

Technical Appendix to:
“Risk Matters:
The Real Effects of Volatility Shocks”

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For completeness, this appendix includes 1) additional papers on the effects of volatility on real variables, 2) the description of NIPA data used in section 2, 3) a brief introduction to the particle filter, 4) some comments on our choice of preferences, 5) the steady-state conditions of the model, 6) a more detailed discussion of the solution of the model, 7) the explanation of how we compute the IRFs of the model, 8) the results of the variance decomposition for the other three countries of our sample, 9) a robustness analysis of some of the main results of the model, and 10) an analysis of the role of volatility (mean and persistence) and debt in the shape of the IRFs of the model.

0.1. Papers on the Effects of Volatility on Real Variables

From a more reduced-form perspective, several papers have documented the effects of volatility on real variables. Hamilton (2008) presents a general review. Guerrón-Quintana (2009) finds that volatility shocks à la Bloom induce depreciations in the real exchange rate in the US particularly vis-a-vis the Canadian dollar. Fatás (2002) discusses the effects of business cycle volatility on growth. Lee *et al.* (1995) show that the conditional volatility of oil prices matter for the effect of oil shocks on the economy. Grier and Perry (2000) and Fountas and Karanasos (2007) relate inflation and output volatility with average output growth, while Elder (2004a and 2004b) links nominal and real volatility. We thank Jim Hamilton for the last references.

0.2. Data

As mentioned in the main text, we use the Emerging Markets Bond Index+ (EMBI+) spread as reported by J.P. Morgan at a monthly frequency. J.P. Morgan compiles an alternative index, EMBI Global, which has more relaxed criteria to include certain bond issues. For example, EMBI+ requires a minimum bid/ask price and a specific number of interdealer broker quotes. These requirements are less strict for EMBI Global. Thus, EMBI Global spreads include both a country-specific spread and a premium for liquidity considerations that are challenging to disentangle. This is the main reason that leads us to prefer EMBI+ for our estimates.

We obtain aggregate data from the International Financial Statistics (IFS) service of the International Monetary Fund, except for Venezuela, for which data come from the Central Bank of Venezuela (the IFS data set has some gaps for Venezuela). The data coverage is: Argentina: 1993.Q1-2004.Q3; Brazil: 1995.Q1-2004.Q1; Ecuador: 1992.Q1-2001.Q2; and Venezuela:

1991.Q1-2004.Q4. Consumption corresponds to household expenditure on goods and services; investment is the sum of gross fixed capital formation and changes in inventories; net exports equal exports of goods and services minus imports of goods and services; finally, output equals the addition of consumption, investment, and net exports. Real variables were obtained by dividing nominal ones by the GDP deflator. All variables were seasonally adjusted using the U.S. Census Bureau's X-12 program. Output, consumption, and investment are H-P filtered.

0.3. Particle Filter

We present a brief introduction to the particle filter. We will concentrate on the main idea of the algorithm and skip most of the technical details. Doucet *et al.* (2001) is an excellent reference for the interested reader. Fernández-Villaverde and Rubio-Ramírez (2007 and 2008) are examples of applications in economics.

We want to evaluate the likelihood of the international risk-free real interest rate $\varepsilon_{tb,t}$ and the country spread deviations $\varepsilon_{r,t}$. Since the explanation of the filter for the likelihood of one process or the other is equivalent, we just take the first case.

The likelihood is costly to evaluate because of the non-linear interaction of volatility and levels. Let us start by stacking all T observations of $\varepsilon_{tb,t}$ in ε_{tb}^T and the parameters of the process in Ψ . Given the Markov structure of our state space representation, we can factorize the likelihood function as:

$$p(\varepsilon_{tb}^T; \Psi) = \prod_{t=1}^T p(\varepsilon_{tb,t} | \varepsilon_{tb}^{t-1}; \Psi)$$

Now, we can derive the factorization:

$$p(\varepsilon_{tb}^T; \Psi) = \int p(\varepsilon_{tb,1} | \varepsilon_{tb,0}, \sigma_{tb,0}; \Psi) d\sigma_{tb,0} \prod_{t=2}^T \int p(\varepsilon_{tb,t} | \varepsilon_{tb,t-1}, \sigma_{tb,t}; \Psi) p(\sigma_{tb,t} | \varepsilon_{tb}^{t-1}; \Psi) d\sigma_{tb,t}$$

and using equation (??):

$$\begin{aligned} p(\varepsilon_{tb}^T; \Psi) &= \int \frac{1}{(2\pi)^{0.5}} \exp \left[-\frac{1}{2} \left(\frac{\varepsilon_{tb,1} - \rho_{tb} \varepsilon_{tb,0}}{e^{\sigma_{tb,0}}} \right)^2 \right] d\sigma_{tb,0} * \\ &* \prod_{t=2}^T \int \frac{1}{(2\pi)^{0.5}} \exp \left[-\frac{1}{2} \left(\frac{\varepsilon_{tb,t} - \rho_{tb} \varepsilon_{tb,t-1}}{e^{\sigma_{tb,t}}} \right)^2 \right] p(\sigma_{tb,t} | \varepsilon_{tb}^{t-1}; \Psi) d\sigma_{tb,t} \end{aligned} \quad (1)$$

Consequently, if we had access to the sequence $\{p(\sigma_{tb,t} | \varepsilon_{tb}^{t-1}; \Psi)\}_{t=1}^T$, we could compute (1).

