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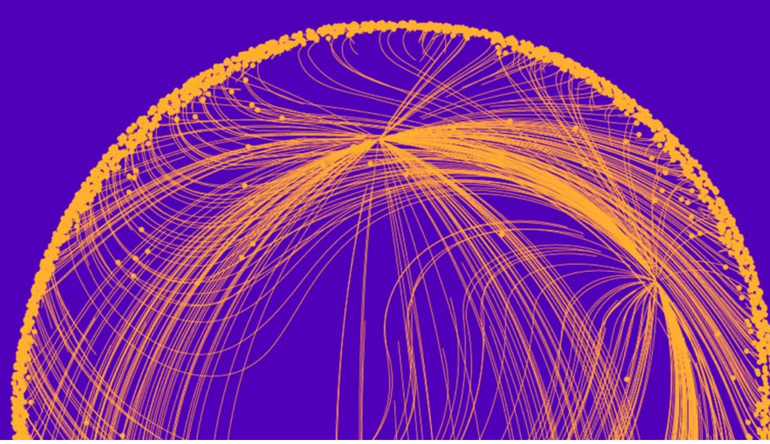

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Sovereign Risk under Diagnostic Expectations *

Stefan Niemann[†] Timm M. Prein[‡]

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Abstract

This paper studies the effects of overreaction to recent news for macroeconomic outcomes in the context of a quantitative model of sovereign debt and default. Overreaction is formalized in terms of diagnostic expectations that excessively extrapolate from current conditions. Examining historical IMF growth forecasts, we find empirical evidence for this behavior and incorporate it into an otherwise standard model of long-term sovereign debt. The model successfully matches salient business cycle statistics, including the distribution of sovereign spreads, and also predicts an empirically plausible default frequency. Counterfactual experiments indicate that diagnostic expectations induce sizeable welfare losses, the bulk of which could be eliminated under rational behavior of the sovereign borrower. This motivates our analysis of fiscal rules in the form of debt or spread limits, which need to trade-off their beneficial effects via reduced debt dilution against the fact that they condition on aggregates that may be subject to market sentiment.

Keywords: sovereign debt; diagnostic expectations; fiscal rules

JEL-Codes: E44, E62, F34, H63

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1 Introduction

The magnitude and volatility of sovereign spreads, in particular for debt issued by less developed countries, constitute an important regularity characterizing international financial markets. Indeed, the cost at which sovereigns can borrow in international markets varies greatly across time and space. But the weak connection between government bond yields and economic fundamentals poses a challenge for our understanding of their joint dynamics (cf. e.g. Aguiar et al., 2016). While much of the heterogeneity in spreads is driven by variation in fundamentals, a substantial part thus appears to be driven by the sentiment surrounding a country and expectations regarding its future.

Accordingly, countries sometimes benefit from borrowing conditions that appear very favorable when assessed with regard to their underlying fundamentals. Such (overly) favorable borrowing conditions can occur, for example, when investors hold (unduly) optimistic expectations about the country's future, a sentiment that is often shared also by the country's government. To the extent that this situation leads to increased borrowing, however, the fallout from such seemingly advantageous episodes is that countries accumulate debt positions that leave them vulnerable to crises. In particular, countries are more prone to debt crises when the initially optimistic outlook is disappointed and the positive sentiment surrounding the country turns sour.[1] On the other hand, pessimistic expectations can lead to concerns about debt sustainability and elevated spreads, which force deleveraging through costly fiscal adjustments.

In this paper, we examine the implications of sentiment-driven overreaction for macroeconomic outcomes in the context of a quantitative model of sovereign debt and default. Specifically, we consider an endowment model for a small open economy with credit market enforcement frictions to study the dynamics of sovereign debt and spreads. We formalize the empirically observed pattern of sentiment-driven spread dynamics in terms of the concept of *diagnostic expectations* (Bordalo et al., 2018). Accordingly, expectations held by market participants are not fully rational, but instead tend to extrapolate from recent, salient news. An attractive feature of diagnostic expectations is that the relevance of this extrapolation mechanism can be captured by a single parameter, γ, which can be estimated from empirical data.[2] Positive values of γ then imply that, in good times, expectations become overly optimistic, which is reflected in benign borrowing conditions at low interest rates. Subsequently, however, reality fails to live up to these optimistic expectations. Their systematic disappointment thus leads to widening spreads, consistent with the evidence discussed above.

When diagnostic expectations are at work in our otherwise standard model along the lines of

[1] Al-Amine and Willems (2022) provide a more detailed account of anecdotes along these lines, pointing, among others, to the course of events during debt crises in Argentina, Mozambique, Russia and Southern Europe.

[2] See Section 2 where we examine country-level growth forecasts published in the IMF's World Economic Outlook (WEO).

Chatterjee and Eyigungor (2012), we can compare the implications of the diagnostic mechanism to those from an alternative economy under rational expectations. We calibrate both models to data from Argentina and find that they are able to match important features of the empirically observed macroeconomic fluctuations. In particular, both models are able to rationalize sizeable debt positions along with large and volatile spreads. A key difference, however, is that the diagnostic model matches these targets at a more plausible default frequency of about 2.5% per year (relative to more than 6% in the rational model). The lower default frequency arises because debt positions that are perceived as relatively safe in the rational model are considered as more risky under diagnostic expectations such that bond prices are globally (except for very high debt positions) depressed relative to their rational counterpart. However, since spreads also display a reduced dependence on the level of debt, the sovereign borrower is actually willing to trade into the risky region so that the average level of debt is similar in both models.

We next use the model to explore alternative settings where diagnostic expectations are counterfactually shut down or alternatively only relevant on one side of the credit market, whereas expectations for the other side are formed rationally. When we remove diagnostic expectations on both market sides, the model predicts spreads with both a lower average level and a lower volatility. However, since the government accumulates higher debt positions, the probability of default actually increases. Nevertheless, the removal of diagnostic expectations aligns equilibrium spreads with fundamentals and thus promises sizeable welfare gains equivalent to 0.65% of average consumption.

When only the sovereign borrower forms diagnostic expectations while creditors are pricing default risk rationally, bond prices are affected by current news no longer directly through creditor sentiment but only indirectly through expectations about the borrower's behavior. As the borrower's debt issuance and default policy remains crucially affected by diagnostic expectations, the bond pricing menu offered by creditors thus inherits important properties – depressed bond prices with weakened dependence on the level of debt – from the fully diagnostic setting. However, the disciplining effect of a diagnostic credit supply disappears such that sovereign defaults occur more frequently. In consequence, eliminating sentiment-driven mispricing of debt in the presence of sustained diagnostic borrowing behavior fails to deliver welfare gains relative to the fully diagnostic baseline model.

Turning to the reverse setting in which the borrower holds rational expectations while creditors are diagnostic, the welfare gains relative to the fully diagnostic baseline model are more substantial, amounting to over 80% of the welfare gains realized under fully rational expectations. The reason is that, conditional on the bond price menu offered by its creditors, the government's debt and default policy are now rational. This allows sustaining higher debt positions at lower spreads. Indeed, the rational borrower's response to bond prices set under the creditors' diagnostic sentiment is so prudent that default risk is almost eliminated.

The fact that the welfare gains relative to the fully diagnostic baseline model predominantly stem from the removal of diagnostic behavior on the borrower side motivates our analysis of fiscal rules constraining the sovereign debtor's choice set. Such 'long-lasting constraint(s) on fiscal policy through numerical limits on budgetary aggregates' (Davoodi et al., 2022, p. 5) are often advocated to contain overborrowing and specifically the debt dilution problem when countries issue long-term debt. Following Hatchondo et al. (2022a), we contrast spread-brake and debt-brake rules and reexamine their performance under diagnostic expectations. This setting gives rise to a trade-off because the familiar benefits from mitigated debt dilution now come at the cost of tying regulation to aggregates (debt levels or spreads, respectively) that might themselves be distorted by market sentiment. Owing to their state-dependent implications for admissible borrowing, this trade-off is particularly relevant for spread-brake rules. Indeed, we find important consequences for the performance and optimal design of fiscal rules: Since the debt dilution problem is accentuated under diagnostic government behavior, the optimal debt-brake rule is significantly tighter than under rational expectations, with a difference in the limit for the debt to output ratio of about 10 to 15 percentage points. By contrast, the optimal spread-brake rule under diagnostic expectations becomes more lenient as it needs to accommodate fluctuations in spreads that are not justified by fundamentals; the driving force behind this effect now lies not on the side of the government but in the way creditors are pricing sovereign debt. For both types of fiscal rules, the maximum welfare gains under the rule are highest when this mispricing is absent. Irrespective of how market participants form expectations, the state-contingency inherent in the spread-brake rule implies that it performs better than the debt-brake rule, and it also offers robustness when its numerical value is not optimally set. Despite these attainable welfare gains, both types of rules need to be enforced with small exit penalties.

Related literature. Our work builds on the large quantitative literature on sovereign debt and default that started with the seminal contributions of Eaton and Gersovitz (1981), Aguiar and Gopinath (2006) and Arellano (2008) and that is excellently surveyed e.g. in Aguiar and Amador (2014), Aguiar et al. (2016), D'Erasmo et al. (2016) and Martinez et al. (2023). Our model specification with long-term debt largely follows Chatterjee and Eyigungor (2012). We introduce diagnostic expectations into this environment, which connects our work to Bordalo et al. (2021) who consider a business cycle model with heterogeneous firms and risky debt.[3] We complement and extend their findings in several directions. First, we provide new evidence supporting the empirical relevance of diagnostic features inherent in the forecasts published in the IMF World Economic Outlook (WEO). Second, we study the quantitative role and welfare effects of diagnostic expectations in a sovereign debt setting. Finally, we use this framework to examine (i) asymmetric configurations for diagnostic versus rational expectations held by creditors and their sovereign borrower, respectively; and (ii) the implications of diagnostic expectations for the performance of fiscal rules.

[3] A similar model of credit markets with diagnostic expectations can be found in Bordalo et al. (2018); Bordalo et al. (2022) provide a non-technical survey of the relevance of overreaction, and specifically diagnostic expectations, in macroeconomics.

By considering an empirically plausible framework for the formation of expectations and the determination of sovereign spreads, our findings also advance the literature on sovereign debt and default. A key observation here is the relatively weak connection between sovereign spreads and fundamentals, including the observed frequency of default, that can be rationalized under diagnostic expectations. With a similar motivation, recent quantitative work has considered the effects of news (Durdu et al., 2013; Dvorkin et al., 2020), uncertainty premia (Pouzo and Presno, 2016; Roch and Roldán, 2023) and learning (Paluszynski, 2023). Interesting parallels exist in particular with the ambiguity approach in Pouzo and Presno (2016) where uncertainty premia arise due to lender concerns about model misspecification. Like ours, their model thus generates elevated, volatile and countercyclical spreads, while keeping the default frequency at an empirically more plausible level – different to e.g. Chatterjee and Eyigungor (2012). However, our diagnostic expectations approach offers remarkable tractability and is based only on a single parameter that can be disciplined empirically: The systematic overreaction to news caused by diagnostic expectations implies predictable forecast errors, a fact we document based on the IMF's World Economic Outlook (WEO).[4] The tractability of the diagnostic expectations mechanism also allows us to consider model variants in which they appear only on one side of the credit market, while the other side holds rational expectations.[5] This is particularly relevant for disentangling the welfare gains associated with switching expectations from diagnostic to rational. Our finding that the borrower side is most important for realizing such welfare gains motivates our detailed analysis of fiscal rules, similar to Alfaro and Kanczuk (2017), Grosse-Steffen et al. (2021) and particularly Hatchondo et al. (2022a,b). Unlike these papers, we assess the optimality of fiscal rules that are linked to distorted fundamentals.

The rest of this paper is organized as follows. Section 2 first provides further background on the concept of diagnostic expectations, which then informs the following analysis of cross-country panel data to assess the relevance of diagnostic extrapolation in IMF growth forecasts. Building on this evidence, Section 3 then sets up our quantitative model. Section 4 details the calibration to quarterly data from Argentina and analyzes the quantitative effects of diagnostic expectations and their interaction with fiscal rules in this setting. Finally, Section 5 concludes.

2 Empirical Evidence

Diagnostic expectations. The concept of diagnostic expectations is founded in the psychology of selective recall and provides a foundation for the overreaction of expectations in financial markets (and elsewhere). The broad idea behind it is as follows. If, relative to previous expectations, some news makes a particular future outcome more likely, then the salience of the news works to

[4]Pouzo and Presno (2016) calibrate their robustness parameter in order to match the historical default frequency. Instead, we leave the default frequency untargeted and achieve close matching based on our externally estimated diagnosticity parameter.

[5]By contrast, Pouzo and Presno (2016) allow uncertainty aversion only on the lender side.

further inflate the perceived likelihood of this outcome beyond the corresponding rational expectation. For example, good news about current output do not only (by virtue of its persistence) increase the objective likelihood of high future output, but also cause (by virtue of selective recall) such outcomes to be overweighted in beliefs.

Formally, for some random variable y_{t+1},

$$\mathbb{E}_t^{\gamma}(y_{t+1}) = \mathbb{E}_t(y_{t+1}) + \gamma \left[\mathbb{E}_t(y_{t+1}) - \mathbb{E}_{t-1}(y_{t+1})\right],$$

where $\mathbb{E}_t(y_{t+1})$ and $\mathbb{E}_t^{\gamma}(y_{t+1})$ denote, respectively, the rational expectation and the diagnostic expectation held at time t, and where the parameter γ captures the degree of diagnosticity in expectations formation. Thus, when $\gamma > 0$, expectations systematically overreact to news as the diagnostic expectation exceeds the rational one by an extra term given by the (rational) forecast revision in the light of these news muliplied by γ. Beliefs are therefore too optimistic in good times and too pessimistic in bad times (Bordalo et al., 2020).

