Behavioral Biases, the Current Account, and Sovereign Default

Nicolas Aragon*

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Abstract

Developing economies borrow in booms and lose market access in downturns, at substantial cost to growth. The standard explanation attributes the borrowing to shocks to trend productivity, which makes the resulting deficits efficient and leaves no role for policy. We show that the same facts arise when growth is mildly persistent but agents form expectations through a disciplined misspecified model following Barberis et al. [1998]. Agents weigh a trend-following and a reversionist model of growth and update by Bayes' rule; runs of same-signed shocks move beliefs toward persistence, and a belief reversal reprices the entire stock of debt at once, producing a default. With long-duration debt, the mechanism generates spread volatility seven times that of the trend-shock benchmark and a default frequency matching the historical record of emerging markets. There is scope for policy: debt caps must be stricter than in a rational economy, growth-contingent debt reduces crises by lowering payments in bad states, and instruments that lean against beliefs stabilize spreads without preventing default. **Keywords:** sovereign default, learning, behavioral biases, capital flows to developing countries, sudden stops, debt sustainability.
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1 Introduction

Emerging markets often experience debt crises followed by contractions in output and loss of market access, with estimated output costs of about 2.5 percentage points in the year of default [Borensztein and Panizza, 2009]. Influentially, Aguiar and Gopinath [2006] show that a small open economy with defaultable debt reproduces salient facts observed in emerging markets: consumption is more volatile than output, the trade balance is countercyclical, spreads are volatile, and default is observed. The driving force in their framework is shocks to the growth rate of productivity rather than transitory shocks around a stable trend. In this environment, the default cycle is an efficient response to changing prospects.

We include a disciplined form of dynamic behavioral biases in an open-economy real business cycle model with default as in Aguiar and Gopinath [2006], but with a mildly persistent shock that can be perceived as more or less permanent depending on history. We show that the same behavioral biases can account for the salient features of developing economies documented by Aguiar and Gopinath [2006]. Agents endogenously move between waves of optimism and pessimism about future growth, and the model reproduces the EMDE moments, but through disciplined expectational mistakes instead of trend shocks. Relative to a rational expectations version of the same economy, the behavioral mechanism raises the volatility of spreads and default frequency bringing the model in line with the data, while preserving the volatility of consumption and output.

We first present evidence of behavioral biases in IMF forecasts. Expanding on the methodology of Amir and Ganzach [1998], we show that IMF forecasts exhibit overoptimism and overpessimism, and that this depends on the sign of the forecast revision in previous periods. The phenomenon is particularly striking for middle-income countries, including emerging Asia, emerging Europe, and Latin America.

The expectation-formation mechanism we adopt is from Barberis et al. [1998], which models investor sentiment parsimoniously and in a disciplined manner. In their model, the underlying asset follows a random walk. However, the investor believes that the world can be in one of two regimes that alternate with some probability: mean-reverting and trend-following. Agents learn across these misspecified models to infer which one is more likely to be behind the data-generating process. Positive shocks followed by positive shocks increase the likelihood that the trend-following model is behind the process, and alternating shocks do the same for the mean-reverting regime. As the agent learns through misspecified models, the economy moves between waves of optimism and pessimism, and between overreaction and underreaction to news.

The underlying reason for agents to use misspecified models arises from the use of heuristics, specifically representativeness and conservatism. Representativeness is part of a series of heuristics introduced by Tversky and Kahneman [1974], in which people observe patterns in random sequences. In this way, agents quickly infer the underlying process from a small sample. Conservatism, identified by Edwards [1968], states that once agents form an impression, they are slow to change it when presented with new evidence. When they need to predict the future realization of a random sequence of shocks, agents using these heuristics are prone to behave in waves of optimism and pessimism.

We embed this learning mechanism and apply it to the growth process in a dynamic stochastic general equilibrium model with default as in Eaton and Gersovitz [1981], Arellano [2008], and Aguiar and Gopinath [2006]. The model can explain the main features of developing economies' stylized facts. First, consumption is more volatile than output. Second, the trade balance is countercyclical. Finally, sudden stops occur when expectations suddenly change from one regime to another.

The behavioral friction opens the door for policy interventions. A debt cap reduces the number of defaults, but a more stringent cap is necessary in the behavioral economy than in the rational expectations economy. A state-contingent instrument that lowers the coupon in bad states reduces the default frequency by reducing the behavioral defaults. Finally, a leaning-against-the-belief instrument stabilizes spreads but does not prevent default.

Related Literature. This paper draws on two branches of the literature: international macroeconomics in developing countries, and behavioral biases and learning in macro. Our model builds on the sovereign-default framework of Arellano [2008], Aguiar and Gopinath [2006], adds long-term debt as in Hatchondo and Martinez [2009], and embeds an expectational block from Barberis et al. [1998] (see Section 3.3).

The literature on equilibrium models for developing economies and sovereign default started with Mendoza [1991] and Eaton and Gersovitz [1981] and spawned an extensive literature. However, standard real business cycle models failed to account for features of the data in developing countries [Aguiar and Gopinath, 2006]. There are two main types of explanations: those relying on non-stationary shocks [Aguiar and Gopinath, 2006] and those that rely on financial frictions [Garcia-Cicco et al., 2010, Chang and Fernández, 2013]. We provide an equilibrium model with stationary shocks and behavioral biases that accounts for the same features.

Even though behavioral economics has had a central role in the finance literature, its incorporation into macroeconomics is more recent [Akerlof, 2002, Hommes, 2021]. There is, however, an extensive literature on imperfect information and learning about the trend [Beaudry and Portier, 2006, Boz et al., 2011, Angeletos and La'O, 2013, Zeev et al., 2017, Ilut and Schneider, 2014, Cao and L'Huillier, 2018, Heymann and Sanguinetti, 1998]. In our paper news shocks are, in a sense, endogenous, and the agent learns in the space of (incorrect) mental models. More importantly, in the literature a rational agent who needs to solve a signal extraction problem will misread trends, but as data accumulate her beliefs converge and the systematic component of her errors disappears [Heymann and Sanguinetti, 1998, Boz et al., 2011]. In those papers, misperception is real but transitional. In our model, the agent learns across misspecified models and her beliefs do not converge. This is similar to the game-theoretic literature on misspecified learning, where beliefs can converge to a biased, self-confirming path [Esponda and Pouzo, 2016, Fudenberg et al., 2021]. There is substantial evidence that macroeconomic forecast errors are not transitional, for public- and private-sector forecasts alike, as we document in Section 2.2.

