

LEARNING ABOUT DEBT CRISES

Radoslaw Paluszynski*

*Department of Economics
University of Houston*

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Abstract

The European debt crisis presents a challenge to our understanding of the relationship between government bond yields and economic fundamentals. I argue that information frictions are an important missing element, and support this theory with empirical evidence on the evolution of forecast errors in years 2008-2014. I build a quantitative model of sovereign default that features rare disaster risk and Bayesian learning about its realizations. Debt crises coincide with economic depressions and develop gradually, while markets update their expectations about future income. Calibrated to Portuguese economy, the model replicates the comovement of bond spreads and output before and after 2008.

Keywords: Sovereign debt, disaster risk, Bayesian learning, long-term debt

JEL Classification Numbers: D83,F34,G15

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1 Introduction

The recent debt crisis in Europe has reopened the discussion about the factors that put governments at risk of sovereign default. The observed weak correlation between interest rates on public debt and economic fundamentals of the peripheral European countries challenges the theoretical links established by a large body of research prior to 2008. This new evidence has led some researchers to revisit the hypothesis of self-fulfilling debt crises ([Aguilar et al. \(2016\)](#)). Other economists, motivated by the same observations, argue that the European episode was driven by external factors such as the intra-EU politics rather than country-specific shocks ([Brunnermeier, James and Landau \(2016\)](#)). In this paper I propose a quantitative theory of the European debt crisis based on idiosyncratic income fluctuations, disaster risk and information frictions that has the potential to resolve this puzzle.

I start by reviewing the timing of comovement between government bond prices with economic fundamentals such as GDP growth or external debt. At the outset of the Great Recession, peripheral EU countries were hit by negative income shocks in the range between two to three standard deviations below their mean. Yet, despite the widespread expansion of debt-to-GDP ratios in 2009, government bond spreads¹ temporarily rose above 150 – 250 basis points in 2009:Q1, only to drop back below 100 – 200 basis points by the second half of 2009. The real stress did not appear in the European bond markets until mid-2010 when Greece, followed by other countries over the next two years, experienced a sharp increase in borrowing costs. Importantly, the economic fundamentals were not much different from 2009, following a short-lived recovery and debt reductions in 2010. This observed dynamics cannot be explained by the canonical quantitative models of sovereign debt.² In these models, the bond price function typically exhibits high elasticity with respect to income shocks, and even more so when output is persistent and debt maturities are long term. Under a standard calibration to European economies, the predicted response to the shocks in early 2009 closely mirrors what in reality did not occur until two years later.

To address this puzzle, I build on two empirical facts regarding that episode. First, the experience of southern European economies in years 2008-2014 can plausibly be interpreted as the realization of a rare disaster risk. The peak-to-trough decline in quarterly real GDP ranges from around 10% for Italy and Portugal to 27% for Greece. As shown by [Barro](#)

¹The bond spread is defined as a difference between the interest rates paid by the given country's government bonds and a risk-free asset, in this case the German long-term government bonds. The spread is expressed in annual terms.

²I am referring to the class of models based on the seminal framework of [Eaton and Gersovitz \(1981\)](#).

(2006), the risk of a recession of such magnitude, together with empirically plausible probabilities of it occurring, have the potential to explain the major asset pricing puzzles. In fact, the combination of size and persistence of GDP declines relative to a trend among those countries is consistent with a great depression episode defined by Kehoe and Prescott (2002). Second, the expectations about future income shocks evolved significantly among financial institutions in years 2008-2014, which I document using the real-time GDP forecast data. In particular, prior to 2008 the forecast root mean square errors are at a similar level across all analyzed countries and forecasting agencies, around 1.5% of 2010 GDP. Then, errors jump to the level of 2.5 – 6% between 2008 and 2011, in all cases overestimating the future GDP growth. This indicates that the negative output shocks at the time were perceived as a fairly typical recession, corresponding in size and persistence to Europe’s post-war business cycle. Finally, in years 2012-2014 the forecasts become much more precise, with individual errors changing sign in many cases (i.e. they underestimated GDP) and overall root mean square errors falling to 1.5 – 3.5%. This is correlated with the agencies becoming more pessimistic about the countries’ economic outlook and revising their forecasts downwards. That is also when we observe the dramatic spikes in the interest rates on European governments’ bonds.

Drawing on these two empirical facts, I propose a new theory of sovereign debt crises in advanced economies. Interest rates on government bonds carry a default premium which varies with the amount of outstanding debt and the expected fluctuations in future GDP. The spikes in default risk for developed countries coincide with rare disaster episodes, rather than the recurring business cycle downturns as is the case for emerging markets. In normal times, which can last for decades, there is little concern about a sovereign debt crisis in the foreseeable future and, as a result, bond prices carry a negligible default premium. When a rare disaster occurs, income is set on a downward trajectory; however agents are not aware of this immediately. In other words, they cannot tell if the shocks they are observing are temporary or permanent in nature. In the presence of long-term debt, this information friction relieves the upward pressure on interest rates, because investors remain optimistic about the economy’s long-run outlook. Over time, as income continues to decline, agents increasingly recognize the underlying disaster and revise their forecasts. The result is a sudden, sharp spike in default risk that follows long periods of relative calmness in bond markets.

In order to assess the quantitative power of this theory I develop an otherwise standard model of sovereign debt that captures the two elements described above in a simple way. Building on the pioneering model of Chatterjee and Eyigungor (2012) with long-term debt, I first introduce a regime-switching income process with implied rare disaster risk. A disaster

is represented by a large and negative shift in the long-run mean income of the economy. Then, I assume agents have incomplete information about the underlying switches between the regimes; market participants learn about them symmetrically in a Bayesian fashion. Using Portugal as a quantitative case study, I calibrate the parameters of the disaster regime by targeting the actual path of long-term GDP forecasts from the dataset discussed above. As a result, the agents in my model exhibit time-varying expectations about future income that mimic those observed in the data. The calibrated disaster regime features a long-run mean income at 22 percent below trend, in line with the definition of a great depression episode of [Kehoe and Prescott \(2002\)](#). I calibrate the remaining structural parameters of the model to replicate key features of the Portuguese economy such as the overall bond spread volatility, average external debt level, and the trade balance volatility. Simulating Portugal’s experience in years 2000-2014, I find that the model simultaneously delivers a low average and a high volatility of the bond spread, in line with the data for the peripheral European countries.³ Finally, I use the model to analyze the actual debt crisis by feeding in the sequence of GDP data from years 2000-2014. Under this specification, I show that the initial adverse income realizations cause an increase in the bond spread of just 1.5% in the first quarter of 2009, which matches the data fully. This is because markets are unsure if they are observing temporary shocks or a permanent regime switch. Over the next two years, the belief about the latter converges to certainty, and agents become convinced that the process has switched to a disaster mode. As a result, we observe a delayed jump in the bond spread to 9% in the first quarter of 2012 (11% in the data), combined with a sharp reduction in government debt (and, in fact, an eventual sovereign default⁴).

More generally, this paper shows that canonical sovereign debt models should place more emphasis on modeling the stochastic income carefully. The simple detrended AR1 process assumed in most studies, while having the advantage of computational simplicity, is not an adequate specification for modeling the recent experience of the European economies. There are two arguments behind this claim. First, AR1 assumes implicitly that the data is stationary around a long-run linear trend. This cannot be confirmed with unit root tests if the 2008-2014 data is included. Second, and more importantly, the AR1 specification is unable to account for the time-varying expectations of future income, because it always mean-reverts in the same direction. As a result, even if a model is calibrated to replicate certain features of the empirical data, it is likely to lack “micro-foundations” in terms of the

³Notice that, unlike in [Chatterjee and Eyigungor \(2012\)](#), only one of those moments is targeted, namely the bond spread volatility.

⁴Recall that Portugal, together with other European countries, received official bailouts in excess of 40 percent of their GDP, to prevent them from defaulting, an element not present in my model.

agents' information sets. This does not appear to be a major problem for modeling emerging market economies, where the expectations about future are generally noisy and do not vary much over the business cycle (see Section 5 for the case of Argentina). However, the data on forecast errors among advanced countries during the Great Recession indicates that a precise modeling of market expectations may be one of the crucial elements in understanding the recent events, in particular the European debt crisis.

1.1 Literature review

This paper is closely related to the quantitative sovereign debt literature, in particular one building on the seminal work of [Eaton and Gersovitz \(1981\)](#) and, more recently, [Aguiar and Gopinath \(2006\)](#) and [Arellano \(2008\)](#). The models presented in these papers set foundations for our understanding of the dynamics of sovereign risk and equilibrium defaults observed in the world. At the same time however, because they assume short-term debt only, such models fall short of matching the quantities of debt observed among the developed countries.

The latest line of sovereign default research, such as [Chatterjee and Eyigungor \(2012\)](#), [Hatchondo and Martinez \(2009\)](#) or [Arellano and Ramanarayanan \(2012\)](#), introduce long-duration bonds as means of getting the models closer to the data and in particular allowing them to better match the observed bond spread behavior. While such models can easily match the average debt ratios of the European countries, they also generate excessive sensitivity of bond spreads to income shocks.

Another branch of sovereign debt literature develops models of non-fundamental debt crises in which a default may be driven by investors' beliefs about the behavior of others. [Cole and Kehoe \(2000\)](#) present a model for Mexico's 1995 episode, while more recently [Conesa and Kehoe \(2015\)](#), [Aguiar et al. \(2016\)](#) and [Bocola and Dovis \(2016\)](#) all analyze the possible role of self-fulfilling equilibria in the European debt crisis. Section 5 discusses how my work relates to those theories.

More generally, this paper is related to the literature on the effects of rare economic disasters on asset pricing models. [Rietz \(1988\)](#) was the first article to propose that a possibility of infrequent market crashes has potential to account the equity premium puzzle using an Arrow-Debreu pricing framework. [Barro \(2006\)](#) shows that this result holds under plausible calibrations of rare disasters inferred using historical data. More recently, [Farhi and Gabaix \(2016\)](#) show that a model with extreme disasters can account for major puzzles in the foreign

exchange rate markets. To the best of my knowledge, this paper is the first to incorporate the idea of disaster risk in a sovereign debt model. The calibration used to generate the main quantitative results is very similar to that of [Barro \(2006\)](#).

The final strand of related literature deals with learning about unobserved economic conditions in macroeconomics. [Boz, Daude and Durdu \(2011\)](#) take the stochastic process of [Aguiar and Gopinath \(2006\)](#) and assume that market participants are unable to distinguish between the incoming permanent and transitory shocks. In a calibrated model, they show that learning can explain some of the observed differences between developed and emerging economies. [Van Nieuwerburgh and Veldkamp \(2006\)](#) build a theory of differential speed of economic expansions and recessions based on the agents' ability to learn about the underlying fundamentals. [Durdu, Nunes and Saprizza \(2013\)](#) show that learning about future productivity through news shocks may be a quantitatively important driver of sovereign bond spreads.

The remainder of this paper is structured as follows. Section [2](#) describes empirical evidence regarding the European debt crisis. Section [3](#) introduces the main model. Section [4](#) calibrates the model and uses it to analyze the European debt crisis and contrast the results with those obtained using a benchmark version of the model. Section [5](#) discusses the role of bailouts and non-fundamental defaults and offers further validations of the theory. Section [6](#) concludes.