This overreaction gives rise to forecast errors that can be systematically predicted. To see this, notice that

$$\begin{aligned}\mathbb{E}_t\left\{y_{t+1} - \mathbb{E}_t^{\gamma}(y_{t+1})\right\} &= \mathbb{E}_t\left\{y_{t+1} - \mathbb{E}_t(y_{t+1})\right\} - \mathbb{E}_t\left\{\gamma\left[\mathbb{E}_t(y_{t+1}) - \mathbb{E}_{t-1}(y_{t+1})\right]\right\} \\ &= -\gamma\mathbb{E}_t\left\{\left[\mathbb{E}_t(y_{t+1}) - \mathbb{E}_{t-1}(y_{t+1})\right]\right\}.\end{aligned}$$

Accordingly, when good news today induce an upward revision of the rational forecast of the future y_{t+1}, then the overreaction of the diagnostic forecast implies that the expected forecast error tomorrow, $\mathbb{E}_t\left\{y_{t+1} - \mathbb{E}_t^{\gamma}(y_{t+1})\right\}$, is negative. This predictability of forecast errors can be examined empirically and allows to estimate the parameter γ from survey data on expectations held by market participants.

Before we do that, it is useful to illustrate the potential of diagnostic expectations about output dynamics to fundamentally alter the dynamic behavior of spreads. To that end, consider a simple partial equilibrium setting where defaultable one-period debt is priced by risk-neutral, deep-pocket investors with a unitary required rate of return.[6] The borrower seeks to roll over a fixed amount of debt and faces an $AR(1)$ endowment process, $\ln y_t = \rho \ln y_{t-1} + \epsilon_t$. Default is triggered by a sufficiently bad endowment draw for the borrower, $y_t < y^*$, where y^* is a given default threshold. For this environment, Bordalo et al. (2018) show that spreads can be approximated as

$$s_t \approx (1-\rho)s_\infty + \rho s_{t-1} - s\rho(1+\gamma)\epsilon_t + s\gamma\rho^2\epsilon_{t-1},$$

where $s_\infty > 0$ is the long-run spread and $s > 0$ is the absolute value of the slope coefficient in the (linear) relationship between spreads and expectations about future output. Under rational expectations ($\gamma = 0$), the behavior of spreads mirrors endowments and follows an $AR(1)$ process with persistence ρ; in case of a positive endowment shock $\epsilon_t > 0$, spreads drop and then display

[6] Relative to our quantitative general equilibrium model in Section 3, the borrower's debt and default policy remain exogenous here, and debt only has a one-period maturity.

mean-reversion. Instead, under diagnostic expectations ($\gamma > 0$), the effect of the endowment shock is first amplified (as investor beliefs become too optimistic, see the term in ϵ_t), followed by a subsequent reversal (as optimism wanes, see the term in ϵ_{t-1}). Spreads thus display excess volatility and contain an inherent pattern of boom-bust dynamics. The strength of these effects is regulated by the diagnosticity parameter γ.

Data and estimation strategy. To gauge the empirical relevance of diagnostic expectation formation at the country level, we examine data covering the period 1990-2020 from the IMF's World Economic Outlook (WEO). The data is obtained from the Historical WEO Forecasts Database (October 2022 release)[7] and described in Celasun et al. (2021). In April (spring) and October (fall) of each year, the WEO reports forecasts for the economic performance (real GDP growth, CPI inflation and current account balance) of IMF member countries. In each round, WEO forecasts are reported for the current year t as well as for each of the next five years $t+h$, $h = 1, ..., 5$. The corresponding realized variables are published as well, as 'first-vintage' data compiled in year $t + 1$ and as 'final-release' data compiled in year $t + 2$.

Based on this structure, we can compute forecast errors at horizon $h = 0, ..., 5$ relating to the first-vintage and final-release outcomes, respectively. Moreover, as there are two forecast rounds within a year, we are able to capture current news in terms of the forecast revision between the respective spring and the fall forecast.

Our empirical exercise focuses on GDP growth. That is, we do not directly look at sovereign spreads, but instead examine the role of sentiment regarding countries' growth prospects, which, in turn, should affect spreads as described above. We are interested in the degree of overreaction in forecasts to current news. If there is overreaction to current news beyond what is warranted by rational expectations, then positive (negative) news today should lead to excessively optimistic (pessimistic) expectations which are then systematically disappointed (outperformed) in the future. In line with our theoretical model, we are particularly interested in the dynamics of the expectations process at short horizons, that is, from one year to the next. However, current-year ($h = 0$) spring and fall forecasts differ from the forecasts with longer horizons since economic outcomes for part of the year targeted by these forecasts are already observed at the time the forecast is produced. Hence, current year forecasts, and particularly those reported in the fall, are really a hybrid of a nowcast and a more traditional forecast.

For this reason, and because we are mainly interested in short-run expectations, we examine the effects of news occurring in year t on forecasts and the associated forecast errors with a horizon $h = 1$. Let $g_{i,t} = ln(y_{i,t}) - ln(y_{i,t-1})$ denote real GDP growth in country i in year t, and let the fundamental dynamics for GDP growth be given by an AR(1)-process,

$$g_{i,t} = \rho \, g_{i,t-1} + \epsilon_{i,t}, \tag{1}$$

where $\rho \in (0, 1)$ is the autocorrelation and $\epsilon_{i,t}$ is an iid shock. The end-of-period (fall) diagnostic

[7] See https://www.imf.org/en/Publications/WEO/weo-database/2022/October.

forecast under current news $\epsilon_{i,t}$ then is

$$E_t^{\gamma}\{g_{i,t+1}\} = \rho\, g_{i,t} + \gamma\rho\epsilon_{i,t}, \tag{2}$$

where γ captures the degree of diagnosticity inherent in expectations formation. Appendix A.1 shows that the within-period (spring to fall) revision in light of current information flows can be written as

$$\Delta E_t^{\gamma}\{g_{i,t+1}\} = (1+\gamma)\rho\Delta_{sf}\epsilon_{i,t}, \tag{3}$$

where $\Delta_{sf}\epsilon_{i,t} = \epsilon_{i,t}^{f} - \epsilon_{i,t}^{s}$ denotes the current news. Accordingly, current news manifest themselves in the forecast revision with a weight $(1+\gamma)\rho$, which reflects (i) the direct effect via measured GDP growth $g_{i,t}^{f}$ and (ii) the additional diagnostic effect via the measured innovation $\epsilon_{i,t}^{f}$, both of which propagate over time with persistence ρ. Finally, the forecast error based on the expectation formed in the fall round of year t and recorded in year $t+1$ is given by

$$fe_{i,t+1} = g_{i,t+1} - E_t^{\gamma}\{g_{i,t+1}\} = \epsilon_{i,t+1} - \gamma\rho\epsilon_{i,t}. \tag{4}$$

Notice how this expression exactly corresponds to the intuition that good (bad) news in year t lead to a forecast revision based on inflated (deflated) expectations for year $t+1$, which are then disappointed (outperformed). Since this happens systematically, forecast errors should thus be predictable by forecast revisions occurring in the previous year. We test this hypothesis for our WEO sample based on the following specification,

$$fe_{i,t} = \alpha_i + \beta_t + \theta\Delta E_{t-1}^{\gamma}\{g_{i,t}\} + \varepsilon_{i,t}, \tag{5}$$

where α_i and β_t are country and year fixed effects, and where the coefficient θ captures the extent to which forecast errors are predictable. Under rational expectations ($\gamma = 0$), we have $\theta = 0$; under diagnostic expectations ($\gamma > 0$) with overreaction to current news, we instead expect $\theta < 0$.

Finally, our strategy for uncovering the diagnosticity parameter γ from the regression (5) of time t forecast errors on the diagnostic forecast revision at time $t-1$ follows ideas from Bordalo et al. (2018). The OLS estimate for θ from this regression is given by

$$\hat{\theta} = \frac{Cov(fe_{i,t+1}, \Delta E_t^{\gamma}\{g_{i,t+1}\})}{Var(\Delta E_t^{\gamma}\{g_{i,t+1}\})}. \tag{6}$$

When diagnostic forecasts and the implied forecast errors are constructed from data from the fall round of the respective WEO reports, it naturally follows that the error term in equation (4) is given by $\epsilon_{i,t} = \epsilon_{i,t}^{f}$. Assuming that spring and fall innovations ($\epsilon_{i,t}^{s}$, $\epsilon_{i,t}^{f}$) have the same variance σ_ϵ^2 and display a within-year correlation of ρ_{sf} but no correlation over time, Appendix A.1 shows that the regression coefficient in (6) becomes

$$\hat{\theta} = -\frac{\gamma}{2(1+\gamma)}.$$

Solving for γ, we thus get an empirical estimate for the degree of diagnosticity,

$$\gamma = -\frac{2\hat{\theta}}{1+2\hat{\theta}}. \tag{7}$$

Results. Table 1 reports OLS estimates from regression (5) applied to the complete panel of 194 countries covered in the WEO. Our baseline specification, which computes the forecast error $fe_{i,t}$ from first-vintage data and estimates equation (5) without further controls besides the country and year fixed effects, is presented in column (1). As seen, a forecast revision in the preceding year is estimated with a significant negative coefficient of $\hat{\theta} = -0.075$. From (7), this corresponds to a degree of diagnosticity of $\gamma = 0.18$. In order to account for output growth dynamics not appropriately captured by the assumed AR(1)-process in (1), column (2) further controls for past output growth and arrives at a forecast revision effect of -0.100, implying an even higher degree of diagnosticity of $\gamma = 0.25$. Columns (3) and (4) repeat the same exercise when the forecast error $fe_{i,t}^{fin}$ is computed from final-release data instead. The resulting coefficient of interest is significant in all specifications and remains fairly unaffected in magnitude. In sum, the WEO panel therefore indicates that a mild, but statistically significant degree of diagnosticity is inherent in the forecasting process.

Table 1: Regression Results WEO Panel

	Dependent variable: forecast error			
	first-vintage, $fe_{i,t}$		final-release, $fe_{i,t}^{fin}$	
	(1)	(2)	(3)	(4)
$\Delta E_{t-1}^{\gamma}\{g_{i,t}\}$	-0.075482^{***}	-0.100399^{***}	-0.066635^{***}	-0.099359^{***}
	(-4.808904)	(-6.224504)	(-3.487318)	(-5.063413)
$g_{i,t-1}$		0.049122^{***}		0.064511^{***}
		(6.300620)		(6.801220)
R^2	0.083410	0.090462	0.074819	0.083106
countries	194	194	194	194
observations	5345	5345	5345	5345

Notes: The table reports OLS estimates from regression (5) at yearly frequency. Country and year fixed effects imposed in all specifications, t-statistics in parentheses. *** denotes significance at the 1% level.

Table 2 complements the analysis from the complete WEO sample by looking at a more focused panel of ten Latin American countries as well as an individual country, Argentina. We report the estimates for the effect of the forecast revision $\Delta E_{t-1}^{\gamma}\{g_{i,t}\}$ on the subsequent forecast error $fe_{i,t}$ (columns (1) and (3)) or $fe_{i,t}^{fin}$ (columns (2) and (4)), respectively. For the panel of Latin

American countries, the coefficient of interest is estimated at $\hat{\theta} = -0.176$ for the first-vintage effect and $\hat{\theta} = -0.150$ for the final-release effect; both estimates are significant at the 5% level. Relative to the results reported in Table 1, these estimates indicate an increased degree of extrapolation in the forecasting process with an implied degree of diagnosticity in the range of $\gamma \approx 0.5$.[8] For Argentina, estimation of equation (5) can rely only on 30 observations. The coefficient of interest is thus estimated only imprecisely, with $\hat{\theta} = -0.201$ for the first-vintage effect and $\hat{\theta} = -0.265$ for the final-release effect. Looking at our preferred specification reported in column (3), the estimate now corresponds to a diagnosticity parameter of $\gamma = 0.67$. Acknowledging the lack of precision due to the small sample size, this implied degree of diagnosticity for Argentina will be used to inform the parameterization of our quantitative model.

Table 2: Regression Results LAC Panel and Argentina

	Dependent variable: forecast error			
	LAC panel		Argentina	
	first-vintage, $fe_{i,t}$	final-release, $fe_{i,t}^{fin}$	first-vintage, $fe_{i,t}$	final-release, $fe_{i,t}^{fin}$
	(1)	(2)	(3)	(4)
$\Delta E_{t-1}^{\gamma}\left\{g_{i,t}\right\}$	-0.176305^{**}	-0.150343^{**}	-0.201268	-0.264978
	(-2.424928)	(-2.050303)	(-1.147158)	(-1.414288)
R^2	0.251366	0.280780	0.044889	0.066673
countries	10	10	1	1
observations	300	300	30	30

Notes: The table reports OLS estimates from regression (5) at yearly frequency. Country and year fixed effects included for the LAC panel, constant included for Argentina, t-statistics in parentheses. ** denotes significance at the 5% level. The LAC panel consists of the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Paraguay and Uruguay.

