Good news is bad news: Leverage cycles and sudden stops☆

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ABSTRACT

We estimate a model with an occasionally-binding collateral constraint, and find that half of productivity shocks are anticipated by households. In the estimated model, good news about productivity raises leverage, increasing the probability that a Sudden Stop occurs in future periods. In the run-up to the Sudden Stop, the economy exhibits a boom period with consumption and investment above trend, consistent with the data. During the Sudden Stop, the nonlinear effects of the constraint induce consumption and investment to fall substantially below trend and the trade balance to reverse sharply, as they do in the data. The risk created by good news is large, with nearly 90% of Sudden Stops occurring after positive news shocks.

1. Introduction

In this paper, we show that an estimated real business cycle model augmented with an occasionally-binding collateral constraint and a predictable component in productivity[1] can match observed business cycle patterns in emerging economies, including around periods known as Sudden Stops. Fig. 1 illustrates the patterns in a seven-year window around identified Sudden Stop events.[2] During the median Sudden Stop episode: (i) gross domestic product (GDP) and private consumption fall about 4 percentage points below trend; (ii) private investment falls 20 percentage points below trend; (iii) the trade balance-to-GDP ratio experiences a reversal of about 6 percentage points; (iv) asset prices fall, and; (v) the country's external debt-to-GDP ratio drops by almost 10 percentage points. In the run-up to these events, the economy experiences a significant trade deficit and rising debt, while GDP, consumption and investment are all above their respective trends.

A predictable component in productivity is important for the model to generate realistic Sudden Stop dynamics. In our model, agents faced with improving growth prospects optimally choose to borrow against their higher future income, increasing their leverage in good times and bringing them closer to an occasionally binding constraint on their debt holdings. On average, the good news is realized, leading to higher long-run consumption and output for the household. However, because good news also brings households closer to the constraint on their leverage, it exposes them to a greater risk that an unfavorable future shock will eventually lead the constraint to bind, thereby leading to a worse outcome *ex post* than they might otherwise have realized had all shocks arrived as surprises. In this sense, good news leads agents to engage in optimistic behavior that is both rational, since it is validated

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   [1] Commonly known as "news" shocks. See Beaudry and Portier (2006) for an early example.
   [2] We identify a Sudden Stop as a situation in which the cyclical component of GDP is at least one-and-a-quarter standard deviations below its trend level and the reversal in the trade balance-to-GDP ratio is at least one-and-a-quarter standard deviations above average. Our definition is similar to the one used in the literature. See, for example, Calvo et al. (2006) and Mendoza (2010). More details on our data and identification strategy are in Appendix A.
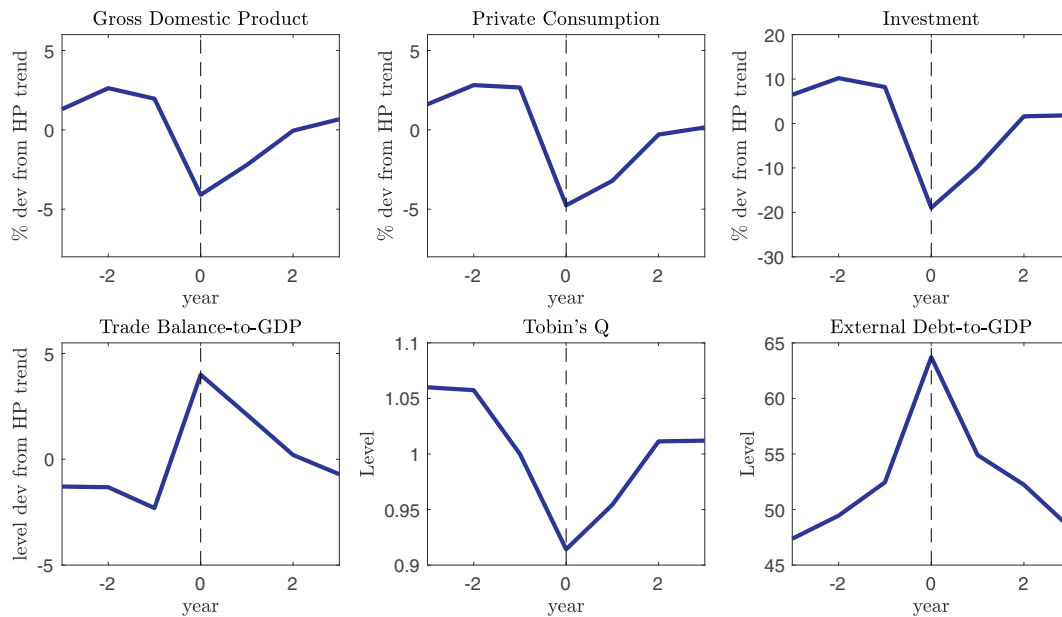
Fig. 1. Sudden Stop Event Study– Data.Note: Events are identified as periods in which the cyclical component of GDP is at least one-and-a-quarter standard deviations below its trend level and the reversal in the trade balance-to-GDP ratio is at least one-and-a-quarter standard deviations above average. The blue line is the cross-country median of the forty-two Sudden Stop events identified during the 1980-2015 period. The event window includes three years before and three years after the Sudden Stop events at date 0. GDP, investment, consumption and trade balance-to-GDP ratio are all HP detrended with a smoothing parameter 10. Tobin's Q and debt-to-GDP ratios are shown in absolute levels.

on average, but also risky, since it reduces the agents' ability to respond to negative shocks that might arrive in the future.

In order to establish that news shocks are quantitatively important for matching emerging economy data, we first estimate our model using a simulated method of moments that targets the standard deviations, as well as the zero and first order cross-autocorrelations of emerging economy GDP growth, consumption growth, investment growth, trade balance-to-GDP ratio, and country interest rates.[3] In addition to a shock to the predictable component of permanent productivity, the model is buffeted by exogenous unexpected disturbances to permanent productivity and the country interest rate. We find that the estimated model assigns just over half of fluctuations in productivity to its predictable component. Bootstrapped confidence bands indicate this share lies between 36 and 68%, which is both statistically and economically significant.

The empirical properties of the trade balance provide crucial identifying information for our estimated news share. Shocks to the country interest rate can account for some fluctuations in the trade balance, and also its modest counter-cyclicality, but their observed size is not large enough to account for its total volatility. Mean-reverting (non-permanent) productivity shocks lead to a strongly positive trade balance during economic booms, a pattern so counter-factual that we do not consider them in our baseline estimation.[4] Meanwhile, unanticipated permanent productivity shocks lead to relatively small fluctuations in these variables and also cannot match observed volatility. In contrast, news shocks, which imply a steeply rising profile of productivity over time, give agents an explicit reason to adjust consumption and investment today, even when current output is (relatively) unchanged. Thus, they lead to much larger— and more realistic — fluctuations in debt and the trade balance.

After demonstrating that the estimated model fits unconditional moments quite well, we show that it also predicts Sudden Stop events

that closely resemble the events identified in Fig. 1. In particular, the model predicts booms in output, consumption, investment, asset prices and rising leverage whenever available information indicates high future growth rates for consumption, i.e. after positive news shocks. In the event of a sufficiently negative realization of actual productivity growth—or any other shock—the additional leverage accumulated by agents during the period of optimism causes the leverage constraint to bind, or to bind more strongly, leading to a debt-deflation spiral. The non-linear effects of the binding credit constraint deliver quantitatively realistic crashes in the event of a crisis, including a simultaneous and deep fall in consumption and borrowing that would otherwise be difficult to deliver in an economy with access to international financial markets.

Existing models of real business cycles, even those with credit market frictions, do not easily generate the set of facts cited above. These models typically require unusually large shocks to account for financial crises and many are designed to study the financial crises in isolation.[5] Moreover, these models have a difficult time generating output and consumption booms in the period leading into the crisis. This is true because good times are usually associated with improved asset prices and, thus, improved net worth of the borrowers, relaxing borrowing constraints according to most common specifications. Thus financial crises in these models, if they occur, typically occur only after a series of bad realizations of shocks. Anticipated shocks address this challenge by introducing the possibility that borrowing and leverage rise in response to good shocks, and therefore increase during times of expansion. Crises in this case can be triggered by good news followed by a bad realization, and indeed even when no change in fundamental is finally observed.

To our knowledge, this paper is the first to estimate a fully non-linear emerging economy business cycle model, and show that it can simultaneously match long run business cycle moments and Sudden Stop dynamics. Guerrieri and Iacoviello (2015) propose a piece-wise linear approach to solve models with occasionally-binding constraints, and Guerrieri and Iacoviello (2017) use this approach to estimate a

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[3] Because the estimator targets *unconditional* moments, it is a good indicator of the overall patterns in the data but is not directly linked to dynamics surrounding Sudden Stops.

[4] The estimation results for the model augmented with mean-reverting productivity shocks are presented in Section 5.

[5] See, among others, Gertler et al. (2007), Gertler and Karadi (2011), Gertler and Kiyotaki (2010).

leverage-constrained model with housing. Mendoza (2010) calibrates a model similar to ours with conventional business cycle shocks to TFP, the country interest rate, and price of imported intermediate goods. Using a correlated shock structure, his model also delivers crises of realistic magnitudes. News shocks about future productivity help our model to better fit the patterns of negative trade balance and rising debt that have been the most powerful predictors of financial crises (see Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012).

The literature on anticipated shocks is long, and has generally focused on linearized models. Recently, such shocks have begun to appear in the literature on small open economies. Jaimovich and Rebelo (2008) describe mechanisms that can lead news shocks to generate comovement in a small open economy. Cao and L'Huillier (2014) consider medium-term business cycles caused by innovations that increase expectations of future productivity, which are not always realized *ex post*. In contemporaneous work, Bianchi et al. (2016) introduce news shocks into a non-linear two-sector endowment economy with the flow collateral constraint of Bianchi (2011). Durdu et al. (2013) have also studied the implications of news in a model with sovereign default. In contrast to Durdu et al. (2013) and Bianchi et al. (2016), our framework incorporates endogenous production and investment, allowing us to study the joint dynamics of output, investment, leverage, and asset prices around Sudden Stop events.

Lorenzoni (2008) and Korinek (2010) also study more theoretical contexts where borrowing is collateralized by assets whose price agents take as given. Akinci and Queralto (2017) develop a model in which banks face an occasionally binding leverage constraint, and show that it matches a set of stylized facts around banking crisis episodes in a group of small open advanced economies. Other related papers include Uribe and Yue (2006); Bianchi and Mendoza (2010); Bianchi (2011); Benigno et al. (2012); Otrok et al. (2012); Bianchi and Mendoza (2013); Fornaro (2015); Ottonello (2015) and Schmitt-Grohé and Uribe (2016).