Unfortunately, this sequence of conditional densities cannot be characterized analytically.

The particle filter is a sequential Monte Carlo procedure that substitutes the density $p(\sigma_{tb,t}|\varepsilon_{tb}^{t-1}; \Psi)$ by an empirical draw from it. In other words, the filter relies on the observation that if we have available a draw of N simulations $\left\{\sigma_{tb,t|t-1}^i\right\}_{i=1}^N$ from $p(\sigma_{tb,t}|\varepsilon_{tb}^{t-1}; \Psi)$, then a Law of Large numbers ensures that:

$$\int p(\varepsilon_{tb,t}|\varepsilon_{tb,t-1}, \sigma_{tb,t}; \Psi) p(\sigma_{tb,t}|\varepsilon_{tb}^{t-1}; \Psi) d\sigma_{tb,t} \simeq \frac{1}{N} \sum_{i=1}^N p(\varepsilon_{tb,t}|\varepsilon_{tb,t-1}, \sigma_{tb,t|t-1}^i; \Psi)$$

where our notation for each draw i indicates in the subindex the conditioning set (i.e., $t|t-1$ is a draw at moment t conditional on information until $t-1$).

To draw from $p(\sigma_{tb,t}|\varepsilon_{tb}^{t-1}; \Psi)$, the particle filter uses the idea of sequential important sampling proposed by Rubin (1988):

Proposition 1. *Let $\left\{\sigma_{tb,t|t-1}^i\right\}_{i=1}^N$ be a draw from $p(\sigma_{tb,t}|\varepsilon_{tb}^{t-1}; \Psi)$. Let the sequence $\left\{\tilde{\sigma}_{tb,t}^i\right\}_{i=1}^N$ be a draw with replacement from $\left\{\sigma_{tb,t|t-1}^i\right\}_{i=1}^N$ where the resampling probability is given by*

$$\omega_t^i = \frac{p(\varepsilon_{tb,t}|\varepsilon_{tb,t-1}, \sigma_{tb,t|t-1}^i; \Psi)}{\sum_{i=1}^N p(\varepsilon_{tb,t}|\varepsilon_{tb,t-1}, \sigma_{tb,t|t-1}^i; \Psi)},$$

Then $\left\{\sigma_{tb,t|t}^i\right\}_{i=1}^N = \left\{\tilde{\sigma}_{tb,t}^i\right\}_{i=1}^N$ is a draw from $p(\sigma_{tb,t}|\varepsilon_{tb}^t; \Psi)$.

Proposition 1, which is just a simple application of Bayes' theorem, builds the draws $\left\{\sigma_{tb,t|t}^i\right\}_{i=1}^N$ recursively from $\left\{\sigma_{tb,t|t-1}^i\right\}_{i=1}^N$ by incorporating the information on $\varepsilon_{tb,t}$. The resampling step is crucial. If we just draw a whole sequence of $\left\{\left\{\sigma_{tb,t|t-1}^i\right\}_{i=1}^N\right\}_{t=1}^T$ without resampling period by period, all the sequences would become arbitrarily far away from the true sequence of volatilities, since it is a zero measure set. Then, the sequence that happened to be closer to the true states would dominate all of the remaining ones in weight and the evaluation of the likelihood would be most inaccurate. Evidence from simulation shows that this degeneracy problem already appears after a small number of observations.

Now that we have $\left\{\sigma_{tb,t|t}^i\right\}_{i=1}^N$, we can draw N exogenous shocks $u_{\sigma_{tb,t+1}}^i$ from a standard

normal distribution and find:

$$\sigma_{tb,t+1|t}^i = (1 - \rho_{\sigma_{tb}}) \sigma_{tb} + \rho_{\sigma_{tb}} \sigma_{tb,t|t}^i + \eta_{tb} u_{\sigma_{tb},t+1}^i \quad (2)$$

to generate $\left\{ \sigma_{tb,t+1|t}^i \right\}_{i=1}^N$. This forecast step places us back at the beginning of Proposition 1, but one period ahead in our conditioning.

The following pseudocode summarizes the description of the algorithm:

Step 0, Initialization: Set $t \rightsquigarrow 1$. Sample N values $\left\{ \sigma_{tb,0|0}^i \right\}_{i=1}^N$ from $p(\sigma_{tb,0}; \Psi)$.