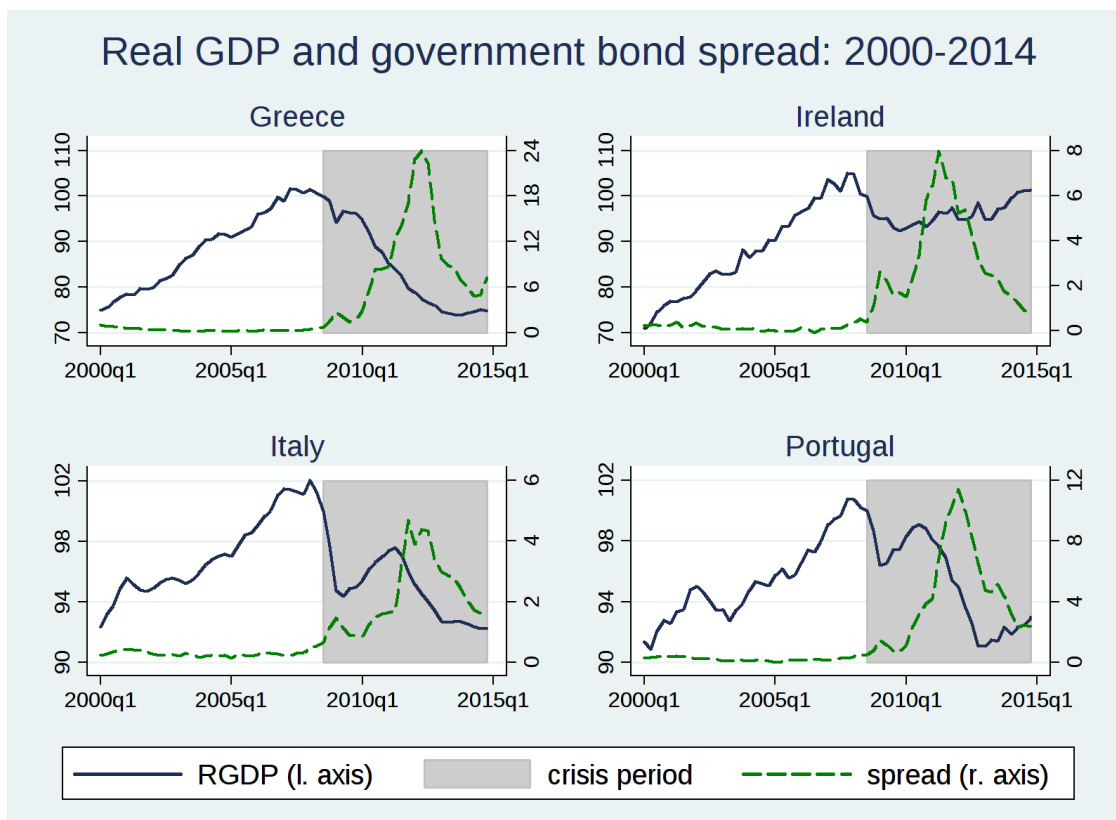
2 Empirical motivation

In this section, I document the dynamic pattern of the European debt crisis and explain how it is at odds with the predictions of typical models of sovereign debt. I also present the empirical evidence that motivates the theory developed in this paper, namely the depth of the output declines and the evolution of forecast errors in years 2008-2014.

2.1 European debt crisis

Prior to 2008, the Eurozone's peripheral economies enjoyed a decade of relative prosperity and stable growth, fueled by the European integration, rising trade and the benefits of common currency. On the other hand, sovereign debt crises had predominantly been a problem of highly volatile emerging market economies over the last few decades. As a result, the securities issued by governments of European countries seemed risk-free to most financial market participants, in spite of the increasing debt stocks and low trend growth in many of these economies. The tendency to put excessive faith in Europe's ability to repay their

debts continued even after the severe recession began in the second half of 2008. Figure 1 depicts the times series of real GDP for four⁵ of the peripheral European economies, together with the spreads on long-term government bond yields.⁶ As can be noticed, markets did not express significant concern about the European governments' ability to repay for a long time following the initial slump in output. Instead, the bond spreads exhibited minor "wiggles" when the financial crisis first hit, and only began a gradual increase afterwards, leading to the dramatic spikes observed around 2011-2012.



Note: The GDP series are in constant 2010 prices, and their values are normalized such that the third quarter of 2008 equals 100 (beginning of the financial crisis - shaded area). The bond spreads are expressed in percentage points and are acquired from the OECD dataset.

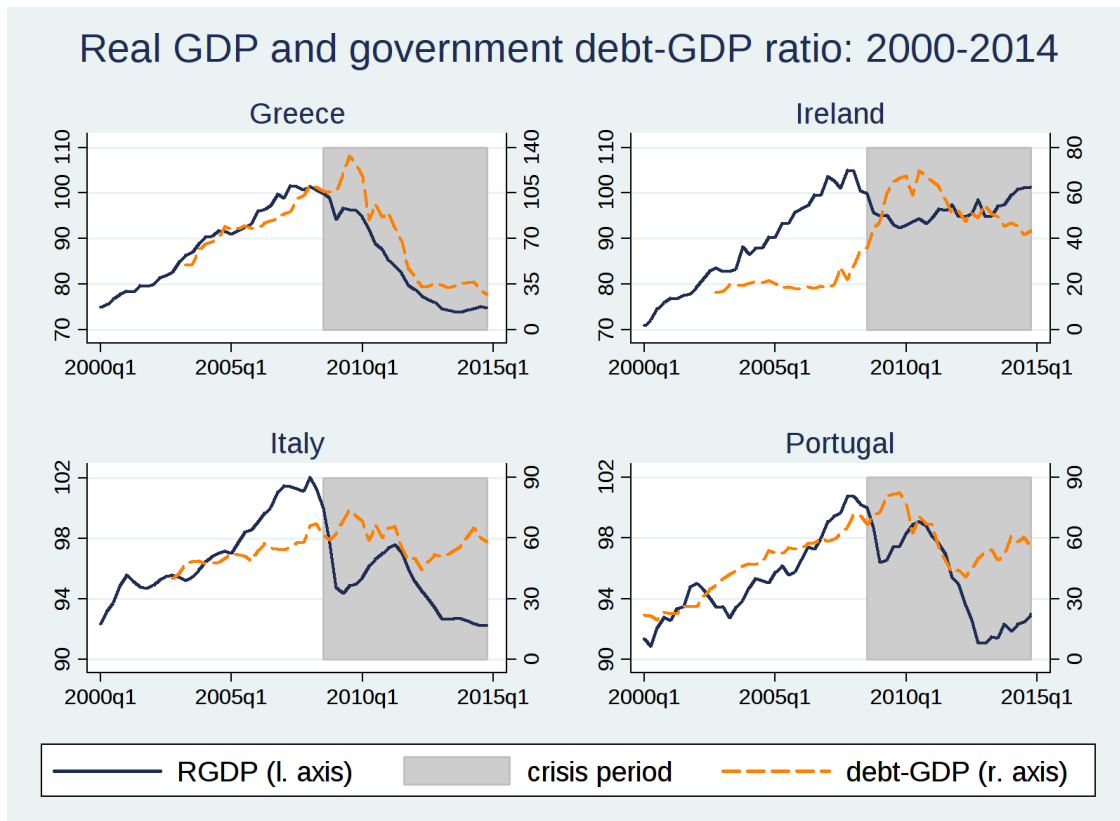
Figure 1: Real GDP and government bond spreads of the peripheral European economies

Another interesting aspect of the European crisis involves the debt policy of national governments in years 2000-2014. Figure 2 shows the evolution of government external debt-to-GDP ratios of the four economies of interest, contrasted with the same path of real GDP over

⁵In this figure, I focus on the cases of Greece, Ireland, Italy and Portugal. The fifth member of the colloquial GIIPS group, Spain, is left out for the purpose of clear exposition. Nevertheless, the empirical patterns discussed in this section can be observed for the Spanish case as well.

⁶The bond spread is defined as the difference between the annualized interest rate on the given ten-year government bonds and the interest rate on the German long-term bonds, assumed to be a risk-free asset.

time.⁷ Two observations stand out in the graph. First, prior to 2008 all economies apart from Ireland exhibited gradually increasing paths of external debt. Such a steady rate of growth in debt continues despite the fact that the economies of Portugal or Italy had been following a slow growth trend since the early 2000s. This fact will be an important departure point for the calibration strategy in Section 4. Second, and more importantly for the present paper, when the negative output shocks first hit in 2008, we see that governments respond by *increasing* their foreign debt on impact, and avoiding any major adjustments for the first two years of the crisis. The sharp debt reductions did not occur until late 2010 and 2011 and were mostly enforced by the international financial institutions (IMF and the



Note: The GDP series are in constant 2010 prices, and their values are normalized such that the third quarter of 2008 equals 100 (beginning of the financial crisis - shaded area). The debt series represent the external debt securities of the general government, and are expressed as fraction of annualized GDP. The data are acquired from the World Bank's Quarterly External Debt Statistics and start at different points in time for different countries (hence the missing observations in the four figures above).

Figure 2: Real GDP and external debt of the peripheral European economies

⁷By “debt” I refer to short- and long-term debt securities and thus exclude other types of liabilities, in particular official and emergency loans.

European Commission), or an actual default in the case of Greece. While such counter-cyclical response may be natural in the canonical models of fiscal policy, it also leads to an increased risk of default in the long run through the lens of a typical sovereign default model.

The moderate reaction of bond spreads to the recession and increasing debt levels in 2009 seems to imply that markets did not express particular concern about the riskiness of long-term securities. Judging with hindsight, the actual debt crisis in Europe seems significantly delayed. As I show in Section 4, existing sovereign debt models generally fail to predict such a lagged increase in bond spreads over time. This is because in the standard theory of default driven by income fluctuations, a sovereign default is conditional on receiving unfavorable realizations of the income shock. As a simple illustration, consider the case of Argentina’s default in the last quarter of 2001. Using the calibration of [Arellano \(2008\)](#), the government in that model defaults on its debt upon receiving an income shock of roughly 2.67 standard deviations below the expected value. Because the random element is assumed to be normally distributed, this implies that Argentina’s shock was unlike 99.24% of all possible shocks. On the other hand, consider Portugal whose data I use for quantitative experiments in this paper. Under the benchmark calibration presented in Section 4, the economy is hit with a shock of 2.56 standard deviations below the mean in Q1 of 2009, which is unlike 98.95% of all normally distributed shocks. And while the Portuguese debt stock is much higher than it was for Argentina, the interest rate spread in the data does not exceed 1.5%. Naturally, this observation may reflect several factors, including an exogenously higher willingness to repay of the European economies. For this reason, we need a calibrated model to resolve this puzzle and I conduct this exercise in Section 4.

2.2 Depth of GDP drops

In order to highlight the magnitude of the decline in economic activity among the peripheral European countries, Table 1 lists the largest peak-to-trough drops since 2007. The numbers provided refer to the drops in real GDP both at face value, and in relation to a 2% trend. Notice that the former ranges from almost 10 percent for the slow-growing economies of Italy and Portugal, up to 27.5 percent in the case of Greece. Recall that the cutoff size of contraction that defines a rare disaster in [Barro \(2006\)](#) is 15 percent. He emphasizes however that using an alternative threshold of 10 percent returns similar results, fundamentally affecting the traditional asset pricing mechanisms. On the other hand, [Kehoe and Prescott \(2002\)](#) define the “great depression” episode as a sustained negative deviation of at least 20 percent in the GDP level net of the 2 percent annual trend growth. Table 1 indicates that

three out of the four analyzed economies satisfy this definition, while Ireland falls just short of it. It should also be mentioned that using the countries’ individual trends rather than the common 2 percent growth rate would make this conclusion even starker.

Country	Largest decline (in %)	
	<i>face value</i>	<i>detrended</i>
Greece	27.5	40.1
Ireland	11.2	18.9
Italy	9.50	22.1
Portugal	9.60	20.2

Note: This table shows the largest recorded declines in real GDP in the period 2007-2016, measured at face value and relative to a 2% trend as in [Kehoe and Prescott \(2002\)](#).