Remark. We conclude this Section with a brief comment. To begin, our preferred interpretation of the WEO forecasts is in terms of an individual forecast rather than a consensus forecast. As such, our results are consistent with the general pattern found in the literature, namely overreaction of expectations at the individual level, but underreaction at the aggregate/consensus level (Coibion and Gorodnichenko, 2012, 2015; Bordalo et al., 2020).[9] That said, it is reasonable to

[8]From (7), the precise results are $\gamma = 0.54$ and $\gamma = 0.43$, respectively.

[9]Bordalo et al. (2020) show that this seemingly conflicting evidence can be reconciled within a dispersed information framework of learning from noisy private signals where individual forecasters hold diagnostic expectations. Intuitively, when $\gamma > 0$, each individual forecaster overreacts to their noisy private signal, but does not react at all to the (unobserved) signals received by other forecasters; this effect can generate rigidity in the consensus forecast provided diagnosticity is not too pronounced relative to the dispersion of private signals.

think of the WEO forecasts as based on at least some aggregation of information (e.g. across individual IMF Departments), which may also explain why our estimates of γ appear moderate relative to other studies, which exploit survey data containing a panel of individual forecasters; most estimates from such studies locate γ in the range between 0.5 and 1.5 (cf. Bordalo et al., 2022).

3 The Model

3.1 The environment

We introduce diagnostic expectations à la Bordalo et al. (2021) in an otherwise standard quantitative model of sovereign debt. We consider a representative agent small open economy that receives a stochastic stream of endowments. A benevolent government has access to credit from a large number of risk-neutral international competitive lenders. External government debt has long maturities, matures probabilistically as in Chatterjee and Eyigungor (2012), and is subject to default risk. In our baseline model, we assume that all agents form their expectations diagnostically.

Preferences and Endowments. Let the representative household's preferences in terms of expected utility be given as

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

where c_t denotes consumption at time t. The per-period utility function $u : \mathcal{R}_+ \to \mathcal{R}$ is continuous, strictly increasing in c, concave, twice differentiable, and satisfies the Inada conditions. The discount factor $\beta \in (0, 1)$ is common to all individuals in the economy.

In each period, the economy receives a stochastic endowment of the tradable good y_t, following an AR(1) process,

$$ln(y_t) = \rho ln(y_{t-1}) + \varepsilon_t,$$

where $|\rho| < 1$, and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

Government. The benevolent government maximizes the representative agent's life-time utility. The government has access to incomplete international financial markets, where it can issue long-duration bonds. Following Chatterjee and Eyigungor (2012), a bond matures with probability δ or pays a fixed coupon, ψ. In each period, the government can decide to default on its outstanding debt obligations, b_t. If the government decides to repay its debt, it chooses a new debt level b_{t+1}, such that consumption will be

$$c_t = y_t + (\delta + (1-\delta)\psi)b_t - q(b_{t+1}, y_t, \varepsilon_t)(b_{t+1} - (1-\delta)b_t),$$

where $q(\cdot)$ denotes the bond price.

If the government decides to default, it will temporarily be excluded from international financial markets and suffer an exogenous output cost. Then, consumption in period t is given by

$$c_t = y_t - \phi(y_t),$$

where $\phi(y_t)$ denotes the output cost of default.

International creditors. External credit is provided by a continuum of identical infinitely-lived international creditors. International creditors have perfect information about the state of the economy, are risk-neutral, and can borrow from international markets at the constant risk-free interest rate r. They demand a risk premium as compensation for the risk of the government choosing to default.

Diagnostic expectations. In our baseline specification, agents on both sides of the credit market form their expectations diagnostically, implying overreaction to news. Agents hence overestimate the probability of future endowment realizations whose likelihood has increased in response to an endowment shock. Following Bordalo et al. (2021), expectations take the following form,

$$E(ln\ y') = \rho ln(y) + \gamma\rho\varepsilon, \tag{8}$$

where γ denotes the strength of overreaction to news. If the endowment shock is positive, $\varepsilon > 0$, agents with diagnostic expectations are too optimistic. Similarly, agents are too pessimistic if a bad endowment shock, $\varepsilon < 0$, occurs. Expectations are rational if $\gamma = 0$.

Timing. The timing is as follows. At the beginning of a period t, the innovation ε_t and thus the endowment y_t realize. All agents observe y_t and ε_t and form diagnostic expectations about future endowment realizations. Given a good credit standing, the government chooses its optimal debt policy. In case of a bad credit standing, at the end of the period, the government draws a random number to determine whether it will regain access to international financial markets in the next period.

3.2 Recursive equilibrium

Government. Given a good credit standing, the government decides whether to repay its debt or to default,

$$V^\gamma(b, y, \varepsilon) = \max\left\{V_R^\gamma(b, y, \varepsilon), V_D^\gamma(y, \varepsilon)\right\}, \tag{9}$$

where $V_R^\gamma(b, y, \varepsilon)$ and $V_D^\gamma(y, \varepsilon)$ are the value functions associated with repayment and default, respectively. The supercript γ signals that expectations within the value function operator are diagnostic.

The value function in case of debt repayment solves

$$V_R^\gamma(b,y,\varepsilon) = \max_{b'} \left\{ u(c) + \beta \int_{y'} V^\gamma(b',y',\varepsilon')\mu(y',y,\varepsilon)dy' \right\} \tag{10}$$

subject to

$$c = y + (\delta + (1-\delta)\psi)b - q(b',y,\varepsilon)(b' - (1-\delta)b)$$

In case of a default, the government does not repay its outstanding external debt obligations b. The economy suffers an output loss, $\phi(y_t)$, and is temporarily excluded from international financial markets. The value function associated with default is given by

$$V_D^\gamma(y,\varepsilon) = u(y_t - \phi(y_t)) + \beta \int_{y'} (1-\theta)V_D^\gamma(y',\varepsilon') + \theta V^\gamma(0,y',\varepsilon')\mu(y',y,\varepsilon)dy', \tag{11}$$

where $\theta \in [0,1]$ denotes the exogenous probability of re-entering international financial markets. The following indicator function describes the default decision of the government,

$$d(b,y,\varepsilon) = \begin{cases} 1 & \text{if } V_R^\gamma(b,y,\varepsilon) < V_D^\gamma(y,\varepsilon) \\ 0 & \text{else.} \end{cases}$$

The set of endowments $y \in \mathcal{Y}$ for which the government defaults is given by

$$\mathcal{D}(b,\varepsilon) = \{y \in \mathcal{Y} : d(b,y,\varepsilon) = 1\}. \tag{12}$$

The perceived default probability follows as

$$\eta(b',y,\varepsilon) = \int_{\mathcal{D}(b',\varepsilon')} \mu(y',y,\varepsilon)dy'. \tag{13}$$

Relative to the probability of default under rational expectations, this expression shows two modifications: First, the current endowment shock ε leads to a distortion of beliefs about future endowments y' as captured by the probability measure $\mu(y',y,\varepsilon)$. And second, the future default set $\mathcal{D}(b',\varepsilon')$ depends on the future endowment shock ε'.

Bond pricing. There is a large number of identical infinitely-lived international creditors. They are risk-neutral and internalize the risk of a default. Following from the zero-profit condition, the bond price function is given by

$$q^\gamma(b',y,\varepsilon) = \frac{1}{1+r} \int_{y'} (1 - d(b',y',\varepsilon'))(\delta + (1-\delta)(\psi + q^\gamma(b'',y''\varepsilon')\mu(y',y,\varepsilon)dy' \tag{14}$$

3.3 Equilibrium definition

The recursive equilibrium for the small open economy is defined as

1. a set of policy functions for borrowing $b'(b,y,\varepsilon)$,

2. a default set $\mathcal{D}(b, \varepsilon)$,

3. the bond price function charged by international private creditors, $q^{\gamma}(b', y, \varepsilon)$,

4. a set of value functions $V^{\gamma}(b, y, \varepsilon)$, $V_R^{\gamma}(b, y, \varepsilon)$, $V_D^{\gamma}(y, \varepsilon)$,

such that:

1. Taking as given the bond price functions $q^{\gamma}(b', y, \varepsilon)$, the government's value functions $V^{\gamma}(b, y, \varepsilon)$, $V_R^{\gamma}(b, y, \varepsilon)$, $V_D^{\gamma}(y, \varepsilon)$, the default set $\mathcal{D}(b, \varepsilon)$, the policy function $b'(b, y, \varepsilon)$, solve (9), (10), (11), and (12).

2. Bond prices $q^{\gamma}(b', y, \varepsilon)$ fulfill equation (14), such that risk-neutral international private creditors earn zero expected profits.

4 Quantitative Analysis

4.1 Calibration

In our quantitative analysis, we apply the model at quarterly frequency to Argentina. We mostly refer to the parameter choices of Chatterjee and Eyigungor (2012) and focus on the time period between 1993:I and 2001:IV. The representative agent's preferences are expressed by the following CRRA utility function,

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma},$$

where we set the risk aversion coefficient σ to 2 as it is standard in the literature. Following Chatterjee and Eyigungor (2012), we set the probability of regaining access to international financial markets, θ, to 3.85%, equivalent to an average of 6.5 years of exclusion. The probability that a bond matures, δ, is set to 5% and the coupon rate is 3%. The risk-free rate, r, equals 1%.

The endowment follows an AR(1) process,

$$ln(y') = \rho ln(y) + \varepsilon.$$

We borrow the parameter values for the autocorrelation, $\rho = 0.930139$, and the volatility, $\sigma_{\varepsilon} = 0.027209$ from Chatterjee and Eyigungor (2012) who use Argentinean linearly detrended quarterly real GDP data for the time 1980:I-2001:IV.[10]

For the parameter γ in the specification of diagnostic expectations,

$$E(ln\ y') = \rho ln(y) + \gamma\rho\varepsilon,$$

we refer to our own analysis from Section 2. For Argentina, we find a value of 0.67.

[10]We refer to the parameter estimates in the absence of transitory shocks.

We use the specification of output costs as in Chatterjee and Eyigungor (2012),

$$\phi(y) = \max\{\xi_0 y + \xi_1 y^2, 0\},$$

where $\xi_1 \geq 0$.

Finally, we internally set the output cost parameters, ξ_0 and ξ_1, and the discount factor, β, such that we match the mean debt-to-output ratio (quarterly rate) of 70%, and a mean and standard deviation of the spread of 8.15 percent and 4.43 percent, where we also refer to the target values used in Chatterjee and Eyigungor (2012). We solve the model using value function iteration. The algorithm is described in Appendix A.2. Table 3 shows that both our baseline diagnostic model as well as a recalibrated version of the model with rational expectations ($\gamma = 0$) match the targeted statistics very well. Notably, however, the diagnostic model achieves this with less impatience on the side of the sovereign borrower and a more moderate parameterization for the output costs of default: $\phi(y)$ is zero over a wider domain and else displays less dependence on the level of output.

Table 3: Calibration

Parameter	**Description**	**Value**	
		Diagnostic	**Rational**
Externally calibrated parameters			
r	Risk-free rate	0.01	
σ	Relative risk aversion	2.0	
ρ	Autocorrelation	0.930139	
σ_ε	Standard deviation of ϵ	0.027209	
δ	Maturing Probability	0.05	
θ	Reentry probability	0.0385	
ψ	Coupon Payment	0.03	
γ	Diagnostic factor	0.67	0
Internally calibrated parameters			
β	Discount factor	0.9585	0.9535
ξ_0	Output cost (intercept)	-0.1576	−0.2636
ξ_1	Output cost (slope)	0.2211	0.3258

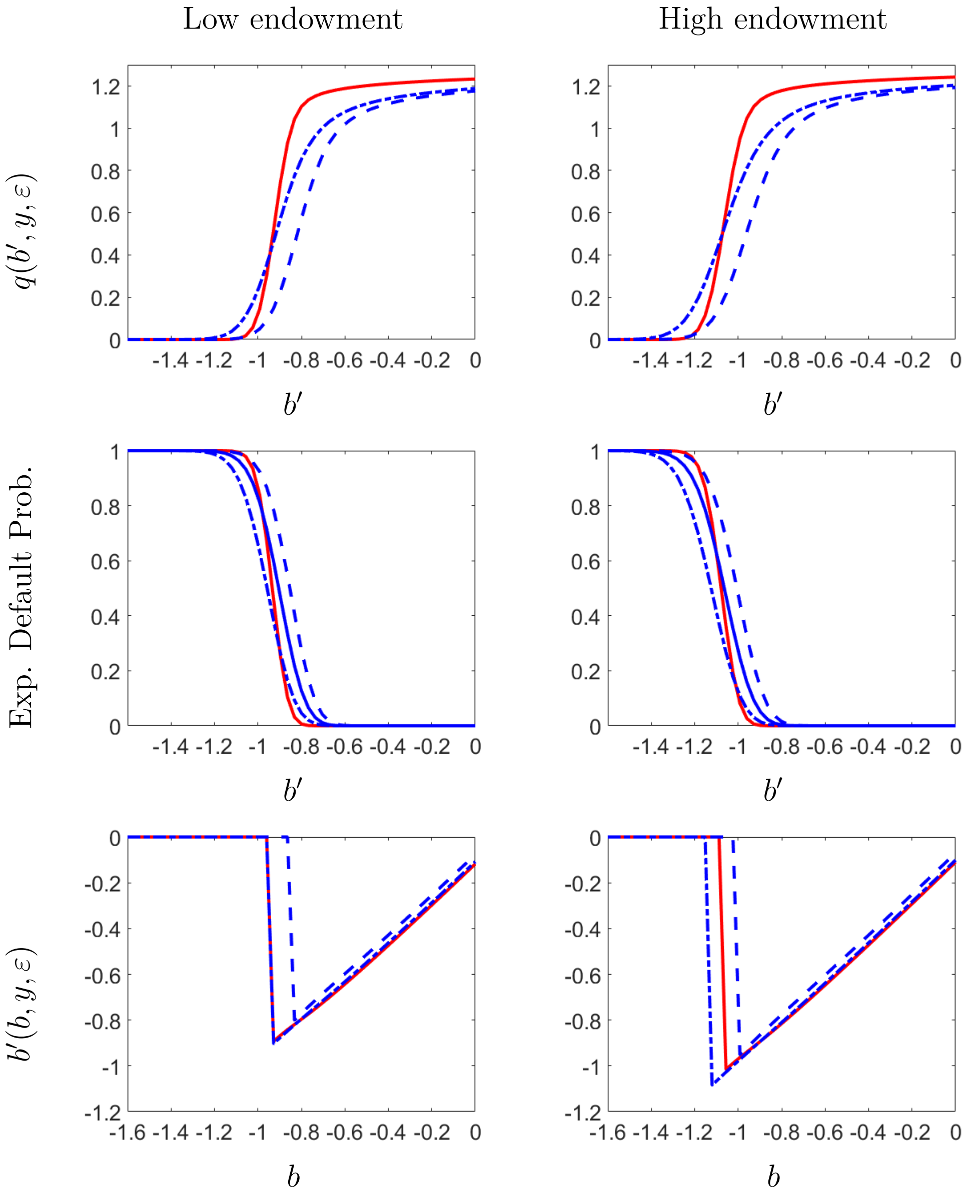
Calibration targets	**Data**	**Simulations**	
		Diagnostic	**Rational**
E (debt/GDP)	70.00	70.00	70.11
E (spread)	8.15	8.15	8.17
std (spread)	4.43	4.48	4.43

Note: Targeted moments are denoted in percentage points. Statistics are based on simulations of 500 000 quarters, where we discard the first 1 000 quarters.