Closest to our model, Jaimovich and Rebelo [2007] present a macroeconomic model with overoptimism and overconfidence. In contrast, we apply these insights to developing-country settings and focus on the dynamics of behavioral biases. Our expectation-formation mechanism generates different beliefs depending on the state of the world, unlike in their paper where biases are static.

The remainder of the paper is organized as follows. Section 2.2 provides forecast-error evidence. Section 3 presents the model. Section 5 shows the quantitative results and discusses the implications. Section 6 analyzes three policy instruments and Section 8 concludes.

2 Empirical Support

2.1 In the Literature

There is a large microeconomic literature that shows the presence of these biases, namely, conservatism and representativeness [see Benjamin, 2019, for a review]. Notwithstanding that, the question is whether this translates into macroeconomic expectations. We now turn to the literature that tests for features of forecasts that support incorporating behavioral biases in macroeconomic data.

The literature documenting biases in macroeconomic forecasts is large. Frankel [2011] and Hellwig [2018] document overoptimism in official forecasts for a panel of countries. Korniotis and Kumar [2011] uses state level data. Hagenhoff and Lustenhouwer [2020] and Ashiya [2003], on the other hand, identify behavioral biases in professional forecasters. Juhn and Loungani [2002] establish overoptimism and mean-reversion for private-sector growth forecasts for a large number of industrialized and developing countries and establish that private sector accuracy is similar to WEO forecasts.

Ho and Mauro [2014] study growth forecasts for more than one hundred countries at horizons up to twenty years. The central finding is that forecasters overestimate the persistence of growth, and this bias is especially large at longer horizons. The consequence is that optimism can turn a stable borrower into a candidate for a debt crisis.

2.2 Evidence from forecast errors

The model's mechanism relies on behavioral biases documented at the micro level, which imply that agents extrapolate runs of growth surprises: optimism rises during expansions and is corrected abruptly when realizations stop confirming the pattern. We confirm that the pattern holds in the specific form implied by the model, using the IMF's Historical WEO Forecasts Database, which records the real GDP growth forecast issued for each country semiannually over 1992-2024.

If agents extrapolate, an upward revision to a growth forecast should be followed, on average, by realized growth below that forecast. Following Bordalo et al. [2018] and Amir and Ganzach [1998], we carry out the following regression

$$FE_t = \alpha + \beta\, FR_t + \varepsilon_t, \tag{1}$$

where FE_t represents the forecast error and FR_t the prior revision, given by

$$FE_t = y_t - f_t^{t-1}, \quad FR_t = f_t^{t-1} - f_t^{t-2}, \tag{2}$$

with f_t^{t-1} representing the fall-vintage forecast of year-t growth issued in year $t-1$ and y_t is realized growth. A negative β implies overreaction: upward revisions predict reversals, and vice versa for a positive β. We split the sample into emerging economies (EMDEs) and advanced economies (AEs).

Table 1 reports the estimates. In AEs β is positive (0.17), the underreaction familiar from the forecasting literature. In EMDEs β is negative (-0.16): an upward revision is followed by growth below the revised forecast. The constant is negative in both groups and twice as large for developing economies, implying that forecasts are optimistic on average, and more so for the EMDEs.

The behavioral mechanism that we embed is not only about the last revision, but also how optimism is built dynamically. Thus, we turn to Columns 3 and 4,

	Forecast error FE_t		Forecast error FE_t	
	EMDE	Advanced	EMDE	Advanced
Revision FR_t	-0.157	$+0.169$		
	(0.052)	(0.063)		
Cumulative revision			-0.217	-0.079
$FR_t + FR_{t-1}$			(0.031)	(0.048)
Constant	-0.927	-0.427	-0.903	-0.470
	(0.087)	(0.081)	(0.084)	(0.080)
Countries	156	40	156	40
Observations	4,738	1,186	4,575	1,146

Table 1: Predictability of growth forecast errors. The dependent variable is the one-year-ahead real GDP growth forecast error, $FE_t = y_t - f_t^{t-1}$, where y_t is realised growth and f_t^{t-1} the fall-vintage IMF WEO forecast issued the previous year. Columns 1–2 regress it on the most recent forecast revision $FR_t = f_t^{t-1} - f_t^{t-2}$; columns 3–4 on the cumulative revision over the two preceding years, $FR_t + FR_{t-1}$. A negative slope indicates that upward revisions are followed by realised growth below forecast. Sample: IMF Historical WEO Forecasts Database, target years 1992–2024, excluding regional aggregates; forecast errors and revisions winsorised at the 1st and 99th percentiles within each group. Standard errors clustered by country in parentheses.

where we regress the forecast error on the cumulative revision on the preceding years $FR_t + FR_{t-1}$. For developing economies the coefficient is negative, meaning that the more the forecasters revised the growth upwards the more they overshoot afterwards. This term is insignificant for advanced economies. Figure 1 highlights the pattern. In Panel (a) the forecast error falls steeply with the cumulative revision for developing economies but is fairly flat for advanced economies. In Panel (b) we plot the mean forecast error for developing countries by the sign of the two preceding revisions. We can observe that when the preceding revisions were positive, the mean forecast error becomes larger in absolute value, implying higher optimism.

3 The model

The environment is the small open endowment economy with defaultable debt of Arellano [2008] and Aguiar and Gopinath [2006]. Unlike Aguiar and Gopinath [2006], the shocks are mildly persistent but the agent extrapolates causing larger effects. We also include long-duration debt, following Hatchondo and Martinez [2009], which is essential for the mechanism.

We first describe Barberis et al. [1998] (hereafter BSV) mechanism in isolation and then set up the recursive problem.