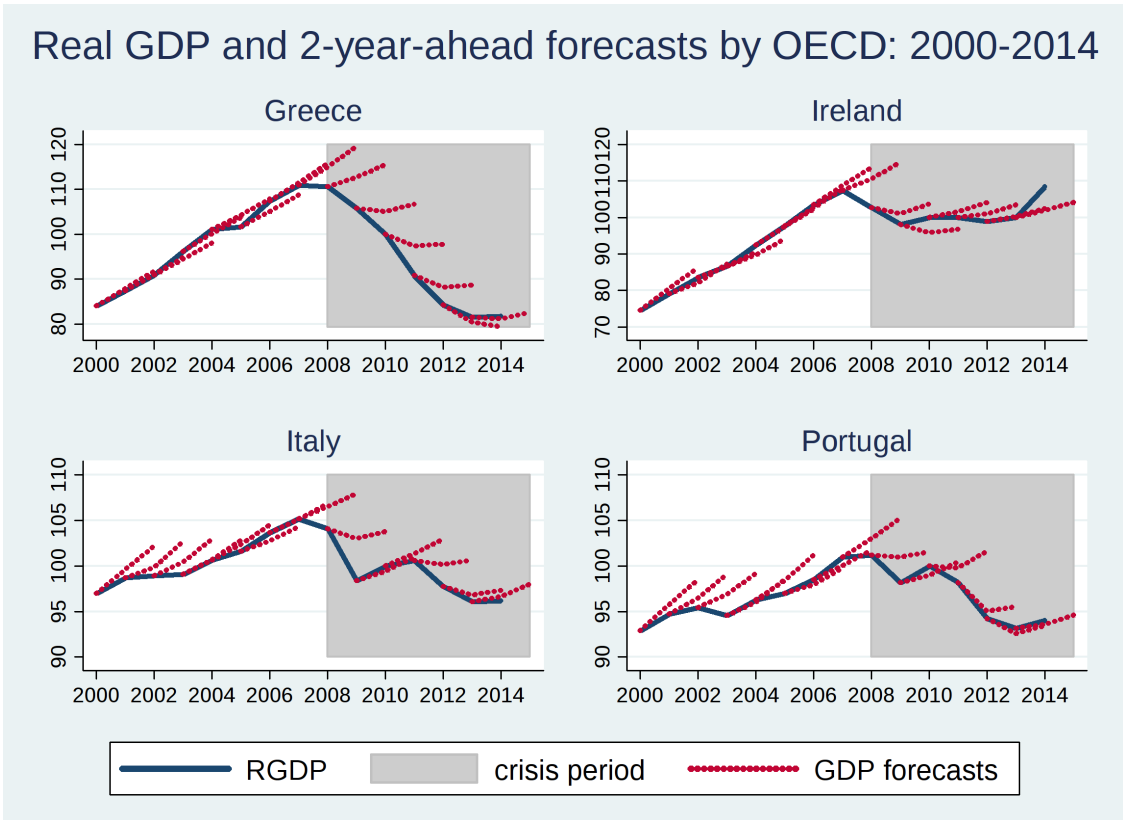
Table 1: Peak-to-trough GDP drops among the peripheral European economies

2.3 Market expectations during the recession

To shed more light on the source of the problem with current sovereign debt models, I look at important outside evidence on the evolution of market expectations. The beliefs about the distribution of future income shocks are a crucial element driving interest rate fluctuations in those models, and thus deserve particular attention.

Figure 3 once again presents the plot of real GDP over time for the European countries, along with the GDP forecasts published every year by OECD.⁸ As can be noticed for the period prior to 2008, while the European economies are still growing along a stable trend the observed forecast errors are small (with some overshooting for Italy and Portugal, whose economies experience a slowdown in the early 2000s). When the financial crisis breaks out, the forecasts are still fairly optimistic, predicting a recovery in years 2008-2010. Over time however, as the GDP continues to plunge we also observe that the forecasts become flatter, indicating that the markets have realized the recovery of output cannot be expected in the short and medium term. From 2012 on, the forecasts essentially line up again with the subsequently realized data for all of the depicted economies. This is also the time when the European bond markets undergo unprecedented turbulences, with surging interest rates and drastic reductions in debt levels, as documented in Figures 1 and 2.

⁸For illustration, in this figure I use the two-year-ahead forecasts of real GDP growth from the Fall issues of OECD’s Economic Outlook (the Spring version only provides one-year-ahead forecasts). In the following subsection I also present the forecast errors from other institutions, public and private alike.



Note: The GDP series are annual and expressed in constant 2010 prices; their values are normalized such that the observation for 2010 equals 100. The red dotted lines represent one- and two-year ahead forecasts published by the OECD Economic Outlook (fall edition) and start in the year when each of them is made.

Figure 3: Forecast and actual real GDP for the peripheral European economies

I analyze the forecast errors before and during the Great Recession by comparing the real-time predictions of three international organizations: OECD, IMF and the European Commission. The historical forecasts of these institutions are available publicly and released every year in two vintages, Spring and Fall (roughly corresponding to May and November, respectively, so they are based on the knowledge of the data for first and third quarter of that year). However, this is not sufficient evidence, because the focus of this paper is the evolution of expectations of private lenders in sovereign bond markets, whose forecasts may differ from the ones posted by public or quasi-public institutions. Indeed, it has been documented in the literature that (see e.g. [Batchelor \(2001\)](#)) that private forecasters are traditionally less biased and more accurate in their predictions than the international organizations mentioned above.

To provide a more complete answer, I obtain the data from *Consensus Economics*, a survey of forecasters from commercial banks, government agencies, think-tanks and research centers.

The queries are collected monthly and ask for a broad range of macroeconomic indicators, in particular the real GDP growth. A consensus forecast is defined as the average prediction across all participants of the survey. Broad literature documents that consensus forecasts do not suffer from several biases that may affect private and public institutions alike, and have traditionally performed better on average than any individual forecaster over the long run (see e.g. [Batchelor \(2001\)](#) and [Cimadomo, Claeys and Poplawski-Ribeiro \(2016\)](#)). In [Table 2](#) I test whether this conclusion holds for the peripheral European economies during the recent debt crisis, and what is the extent and direction of the forecast errors.

Root mean square error	OECD	IMF	EC	CE
<i>(a) Pre-recession sample: 2001-2007</i>				
Greece	1.59	1.77	1.58	1.66
Ireland	1.51	1.41	1.46	1.24
Italy	1.21	1.33	1.21	1.18
Portugal	1.52	1.44	1.39	1.51
<i>(b) Recession - first stage: 2008-2011</i>				
Greece	6.21	6.36	6.57	6.43
Ireland	5.69	5.79	5.83	5.74
Italy	3.23	3.30	3.44	3.37
Portugal	2.60	2.56	2.61	2.67
<i>(c) Recession - second stage: 2012-2014</i>				
Greece	3.48	3.86	3.72	3.29
Ireland	4.13	4.09	4.07	4.09
Italy	2.17	2.26	2.32	2.09
Portugal	1.13	1.77	1.13	1.48

Note: The table presents root mean square errors of one-year-ahead forecasts of real GDP level. The forecasts are acquired from four alternative sources: OECD, IMF, European Commission, and Consensus Economics Inc. The bias is expressed in percentage of the 2010 level of real GDP for each of the four countries. All forecasts come in two vintages, Spring and Fall, which I use jointly. The number of forecasters participating in Consensus Economics surveys varies over time and across countries, with a minimum of four and a maximum of twenty in the entire sample.

Table 2: Root mean square errors in real-time historical forecasts for different time frames

I use one-year-ahead forecasts from each of the four institutions, combining both vintages in every year.⁹ To ensure direct comparability, I consider the May and November issues of the Consensus Economics survey which roughly coincide in time with the Spring and Fall reports of the IMF, OECD and the European Commission. [Table 2](#) documents the root

⁹While OECD and the European Commission also publish up to two-year ahead, and IMF up to five-year-ahead forecasts, the Consensus Economics survey is limited to next-year predictions only.

mean square errors (RMSE) observed for each of the four countries of interest during three separate time periods: a pre-recession sample of 2001-2007 and the two stages of the Great Recession, namely 2008-2011 and 2012-2014. The bias is expressed in percentage of each country’s 2010 real GDP level and can take positive values only.¹⁰ As a non-linear measure, RMSE punishes fewer but large mistakes more heavily than frequent and small ones. There are several interesting observations to be made about the data in Table 2. First, prior to 2008 the RMSE is of very similar size for all countries and forecasting agencies, around 1.5% of 2010 real GDP. Second, in years 2008-2011 the errors increase sharply, reaching 5 – 6% for Greece and Ireland (which were growing fast before the recession) and 2.5 – 3.5% for Italy and Portugal (whose trend growth had been much slower in the 21st century). Third, in years 2012-2014 the RMSE, while in most cases still above the pre-recession level, drops significantly for all analyzed countries.¹¹ Finally fourth, the Consensus Economics forecasts *do not* outperform the international organizations, but instead tend to do worse than either IMF or OECD, especially during the first stage of the recessions in 2008-2011. Interestingly, consensus forecasts do much better prior to 2008, in line with the findings of earlier studies such as [Batchelor \(2001\)](#). This indicates that private-sector expectations were likely to exhibit excessive optimism especially at the beginning of the Great Recession.

Large forecast errors at the height of the crisis became a subject of intense critique and have recently led the OECD to publish a study to evaluate the source of mistakes. In a “Post Mortem”, [Pain et al. \(2014\)](#) write:

GDP growth was overestimated on average across 2007-12, reflecting not only errors at the height of the financial crisis but also errors in the subsequent recovery. (...)

The repeated assumption that the euro crisis would dissipate over time, and that sovereign bond yield differentials would narrow, has been a more important source of error. (...)

The OECD was not alone in finding this period particularly challenging. The profile and magnitude of the errors in the GDP growth projections of other international organisations and consensus forecasts are strikingly similar.

In their *ex post* reflection, the OECD points to the repeated expectation of a swift recovery as the main source of forecast errors. This can be interpreted precisely as the process of

¹⁰Additional analysis of the average bias in forecasts shows that these errors are caused by overestimating growth in all years between 2008 and 2011. Interestingly, in 2012-2014 the average bias falls much more than RMSE or the mean absolute bias (indicating that the errors of opposite signs canceled each other out), and in the case of Ireland it changes sign altogether.

¹¹The seemingly high errors for Ireland are actually caused by underestimating the high growth rate this country had in 2014 alone.

learning about the distribution of future income shocks. In order to not appear as the only culprit, the OECD also emphasizes that the excessively optimistic forecasts have been common among other influential forecasters associated with international organizations and consensus measures. This claim is confirmed beyond doubt in Figure 3 and Table 2.

3 Model

In this section I present a model of sovereign debt that features an augmented specification of output process and incomplete information about its realizations.

3.1 Economic environment

Consider a representative-agent small open economy with a benevolent sovereign government that borrows internationally from a large number of competitive lenders. Time is discrete and there is no production or labor. Instead, the economy faces a stochastic stream of endowment realizations. Markets are incomplete and the only asset available for trading is the one-period non-contingent bond.

Endowment process Suppose the country's endowment follows an autoregressive regime-switching process. I assume that there are two possible regimes, High and Low, and each of them is characterized by its own long-run mean. For simplicity, the persistence and variance parameters are assumed to be constant across regimes. Specifically, the evolution of output, detrended with a deterministic long-run mean growth rate, is given by

$$y_t = \mu_j(1 - \rho) + \rho y_{t-1} + \eta \varepsilon_t \quad (1)$$

where $\varepsilon_t \sim \mathcal{N}(0, 1)$ is an *i.i.d.* random shock and $\rho, \eta, \{\mu_j\}_{j=L,H}$ are parameters of the two regimes. Regimes change according to a Markov process with the transition probability matrix given by

$$\Pi = \begin{bmatrix} \pi_L & 1 - \pi_L \\ 1 - \pi_H & \pi_H \end{bmatrix} \quad (2)$$

The specification of a bimodal stochastic process of endowment in formula (1) is non-standard in the sovereign debt literature. It is motivated by the growth pattern of European economies in the recent decade, illustrated in Figures 1-2. This growth pattern differs considerably from the one of most emerging economies which exhibit frequent ups and downs around the trend.

Preferences The representative household has preferences given by the expected utility of the form:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t) \quad (3)$$

where I assume the function $u(\cdot)$ is strictly increasing, concave and twice continuously differentiable. The discount factor is given by $\beta \in (0, 1)$.

Government In each period, the government chooses a consumption rule and the level of debt holdings to maximize the household's lifetime utility. The only asset available is the long-duration zero-coupon bond. In the spirit of [Chatterjee and Eyigungor \(2012\)](#) and [Hatchondo and Martinez \(2009\)](#), I assume that bonds mature probabilistically and pay a fixed coupon in every period. The government may save at an international risk-free interest rate. If it decides to borrow, however, the government is not committed to repay the debt next period. Consequently, the bond is priced endogenously by risk-neutral lenders to account for the possibility of default as well as debt dilution in the future. As it is commonly assumed in the sovereign debt literature, the government who refuses to honor its obligations faces an exogenous cost of default and is further excluded from borrowing in the financial markets, with a certain probability of being readmitted in every subsequent period.

Market clearing There is no storage technology and, under the aforementioned assumptions on the utility function, implies that the endowment is fully divided between current consumption and net borrowing. This market clearing condition is given by

$$c_t = y_t - b_t (\delta + (1 - \delta)\kappa) + q_t (b_{t+1} - (1 - \delta)b_t) \quad (4)$$

where q_t is the price of the debt stock b_{t+1} (to be repaid next period), δ is the rate at which bonds mature every period and κ is a fixed coupon.

Bond prices International lenders are perfectly competitive and have “deep pockets” in the sense that potentially even large losses do not affect their decisions. In equilibrium the lenders make expected zero profit and as a result, the bond pricing formula compensates them only for the default risk implied in the government's decisions.