This paper proceeds as follows. Section 2 lays out the basic model used in our analysis. Section 3 summarizes our solution method and estimation procedure. In Section 4, we highlight our main results regarding the drivers of Sudden Stops in the model economy, and examine the model's ability to match historical Sudden Stop episodes. In Section 5, we examine the robustness of our conclusion about the importance of anticipated shocks to several of our calibration choices. Finally, Section 6 concludes. Additionally, replication files and instructions can be found at www.chahrour.net/goodnews_replication.

2. Model

The model economy resembles the small open economy RBC model of García-Cicco et al. (2010), with the addition of a collateral constraint as in Mendoza (2010). The core model, as presented in García-Cicco et al. (2010), is modified to allow for gradual detrending of labor in the utility function, as well as adjustment costs to both labor and debt.

The economy is populated by a continuum of infinitely-lived representative firm-households who choose per-period consumption, hours, investment (c_t, h_t, i_t, respectively), the next-period capital stock, k_{t+1}, and the amount of debt, d_{t+1}, incurred in period t to be repaid in $t + 1$. Agents seek to maximize the discounted expected future flow of utility,

$$\max_{\{c_t, h_t, i_t, k_{t+1}, d_{t+1}\}} E_0 \sum_{t=0}^{\infty} \beta^t U\left(c_t, \tilde{X}_{t-1} h_t\right) \tag{1}$$

subject to the constraints.

$$k_{t+1} = (1-\delta)k_t + i_t \tag{2}$$

$$
\begin{aligned}
c_t + i_t = {} & F(k_t, X_t h_t) + \frac{d_{t+1}}{R_t} - d_t - g_t - \chi(R_t-1)w_t h_t - \\
& k_t \Phi_k\left(\frac{i_t}{k_t}\right) - y_t \Phi_d\left(\frac{\Delta d_{t+1}}{y_t}\right) - X_{t-1} h_{t-1} \Phi_h\left(\frac{h_t}{h_{t-1}}\right) + \tau_t
\end{aligned} \tag{3}
$$

$$\kappa \geq \frac{\frac{d_{t+1}}{R_t} + \chi R_t w_t h_t}{q_t k_{t+1}} \tag{4}$$

Eq.(2) represents a standard process for the evolution of capital, which depreciates at rate δ.

Eq.(3) is the intertemporal budget constraint. The resources available to households are governed by a constant-returns-to-scale technology, $y_t = F(k_t, X_t h_t)$, requiring capital and labor and buffeted by a non-stationary labor-augmenting productivity shock, X_t. Each period the household must pay off old debt, may incur new liabilities, and funds an exogenous stream of unproductive government spending, g_t, which we assume to be constant in our baseline model. In addition, the representative firm-household must finance a fraction χ of their wage bill in advance of production with working capital loans.

The second line of Eq.(3) reflects three costs of adjustment faced by households. The cost of adjusting capital, parameterized by $\Phi_k(i_t/k_t)$, is standard in the literature, and gives rise to a Tobin's Q pricing relationship for installed capital. Labor adjustment costs, $\Phi_h(h_t/h_{t-1})$, are included to give firms an incentive to bring forward a portion of any expected future increase in labor demand, giving "good" news the ability to boost output contemporaneously. Finally, the small open economy pays a cost, $\Phi_d(\Delta d_{t+1}/y_t)$, to change its indebtedness position vis-à-vis the rest of the world. For computational simplicity, we assume that adjustment costs paid are returned as a lump-sum transfer, τ_t, to the household, so that the second row of Eq.(3) nets to zero in equilibrium.

The key household constraint for the questions of this paper is the occasionally binding collateral constraint given by Eq.(4). The right hand side of the equation defines leverage in the economy as the ratio of total borrowing (including working capital loans required to hire labor) divided by the agent's assets, which are given by total capital times its price. The price, q_t, is exogenous to the agent but determined in equilibrium by Tobin's Q. Similar constraints have been used by many authors, including Kiyotaki and Moore (1997) and Mendoza (2010). In addition to the price of installed capital, consumers take the real wage, w_t, and the world interest rate on external borrowing, R_t, as given. In equilibrium, the real wage is given by $w_t = -U_{h, t}/U_{c, t}$, which is the equilibrium wage that would emerge in a standard decentralization of our economy.

We note here that the environment incorporates two pecuniary externalities of the type emphasized by Bianchi (2011), and driven by the presence of the prices w_t and q_t in the collateral constraint. Mendoza and Smith (2006) and Mendoza (2010) argue that the quantitative effects of these externalities under this specification of the collateral constraint are rather small, and solve their model using a method that ignores them; whether this remains the case in our environment is not immediately clear and our solution method takes them into account.

In this context, the household Euler equations for debt and capital are given by

$$\lambda_t = \beta \mathbf{E_t} \frac{R_t \lambda_{t+1}}{1-\mu_t}\left[1 - \Phi'_d\left(\frac{\Delta d_{t+2}}{y_{t+1}}\right)\right] + \Phi'_d\left(\frac{\Delta d_{t+1}}{y_t}\right) \tag{5}$$

$$
\begin{aligned}
\lambda_t = {} & \beta \mathbf{E_t} \frac{\lambda_{t+1}}{q_t(1-\mu_t \kappa)}\Big[F_k(k_{t+1}, X_{t+1} h_t) + (1-\delta)q_{t+1} \\
& + \Phi'_k\left(\frac{i_{t+1}}{k_{t+1}}\right)\frac{i_{t+1}}{k_{t+1}} - \Phi_k\left(\frac{i_{t+1}}{k_{t+1}}\right)\Big]
\end{aligned} \tag{6}
$$

where $\lambda_t \geq 0$ is the Lagrange multiplier on the household budget

constraint (3) and $\lambda_t \mu_t \geq 0$ is the Lagrange multiplier on the leverage constraint (4). From Eq.(5), it is clear that when the leverage constraint binds, and $\mu_t > 0$, there is an implicit interest rate premium of $1/(1 - \mu_t)$, to which households respond by lowering their debt holdings. From Eq. (6), it is similarly apparent that $\mu_t > 0$ lowers the effective return on capital, and that this effect is larger the larger is κ.

Because of these premia, in periods of a binding constraint, agents will tend to lower both debt and capital holdings simultaneously, i.e. engaging in saving in terms of debt, but in dissaving from the perspective of capital holdings. This pattern is the key reason why the model with a constraint is well-suited to deliver the qualitative patterns surrounding Sudden Stop episodes.

To complete our description of the model, we now describe the exogenous processes driving the economy. We restrict our attention to permanent productivity and country interest rate shocks in the baseline specification, abstracting from shocks to the stationary component of productivity. Stationary productivity shocks have been shown to help match business cycle moments in linearized models of emerging economies (see García-Cicco et al., 2010, for an example) but we show in Section 5 that they provide only a very modest improvement of fit in our framework.

The labor-augmenting productivity shock is nonstationary and its growth rate, $\gamma_t \equiv \frac{X_t}{X_{t-1}}$, evolves according to the process

$$\log(\gamma_t/\gamma) \quad = \rho_x \log(\gamma_{t-1}/\gamma) + \epsilon^H_{t-H} + \epsilon^0_t. \tag{7}$$

In the above equation, γ denotes the long run growth rate of productivity. The shock ϵ^H_{t-H} is a "news" shock, realized and observed by agents at time $t - H$, but not affecting productivity until time t. Conversely, ϵ^0_t is a productivity shock that is observed and influences productivity contemporaneously.

Consistent with the evidence of Uribe and Yue (2006) and Akinci (2013), we assume that the gross real interest rate that the economy faces in international markets follows the process,

$$\log(R^*_t/R^*) \quad = \rho_r \log(R^*_{t-1}/R^*) + \epsilon_{R,t} \tag{8}$$

where R^* is the long-run level of the interest rate.

We collect all exogenous shocks in a vector $\epsilon_t \equiv [\epsilon^H_{t-H}, \epsilon^0_t, \epsilon_{R,t}]'$. The elements of ϵ_t are assumed to be mutually orthogonal, i.i.d. and normally distributed with standard deviations σ_{news}, σ_{surp}, and σ_r, respectively.

Under the preferences we assume in the next section, the disutility of labor must be detrended in order for the economy to have a balanced growth path. We generalize the approach taken by García-Cicco et al. (2010) and assume that this term follows an exponential moving average process, $\tilde{X}_t = \tilde{X}^{\varphi}_{t-1} X^{1-\varphi}_t$. When $\varphi = 0$, this specification reduces to the case of García-Cicco et al. (2010). Setting φ close to one smoothes the discontinuity in the hours response to productivity shocks that occurs when past productivity shocks affect the disutility of labor.

Finally, to ensure that agents borrow in equilibrium, we calibrate the economy so that agents exhibit a degree of "impatience" relative to world investors. That is, in the long run,

$$\beta R^* \gamma^{-\sigma} < 1 \tag{9}$$

In this framework, the interest rate faced by a small open economy on its external borrowing, R_t, is equal to the world interest rate, R^*_t.[6] In Section 3, we estimate the parameter β that best matches the data.

The complete set of first order conditions for the representative firm-household can be found in Appendix B.

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[6] We have considered several different methods of stationarizing debt-to-GDP in the constrained economy; while each requires slightly different parameters to match the data, the consequences for the dynamics of the economy once it is calibrated to match the target moments are remarkably similar.

3. Solution and estimation

3.1. Functional forms

We specify preferences with a version of the utility function introduced in Greenwood et al. (1988), modified to allow for balanced growth,

$$U\left(c_t, \tilde{X}_{t-1} h_t\right) = \frac{\left[c_t - \theta\omega^{-1}\tilde{X}_{t-1} h^{\omega}_t\right]^{1-\sigma} - 1}{1-\sigma} \tag{10}$$

These preferences eliminate the wealth effect on labor supply by making the marginal rate of substitution between consumption and labor independent of consumption. In Eq.(10), the parameter σ is the coefficient of relative risk aversion, and ω is inversely related to the wage elasticity of labor supply.

The production function is given by

$$F(k_t, X_t h_t) = k^{\alpha}_t (X_t h_t)^{1-\alpha} \tag{11}$$

In Eq.(12), the parameter α measures the share of capital in total output.

