Behavioral Biases, the Current Account and Default

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Abstract

We include behavioral biases as in Barberis et al. [1998] in a real business cycle model with default and trend shocks. Agents infer the trend process using misspecified mental models. The misspecification responds to two known heuristics: representativeness and conservatism, which leads to behavioral responses from the agents creating waves of optimism, pessimism, overreaction, and underreaction. We present suggestive evidence from IMF forecasts that these biases are indeed present. The model can explain stylized facts in developing economies: high consumption to output volatility, counter-cyclical trade balance, and frequent defaults. The model is observationally equivalent to other proposed explanations for these effects but with potentially different policy implications.

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1 Introduction

We include dynamic behavioral biases into an open economy real business cycle model with trend shocks and default as in Aguiar and Gopinath [2006]. We show that behavioral biases can account for features of developing economies such as debt crises, the excess volatility of consumption, and the countercyclicality of the trade balance [Aguiar and Gopinath, 2006]. Agents endogenously move between waves of optimism and pessimism about the future trend. The model is observationally equivalent to Aguiar and Gopinath [2006], not due to external random trend shocks, but due to disciplined expectational mistakes.

We first present evidence from behavioral biases in IMF forecasts. Expanding on the methodology from 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 and Europe, and Latin America.

The expectation formation mechanism we adapt 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 two regimes that alternate with some probability: mean-reverting and trend-following. Agents learn across these misspecified models to know 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 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 coined by Tversky and Kahneman [1974], in which people observe patterns in random sequences. In this way, agents quickly infer the underlying process based on 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, overreaction, and underreaction.

We extend this learning mechanism to a large state space and apply this to trend shocks 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 because the agent expects higher wealth that does not materialize in the future. Second, the trade balance is countercyclical because periods of optimism lead the agent to take debt on its permanent income. Finally, sudden stops occur when expectations suddenly change from one regime to another. This alternative explanation for the facts opens the possibility for macro-prudential policy to calm expectations.

Related Literature. This paper deals with two branches of the literature: international macroeconomics in developing countries and behavioral biases and learning in macro.

The literature on equilibrium models for developing economies started with Mendoza [1991] and spanned an extensive literature. However, standard real business cycles models failed to account for features of the data in developing countries [Aguiar and Gopinath, 2006]. There are mainly 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 can also account for those features.

Even though behavioral economics had a central role in financial literature, attempting to incorporate behavioral features in macroeconomics is relatively new [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, Dai et al., 2016, Zeev et al., 2017, Ilut and Schneider, 2014, Cao and L'Huillier, 2018, Heymann et al., 2001]. In our paper "news" are, in a sense, endogenous, and the agent learns in the space of (incorrect) mental models.

Closest to our model, Jaimovich and Rebelo [2007] present a macroeconomic model with overoptimism and overconfidence. In contrast, we apply these insights to developing countries' issues and focus on the dynamic aspect 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.[1]

There is also a branch of the literature testing for behavioral biases in macroeconomic data. Using state-level data, Korniotis and Kumar [2011] find an effect of biases on the macroeconomy. Hagenhoff and Lustenhouwer [2020] identifies behavioral biases in professional forecasters. Ashiya [2003] studies overreaction and underreaction in Japanese forecasters. We adapt that methodology to a panel of predictions by the same forecaster, the IMF and find evidence of biases.

2 Some Evidence

There is ample statistical evidence on price overreaction and underreaction in financial markets, including exchange rates and commodity prices [Park and Sohn, 2013, Barberis and Thaler, 2003, Frankel and Froot, 1990]. Using macroeconomic data Hagenhoff and Lustenhouwer [2020] and Ashiya [2003] find the presence of biases in professional forecasters. On the other hand, there is a large body of empirical and experimental evidence on the behavioral biases present in our paper [Baker and Nofsinger, 2010].

