&P versus model predicted ratings



Note: Chart compares actual S&P rating with 4- and 8- quarter ahead model predicted ratings.

Figure 8: Actual ratings by Fitch versus model predicted ratings



Note: Chart compares actual Fitch rating with 4- and 8- quarter ahead model predicted ratings.

5. Conclusions

In this paper, we introduce an elaborated econometric technique to estimate the determinants of sovereign ratings for a sample of seven euro area countries. The results suggest that sovereign ratings of the three major rating agencies can be explained by a relatively small number of macroeconomic and institutional fundamentals. We also find some evidence for a structural change around the year 2010. After 2010, ratings seem to be less sticky and rating agencies put more weight on fundamentals.

At the same time, our results suggest that rating agencies cannot be made responsible for broad-based procyclical behaviour in the euro area crisis, which is the opposite finding to what Ferri et al. (1999) claim for the case of the East Asian crisis in 1997/1998. For most countries the size of the downgrades was in line or, as in the case of Greece, even below the deterioration of fundamentals. We do however find some evidence for conservative rating assessments in Ireland and Spain.

Looking ahead, it is doubtful whether ratings for some of these countries will return to the pre-crisis levels anytime soon. First, notwithstanding recent improvements, uncertain growth prospects and high debt levels will remain important risk factors for the period ahead. Second, the downgrades of a number of euro area sovereigns since 2010 may, to a certain extent, be explained by the correction of excessive optimism in the pre-crisis period, when default of government debt issued by a euro area sovereigns was treated as a very low probability event. Only in the course of the crisis it became clear to rating agencies (as well as to investors on bond markets) that the removal of the exchange rate risk did not mean that euro area sovereigns were protected from default but that the absence of the exchange rate as an adjustment tool increased these economies' vulnerabilities to asymmetric shocks.

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Appendix A: Order probit: formulation and estimation

The estimation of credit rating is done using the Bayesian panel data ordered probit model. For this purpose, we slightly modify the algorithm by Müller and Czado (2005) who use Gibbs sampler extended by the multigrid move by Liu and Sabatti (2000). See also Hasegawa (2009) for a general treatment of this kind of models.

We summarize here details of the algorithm. The model is:

(A.1) $$y_{it} = k \Leftrightarrow y_{it}^* \in [c_{k-1} c_k)$$

where y_{it} is the rating of country *i* at time *t*, y_{it}^* is the corresponding numerical latent variable, and $c = \{c_0 \dots c_\tau\}$ are cut-off values. In other words, a country i has rating k in year t if the latent variable y_{it}^* falls into the interval $[c_{k-1} c_k)$.

The latent variable is assumed to follow the autoregressive linear model:

(A.2) $$y_{it}^* = X_{it}\beta + \beta_0 + \phi y_{it-1}^* + \varepsilon_{it}$$

where X_{it} are observed macroeconomic and institutional variables, β is the vector of unknown regressors, $\phi \in (-1\ 1)$ is the autoregressive parameter that models the persistence in rating, and ε_{it} are random disturbances distributed as an i.i.d. $N(0,\omega^2)$ sequence. As usual, for identification, we set $c_0 = -\infty$, $c_1 = 0$, $c_\tau = \infty$ and $\omega^2 = 1$.

The model can be easily extended by country fixed or random effects, or even to be casted in hierarchical Bayesian framework that would allow for limited variation in parameters across countries. However, we do not do opt for this, as this do not significantly contribute to the improvement of the model properties. In fact, estimation the model without variation in parameters and without country fixed effects can be seen as a virtue of parsimonity.

A.1 Estimation

The unknown parameters $\theta = \{\beta, \beta_0, \phi, \boldsymbol{c}\}$ are estimated using a Gibbs sampler along with unobserved latent variables y_{it}^* and the likewise unobserved initial condition y_{i0}^*. For sake of brevity, we include β_0 into the vector β and the matrix of regressors X_{it} is expanded accordingly.

For the estimation, we use the following priors:

- The prior on regression coefficient is normal $\beta \sim N\left(\underline{\beta}, \underline{\Sigma}\right)$, (improper prior $\underline{\Sigma}^{-1} \longrightarrow \mathbf{0}$ is allowed);
- We use the truncated normal distribution as the prior for $\phi \sim TN_{(-1,1)} N(\underline{\phi}\ \underline{\sigma}_\phi^2)$; to ensure stationarity, the distribution is concentrated on the interval $(-1\ 1)$.
- The prior on the initial condition is improper: $y_{i0}^* \sim N(0, \kappa_0^{-2})$, with $\kappa_0 \to 0$;
- The prior on $\boldsymbol{c}$ is uniform with the restriction that $c_{k-1} < c_k$.