Finally, we use a quadratic specification for all adjustment costs. Specifically,

$$\Phi_k(i/k) \quad = \frac{\phi_k}{2}\left(\frac{i_t}{k_t} - \delta\right)^2 \tag{12}$$

$$\Phi_h(h'/h) \quad = \frac{\phi_h}{2}\left(\frac{h_t}{h_{t-1}} - 1\right)^2 \tag{13}$$

$$\Phi_d(\Delta d'/y) \quad = \frac{\phi_d}{2}\left(\frac{d_{t+1} - d_t}{y_t} - (\gamma - 1)\frac{d}{y}\right)^2 \tag{14}$$

where the parameters ϕ^k, ϕ^h and ϕ^d govern the cost of adjusting capital, labor, and debt, respectively.

3.2. Numerical solution

Before solving the model, we stationarize the economy by dividing all trending variables by X_{t-1}. The resulting stationary first order conditions and corresponding balanced growth paths are described in Appendix C.

We solve the stationary model using a parameterized expectations approach. The approach consists of using parametric functions to approximate agents' one-step-ahead conditional expectations as functions of the aggregate state vector. This method is particularly helpful for our context because it minimizes the additional computational burden created by the introduction of additional states tracking past news that has arrived in the economy. We describe our method in detail in Appendix D.

3.3. Estimation

We calibrate several preference and production parameters to standard values. We fix these parameters a priori and do not vary them in our calibration. These parameters are listed in Table 1 and we examine robustness to several of these choices in Section 5.

A few of the parameters listed in Table 1 warrant discussion. We fix the adjustment costs parameters ϕ_h and ϕ_d for different reasons. We included the labor adjustment following Jaimovich and Rebelo (2008), because it can give news a role in delivering contemporaneous output boosts in response to good news. When we estimated this parameter, we found its value depends a lot on the details of the empirical specification, so we fixed it to an intermediate value.

Table 1
Calibrated model parameters.

Parameter	Concept	Value
σ	Risk aversion	2.000
ω	Labor elasticity	1.900
R^*	Long run interst rate	1.085
α	Capital share	0.330
δ	Capital depreciation rate	0.126
$\bar{h}$	Steady-state hours normalization (implies θ)	0.200
$\frac{g}{y}$	Unconditional Gov. Exp.-to-GDP ratio	0.110
γ	Long run productivity growth	1.005
χ	Share of working capital	0.500
φ	Degree of slow detrending in the preferences	0.900
ϕ_h	Labor adjustment cost	1.000
ϕ_d	Debt adjustment cost	0.500
$\frac{d}{y}$	Unconditional Debt-to-GDP ratio	0.484
$\bar{\mu}$	Unconditional implicit premium	0.010
ρ_r	Autocorrelation of R	0.752
σ_r	Std. of R shock	0.021

Table 2
Estimated model parameters.

Parameter	Concept	Estimate	5%	95%
ϕ_k	Capital Adjustment Cost	2.875	2.410	3.506
β	Discount factor	0.914	0.912	0.916
κ	Collateral Constraint	0.444	0.399	0.502
ρ_x	Autocorr. of TFP growth	0.356	0.248	0.439
σ_{news}	Std. of News shock	0.032	0.025	0.041
σ_{surp}	Std. of Surprise shock	0.030	0.024	0.038

In contrast, for the debt adjustment cost, we found that the estimation procedure typically selects extremely high values for this parameter, such that it would lead to counter-factually small volatility for trade balance and debt. For this reason, we chose to fix this parameter *ex ante* and show an alternative value in our robustness table.

Included in Table 1 are two values that do not map into a single parameter in our specification of the economy. The first of these, $\frac{d}{y}$, is the average debt-to-GDP ratio of roughly 48%. Our target for debt-to-GDP corresponds to the average debt ratio in the data used for Fig. 1.

The second is a value $\bar{\mu}$, which we fix at 1.0%. Since μ_t is latent, it does not map directly to an observable quantity in our data. Nevertheless, it is closely related to the frequency with which the constraint binds (recall $\mu_t \geq 0$) and, therefore, with the risk premia earned by capital in the economy. In particular, we have found that a higher target for $\bar{\mu}$ corresponds to a higher Sharpe ratio in the model economy. The target we adopt here implies a Sharpe ratio of 0.195, which is slightly smaller than the empirical ratio of 0.243 reported by Donadelli and Prosperi (2011).

To ensure that the estimated model matches these calibrated values, we augment the loss function underlying our estimation (described below) with extremely large weights on deviations from these moments. Adding these additional targets to our estimation procedure is important for anchoring the model near an empirically realistic debt level and identifying a plausible degree of excess impatience embodied in the parameter β.

We also need to choose H, the horizon of anticipation in our economy. In our baseline specification, we choose H = 3 years because it corresponds to the longest news horizons that have been estimated in linear economies. (For example, see Schmitt-Grohé and Uribe (2012), who estimate news shocks at horizon 4, 8, and 12 quarters.) Longer news horizons give the economy time to build debt in response to good news and, indeed, debt volatility is higher in the model estimated with longer news horizons. Nevertheless, beyond a horizon of 2 the difference is not large, as most of the adjustment to the future information occurs in the two years before the news takes effect.

Finally, because we have direct observations on country interest rates, R_t^*, we fix *ex ante* ρ_r and σ_r to values that, in population, match the standard deviation and autocorrelation in our target interest rate data.[7]

We estimate the remaining parameters, $\Omega = \{\phi_k, \beta, \kappa, \rho_x, \sigma_{news}, \sigma_{surp}\}$, using a simulated method of moments, and present the results in Table 2. Our target moments are standard deviations, along with zero and first order cross-autocorrelations of output growth, consumption growth, investment growth, the trade balance-to-GDP ratio, and

the country interest rate. Although we report external debt in our event study, we do not use it as target moment as these data incorporate debt denomination/valuation effects that our model is not equipped to capture. Altogether, our targets consist of 40 independent moments from the data.

In our data sample underlying our target moments, we have 31 countries, with samples of roughly 36 years each. We compute the target moments for each of these countries and then target the mean across countries for each moment, dropping the two highest and two lowest observations for each. Since our actual data is unbalanced, we compute our target moments using the maximum available data sample within each country, for each pair of variables. We denote the vector of these target moments by the 1×40 vector, M_{data}.

For a given set of parameters, Ω, we then use the model to generate a simulation of $T = 5000$ years from the model economy and then compute the model analogue moments by dividing the long simulation into "synthetic" countries, each with 36 years of data. We collect the mean of these moments in a 1×40 vector, $M_{mod}(\Omega)$. Our GMM estimator is then

$$\hat{\Omega} = \text{argmin}_{\Omega}[M_{data} - M_{mod}(\Omega)]V[M_{data} - M_{mod}(\Omega)]' \qquad (15)$$

where V denotes a diagonal matrix used to weight deviations from the target moments.

As a default, we weigh the difference between the model moments and targets according to the inverse variance of the target moment across (all available) countries for that moment in the true data. In several experiments we performed, the estimated model with these default weights over-predicted the standard deviation of consumption, investment, and trade balance in favor of better matching cross variance terms. Because these second moments are salient in the related literature, our baseline estimation places three times the default weight on deviations from our target standard deviations. We show in Section5 that this choice does not drive our results on the importance of news shocks.

After formulating the weighted loss function, we estimate the model parameters using Matlab's lsqnonlin least-squares optimizer. In experiments on a linear version of the model, we found that this optimizer did very well finding global optima with relatively few evaluations of the loss function. We have also re-estimated the economy from different starting points, and find that the procedure delivers the same result each time. Hence, we feel confident that the parameters we report are indeed the best fitting parameters in the parameters space.

Our standard errors are based on 500 bootstrapped samples. In each of these samples, we draw with replacement a random selection from the 31 countries in our original data. We then reestimate the model using the exact same procedure employed to estimate the baseline economy, initializing each search at our baseline estimates. We find that the share of news, defined as $\sigma^2_{news}/(\sigma^2_{news} + \sigma^2_{surp})$, ranges between 35.9% and 68.0% within the 90% confidence region of the simulations.

In addition to estimating the baseline economy, we also estimated several different specifications, including a version of the model in which we did not allow for productivity to have an anticipated component. We discuss this restricted estimation at length in Section4, and additional robustness tests in Section5.

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[7] More details about the measurement of the country interest rates are presented in Appendix A.

Table 3
Comparing Model and Data: Business Cycle Moments.

	Δgdp	Δc	Δi	TBY	R
Standard Deviation					
Baseline Model	4.58	5.07	15.11	4.76	2.84
Model w/o News	4.35	5.02	18.16	3.91	2.84
Data	4.06	4.97	16.29	4.50	3.11
	[3.31, 4.92]	[3.93, 6.32]	[11.57, 19.12]	[3.27, 5.51]	[1.52, 4.78]
Auto-Correlation					
Baseline Model	0.45	0.09	−0.14	0.52	0.63
Model w/o News	0.43	0.13	−0.17	0.40	0.63
Data	0.32	0.27	0.11	0.70	0.73
	[0.15, 0.49]	[0.13, 0.45]	[−0.03, 0.24]	[0.60, 0.79]	[0.58, 0.86]
Corr. with Δgdp					
Baseline Model	–	0.75	0.49	−0.29	−0.12
Model w/o News	–	0.90	0.54	−0.49	−0.13
Data	–	0.75	0.74	−0.14	−0.20
	–	[0.62, 0.88]	[0.64, 0.86]	[−0.34, 0.11]	[−0.45, 0.05]

Note: Data denotes unconditional mean values across the countries in our sample after dropping the two highest and two lowest outliers for each moment. Square brackets denote the interquartile range for each moment across the full sample of countries. Model implied second moments are unconditional means across all pseudo-countries simulated using the estimated model. Variables Δgdp, Δc, and Δi denote the growth rates of output per capita, consumption per capita, and investment per capita, respectively. *TBY* and *R* denote the ratio of the trade balance-to-output and country interest rates, respectively.

4. Results

In this section, we present our estimation results and argue that news shocks play an important role in helping the model match the data. We then show that news shocks also play an important role in driving dynamics around Sudden Stop events and explore their importance in driving endogenous risk in the economy.

4.1. Long-run business cycle moments

Table 3 provides numerical values for several key moments in the estimated baseline economy, the model economy estimated without news,[8] and the data. Both estimated models do a good job at matching the empirical standard deviations of output, consumption, and investment growth. Differences emerge however, in the ability of the no-news model to match the estimated volatility of the trade balance, with the estimated no-news model implying somewhat lower volatility.