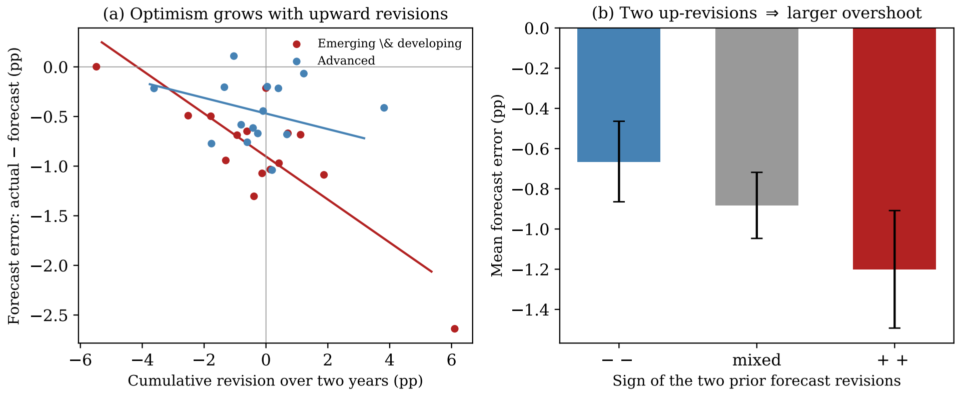

Figure 1: Growth forecast errors and prior revisions. Panel (a): binned-mean forecast error against the cumulative forecast revision over the two preceding years, with OLS fits on the underlying country-year data. The slope is steeply negative for emerging and developing economies and flat for advanced economies. Panel (b): mean forecast error for EMDEs by the signs of the two prior revisions, with 95% confidence intervals. The overshoot grows monotonically from two down-revisions to two up-revisions. Source: IMF Historical WEO Forecasts Database, 1992–2024.

3.1 The Barberis–Shleifer–Vishny mechanism

BSV designed the mechanism to reconcile two robust but seemingly contradictory regularities in financial markets: *underreaction* of prices to individual news announcements or short-horizon momentum and *overreaction* to extended sequences of similar news that lead to long-horizon reversals. BSV develop a model of investor beliefs that provides a rationale for these observations.

A two-state example. Consider a variable that can take a high or a low value each period. For BSV this represents a firm's earnings surprise and in our model it will represent the growth-rate innovation. In BSV's original example, the true data generating process is i.i.d. but the agents believe that the world alternates between two markovian regimes,

- **a trend-following model** ($M1$), under which a positive surprise is likely to be followed by another positive surprise (persistence);
- **a reversionist model** ($M2$), under which a positive surprise is likely to be followed by a negative one (mean reversion).

The agent does not observe which regime is active but must instead infer it from the observed realizations. She holds a prior probability π_t that the trend-following model governs the data and updates it by Bayes' rule as each realization of the

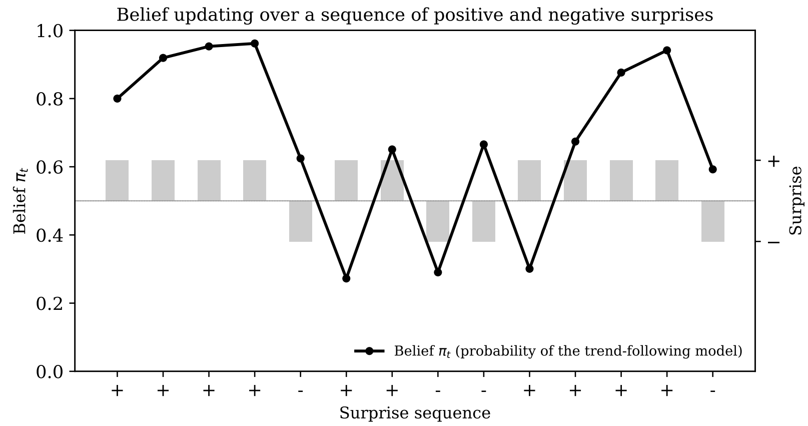

Figure 2: The belief-updating mechanism in a two-state example. The weight on the trend-following model rises through a run of same-signed surprises and falls sharply at each reversal.

variable arrives. Thus, if she observes several consecutive positive surprises, she increases the subjective probability that the trend-following regime is behind the process. Therefore, the belief π_t rises and she expects the run to continue. A surprise that breaks the pattern is associated with the reversionist regime, so π_t falls and the agent expects further reversals. Figure 2 illustrates the dynamics for the two-state example. Once there is a sequence of good realisations, as evidence of a good trend, π increases. A single reversal breaks the pattern and the belief collapses.

Underlying this phenomenon are two heuristics of Tversky and Kahneman [1974] and Edwards [1968] built into the transition probabilities. First, *Conservatism*, which is the tendency to update beliefs too little in response to a single new signal. The agent underreacts to news, and drifts in the direction of the news. Second, *Representativeness* or the tendency to read a systematic pattern when faced with a noisy sample. This persuades the agent to expect persistence after observing a sequence of same-signed surprises and the belief overreacts, only to reverse when the run ends. The agent in BSV is not irrational in a mechanical sense: she applies Bayes' rule correctly but is doing so in a space of misspecified models, none of which is the true one.

BSV apply this mechanism to a single risk-neutral investor pricing one asset, and show it reproduces the momentum-and-reversal pattern of the cross-section of stock returns. We embed the identical belief block in a general-equilibrium open-economy model, where the asset that is misperceived is the growth rate of national income. Thus, the agent's beliefs govern a sovereign's borrowing and default decisions.

The optimism and pessimism generated by BSV will lead to overborrowing, countercyclical trade balances, and belief-driven default. We depart in one way from BSV in order to discipline our model: we pin down $M2$ residually so that the two models average the true process. We detail this in Section 3.3.

3.2 Environment

A representative agent has preferences

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\theta}}{1-\theta}, \qquad \theta > 0,\ \beta < 1,$$

where $\mathbb{E}$ denotes expectations under the agent's subjective beliefs. The endowment is $y_t = \Gamma_t$, where the stochastic trend is governed by $\Gamma_t = g_t \Gamma_{t-1}$. The true process for the growth rate is

$$\ln g_t = (1-\rho_g)\big(\ln \mu_g - c\big) + \rho_g \ln g_{t-1} + \epsilon_t^g, \qquad \epsilon_t^g \sim N(0, \sigma_g^2), \tag{3}$$

with $c = \frac{1}{2}\sigma_g^2/(1-\rho_g^2)$ a mean-correction term so that μ_g is the unconditional mean growth. There is no transitory shock.

