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Niemann, Stefan; Prein, Timm

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Sovereign Risk under Diagnostic Expectations *

Stefan Niemann^{\dagger} Timm M. Prein^{\ddagger}

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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 (spread limits), which need to trade-off their beneficial effects via reduced debt dilution against the fact that they condition on spreads that may be subject to market sentiment.

Keywords: sovereign debt; diagnostic expectations; fiscal rules

JEL-Codes: E44, E62, F34, H63

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[†]University of Konstanz, stefan.niemann@uni-konstanz.de.

[‡]University of Helsinki and Helsinki Graduate School of Economics, timm.prein@helsinki.fi.

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. This can happen 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. This is particularly the case when the initially optimistic outlook is disappointed and the positive sentiment surrounding the country turns sour.

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. Substantiating this narrative with more systematic empirical evidence, they regress sovereign spreads S_{it} on country fundamentals X_{it} ,

$$\ln S_{it} = \alpha + \beta \mathbb{X}_{it} + \mu_{it},$$

and examine the role of the residual μ_{it} , interpreted as a sentiment-driven mispricing factor, for subsequent economic outcomes.¹ Specifically, they consider spread dynamics at different quarterly horizons h = 1, ..., 6 to estimate (by pooled OLS) the effects of past mispricing,

$$\ln S_{it} - \ln S_{it-h} = \delta + \eta \mu_{it-8} + \epsilon_{it}.$$

Figure 1 below presents their estimated coefficient $\hat{\eta}$ together with the 95% confidence interval at the different horizons h. As seen, $\hat{\eta}$ is found to be significantly negative. This implies that optimistic sentiment $\mu_{it-8} < 0$ (that is, spreads eight quarters ago lying below the value justified by fundamentals) tends to be followed by a persistent widening of spreads. This is suggestive of lending taking place at non-rational rates: Relative to creditors providing funds at rates consistent with $\mu_{it-8} = 0$, those lending at $\mu_{it-8} < 0$ are earning lower flow returns and might also suffer from capital losses on their investment.

 $^{^{1}}$ Their approach can thus be seen as an application of the ideas in Gilchrist and Zakrajšek (2012) to the setting of sovereign lending.



Figure 1: Sentiment reversals in Al-Amine and Willems (2022).

In this paper, we examine the implications of this behavior 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 documented 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. 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 estimates reported above.

When this diagnostic mechanism is at work in our otherwise standard model along the lines of Chatterjee and Eyigungor (2012), its quantitative implications can be compared 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 2.4% per year (relative to about 6.2% in the rational model). This is because debt positions that are perceived as relatively safe in the rational model are perceived as more risky under diagnostic expectations so that bond prices are globally (except for very high debt positions) depressed relative to their rational counterpart. But 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. This is achieved by varying the degree of diagnosticity γ away from its calibrated baseline value at $\gamma = 0.67$ (but keeping all other model parameters unchanged). When diagnostic expectations are removed on both market sides, the model predicts spreads with both a lower average level and a lower volatility. But since the government accumulates higher debt positions, the probability of default is actually increased. Nevertheless, the removal of diagnostic expectations promises sizeable welfare gains equivalent to almost one percent of average consumption.

When only the sovereign borrower forms diagnostic expectations while creditors are pricing default risk rationally, we find that the borrower's default policy remains crucially affected by diagnostic sentiment. In consequence, the bond pricing menu offered by creditors inherits important properties – depressed bond prices and weakened dependence on the level of debt – from the fully diagnostic setting. On the other hand, bond prices no longer depend on current news, which facilitates better consumption insurance and small welfare gains relative to the fully diagnostic baseline model.

Turing 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 approximately two thirds 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 actually 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 rules are often motivated in view of the debt dilution problem when countries issue long-term debt, but under diagnostic expectations they also aim at addressing distortions which arise because sovereign spreads deviate from the value that is justified by economic fundamentals. At the same time, however, the disconnect between spreads and fundamentals calls for caution in the design of such rules, especially when they are anchored in spreads (Hatchondo et al., 2022a). When we evaluate the welfare consequences of fiscal rules in the context of our quantitative model, we find that spread limit have generally positive welfare effects, which materialize because they contain the debt dilution problem and thus support better bond prices. The tightness of the fiscal rule (as measured by the maximum spreads tolerated) actually has non-monotonic effects, with the maximum welfare gains realized under an annualized spread limit of about two percent for our diagnostic baseline model. Comparing these results to those obtained from the alternative rational expectations model, the welfare gains are smaller. This reflects the potential problems associated with fiscal rules conditioning on the level of spreads, when the latter are subject to sentiment. However, these problems are more than compensated by the beneficial effects coming from reduced default risk.