Denote:

$$\boldsymbol{b}^T = [\beta^T \phi]^T, \qquad \underline{\boldsymbol{b}}^T = \left[\underline{\beta}^T\ \underline{\phi}\right], \qquad \underline{\Omega} = \begin{bmatrix} \underline{\Sigma} & 0 \\ \mathbf{0} & \underline{\sigma}_\phi^2 \end{bmatrix}$$

Let also $\tilde{X}_i$ be the data for the country *i* expanded by the lagged latent variables:

$$\tilde{X}_i = \begin{bmatrix} X_{i1} & & y_{i0}^* \\ & \vdots & \\ X_{iT_i} & & y_{T_i-1}^* \end{bmatrix}$$

We allow for unbalanced panels as T_i need not to be equal to T_j for $i \neq j$.

The Gibbs sampler iterates as follows:

- Given data and the parameters ***c***, sample ***b*** from the normal distribution with the mean $\overline{\boldsymbol{b}} = \overline{\Omega}^{-1}[\Omega_0 \underline{\boldsymbol{b}} + \Sigma_i \tilde{X}_i^T y_i^*]$ and the covariance matrix $\overline{\Omega} = \underline{\Omega}^{-1} + \Sigma_i \tilde{X}_i^T \tilde{X}_i$. Accept this sample if the element of **b** corresponding to ϕ is less than 1 in the modulus.[6]
- Given the parameters ***b***, ***c*** and the data, sample latent variables as follows:

  – The initial values are sampled from the normal distribution $y_{i0}^* \sim N\left(\frac{\phi(y_{i1}^* - X_{it}\beta)}{\phi^2}, \frac{1}{\phi^2}\right)$;

  – For $t = 1, \ldots, T_i - 1$, the latent variables are sampled from the truncated normal distribution $y_{it}^* \sim TN_{(c_{y_{it}-1}, c_{y_{it}})}\left(\frac{(\phi y_{it-1}^* + X_{it}\beta) + \phi(y_{it+1}^* - X_{it+t}\beta}{1+\phi^2}, \frac{1}{1+\phi^2}\right)$;

  – Finally, the last value of latent variables are sampled from the truncated normal distribution $y_{it}^* \sim TN_{(c_{y_{it}-1}, c_{y_{it}})}\left(\frac{\left(\phi y_{iT_i-1}^* + X_{iT_i}\beta\right)}{1+\phi^2}, \frac{1}{1+\phi^2}\right)$;
- Given the data and the rest of the parameters, sample the elements c_k $(k = 2 \ldots n)$ of **c** from the uniform distribution with the lower bound $c_{kL} = \max(c_{k-1}, max_{y_{it}=k+1} y_{it}^*)$ and the upper bound $c_{kU} = \min(c_{k-1}, min_{y_{it}=k+1} y_{it}^*)$.
- Each iteration is completed by the multigroup move, i.e., latent variables y_{it}^*, cut-off values c_k and the regressors β (but not the autoregressive parameter ϕ) are re-scaled by $\sqrt{\varsigma}$, where ς is a draw from the gamma distribution $\Gamma(a, b)$, with $a = \frac{\Sigma_i T_i + K + p + 1}{2}$ (*p* is the number of elements in the vector β) and $b = \frac{\Sigma_i \Sigma_{t=1}^{T_i}(y_{it}^* - X_{it}\beta - \phi y_{it-1}^*) + \underline{\beta}^T \underline{\Sigma}^{-1} \underline{\beta}}{2}$.

We implemented this algorithm in Matlab (version R2012b). Matlab codes are available from authors upon request.[7]

A.2 Maximum aposterior predictive rating

Based on the input of Gibbs sampler, we construct the maximum aposterior predictive rating as follows. Based on the output from the Gibbs sampler of the parameters $\beta^{(r)}$, $\beta_0^{(r)}$, $\phi^{(r)}$, $c_k^{(r)}$ and the sampled latent variables $y_{it}^{*(r)}$ we sample the predictive distribution of latent variables from (4.2)[8]:

[6] Hence, we sample the vector ***β*** jointly with the autoregressive coefficient φ and retain the draw if the drawn value of ϕ satisfies the stationarity restriction. As an alternative, we considered the sampler, where the vector β is sampled in one step, and the parameter ϕ is sampled in the next step using the Metropolis algorithm with the proposal density centered at the mode of the conditional distribution for ϕ. Although this alternative has the advantage that samples of β are always accepted, mixing of a such chain is nevertheless slower due to slow updates of the parameter ϕ. Further details are available from the authors.