The agent trades a long-duration bond with the rest of the world. We use a geometric-coupon structure following Hatchondo and Martinez [2009] and Chatterjee and Eyigungor [2012]. A unit of the bond issued at t promises a coupon of 1 at $t+1$, δ_c at $t+2$, δ_c^2 at $t+3$, etc. Setting $\delta_c = 0$ is the case of a one-period bond as in Aguiar and Gopinath [2006], and a larger δ_c implies longer duration. The geometric decay has a convenient aggregation property: the portfolio of claims issued at different dates can be summarized by a_t, the face-value-equivalent stock of outstanding debt.

This specification has two properties that we use. First, absent new issuance the stock simply decays at rate δ_c each period, and the coupon payment due in the current period is a_t. Second, if the sovereign chooses a new stock a_{t+1}, it must sell $g_t a_{t+1} - \delta_c a_t$ bonds this period, where the g_t is the trend-correction for the new stock, priced at q_t per unit. This aggregation is the reason why the beliefs reprice the whole stock of debt at different maturities.

3.3 Beliefs

The agent does not know the real process, (3). She instead entertains two mental models of the growth process as in BSV. Under the first model, $M1$, she believes that it is trend-following:

$$(M1) \quad \ln g_t = (1-\rho_g^{M1})(\ln \mu_g - c) + \rho_g^{M1} \ln g_{t-1} + \epsilon_t^{M1}, \qquad \epsilon_t^{M1} \sim N(0, \sigma^{2,M1}), \tag{4}$$

with $\rho_g^{M1} > 0$ implying that a high realization raises the conditional mean of the next draw.

The second model, $M2$ will be defined residually, so that a fixed mixture of the two mental models reproduces the true transition kernel:

$$\lambda_1 \, M1 + (1-\lambda_1) \, M2 = \Pi^{\text{true}}. \tag{5}$$

where $M1$ and $M2$ are the discretized transition matrices under mental models $M1$ and $M2$ and λ_1 is a weight. We use equation (5) to discipline the model and pin down $M2$. Under (5) the two mental models average out to the truth, and the agent will be wrong on the sequencing of updates but not on average. In this way, we do not impose reversionism on $M2$, unlike BSV, and instead we verify this numerically. See Section 4.

The agent believes the world switches between the two models with fixed probabilities λ_1 and λ_2 that govern the move from $M1$ to $M2$ and from $M2$ to $M1$ respectively. The same λ_1 plays both roles in the model: it is the mixture weight in (5) that pins down $M2$ and the probability of leaving $M1$ in the updating rule below, and in the implementation it is a single parameter. She updates the posterior π_t that $M1$ is behind the dgp, by Bayes' rule:

$$\pi_{t+1} = \frac{\omega_{1t} \, \Pr(g_{t+1} \mid M1, g_t)}{\omega_{1t} \, \Pr(g_{t+1} \mid M1, g_t) + \omega_{2t} \, \Pr(g_{t+1} \mid M2, g_t)}, \tag{6}$$

where $\omega_{1t} = (1-\lambda_1)\pi_t + \lambda_2(1-\pi_t)$ and $\omega_{2t} = \lambda_1 \pi_t + (1-\lambda_2)(1-\pi_t)$ are the predictive weights the agent places on $M1$ and $M2$ respectively before the current realization is observed.

The belief π_t is a state variable: it summarizes the entire history of shocks relevant for forecasting. International investors share the agent's beliefs so there is no disagreement between borrower and lender.

3.4 Recursive problem

Let $V(a, g_{-1}, \pi_{-1})$ be the value of a sovereign entering the period with debt a, having experienced previous growth g_{-1} and carrying a prior belief π_{-1}. At the start of the period the growth realization g arrives and the belief is updated to π by Bayes' rule (6). Following Kreps [1998], the agent solves the problem under *anticipated utility*: she treats the current π as permanent when optimizing, which preserves the recursive structure.

The sovereign then chooses between repaying, with value V^G, and defaulting, with value V^B:

$$V(a,g,\pi) = \max\{V^G(a,g,\pi),\ V^B(g,\pi)\}.$$

In good standing,

$$V^G(a,g,\pi) = \max_{a'} \Big\{ u(c) + \beta\, \tilde{\mathbb{E}}\, V(a',g,\pi) \Big\}, c = y + a - q(a',g,\pi)\big(g\,a' - \delta_c\, a\big),$$

where $\tilde{\mathbb{E}}$ is the expectation under the updated belief, with π being updated via (6) at the start of the period.

The budget constraint shows that consumption, c, is the residual of the endowment y, plus the aggregated coupon payment due this period, a, minus the new issuances $g\,a' - \delta_c\, a$ at price $q(a',g,\pi)$. Default triggers a proportional output cost χ and temporary financial autarky, with reentry probability ψ:

$$V^B(g,\pi) = u\big((1-\chi)y\big) + \beta\Big[\psi\, \tilde{\mathbb{E}}\, V(0,g,\pi) + (1-\psi)\, \tilde{\mathbb{E}}\, V^B(g,\pi)\Big].$$

Risk-neutral investors have an opportunity cost r^* and price a newly issued unit of the bond consistently with the sovereign's default policy $D(a',g,\pi) \in \{0,1\}$ and with their own expectation of what that unit will be worth going forward. A unit issued today pays 1 next period if the sovereign has not defaulted, plus a claim worth $\delta_c\, q(a'',g',\pi')$, representing the continuation value of its remaining geometrically declining coupon stream, priced at whatever the market charges for new issuance in next period's state, where a'' denotes the sovereign's issuance policy in that state:

$$q(a',g,\pi) = \frac{1}{1+r^*}\, \tilde{\mathbb{E}}\Big[\big(1-D'\big)\big(1 + \delta_c\, q(a'',g',\pi')\big)\Big]. \tag{7}$$

Equation (7) is a key source of amplification for the model. Given that $q(a'',g',\pi')$ on the right-hand side is itself a function of next period's belief, the price of a bond issued today already embeds the market's view of how beliefs are likely to evolve; and because the same price multiplies the entire outstanding stock through $\delta_c a$ in the budget constraint, a swing in π reprices the sovereign's existing debt in full, without any change in fundamentals or in the quantity of debt outstanding. Setting $\delta_c = 0$ collapses (7) to the one-period bond price of Aguiar and Gopinath [2006], $q(a',g,\pi) = \tilde{\mathbb{E}}(1-D')/(1+r^*)$, under which only newly issued debt is exposed to beliefs and the amplification is absent. We discuss this further in Section 7.