Related literature. Our work builds on the 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). Our 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. We complement their findings with new results from a sovereign debt setting, including the detailed analysis of asymmetric configurations for diagnostic versus rational expectations held by creditors and their sovereign borrower. Moreover, we provide original evidence supporting the empirical relevance of diagnostic features inherent the forecasts published in the IMF World Economic Outlook (WEO). We also advance the literature on sovereign debt and default by considering an empirically plausible framework for the formation of expectations and the determination of sovereign spreads. 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). Finally, we examine the case for fiscal rules in this setting, similar to Hatchondo et al. (2022a,b).

Our model is successful in matching salient business cycle statistics, including the distribution of spreads, but at an empirically more plausible default frequency relative to Chatterjee and Eyigungor (2012). Similar results are obtained in Pouzo and Presno (2016), but our diagnostic expectations approach is more tractable and based only on a single parameter that can be estimated from expectations data. A key prediction in this context is that forecast errors for the underlying output process are predictable, a fact we document empirically based on the IMF's World Economic Outlook (WEO). 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. This is particularly relevant when examining the welfare gains from switching expectations from diagnostic to rational. Our finding that the borrower side is most important for realizing such welfare gains finally motivates our analysis of fiscal rules.

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 further inflate the perceived likelihood of this outcome beyond the corresponding rational expectation. For example, good news about the current endowment does not only (by virtue of its persistence) increase the objective likelihood of a high future endowment, but it also causes (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.² Thus, when $\gamma > 0$, expectations systematically overreact to news: Beliefs are too optimistic in good times and too pessimistic in bad times (Bordalo et al., 2020).

To illustrate the potential of diagnostic expectations to fundamentally alter the dynamic behavior of spreads, 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.³ 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. 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 mean-reversion. Instead, under diagnostic expectations ($\gamma > 0$), the effect of the endowment shock is 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}).

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

²The parameter γ can be estimated from survey data on expectations held by financial market participants. Most estimates available to date are in the range $\gamma \approx 1$ (cf. Bordalo et al., 2022). Our own estimate obtained on the basis of growth forecasts from IMF's World Economic Outlook (WEO) is somewhat lower.

³Relative 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.

Economic Outlook (WEO). The data is obtained from the Historical WEO Forecasts Database (October 2022 release)⁴ 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 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. Similarly, the within-period (spring to fall) revision in light of current information flows can be written as⁵

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

⁴See https://www.imf.org/en/Publications/WEO/weo-database/2022/October.

⁵In detail, 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 $g_{i,t}^f = \epsilon_{i,t}^f - \epsilon_{i,t}^s$.

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

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

$$\hat{\theta} = \frac{Cov(fe_{i,t+1}, \Delta E_t^{\gamma} \{g_{i,t+1}\})}{Var(\Delta E_t^{\gamma} \{g_{i,t+1}\})}.$$
(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 equations (3) and (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, the regression coefficient in (6) becomes⁶

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

 $\overline{\rho g_{i,t-1}^f + \epsilon_{i,t}^f}$. The two associated forecasts are

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

which implies a spring to fall forecast revision of

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

⁶In detail, we have

$$Cov(fe_{i,t+1}, \Delta E_t^{\gamma} \{g_{i,t+1}\}) = Cov(g_{i,t+1} - E_t^{\gamma} \{g_{i,t+1}\}, \Delta E_t^{\gamma} \{g_{i,t+1}\})$$

= $Cov(\epsilon_{i,t+1}^f - \gamma \rho \epsilon_{i,t}^f, (1+\gamma)\rho(\epsilon_{i,t}^f - \epsilon_{i,t}^s))$
= $-\gamma(1+\gamma)\rho^2 \sigma_{\epsilon}^2 (1-\rho_{sf})$

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 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 a degree of diagnosticity in the range of $\gamma \approx 0.5.^7$ 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.

and

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

Hence, the regression coefficient becomes

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

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

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

Table 1: Regression Results WEO Panel

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.

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 endowment. 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 houshold'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 stream 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 $\varepsilon_t \sim N(0, \sigma_{\varepsilon}^2)$.

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

Table 2: Regression Results LAC Panel and Argentina

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.