Step 1, Prediction: Sample N values $\left\{ \sigma_{tb,t|t-1}^i \right\}_{i=1}^N$ using $\left\{ \sigma_{tb,t-1|t-1}^i \right\}_{i=1}^N$, the law of motion for states and the distribution of shocks $u_{\sigma_{tb},t}$.

Step 2, Filtering: Assign to each draw $\left(\sigma_{tb,t|t-1}^i \right)$ the weight ω_t^i in Proposition 1.

Step 3, Sampling: Sample N times with replacement from $\left\{ \sigma_{tb,t|t-1}^i \right\}_{i=1}^N$ using the probabilities $\left\{ \omega_t^i \right\}_{i=1}^N$. Call each draw $\left(\sigma_{tb,t|t}^i \right)$. If $t < T$ set $t \rightsquigarrow t + 1$ and go to step 1. Otherwise stop.

With the output of the algorithm, we just substitute into our formula

$$\begin{aligned} p(\varepsilon_{tb}^T; \Psi) &\simeq \frac{1}{N} \sum_{i=1}^N \frac{1}{(2\pi)^{0.5}} \exp \left[-\frac{1}{2} \left(\frac{\varepsilon_{tb,1} - \rho_{tb} \varepsilon_{tb,0}}{e^{\sigma_{tb,0|0}^i}} \right)^2 \right] * \\ &* \prod_{t=2}^T \frac{1}{N} \sum_{i=1}^N \frac{1}{(2\pi)^{0.5}} \exp \left[-\frac{1}{2} \left(\frac{\varepsilon_{tb,t} - \rho_{tb} \varepsilon_{tb,t-1}}{e^{\sigma_{tb,t|t-1}^i}} \right)^2 \right] \end{aligned} \quad (3)$$

and we obtain the estimate of the likelihood. Del Moral and Jacod (2002) and Künsch (2005) provide weak conditions under which the right-hand side of the previous equation is a consistent estimator of $p(\varepsilon_{tb}^T; \Psi)$ and a central limit theorem applies.

0.4. Preferences

In the main text of the paper we assume that the preferences for the representative household are given by:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-v}}{1-v} - \omega \frac{H_t^{1+\eta}}{1+\eta} \right). \quad (4)$$

In international macroeconomics, and following the findings by Correia *et al.* (1995), it is common to use Greenwood-Hercowitz-Huffman (GHH) preferences instead of (??). The reason is that the GHH specification, with its absence of wealth effects on labor supply, is better suited to match the second moments of small open economies. Indeed, in the working paper version of this paper, Fernández-Villaverde *et al.* (2009), we employed GHH preferences. When these GHH preferences are used, all the quantitative results for volatility shocks were even stronger. The reason is that under GHH preferences, labor supply depends only on the real wage, and hence it does not directly react to a negative shock to the level or volatility of the interest rate. Thus, consumption must take the brunt of the adjustment to the shock. In the current version of the paper, we switch to (??) because it is easier to compare with the results from closed economies and because it can be understood as a conservative lower bound on the effects of volatility shocks.

0.5. Steady State of the Model

The deterministic steady state is given by the solution to the following set of equations:

$$\begin{aligned}
C^{-\nu} &= \lambda, \\
\beta \left[(1 - \delta) \varphi + \alpha \frac{Y}{K} \lambda \right] &= \varphi, \\
\omega H^{\eta+1} C^{\nu} &= (1 - \alpha) Y, \\
\lambda &= \varphi, \\
\frac{D}{1 + r} &= D - Y + C + I, \\
Y &= K^{\alpha} H^{1-\alpha}, \\
I &= \delta K.
\end{aligned}$$

We will calibrate the value of D to ensure that the model generates an ergodic distribution of debt with an average that matches the mean value of net exports to output observed in the data. In addition, r is set at the mean of the country's real interest rate (T-bill plus EMBI). Hence, we have a system of 7 equations for 7 unknowns: C , H , λ , φ , K , I , and Y .

0.6. Computation

We start by describing in more detail the structure of our solution. Since the optimal decision rules depend on the states and the innovations, we define $s_t = (States'_t, \xi'_t)'$ as the vector of arguments of the policy function. Also, we call s_t^i to the i -th entry of s_t and ns to the cardinality of s_t . Thus, we can write the third-order approximation to the laws of motion of the endogenous states. First, we have a law of motion for capital:

$$\widehat{K}_{t+1} = \psi_i^K s_t^i + \frac{1}{2} \psi_{i,j}^K s_t^i s_t^j + \frac{1}{6} \psi_{i,j,l}^K s_t^i s_t^j s_t^l,$$

where each term $\psi_{i,\dots}^K$ is a scalar and where we have followed the tensor notation:

$$\begin{aligned} \psi_i^K s_t^i &= \sum_{i=1}^{ns} \psi_i^K s_t^i \\ \psi_{i,j}^K s_t^i s_t^j &= \sum_{i=1}^{ns} \sum_{j=1}^{ns} \psi_{i,j}^K s_t^i s_t^j \end{aligned}$$

and

$$\psi_{i,j,l}^K s_t^i s_t^j s_t^l = \sum_{i=1}^{ns} \sum_{j=1}^{ns} \sum_{l=1}^{ns} \psi_{i,j,l}^K s_t^i s_t^j s_t^l$$

that eliminates the symbol $\sum_{i=1}^{ns}$ when no confusion arises. Similarly, we have a law of motion of investment:

$$\widehat{I}_t = \psi_i^I s_t^i + \frac{1}{2} \psi_{i,j}^I s_t^i s_t^j + \frac{1}{6} \psi_{i,j,l}^I s_t^i s_t^j s_t^l,$$

and foreign debt:

$$\widehat{D}_t = \psi_i^D s_t^i + \frac{1}{2} \psi_{i,j}^D s_t^i s_t^j + \frac{1}{6} \psi_{i,j,l}^D s_t^i s_t^j s_t^l$$

Finally, we have the law of motion for the technology shock

$$X_t = \rho_x X_{t-1} + e^{\sigma_x} u_{x,t}$$

the deviation of the real interest rate due to the country spread, (??), the deviation of the real interest rate due to the international risk-free real rate, (??), and the volatilities, (??) and (??). For the case of the law of motion for the deviation of the real interest rate due to the country spread, (??), and the deviation of the real interest rate due to the international risk-free real

rate, (??), we also consider third-order approximations instead of their exact form to keep the order of the approximation consistent across equations. Our solution, including calculating all the analytic derivatives, is implemented in **Mathematica**.

In all our simulations, we follow Kim *et al.*'s (2003) pruning approach to get rid of spurious higher order terms in our simulations. Furthermore, we rule out volatility shocks larger than one standard deviation because of convergence issues (technically, the convergence results of perturbation depend on the shocks to the model being bounded).

In the main part of the paper, we argued that a third-order approximation was important if we wanted to evaluate the effects of volatility shocks independently of real interest rate shocks. We provide now some evidence that the effects on allocations of the higher order terms are non-trivial.

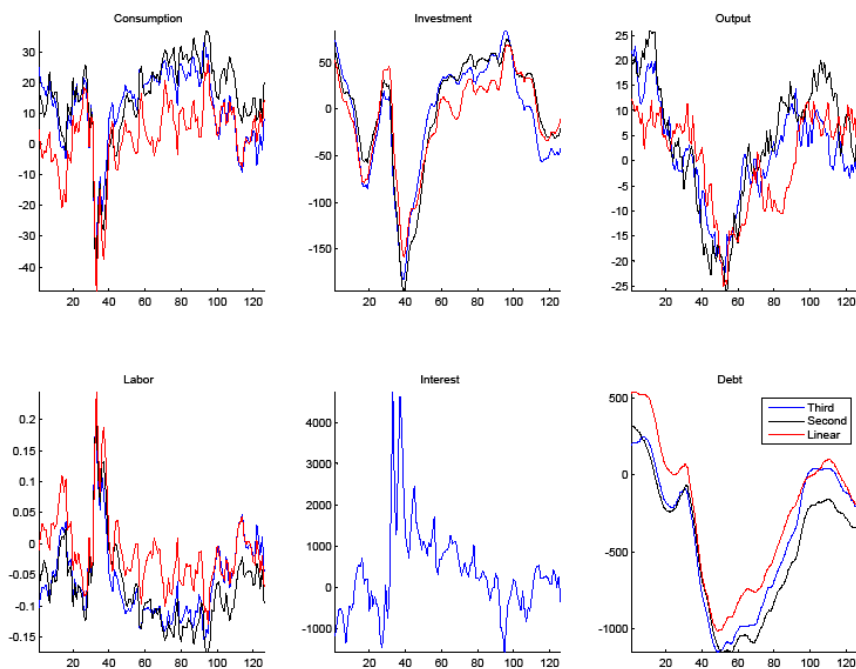


Figure A1: Simulation, Different Approximations

We simulate the Argentinian economy for 500 periods (after a period of burn-in to eliminate the effect of initial conditions) at the benchmark calibration parameter values and we follow the results for the deviations of consumption, investment, output, labor, and debt with respect to the steady state when we have a first-, second-, and third-order approximation. The interest rate evolution was kept the same in all three simulations. We plot the results in figure A1. We see how,

even if the general pattern of behavior is similar, there are non-trivial differences, in particular in investment, debt, and consumption. The differences are particularly salient between, on the one hand, the first-order approximation, and on the other hand, the second- and third-order approximations. The presence of a constant in the second-order approximations that reflects precautionary behavior is largely responsible for the permanent differences in levels that we see, for example, in the consumption series.