This section provides evidence that suggests the presence of behavioral biases in forecasts using the IMF's forecasts from 2008 until 2020. We adapt the methodology by Amir and Ganzach [1998] to study the presence of dynamic behavioral biases in IMF forecasts. The biases we focus on are optimism, pessimism, overreaction, and underreaction. These behaviors arise from the expectation formation mechanism from Barberis et al. [1998], which relies on the heuristics of representativeness.

Methodology. Identifying behavioral biases is challenging. Positive forecast errors can mean that the analyst is being optimistic or that is overreacting to (positive) new information. Thus, a positive forecast error is compatible with both *(i)* an optimistic analyst and *(ii)* a pessimistic analyst overreacting to new information. A positive forecast revision and negative forecast error can also be equivalent to overreaction and pessimism. In the appendix, Figure 4

[1]Other papers have highlighted the role of behavioral biases in specific issues, for example Bertasiute et al. [2020].

shows all possible observational outcomes of different biases.

In order to disentangle the effects, Amir and Ganzach [1998] regress forecast errors on forecast revisions. Let $f_{t,i}^{t-2}$ be the forecast in $t-2$ for period t and country i, and $f_{t,i}^{t-1}$ the revised forecast in $t-1$ for t for the same country i. Let g_i^t be the realized growth rate of country i. Thus, the forecast error is $FE_i^t \equiv f_{t,i}^{t-1} - g_i^t$ and the forecast revision is $FR_i^t \equiv f_{t,i}^{t-1} - f_{t,i}^{t-2}$.

$$FE_i^t = \alpha + \beta FR_i^t + \epsilon_i^t \tag{1}$$

When $\alpha > 0$, there is evidence of optimism, and when the reverse is true, there is evidence of pessimism. The reason is that forecast errors should be uncorrelated with the past, and thus the constant term should be zero. On the other hand, $\beta > 0$ implies overreaction to new information, and when the converse is true, there is evidence of underreaction. In order to differentiate periods of good news and bad news, we split the sample depending on whether the forecast revisions in the previous period j were positive (FR_{t-j}^+) or negative (FR_{t-j}^-).

Table 1 presents the estimates of (1) separated by the sign of the previous forecast revisions, for all countries and middle income countries (Emerging Asia, Latin America, and Emerging Europe). When there were positive forecast revisions in the last two periods, the forecast is overoptimistic and underreacts to news for middle income countries. However, there is no such effect when countries are pooled together. There is no effect for the case of bad news in the preceding two periods, but there is evidence of pessimism and underreaction for middle income countries. The same pattern is observed when focusing on only one period of positive forecast revisions.

	$FR^{+}_{t-1}, FR^{+}_{t-2}$		$FR^{-}_{t-1}, FR^{-}_{t-2}$	
	All Countries	Middle Income	All countries	Middle Income
Constant	0.29	0.77*	-1.44***	-1.3
	(0.38)	(0.46)	(0.29)	(0.42)
FR	-0.20***	-0.14*	-0.11***	-0.002
	(0.05)	(0.08)	(0.02)	(0.03)
Observations	815	342	948	336
R2	0.10	0.16	0.10	0.14

	FR^{+}_{t-1}		FR^{-}_{t-1}	
	All Countries	Middle Income	All countries	Middle Income
Constant	0.39	0.96**	-1.33***	-0.92*
	(0.31)	(0.46)	(0.35)	(0.5)
FR	-0.05*	0.066	-0.077***	0.09**
	(0.03)	(0.06)	(0.02)	(0.03)
Observations	1449	595	1673	625
R2	0.05	0.11	0.05	0.10