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 a longduration bond. 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 markes and it will 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. All agents form their expectations diagnostically, such that they will overreact to news. Diagnostic expectations imply that agents overestimate the probability of future endowment realizations whose likelyhood has increased in response to an endowment shock. Following Bordalo et al. (2021), expectations take the following form:

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

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 build diagnostically expectations about the future endowment realizations. Given a good credit standing, the government chooses its optimal debt policies. 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:

$$V^{\gamma}(b, y, \varepsilon) = \max\left\{V_{R}^{\gamma}(b, y, \varepsilon), V_{D}^{\gamma}(y, \varepsilon)\right\},\tag{8}$$

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

The value function in case of debt repayment solves:

$$V_R^{\gamma}(b, y, \varepsilon) = \max_{b'} \left\{ u(c) + \beta \int_{y'} V^{\gamma}(b', y', \varepsilon') \mu(y', y, \varepsilon) dy' \right\}$$
(9)

subject to

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

In case of a default, to 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:

$$V_D^{\gamma}(y,\varepsilon) = u(y_t - \phi(y_t)) + \beta \int_{y'} (1-\theta) V_D^{\gamma}(y',\varepsilon') + \theta V(0,y',\varepsilon') \mu(y',y,\varepsilon) dy', \tag{10}$$

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:

$$\mathcal{D}(b,\varepsilon) = \{ y \in \mathcal{Y} : d(b,y,\varepsilon) = 1 \}.$$
(11)

The default probability follows as:

$$\eta(b', y, \varepsilon) = \int_{\mathcal{D}(b', \varepsilon)} \mu(y', y) dy'.$$
(12)

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:

$$q^{\gamma}(b',y,\varepsilon) = \frac{1}{1+r} \int_{y'} (1-d(b',y',\varepsilon'))(\delta+(1-\delta)(\psi+q^{\gamma}(b'',y''\varepsilon')\mu(y',y,\varepsilon)dy')$$
(13)

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 (8), (9), (10), and (11).
- 2. Bond prices $q(b', y, \varepsilon)$ fulfill equation (13), 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 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 risk aversion, σ , to a level of 2 as it is standard in the literature. Following Chatterjee and Eyigungor (2012), we set the probability of regaining accress 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, $\rho = 0.9548503$, and the volatility, $\sigma_{\varepsilon} = 0.027092$ from Chatterjee and Eyigungor (2012) who use Argentinean linearly detrended quarterly real GDP data for the time 1980:I-2001:IV.

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.

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 $\xi_1 \ge 0$.

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 of 70%, and a mean and standard deviation of the spread of 0.0815 and 0.0443, 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.1. Table 3 shows that both our baseline diagnostic model as well as a recalibration version of the model with rational expectations ($\gamma = 0$) match the targeted statistics very well.

4.2 Policy functions

We first study the effects of diagnostic expectations on optimal debt policy and bond pricing. The black lines in Figure 2 show the borrowing decisions and the bond price functions for low (dashed)

Parameter	Description	Value					
		Diagnostic	Rational				
Externally ca							
r	Risk-free rate	0.0	0.01				
σ	Relative risk aversion	2.0					
ho	Autocorrelation	0.948503					
$\sigma_{arepsilon}$	Standard deviation of ϵ	0.027	092				
δ	Maturing Probability	0.0	0.05				
heta	Reentry probability	0.03	85				
ψ	Coupon Payment	0.03					
γ	Diagnostic factor	0.67	0				
Internally cal	librated parameters						
eta	Discount factor	0.957	0.950				
ξ_0	Output cost (intercept)	-0.105	-0.184				
ξ_1	Output cost (slope)	0.1680	0.2462				
Calibration targets Data		Simulations					
		Diagnostic	Rational				
E (debt/GDF)	P) 70.00	70.42	70.56				
E (spread)	(spread) 8.15		8.22				
std (spread)	4.43	4.33	4.38				

Table	3:	Calibration

and high (dash-dotted) realizations of the shock innovation ε of -3.6% and +3.6%, respectively. The left (right) column refer to endowment realizations 4.02 below (above) the trend.

Beginning with bond prices (middle panels of Figure 2), it is evident that current news act as shifters for the bond price function $q(b', y, \varepsilon)$.⁸ 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, instead, there is no such dependence. Comparison across the two alternative models⁹ 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 bottom panels of Figure 2 which display the expected probability of default occurring in the next period. In case of the solid lines, the perceived probability of default coincides with the actual default probability (as, also in the diagnostic

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.

⁸For 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.