Because the scale of figure A1 makes it difficult to appreciate our point, in figure A2 we zoom in on a section of the simulation for investment in the center of the sample. We can see how around periods 30 to 40, in the first-order approximation, investment is falling; in the second-order approximation, it is stable; and in the third-order approximation, investment is rising. We could hardly have a clearer picture: as a response to the same real interest rate shocks, each level of approximation tells us a different history about the evolution of investment.

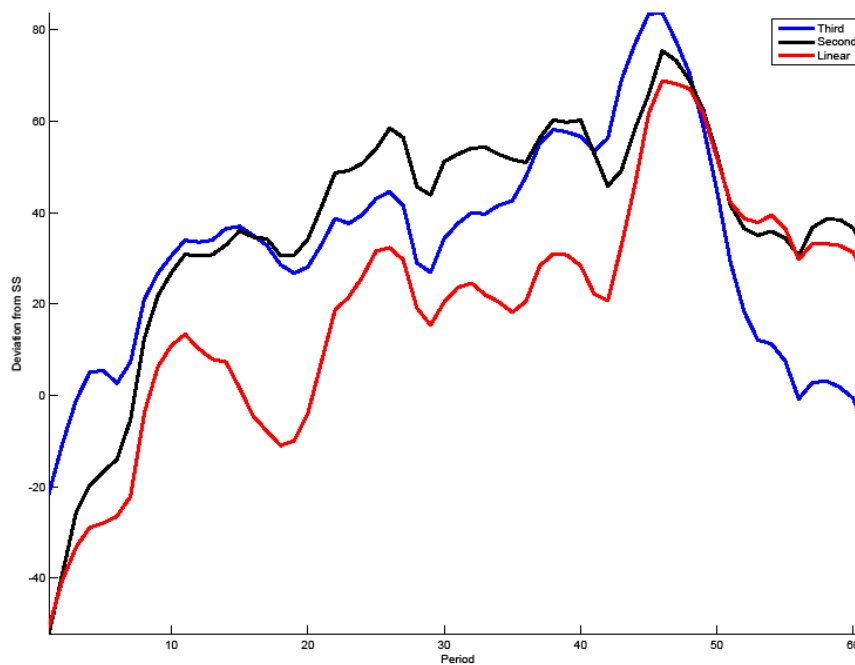


Figure A2: Evolution of Investment

0.7. Computing Impulse Responses

As argued in the main section, our higher order approximation makes the simulated paths of states and controls in the model move away from their steady-state values. Consequently, computing

impulse responses as percentage deviations of the model’s steady state is not informative. To compute the impulse responses reported in the paper, we proceed as follows:

1. We simulate the model, starting from its steady state, for 2096 periods. We disregard the first 2000 periods as a burn-in.
2. Based on the last 96 periods, we compute the mean of the ergodic distribution for each variable in our model. Adding more periods has essentially no impact on the mean.
3. Starting from the ergodic mean and in the absence of shocks, we hit the model with a one-standard-deviation shock to the volatility process $u_{\sigma,t}$.
4. We report the resulting impulse responses as percentage deviations from the variables’ ergodic means.

In the context of a threshold model, Koop *et al.* (1996) have argued that the use of the standard impulse response functions may be misleading. These authors urge the use of the so-called generalized impulse response to overcome the drawbacks reported in their manuscript. We computed the generalized impulse response, but we essentially found no differences between this procedure and the one outline above. We choose to report the traditional impulse responses in the main body of the paper, since they are easier to interpret than the generalized impulse response functions.

0.8. Variance Decompositions

For completeness, we include the results of the variance decomposition in the other three countries of our sample. Table A1 reports the results for Ecuador, table A2 for Venezuela, and table A3 for Brazil, all of which follow patterns very similar to the results in the main text.

Table A1: Variance Decomposition: Ecuador

	All three shocks	Only prod.	Prod. and Rate	Rate	Rate and Volatility	Only vol.
σ_y	2.23	1.89	2.05	0.72	1.02	0.17
σ_c	4.67	0.84	3.20	3.13	4.64	0.61
σ_i	20.4	3.11	14.3	14.1	20.3	3.20
σ_{nx}	3.46	7.93	3.58	4.62	2.91	1.75

Table A2: Variance Decomposition: Brazil

	All three shocks	Only prod.	Prod. and Rate	Rate	Rate and Volatility	Only vol.
σ_y	4.52	4.50	4.51	0.24	0.28	0.01
σ_c	1.96	1.53	1.80	1.00	1.24	0.03
σ_i	7.41	5.04	6.68	4.60	5.52	0.18
σ_{nx}	2.51	1.91	3.03	3.96	5.09	0.34

Table A3: Variance Decomposition: Venezuela

	All three shocks	Only prod.	Prod. and Rate	Rate	Rate and Volatility	Only vol.
σ_y	4.56	4.48	4.54	0.57	0.67	0.04
σ_c	2.26	1.48	2.02	1.42	1.73	0.08
σ_i	16.9	8.83	14.9	12.4	14.7	0.54
σ_{nx}	6.57	2.84	5.46	5.46	7.89	0.26

0.9. Robustness Checks

To keep our investigation focused, we consider robustness analysis only for Argentina. However, the lessons we learn from the Argentinian case about the performance of the model under alternative scenarios are general for all four countries in our sample.