[7] The density of the gamma distribution Γ(a, b) is $f_{\Gamma(a)}(x) = \frac{b^a x^{a-1} e^{-bx}}{\Gamma(a)} \mathbf{1}_{x\geq 0}$. Note that the Statistical Toolbox of Matlab uses a different parametrization of the gamma density. Use sqrt(gamrnd(a, 1/b)) to perform this draw in Matlab.

$$\hat{y}^{*(r)}_{it|(-1)} = X_{it}\beta^{(r)} + \beta_0^{(r)} + \phi^{(r)} y^{*(r)}_{it-1} + \varepsilon^{(r)}_{it}$$

Then, based on (4.1), we obtain the samp*l*e from the predictive distribution of ratings:

$$\hat{y}^{(r)}_{it|(-1)} = k \;\Leftrightarrow \hat{y}^{*(r)}_{it|(-1)} \quad \in [c^{(r)}_{k-1}\; c^{(r)}_{k})$$

Finally, the maximum aposterior predictive rating is the mode of the predictive distribution of $\hat{y}_{it}$, i.e.:

$$Rating_{it}^{MAP_h} = argmax_k \sum_{r:\hat{y}^{(r)}_{it|(-1)}=k} 1$$

which is the quantity that we report in the graphs. It is also straightforward to construct Bayesian credible intervals for the predicted values.

By obvious generalization, it is possible to construct the multiperiod-predictive ratings for horizon h:

$$Rating_{it}^{MAP_h} = argmax_k \sum_{r:\hat{y}^{(r)}_{it|(-h)}=k} 1$$

where

$$\hat{y}^{(r)}_{it|(-h)} = k \;\Leftrightarrow \hat{y}^{*(r)}_{it|(-1)} \quad \in [c^{(r)}_{k-1}\; c^{(r)}_{k})$$

and

$$\hat{y}^{*(r)}_{it|(-h)} = \sum_{\chi=0}^{h-1} \phi^{(r)^{\chi}} (X_{it-\chi}\beta^{(r)} + \beta_0^{(r)} + \varepsilon^{(r)}_{it-\chi}) + \phi^{(r)^{h}} y^{*(r)}_{it-h}$$

[8] Note that $\hat{y}^{(r)}_{it|(-1)}$ is not the output from the Gibbs sampler. Using $y^{*(r)}_{it|(-1)}$ instead of $\hat{y}^{(r)}_{it|(-1)}$ would make the whole exercise trivial. $\hat{y}^{(r)}_{it|(-1)}$ is the value of the latent variable conditional on parameters, the current value of fundamentals and the past value of the latent variable.

Appendix B: Regression results using the pooled OLS

As we noted in the main part of the paper, we estimate model (4.2) also using a naïve approach of transforming the ratings into the numerical scale and then estimating the model using the pooled OLS regression. In this appendix, we report the estimation results which confirm our finding of a structural break in rating agency behaviour around 2010. The autoregressive coefficient ϕ (lagged value) is statistically less significant for the post-2010 period than for the full sample or for the sample prior 2010. Also, the two fiscal variables (the debt-to-GDP ratio and the change in the trend of the debt-to-GDP ratio) have larger coefficients for the post 2010 sample. In most cases the difference is statistically significant.