3.2 Information structure

The two state variables mentioned so far, current bond holdings (b_t) and income (y_t), are standard in sovereign debt literature. In addition, this model features another exogenous

stochastic variable, $z_t \in \{z_L, z_H\}$ representing the regime (Low or High) in which the economy is currently operating. While all agents know the latest income realization, they have incomplete information about the current regime. Instead of observing it directly, agents form a belief p_t defined as their perceived probability of being in the High regime, formally $p_t \equiv \text{Prob}(z_t = z_H)$. Intuitively, this variable can be thought of as market sentiment about the economy's expected future income path. As I show in Section 4, the belief about regime is quantitatively significant and appears to have fluctuated significantly in years 2008-2014.

3.3 Timeline

In every period, the timing of events is as follows:

1. The new regime $z \in \{z_L, z_H\}$ is drawn, with the probability distribution given by (2).
2. The new realization of endowment y is drawn, according to the newly updated regime z and conditional on its level from last period.
3. International lenders observe the endowment level y and mechanically form a new prior belief p about the output regime, conditional on the previous and current endowment realizations, as well as the last period's belief.
4. Default and redemption decisions take place:
 - The government that has recently defaulted on its debt draws a random number to determine whether it can be readmitted to the financial markets.
 - The government that has recently been current on its debt decides whether to repay or default this period.
5. Equilibrium allocations take place:
 - If the government defaults, it is excluded from financial markets this period and simply consumes its endowment, subject to a default penalty.
 - If the government repays, it chooses the new allocation of bonds b' , while the lenders post the bond price $q(b', y, p)$.

3.4 Recursive formulation

In the following section I formalize the economic environment by stating the problems faced by market participants in recursive form. To begin, define the vector of aggregate state

variables that are common knowledge as $\mathbf{s} = (b, y, p)$.

Government The government that is current on its debt obligations has the general value function given by

$$v^0(\mathbf{s}) = \max_{d \in \{0,1\}} \left\{ (1-d)v^r(\mathbf{s}) + dv^d(y, p) \right\} \quad (5)$$

A sovereign who defaults ($d = 1$) is excluded from international credit markets and has probability θ of being readmitted every subsequent period. The associated default value is

$$v^d(y, p) = u(h(y)) + \beta \sum_{z \in \{z_L, z_H\}} \sum_{z' \in \{z_L, z_H\}} \text{Prob}(z) \pi(z'|z) \times \int f_{z'}(y', y) \left[\theta v^0(0, y', p') + (1-\theta)v^d(y', p') \right] dy' \quad (6)$$

subject to the law of motion for the belief

$$p'(y, p, y') = \frac{\left[p \pi(z_H|z_H) + (1-p) \pi(z_H|z_L) \right] f_{z_H}(y', y)}{\sum_{z'=z_L, z_H} \left[p \pi(z'|z_H) + (1-p) \pi(z'|z_L) \right] f_{z'}(y', y)} \quad (7)$$

In equation (6), $h(\cdot)$ is a reduced-form representation of the output cost of defaulting¹²; $f_{z'}(y'|y)$ denotes the probability density of transitioning from state y to state y' given that tomorrow's regime is z' . $\text{Prob}(z_H)$ is equal to p and $\text{Prob}(z_L)$ is $1-p$, $\pi(z'|z)$ is the probability of transitioning from regime z today to z' tomorrow. The next period belief p' , described in equation (7), depends on the current and future income realization, as well as the current belief p . It is a simple application of Bayes' rule and takes into account a potential regime switch at the beginning of next period, according to the transition matrix given by (2).

The value of the government associated with repayment of debt is given by

$$v^r(\mathbf{s}) = \max_{c, b'} \left\{ u(c) + \beta \sum_{z \in \{z_L, z_H\}} \sum_{z' \in \{z_L, z_H\}} \text{Prob}(z) \pi(z'|z) \int f_{z'}(y', y) v^0(\mathbf{s}') dy' \right\} \quad (8)$$

subject to the law of motion for the belief in formula (7) and

$$c = y - b(\delta + (1-\delta)\kappa) + q(b', y, p)(b' - (1-\delta)b) \quad (9)$$

where equation (9) is the budget constraint.

¹²Quantitative sovereign debt models typically assume an exogenous punishment in the case of default in order to facilitate calibration of the model to the data. For the specific functional form, see Section 4.3.

Having characterized the two value functions of the government, it is straightforward to derive the optimal default policy as a function of today's state variables

$$d(\mathbf{s}) = \begin{cases} 1, & \text{if } v^d(y, p) > v^r(\mathbf{s}) \\ 0, & \text{if } v^d(y, p) \leq v^r(\mathbf{s}) \end{cases} \quad (10)$$

International Lenders Every period the lenders only observe (b, y) and share a common market belief p . Although they do not see the current regime z , they know its distribution and independently update their belief about it, as described by the law of motion in formula (7). The denominator in those equations is always greater than zero and the resulting next period belief p' is strictly interior on the interval $(0, 1)$.

As it is common in the quantitative models of sovereign debt, lenders are competitive and risk-neutral by assumption. The resulting equilibrium bond price is such that they make zero profit in expectation (according to their imperfect information). The bond price function is

$$q(b', y, p) = \frac{1}{1 + r^*} \left(\sum_z \sum_{z'} \text{Prob}(z) \pi(z'|z) \times \int f_{z'}(y', y) (1 - d(\mathbf{s}')) [\delta + (1 - \delta) (\kappa + q(g(\mathbf{s}'), y', p'))] dy' \right) \quad (11)$$

where $\mathbf{s}' = (b', y', p'(y, p, y'))$, $d(\cdot)$ and $g(\cdot)$ are the government's optimal decisions with respect to default and new debt, respectively, and r^* is the risk-free rate of interest.

Concluding this section, Definition 1 introduces the standard concept of a Markov Perfect Bayesian Equilibrium. In this equilibrium the posterior beliefs of agents must be specified at all states and for all strategies of other players (including those involving off-equilibrium actions). The agents' best responses must belong to the set of stationary Markov strategies.

Definition 1 *A Markov Perfect Bayesian Equilibrium for this economy consists of the government value functions $v^r(\mathbf{s})$, $v^d(y, p)$ and policy functions $c(\mathbf{s})$, $b'(\mathbf{s})$, $d(\mathbf{s})$ and the bond price schedule $q(b', y, p)$ such that:*

1. *Policy function d solves the government's default-repayment problem (5).*
2. *Policy functions $\{c, b'\}$ solve the government's consumption-saving problem in (8).*
3. *Bond price function q is such that the lenders make zero expected profit (subject to their imperfect beliefs).*

4 Quantitative analysis

In this section I calibrate the model to Portuguese data and discuss its mechanics. As an empirical test and the main result of this paper, I use the calibrated model to simulate an actual debt crisis episode and compare the predictions to those of a benchmark model.

4.1 Data

I use the data for Portuguese economy as the case study for the theory developed in this paper. The model could also be calibrated to other European economies discussed in Section 2. The Portuguese episode is the most clear-cut case however, because it does not coincide with other major economic events such as a banking crisis (like the one that occurred in Ireland) or Mario Draghi’s “whatever it takes” speech and the introduction of the Outright Monetary Transactions (OMT) program in the summer of 2012, at the peak of the debt crises in Italy and Spain. Portugal is also a particularly relevant laboratory for a sovereign default model because it easily satisfies its core assumptions, i.e. it is arguably a small open economy and the vast majority of its debt securities were held externally.¹³ While in principle Greece is also a plausible candidate, the validity of its macroeconomic data has been questioned.

Quarterly data for real GDP are taken from OECD and cover the period 1960:Q1-2014:Q4. Consumption, current account series and interest rates on long-term government bonds, also from OECD, span the time frame 1995:Q1-2014:Q4. Government debt data is acquired from World Bank’s Quarterly External Debt Statistics (I use the real debt securities only).

The identification strategy for the model’s parameters is in line with the general approach in the literature. In what follows, I first calibrate the parameters of the income process (1) separately from the core model, by targeting the path of long-run GDP forecasts from the data. Then, I pick the remaining structural parameters of the model partly from the literature and partly to match certain very general characteristics of the Portuguese economy.

4.2 Calibration of the income process

I start by calibrating the endowment process introduced in (1). Pinning down the parameters of this equation is conceptually the most significant element of the present paper, as it determines the speed with which markets learn about an underlying regime switch. Recall that the interpretation of the low regime assumed in this paper is that of a rare disaster. However,

¹³See [Andritzky \(2012\)](#).

because we do not have enough historical data to account for such episodes (the previous one being the Great Depression), it is not a valid approach to estimate a Markov-switching AR(1) process based on the current national accounts data. The result of such estimation will not be capable of matching the size and frequency of large depressions, such as the one we have observed for European economies since 2008. Instead, the obtained low regime will represent one of the regular recessions Europe has experienced in the recent decades.

I proceed to calibrate equation (1) in three steps. First, I fix the probabilities of switching between regimes based on the historical experience. By all accounts, the recession in southern European countries has been the worst since the Great Depression.¹⁴ This gives us roughly 60 years or 240 quarters of high regime duration.¹⁵ Conversely, the Great Depression lasted for about 10 years, or 40 quarters, which I use to pin down the expected low regime duration. The resulting probabilities of staying in the high and low regimes are therefore 0.996 and 0.975, respectively. The exact numbers behind of these probabilities are not crucial for the results because, given their predetermined values, I use another data source below to discipline the level of the depression regime. What matters however is to capture the right order of magnitude - intuitively, the low regime ought to be rare and severe enough so that it clearly distinguishes from a regular economic contraction.¹⁶

As a second step, I use historical GDP data to estimate the persistence and variance parameters of the AR(1) process. The unconditional mean of the high regime μ_H is normalized to zero, like in most previous studies. Then, for any given choice of the low regime mean μ_L (think of it as a generic step in the estimation algorithm), I use Maximum Likelihood to estimate ρ and η in (1) on GDP data from 1960:Q1 to 2014:Q4, assuming that the regime switches from high to low in 2008:Q3.¹⁷ The data is in constant prices and the linear trend is removed.¹⁸ The resulting estimates for the persistence and variance of output (at the

¹⁴While Portugal was not affected that much by the Great Depression itself, it subsequently suffered during the 1934-1936 civil war in Spain, with the peak-to-trough decline in real GDP of 12.5%. Following the 1930s, the 2008-2014 episode is by far the most severe contraction in Portuguese economic history. It comes close to satisfying the defining criteria of a great depression established by [Kehoe and Prescott \(2002\)](#).

¹⁵I ignore the second world war in my calculations as the model is not designed to account for such events.

¹⁶While stylized, this type of approach to calibration is common for models with disaster risks. For example, pooling 60 episodes in 35 countries [Barro \(2006\)](#) sets the probability of entering a disaster event at 1.7% annually, almost the same as the number I use. More recently, [Coibion, Gorodnichenko and Wieland \(2012\)](#) take a similar approach to approximate the frequency of interest rates in the US hitting the zero lower bound, which occurred for the first time since the second world war.

¹⁷While the precise beginning of the crisis is not indisputable, it is commonly associated with the bankruptcy of Lehman Brothers in September 2008. Around that time we can also observe the beginning of a slump in GDP series for most European countries.

¹⁸Because of the growth trend shifts for European economies over this relatively long sample, I follow

optimal choice of μ_L , to be discussed below) are 0.94 and 0.01, respectively.

Finally, it remains to pin down the unconditional mean of the low regime (i.e. the size of the disaster). While it is impossible to find the “true” value of this parameter, it must at least correspond to the markets’ expectation about the depth of the ensuing depression in years 2008-2014. To capture this information, I use the historical GDP forecast data published by the IMF. As discussed in section 2.3, the forecasts are released twice a year (spring and fall) and consist of the projected GDP growth rates for up to five years ahead.¹⁹ I use the growth rates for three years ahead,²⁰ convert them to levels, take logarithms and remove the previously estimated trend (so that the forecasts directly comparable to the model’s units).

For every given set of parameters of the output equation I generate a corresponding path of forecasts made by the agents in my model. I first feed in the actual GDP observations for Portugal between 2000 and 2014 and create a sequence of beliefs that result from Bayesian updating. Then, for every first and third quarter between 2008 and 2014 (corresponding to the spring and fall releases of IMF’s predictions which are published in May and November, respectively) I generate a sequence of model-implied annual forecasts, for three years ahead. I finally pick the value of low regime mean μ_L to minimize the sum of deviations between the forecasts in the data and those implied by the model.