	Middle Income		
	$FR^{+}_{t-1}, FR^{-}_{t-2}$	$FR^{-}_{t-1}, FR^{+}_{t-2}$	$FR^{-}_{t-1}, FR^{+}_{t-2}, FR^{-}_{t-3}$
Constant	-1.29	-1.17*	-2.6
	(1.44)	(0.57)	(2.4)
FR	0.38***	0.011*	-0.34
	(0.09)	(0.06)	(0.14)
Observations	219	251	85
R2	0.18	0.14	0.30
	$FR^{-}_{t-1}, FR^{+}_{t-2}, FR^{+}_{t-3}$	$FR^{+}_{t-1}, FR^{-}_{t-2}, FR^{-}_{t-3}$	$FR^{+}_{t-1}, FR^{-}_{t-2}, FR^{-}_{t-3}$
Constant	. -0.76	-1.01.	-1.27
	(0.53)	(0.77)	(1.7)
FR	0.14**	0.35**	0.32**
	(0.06)	(0.12)	(0.14)
Observations	153	103	103
R2	0.20	0.31	0.23

Standard errors in parentheses. *** $p < 0.01, **p < 0.05, *p < 0.1$

Table 1: Regression results. All regressions include year fixed effects.

In the bottom part of Table 1 the results of the regression conditioning on alternating signs of forecast revisions in middle income countries are shown. All coefficients on the constant but one are statistically insignificant. In the case of a statistically positive coefficient (positive news followed by negative news in the previous periods), there is some evidence of optimism, which is consistent with the analyst expecting mean reversion. Notice that in this case, there are several cases of overreaction. When news alternate, there is an overreaction to news, but when news are consistently positive or negative (Table 1), there is underreaction to good news.

These regressions show some evidence suggestive of behavioral biases in IMF forecasts, particularly in middle income countries. Moreover, they exhibit dynamic effects depending on the sign of forecast revisions.

3 The Model

3.1 Expectations: two state example

This section presents the expectation formation mechanism in Barberis et al. [1998]. Suppose that the state of the world can be either y^+ or y^-. The real process is *i.i.d*, but the investor uses two mental models, which she believes to be the possible data generating processes. The first model, $M1$, is "trend-following" or high persistence. In this case, a positive shock is expected to be followed by another positive shock with a high probability, π^H, and vice versa for negative shocks. The second model, $M2$, is "reversionist" and expects positive shocks to be more likely succeeded by negative shocks, with probability $1 - \pi^L$. The transition matrices for the example are in Figure 1.

The investor believes that $M1$ and $M2$ switch as the data generating process with probability γ. In order to make decisions, the investor needs to forecast y. Thus, she attempts to assign probabilities π_t to each model as the true underlying process. Thus, at any point t, she calculates $\pi_t = Pr(M1^{t+1}|y_t, y_{t-1}, \pi_{t-1})$ using Bayes Rule. Barberis et al. [1998] show that this structure generates overreaction, underreaction, overconfidence, and overoptimism.

In Figure 1 there is an example. The shock can be high or low and is *i.i.d.* However, the agent forms beliefs thinking one of the two models is real. In the first periods, shocks are alternating between high and low shocks, thus

$M1$	$y_{t+1}=y^+$	$y_{t+1}=y^-$
$y_{t+1}=y^+$	π^H	$1-\pi^H$
$y_{t+1}=y$	$1-\pi^H$	π^H
$M2$	$y_{t+1}=y^+$	$y_{t+1}=y^-$
$y_{t+1}=y^+$	π^L	$1-\pi^L$
$y_{t+1}=y$	$1-\pi^L$	π^L

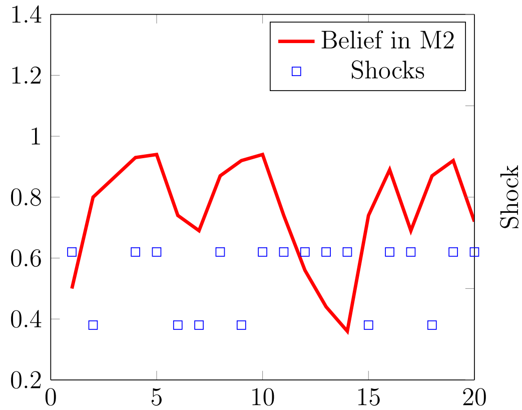

Figure 1: Left panel: Transition matrix for the two mental models, $M1$ and $M2$. Right panel: beliefs (left axis) and shocks (right axis) across periods

the probability of being in $M2$, the reversionist model, increases. Between periods 10 and 15, there are several periods of positive shocks, and thus the probability of being in the reversionist model plummets. The model's logic is that agents tend to underreact, but after repeated observation of news, they may overreact to new information.