A first robustness analysis is the introduction of working capital. Our benchmark model does not have working capital: firms do not need to borrow to pay their wage bill in advance. We did not add this channel, which Neumeyer and Perri (2005) have emphasized as a source of fluctuations in emerging economies, to keep the model as simple as possible and to show that it is not required to get our main results, which we thought was a significant finding. However, it is relatively easy to extend the model to capture this feature.

Let Θ be the fraction of the wage bill that must be paid in advance. This means that if the firm borrows funds at the international rate $1 + r_t$, its problem is:

$$\max Y_t - R_t K_t - \Theta (1 + r_t) W_t H_t - (1 - \Theta) W_t H_t$$

The optimality conditions of the firm are then $R_t = \alpha Y_t / K_t$ and $W_t = ((1 - \alpha) / (1 + \Theta r_t)) Y_t / H_t$. All the other equilibrium conditions of the model are the same except the static first-order con-

dition of the household determining labor supply:

$$\theta H_t^\omega = \frac{(1 - \alpha)}{1 + \Theta r_t} Y_t,$$

We re-compute the model with working capital for the Argentinean case. We set $\Theta = 1$, that is, the extreme case where all of the wage bill needs to be paid in advance (the opposite case, $\Theta = 0$, gives us back the model of section 3). We picked this value because even with $\Theta = 1$, our main results regarding the importance of volatility shocks are virtually unchanged. All the other parameters are the same as in our benchmark calibration.¹

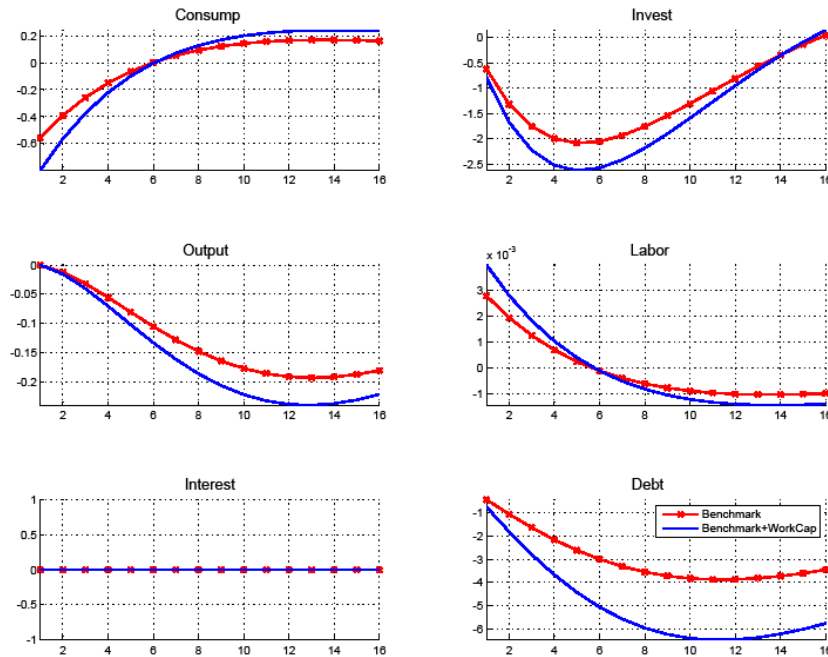


Figure A3: IRFs for Argentina, with and without Working Capital

We plot our results for the case of a volatility shock in figure A3. The differences, as seen in this figure, are small. A volatility shock has an effect because it changes the uncertainty tomorrow, while working capital affects the costs of the firm today. Since the problem of the firm is static, the IRFs have only minor differences because of the differences in the ergodic distribution induced by working capital. Therefore, the IRFs are close to each other. If anything, our results

¹We undertook an additional experiment where we recalibrated the parameters to match the data with the new feature of working capital. The results were nearly identical and we do not report them to simplify the exposition.

suggest slightly higher effects of volatility shocks when working capital is considered, particularly in the case of debt, which goes down 6.5 percent instead of the 4 percent of the benchmark case. In the working paper version of the paper, we also explored other alternatives, including Uzawa preferences and changes in parameter values.