Table 4: OLS estimation of the rating equation

					Full sample				
		Moody's			**S&P**			**Fitch**	
Variable	*l.c.i.*	*OLS*	*u.c.i.*	*l.c.i.*	*OLS*	*u.c.i.*	*l.c.i.*	*OLS*	*u.c.i.*
Institutional quality (WGI)	-0.172	0.005	0.181	-0.125	0.034	0.194	-0.128	0.033	0.195
Government debt	-0.576	-0.356	-0.135	-0.463	-0.272	-0.080	-0.548	-0.339	-0.129
Government debt change	-0.084	-0.056	-0.029	-0.080	-0.055	-0.030	-0.077	-0.052	-0.026
GDP per capita	-0.198	0.008	0.215	-0.122	0.065	0.251	-0.130	0.059	0.248
Unemployment rate	-0.030	-0.016	-0.002	-0.020	-0.008	0.004	-0.027	-0.014	-0.002
Constant	0.959	0.981	1.003	0.956	0.978	1.000	0.937	0.963	0.988
Lagged value	0.119	0.742	1.365	-0.006	0.567	1.140	0.361	1.050	1.739
					Sample: prior 2010				
		Moody's			**S&P**			**Fitch**	
	l.c.i.	*OLS*	*u.c.i.*	*l.c.i.*	*OLS*	*u.c.i.*	*l.c.i.*	*OLS*	*u.c.i.*
Institutional quality (WGI)	-0.045	0.033	0.110	-0.019	0.066	0.152	-0.035	0.051	0.138
Government debt	-0.221	-0.127	-0.032	-0.191	-0.101	-0.012	-0.284	-0.175	-0.066
Government debt change	-0.024	-0.013	-0.002	-0.038	-0.027	-0.015	-0.028	-0.016	-0.003
GDP per capita	-0.056	0.045	0.145	-0.067	0.033	0.134	-0.035	0.070	0.174
Unemployment rate	-0.005	0.001	0.008	-0.006	0.001	0.009	-0.004	0.004	0.011
Constant	0.937	0.960	0.984	0.951	0.973	0.995	0.919	0.945	0.970
Lagged value	0.366	0.751	1.136	0.114	0.492	0.869	0.638	1.145	1.652
					Sample: post 2010				
		Moody's			**S&P**			**Fitch**	
	l.c.i.	*OLS*	*u.c.i.*	*l.c.i.*	*OLS*	*u.c.i.*	*l.c.i.*	*OLS*	*u.c.i.*
Institutional quality (WGI)	-1.700	-0.769	0.162	-0.833	-0.138	0.558	-1.147	-0.430	0.287
Government debt	-7.334	-5.066	-2.797	-4.939	-3.271	-1.603	-5.422	-3.637	-1.853
Government debt change	-0.543	-0.344	-0.144	-0.530	-0.343	-0.155	-0.450	-0.274	-0.098
GDP per capita	0.037	0.977	1.916	0.372	1.307	2.241	0.259	1.098	1.938
Unemployment rate	-0.171	-0.089	-0.007	-0.081	-0.026	0.028	-0.119	-0.060	0.000
Constant	0.620	0.737	0.853	0.659	0.768	0.877	0.625	0.741	0.857
Lagged value	4.731	10.274	15.817	2.330	6.313	10.297	3.767	8.582	13.398

Note: OLS = OLS point estimates; l.c.i. = 25% confidence interval; u.c.i. = 97.5% confidence interval.

Appendix C: Model prediction statistics

Table 5: Performance comparison of various models (full sample)

RMSE (absolute)

	BMPS model			Random walk model			Autoregressive m.			Extended model I			Extended model II		
	1q	4q	8q	1q	4q	8q	1q	4q	8q	1q	4q	8q	1q	4q	8q
Moodys	0.544	1.295	1.550	0.570	1.558	2.663	0.904	2.176	3.311	0.640	1.201	1.354	0.639	1.389	1.721
S&P	0.492	1.170	1.468	0.501	1.279	2.012	0.500	1.352	2.135	0.497	1.133	1.513	0.484	1.150	1.576
Fitch	0.470	1.131	1.244	0.512	1.279	2.074	0.509	1.292	2.039	0.525	0.978	1.139	0.489	1.104	1.372

RMSE (relative to BMPSmodel)

		Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
		+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys		1.048	1.203	1.717	1.662	1.680	2.136	1.176	0.927	0.874	1.175	1.073	1.110
S&P		1.019	1.093	1.371	1.016	1.156	1.455	1.010	0.968	1.031	0.982	0.983	1.074
Fitch		1.090	1.131	1.668	1.082	1.142	1.639	1.116	0.865	0.916	1.040	0.976	1.103

MAE (absolute)

	BMPS model			Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys	0.158	0.560	0.699	0.128	0.516	1.021	0.237	0.764	1.280	0.210	0.497	0.591	0.220	0.616	0.816
S&P	0.124	0.458	0.705	0.124	0.474	0.878	0.124	0.490	0.900	0.134	0.506	0.743	0.132	0.544	0.839
Fitch	0.118	0.481	0.619	0.117	0.470	0.890	0.116	0.466	0.874	0.168	0.463	0.642	0.142	0.567	0.801

MAE (relative to BMPS model)

		Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
		+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys		0.806	0.921	1.462	1.494	1.363	1.832	1.327	0.887	0.846	1.392	1.100	1.169
S&P		0.998	1.035	1.245	1.000	1.070	1.276	1.076	1.106	1.054	1.062	1.188	1.189
Fitch		0.997	0.978	1.438	0.983	0.969	1.413	1.426	0.962	1.037	1.212	1.178	1.294

Note: Extended model I is BMPS model plus the current account-to-GDP ratio, the inflation rate, real GDP growth and Target 2 balance. Extended model II includes the long-run averages of the respective variables.