In addition to overall volatility of the trade balance, the correlation between output growth and consumption growth is counterfactually high in the no-news model, while the trade balance is too negatively correlated with output growth. News helps solve the first of these problems by introducing an additional reason for consumption to fluctuate even when productivity (and therefore GDP) does not, and the relatively mild correlation between output growth and the trade balance-to-output ratio reflects the same force, as households borrow to finance the expectations-driven component of consumption.

Table 4 provides an additional perspective regarding which of the features of the data drive our finding of a substantial news share. The table presents the three moments with the largest contribution to the improvement in the loss function when the model is estimated with news, relative to the version estimated without. Consistent with our observations above, the top three contributors are all related to the trade balance. The largest contribution to the improvement in loss function is the higher autocorrelation of the trade balance implied by the model with news - which Table 3 shows is both persistent and tightly estimated. The model with news also improves substantially on the comovement between the interest rate and the trade balance, as well as the correlation of the trade balance with output, which is too strongly counter-cyclical in the model without news.

Table 4
Contribution to Fit Improvement.

Moment	Contribution
$Corr(TBY_t, TBY_{t-1})$	0.31
$Corr(TBY_t, R_t^*)$	0.23
$Corr(TBY_t, \Delta GDP_t)$	0.14

Note: Let $Res^{base} \equiv [M_{data} - M_{mod}(\hat{\Omega}^{base})]$ be the vector of residuals for the baseline estimation, and Res^{no} the corresponding residuals for the model estimated with no news. The contribution of moment m is given by $\frac{(Res_m^{no\,2} - Res_m^{base\,2})V_m}{\sum_{j=1}^{40}(Res_j^{no\,2} - Res_j^{base\,2})V_j}$. Note that contributions can be negative as well as positive.

4.2. News shocks and Sudden Stop events

4.2.1. Baseline model

Fig. 2 displays the dynamics of our estimated baseline model around Sudden Stop events, along with the empirical analogues from actual Sudden Stops. We identify a Sudden Stop in model generated data exactly as in Fig. 1, as a period in which the cyclical component of GDP is at least one-and-a-quarter standard deviations below its trend level and the reversal in the trade balance-to-GDP ratio is at least one-and-a-quarter standard deviations above average.

In our baseline model, the probability of a Sudden Stop identified by these criteria is roughly 1.4%. This is somewhat lower than the frequency of Sudden Stops in our data, which is close to 4%.[9] Recall, however, that the empirical Sudden Stop probability is not used as a target in the calibration or estimation of the model parameters. One potential cause of the shortfall in Sudden Stop frequency may be the cross-country correlation in these events, something that our class of small open economy models does not capture by construction.[10] Still, it is clear the estimated baseline model is not able to fully account for the frequency of events in our data. The estimated model without news faces similar difficulty, as it also experiences identified events with a probability of roughly 1.4%.

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[8] Our estimates for the model without news are presented in the second row of Table 5 in Section 5.

[9] Other authors have found somewhat lower Sudden Stop rates using different samples. For example, Mendoza (2010) report that the frequency of Sudden Stops in the dataset of Calvo et al. (2006) is 3.3% for the 1980–2005 period. Schularick and Taylor (2012) report an annual probability of crises of 2% since the 1945s, with none reported in the 1945–1971 period.

[10] For example, 8 of our 42 identified events occur during the financial crisis, between 2009 and 2010.
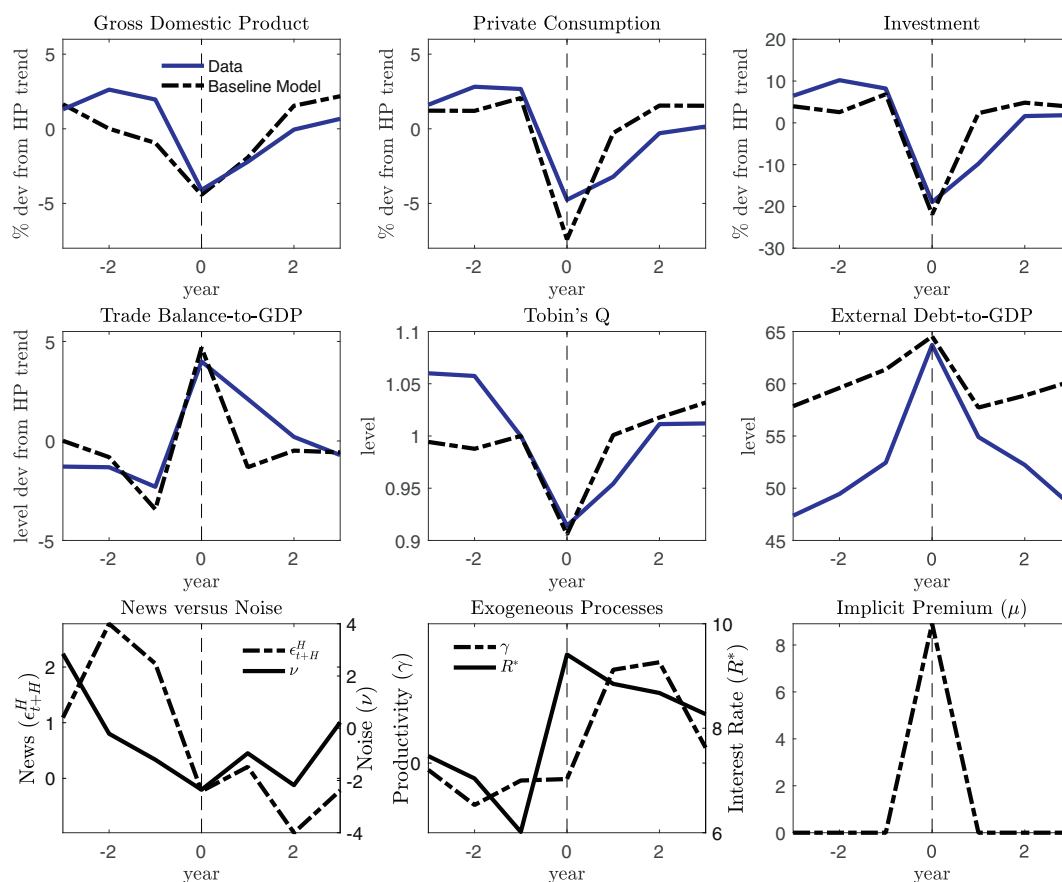
Fig. 2. Sudden Stop Event Study– Model versus Data.Note: Dashed lines in the first two rows of the figure show the model implied cross country medians of Sudden Stops, identified using the same definition of events as in Figure 1. Events from actual data are shown by solid blue lines. GDP, consumption, investment, and trade balance-to-GDP ratio are all HP detrended with a smoothing parameter 10. Tobin's Q and debt-to-GDP ratios are shown in absolute levels.

Turning back to model implied Sudden Stop dynamics as depicted in Fig. 2, the dashed black line shows the cross-country medians of different variables three years before and after Sudden Stop events. Our baseline model does a good job in replicating the majority of the observed empirical dynamics around these events. In the three years prior to the crisis, the economy experiences a concurrent boom in output, consumption, and investment, consistent with the data. Output falls below trend in the period prior to the Sudden Stop, then declines further to around 4% below trend in the event period. The total fall of output, from peak-to-trough, is nearly 6%, largely in line with the data. As a contrast, Mendoza (2010)'s calibrated model delivers an overall peak-to-trough change of just over 4%. For consumption, the peak-to-trough fall is over 8%, which is very close to to data, and is also substantially larger than the fall implied by Mendoza (2010)'s model. The model also delivers a quantitatively realistic investment boom prior to the Sudden Stop event, which is about 10% in the data, and matches the bust period very well, too.

The model is also successful at matching the pattern of the trade balance around the period of the Sudden Stop. The trade balance-to-GDP ratio is well below trend in the period prior to the event, and the reversal in the Sudden Stop period follows the data remarkably well. The model shows a corresponding increase in the debt-to-GDP ratio in years prior to the event, peaking in the crisis year around 65% of GDP. The model also generates a substantial debt deleveraging of about five percentage points of output in the year after the Sudden Stop. Finally, the magnitude of the decline in model-implied asset prices from peak-to-trough is in line with the data and somewhat larger than in Mendoza (2010).

The final row of Fig. 2 sheds some light on the constellation of shocks leading up to Sudden Stop events. The dashed line in the first panel

shows that news about future productivity is very positive in the two periods prior to the Sudden Stop. Meanwhile, the second panel shows that Sudden Stops typically occur in periods when current productivity growth is low; a Sudden Stop today is more likely when past expectations have been optimistic—indicating positive news shocks in the periods prior to event—and when productivity is low today—corresponding to bad contemporaneous growth shocks. We examine this observation further in Section 4.2.3.

The second panel in the last row of Fig. 2 also shows that the median Sudden Stop in the model is preceded by somewhat below-average interest rates, indicating that interest rates play a modest role in driving the increase of leverage and the debt-to-GDP ratio before a Sudden Stop event. Interest rate increases in the event period, however, play a somewhat more important role in exacerbating the downturn. The last panel of the figure, which plots the implied interest rate premium experienced by the economy in the crisis period, shows that at the same time interest rates are rising, the leverage constraint is binding – a combination that leads to the strong deleveraging and fall in investment depicted in the rows above.

Overall, the patterns around Sudden Stop periods can be summarized as: optimism and borrowing prior to the event, and a combination of bad productivity surprises and rising interest rates during the event. The empirical pattern of rising debt and economic optimism, followed by financial crisis and below trend output strongly resembles the patterns identified by Mian et al. (2017).