As a final robustness check, we discuss the implications of the priors for our estimates. To that end, we re-estimate the processes (??) and (??) for Argentina with two alternative priors and report the results in table A4. For the first option (Case I), we select relatively uninformative priors for ρ_r and ρ_{σ_r} centered in 0.5, while the other parameters' priors remain the same as in the original exercise. For the same reason as in the original prior (to minimize the impact of stochastic volatility), we endow ρ_r with a tighter prior. Under this prior, the posterior ρ_r still is concentrated around 1. For the second alternative (Case II), we center ρ_r around its OLS estimates, and the other priors are left as in the baseline setup. Overall, the estimates are again similar to those in table 3.

Table A4: Alternative Priors

	Case I		Case II	
	Prior	Median Posterior	Prior	Median Posterior
ρ_r	$\mathcal{B}(0.5, 0.1)$	0.98 [0.97, 0.99]	$\mathcal{B}(0.96, 0.02)$	0.99 [0.98, 0.99]
σ_r	$\mathcal{N}(-5.3, 0.4)$	-6.00 [-6.55, -5.25]	$\mathcal{N}(-5.3, 0.4)$	-5.73 [-6.48, -4.86]
ρ_{σ_r}	$\mathcal{B}(0.5, 0.2)$	0.87 [0.72, 0.96]	$\mathcal{B}(0.9, 0.1)$	0.94 [0.83, 0.99]
η_r	$\mathcal{N}(0.6, 0.3)$	0.52 [0.38, 0.72]	$\mathcal{N}(0.6, 0.3)$	0.48 [0.35, 0.65]

We finish by showing that our findings for Argentina are not dependent on the effects of the Corralito and the partial default on sovereign debt. In table A5, we re-estimate the process for the spread of Argentina without the data after the onset of the Corralito (December 1, 2001). The medians of the posteriors for the stochastic volatility parameters, ρ_σ and η_r , are 0.95 and 0.47, nearly the same as 0.94 and 0.46 in the case with the Corralito data. Not surprisingly, the variances of the posterior are bigger, since we use many fewer observations for the estimation. The medians of ρ_r and σ_r change a bit more (the persistence of interest rate shocks falls to 0.91), but they are still quite close to the original ones.

Table A5: Argentina before the Corralito
(95 percent set in parenthesis)

	Prior	Median Posterior
ρ_r	$\mathcal{B}(0.9, 0.02)$	0.91 [0.86, 0.94]
σ_r	$\mathcal{N}(-5.3, 0.4)$	-5.51 [-6.31, -4.69]
ρ_σ	$\mathcal{B}(0.9, 0.1)$	0.95 [0.84, 0.99]
η	$\mathcal{N}(0.5, 0.3)$	0.47 [0.27, 0.75]

0.10. Exploring the Role of Volatility and Debt

In this last subsection, we explore how the IRFs of the model depend on different properties of the volatility process and on the country's level of debt. The goal of the subsection is to offer further insights into the mechanisms at work in the paper.

We start, in figure A4, by plotting the IRFs, for the Argentinean case, of a one-standard-deviation shock to volatility and to a two-standard-deviation shock to the volatility of the country spread. In this way, we can see how the higher-order terms induce strong non-linearities: while consumption falls less than twice in the high volatility case, output falls more than twice. This difference is due to the much more acute need to pay back the debt in the high volatility shock case.

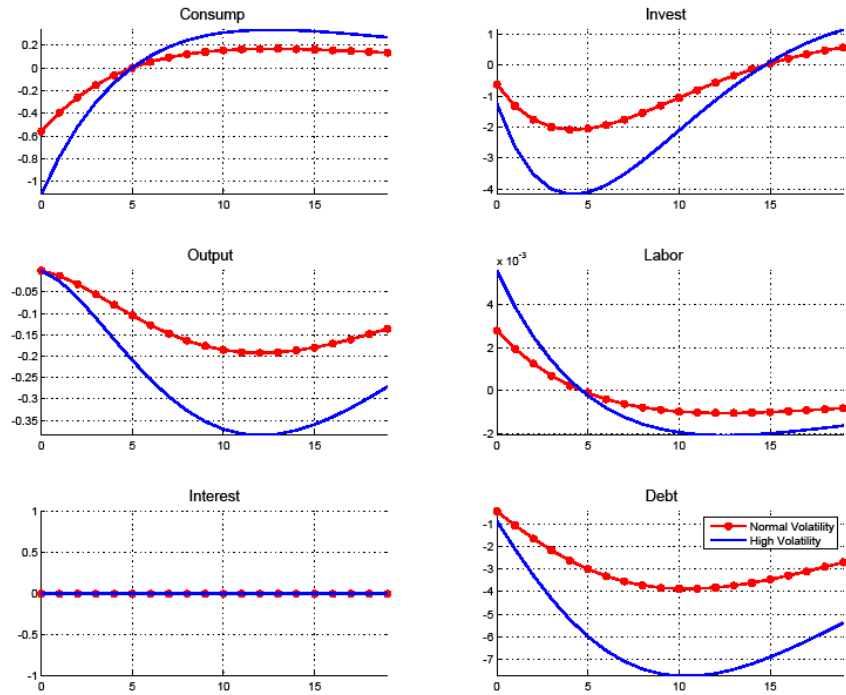


Figure A4: High versus Normal Volatility

In figure A5, we illustrate how the persistence of volatility is key. When we reduce the persistence of the volatility shock to the country spread to 0.75, most of the effects of a one-standard-deviation shock to volatility disappear: the representative household knows that volatility will revert quickly to its mean value and, therefore, it is less keen on paying back the debt.