3.2 The Framework

The model uses the framework of Aguiar and Gopinath [2006], which itself expands Eaton and Gersovitz [1981] (and the quantitative version by Arellano [2008]) with trend shocks. There is one country that has one-period debt with the rest of the world, and if it defaults, it will be punished by an output cost and financial autarky for a stochastic length of time.

The economy has an endowment y_t, and the representative agent has constant risk aversion preferences given by

$$u = \frac{c^{1-\theta}}{1-\theta}$$

where $\beta \leq 1$ is the discount factor. The endowment follows :

$$y_t = e^{z_0}\Gamma_t$$

where e^{z_0} is a constant, and $\Gamma_t = g_t \Gamma_{t-1}$, with the growth rate of the trend being represented by g_t. The true processes is given by

$$\ln g_t = \quad (1-\rho_g)\left(\ln(\mu_g) - c\right) + \rho_g \ln g_{t-1} + \epsilon_t^g$$

where $|\rho_g| < 1$, $\epsilon_t^g \sim N(0, \sigma_g^2)$ and $c = \frac{1}{2}\frac{\sigma_g^2}{1-\rho_g^2}$. There is no transitory shock. The process for the growth rate, implies that output will be permanent higher in all future periods. As in Aguiar and Gopinath [2006], we assume $E \lim_{t\to\infty} \beta^t \Gamma_t^{1-\theta} = 0$ to ensure a well defined problem.

The agent has access to one-period international bonds, a_t, that pay one unit of the consumption good. The price is q_t. At the beginning of the period, the country decides whether to default. If it defaults, the value of such action is V^B. If the agent decides to repay the debt, the country will be in good credit standing and get V^G. Thus, the value of the agent is $V(a_t, z_t, g_t) = \max\{V^G, V^B\}$. If defaults, the agent will consume its endowment after paying a proportional penalty given by $(1-\delta)$. The continuation value will depend on its redemption probability, λ.

The value of default is given by

$$V^B(0, g_t, g_{t-1}, \pi_{t-1}) = u((1-\delta)y_t) + \lambda\beta\tilde{E}_t V(0, g_{t+1}, g_t, \pi_t) + (1-\lambda)\tilde{E}_t V^B(0, g_{t+1}, g_t, \pi_t)$$

With probability λ, the country is redeemed and continues with a clean slate. The exogenous states is g_t. Notice that given that the agent uses previous information on the shocks to make inferences, the belief from the previous period, π_{t-1} is also a state variable. $\tilde{E}$ represents the fact that the agent is not using the true data generating process to make inferences.

The value of keeping a good credit standing is given by

$$\begin{aligned} V^G(a_t, g_t, g_{t-1}, \pi_{t-1}) \quad &= \max_{c_t} \left\{ u(c_t) + \beta\tilde{E}V(a_{t+1}, g_{t+1}, g_t, \pi_t)) \right\} \\ s.t \quad & \qquad c_t = y_t + a_t - q_t a_{t+1} \end{aligned}$$

International investors are risk-neutral and have an opportunity cost of r^*. They are aware of the agent's problem and know that default, $D(a_t, g_t) = 1$ will happen if $V^B \geq V^G$. Thus, investors price the bond at

$$q_t(a_{t+1}, g_t) = \frac{\tilde{E}_t(1 - D_{t+1})}{1 + r^*}$$

Thus, the higher the expected probability of repayment, the higher the bond price. Notice that international investors share the same belief structure as the domestic agent.