4 Calibration and solution

We calibrate using all the standard preference and technology parameters from Aguiar and Gopinath [2006] and calibrating the growth process to EMDE data. Table 2 presents the values. The true growth process is set to a mildly persistent level of $\rho_g = 0.30$ and a standard deviation of the innovation of 0.025 that matches the unconditional growth volatility of EMDEs. This is obtained from an autoregression on EMDE data and consistent with the finding of Garcia-Cicco et al. [2010] that the strong stochastic trend which Aguiar and Gopinath [2006] identify in short samples does not survive in longer data. We discuss this further in Section 7.

We set the discount factor $\beta = 0.85$ to hit the default frequency and the default cost $\chi = 0.032$ to hit spread volatility. The only parameters that differ are those that govern the debt maturity structure and beliefs.

Three parameters govern the belief and the debt dynamics that are new relative to Aguiar and Gopinath [2006]. The term structure of the debt stock is set at 5 years using $\delta_c = 0.95$, in the range used by Chatterjee and Eyigungor [2012]. Regarding beliefs, the mixture weight λ_1 and switch parameter λ_2 control the movement of beliefs and are jointly calibrated.

The models that the agent uses are misspecified. The trend-following model, $M1$, has a persistence in growth-rate of $\rho_g^{M1} = 0.72$, higher than the true persistence of 0.30. Under this model, the latest surprises are extrapolated forward. The second model, $M2$, is pinned down residually by (5) with an implied persistence of essentially zero, $\hat{\rho}^{M2} = 0.0$. The shock is thus reversionist in the sense that it treats surprises as transitory as in Barberis et al. [1998]. Thus, a surprise carries no information on the next shock, and both a bad and a good realization are expected to be followed by average growth. Therefore, the beliefs will provide a dynamic that will lead the agent to oscillate between a persistent model ($M1$) and a transitory-reversionist model ($M2$). The true process is a mixture of the two.

The model is solved by value-function iteration on a discretized state space (a, g, π). We discretize all stochastic processes into a finite grid and detrend variables by Γ_{t-1} before solution. The belief interval is also discretized, $\pi \in [0, 1]$, to solve the sovereign's problem and the bond-price fixed point (7) at each grid value. In the simulation, we compute the Bayesian belief path (6), selecting the policy function for the realized belief in each period. As in Aguiar and Gopinath [2006], the moments are computed over contiguous spells of good credit standing and averaged across simulations, and spreads are annualized before HP-filtering.

	Parameter	Value	Target
Preferences and technology			
Risk aversion	θ	2	Aguiar and Gopinath [2006]
World interest rate	r^*	0.01	Aguiar and Gopinath [2006]
Redemption probability	ψ	0.10	Aguiar and Gopinath [2006]
Mean growth rate	μ_g	1.001	Aguiar and Gopinath [2006]
Std. of growth innovation	σ_g	0.025	EMDE volatility
Autocorr. of growth (DGP)	ρ_g	0.30	EMDE persistence
Discount factor	β	0.85	Default frequency
Default output cost	χ	0.032	Spread volatility
Bond coupon decay	δ_c	0.95	≈5-year duration
Belief parameters (perceived models $M1$, $M2$)			
Persistence of $M1$ (trend-following)	ρ_g^{M1}	0.72	Jointly, §5
Std. dev. of $M1$ (overconfidence)	σ_g^{M1}	0.02	Jointly, §5
Model mixture weight	λ_1	0.45	Jointly, §5
Belief inertia (switch probability)	λ_2	0.30	Jointly, §5
Implied persistence of $M2$	$\hat{\rho}^{M2}$	0.00	Residual construction

Table 2: Calibration. Standard preference and technology parameters follow Aguiar and Gopinath [2006]. The true data-generating process for the growth rate is a stationary AR(1) with persistence $\rho_g = 0.30$, in the range implied by the data. The innovation standard deviation is set to match the unconditional volatility of growth. The trend-following model $M1$ has persistence 0.72. The reversionist model $M2$ is defined residually so that $\lambda_1 M1 + (1 - \lambda_1)M2$ equals the true process. The four belief parameters are calibrated jointly to the business-cycle targets of Section 5.

5 Results

We now present the quantitative properties of the model. We compare the behavioral version against a Rational Expectations model, where the true growth process is used in forming expectations. This comparison isolates the purely behavioral component.

5.1 Business Cycle Moments

Table 3 presents the results. The behavioral model accounts for the volatility of spreads and the frequency of defaults without distorting the moments of output and consumption or their comovement. Under rational expectations the spread is nearly constant, so its volatility is only 0.3 percentage points, an order of magnitude below the 3.2 in the data. The behavioral mechanism, on the other hand, raises it to 2.1, close to the data. The default frequency rises in the same way, from 32 per ten thousand quarters under rational expectations to 117 in the behavioral model, matching the data more closely. Under rational expectations defaults still occur after a bad sequence of shocks, since these are mildly persis-

	Data	Rational expectations	Behavioral model
Volatilities (%)			
$\sigma(y)$	4.08	4.09	3.80
$\sigma(c)$	4.85	3.95	3.99
$\sigma(TB/Y)$	1.36	0.58	2.07
$\sigma(R_s)$	3.17	0.28	2.07
Comovements			
$\rho(c, y)$	0.96	0.91	0.81
$\rho(TB/Y, y)$	−0.89	−0.17	−0.02
$\rho(R_s, y)$	−0.59	0.28	0.01
Default frequency (per 10,000 quarters)			
Unconditional	110	32	117

Table 3: Business-cycle moments. Model statistics are averages over simulations of 4,000 quarters. Output, consumption and the trade balance are HP-filtered (smoothing=1600) in logs. Spreads are annualised before filtering. Second moments are computed over contiguous spells of good credit standing, following Aguiar and Gopinath [2006]. The default frequency is unconditional. Both model columns share the same calibration of Table 2 and differ only in expectations.

tent, but substantially less often than in the data. Under the behavioral model a few bad shocks are extrapolated as persistent, marking down the market value of debt far more drastically than under the correct model, and default follows more frequently.