4.2.2. Comparison to models without news

To better understand the role that news shocks play in delivering realistic Sudden Stop dynamics, we provide corresponding event studies in two different counter-factual scenarios. The first scenario, displayed
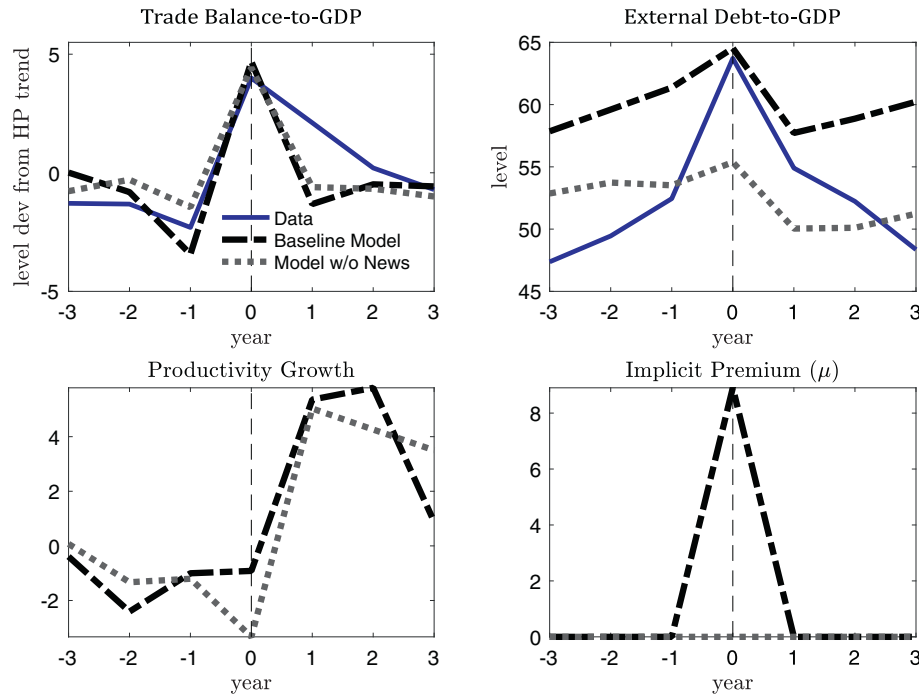
Fig. 3. Sudden Stop Event Study– Estimated model without News.Note: Dashed lines show the model implied cross country medians of Sudden Stops, identified using the same definition of events as in Figure 1. Dotted lines display the cross country medians of Sudden Stops in a re-estimated model without news shocks. Events from actual data are shown by solid blue lines. Trade balance-to-GDP is HP detrended with a smoothing parameter 10, and debt-to-GDP ratio is shown in absolute levels.

in Fig. 3, compares events identified in the model estimated with news to events identified in the model estimated without news shocks. Thus, the figure compares different models, each with parameters estimated to best match unconditional moments, and hence the events identified generally do not occur at the same points in each economy's history.

As in our estimation results, the dynamics of trade balance (as long with the debt-to-GDP ratio) turn out to be key for understanding the differences between the models. In particular, the estimated model without news shocks predicts a smaller increase in the trade deficit and a smaller rise in indebtedness prior to Sudden Stop events. Similarly, at the date of the event, the reversal of trade balance and the size of debt decumulation are somewhat smaller in the no-news model, despite the fact that events in the no-news model correspond to a bigger collapse in productivity.

The final panel of the Figure shows that it is only in the model with news that the median Sudden Stop event corresponds to a binding leverage constraint and, therefore, to a positive interest rate premium. Indeed, empirical analyses of crisis events, including Gertler et al. (2007), Bocola (2016), and Akinci and Queralto (2017), consistently show that interest rate spreads rise strongly at such moments. Moreover, narrative evidence from these periods strongly suggests that financial constraints play an important role. Thus, our finding that the model with news delivers large interest rate premia around these events is a further indicator that it provides a more realistic account of these episodes.

Fig. 4 offers a second perspective on the importance of news, in this case designed to better isolate the effects of anticipation in the baseline economy. In the figure, we plot a counter-factual scenario in which the model parameters and shock histories are exactly the same as under the baseline estimation. We then use events identified in the baseline economy with anticipation, and look at the patterns around these events in the counter-factual no-anticipation economy.

The figure shows that, other than for output, anticipation plays a crucial role in pre- and post-crisis dynamics. In particular, prior to the event, consumption is a full two percentage points higher relative to the counter-factual economy. This higher consumption is a direct result

of agents' optimism, coming from good news that is not available to agents in the counter-factual economy. Similarly, investment in the model with anticipation is substantially above trend in the period prior to the crisis. To support these higher consumption and investment levels, the economy with news runs a trade-deficit that is roughly three times larger than in the counter-factual economy, while the run-up in debt is correspondingly much larger in the model with news.

Conversely, in the period of the Sudden Stop, the depth of the economic crisis is much larger in the model with anticipation. The one period fall in consumption is roughly 1.5 times that of the counter-factual economy, with even larger multiples for investment and asset prices. Overall, the reversal in the trade balance is almost twice as large in the baseline economy, relative to the no-anticipation economy. Additionally, as in the re-estimated model depicted in Fig. 3, the financial constraint again does not bind in the median event in the counter-factual economy depicted in Fig. 4.

Overall, we take the results in Figs. 3 and 4 as a strong evidence that news is playing a very important role in delivering realistic Sudden Stop events. The predictable component of productivity is especially important for the model to generate the most well-known characteristic of empirical Sudden Stop dynamics, i.e. a sudden reversal in trade deficit, rising and then quickly falling debt, and a period of financial disruption with skyrocketing interest rate spreads.

4.2.3. News versus noise

Under the current specification of our exogenous process, agents' expectation of the future productivity innovation conditional on their observation of the news shock is

$$E\left[\epsilon_{t+H}^0 + \epsilon_t^H | \epsilon_t^H\right] = \epsilon_t^H \tag{16}$$

Effectively, agents are certain that the news component, ϵ_t^H, will be realized, but they are completely ignorant of other potential surprises, ϵ_{t+H}^0, that may occur H periods in the future.
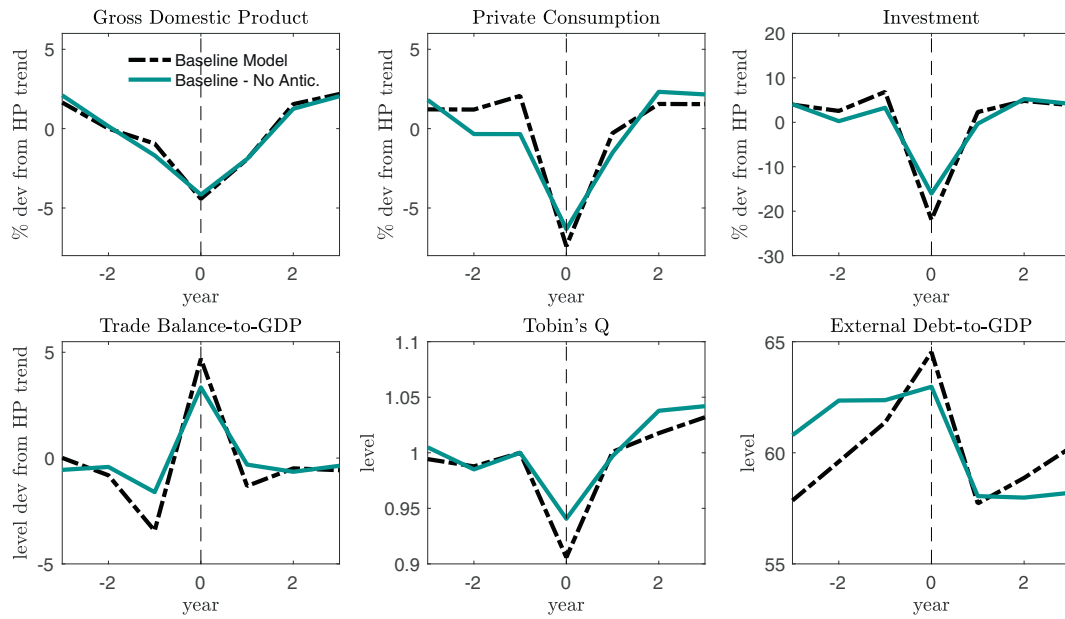
Fig. 4. Sudden Stop Event Study– Counter-factual model no anticipation.Note: Dashed lines show the model implied cross country medians of Sudden Stops, identified using the same definition of events as in Figure 1. Dotted lines display the cross country medians at identical points in history, in the counter-factual case that agents do not anticipate any future productivity shocks. Events from actual data are shown by solid blue lines. GDP, consumption, investment, and trade balance-to-GDP ratio are all HP detrended with a smoothing parameter 10. Tobin's Q and debt-to-GDP ratios are shown in absolute levels.

A natural alternative formulation for belief formation is to assume that agents receive a noisy signal, $s_t = \epsilon^0_{t+H} + v_t$, with $v_t \perp \epsilon^0_{t+H}$ and $\epsilon^H_t = 0, \forall t$. In this case, the the signal pertains to the full realization of the future productivity shock. Under this signaling paradigm, the conditional expectation of agents is

$$E\left[\epsilon^0_{t+H} | s_t\right] = \kappa s_t \tag{17}$$

with $\kappa \equiv \frac{\sigma^2_\gamma}{\sigma^2_\gamma + \sigma^2_v}$. A benefit of this "noise" model of foresight is that the signal noise v_t is completely orthogonal to fundamental shocks past, present, or future. Thus, the shock v_t corresponds to the optimism of agents relative to what actually happens: It is a pure shock to beliefs.

Recently, Chahrour and Jurado (2018) have demonstrated that, in fact, these two perspectives on learning are observationally equivalent. We can use their result to back out the implicit "excess optimism"— or noise shock— affecting agents beliefs from our history of news and surprise shocks. Setting equal the expectations in (16) and (17), we have that

$$v_t = \frac{1-\kappa}{\kappa} \epsilon^H_{t+H} - \epsilon^0_{t+H} \tag{18}$$

where $\sigma^2_v = \sigma^2_{surp}(1 + \sigma^2_{surp}/\sigma^2_{news})$.

In addition to plotting ϵ^H_{t+H}, the bottom left panel of Fig. 2 isolates the noise component embodied in the beliefs of private agents in the run-up to a Sudden Stop. The solid line in this figure shows that the noise component of beliefs, v_t, is elevated precisely three years prior to these events, then returns to zero in periods minus two and minus one. Meanwhile, the news component is roughly zero three periods prior to the event, and strongly positive in the remaining two periods before the event. Taken together, these lines show that optimism about productivity is a pervasive feature in the periods before the Sudden Stop: agents forecast above average productivity growth for the crisis period, when in fact it turns out to be below average, while correctly forecasting above average productivity for subsequent periods— good outcomes that arrive too late to forestall the Sudden Stop.

4.2.4. News as a risk shock

To what degree does good news today predict future negative outcomes? Fig. 5 plots the probability that a Sudden Stop occurs in future periods as a function of the percentile of the current news shock hitting the economy. The first panel, which plots the probability of an event one period forward, demonstrates a strong upward slope: the constraint is roughly five times more likely to bind tomorrow if the news arriving today is in the 95th percentile relative to the 5th percentile.