4.2 Policy functions

We first study the effects of diagnostic expectations on the pricing and default risk of sovereign debt under diagnostic expectations. The blue lines in Figure 1 show the bond price functions, the expected probability of default and the borrowing decisions for low (dashed) and high (dash-dotted) realizations of the shock innovation ε of -3.6% and $+3.6\%$, respectively. The left (right) column refers to endowment realizations 3.49% below (above) the trend.

Figure 1: Policy Functions



Notes: The graphs show the bond price, the expected default probability and the debt policy. Blue lines refer to the benchmark model with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dash-dotted). Solid red lines denote the functions for a parameter variation of the diagnostic factor ($\gamma = 0$), implying rational expectation formation. For the expected default probability, solid blue lines represent expectations in the benchmark model for a realization of $\varepsilon = 0$. Low (high) endowment refers to levels of -3.49% (3.49%) around the trend.

Beginning with bond prices (top panels of Figure 1), it is evident that current news act as shifters for the bond price function $q(b', y, \varepsilon)$.[11] For the diagnostic model, there is thus a family of distinct functions, two of which are displayed in the figure, depending on whether the current realization of the shock is good ($\varepsilon = 0.036$) or bad ($\varepsilon = -0.036$). For the rational model where the degree of diagnosticity is $\gamma = 0$ for all market participants (red lines), instead, there is no such dependence. Comparison across the two alternative models[12] further reveals that diagnostic bond prices are globally (except for very high debt positions) lower than their rational counterpart.

The underlying reason becomes evident from the middle panels of Figure 1 which plot $\eta(b', y, \varepsilon)$, that is, the expected probability of default occurring in the next period as characterized in equation (13). In case of the solid lines, the perceived probability coincides with the actual default probability of the respective model (as, also in the diagnostic model, there is no distortion of beliefs when $\varepsilon = 0$). But the anticipation of market participants' potential overreaction to a bad shock in the next period, which may trigger default due to excessive pessimism, nevertheless increases the expected probability of default. Hence, a key mechanism behind the global reduction of bond prices is the expectation that *future* market sentiment makes default more likely.[13] As seen from the dashed and dash-dotted lines, this forward-looking mechanism remains relevant also under non-zero realizations of the current shock ε, which lead to additional distortions in the percieved probability measure $\mu(y', y, \varepsilon)$. In particular, even under a good current shock (dash-dotted lines), the prospect of a potential negative shock in the future is sufficiently strong to depress bond prices. This is because the considered environment with long-term debt implies a pronounced impact of debt dilution risk and increased default risk over several consecutive periods.[14]

More importantly, bond prices under diagnostic expectations also display more dependence on the level of debt in the region that was considered safe under rational expectations, but less dependence on the level of debt in the risky region where default risk matters. This has important implications for the sovereign borrower's debt policy (bottom panels of Figure 1). Comparing the diagnostic to the rational model, pessimistic sentiment following a bad shock is seen to induce a more cautious debt policy in the diagnostic model; following a good shock, however, the debt policy basically (i.e., up to the default threshold) coincides with that of the rational model. This asymmetry

[11] For reference, notice also that the risk-free bond price is $q^{rf} = (\delta + (1-\delta)\psi))/(\delta + r)$, which equals 1.3083 for our parameter choice.

[12] Recall that the parameterization across the two models is identical, except for the diagnosticity parameter γ.

[13] For extremely high debt positions, the prospect of negative future sentiment (when $\varepsilon' < 0$) has only a limited effect as the probability of default is already very close to one. Hence, the effect of positive future sentiment (when $\varepsilon' > 0$) dominates and actually leads to a lower default expectation in the diagnostic model. This also explains the positive effect on bond prices for very high debt positions seen in the top panels of Figure 1.

[14] Figure 10 in Appendix A.3 shows the bond pricing functions and the debt policy for an environment with a debt covenant along the lines of Hatchondo et al. (2016), which eliminates the debt dilution problem by compensating creditors for changes in the value of outstanding debt when new liabilities are issued. Diagnostic expectations continue to have a quantitatively relevant effect – depressed level and reduced dependence on the level of debt – on bond prices also in this setting.

implies that the rational model records higher average debt levels and ultimately also a higher probability of default (cf. Table 4 below). At the same time, however, the flatter bond pricing function under diagnostic expectations implies that the sovereign borrower is willing to accumulate debt positions that are associated with higher spreads. Moreover, the sentiment swings that are present in the diagnostic model give rise to increased spread volatility and a disconnect from fundamentals.

4.3 Business cycle statistics

Overall, the diagnostic model is successful in matching standard business cycle regularities of the Argentinean economy. Consumption is highly correlated with output but displays a higher volatility. This is the result of a similarly volatile and countercyclical trade balance, indicative of the limited scope of insurance provided through international financial markets. Sovereign spreads are also countercyclical and have a mean and volatility of more than 8% and 4%, respectively. Focusing on columns (1) to (4) of Table 4, we can assess the performance of the baseline diagnostic model with $\gamma = 0.67$ (column (2)) relative to the rational model (either recalibrated or as a simple variation from the baseline model with $\gamma = 0$). The most striking difference between the diagnostic model and the recalibrated rational model in column (4), which is similarly successful in matching the targeted moments (cf. Table 3),[15] lies in the untargeted implications for the predicted default frequency. Despite the challenges for determining the true default frequency from the data, there is a consensus in the literature (cf. Arellano, 2008; Hatchondo et al., 2016; Pouzo and Presno, 2016) that it is about 3% annually for Argentina. The diagnostic model is able to generate high and volatile spreads under a predicted annual default frequency of about 2.5%. By contrast, the rational model predicts an annual default frequency of more than 6%. Another difference between the diagnostic and the rational model is that the former records default events not exclusively in very bad times, in line with the evidence in Tomz and Wright (2007); hence the average output drop when defaulting is higher at 5.8% relative to 4.4% and thus closer to the empirical statistic.

In order to examine the quantitative relevance of diagnostic sentiment swings for default behavior and the uncoupling of spread dynamics from fundamentals, it is useful to also consider a variation of the diagnostic baseline model in which the degree of diagnosticity is set to $\gamma = 0$. As seen from column (3), when diagnosticity is shut down, both the magnitude and the volatility of spreads decrease significantly, whereas the average level of debt and the default frequency increase. The overall effect of these changes, that is, additional lending at more favorable and less volatile rates, materializes in sizeable welfare gains, expressed in terms of the equivalent variation in

[15] Table 6 in Appendix A.4 further details the behavior of spreads as described by the percentiles of their distribution. By design, both the diagnostic and the rational model match the average spread of about 8% very well. Given the skewed spread distribution generated by rare debt crises, the median is throughout lower than the mean, both in the data and all model variants. But the diagnostic model matches the empirical quantiles slightly better than the rational model and significantly outperforms the model variation with $\gamma = 0$.

consumption, of 0.65%.[16]

Table 4: Business Cycle Statistics

	(1) Data	(2) Full Diagnostic Benchmark $\gamma = 0.67$	(3) $\gamma = 0$	(4) Rational	(5) DE gvnt. RE creditor $\gamma = 0.67$	(6) RE gvnt. DE creditor $\gamma = 0.67$
$\sigma(c)/\sigma(y)$	1.09	1.05	1.03	0.99	0.97	1.09
$\sigma(TB/y)/\sigma(y)$	0.17	0.29	0.28	0.29	0.29	0.25
$\sigma(s)$	4.43	4.48	1.81	4.43	5.32	3.62
$\rho(c, y)$	0.98	0.96	0.96	0.96	0.95	0.97
$\rho(TB/y, y)$	−0.88	−0.24	−0.22	−0.17	−0.07	−0.32
$\rho(s, y)$	−0.79	−0.67	−0.70	−0.63	−0.58	−0.55
$E(s)$	8.15	8.15	3.97	8.17	8.29	5.68
$E(\|\Delta s\|)$	1.71	2.60	0.84	1.92	2.03	1.81
$\sigma(\|\Delta s\|)$	2.70	3.64	1.23	2.96	3.79	3.71
Max. s	29.71	51.89	18.02	40.30	61.48	157.77
Mean debt output ratio (%)	70.00	70.00	80.83	70.11	72.14	75.02
Mean drop in y (at default)	−6.4	−5.78	−5.05	−4.43	4.21	6.32
Default frequency (%)		0.62	0.81	1.59	1.44	0.09
Welfare equivalent (in %)	–	–	0.65	–	−0.01	0.57

Notes: All statics are based on non-exclusion periods out of 500000 observations, where the first 1000 were discarded. We also exclude the first four periods after market re-entry. The series for y, c, and TB/y are logged and linearly detrended. Spreads are denoted in annualized values, default probabilities are quarterly. The data values are taken from Chatterjee and Eyigungor (2012) except for the drop in output around default, for which we refer to Pouzo and Presno (2016).

4.4 Generalized impulse responses

What is the impact of diagnostic expectations for the dynamics of capital flows and spreads after a bad endowment shock, and how does it depend on the state of the economy? To answer these questions, it is useful to examine the generalized impulse responses depicted in Figure 2. The exercise here is to look at the average impact response of borrowing and spreads to a negative endowment shock in period two (ε_2 one standard deviation below normal), depending on the history in period one as given by the preceding endowment shock ε_1. We consider realizations

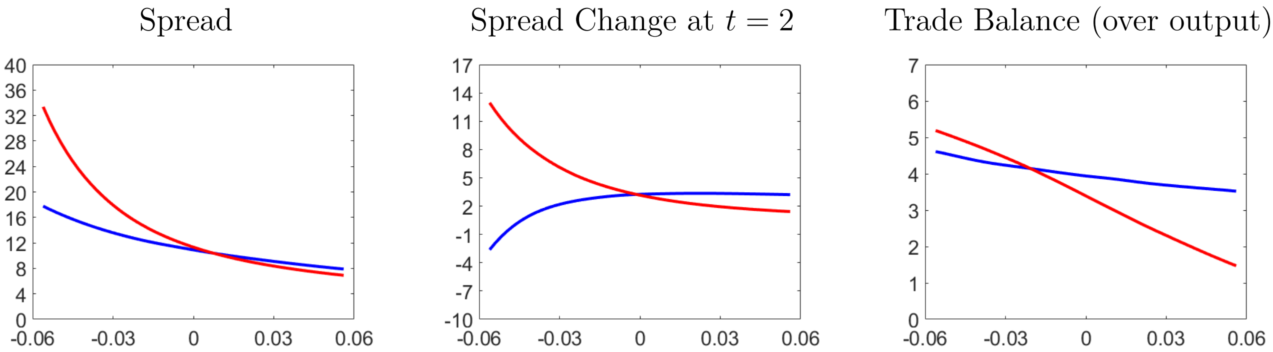
[16]In detail, welfare effects are computed based on the comparison of the lifetime utility of a rational representative agent in our diagnostic benchmark economy and a counterfactual economy with a different expectations regime. Following Durdu et al. (2013), we compute the welfare gain as the equivalent variation in consumption,

$$\Delta = \left(\frac{V(*)}{V(\circ)}\right)^{\frac{1}{(1-\sigma)}} - 1,$$

where V is the expected lifetime utility of the representative agent. '$*$' and '$\circ$' refer to the counterfactual model and the benchmark model, respectively.

for this past shock ranging from minus to plus two standard deviations; owing to its diagnostic effect, we can thus explore situations of optimistic or pessimistic sentiment.