These gains do not come at the expense of the real quantities: the volatilities of output (3.8) and consumption (4.0) and their comovement (0.81) are essentially unchanged across the two models and in line with the data. Output volatility is in fact slightly lower under the behavioral model, a composition effect, since the moments are averaged over spells of good standing and the behavioral economy defaults more often. As in Aguiar and Gopinath [2006], the model does not match the magnitude of the comovement between the trade balance and output, a caveat shared with the rational expectations benchmark.

5.2 The belief mechanism

The belief π is the weight on the trend-following model, leading to either optimism or pessimism. Under positive growth surprises, it implies optimism and reduces the price of short term debt. However, on the long maturity claims it may have opposite effects since a long bond is exposed to the whole future path, where a reversion to persistent negative shocks is possible. Thus, the same belief that makes short term debt safe can make long term debt dangerous. In our calibration, the spread on sovereign's long duration debt is higher under trend-

Current growth (% from mean)	Reversionist ($\pi = 0$)	Trend-following ($\pi = 1$)	Difference (TF − rev.)
−5.0	1.38	40.98	+39.60
−2.5	1.53	19.40	+17.86
0.0	1.46	13.04	+11.57
+2.5	1.41	10.66	+9.25
+5.0	1.38	9.45	+8.07

Table 4: Annualised spread (percentage points) on the long-duration bond, holding the debt level fixed at its ergodic value ($|a| = 0.020$) and varying the current growth realisation and the belief π. Columns report the two extremes, pure reversionist ($\pi = 0$) and pure trend-following ($\pi = 1$). Holding growth fixed, trend-following beliefs are associated with a higher spread at every growth state, and the gap widens sharply as growth falls. The reversionist spread is nearly flat across growth states, because a bond priced under mean-reverting beliefs is insured against the current realisation lasting.

following beliefs, and the gap becomes larger as growth falls.

With long duration debt, the movement in beliefs marks down the entire stock of debt outstanding. Table 4 reports the belief-conditional spread on the long-duration bond, holding the debt level and current growth fixed and varying only the belief. The reversionist spread is nearly flat across growth states, while the trend-following spread rises steeply as growth falls.

The interaction of belief with the sequence of shocks determines when crises occur. Table 5 sorts simulated quarters by whether the recent run of shocks was favourable or adverse and by the belief. When growth first falls, the break in pattern pushes π towards reversion: the market understands the fall as temporary and the sovereign, expecting recovery, holds on. Only if the low growth persists does π rise, as the market comes to believe the trend-following model is behind the process; at that point the accumulated deterioration is extrapolated forward and default follows.

An example of a simulated crisis is shown in Figure 3. Recurrent favorable growth surprises drive beliefs upwards and the sovereign accumulates debt. A reversal is first believed to be transitory, but a persistent sequence of negative surprises moves the belief toward the trend-following model, now at low growth. Thus, the outstanding stock of debt is repriced and the annualized spread jumps and default ensues.

Shock sequence	Belief	Spread (pp)	Defaults (per 10,000q)
Good run	Trend-following ($\pi = 1$)	9.97	0
	Reversionist ($\pi = 0$)	1.40	60
Bad run	Trend-following ($\pi = 1$)	26.81	6,805
	Reversionist ($\pi = 0$)	1.45	157

Table 5: Spreads and default frequency by the sequence of recent shocks and the belief. A good (bad) run is a quarter in which at least three of the last four growth realisations were above (below) the mean. Spreads are read from the bond-price schedule at the belief extremes $\pi = 1$ (pure trend-following) and $\pi = 0$ (pure reversionist), holding the debt level fixed at its ergodic value. Under reversionist beliefs the spread is nearly flat across runs and defaults are rare. Under trend-following beliefs a bad run is priced as a persistent deterioration, raising the spreads and default rates.

6 Policy

We now explore different policies that can improve upon the laissez-faire equilibrium. We consider three policy instruments: debt caps, growth-indexed bonds, and a "lean against the belief" instrument, comparing each to a rational expectations framework in which defaults are efficient responses to bad shocks.

The debt cap works as in models of the Eaton-Gersovitz class, but the cap that reduces defaults to zero must be tighter under the behavioral model. Growth-indexed bonds help reduce the number of defaults relative to the rational expectations model. Finally, the "leaning-against-the-belief" instrument taxes debt issued when the market is overly optimistic. This instrument reduces spread volatility but not the number of defaults.

6.1 A borrowing cap

We first study a borrowing cap as the first macroprudential response. In the left panel of Figure 4 the bond price and the quantity of debt is presented, and the right panel shows the resources (price times quantity) raised. The model presents a fairly flat price schedule and then collapses, at the point where one more unit of debt issued makes default certain. Thus, lenders do not buy the debt at any price and there is a market-imposed ceiling to the debt a sovereign can take. This endogenous debt ceiling is a feature of Eaton-Gersovitz models as Arellano [2008] or Aguiar and Gopinath [2006]. A debt cap below the frontier can thus eliminate defaults.

This ceiling is almost the same under both beliefs: the belief moves the price along the frontier, not its location. A debt cap, seen in Table 6, works for both the rational and the behavioral economy in reducing the number of defaults. The

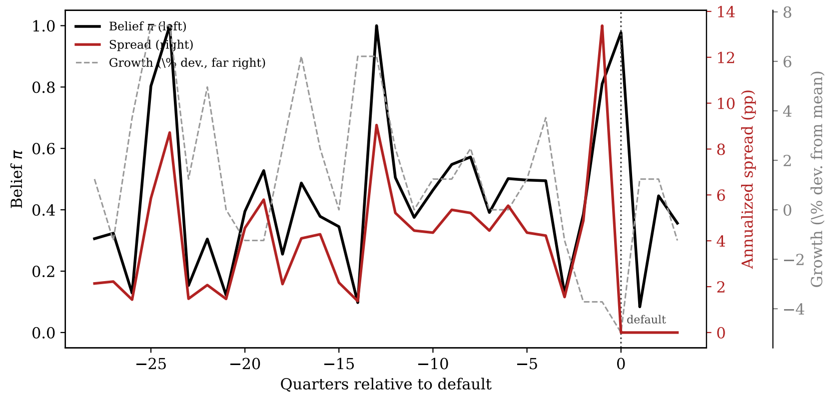

Figure 3: A simulated belief-driven debt crisis. Solid black: belief π_t (the probability assigned to the trend-following model); grey: normalized growth shock; red (right axis): annualized spread. The dotted vertical line marks a default. The spread spikes as a bad run is extrapolated under trend-following beliefs

benefit is higher under the behavioral framework given that the baseline has a larger volatility of spreads and number of defaults. Moreover, the cap needs to be more stringent for the behavioral economy.