The second panel of Fig. 5 shows that the relationship between news and future negative outcomes is even stronger two periods ahead. In this case, a high news shock implies that a Sudden Stop two periods in the future is >10 times more likely, compared to a case with a very low news shock. Indeed, nearly 90% of Sudden Stop events in the model economy are preceded by positive news shocks two periods prior. The strong convexity of this figure shows that very high values of the news shock are especially good predictors of Sudden Stop risk, though they remain unlikely events.

Taken along with the plots in Figs. 2, 3, and 4, the panels of Fig. 5 provide strong evidence that foresight is a major driver of crises in our estimated economy. Even when rational, high levels of optimism about productivity drive an increase of Sudden Stop risk of a full order of magnitude.

5. Robustness

In this section, we examine the robustness of our results. In particular, we are interested in assessing whether our conclusion that news shocks play an important role is robust to the assumptions that we made in our baseline estimation. To do this, we consider a range of experiments in which we adjust the value of one of our baseline parameters and re-estimate the economy. Table 5 displays these cases, along with the associated parameter estimates and the value of the loss function achieved at those points.

For reference, the first row of Table 5 presents these values from our baseline estimation. The second row of Table 5 displays the estimated values for the model with no news shocks. As shown earlier, this model does not match the data as well as the model with news. This is
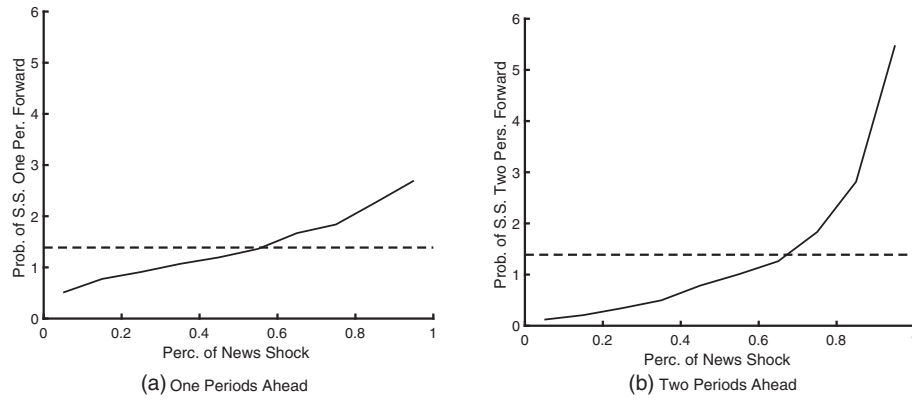
Fig. 5. Sudden Stop Probabilities.Note: The figure plots the probability of a Sudden Stop event occurring one (panel a) or two (panel b) periods hence, conditional on the percentile of the news shock today. The dashed line gives the unconditional probability of a Sudden Stop in the model economy.

reflected in a loss function that is substantially larger than the baseline model. While computational limitations make formal hypothesis testing difficult in our case, we believe the bootstrap standard errors, the qualitative differences in moments, and the limitations of the no-news model in matching Sudden Stop event patterns together provide compelling evidence that the model with news fits the data significantly better.

The third and fourth rows of the table consider an estimation in which we change the target for $\overline{\mu}$, the average interest rate premium experienced in the economy. When $\overline{\mu}$ is set to a higher value, the estimated share of news is somewhat higher and conversely it is somewhat lower when $\overline{\mu}$ is set to a lower value. Notice also that β is lower for higher $\overline{\mu}$. As noted above, higher values for $\overline{\mu}$ correspond to higher risk premia in the economy and therefore higher Sharpe ratios. Since the Sharpe ratio under our baseline target for $\overline{\mu}$ is 0.195, our baseline calibration of this parameter is - if anything - conservative in terms of its implications for the importance of anticipation in the economy.

The next two rows of the table present estimations of the model in which we consider both a shorter and a longer horizon of anticipation. The data seem to prefer the longer news horizon to some degree, but the difference with respect to our baseline is modest. Most importantly, the estimated share of news does not seem to depend in a strong way on this parameter. Although we do not report them, the event study analysis is also extremely similar across these specifications.

The next four rows of the table consider how our results are influenced by our calibration of adjustment cost parameters. As indicated by the value of the loss function in the table, the data prefer a larger value for ϕ_d. As discussed above, such a calibration would necessarily

under-predict the volatility of the trade balance, but it improves on trade balance autocorrelation. As the table shows, when ϕ_d is somewhat higher than our baseline value, the estimated volatility of news shocks goes up again indicating that we have taken a fairly conservative baseline in terms of estimating a modest news share. The table also shows that our results are robust to our choice of ϕ_h.

We next examine the importance of our assumption about χ. Once again, it appears that the role of news is relatively unaffected by this choice and, although we do not report it, the event study is quite similar to our baseline model. The loss function indicates, however, that the data do prefer to some degree a higher value for this parameter. We have maintained our baseline choice of χ in order to ensure the reader that none of our results rely on choosing an implausibly large value for this parameter.

Next, we explore the importance of the parameter ρ_x. When $\rho_x = 0$, the distinction between anticipated and surprise shocks becomes more stark. Indeed, assuming this increases the estimated share of news modestly, as well as the total size of productivity shocks (which effectively maintains the overall variability of TFP growth). Again, other parameters are only modestly different.

In the penultimate row of the table, we re-estimate the economy using only baseline weights in the GMM weighting matrix, V. We once again find that this decision does not affect our results in an important way, although - as noted earlier - total volatility in the economy rises.

Finally, we estimate a model with an additional temporary component in productivity. Previous authors, including García-Cicco et al. (2010), have found that such shocks can play an important role in

Table 5
Robustness of the Estimation Results.

	ϕ_k	κ	β	ρ_x	σ_n	σ_s	ρ_a	σ_a	Loss
Baseline Model	2.875	0.444	0.914	0.356	0.032	0.030	–	–	5771
Model w/o News	1.891	0.377	0.914	0.324	–	0.042	–	–	7107
Baseline Model w/									
$\overline{\mu} = .015$	2.592	0.428	0.910	0.375	0.034	0.028	–	–	6252
$\overline{\mu} = .005$	3.119	0.462	0.918	0.277	0.030	0.035	–	–	5325
$H = 2$	2.738	0.424	0.914	0.356	0.033	0.030	–	–	6180
$H = 4$	2.761	0.449	0.914	0.324	0.031	0.032	–	–	5670
$\phi_d = 0$	3.204	0.409	0.915	0.244	0.026	0.034	–	–	7895
$\phi_d = 1$	2.154	0.448	0.913	0.360	0.035	0.030	–	–	5027
$\phi_h = 0$	2.413	0.443	0.914	0.456	0.026	0.025	–	–	5536
$\phi_h = 2$	2.620	0.443	0.914	0.317	0.033	0.033	–	–	5976
$\chi = 0.4$	2.479	0.427	0.914	0.336	0.031	0.032	–	–	5881
$\chi = 0.6$	2.963	0.457	0.914	0.377	0.031	0.030	–	–	5701
$\rho_x = 0.0$	2.236	0.405	0.916	–	0.039	0.037	–	–	6839
No weights	2.686	0.486	0.911	0.277	0.044	0.039	–	–	N/A
A shocks	3.199	0.492	0.913	0.550[*]	0.024	0.014	0.828	0.020	5499

Note: Parameter values denoted with a dash (−) indicate parameter is not estimated in corresponding specification. N/A for no weights loss value indicates that loss function is not comparable to other values in the table. Parameters marked with an asterisk (*) indicate that parameter achieved upper bound imposed on parameter space.

driving emerging economy business cycles. According to the point estimate, the temporary productivity shock is substantial. Nevertheless, the improvement in model fit is modest, and the shock draws the most volatility away from the surprise shock to productivity growth, so that the share of permanent TFP shocks that are anticipated actually rises to nearly three quarters ($\frac{0.024^2}{0.024^2 + 0.014^2} \approx 0.75$) The persistence of the permanent TFP also rises, implying further predictability of future productivity developments.

We have also performed additional checks regarding our assumption that adjustment costs in the economy are returned lump-sum to households. The average debt, labor, and capital adjustment costs are 0.05%, 0.02% and 0.18% of GDP, respectively. In the 99% percentile, these amount to 0.35%, 0.15%, and 1.16% of GDP. Adding the labor and capital adjustment costs as real resource costs is straightforward and re-estimating with these two costs in place leads negligible changes in our estimates.

Altogether, we believe these results indicate that our conclusion is quite robust to the details of our calibration choices. Combined with the statistical significance we found in our bootstrap procedure, we take this as strong evidence that the data are best matched with an economy driven in large part by forecastable shocks.

6. Conclusions

This paper demonstrates that shocks to expectations about future productivity growth are a good candidate for explaining the observed patterns in emerging economies of concurrent growth and leverage expansion followed by occasional reversals in both leverage and real economic variables. The presence of an occasionally binding collateral constraint amplifies these reversals substantially, yielding the characteristic features of Sudden Stops. The simple estimated model presented here does a remarkably good job at matching the empirical stylized facts about Suddens Stops quantitatively. Moreover, the arrival of good news leads to a high-probability of "tail" outcomes, including large decreases in consumption. The presence of externalities in this context, and consequently the insufficiently strong precautionary motives faced by agents, suggests the possibility that the information contained in news shocks could, in fact, be detrimental to welfare. We plan to examine this possibility in future work.

Acknowledgements

Appendix A. Data appendix

A.1. Definition of sudden stops

We collect annual data for 31 emerging market economies (EME) from 1980 to 2015. We restrict our attention to the sample of EMEs included in the analysis of Calvo et al. (2006), who filter countries based on their level of integration with the global bond markets.[11] The complete list of EMEs includes Algeria, Argentina, Brazil, Bulgaria, Cote d'Ivoire, Chile, Colombia, Croatia, Czech Republic, Dominican Republic, Ecuador, El Salvador, Hungary, Indonesia, Lebanon, Malaysia, Mexico, Morocco, Panama, Peru, Philippines, Poland, Russia, South Africa, South Korea, Thailand, Tunisia, Turkey, Ukraine, Uruguay, and Venezuela.

Our data source, unless otherwise indicated, is the World Bank's World Development Indicators. All data are in annual frequency. Data for GDP, private consumption and private investment are expressed in constant local currency units (LCU) and converted into per capita terms using total population data. The trade balance-to-GDP ratio is calculated as the ratio of external balance on goods and services to GDP (both of which are expressed in current LCUs). External Debt Stock-to-GDP ratio is calculated as the ratio of total external debt stock of a country to its GDP (both of them are expressed in current US dollars). Our dataset does not include a measure of Tobin's Q, so the empirical line plotted in the figures is derived from Mendoza's (2010) calculations, with flat extrapolation for the periods not covered by his event study. Finally, EMBI data come from Bloomberg, and the US 3-month Tbill and the US GDP deflator data come from the FRED database of the St. Louis Federal Reserve Bank.