The agent believes there are two possible processes in governing the trend,

$$\begin{array}{lrcl}(M1) & \ln g_t & = & (1-\rho_g^{M1})\left(\ln(\mu_g)-c\right)+\rho_g^{M1}\ln g_{t-1}+\epsilon_t^{M1} \\ (M2) & \ln g_t & = & (1-\rho_g^{M1})\left(\ln(\mu_g)-c\right)+\rho_g^{M2}\ln g_{t-1}+\epsilon_t^{M2},\end{array}$$

with persistence $\rho_g^{M1} > \rho_g^{M2}$ and $\epsilon_t^{Mi} \sim N(0, \sigma^{2,Mi})$ for $i = 1, 2$, where we allow the variance to be potentially misperceived. Finally, the agent believes the world switches across regimes with probability γ. Thus, the agent believes that the data generating process behind the observed sequence of shocks is $M1$ with probability

$$\pi_{t+1} = \frac{(1-\gamma)\pi_t + \gamma(1-\pi_t)Pr(g_{t+1}|M1, g_t)}{\left((1-\gamma)\pi_t + \gamma(1-\pi_t)\right)Pr(g_{t+1}|M1, g_t) + \left(\gamma\pi_t + (1-\gamma)(1-\pi_t)\right)Pr(g_{t+1}|M2, g_t)}$$

A final point is whether the agent understands that her forecast probabilities will change in the following period, and thus the problem would not admit a simple recursive structure. Kreps [1998] shows a problem in which an agent updates using Bayes' law but is myopic with respect to her future updating of probabilities. Kreps [1998] calls this "anticipated utility" and shows that is a good approximation to the rational expectations equilibrium.

3.3 Calibration and Model Solution

We calibrate the model exactly as Aguiar and Gopinath [2006] (AG, henceforth) in order to match Argentinian data. The values of the parameters are in Table 3 in Appendix B. The true data generating process has the same mean and variance as in AG, but without any autocorrelation, $\rho^g = 0$. We set $M1$ to be the trend following model with $\rho_g^{M1} = .11$ and $\sigma_g^{2,M1} = 0.02$, showing more precision in beliefs than in the true data generating process ($\sigma_g^2 = 0.03$). In order to discipline the model, we choose values for $M2$ such that, on average, the processes $M1$ and $M2$ generate the data generating process. Finally, we set $\gamma = .2$ so that regimes changes are rare. All lagged state variables, (s_{t-1}, π_{t-1}) are summarized in the process of Bayesian updating. Our solution method discretizes the distribution, $\pi \in [0, 1]$ and solves the agent's problem for each possible probability on the grid. Expectations are computed dynamically via Bayes' Rule when simulating the model, and the relevant policy function is used in each state to obtain optimal responses.

4 Results

In Figure 2 we can observe a sample path of beliefs in $M1$ (trend-following model with low variance) and shocks. In the left panel, we can observe that in period 5, there is a negative shock, but expectations do not react. Afterward, this is followed by high shocks. However, in period 11, a large shock induces a sudden reversal of expectations. Given the intermittent behavior of shocks afterward, the probability oscillates between low and high values. In the right panel, we can observe the slow build-up of more optimistic expectations with a sequence of good shocks. During the simulations, the maximum value for the probability of $M1$ is 0.92, and the minimum is 0.01.