6.2 A growth-indexed bond

We now turn to analyzing a contingent bond. Assume that this bond is contingent on growth and pays $(1-\phi)+\phi\,(g/\bar{g})$ per unit. At $\phi = 0$ this is the baseline bond presented in previous sections and at $\phi = 1$ the coupon is proportional to growth. In other words, the bond pays more when the economy is strong and less when growth is weak.

Table 7 presents the results. Full indexation reduces defaults by 42% because the coupon is reduced in the low growth states and thus weakens the incentive to default. The instrument buys a lower and less catastrophic default rate at the cost of a slightly more variable price.

Importantly, the instrument is not effective under Rational Expectations given that these are efficient responses to bad sequences of negative surprises. Thus, changing the payments does not change the overall incentives. The instrument is thus effective at partially reducing defaults caused by the behavioral component.

6.3 Leaning against the belief

We now turn to a policy that acts on beliefs, as a counterpart of the “leaning against the wind” policies in the asset prices literature. [See, for example, Caines

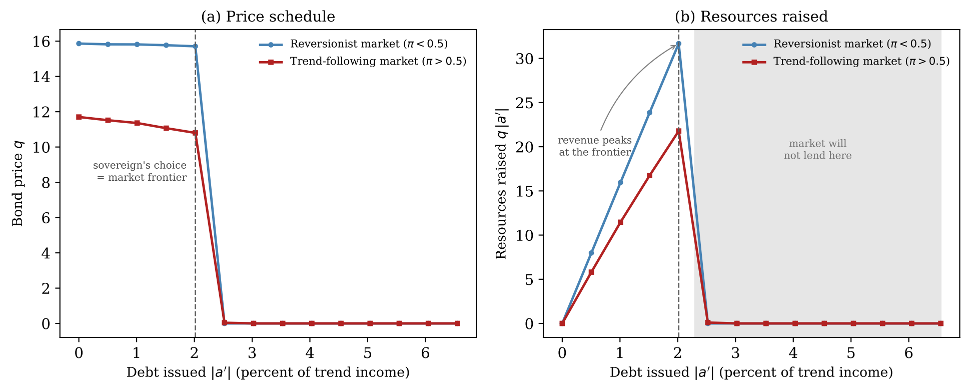

Figure 4: The bond price schedule (panel a) and resources raised, $q\,|a'|$ (panel b), at the ergodic debt level and mean growth, under a trend-following market ($\pi > 0.5$) and a reversionist one ($\pi < 0.5$). The price holds up to a threshold quantity and then falls to zero. In the shaded region, no lender will extend funds at any price. The threshold is in the same place under both beliefs.

and Winkler, 2021, Adam and Woodford, 2021, Boehl, 2022]. We use this idea in a sovereign debt setting. We consider two modeling approaches. First, we create a wedge in the price of debt. In this case, the sovereign faces the price $q\,(1-\kappa\cdot(\pi-\frac{1}{2}))$. Thus, debt is costlier under trend-following beliefs and cheaper otherwise.

Second, we suppose an institution that discourages the agent from reading the trend - i.e., acting on beliefs directly. We do so by shifting the priors towards the reversionist model. From (6), the agent's posterior evolves through two switching probabilities: λ_1, the probability of leaving the trend-following model and λ_2, the probability of entering it. We do a stylized intervention using $\zeta \in [0,1)$ that raises the rate at which the agent abandons the trend-following model and lowers the rate at which she adopts it,

$$\lambda_1(\zeta) = \lambda_1 + \zeta\,(1-\lambda_1), \qquad \lambda_2(\zeta) = (1-\zeta)\,\lambda_2, \tag{8}$$

with $\zeta = 0$ the baseline economy. The updating rule (6) is otherwise unchanged. The intervention only tilts the regime-switching prior against persistence, so that a run of same-signed surprises moves π less far toward the trend-following model than it otherwise would.

The results are in Table 8. The table shows that the volatility of spreads is reduced substantially under both interventions but the number of defaults remains qualitatively similar. The reason is that the instruments act on beliefs but not on the stock of debt that gets repriced after bad shocks. Leaning against the

	Rational expectations			Behavioral		
Debt cap $\lvert a' \rvert \leq$	$\sigma(R_s)$	Def.	$\sigma(c)$	$\sigma(R_s)$	Def.	$\sigma(c)$
No cap (baseline)	0.28	32	3.95	2.07	117	3.99
0.020	0.00	0	4.07	0.17	2	4.02
0.015	0.00	0	4.10	0.00	0	4.10

Table 6: The effects of a debt cap on the volatility of spreads, $\sigma(R_s)$, volatility of consumption, $\sigma(c)$, and defaults in the rational and the behavioral economies. The cap raises consumption volatility by the same amount in both economies as the sovereign loses the ability to borrow against shocks. The crises and spread volatility are larger in the behavioral economy, where the extrapolative misperception generates them. Moreover, the ceiling that eliminates default is not the same across the two. The misperception pushes the sovereign toward default at debt levels the rational economy carries safely, so the cap that eliminates crises must be stricter under behavioral beliefs than under the standard model.

	Rational expectations			Behavioral		
Indexation	$\sigma(R_s)$	Def.	$\sigma(c)$	$\sigma(R_s)$	Def.	$\sigma(c)$
None ($\phi = 0$)	0.28	32	3.95	2.07	117	3.99
Half ($\phi = 0.5$)	0.12	32	3.96	2.49	76	4.26
Full ($\phi = 1$)	0.12	32	3.96	2.50	68	4.23

Table 7: Growth-indexed debt in the rational and behavioral economies. The coupon pays $(1-\phi)+\phi\,(g/\bar{g})$ per unit, so $\phi = 0$ is the ordinary bond and $\phi = 1$ a fully growth-indexed one. $\sigma(R_s)$ is the volatility of the spread in percentage points, “Def.” the default frequency per ten thousand quarters, and $\sigma(c)$ the volatility of consumption in percent. Under rational expectations indexation leaves the default frequency unchanged - these are efficient responses to genuinely adverse growth sequences. Under behavioral beliefs indexation lowers the default frequency by more than a third. The instrument removes the excess crises produced by belief reversals.

belief moves the price of debt but does not affect the payments in the event of a default.