⁹Recall that the parameterization across the two models is identical, except for the diagnosticity parameter γ .



Figure 2: Policy Functions

Notes: The graphs show the debt policy and the bond price. Black lines refer to the benchmark model with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dash-dotted). Solid grey lines denote the functions for a parameter variation of the diagnostic factor ($\gamma = 0$), implying rational expectation formation. For the expected default probability, solid black lines represent expectations in the benchmark model for a realization of $\varepsilon = 0$. Low (high) endowment refers to levels of -4.02% (4.02%) around the trend.

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, the key mechanism behind the global reduction of bond prices is the expectation that future market sentiment makes default more likely.¹⁰ As seen from the dashed and dash-dotted lines, this forward-looking mech-

¹⁰For extremely high debt positions, the effect of negative sentiment (when $\varepsilon' < 0$) is limited as the probability of default is already very close to one. Hence, the effect of positive sentiment (when $\varepsilon' > 0$) dominates and actually leads to a lower default expectation in the diagnostic model. This also explains

anism remains relevant also under non-zero realizations of the current shock ε . In particular, even under a good current shock (see the 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.¹¹

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 (top panels of Figure 2). 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 coincides with that of the rational model. This asymmetry 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 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. 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 relative to the rational model in column (4), which is similarly successful in matching the targeted moments (cf. Table 3), lies in its untargeted implication for the predicted default frequency. Despite the challenges for determining the true default frequency from the data, there seems to be a consensus in the literature (cf. Arellano, 2008; Hatchondo et al., 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; hence the average output drop when defaulting is higher at 5.6% relative to 4.1%.

the positive effect on bond prices for very high debt positions reported above.

¹¹Figure 8 in Appendix A.2 shows the debt policy and bond pricing functions for an environment with one-period debt. There is a strong negative effect on bond prices also in this setting because of the strong diagnostic effect regarding the imminent future when the entirety of the outstanding debt is due.

In order to examine the quantitative relevance of sentiment swings for uncoupling spread dynamics from fundamentals, it is useful to consider a variation of the diagnostic 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 materializes in sizeable welfare gains, expressed in terms of the equivalent variation in consumption, of 0.95%.¹²

 Table 4: Business Cycle Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	(1) Data	(2) Full Diam	(U)	(±) Detional	DF grant	\mathbf{PE} grant
	Data	Dan alerra anla	nostic	national	DE gviit.	DE and it a
		Benchmark			RE creditor	DE credito
		$\gamma = 0.67$	$\gamma = 0$		$\gamma = 0.67$	$\gamma = 0.67$
$\sigma(c)/\sigma(y)$	1.09	1.39	1.37	1.40	1.31	1.37
$\sigma(TB/y)/\sigma(y)$	0.17	0.81	0.94	1.03	0.98	0.60
$\sigma(TB/y)$		2.87	3.31	3.64	3.53	2.11
$\sigma(s)$	4.43	4.33	1.86	4.38	5.31	3.83
ho(c,y)	0.98	0.90	0.89	0.86	0.86	0.94
ho(TB/y,y)	-0.88	-0.35	-0.27	-0.24	-0.16	-0.51
ho(s,y)	-0.79	-0.54	-0.58	-0.53	-0.46	-0.46
ho(s,b')		0.15	0.06	-0.04	-0.21	0.37
E(s)	8.15	8.03	4.14	8.22	8.16	5.98
$E(\Delta s)$	1.71	2.55	0.87	1.95	2.05	1.91
$\sigma(\Delta s)$	2.70	3.55	1.22	2.95	3.85	3.94
Max. s	29.71	48.52	18.25	40.74	59.85	183.72
Mean debt output ratio $(\%)$	70.00	70.42	80.01	70.56	70.54	76.21
Mean Drop in y (around default)	-6.4	-5.58	-4.77	-4.14	-3.92	-6.05
Default frequency $(\%)$		0.61	0.83	1.56	1.49	0.08
Welfare equivalent (in %)	_	_	0.95	_	0.03	0.64

Notes: All statics are based on non-exclusion periods out of 500 000 observations, where the first 1000 were discarded. The series for y and c are HP filtered with factor 1600. Spread are denoted in annual values, default probabilities are quarterly. The data values are taken from Chatterjee and Eyigungor (2012) except for the drop in output around default, which is taken from Pouzo and Presno (2016).

Table 5 zooms in on the behavior of spreads by reporting also percentiles of their distribution. By design, both the diagnostic and the rational model match the average spread very well. Given the

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

where V is the expected lifetime utility of our representative agent. '*' and ' \circ ' refer to the model without diagnostic expectation formation and the benchmark model, respectively.