Consistent with Calvo et al. (2006), a Sudden Stop event in our paper is identified as a situation in which the cyclical component of GDP is at least one-and-a-quarter standard deviations below its trend level and the reversal in the trade balance-to-GDP ratio is at least one-and-a-quarter standard deviations above average. Both standard deviations are computed after dropping the two most extreme values from each series. The same definition of Sudden Stops is used to produce actual and theoretical dynamics of Sudden Stop events. Mendoza (2010) takes Sudden Stop dates as given from Calvo et al. (2006). The actual dynamics of Sudden Stop events presented in Figure1 of Mendoza (2010) and Fig. 1 in this paper are fairly similar.[12]

Using this definition of Sudden Stops, we identified forty-two Sudden Stops episodes during the 1980–2015 period. The sample includes major crisis episodes (Mexico 1995, Turkey 2001), East Asian crisis episodes (Indonesia 1998, Korea 1998, Thailand 1998, Malaysia 1998) and the Russian crisis episode in 1999, Ecuador in 1999, Argentina in 2002. Our Sudden Stop filter also captures the Latin American Debt Crisis episodes of the 1980s.

A.2. Interest rate data and estimation

The world interest rate that countries in our sample can borrow in the international financial markets, R_t^*, is measured as the sum of J. P. Morgan's EMBI + sovereign spread and the U.S. real interest rate. The latter is calculated as the 3-month gross U.S. Treasury bill rate deflated using a measure of the expected U.S. inflation (see Schmitt-Grohé and Uribe (2016) for details of the calculation of the expected U.S. inflation). We compute standard deviations and autocorrelations for each country in the sample, drop the two highest and lowest observations of each, and then select the parameters in Eq.(8) to match the mean of the remaining observations in population. The target and simulated interest rates moments reported in Section3.3 are not a perfect match because simulation moments are averaged across several samples of relatively few (36) periods.

Appendix B. Optimality conditions

Let the multipliers on the constraints in Eqs.(3)through (4) be given by λ_t, $\lambda_t q_t$, and $\lambda_t \mu_t$ respectively. After imposing our functional forms for preferences and production, the first order conditions of the

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[11] More precisely, Calvo et al. (2006) sample of EMEs is composed of those countries tracked by JP Morgan to construct its global Emerging Market Bond Index.

[12] Calvo et al. (2006) identifies thirty-three Systemic Sudden Stop events for the 1980–2005 period. They define systemic Sudden Stop events as episodes with mild and large output collapses that coincide with large spikes in the EMBI spread and large reversals in capital flows.

representative firm-household problem are

$$\lambda_t = \left[c_t - \theta\omega^{-1}\tilde{X}_{t-1}h_t^\omega\right]^{-\sigma} \tag{19}$$

$$w_t = \theta\tilde{X}_{t-1}h_t^{\omega-1} \tag{20}$$

$$\frac{(1-\mu_t)}{R_t} = \beta\mathbf{E_t}\frac{\lambda_{t+1}}{\lambda_t}\left[1-\Phi'_d\left(\frac{\Delta d_{t+2}}{y_{t+1}}\right)\right] + \Phi'_d\left(\frac{\Delta d_{t+1}}{y_t}\right) \tag{21}$$

$$\begin{aligned}
w_t &= (1-\alpha)\left(\frac{k_t}{h_t}\right)^\alpha X_t^{1-\alpha} - X_{t-1}\Phi_{h'}\left(\frac{h_t}{h_{t-1}}\right) - \chi(R_t-1)w_t \\
&\quad + \beta\mathbf{E_t}\frac{\lambda_{t+1}}{\lambda_t}\left[X_t\left(\frac{h_{t+1}}{h_t}\right)\Phi_{h'}\left(\frac{h_{t+1}}{h_t}\right) - X_t\Phi_h\left(\frac{h_{t+1}}{h_t}\right)\right]
\end{aligned} \tag{22}$$

$$q_t = 1 + \Phi'_k\left(\frac{i_t}{k_t}\right) \tag{23}$$

$$\begin{aligned}
q_t(1-\mu_t\kappa) &= \beta\mathbf{E_t}\frac{\lambda_{t+1}}{\lambda_t}\left[\alpha\left(\frac{k_{t+1}}{X_{t+1}h_{t+1}}\right)^{\alpha-1}\right. \\
&\quad \left. + (1-\delta)q_{t+1} + \Phi'_k\left(\frac{i_{t+1}}{k_{t+1}}\right)\frac{i_{t+1}}{k_{t+1}} - \Phi_k\left(\frac{i_{t+1}}{k_{t+1}}\right)\right]
\end{aligned} \tag{24}$$

the constraints in Eqs.(3)–(4), as well as the complementary slackness conditions $\mu_t \geq 0$ and

$$\mu_t\left(\kappa - \frac{\dfrac{d_{t+1}}{R_t} + \chi R_t(w_t h_t)}{q_t k_{t+1}}\right) = 0 \tag{25}$$

Appendix C. Stationary equilibrium and model steady-state

Let $\tilde{z}_t \equiv z_t/X_{t-1}$, for $z_t \in \{c_t, k_t, w_t, i_t, d_t\}$, and let $\tilde{\lambda}_t \equiv \frac{\lambda_t}{X_{t-1}^{-\sigma}}$. Then the stationary first order conditions of the economy, excluding those of the exogenous shock processes, are the following:

$$\tilde{\lambda}_t = \left[\tilde{c}_t - \theta\omega^{-1}\tilde{\gamma}_{t-1}^{\frac{\varphi}{\varphi-1}}h_t^\omega\right]^{-\sigma} \tag{26}$$

$$\tilde{w}_t = \theta\tilde{\gamma}_{t-1}^{\frac{\varphi}{\varphi-1}}h_t^{\omega-1} \tag{27}$$

$$\begin{aligned}
\frac{(1-\mu_t)}{R_t} &= \beta\mathbf{E_t}\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\gamma_t^{-\sigma}\left[1-\phi_d\left(\frac{\gamma_{t+1}\tilde{d}_{t+2}-\tilde{d}_{t+1}}{\tilde{y}_{t+1}}-(\gamma-1)\frac{d}{y}\right)\right] \\
&\quad + \phi_d\left(\frac{\gamma_t\tilde{d}_{t+1}-\tilde{d}_t}{\tilde{y}_t}-(\gamma-1)\frac{d}{y}\right)
\end{aligned} \tag{28}$$

$$\begin{aligned}
\tilde{w}_t &= (1-\alpha)\left(\frac{\tilde{k}_t}{h_t}\right)^\alpha\gamma_t^{1-\alpha} - \phi_h\left(\frac{h_t}{h_{t-1}}-1\right) - \chi(R_t-1)w_t \\
&\quad + \beta\mathbf{E_t}\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\gamma_t^{1-\sigma}\left[\phi_h\left(\frac{h_{t+1}}{h_t}-1\right)\frac{h_{t+1}}{h_t}-\frac{\phi_h}{2}\left(\frac{h_{t+1}}{h_t}-1\right)^2\right]
\end{aligned} \tag{29}$$

$$q_t = 1 + \phi\left(\frac{\tilde{i}_t}{\tilde{k}_t}-\delta\right) \tag{30}$$

$$\begin{aligned}
q_t(1-\mu_t\kappa) &= \beta\mathbf{E_t}\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\gamma_t^{-\sigma}\left[\alpha\left(\frac{\tilde{k}_{t+1}}{\gamma_{t+1}h_{t+1}}\right)^{\alpha-1}+(1-\delta)q_{t+1}\right. \\
&\quad \left. + \phi_k\left(\frac{\tilde{i}_{t+1}}{\tilde{k}_{t+1}}-\delta\right)\frac{\tilde{i}_{t+1}}{\tilde{k}_{t+1}}-\frac{\phi_k}{2}\left(\frac{\tilde{i}_{t+1}}{\tilde{k}_{t+1}}-\delta\right)^2\right]
\end{aligned} \tag{31}$$

$$\frac{\gamma_t\tilde{d}_{t+1}}{R_t} = \tilde{d}_t + \tilde{c}_t + \tilde{i}_t + \chi\tilde{w}_t h_t(R_t-1) - \tilde{k}_t^\alpha(\gamma_t h_t)^{1-\alpha} \tag{32}$$

$$\tilde{\gamma}_t = \tilde{\gamma}_{t-1}^\varphi\gamma_t^{1-\varphi} \tag{33}$$

as well as the complementary slackness conditions $\mu_t \geq 0$ and

$$\mu_t\left(\kappa - \frac{\dfrac{\tilde{d}_{t+1}}{R_t} + \chi R_t\tilde{w}_t\tilde{h}_t}{q_t\tilde{k}_{t+1}}\right) = 0 \tag{34}$$

and the equilibrium definition $\tilde{w}_t = \theta h_t^{\omega-1}$.

Linearization requires that we solve the for non-stochastic steady of the economy. To do this, we assume values for $\overline{h}$ and $\overline{d/y}$, and then find the values of θ and long-run debt that are consistent with our assumptions. Rearranging Eq.(31) and imposing steady-state implies that

$$\frac{k}{h} = \left[\frac{\frac{\gamma^\sigma}{\beta}-1+\delta}{\alpha}\right]^{\frac{1}{\alpha-1}} \tag{35}$$

Given our assumption for $\overline{h}$, the long run capital level follows immediately. From there, the resource constraint and the production function can be used to determine consumption, and Eq.(27) can be solved for θ.