7 Interpretation and scope

We now turn to discuss several of the features of the model and its scope.

Long Term Debt is essential. The behavioral mechanism raises spread volatility only when combined with long-maturity debt. Under one-period debt the sovereign re-optimizes every period and avoids the steep region of the bond schedule when beliefs turn. Thus, realized spreads are smooth regardless of the belief process. Including a longer maturity breaks this escape: the sovereign inherits a stock it cannot roll off in a single period, which is then repriced by belief

Lean against belief (price wedge)	$\sigma(R_s)$ (pp)	Default frequency (per 10,000q)
Moderate ($\kappa = 0.3$)	1.80	91
Strong ($\kappa = 0.6$)	0.90	115
Persistence prior		
Moderate ($\zeta = 0.4$)	1.32	110
Strong ($\zeta = 0.8$)	0.85	91

Table 8: Instruments and their effect on the volatility of the spread and the frequency of default. A wedge in the price of debt linked to the belief, and a prior that shifts weight away from the trend-following model both lower spread volatility but leave the default frequency essentially unchanged.

swings during a reversal. The interaction of belief dynamics with debt duration produces the result. In other words, crises in this setup are repricings of beliefs about duration, not realizations of fundamental shocks.

Why developing countries?. Given that we aim to explain debt in developing economies, a natural question is whether lower-income countries are more "behavioral" than industrialized countries. First, the behavioral traits here depend on the intrinsic volatility of the process. Thus, inherently more volatile countries leave room for larger behavioral distortions: it is harder to distinguish a persistent from a transitory shock when the variance is large. This is reinforced by more frequent structural breaks. Second, exchange rates and commodity prices have a documented behavior similar to financial instruments (for example Tang and Xiong [2012]), and in middle income countries output is more related to swings in the exchange rate. Finally, there is evidence that poor people are more prone to behavioral biases than rich people [Bernheim et al., 2015].

Should learning rule this process out?. First, Barberis et al. [1998] show that, even after five years of data, 80% of the time, investors consider the behavioral model just as good as the true model. Second, yet another behavioral bias can be present: confirmation bias [Rabin and Schrag, 1999] that slows the abandonment of the currently used model. This bias would limit the Bayesian updating in favor of slower learning. Finally, Weitzman [2007] rationalizes the equity premium puzzle with parameter uncertainty. In that context, Bayesian updating of unknown structural parameters adds a tail thickening effect to posteriors. Thus expectations are very sensitive to subjective prior beliefs even with asymptotically infinite data. In other words, the friction in the model lies in how the agent reads the growth process. This is reinforced by the fact that the true process is itself hard to identify: Aguiar and Gopinath [2006] argue that it is non-stationary, whereas Garcia-Cicco et al. [2010] show that a strong stochastic trend does not survive in long data and that EMDE growth is better described as mildly persistent but stationary, revealing itself as such only in very long samples. We view our work as complementary to both views. The short-run indistinguishability of the process fuels the misperception: unable to observe the long trend, the agent over-extrapolates, using a misspecified model that fits short samples with full information, as in Esponda and Pouzo [2016].

Premium in optimistic times. The model delivers a high spread in optimistic times – meaning, trend-following during good times. The reason is that with long term debt, the optimism for the good shocks is neutralized by the possibility of the model receiving a bad shock and thus having a reversal into a negative trend. We understand this as a version of the peso problem [Krasker, 1980]. The term originates with the observation that Mexican deposit rates stood persistently above comparable U.S. rates through the early 1970s despite a peso long pegged to the dollar, a gap the market was pricing for a devaluation that arrived only in 1976. The same pattern recurred before the 1994 "Tequila" crisis, when Mexico's currency risk premium stayed elevated under an announced exchange-rate band that the market did not fully believe. Our model generates a similar effect without a true regime change, but through beliefs. Spreads in our model are higher if the investors are trend-following than under a reversionist (closer to truth) model. An extension of the model to allow for lower spreads during optimism is that the agent has a misperception about the mean of the process as well, which we leave for further research. We use a version where there is learning only about persistence to isolate the extrapolative misperception of the growth process.

8 Conclusion

This paper has presented a parsimonious and disciplined model of behavioral biases embedded in a business cycle model with default and long term debt. The model can replicate features of the data that are especially relevant for developing countries such as excess consumption volatility, countercyclical trade balance, volatile spreads, and default. The mechanism does not reproduce the observed comovement of spreads with output and the trade balance, a limitation shared with Aguiar and Gopinath [2006]. An extension where transitory shocks move the incentives to default alongside the perceived trend may address this.

In our model, the real data generating process is stationary (as Garcia-Cicco et al. [2010] find with sufficiently long data), but the agents perceive it as going through different misperceived trends. The dynamics of the model are consistent with stylized facts. The agent oscillates between optimism and pessimism about a non-existent trend, and borrows to smooth her perceived permanent income. The effect also relies on overconfidence as in a lower perceived variance, consistent with the findings of Jaimovich and Rebelo [2007].

For developing economies, a borrowing boom followed by a sudden stop is observationally the same whether this is driven by news about the future or by extrapolating. However, the two readings imply different things about whether this is efficient borrowing or a costly behavioral mistake. Policy implications are potentially different and business cycle moments alone are not enough to distinguish these. Whereas in Aguiar and Gopinath [2006] the equilibrium is constrained efficient, if the cause for cycles is due to behavioral misinterpretations, there is scope for macroprudential policy or countercyclical policies.

Our results in particular highlight the need for tools that act through the pricing of long-duration debt rather than through quantities. A borrowing cap can eliminate crises if it is set at a more stringent level than in a rational expectations economy, at the cost of worse consumption smoothing. Contingent bonds reduce the frequency of behavioral defaults by reducing the excess crises that follow from extrapolation. Instruments that “lean against beliefs” stabilize the spread but leave defaults largely unchanged, since they act on the price rather than on the payment owed in bad states.

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