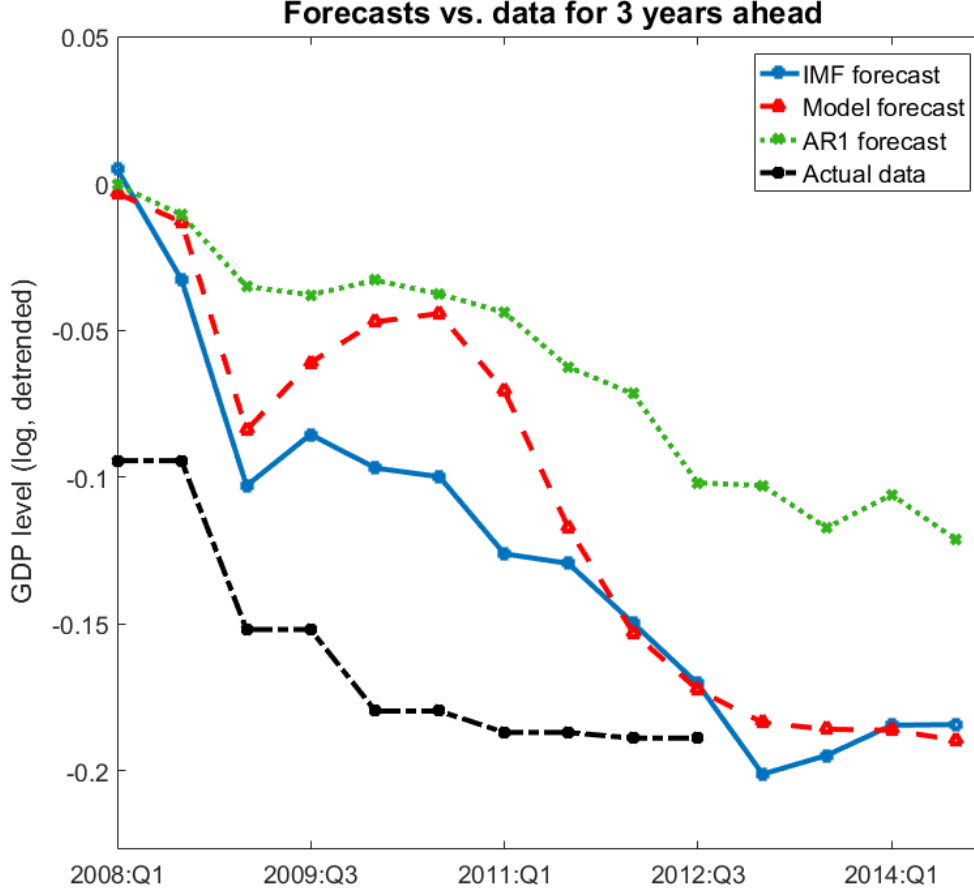
Figure 4 depicts the result of matching model-generated forecasts to the historical ones published by IMF for 3 years ahead.²¹ As can be noticed, the match is very close initially for years 2008-2009, and then for 2012-2014. For the middle two years of the recession, 2010 and 2011, the two sets of forecasts diverge in that agents in the model are too optimistic about the prospects of recovery. This divergence is reasonable however given the simple two-regime specification of the output process. It can be implied from this forecast data that in 2010 and 2011 the IMF was very cautious about predicting a recovery, but also did not foresee the

Bai and Perron (1998) to identify statistically significant structural breaks in the growth rate of Portuguese economy. Two breakpoints are detected, at 1974:Q2 and 1999:Q4, which are very intuitive as they coincide with the democratic revolution in Portugal and accession to the Euro zone, respectively. The estimated quarterly trend growth rates for the three time windows are 1.6%, 0.8% and 0.4%.

¹⁹I use IMF data because of the longest horizon of their forecasts. For a shorter horizon it is plausible that forecasters form their projections using outside information (which shows up as the ϵ term in my output process specification (1)). As the forecast horizon extends, they must instead rely on long-run trend of the economy, described in my model by the parameters of interest, i.e. persistence and unconditional means.

²⁰The results for four- and five-years ahead forecasts are very similar. Using three-years ahead ones has an advantage of allowing me to compare most of the predictions to actually realized data.

²¹This horizon is selected for illustration purposes. Analogous pictures can be generated for the four- and five-year-ahead projections.



Note: Each point on the graph represents an annual detrended log-GDP level for three years ahead (for example, 2008 : Q1 corresponds to the GDP level in 2011). The solid blue line plots the actual IMF forecasts (Q1 and Q3 refer to the spring and fall issues, respectively), while the dashed red line denotes the ones generated by the calibrated model. Additionally, the dashed-dot black line shows the actual realized data that the corresponding forecasts refer to (only available until 2012 : Q3, when the projection for year 2015 was made). Additionally, the dotted green line plots the forecasts made using a simple AR1 specification with zero unconditional mean.

Figure 4: Historical GDP forecasts: IMF- and model-generated projections.

subsequent slump. The model is not capable of replicating this because the only two regimes available are “normal times” or “rare disaster”, and in the longer horizon the economy must converge to one of them. This divergence is not a problem however, because what really matters for calibration of the model is to capture the magnitude of the depression perceived by the markets. This goal is achieved by selecting $\mu_L = -0.22$, which means that the markets expect the average income level in the depression regime to be roughly 20% below the trend. Table 3 summarizes the calibrated parameters of the income process.

Regime	Mean μ	Persistence ρ	St. dev. η	Transition Prob.	
				Low	High
Low	-0.2188	0.9408	0.0104	0.975	0.025
High	0.00	0.9408	0.0104	0.004	0.996

Table 3: Parameters of the regime-switching endowment process

It should be emphasized that the estimated regime-switching model in Table 3 provides a much better fit to Portuguese data than a single-mean AR1 process. I will use two arguments to make this point. First and foremost, notice that AR1 implicitly assumes that the underlying data is stationary around its long-run mean. This is the case for Portugal’s GDP only until 2008:Q2, where the Dickey-Fuller (DF) test rejects a null hypothesis of unit root with p-value below 0.01. However, Table 4 shows that as we include the most recent data (until 2011 and 2014), this conclusion no longer holds and a unit root cannot be rejected at any level of significance. On the other hand, conducting a Markov-switching version of the DF test under the parametrization from Table 3 allows us to reject the unit root hypothesis with 10% significance. The intuition behind this conclusion is straightforward in that the post-2008 drift away from the zero mean is largely explained by the regime switch, rather than a random walk component. Second, the goodness-of-fit is significantly higher under regime switching. To show this, I estimate the detrended AR1 process for years 1960-2011 to be 0.9467 and 0.0107, respectively.²² Then, the likelihood ratio test statistic is 22.5 and has approximately a chi-squared distribution with three degrees of freedom (the number of additional parameters in the extended model), resulting in a p-value below 0.01. This suggests that we can reject the null model (single-regime AR1) at virtually all levels of significance.

A natural robustness concern involves comparing the parameters in Table 3 with alternative estimation results for a regime-switching process. In particular, I consider two possible approaches. First, let us keep the assumption that regime is high for all quarters prior to 2008:Q3, and then permanently switches to low (so that we retain the “disaster risk” interpretation of the model). I then use Maximum Likelihood to estimate all parameters of (1), including the switching probabilities π_{ij} and the depression mean μ_L , without referring to outside information (historical experience and forecast data). The obtained parameter values are as follows: $\rho = 0.93$, $\eta = 0.0103$, $\mu_L = -0.18$, $\pi_{HH} = 0.9948$, $\pi_{LL} = 1$. Notice that the only significant deviation from the estimates in Table 3 is in the probability of

²²Once again, I use a broken linear trend with two statistically significant breakpoints detected using the Bai and Perron (1998) test at 1974:Q2 and 1999:Q4. Due to the non-stationarity issue described above, I do not use the final three years of the sample, i.e. 2012-2014, because including them makes the estimate of persistence ρ is indistinguishable from 1.

Model	Period	t-statistic	p-value
Simple AR1	1960:Q1-2014:Q4	0.570	0.838
	1960:Q1-2011:Q4	-1.059	0.263
	1960:Q1-2008:Q2	-2.608	0.009
Markov switching	1960:Q1-2014:Q4	-2.717	0.089

Note: The Markov-switching Dickey-Fuller test follows [Hall, Psaradakis and Sola \(1999\)](#). The empirical distribution of the t-statistic is constructed by simulating equation (1) under the null hypothesis of a unit root with a discrete switch in unconditional means in 2008:Q3.

Table 4: Dickey-Fuller test for different specifications and time periods

switching from the depression back to normal times, for which a corner solution is obtained. Consequently, the overall log-likelihood increases by just 0.0002. The second alternative is to identify regimes in the data with Kalman filter and estimate (1) using a variant of the Expectation-Maximization algorithm, as described by [Hamilton \(1990\)](#). This approach yields the following estimates for the sample from 1960 to 2011: $\rho = 0.96$, $\eta = 0.009$, $\mu_H = 0.04$, $\mu_L = -0.43$, $\pi_{HH} = 0.958$, $\pi_{LL} = 0.771$. Notice that now the high regime mean is no longer normalized to zero and takes a small positive value, while the low regime has the unconditional mean twice as large (in absolute value) as in Table 3. As switching is much more likely under this specification, and it does not last very long, we detect several instances of the low regime over time, in particular around 1969, 1974, 1983, 1992, 2008-2009 and 2011-2014. However, because the bad regime is now so stark and relatively more frequent, the learning process about an underlying switch turns out to be very fast and does not align with the evidence from forecast data presented in Table 2.

4.3 Functional forms and calibration

To select the remaining structural elements of the model I follow the general trends in the literature in that I fix the value of some non-controversial parameters, and I use a moment-matching exercise to pin down the more problematic ones. A representative household's utility is a CRRA function of the form $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$, with risk aversion parameter set at the standard level of 2. The risk-free interest rate is set equal to 1% (quarterly value) and the probability of re-entry after default is fixed at 0.049, following [Cruces and Trebesch \(2013\)](#) who find that the average time to re-enter the credit market was 5.1 years in 1970-2010. Using OECD data I find that the average maturity of Portugal's debt in years 1996-2010 was 4.73 years, which translates into an average quarterly maturity rate of 0.053. The coupon payment is set to 0.0125 following [Salomao \(2015\)](#), which implies an annual coupon of 5%.

The output cost of default is parametrized as $h(y) = \max \{0, -d_0 y + d_1 y^2\}$ following [Chatterjee and Eyigungor \(2012\)](#). The two parameters of the default penalty function, d_0 and d_1 are calibrated jointly with the discount factor β using the simulated method of moments. The economy's income path in years 1998-2014 is simulated 10,000 times, starting from the actual GDP and debt levels observed in 1998:Q1 and under the assumption that the regime switches from High to Low in 2008:Q3.²³ The idea behind identification strategy is to match certain very general characteristics of the Portuguese experience during that time period. To this end, I use information from the following moments of Portugal's economy in years 1998-2014: average ratio of external debt securities to GDP of 47.5%;²⁴, standard deviation of the bond spread of 2.83%, and the standard deviation of trade balance to GDP equal to 3.75%. The amount of debt in the economy is naturally an important piece of information to identify relative impatience of the government and the punishment for default. Standard deviation of the spread observed in the data is the best measure of relative riskiness of European economies.²⁵ Finally, the volatility of trade balance is an informative moment because it captures the persistent trade deficits prior to 2008 among the southern European economies, and their sharp reversals in years 2008-2014. Table 5 presents a summary of the parameter values that provide the closest match to the empirical moments. The model achieves a very close match in terms of the average amount of debt and the volatility of bond spread. This is at the partial expense of the trade balance volatility which remains slightly too in the simulations. It should be emphasized however that this moment is very sensitive to the selected time period in the data (for example, it falls to 1.91% for years 1998-2011). In addition, the volatility of trade balance relative to the standard deviation of GDP is roughly equal to 0.5 in both the model and the data. The resulting parameter vector contains the value of β equal to 0.986 which is a high number for this class of models. This value is crucial however to simultaneously match a high debt stock, low interest rate volatility, and a very gradual path of debt accumulation evident in Figure 2, which is affected by β through the implicit Euler equation in the model.

²³An alternative would be to simulate the economy over many years and calibrate to its long-run business cycle statistics outside of default, following [Chatterjee and Eyigungor \(2012\)](#). However, as it will become clear from Table 6 describing the simulation results, years 1998-2014 were a highly non-stationary period for the European economies, including slow accumulation of debt towards a steady state level.