¹²In detail, the welfare effects of diagnostic expectations are computed by a comparison of the lifetime utility of a representative agent in our benchmark economy and the counterfactual economy in which diagnostic behavior is eliminated, $\gamma = 0$. Following Durdu et al. (2013), we compute the welfare gain as the equivalent variation in consumption,

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 $\gamma = 0$.

	(1)	(2)	(3)	(4)
	Data	Full Diagnostic		Rational
		$\gamma=0.67$	$\gamma = 0$	
$Q_{0.10}(s)$	4.40	4.36	2.43	4.51
$Q_{0.25}(s)$	5.98	5.47	2.98	5.58
$Q_{0.50}(s)$	7.42	6.99	3.72	7.05
$Q_{0.75}(s)$	8.45	9.17	4.77	9.31
$Q_{0.90}(s)$	11.64	12.53	6.25	13.07

Table 5: Quantiles of Spreads

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

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 3. The exercise here is to look at the impact response of borrowing and spreads to a negative endowment shock in period 2 (ε_2 one standard deviation below normal), depending on the endowment situation in period 1 (ε_1 ranging from minus to plus two standard deviations).

In the calibrated rational model (grey), the bad shock in period 2 induces a hike in spreads, ranging from about 8% when the preceding shock in period 1 was very good to more than 30% after a very bad shock in period 1. Expressed in terms of spread changes between periods 1 and 2, the bad shock in period 2 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 2 was preceded by a more benign shock in period 1. This pricing pattern induces the sovereign borrower to decumulate debt, as seen from the unambiguously positive response of the trade balance.

The impact response of spreads in period 2 is qualitatively similar but more contained in the diagnostic model (black). Turning to spread changes between periods 1 and 2, however, there is a striking difference to 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. On the other hand, a sequence of two negative shocks actually leads to a drop in spreads between periods 1 and 2; this is because the market is already conditioned by pessimistic sentiment so that the negative shock in period 2



Figure 3: 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 1 by shock innovations of up to +/-5.58%, where the largest shocks are about 2 standard deviations. In period 2, the economy is hit by a negative shock innovation of one standard deviation (-2.71%). The graphs plot the initial period 2 responses of the bond spread, its change relative to period 1 and the trade balance over output. The graphs compare the model under diagnostic (black) and rational expectations (grey).

actually records as positive news. In sum, therefore, the change in spreads now depends negatively on the period 1 shock.¹³ This pattern is inherited by the trade balance, which displays a positive impact response but is now less dependent on the period 1 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. In analogy to the baseline from Figure 2, Figure 4 plots the policy 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 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, the default frequency increases substantially to about 6% annually, which undermines the benign effect of improved insurance

¹³When the period 1 shock was neutral ($\varepsilon_1 = 0$) so that there is no distortion of beliefs in the diagnostic model, the change in spreads is identical across the two models. Figure 9 in Appendix A.3 revisits the analysis of generalized impulse responses also for model variations where diagnostic expectations are relevant only on one side of the credit market.



Figure 4: Policy Functions – DE government, RE creditors

Notes: The graphs show the debt policy and the bond price. Black lines refer to the benchmark model with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dash-dotted). Solid grey lines denote the functions for the model with diagnostic government and rational creditors. Low (high) endowment refers to levels of -4.02% (4.02%) around the trend.

and, at a consumption equivalent variation of 0.03%, almost completely eliminates the welfare gains relative to the diagnostic baseline economy.

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. Figure 5 plots the policy functions relevant for this alternative asymmetric configuration.

As seen, the family of bond pricing functions looks qualitatively similar to the diagnostic baseline model. But the rational government responds to volatile menu with a more prudent debt policy,



Figure 5: Policy Functions – RE government, DE creditors

Notes: The graphs show the debt policy and the bond price. Black lines refer to the benchmark model with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dash-dotted). Solid grey lines denote the functions for the model with rational government and diagnostic creditors. Low (high) endowment refers to levels of -4.02% (4.02%) around the trend.

that is, it issues less debt when $\varepsilon < 0$ and more debt when $\varepsilon > 0$. Again, this is visible from the cyclical behavior of the trade balance, which is now more countercyclical (cf. column (6) of Table 4). While consumption insurance is 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 of 0.64% consumption equivalent variation. In other words, while a rational supply side of the credit market allows for only very modest welfare gains, rationality on the demand side allows for capturing welfare gains of about two thirds of the overall welfare gains from completely eliminating diagnostic behavior on both sides of the credit market.