Figure 2: Generalized Impulse Responses



Notes: We take the state of the economy after 1000 periods without a shock innovation ($\varepsilon = 0$). We employ scenarios, where the economy is hit in period one by shock innovations of up to $+/-5.61\%$, where the largest shocks are about two standard deviations. In period two, the economy is hit by a negative shock innovation of one standard deviation (-2.72%). The graphs plot the initial period two responses of the bond spread, its change relative to period one and the trade balance over output. The graphs compare the model under diagnostic (blue) and rational (recalibrated, red) expectations.

In the rational model (recalibrated, red), sentiment plays no role. The bad shock in period two then induces a hike in spreads, ranging from about 8% when the preceding shock in period one was very good to more than 30% after a very bad shock in period one. Expressed in terms of spread changes between periods one and two, the bad shock in period two thus always leads to higher spreads, whereby the change is most pronounced after a sequence of two bad shocks and more modest if the bad shock in period two was preceded by a more benign shock in period one. Given the underlying procyclical debt policy, the adverse shock in period two induces debt decumulation, as seen from the unambiguously positive response of the trade balance, the magnitude of which is driven by the behavior of spreads.

In the diagnostic model (blue), the impulse responses follow a qualitatively and quantitatively different pattern. As seen from the left panel, the impact response of spreads in period two is more contained, with a maximum hike in spreads to about 17%, which is about half the value observed in the rational model. Turning to the spread changes between periods one and two (middle panel), the difference between the two models is even more striking: Unlike the rational model, the increase in spreads is now most pronounced when the underlying shocks are first positive and then negative, which corresponds to the idea of initially optimistic sentiment being disappointed by bad news. There is thus fragility in good times. On the other hand, a history initiated by a sufficiently negative shock in period one actually leads to a drop in spreads; this is because the market is already conditioned by pessimistic sentiment so that the negative shock in period two actually records as positive news. In sum, therefore, the change in spreads now depends positively on the period one shock.[17] This pattern is inherited by the trade balance,

[17]When the period one shock was neutral ($\varepsilon_1 = 0$) so that there is no distortion of beliefs in the

which displays a positive impact response but is now significantly less dependent on the period one shock.

4.5 Asymmetric configurations

Appropriate policy implications to address the repercussions from diagnostic behavior on international credit markets need to condition on its ultimate source. This section therefore contrasts between asymmetric scenarios where diagnostic expectations are relevant only on one side of the market, whereas the other side operates under rational expectations.

We begin with the case in which only the sovereign borrower is diagnostic, but international creditors are rational. The top panels of Figure 3 plot the bond pricing functions relevant for this asymmetric configuration. Most importantly, with rational creditors, there is no longer a family of bond pricing functions, but instead a unique one. The pricing of default risk is now actuarily fair, conditional on the borrower's diagnostic behavior. Indeed, the terms at which the government can incur debt provide better insurance compared to the fully diagnostic baseline model. It responds to this by issuing more debt when $\varepsilon < 0$ and less debt when $\varepsilon > 0$, which also manifests itself in a less countercyclical trade balance (cf. column (5) of Table 4). At the same time, however, inspection of the debt policy functions (not reported here) reveals that, under rational credit supply, the disciplining effect of diagnostic debt pricing on the government's borrowing behavior disappears.[18] The diagnostic government' debt policy thus becomes more ambitious, which implies increased sovereign risk. Indeed, the volatility of sovereign spreads increases to 5.3% and the annual default frequency rises to almost 6%, which undermines the benign effect of improved insurance and, at a consumption equivalent variation of -0.01%, completely eliminates the welfare gains relative to the diagnostic baseline economy.[19]

The findings are quite different when we instead consider the case in which the sovereign borrower is rational, but debt is priced by diagnostic creditors. The bottom panels of Figure 3 plot the bond pricing functions relevant for this alternative asymmetric configuration. While the family of bond pricing functions looks qualitatively similar to the diagnostic baseline model, they become steeper, that is, more sensitive to the amount of outstanding debt. Since diagnostic credit supply ceteris paribus also entails increased volatility in bond prices, the provision of insurance is thus poorer, and the rational government responds to this situation with a more procyclical debt policy. Again, this is visible from the cyclical behavior of the trade balance, which is now more countercyclical (cf. column (6) of Table 4). On the other hand, rational expectations on the side of the sovereign government also imply a more prudent borrowing behavior.[20] While consumption insurance is

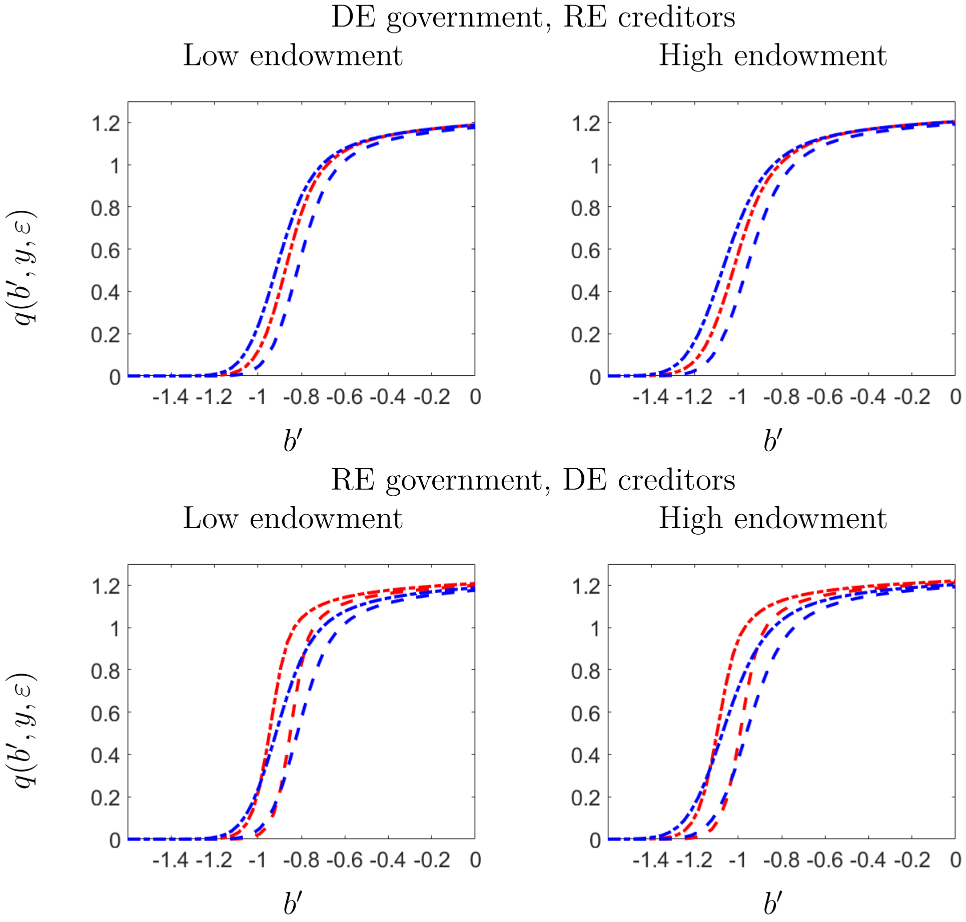
diagnostic model, the change in spreads is very similar across the two models.

[18] Quantitatively, the most relevant change affects the debt policy in states with a high endowment y but a negative shock ε. In this situation, the government now issues substantially more debt than in the baseline model.

[19] The slightly negative welfare effect recorded here reflects the output losses associated with an increased incidence of sovereign default.

[20] This prudence relative to the baseline model is now most visible in situations with a high endowment

Figure 3: Bond Pricing Functions



Notes: The graphs show the debt policy and the bond price. Blue lines refer to the benchmark model with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dash-dotted). Red lines denote the functions for the models with asymmetric configurations. Top panels: diagnostic government and rational creditors. Bottom panels: rational government and diagnostic creditors. Low (high) endowment refers to levels of -3.49% (3.49%) around the trend.

thus worse, the average debt position is higher and the default frequency drops to almost zero. This, in turn, is internalized by creditors so that spreads are much lower and less volatile than in the diagnostic baseline economy. Accordingly, the switch from diagnostic to rational expectations on the side of the sovereign borrower comes with welfare gains corresponding to a consumption equivalent variation of 0.57%. In other words, while a rational supply side of the credit market fails to generate welfare gains, rationality on the demand side allows for capturing more than 80% (0.57%/0.65%) of the overall welfare gains from completely eliminating diagnostic behavior on both sides of the credit market.[21]

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y and a positive shock ε.

[21]Figure 11 in Appendix A.5 complements the bond pricing functions from Figure 3 by analyzing the generalized impulse responses for the above model variations where diagnostic expectations are relevant only on one side of the credit market as well as for a version where the diagnosticity parameter is symmetrically set to $\gamma = 0$. A key observation from this exercise relates to the behavior of equilibrium spreads: Regardless of the mode of government expectations, the way how sovereign creditors form their expectations is responsible for shaping the response of spreads to ε-shocks.

4.6 Fiscal rules

The analysis so far illustrates the role of expectations held on both sides of the bond market, which matter along two distinct dimensions, namely with respect to (i) future output, and (ii) future budget balances and default decisions. The effects along the first dimension arise quite mechanically, as seen from the specification in (8). By contrast, the second dimension allows for subtler interactions. In particular, the observation that the welfare costs of diagnostic expectations are predominantly rooted in the sovereign borrower's behavior makes it interesting to think about possible mechanisms to steer expectations about future fiscal policy. Fiscal rules are an important and empirically relevant institution in this regard. We follow Hatchondo et al. (2022a) and contrast two alternative specifications: First, a *debt-brake rule*, which imposes a ceiling on admissible fiscal deficits when the level of debt exceeds a threshold; and second, a *spread-brake rule*, which follows a similar logic but instead conditions on a threshold for sovereign spreads.

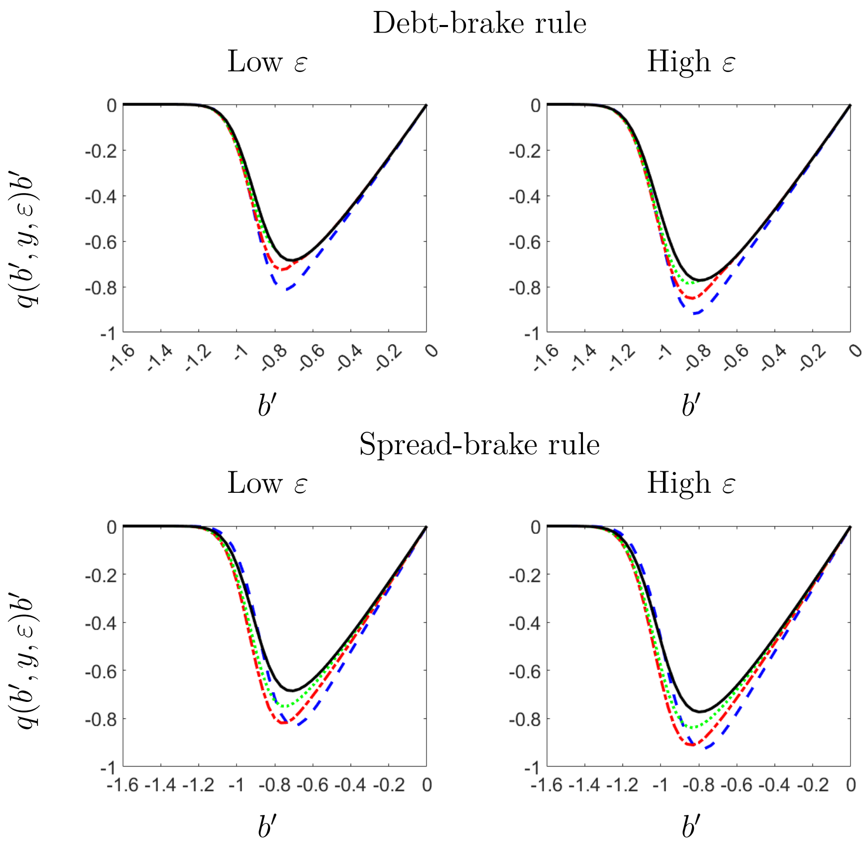
In the context of sovereign debt markets, fiscal rules have been advocated as tools to address over-borrowing and specifically the debt dilution problem, which arises in environments with long-term debt because issuing additional debt then makes debt issued in the past more risky. Consistent with the fundamental insights from Weitzman (1974), Hatchondo et al. (2022a) show for this environment that risk or uncertainty about borrowing costs generally makes (the price-based) regulation through a spread brake superior to (the quantity-based) regulation via a debt brake. Here, we reexamine the performance of both types of fiscal rules under diagnostic expectations, which may systematically affect the supply of bonds issued by the sovereign government as well as the demand for these bonds by international creditors. In this setting, fiscal rules continue to mitigate the debt dilution problem by disciplining the sovereign's dynamically inconsistent borrowing behavior. However, these rules may now be problematic as they are based on aggregates (debt levels or spreads, respectively) that might themselves be distorted due to the diagnostic expectations held by bond market participants. This gives rise to a trade-off regarding the appropriate design of fiscal rules. Moreover, to the extent that diagnostic effects are more relevant for spreads rather than for debt levels, the relative assessment of debt versus spread brakes might change.