Appendix D. Solution method

Before solving the model, we eliminate variables, reducing Eqs.(26)–(34) to three expectational equations and the complementary slackness condition on leverage. The minimum state representation of our economy is given by

$$x_t = [k_t, d_t, h_{t-1}, R_t^*, \tilde{\gamma}_t, \gamma_t, \epsilon_{t-H}^H, ..., \epsilon_t^H] \tag{36}$$

Collect a spanning set of basis functions (specified later) of the states in the vector, $s_t(x_t)$. Our solution procedure centers around approximating the three expectations terms

$$\tilde{E}_t^1 \equiv \beta\mathbf{E_t}\tilde{\lambda}_{t+1}\left[1-\phi_d\left(\frac{\gamma_{t+1}\tilde{d}_{t+2}-\tilde{d}_{t+1}}{\tilde{y}_{t+1}}-(\gamma-1)\frac{d}{y}\right)\right] \tag{37}$$

$$\begin{aligned}
\tilde{E}_t^2 &\equiv \beta\mathbf{E_t}\tilde{\lambda}_{t+1}\left[\alpha\left(\frac{\tilde{k}_{t+1}}{\gamma_{t+1}h_{t+1}}\right)^{\alpha-1}+(1-\delta)q_{t+1}\right. \\
&\quad \left. + \phi_k\left(\frac{\tilde{i}_{t+1}}{\tilde{k}_{t+1}}-\delta\right)\frac{\tilde{i}_{t+1}}{\tilde{k}_{t+1}}-\frac{\phi_k}{2}\left(\frac{\tilde{i}_{t+1}}{\tilde{k}_{t+1}}-\delta\right)^2\right]
\end{aligned} \tag{38}$$

$$\tilde{E}_t^3 \equiv \beta\mathbf{E_t}\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\left[\phi_h\left(\frac{h_{t+1}}{h_t}-1\right)\frac{h_{t+1}}{h_t}-\frac{\phi_h}{2}\left(\frac{h_{t+1}}{h_t}-1\right)^2\right] \tag{39}$$

with parametric functions $g^1(s_t)$, $g^2(s_t)$, and $g^3(s_t)$, respectively. Given good approximating functions $g^i(s_t)$ and current states, a good non-linear solver can then be used to generate a corresponding history for endogenous variables, $v_t(x_t)$, at any point in the state space. Note that included in the vector $v_t(x_t)$ are jump variables (e.g. c_t) and future-period state-variables (e.g. k_{t+1}).

To arrive at good approximating functions $g^i(s_t)$, we first conjecture an initial relationship

$$\tilde{E}_t^i \approx \beta^i s_t \tag{40}$$

based on a linearized solution to the model economy. We then simulate a history of normal shocks, $\{\epsilon_t\}$, $t \in [1, 2, 3..., 5000]$ using a fixed starting
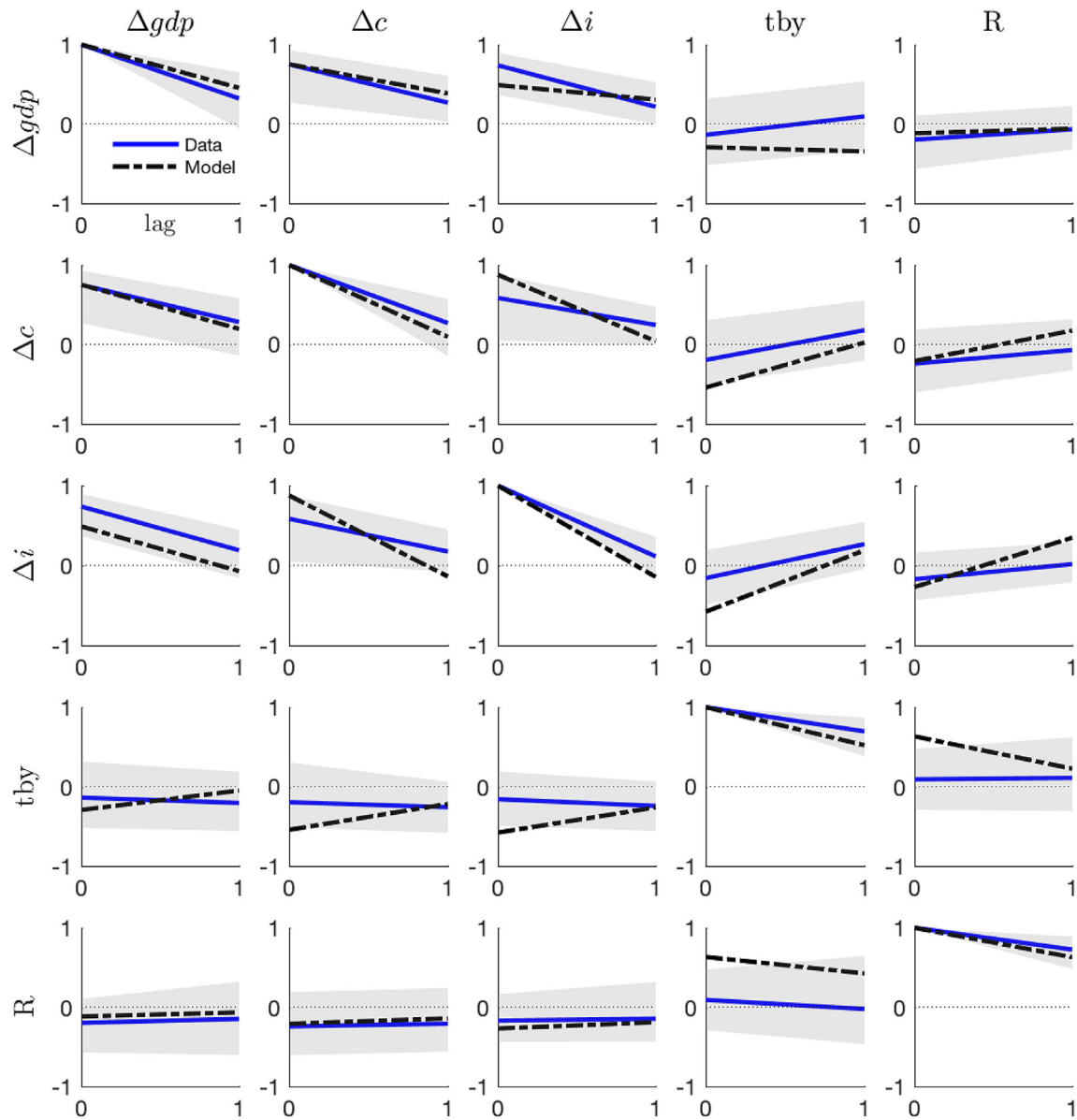
Fig. 6. Unconditional Cross-Correlations– Model versus Data.

point in the random number generator. For each point t, we conjecture a set of endogenous outcomes for time t, again based on a linearization of the economy.

At this point, a standard parameterized expectations approach would solve the model equations given the conjectured approximating relationship in (40), to arrive a realized history $\{v_t\}$. Given this history, realized analogues of (37)–(39) can be computed, and updated values for β^i computed by regressing time $t + 1$ realizations of these values on $\{s_t\}$. The procedure is then repeated until convergence, so that an approximate equilibrium is a fixed point of the mapping

$$\{v_t\} = \mathcal{T}^\infty(\{v_t\}),$$

where $\mathcal{T}^\infty$ captures the solution and updating procedure. The meaning of the ∞ superscript will be clear momentarily.

Our procedure extends this basic approach in a few respects. First, rather than using the approximate relationship in (40) to directly compute time t expectations, we explicitly solve the economy forward. Starting from each t, we consider several potential futures, each

characterized by potential realizations of shocks, ϵ_t. We iterate forward in the future for a finite τ periods, finally using the relationship in (40) to terminate the recursion at $\tau + 1$ periods. For the values of $\{\epsilon_t\}$, we use the standard multivariate normal Gaussian-Hermite quadrature points. In our baseline, we use two points per shock, so that for each point in the initial simulation there are $n' = 8$ potential continuations, i.e. if $\tau = 1$, we consider a total of 40,000 continuations for our original sample of 5000 periods. We considered using more quadrature points but found that did not have any effect on our simulations. We then sum these potential futures using the Gaussian-Hermite quadrature weights, to arrive at time t expectations for the terms in (37)–(39). Notice that when $\tau = 0$, this extended method collapses into the basic parameterized expectations method described above.

This extended approach has two benefits. First, it allows us to compute expectation approximations that explicitly account for the non-linearities associated with realizations at horizons 1 through τ, effectively delaying use of the parameterized expectation functions towards the future where they have smaller impact on current actions. Second, we can use the computed expectations, which have already

integrated out future randomness, to compute a more precise estimate of the approximation coefficients, $\{\beta^i\}$, since there is no longer any error associated with random future realizations. In experiments, we found that this approach with $\tau = 1$ leads to significantly higher accuracy in our solution, as judged by an extremely accurate (and much slower!) grid based solution method which we have applied to a more simple version of the model. Setting $\tau > 1$ did not lead to significant additional improvements.

One important detail in this procedure is the approximating basis function implicit in our definition of $s_t(x_t)$. We considered approximating basis (i.e. extended state space) that include the terms in x_t plus all second and third-order cross terms created by multiplying elements of x_t. The full set of cross terms leads to ill-conditioned regressions as many of these variables are nearly collinear. In our baseline model, we therefore use a subset of 19 of these higher-order terms. We selected these terms by applying a "forward-fit" algorithm to an initial simulation of the model. The procedure gradually increases the set of regressors, at each step taking the variable with the most additional explanatory power, until additional variables add negligible explanatory power. The procedure did not select any 3rd-order terms. After estimating, we resolved the model at our baseline parameters using the larger set of regressors and found no change in the equilibrium dynamics of the model.

A second important detail involves our approach to solving Eqs. (26)–(34), taking as given our parameterization of expectations. Standard descriptions of this algorithm involve fully solving these equations before revising the expectation parameters. But this requires hundreds or thousands of evaluations of the model equations per sample period, per iteration on the expectations of agents. Thus, rather than fully solving the model equations before updating our parameterized expectation functions, we take only a single Newton-Raphson step towards the solution for each point in the simulation before updating our expectation parameters. This adjustment increases the speed of our solution procedure by at least two orders of magnitude and, equally importantly, delivers far more stable performance as it ensure that beliefs and actions evolve away from their initial point in tandem.

Hence, irrespective of τ, we advocate solving a fixed point of the mapping

$$\{v_t\} = \mathcal{T}^N(\{v_t\})$$

where N (in our case $N = 1$) captures the fact that we do not fully solve model equations at each iteration on beliefs. A fixed point of $\mathcal{T}^N$ is guaranteed to be a fixed point of $\mathcal{T}^\infty$ so long as equation residuals at that point are zero, which we always check once the algorithm has converged.

D.1. Model fit figure

Fig.6 compares the autocorrelation structure of the data with that implied by the estimated model. Solid lines represent means, after dropping outliers, from the sample of 31 countries, while dashed lines represent the corresponding means across the 138 ($\approx 5000/36$) artificial samples from the simulated model. Light-blue bands depict the empirical range of these covariances, after dropping the two highest and lowest values for each point plotted.[13]

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[13] Dropping 4 out of 31 observations means these bands correspond roughly to the 90% confidence bands of the empirical distribution.

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