4.6 Fiscal rules

The finding that the welfare costs of diagnostic behavior are predominantly rooted on the side of the sovereign borrower provides motivation for examining the effects fiscal constraints. In the context of sovereign debt markets, fiscal rules have been advocated as tools to address debt dilution and overborrowing problems (cf. Hatchondo et al., 2022a). Given our emphasis on diagnostic distortions in the pricing of sovereign debt, spread rules, that is, constraints that create an upper bound for admissible spreads at which the sovereign borrower is allowed to issue liabilities, are particularly interesting. On the one hand, spread rules discipline the dynamically inconsistent borrowing behavior with outstanding long-term debt position – the debt dilution problem. But on the other hand, such rules may be problematic as they condition of spreads that may themselves be distorted due to diagnostic expectations held by international lenders. This gives rise to a trade-off regarding the appropriate design of fiscal rules, which we study in this section.

To study how diagnostic expectations affect the welfare benefit from fiscal rules, we incorporate a spread brake rule along the lines of Hatchondo et al. (2022a) into our model. The rule implies that borrowing must be below a threshold which is defined by a limit on the interest rate spread for new debt. Let the threshold be denoted by $\bar{b}_s(y, \varepsilon, \bar{r}_s)$, where \bar{r}_s is the spread limit. Following the rule, it must hold that $b' \leq \max\{\bar{b}_s, b-\lambda\}$, such that, if the initial debt is above the debt limit, there must be at least a debt reduction of size λ . We follow the baseline calibration of Hatchondo et al. (2022a) and assume that the minimum debt reduction equals the amount of maturing debt $\lambda = \delta b$.

Our quantitative findings are contained in Figures 6 and 7.

TO BE COMPLETED.

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 (spread limits), which need to trade-off their beneficial effects via reduced debt dilution against the fact that they condition on



Figure 6: Fiscal Rules - Benchmark Model

Notes: The graphs show the mean spread (annualized, in %, the mean debt to output ratio, the default frequency (quarterly, in %), and the welfare equivalent with respect to the benchmark model for different spread brake rules, denoted on the x-axis.

spreads that may be subject to market sentiment.



Figure 7: Fiscal Rules - Benchmark Model (black) vs. Recalibrated (grey)

Notes: The graphs show the mean spread (annualized, in %, the mean debt to output ratio, the default frequency (quarterly, in %), and the welfare equivalent with respect to the benchmark model for different spread brake rules, denoted on the x-axis.

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A Appendix

A.1 Appendix: 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 $V_{(0)}^{\gamma}(b, y, \varepsilon)$, $V_{R,(0)}^{\gamma}(b, y, \varepsilon)$, and $V_{D,(0)}^{\gamma}(y, \varepsilon)$, and the bond price function $q_{(0)}^{\gamma}(b, y, \varepsilon)$. 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 $q_{(0)}^{\gamma}(b, y, \varepsilon)$ via equation (13). 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 $V_{(0)}^{\gamma}(b, y, \varepsilon)$, $V_{R,(0)}^{\gamma}(b, y, \varepsilon)$, and $V_{D,(0)}^{\gamma}(y, \varepsilon)$, and the bond price function $q_{(0)}^{\gamma}(b, y, \varepsilon)$. We iterate until the value functions and the bond price function converge.

A.2 One-period debt

A.3 Generalized impulse responses



Figure 8: Policy Functions with One-Period Debt

Notes: The graphs show the debt policy and the bond price for the model with one-period debt. Black lines refer to the benchmark model with realizations of $\varepsilon = -0.036$ (dashed) and $\varepsilon = 0.036$ (dashdotted). Solid grey lines denote the functions for a parameter variation of the diagnostic factor ($\gamma = 0$), implying rational expectation formation. For the expected default probability, solid black lines represent expectations in the benchmark model for a realization of $\varepsilon = 0$. Low (high) endowment refers to levels of -4.02% (4.02%) around the trend.



Figure 9: 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 1 by shock innovations of up to +/-5.58%, where the largest shocks are about 2 standard deviations. In period 2, the economy is hit by a negative shock innovation of one standard deviation (-2.71%). The graphs plot the initial period 2 responses of the bond spread, its change relative to period 1 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 rational creditors (grey, middle panel); and (iii) the model with rational government and diagnostic creditors (grey, bottom panel).