To formally analyze these issues, we incorporate fiscal rules along the lines of Hatchondo et al. (2022a) into our model. The *debt-brake rule* imposes a limit on borrowing to keep the level of outstanding debt below a given threshold $\bar{b}$; specifically, $b' \geq \min\left\{\bar{b}, b - \lambda\right\}$. Accordingly, if outstanding debt is below the debt limit, then the government can borrow up to the limit. However, if outstanding debt exceeds the debt limit, the rule demands a gradual reduction of debt by an amount $\lambda < 0$ until the limit is satisfied again. Similarly, the *spread-brake rule* imposes an upper bound $\bar{r}_s$ on the spreads relevant for new debt, which implies a threshold $\bar{b}_s(y, \varepsilon, \bar{r}_s)$ for admissible borrowing; formally, $b' \geq \min\{\bar{b}_s(y, \varepsilon, \bar{r}_s), b - \lambda\}$. For both rules, we follow the baseline calibration of Hatchondo et al. (2022a) and assume that the minimum debt reduction equals the amount of maturing debt, that is, $\lambda = \delta b$.

A key difference between the two rules, however, is that the debt brake is based on a numerically fix threshold $\bar{b}$, while the spread brake has a state-dependent debt limit $\bar{b}_s(y, \varepsilon, \bar{r}_s)$. This difference is at the heart of the prices versus quantities debate, which, under rational expectations, is generally resolved in favor of the price-based regulation through a spread brake. Under diagnostic expectations, however, the state-dependent debt limit $\bar{b}_s(y, \varepsilon, \bar{r}_s)$ is not immune to sentiment swings driven by the output innovation ε. Market optimism (pessimism) can therefore lead to an unduly lenient (tight) debt limit, thus generating variation in borrowing conditions that is not justified by fundamentals. By contrast, the numerically fix threshold $\bar{b}$ underlying the debt brake is free from this problem; this captures the exact sense in which diagnostic effects are more relevant for spreads than for debt levels.

Borrowing sets. Concentrating on our baseline diagnostic model, Figure 4 shows the borrowing sets available to the government under fiscal rules of varying tightness, contrasting debt-brake rules in the top panels and spread-brake rules in the bottom panels. Both types of rules are capable of

Figure 4: Fiscal Rules: Borrowing Set

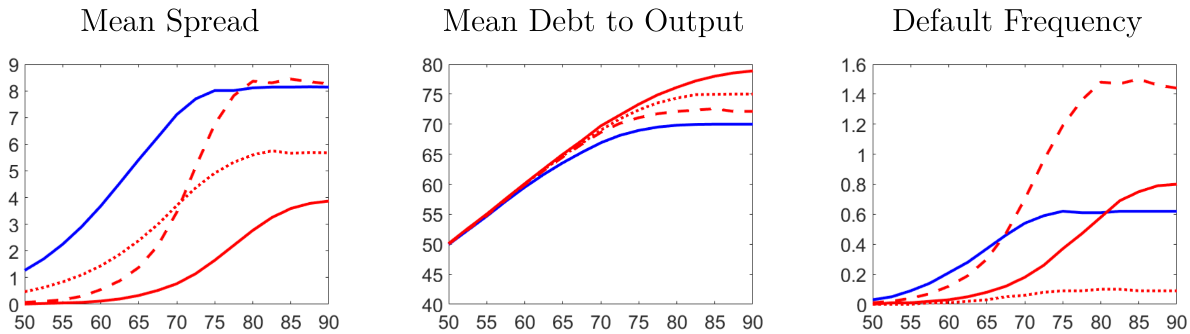


Notes: The graphs show the market value of the debt stock. Black lines represent the benchmark model. Top panels: Blue, red, and green lines refer to the model with debt brake rules of 60%, 70%, and 80%. Bottom panels: Blue, red, and green lines refer to the model with spread brake rules of 0.1%, 3.5%, and 7%. Low and high shock innovation refer to values of $\varepsilon = -0.036$ and $\varepsilon = 0.036$, respectively. All functions refer to endowment realizations, y, on the trend.

generating additional borrowing space as given by the market value of the stock of outstanding debt, $q(b', y, \varepsilon)b'$. This happens because fiscal constraints allow managing expectations about future fiscal policy so that debt can normally be issued at more favorable terms. However, there is actually a twofold effect underlying the depicted debt Laffer curves: On the one hand, a tighter rule limits future debt dilution and thus leads to higher bond prices. But for high debt levels ($b < \bar{b}$ or $b < \bar{b}_s(y, \varepsilon, \bar{r}_s)$, respectively) the fiscal rule prescribes costly deleveraging and may thus lead to default; anticipation of this scenario works to depress bond prices, whereby the effect becomes more prominent with increased debt positions and under a tighter rule. In consequence, a tighter fiscal rule expands the borrowing set whenever the first effect dominates, which is generally the case for debt positions chosen by an optimizing government. Moreover, the expansion of the borrowing set is stronger when the current output innovation, ε, is high as diagnostic expectations then discount the second effect (that is, the prospect of a future default) more strongly. But regardless of the current ε, the peak of the debt Laffer curve is not necessarily moving monotonically with the tightness of the rule.[22]

Equilibrium outcomes and welfare. Looking at their implications for the available borrowing set in Figure 4, it appears that, at least qualitatively, the considered debt-brake and spread-brake rules have very similar effects. This assessment is changed when examining the equilibrium implications for sovereign spreads, average debt positions and default frequencies. Figure 5 shows these outcomes for debt-brake rules of varying tightness and depending on the relevant regime for expectations formation. As expected, rules based on a sufficiently tight debt limit $\bar{b}$ are effective

Figure 5: Debt Brake: Macroeconomic Outcomes under Varying Diagnosticity



Notes: The graphs show the mean spread (annualized, in %), the mean debt to output ratio, and the default frequency (quarterly, in %) for different debt-brake rules, denoted on the x-axis. Solid blue (red) lines refer to the benchmark model (model with $\gamma = 0$). Dashed (dotted) lines refer to the model with rational (diagnostic) creditors and a diagnostic (rational) government.

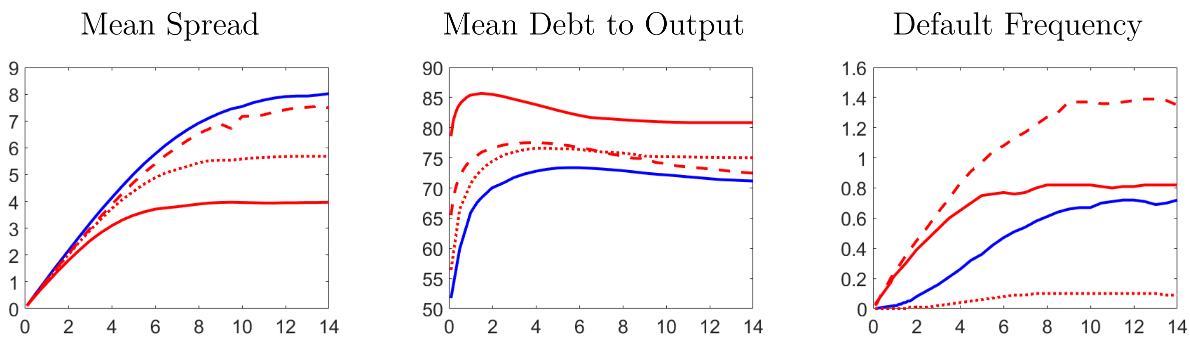
instruments to contain average debt positions.[23] Across all considered models, also average spreads and the frequency of default fall monotonically in the tightness of the debt rule. The strongest effects are recorded for the model with a diagnostic government and rational creditors.

[22]For example, under the tightest debt- and spread-brake rules considered in Figure 4 (blue lines), the maximum value of the stock of outstanding debt, $q(b', y, \varepsilon)b'$, is reached for a lower level of borrowing b' than under more lenient rules.

[23]Average debt for the most lenient debt-brake rule considered here ($\bar{b}$ at a debt to output ratio of 90%) basically coincides with the unrestricted simulation averages reported in Table 4.

Figure 6 repeats the same exercise for spread-brake rules of varying tightness. Again, a tighter

Figure 6: Spread Brake: Macroeconomic Outcomes under Varying Diagnosticity

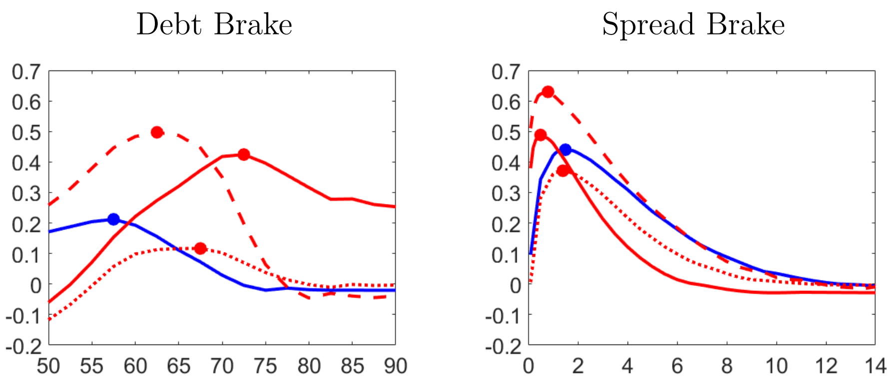


Notes: The graphs show the mean spread (annualized, in %), the mean debt to output ratio, and the default frequency (quarterly, in %) for different spread-brake rules, denoted on the x-axis. Solid blue (red) lines refer to the benchmark model (model with $\gamma = 0$). Dashed (dotted) lines refer to the model with rational (diagnostic) creditors and a diagnostic (rational) government.

rule leads to lower average spreads and default frequencies. The implications for average debt, however, are non-monotonic. The hump-shaped relationship seen in the middle panel reflects two countervailing effects: On the one hand, relaxing the spread limit allows the government to accumulate higher debt positions. However, on the other hand, the increased scope for debt dilution under a laxer rule leads to higher spreads, which induces the government to choose lower debt levels.

The associated welfare consequences are shown in Figure 7 and Table 5.

Figure 7: Welfare Effects under Varying Diagnosticity



Notes: The graphs show the welfare equivalent with respect to the benchmark model for different debt-brake (left panel) and spread-brake (right panel) rules. Solid blue (red) lines refer to the benchmark model (model with $\gamma = 0$). Dashed (dotted) lines refer to the model with rational (diagnostic) creditors and a diagnostic (rational) government.

The left panel considers the effects under debt-brake rules of varying tightness. As seen, such rules offer the potential for sizeable welfare gains. Consistent with the findings from Figure 5, the attainable gains are largest, at about 0.50%, in the setting where debt is priced rationally but the

Table 5: Optimal Fiscal Rules

	(1)	(2)	(3)	(4)
	Debt Brake		Spread Brake	
	$\overline{b}^*/y(\%)$	$CE(\%)$	$\overline{r}_s^*(\%)$	$CE(\%)$
DE ($\gamma = 0.67$)	57.5	0.2121	1.5	0.4399
DE gvnt./RE cred.	62.5	0.4970	0.8	0.6296
RE gvnt./DE cred.	67.5	0.1166	1.4	0.3711
RE ($\gamma = 0$)	72.5	0.4242	0.5	0.4883

Notes: $CE(\%)$ denotes consumption equivalent welfare gains.

debt brake, at a debt-to-GDP ratio of 62.5%, prevents the diagnostic government from exploiting this too aggressively.[24] Variations across the different models are best understood by recognizing that the optimal debt-brake rule is relatively tight in the model versions with a diagnostic government and laxer when the government is rational; by contrast, the way expectations are formed on the side of international creditors plays only a smaller role. The welfare-maximizing design of debt-brake rules thus corresponds to the underlying distortion, which Section 4 demonstrated to be rooted predominantly on the debtor side. Common to all considered models is that the optimal debt-brake rule reduces debt-to-GDP by about 10 percentage points relative to the unregulated average debt positions reported in Table 4. This implies that the optimal tightness of the rule varies substantially. Excessive tightness of the debt-brake rule can be detrimental, particularly when the government is rational. For example, setting the debt limit to 50%, a value that yields benign welfare effects in the two considered environments with a diagnostic government, leads to welfare losses of up to 0.1% in the rational model with $\gamma = 0$.

The right panel of Figure 7 examines spread-brake rules of varying tightness. For all considered model versions, a first striking difference compared to the case of the debt brake is that the spread brake generally allows for substantially higher welfare gains and that there is virtually no risk of generating welfare losses relative to the underlying model without fiscal rule. That said, the attainable welfare gains now display a pronounced sensitivity to the chosen spread limit $\overline{r}_s$, which is tied to the hump-shaped effects on the average debt levels discussed in the context of Figure 6 – the trade-off between excessive tightness and debt dilution.[25] Among the model variants considered, there now emerge two pairs where spread brakes have quantitatively similar welfare effects. The highest welfare gains are attainable in the two settings where credit supply is priced rationally. In comparison, the two models with diagnostic spreads offer only lower

[24] We search for the optimal debt-brake rule on an equally-spaced grid from 50% to 90% with a distance of 2.5%. Similarly, we use a two-stage grid search assessment for the spread-brake rule. We first consider 29 grid points within the range from 0.1% to 14%. Then, we focus on an interval of 1% around the welfare-maximizing rule and consider grid points of 0.1% distance.

[25] Average debt levels, in turn, matter for welfare because of the frontloading motive implied by the sovereign borrower's relative impatience.