²⁴Because the model does not include post-default renegotiation, I follow [Chatterjee and Eyigungor \(2012\)](#) to calibrate only the true "unsecured" portion of the debt. While Portugal in the end did not default and it is difficult to know how much of its debt was in fact unsecured, the best guess is 0.535, the haircut rate in the case of Greek default of 2012.

²⁵Earlier studies concerned with emerging markets' debt crises often use the long-run default probability to approximate for the riskiness. As Table 6 explains, this moment is much less informative in the case of the European economies.

Finally, in order to make a meaningful comparison with a literature benchmark, I also calibrate a “standard” sovereign debt model with long-term debt, in the spirit of [Chatterjee and Eyigungor \(2012\)](#) or [Hatchondo and Martinez \(2009\)](#), based on a simple AR1 specification of the output process and full information. As mentioned before, the estimated persistence and variance parameters are 0.9467 and 0.0107, respectively. Calibration of the structural parameters closely follows the strategy described above and is summarized in the third column of Table 5. Notice that the AR1 model also comes short in terms of matching the standard deviation of trade balance. Keep in mind however that this moment poses a general challenge for sovereign debt models (see for example [Arellano \(2008\)](#) or [Chatterjee and Eyigungor \(2012\)](#)) and it is very sensitive to the selected time period in the data.²⁶

Symbol	Meaning	AR1	Learning	Source
σ	Risk aversion	2	2	Literature
r^*	Risk-free rate	0.01	0.01	Literature
θ	Re-entry probability	0.049	0.049	Literature
δ	Probability of maturing	0.053	0.053	Data
κ	Coupon payment	0.0125	0.0125	Data
d_0	Default cost par.	-1.201	-1.038	Calibration
d_1	Default cost par.	1.320	1.312	Calibration
β	Discount factor	0.970	0.986	Calibration
Calibration targets		AR1	Learning	Data
E (debt/GDP)		48.48	47.67	47.5
st.dev. (spread)		2.83	2.83	2.83
st.dev.(TB/Y)		2.98	3.38	3.75

Note: targeted moments are given in percentage points. Simulations are repeated 10,000 times for a period of 1998-2014.

Table 5: Calibration of structural parameters of the model

4.4 Characterization of the equilibrium

In the following section I first characterize some of the key properties of the equilibrium, and then show how the model’s simulated behavior compares with actual data. The model is solved numerically by value function iteration using a continuous choice of next period debt and cubic spline interpolation to evaluate off-grid points, similarly as described in [Hatchondo, Martinez and Sapriza \(2010\)](#). I use 31 points for the grids of debt and income, and 21 points for the grid of beliefs. The model is solved on a computer cluster with 32 nodes.

²⁶An alternative calibration, in which the trade balance volatility is matched closely at the expense of higher average debt-to-GDP ratio, does not affect the results significantly.

4.4.1 Model mechanics

To understand how the model works, it is instructive to examine how the government's optimal decisions change with respect to state variables. Figure 5 shows the default and debt policies for different levels of prior belief. On the left-hand side panel, any combination of current debt and income above the line corresponding to some belief p indicates repayment, and below the line indicates default. Not surprisingly, higher belief about being in the good regime induces the government to default in a smaller number of states. This relationship is strictly monotonic in the level of prior belief (but not necessarily linear). A natural corollary to this result is that international lenders offer higher prices to the government they assign a larger probability of being in the high regime. The right-hand side panel of Figure 5 shows that higher prior belief leads the government to borrow more. In this model, agents are impatient and would rather consume today than tomorrow. When making their debt decisions though, they need to weigh their impatience against the expected income level in the future. A higher chance of being in economic depression next period implies that the government must restrict its consumption today and reduce foreign debt in order to decrease the probability of defaulting tomorrow and to secure a high bond price today. Consequently, higher market belief has a strictly monotonic, increasing effect on the optimal debt level.

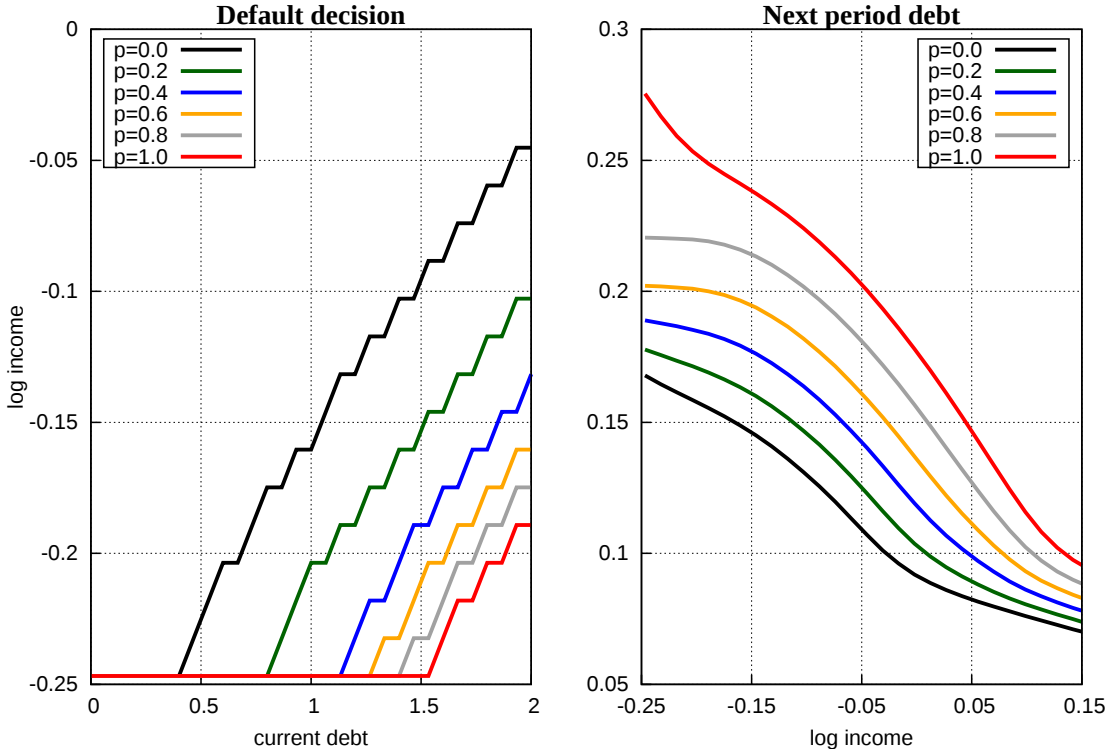


Figure 5: Default sets and bond price policy functions for different beliefs

Figure 6 plots government bond prices as functions of the next period debt choice, at several different levels of belief.²⁷ The information about current regime is important in determining future default risk and leads to large differences in the offered bond prices. The highest (red) line represents the bond price schedule when markets are fully convinced the economy is in the high regime. As a result, the government is able to secure an almost maximum price for its bonds, regardless of its choice of next period debt (within reasonable bounds). By contrast, the lowest (black) line represents the schedule if the markets believe the economy is currently in a depression. Because default risk is much higher in such circumstances, the government is offered very low prices for its debt. Finally, the schedules in the mid-range are increasing monotonically as the belief of being in the high regime improves.

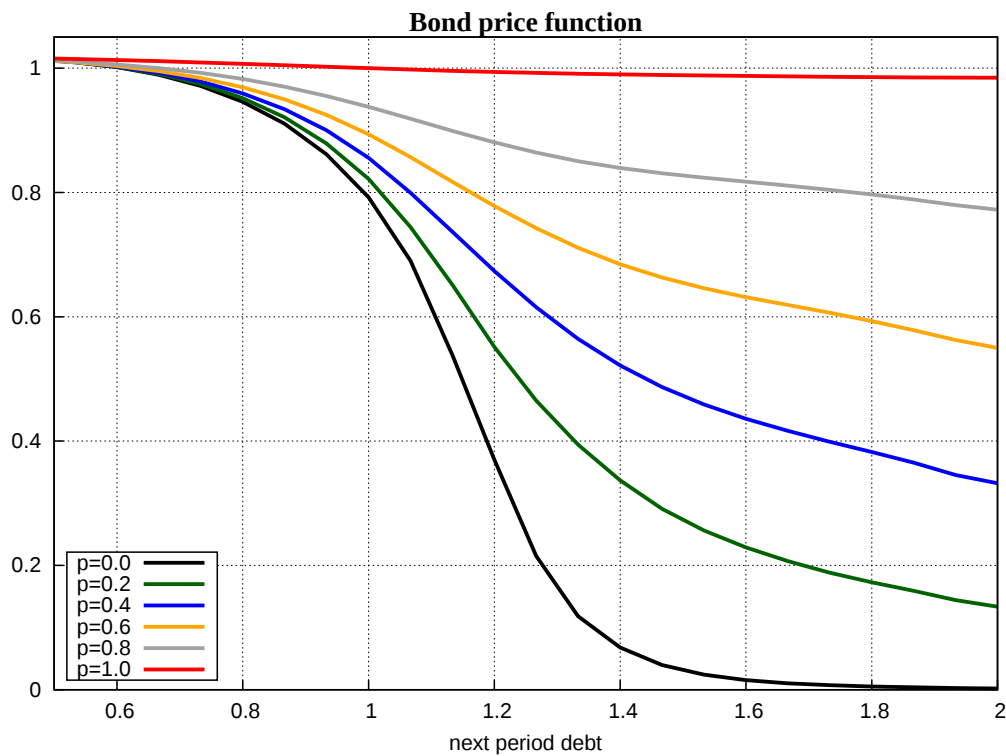


Figure 6: Bond price as function of next period debt for different beliefs

4.4.2 Simulated behavior

In the next step, I analyze the model's behavior in simulations. As discussed in Section 4.3, the model exhibits widely different behavior in the long run versus the short sample that aims at mimicking the period of 1998-2014 for the European economies.

²⁷This graph does not say anything about optimality of different debt choices, it only depicts the possible price schedule

Table 6 presents the simulated business cycle moments in the long and short sample, contrasted with those observed in the data. It can immediately be noticed that the model simulated in the short run performs much closer to actual data in terms of correlations between the main variables, and the moments of the bond spread and debt. In particular, notice that the average debt-to-GDP ratio for Portugal in the long run implied by the model is 74.3%, much higher than in the data for 1998-2014. This is due to the fact that the government is gradually accumulating debt towards its steady-state level for most of 2000s. The short-run simulations are able to capture this transition. On the other hand, the model vastly overshoots the volatility of consumption relative to GDP in the short run (a common feature of sovereign debt models, here magnified due to the relatively large stock of debt held). Finally, notice that the long-run default probability in the model is low, implying less than one default per 100 years. By comparison, [Reinhart and Rogoff \(2009\)](#) identify four sovereign defaults in Portugal's history since 1800, while [Standard & Poor's \(2014\)](#) identify three, implying an annual long-run probability of 1.5 – 2% (in Table 6 I use the average of those numbers). However, all the defaults occurred in 19th century and thus the informativeness of this moment is arguable. The obtained low default probability is actually reasonable given that the model is calibrated to jointly match a high debt-to-GDP ratio and fairly low volatility of spread. Such a combination of data moments may be the effect of Portugal's membership in the Euro area and the implicit bailout guarantees associated with it.

Statistic	Long run	Short run	Data
$E(s)$	0.89	1.34	1.78
$std(s)$	3.42	2.83	2.83
$std(c)/std(y)$	1.01	1.42	0.94
$std(tb)/std(y)$	0.34	0.54	0.53
$corr(y, c)$	0.94	0.96	0.97
$corr(y, tb)$	0.16	-0.62	-0.94
$corr(y, s)$	-0.26	-0.76	-0.72
$corr(s, tb)$	0.39	0.77	0.72
$E(debt/y)$	74.27	47.67	47.50
Default prob.	0.7		1.75

Note: moments for the bond spread, debt-to-GDP ratio and the long-run default probability (annual) are given in percentage points. Long-run simulations extend to a horizon of 10,000 quarters and are repeated 10,000 times, following closely [Chatterjee and Eyigungor \(2012\)](#). Short-run simulations span the period of 1998-2014 and are repeated 10,000 times starting from the actual levels of debt and GDP observed in 1998:Q1. Consumption data is detrended using the common GDP trend.