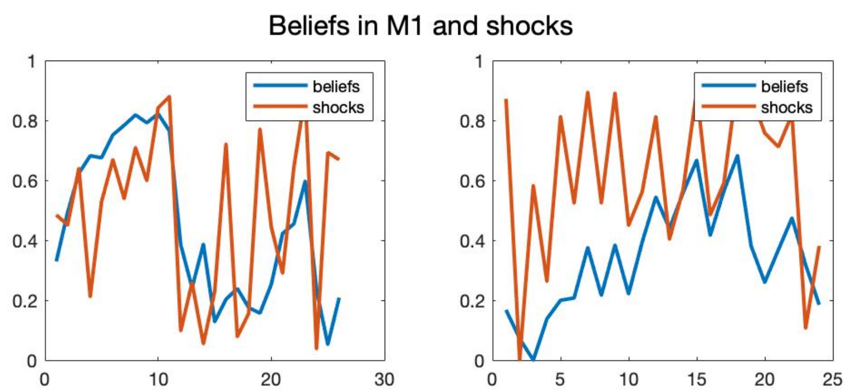

Figure 2: Sample of simulated beliefs (probability of $M1$) and shocks. Shocks are normalized to be between 0 and 1.

In Figure 3, we can observe default regions under each mental model if they were believed to be the true model with certainty. The slope for the default region under the trend following model, $M1$, is steeper. In other words, the agent is less likely to default at higher levels of the shock even when debt is high, given that there is an expectation of the shock remaining higher. The expectational switch between the regions will cause the excess default with respect to a traditional model.

The results of the simulated economy are in Table 2. The behavioral aug-

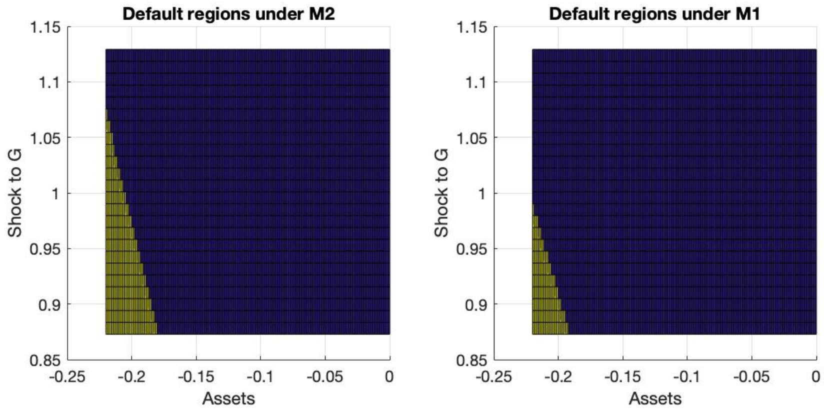

Figure 3: Default region for the case of pessimistic beliefs and optimistic beliefs. The yellow region represents combinations of the productivity state and assets for which the optimal choice is default. The blue shaded represents the non-default region. The vertical axis represents the realization of the shock. The horizontal axis represents assets normalized by (mean) trend income.

	Data	RBC Transitory	AG Trend Trend	Behavioral
$\sigma(y)$	4.08	4.32	4.45	4.14
$\sigma(c)$	4.85	4.37	4.71	4.46
$\sigma(TB/Y)$	1.36	0.17	0.95	1.17
$\sigma(R_s)$	3.17	0.04	0.32	2.25
$\rho(c, y)$	0.96	0.99	0.98	0.97
$\rho(TB/y, y)$	-0.89	-0.33	-0.19	-0.15
$\rho(R_s, y)$	-0.59	0.51	-0.03	0.01
$\rho(R_s, TB/Y)$	0.68	-0.21	0.11	0.30
Default per 10,000 quarters	75	2	23	53

Table 2: Results are averages over 500 simulations. Simulated data is HP-filtered as empirical data. Standard deviations are percentages.

mented model replicates qualitatively the features of the data, including the puzzles on which AG focus. These puzzles include the excess volatility of consumption to output, a trade balance with larger variance than output, a countercyclical trade balance, and a plausible frequency of defaults. The behavioral augmented model also explains the dispersion of interest rates to a better extent. The underlying dynamic is driven by the fact that the economy moves between waves of optimism into waves of pessimism even though the true data generating process has no persistence. Thus, after a sequence of good shocks, the agent believes the process to be persistently high. This belief persuades her to take debt to smooth out her future income. When expectations suddenly reverse, a debt crisis arises.