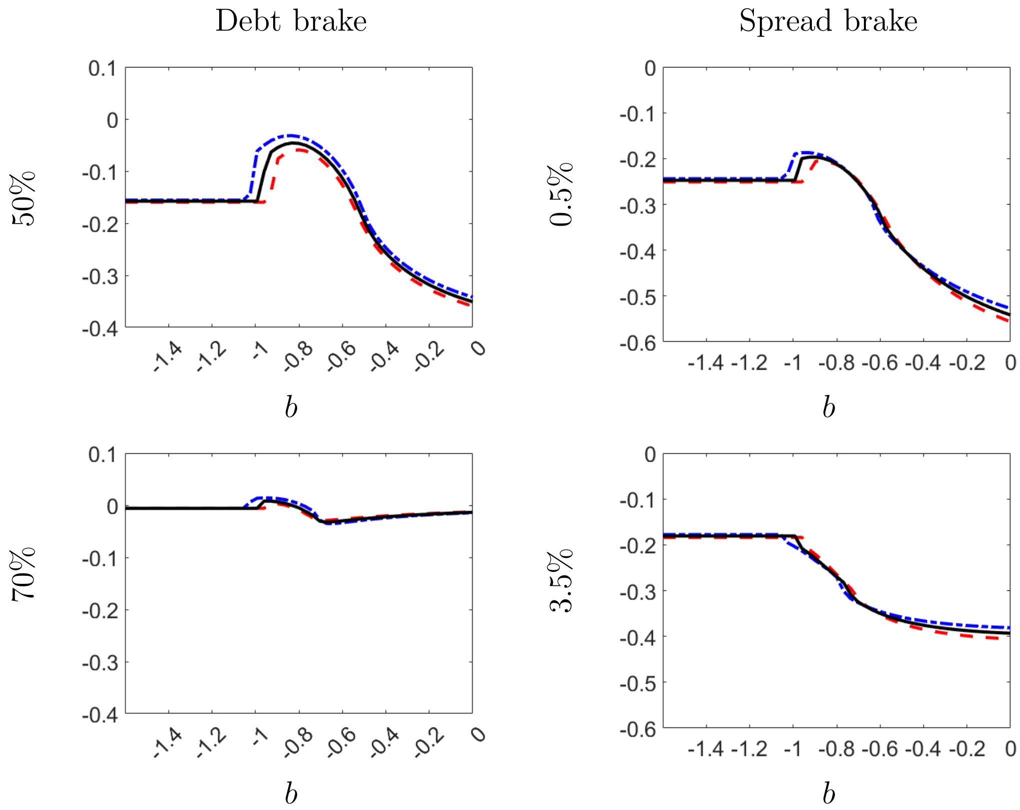
maximum gains, but a less steep welfare gradient under suboptimal choices of the spread limit $\overline{r}_s$. Both differences are easily explained: The level shift observed for the welfare maxima across the two model pairs reflects the cost of conditioning on a state-dependent debt limit $\overline{b}_s(y, \varepsilon, \overline{r}_s)$, which is subject to non-fundamental distortions when creditors are diagnostic. And the resulting volatility of sovereign spreads provides discipline on the government's borrowing behavior so that debt dilution concerns are less pronounced, implying a reduced costs of setting a too lenient spread-brake rule. The benefits from reducing debt dilution remain a key determinant of optimal spread-brake rules, however. Hence, the rules' optimal tightness is shaped by the trade-off between the benefits from reduced debt dilution and the costs from a tighter spread limit that is subject to diagnostic mispricing. The optimal spread-brake rule is therefore relatively tight in the model versions where international creditors are rational and laxer when credit supply features diagnostic expectations. Specifically, the optimal spread-brake rule in the rational model with $\gamma = 0$ is at $\overline{r}_s = 0.5\%$; in the model with a diagnostic government but rational creditors, it is only marginally higher at $\overline{r}_s = 0.8\%$. By contrast, the two models with diagnostic credit supply have optimal spread brakes at $\overline{r}_s = 1.4\%$ in the model with a rational government but diagnostic creditors and at $\overline{r}_s = 1.5\%$ in the fully diagnostic baseline model. Thus, in contrast to the pattern for the optimal spread brakes, the design of optimal spread-brake rules needs to be informed predominantly by the way expectations are formed on the supply side of the credit market, while demand-side expectations play only a minor role.

Stability. We conclude our analysis of fiscal rules by examining their stability when the regulated borrower has the option of abandoning the rule, either permanently or just for one period. In both cases, we compute the welfare effects of abandoning the rule and express the relevant consumption-equivalent variation in terms of the penalty needed to prevent an exit from the considered rule. Throughout, we concentrate on the baseline model with diagnostic expectations on both market sides. Accordingly, the welfare metric underlying the exit decision is now the diagnostic government's value function $V^{\gamma}(b, y, \varepsilon)$ given in (9).[26]

Beginning with the stability against the option to permanently abandon the rule, Figure 8 illustrates how the necessary exit penalty depends on the debt level, the endowment level and the current shock ε. The findings for the permanent exit scenario basically mirror the welfare effects described in Figure 7. For all spread-brake rules considered (right panels), the computed exit penalty is negative, indicating that the diagnostic government never wants to abandon the rule. The reason is straightforward: Under a spread-brake rule, the government faces lower interest rates for any available borrowing choice (see the borrowing sets in Figure 4). While this benign effect also exists for the debt-brake rule (left panels), the penalty needed to prevent exit is no longer unambiguously negative. Specifically, a too lenient debt limit (bottom left panel) may render abandoning the rule attractive even if the exit is permanent. This happens for relatively high

[26]This is in contrast to the welfare assessments in Tables 4 and 5 and Figure 7, which condition on the lifetime utility of a rational representative agent.

Figure 8: Fiscal Rules: Welfare Penalty to Avoid Permanent Exit – Diagnostic Model



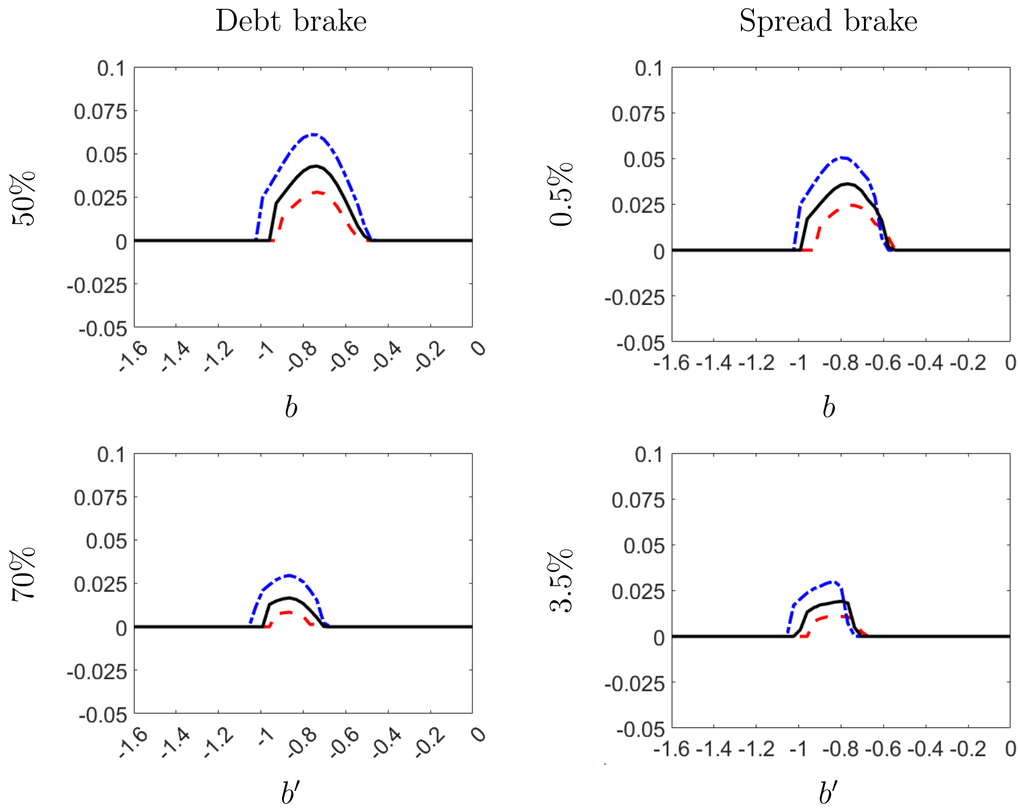
Notes: The graphs show the welfare penalty needed to prevent the government from permanently abandoning the relevant fiscal rule in terms of the consumption equivalent for different levels of initial indebtedness. The left panels consider debt-brake rules of 50% and 70% (relative to on-the-trend output). The right panels consider spread-brake rules of 0.5% and 3.5%. Dashed, solid, and dash-dotted lines refer to shock innovations of $\varepsilon = -0.036$ (dashed), $\varepsilon = 0$ (solid), and $\varepsilon = 0.036$ (dash-dotted).

debt positions that do not yet trigger default but where compliance with the rule would demand costly deleveraging. A final interesting point relevant to both types of rules is that exit becomes relatively more attractive in good circumstances, i.e., when the endowment shock ε is high.[27] The explanation here rests on two mechanisms. First – for both types of rules – the optimism following a high ε shock induces the diagnostic government to (seek to) issue more debt and hence tilts its evaluation of its choice alternatives in favor of exiting. And second – for the debt-brake rule only – the fact that the fix borrowing limit $\bar{b}$ does not respond to the good circumstances then implies that the conditions for compliance are perceived as unduly restrictive.

Figure 9 examines the penalty needed to prevent a one-period deviation from the fiscal rule. Different from the case of permanent exit, the one-period exit scenario assumes commitment to the underlying rule in the future so that the bond price faced by the government contemplating to abandon the rule always coincides with the equilibrium price under the rule. The penalty computed here thus captures the pure effect of the constraint on current deficits imposed by the relevant fiscal rule. For a rational government, this penalty would be non-negative by con-

[27]A similar effect also applies for high endowment levels y (not shown here).

Figure 9: Fiscal Rules: Welfare Penalty to Avoid One-Period Exit – Diagnostic Model



Notes: The graphs show the welfare penalty needed to prevent the government from abandoning the relevant fiscal rule for 1(!) period (and sticking with it forever after) in terms of the consumption equivalent for different levels of initial indebtedness. The left panels consider debt-brake rules of 50% and 70% (relative to on-the-trend output). The right panels consider spread-brake rules of 0.5% and 3.5%. Dashed, solid, and dash-dotted lines refer to shock innovations of $\varepsilon = -0.036$ (dashed), $\varepsilon = 0$ (solid), and $\varepsilon = 0.036$ (dash-dotted).

struction. In the diagnostic setting considered here, sentiment effects may blur this assessment. But conditioning on the neutral shock, $\varepsilon = 0$, that does not induce any diagnostic effects actually removes these distortions. The solid lines thus show that both the debt-brake rule and the spread-brake rule generally need to be enforced with small penalties to prevent one-period exit deviations. Relative to this quasi-rational situation, and again for both types of rules, the penalty needed to sustain compliance with the relevant rule increases when $\varepsilon > 0$ (dash-dotted lines) and decreases when $\varepsilon < 0$ (dashed lines). Again, this reflects the diagnostic effect on the government's desired debt policy. Throughout, however, the magnitude of the necessary penalty remains fairly modest, and particularly so for spread-brake rules.

5 Conclusions

This paper has examined studies the implications of overreaction to recent news in the context of a quantitative model of sovereign debt and default. Overreaction is formalized in terms of diagnostic expectations that excessively extrapolate from current conditions. Examining historical IMF growth forecasts, we find empirical evidence for this behavior and incorporate it into an otherwise standard model of long-term sovereign debt. The model successfully matches salient business cycle statistics, including the distribution of sovereign spreads, and also predicts an empirically plausible default frequency. Counterfactual experiments indicate that diagnostic expectations induce sizeable welfare losses, the bulk of which could be eliminated under rational behavior of the sovereign borrower. This motivates our analysis of fiscal rules, which need to trade-off their beneficial effects via reduced debt dilution against the fact that they condition on aggregates that may be distorted by market sentiment. While this latter concern is more relevant for spread-brake rules, they offer robustness and generally perform better than debt-brake rules. Both types of rules need to be enforced with small exit penalties.