Table 6: Simulated behavior of the model

Table 7 highlights the main difference between the benchmark model based on a simple AR1 process, and the model with disaster risk and learning. The first two moments of the simulated bond spreads are presented for each model, and contrasted with the data. The standard deviation of spread is a targeted moment, so it is matched exactly in both cases. However, the mean spread is not a calibration target, and for the AR1 model it overshoots the level of standard deviation, producing a *coefficient of variation* smaller than 1 (reported in the last column). On the other hand, the model with learning generates a mean spread slightly over 1% resulting in the coefficient of variation greatly above 1, in line with Portuguese data.

Country	Bond spreads (in %)		
	μ	σ	c_v
Model-AR1	3.46	2.83	0.82
Model-learning	1.34	2.83	2.11
Data-Portugal	1.78	2.83	1.59

Table 7: Bond spread moments in the simulations and the data

The intuition behind the result presented in Table 7 is the following. In the standard AR1 model with long-term debt a sovereign default is possible virtually always, within the time horizon of bond maturity. Consequently, the spread never falls to 0, although it may on average be much smaller than the ones obtained for emerging market economies as shown in Chatterjee and Eyigungor (2012) and other studies. On the other hand, in the model with learning, sovereign defaults are limited entirely to the times when the economy switches to the disaster regime. Hence, most of the time while the economy is doing fine and the market-wide belief is almost 1, lenders do not fear that default is a possibility in any predictable future. As a result, bonds spreads are very close to zero, and the average spread is low even if a debt crisis eventually does occur.

Table 8 generalizes this point by documenting the difference in bonds spread moments of other peripheral European countries discussed in Section 2 and emerging market defaulters (which are the examples originally discussed by Arellano (2008)). As can be noticed, the former tend to have a coefficient of variation of the bond spread above 1, implying that average spread is low relative to its volatility. On the other hand, emerging market defaulters tend to have average spreads that exceed their standard deviations significantly, resulting in a coefficient of variation smaller than 1. Consequently, as Table 7 shows, the benchmark AR1 model seems to be a better description of the debt crisis experienced by an emerging market

economy, while the model with disaster risk developed in this paper is a better description of the recent episode experienced by developed European nations. A natural caveat related to the interpretation of Table 8 is that emerging market economies are additionally affected by recurring high rates of inflation, affecting the average levels of nominal spreads. While this factor has not been present for the southern European economies since 1999, they too experienced this problem which resulted in much higher average spreads.

	Bond spreads (in %)		
European	μ	σ	c_v
Greece	4.48	5.58	1.25
Ireland	1.25	1.84	1.48
Italy	1.34	1.52	1.14
Emerging	μ	σ	c_v
Argentina	10.25	5.58	0.54
Ecuador	16.91	10.72	0.63
Russia	19.41	17.60	0.91

Note: bond spread moments for European countries are computed with OECD data covering 1995:Q1-2014:Q4, while the moments for emerging economies are taken from [Arellano \(2008\)](#).

Table 8: Bond spread statistics for European vs. emerging market economies

4.5 Event analysis of the European debt crisis

In this section, I use the calibrated model to analyze the timing and pattern of events during the debt crisis in Portugal. I start with the benchmark, a one-regime full-information version of the model, and then move on to the predictions of the actual model with learning.

4.5.1 Benchmark case - AR1

I start by feeding in the actual detrended GDP observations for Portugal into the benchmark AR1 version of the model. Figure 7 presents the simulated evolution of debt-to-GDP ratio and the bond spread in that model and the data (I use the same time series that are depicted in Figures 1 and 2). The economy is started in the first quarter of 1998 with the actual debt and GDP levels observed in the data. I use the model-implied decision rules and bond prices in response to the true path of income shocks. As can be noticed, the government accumulates debt at a fast pace until year 2003 when Portugal first experiences a minor recession (part of this increase occurs prior to 2000, so that it is not included in the figure). Subsequently, until the beginning of the Great Recession, the process of debt accumulation is much slower.

Throughout this period, the bond spread is strictly positive and responds actively to negative income shocks experienced by Portugal's economy, in particular during the recession of 2002-2003. When the Great Recession starts, the spread jumps up to over 15% in 2009:Q1 due to the extreme negative shock that hits Portuguese GDP. The government reduces its debt sharply, which causes the spread to fall back. All these predictions are clearly at odds with the data - the bond spread was virtually zero up until 2009, and debt accumulation was much slower. In 2009 the bond spread temporarily rose to merely 1.5%, while the government actually increased its external debt-GDP ratio. In 2010 the spread falls back both in the model and the data, and it again starts rising in 2011 leading to a predicted default in the last quarter of 2011. Clearly, the exact numerical predictions should be taken with a grain of salt, due to the fact that this model ignores the existence of the European Union and international emergency bailouts that actually prevented the Portuguese government from defaulting. With a richer institutional framework, the predicted increase in spreads in years 2003 and 2009 would probably be smaller, but it would not eliminate the mechanism that generates the excessive sensitivity of bond prices to current income shocks.

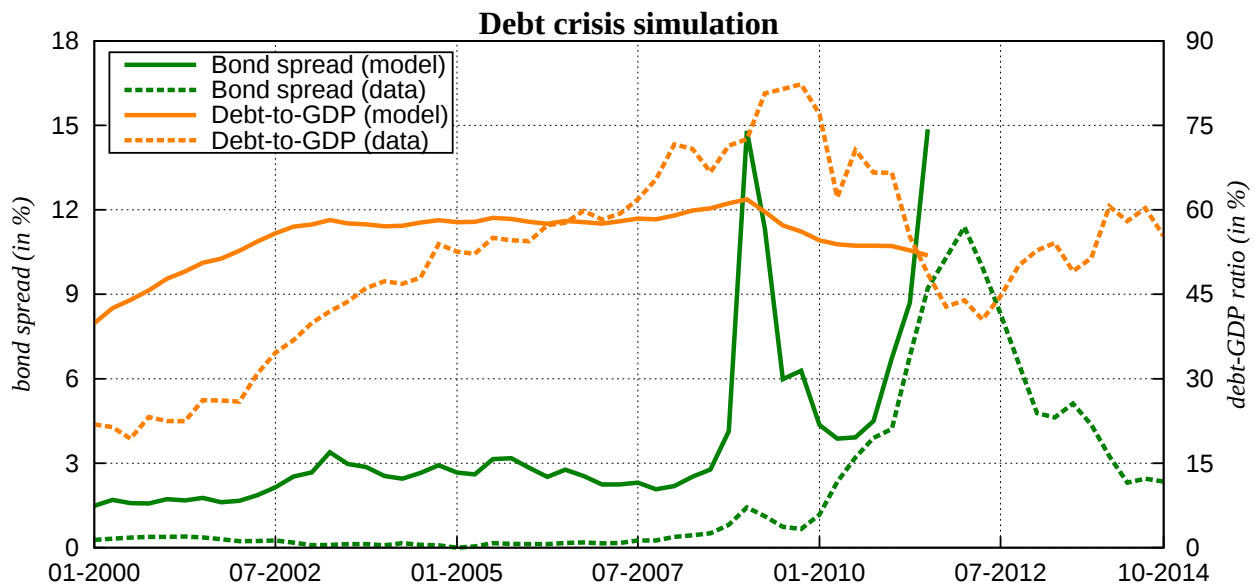


Figure 7: Simulated debt crisis in the benchmark AR1 model

4.5.2 Model with disaster risk and learning

Now I conduct a simulation under the assumption that markets and the government share a common belief about the output regime in which the economy is operating. The upper panel of Figure 8 presents the evolution of debt-to-GDP ratio and bond spread for the actual path of Portuguese GDP realizations. The economy is once again started in 1998 with the actual levels of debt and GDP, and the behavior of debt and interest rates is simulated over time

(upper panel) and contrasted with the data. The lower panel tracks the evolution of market belief about the economy type. One immediate observation is that this model predicts the accumulation path of government debt at a much more gradual rate, partly due to the higher discount factor obtained in the calibration of this model, relative to the benchmark. At the same time, the bond spread remains approximately zero for most of the 2000s. This is caused by the fact that markets are fully convinced that the economy is in a high regime and are not worried about the possibility of default (agents know that in the long run, sovereign defaults for this economy are associated with the disaster regime). When the major negative shock arrives in 2009:Q1 the belief immediately drops, but only partially, resulting in an increase in the spread up to 1.5%, in line with the data. As the belief starts to pick up in consequence of Portugal's short-lived recovery of 2010, the spread falls back to almost zero. In 2011-2012 it starts increasing again, upon receiving further adverse income shocks. Once the belief drops to zero, meaning that everybody realizes the regime has switched to a depression, the spread explodes and the government is forced to default in 2012:Q4. While in reality Portugal did not default on its debt, this prediction is not unreasonable, given that the country received a bailout from the European Commission and the IMF covering over 40% of its GDP. Notice

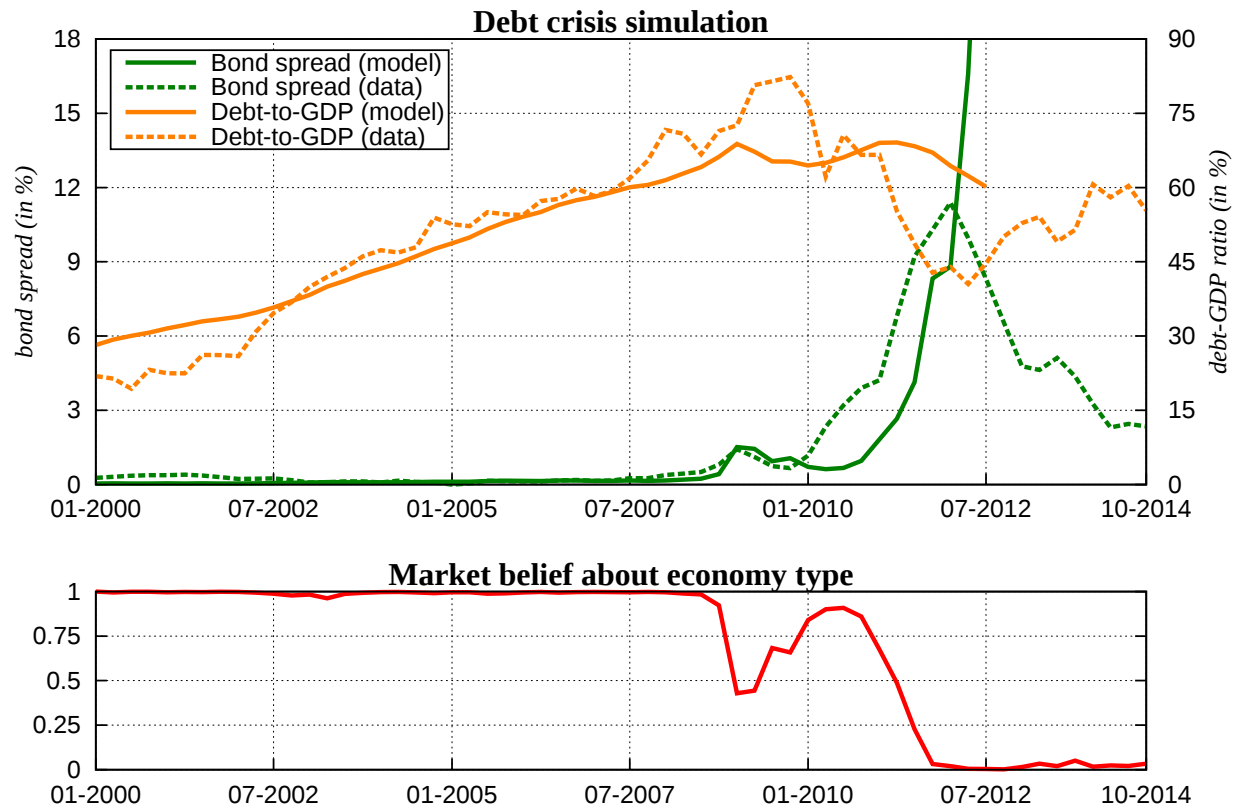


Figure 8: Simulated debt crisis in the model with disaster risk and learning

also that the bond spread in the data starts rising faster following the 2010 recovery than in the model. This is a result of the significant recovery in the belief shown in the lower panel of Figure 8, resulting in a lag of roughly two quarters that it takes for the belief to drop from the still high level of around 0.7 in 2011:Q1. In reality, investors began raising concern about the government’s repayment possibility much earlier, which could plausibly be explained by external factors, such as the intra-EU politics (I discuss it in Section 5).