5 Discussion

Three things require discussion: the specificity of the model for developing economies, and the possibility of learning the true process.

Why developing countries?. There is evidence that poor people are more prone to behavioral biases than rich people [Bernheim et al., 2015]. Moreover, the behavioral traits here depend on the intrinsic volatility of the process. Thus, inherently more volatile countries would leave room for more considerable behavioral distortions. Finally, exchange rates and commodity prices have a documented behavior similar to financial instruments (for example Hsu et al. [2013]), and in middle income countries output is more related to swings in the exchange rate.

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]. 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.

6 Conclusion

This paper has presented a parsimonious and disciplined model of behavioral biases embedded in a business cycle model with default. The model can replicate features of the data that are especially relevant for developing countries. The real data generating process is stationary (as Garcia-Cicco et al.

[2010] find out with sufficiently long data), but the agents perceive it as going through different trends. The dynamics of the model are consistent with stylized facts. It is important to underline that the effect relies on overconfidence as well (i.e., less perceived variance) as consistent with the findings of Jaimovich and Rebelo [2007]. Policy implications are potentially different from a model with trend shocks. Whereas in Aguiar and Gopinath [2006] the equilibrium is efficient, if the cause for cycles is due to behavioral misinterpretations, there is scope for macroprudential policy or countercyclical policies.

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7 Appendix

A. Observational Equivalences

<table>
<tr><th rowspan="2"></th><th colspan="2">Positive revision</th><th colspan="2">Negative revision</th></tr>
<tr><th>Effect</th><th>Joint effect</th><th>Effect</th><th>Joint effect</th></tr>
<tr><td rowspan="2">Optimism & Over-reaction</td><td>+</td><td rowspan="2">+</td><td>+</td><td rowspan="2">?</td></tr>
<tr><td>+</td><td>–</td></tr>
<tr><td rowspan="2">Optimism & Under-reaction</td><td>+</td><td rowspan="2">?</td><td>+</td><td rowspan="2">+</td></tr>
<tr><td>–</td><td>+</td></tr>
<tr><td rowspan="2">Pessimism & Over-reaction</td><td>–</td><td rowspan="2">?</td><td>–</td><td rowspan="2">–</td></tr>
<tr><td>+</td><td>–</td></tr>
<tr><td rowspan="2">Pessimism & Under-reaction</td><td>–</td><td rowspan="2">–</td><td>–</td><td rowspan="2">?</td></tr>
<tr><td>–</td><td>+</td></tr>
</table>

Figure 4: Observational equivalence of some behavioral biases. Source Amir and Ganzach [1998].

B. Solution and Calibration

The solution method discretizes the distribution, $\pi \in [0, 1]$ and solves the agent's problem for each possible probability on the grid. Expectations are computed dynamically via Bayes' Rule when simulating the model, and the relevant policy function is used in each state to obtain optimal responses. Note that the agent acts as if her forecast probabilities will not change in the future for this to admit a simple recursive structure. This "anticipated utility" is a good approximation to rational expectations [Kreps, 1998].

General parameters

Risk aversion	θ	2
World interest rate	r^*	0.01
Output cost	δ	0.02
Redemption prob.	λ	0.10
Mean growth rate	μ_g	1.001
Transitory prod	-	NA
Trend prod		
Std Dev.	σ_g	0.032
Persistence.	ρ_g	0.0

Expectational parameters

σ_g^{M1}	0.02	
ρ_g^{M1}	0.11	
σ_g^{M2}	0.03	Match DGP
ρ_g^{M2}	0.001	Match DGP
γ	0.3	

Table 3: Calibration. Standard values are from AG. The true data generating process (DGP) does not display any autocorrelation. The parameters for model $M2$ are set such that $M1$ and $M2$ behave as the DGP