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A Appendix

A.1 Derivations for Section 2

Derivation of equation (3): The data available at the time of the spring forecast is $g_{i,t}^s = \rho\, g_{i,t-1}^f + \epsilon_{i,t}^s$. The incremental news $\Delta_{sf}\epsilon_{i,t} = \epsilon_{i,t}^f - \epsilon_{i,t}^s$ available at the time of the fall forecast then implies an update with $g_{i,t}^f = \rho\, g_{i,t-1}^f + \epsilon_{i,t}^f$. The two associated forecasts are

$$\begin{aligned}
E_t^{\gamma,s}\{g_{i,t+1}\} &= \rho\, g_{i,t}^s + \gamma\rho\epsilon_{i,t}^s = \rho\,(g_{i,t}^f - \Delta_{sf}\epsilon_{i,t}) + \gamma\rho\epsilon_{i,t}^s,\\
E_t^{\gamma,f}\{g_{i,t+1}\} &= \rho\, g_{i,t}^f + \gamma\rho\epsilon_{i,t}^f,
\end{aligned}$$

which implies a spring to fall forecast revision of

$$\Delta E_t^{\gamma}\{g_{i,t+1}\} = E_t^{\gamma,f}\{g_{i,t+1}\} - E_t^{\gamma,s}\{g_{i,t+1}\} = \rho\Delta_{sf}\epsilon_{i,t} + \gamma\rho\Delta_{sf}\epsilon_{i,t} = (1+\gamma)\rho\Delta_{sf}\epsilon_{i,t}.$$

Derivation of equation (7): Assuming that spring and fall innovations $(\epsilon_{i,t}^s, \epsilon_{i,t}^f)$ have the same variance σ_ϵ^2 and display a within-year correlation of ρ_{sf} but no correlation over time, we have

$$\begin{aligned}
Cov(fe_{i,t+1}, \Delta E_t^{\gamma}\{g_{i,t+1}\}) &= Cov(g_{i,t+1} - E_t^{\gamma}\{g_{i,t+1}\}, \Delta E_t^{\gamma}\{g_{i,t+1}\})\\
&= Cov(\epsilon_{i,t+1}^f - \gamma\rho\epsilon_{i,t}^f, (1+\gamma)\rho(\epsilon_{i,t}^f - \epsilon_{i,t}^s))\\
&= -\gamma(1+\gamma)\rho^2\sigma_\epsilon^2(1-\rho_{sf})
\end{aligned}$$

and

$$\begin{aligned}
Var(\Delta E_t^{\gamma}\{g_{i,t+1}\}) &= Var((1+\gamma)\rho\Delta_{sf}\epsilon_{i,t})\\
&= Var((1+\gamma)\rho(\epsilon_{i,t}^f - \epsilon_{i,t}^s))\\
&= (1+\gamma)^2\rho^2 2\sigma_\epsilon^2(1-\rho_{sf}).
\end{aligned}$$

Hence, the regression coefficient becomes

$$\hat{\theta} = \frac{Cov(fe_{i,t+1}, \Delta E_t^{\gamma}\{g_{i,t+1}\})}{Var(\Delta E_t^{\gamma}\{g_{i,t+1}\})} = -\frac{\theta(1+\gamma)\rho^2\sigma_\epsilon^2(1-\rho_{sf})}{(1+\gamma)^2\rho^2 2\sigma_\epsilon^2(1-\rho_{sf})} = -\frac{\gamma}{2(1+\gamma)}.$$

Solving for γ, we get

$$\gamma = -\frac{2\hat{\theta}}{1+2\hat{\theta}}.$$

A.2 Numerical algorithm

We use value function iteration to solve the model. Our algorithm closely follows Hatchondo et al. (2016) and employs cubic spline interpolations. The equilibrium of the finite-horizon economy serves as an approximation of the equilibrium. We simultaneously iterate on the value functions and the bond price function.

We employ the following algorithm to solve the model. We define equidistantly spaced grids for external debt $b \in [\underline{b}, \overline{b}]$, the endowment $y \in [\underline{y}, \overline{y}]$, and the shock innovation $\varepsilon \in [\underline{\varepsilon}, \overline{\varepsilon}]$. We set initial guesses for the value functions $V^{\gamma}_{(0)}(b, y, \varepsilon)$, $V^{\gamma}_{R,(0)}(b, y, \varepsilon)$, and $V^{\gamma}_{D,(0)}(y, \varepsilon)$, and the bond price function $q^{\gamma}_{(0)}(b, y, \varepsilon$. Given the guesses for the value functions, we find candidate values for $b'_{(0)}(b, y, \varepsilon$ for every grid point $(b, y, \varepsilon) \in [\underline{b}, \overline{b}] \times [\underline{y}, \overline{y}] \times [\underline{\varepsilon}, \overline{\varepsilon}]$ via a global search procedure. We take these candidate values as initial guesses and employ the FORTRAN optimization routine BCPOL from the IMSL library to find optimal values. We can then compute the bond price $q^{\gamma}_{(0)}(b, y, \varepsilon)$ via equation (14). To evaluate expected continuation values and expected policies, we use Gauss-Hermite quadrature points and weights. We employ cubic spline interpolation to compute values for policies and productivity realizations off the grid. Specifically, we use bidimensional Akima (1996) spline interpolation, first, to determine expectation values over y and ε, and second, over b and ε to specify optimal policies.

We take the solutions found at each grid point to update the value functions $V^{\gamma}_{(0)}(b, y, \varepsilon)$, $V^{\gamma}_{R,(0)}(b, y, \varepsilon)$, and $V^{\gamma}_{D,(0)}(y, \varepsilon)$, and the bond price function $q^{\gamma}_{(0)}(b, y, \varepsilon)$. We iterate until the value functions and the bond price function converge.

A.3 Debt Covenant

To study the impact of diagnostic expectations in the absence of debt dilution, we follow Hatchondo et al. (2016) and introduce a debt covenant such that the value of long-term bonds no longer depends on the future borrowing decisions. The convenant is defined as

$$\mathcal{C}(b, y, \varepsilon, b') = \max\{q((1-\delta)b', y, \varepsilon) - q(b', y, \varepsilon), 0\}.$$

The government now compensates creditors for changes in the value of outstanding debt obligations due to changes of the debt stock. Thus, the budget constraint becomes

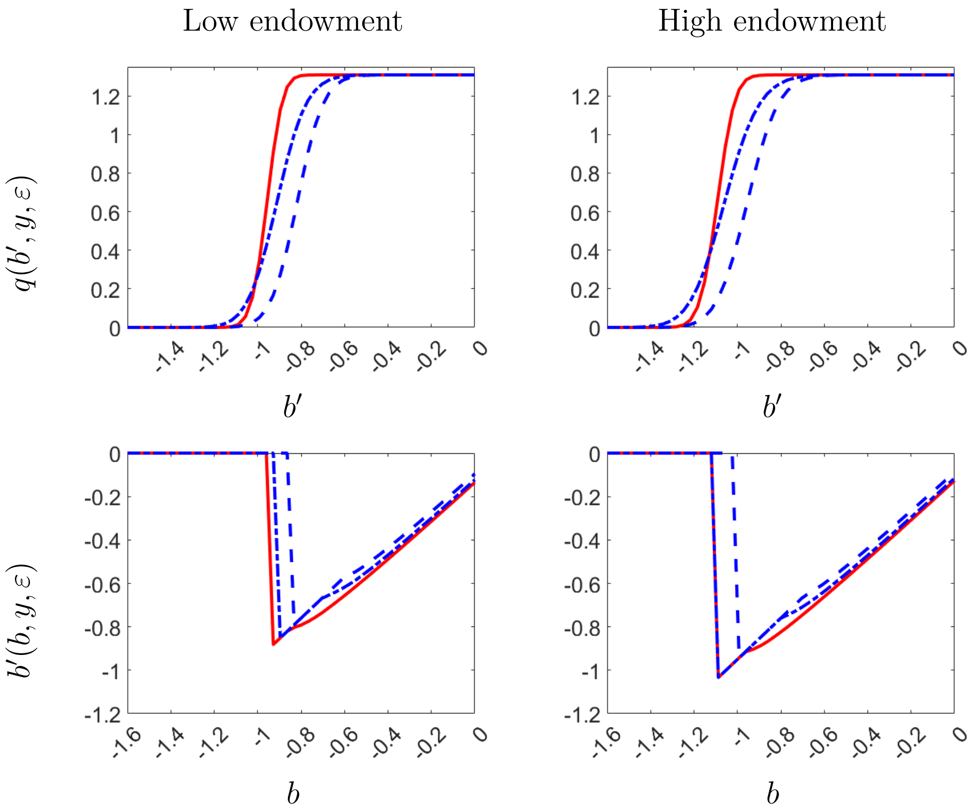
$$c = y + (\delta + (1-\delta)\psi)b - q^{\gamma}(b', y, \varepsilon)(b' - (1-\delta)b) + (1-\delta)b\,\mathcal{C}(b, y, \varepsilon, b').$$

The bond prices accounts for the compensation through debt covenants as follows,

$$q^{\gamma}(b', y, \varepsilon) = \frac{1}{1+r} \int_{y'} (1 - d(b', y', \varepsilon'))\left[\delta + (1-\delta)\left[\psi + (q^{\gamma}(b'', y''\varepsilon') + \mathcal{C}(b', y', \varepsilon', b''))\right]\right] \mu(y', y, \varepsilon) dy'.$$

Figure 10 plots bond prices and the debt policy in the presence of a debt covenant for the model under the benchmark calibration (blue) and the model in which we shut down diagnosticity, $\gamma = 0$ (red).

Figure 10: Policy Functions



Notes: The graphs show the debt policy and the bond price for the model with the debt covenant. Blue lines refer to the benchmark calibration with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dash-dotted). Solid red lines denote the functions for a parameter variation of the diagnostic factor ($\gamma = 0$), implying rational expectation formation. Low (high) endowment refers to levels of -3.49% (3.49%) around the trend.

A.4 Spread distribution

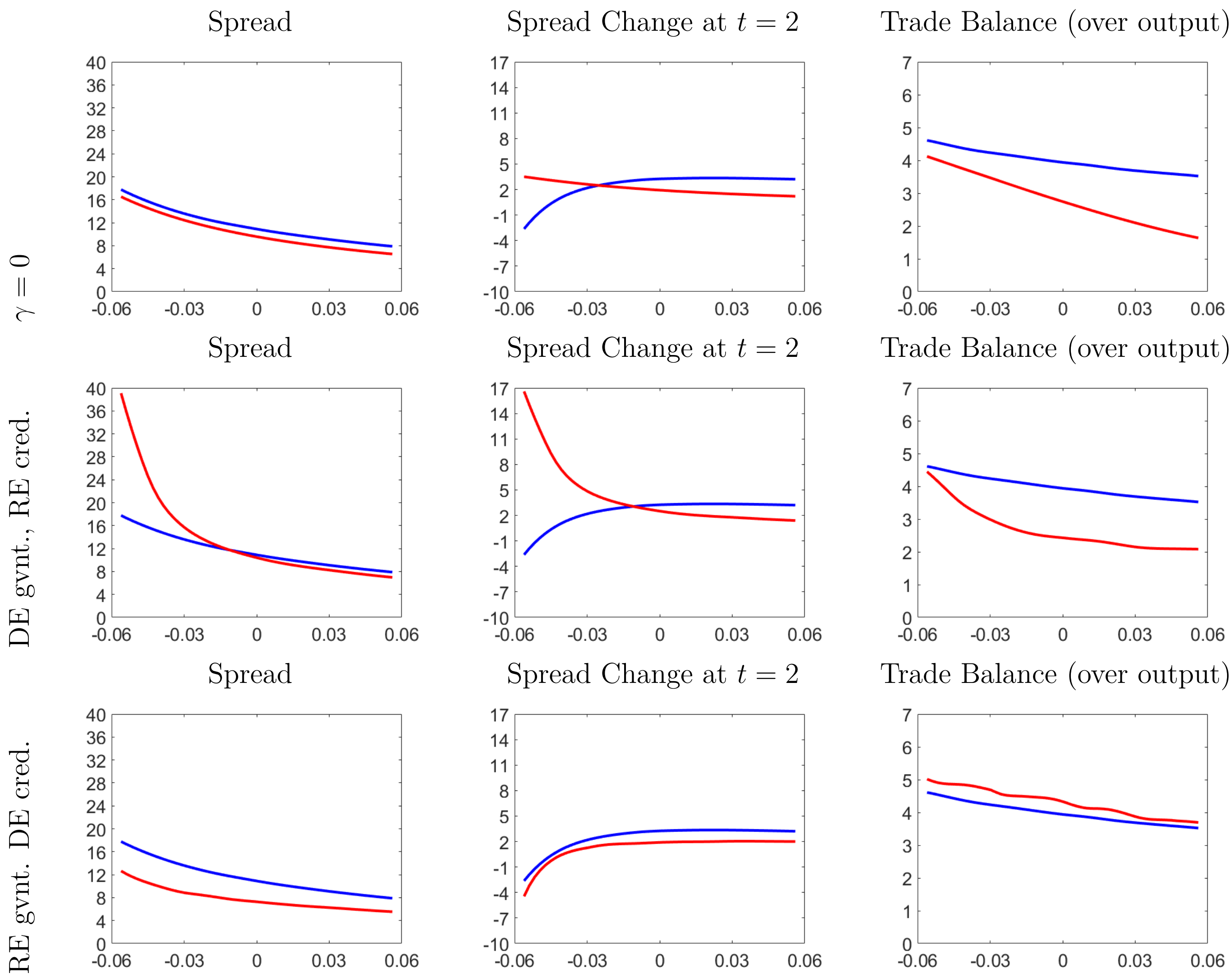
Table 6: Quantiles of Spreads

	(1) Data	(2) Full Diagnostic $\gamma = 0.67$	(3) $\gamma = 0$	(4) Rational
$Q_{0.10}(s)$	4.40	4.23	2.26	4.22
$Q_{0.25}(s)$	5.98	5.36	2.79	5.25
$Q_{0.50}(s)$	7.42	6.93	3.48	6.72
$Q_{0.75}(s)$	8.45	9.2	4.44	8.98
$Q_{0.90}(s)$	11.64	12.71	5.89	12.75

Notes: $Q_\alpha(s)$ denotes the α-th quantile of the spread.

A.5 Generalized impulse responses

Figure 11: Generalized Impulse Responses – Variations of γ



Notes: We take the state of the economy after 1000 periods without a shock innovation ($\varepsilon = 0$). We employ scenarios, where the economy is hit in period one by shock innovations of up to $+/-5.58\%$, where the largest shocks are about two standard deviations. In period two, the economy is hit by a negative shock innovation of one standard deviation (-2.71%). The graphs plot the initial period two responses of the bond spread, its change relative to period one and the trade balance over output. The graphs compare the benchmark model (black) with (i) the parameter variation of $\gamma = 0$ (grey, top panel); (ii) the model with diagnostic government and rational creditors (grey, middle panel); and (iii) the model with rational government and diagnostic creditors (grey, bottom panel).