Table 6: Performance comparison (estimation period 1995Q1-2009Q4, extrapolated full sample)

RMSE (absolute)

	BMPS model			Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	1q	4q	8q	1q	4q	8q	1q	4q	8q	1q	4q	8q	1q	4q	8q
Moodys	1.259	1.885	2.001	0.570	1.558	2.663	1.103	2.925	3.633	2.552	3.332	3.462	2.080	2.564	2.670
S&P	0.873	1.846	2.335	0.501	1.279	2.012	0.757	1.894	2.737	1.228	2.525	2.842	0.855	1.947	2.291
Fitch	0.791	1.569	1.796	0.512	1.279	2.074	0.620	1.757	2.612	1.874	2.256	2.379	1.191	2.037	2.155

RMSE (relative to BMPS model)

		Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
		+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys		0.453	0.826	1.331	0.876	1.552	1.816	2.028	1.767	1.731	1.653	1.360	1.335
S&P		0.575	0.693	0.862	0.867	1.026	1.172	1.408	1.368	1.217	0.980	1.054	0.981
Fitch		0.648	0.815	1.155	0.784	1.120	1.455	2.369	1.438	1.325	1.506	1.298	1.200

MAE (absolute)

	BMPS model			Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys	0.431	0.788	0.840	0.128	0.516	1.021	0.349	1.135	1.485	1.000	1.231	1.318	0.866	1.108	1.180
S&P	0.300	0.829	1.124	0.124	0.474	0.878	0.240	0.841	1.271	0.457	1.136	1.361	0.317	0.907	1.180
Fitch	0.271	0.724	0.888	0.117	0.470	0.890	0.169	0.766	1.226	0.773	1.040	1.139	0.457	0.974	1.089

MAE (relative to BMPS model)

		Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
		+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys		0.296	0.655	1.216	0.810	1.440	1.768	2.319	1.562	1.569	2.007	1.405	1.406
S&P		0.413	0.572	0.781	0.803	1.015	1.131	1.527	1.371	1.211	1.059	1.095	1.050
Fitch		0.433	0.650	1.003	0.625	1.058	1.381	2.852	1.437	1.282	1.687	1.346	1.226

Note: See Table 5.

Table 7: Performance comparison of various models (estimation period 2010Q1-2014Q2, extrapolated full sample)

RMSE (absolute)

	BMPS model			Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	1q	4q	8q	1q	4q	8q	1q	4q	8q	1q	4q	8q	1q	4q	8q
Moodys	0.589	1.275	1.517	0.570	1.558	2.663	0.522	2.072	3.496	1.649	1.772	2.048	0.554	1.459	1.953
S&P	0.588	1.293	1.553	0.501	1.279	2.012	0.475	1.452	2.362	1.749	2.147	2.256	0.472	1.169	1.531
Fitch	0.694	1.099	1.212	0.512	1.279	2.074	0.455	1.552	2.304	1.866	2.011	2.054	0.549	1.097	1.520

RMSE (relative to BMPS model)

	Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys	0.967	1.222	1.755	0.886	1.625	2.305	2.798	1.390	1.350	0.939	1.144	1.287
S&P	0.853	0.989	1.296	0.807	1.123	1.521	2.976	1.661	1.453	0.804	0.904	0.986
Fitch	0.738	1.163	1.712	0.656	1.411	1.901	2.687	1.829	1.695	0.790	0.998	1.254

MAE (absolute)

	BMPS model			Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys	0.260	0.734	0.925	0.128	0.516	1.021	0.132	1.692	3.015	1.031	1.176	1.372	0.183	0.843	1.275
S&P	0.277	0.760	0.972	0.124	0.474	0.878	0.111	1.079	1.989	1.111	1.426	1.537	0.132	0.674	1.054
Fitch	0.355	0.707	0.832	0.117	0.470	0.890	0.116	1.259	1.913	1.253	1.426	1.449	0.188	0.640	0.994

MAE (relative to BMPS model)

	Random walk model			Autoregressive m.			Extended model: I			Extended model: II		
	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q	+1q	+4q	+8q
Moodys	0.492	0.703	1.104	0.507	2.305	3.259	3.973	1.602	1.482	0.704	1.149	1.378
S&P	0.447	0.623	0.903	0.400	1.419	2.046	4.014	1.876	1.581	0.476	0.887	1.084
Fitch	0.330	0.666	1.070	0.326	1.782	2.299	3.533	2.018	1.742	0.531	0.905	1.195

Note: See Table 5.

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