While the model with learning improves greatly the predictions of existing models in terms of the dynamics of interest rates, it still fails to capture the behavior of government debt during a debt crisis. As it was pointed out on Figure 2, upon receiving the large output shocks in 2008-2009, governments of Portugal and other countries responded by increasing their external debt stocks. On the other hand, the government in our model reduces it in order to avoid a larger increase in interest rate. This is partly due to the large fluctuations in the belief in response to the early shocks to output. One way to get more control over the speed of learning is to augment the model with a news shock in the spirit of [Durdu, Nunes and Sapriza \(2013\)](#).²⁸ In that world, agents receive news about the bad income shock next period and are less surprised to see the highly negative growth rate (such as in 2009:Q1), thus lowering their doubt about the possible regime switch.

5 Discussion

In this section, I address the two alternative stories that are often cited in the context of the European debt crisis, namely the effect of international bailouts and the self-fulfilling crises. I also provide an explanation for why the model presented here goes a long way in explaining the European episode, but does not necessarily help with the emerging market debt crises.

5.1 Bailouts and the European debt crisis

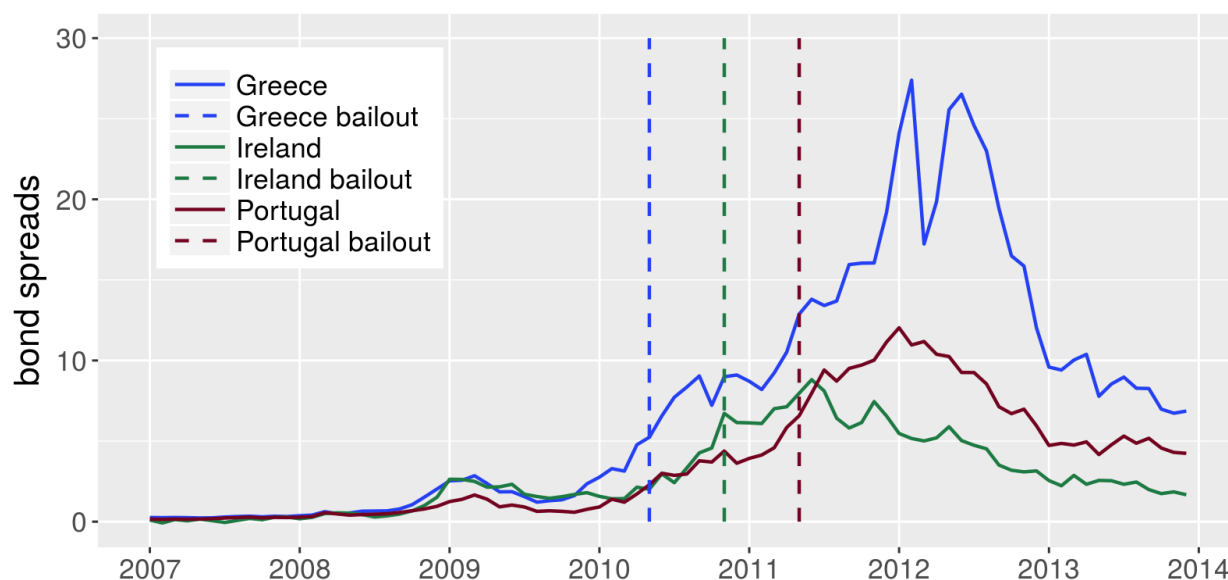
The impact of emergency loans on sovereign debt crisis has long been recognized by the literature. In years 2008-2014 this factor has been particularly pronounced, with a total of eight European nations getting official bailouts sponsored by the European Commission and the International Monetary Fund. The scale of these loans was historically unprecedented, amounting to roughly 40% of GDP for Ireland and Portugal, and almost 100% in the case of Greece, and with maturities extending up to 30 years into the future.²⁹ The effect of such

²⁸The results with such augmented model are available upon request.

²⁹Detailed information about the bailout programs can be found at ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-financial-assistance.

interventions cannot be disregarded - in their analysis of Argentina [Aguiar and Gopinath \(2006\)](#) show that incorporating the IMF loan leads to over 60 percent lower standard deviation of the interest rate than in the benchmark case. The effect shows up clearly in [Table 6](#) where, for a targeted level of bond spread volatility, the simulated long-run default probability is much lower than historical evidence would suggest. This disconnect is best explained by the existence of a lender of last resort that prevents governments from defaulting.

Apart from impacting the levels of country risk, it is interesting to consider whether the EU bailouts politics could account for the dynamics of the European crisis. While quantitative work on this topic is scarce, such a narrative is presented by some economists, e.g. [Brunnermeier, James and Landau \(2016\)](#). In their view, the European debt crisis began with the Deauville meeting between German chancellor Angela Merkel and French President Nicolas Sarkozy in October 2010, where they agreed on the “private sector participation” in the resolution of the crisis (i.e. allowed for haircuts on private bond holdings). There are three main doubts surrounding this hypothesis, best visualized in [Figure 9](#) which presents the plot of bond spreads at monthly frequency for Greece, Ireland and Portugal along with the announcements of their emergency packages marked with vertical lines. First, the movements in bond spreads in early 2009 indicates that the debts of EU countries were not perceived as



Note: Bailouts are marked for the quarter when the official announcement of an emergency loan was first made. The Deauville meeting occurred just before the Irish bailout (green vertical line).

Figure 9: Bond spreads and announcement of bailouts during the European debt crisis

fully guaranteed, despite the fact that two other member states (Hungary and Latvia) had been successfully bailed out in 2008. Second, the bond spreads for all countries had already been on the rise prior to the Deauville meeting (which occurred just before the Irish bailout), surpassing their levels from early 2009, and their slope did not change significantly following it. Third, the bond spreads continue to rise in the aftermath of the bailout announcements at individual rates for each country, reaching a peak at separate points in time in the course of a year (starting with Ireland in June 2011, followed by Portugal, Greece and Italy in July 2012). If the sudden change in the EU policy was the main driver of default risk, it would have been an aggregate shock, affecting all members simultaneously.

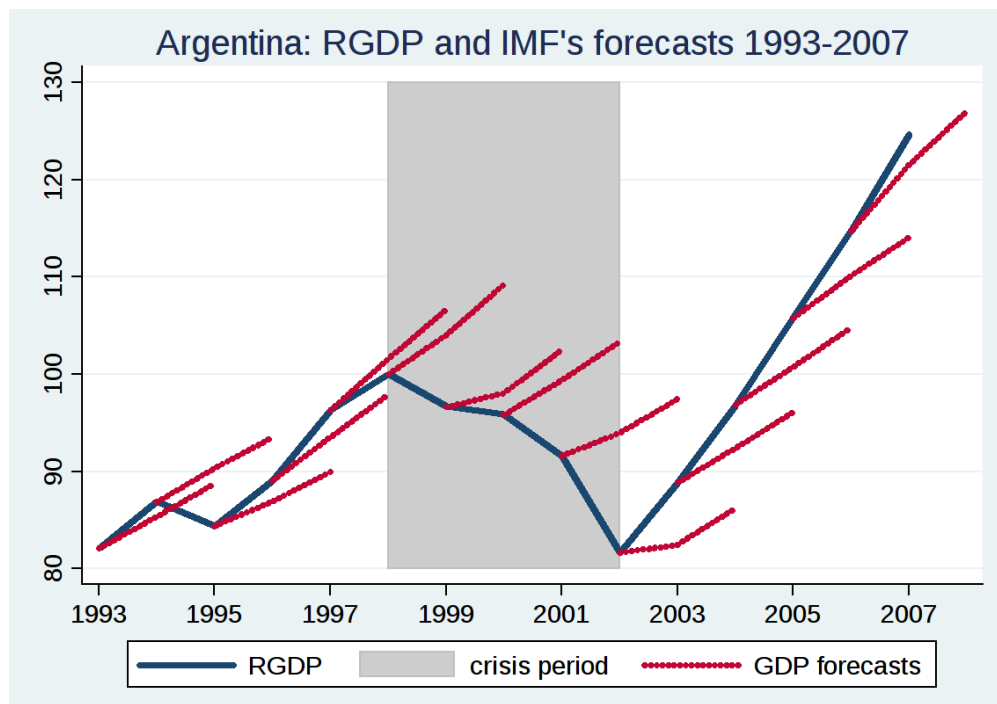
5.2 Self-fulfilling debt crises

Another strand of recent literature postulates that the European debt crisis may have been self-fulfilling in its nature. In particular, [Aguiar et al. \(2016\)](#) provide similar evidence as the one depicted in Figure 1 to argue that the sharp movements in sovereign spreads are only weakly correlated with fundamental factors. Instead they present a model with multiple equilibria in the spirit of [Cole and Kehoe \(2000\)](#) where the shifts in creditors' beliefs about the behavior of other lenders may drive the spread dynamics. However, they do not provide explicit quantitative evidence that the large increase in bonds spreads of Greece, Ireland or Portugal in 2011-2012 was a result of a sunspot equilibrium. Instead, their motivating narrative regarding the Portuguese episode concerns a debt swap in late 2012, when the government bond yields had already been declining from a peak in January 2012.

The story of [Aguiar et al. \(2016\)](#) seems better fit to the Italian episode, in which the rise in interest rates was cut short in the summer of 2012 by the introduction of the Outright Monetary Transactions program and the “whatever it takes” speech of the European Central Bank president Mario Draghi. Such actions are textbook policy interventions aimed at restoring confidence among creditors and they seemed to have worked well. Yet, even in the case of Italy, it is unclear to what extent was the debt crisis self-fulfilling. In a recent paper, [Bocola and Dovis \(2016\)](#) use the information contained in interest rate spreads and the observed maturity choice of the government to quantify the contribution of the self-fulfilling component in Italy's debt crisis episode. They find that only 12% of the spread increase can be attributed to the rollover risk. Similarly for Portugal, OECD statistics show that its debt maturity remained roughly unchanged during the debt crisis. In the lens of [Bocola and Dovis \(2016\)](#)'s methodology, the fact that government did not increase issuances of long-term debt suggests that there was little concern about non-fundamental source of default risk.

5.3 Learning about debt crises in emerging market economies

Aguiar and Gopinath (2006) show that emerging market bond spreads are better captured by a model with permanent growth shocks to income, rather than transitory ones. It is natural to ask how the model developed in this paper can be applied to the previous debt crises. To answer this question, Figure 10 plots the evolution of GDP forecasts for Argentina, a representative emerging market economy, around the time of its crash in 2001.³⁰ Two differences stand out in comparison with Figure 3 which plots the analogous data for European countries. First, even though Argentina's contraction is equally steep and much deeper than the one of Portugal or Italy, a swift recovery follows. Unlike the European economies, Argentina returns to its peak output level of 1998 within six years. Second, forecasts for Argentina have an almost invariant slope over time, regardless of whether the economy is currently in a boom or a bust. As a result, large forecast errors arise most of the time, overestimating future GDP during a recession and underestimating it during a recovery. This suggests that forecasters have noisy information about Argentina's economy and form their projections



Note: The GDP series is annual and expressed in constant prices; values are normalized such that it equals 100 in 1998. The red dotted lines represent one- and two-year ahead forecasts published in the fall of each year by IMF. The shaded area marks Argentina's debt crisis of 1998-2002.

Figure 10: Forecast and actual real GDP for Argentina

³⁰I use IMF projections as it is the only source of forecast data out of the four I discuss in Section 2.3 that contains Argentina.

based on the average long-run trend growth. As a result, while adding a regime-switching process with learning about its realizations to a model of emerging market debt crises is a possibility, there is relatively little information to be inferred from historical forecast data. Consequently, the procedure developed in this paper would not prove very useful.

6 Conclusion

In their seminal contribution, [Lucas and Sargent \(1979\)](#) make the following remark about general equilibrium macroeconomic models:

It has been only a matter of analytical convenience and not of necessity that equilibrium models have used the assumption of stochastically stationary shocks and the assumption that agents have already learned the probability distributions they face. Both of these assumptions can be abandoned, albeit at a cost in terms of the simplicity of the model.

This paper shows that learning about the probability distributions of future income shocks was an important driver of the European debt crisis. It impacted not only the movements in asset prices, but also the real variables such as government debt. I show that an otherwise standard quantitative model of sovereign debt can be augmented to incorporate this learning process and match the markets' gradually evolving beliefs over time. As a result, we obtain a delayed pattern of bond spread increases during the Great Recession in Europe.

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