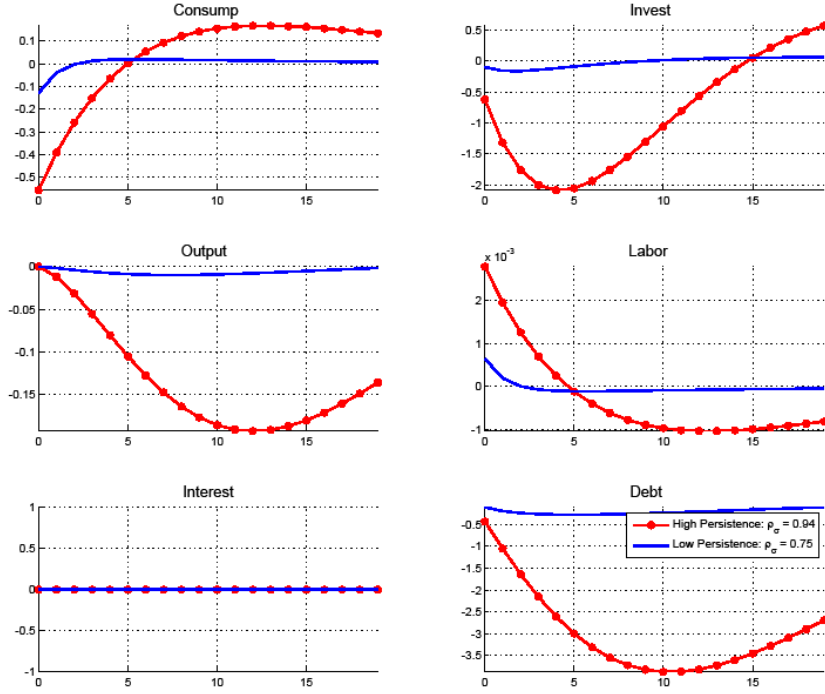


Figure A5: High versus Low Persistence of Volatility

Finally, in figure A6, we plot the IRFs to a one-standard-deviation shock to volatility in the benchmark Argentinean calibration and the IRF when we double the net exports to output ratio in the ergodic distribution (which corresponds to higher debt). Higher debt means a bigger drop in consumption, investment, and consumption. Debt also falls more in absolute terms but less in percentage terms, since now it is twice as costly to reduce its level by 1 percent.

Thus, we conclude by highlighting both the non-linearities in the IRFs and the importance of persistence and net exports over output in explaining the size of the responses to volatility shocks.

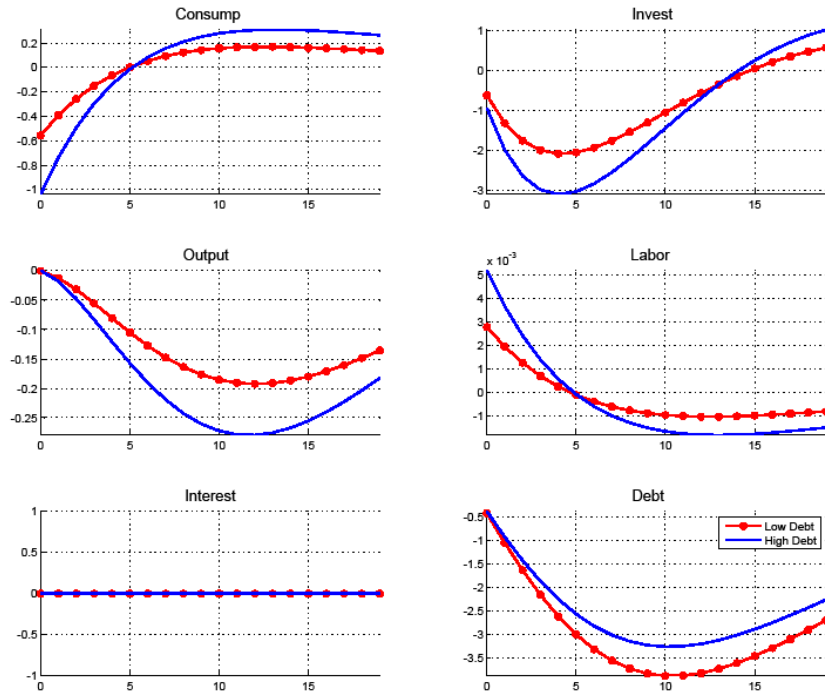


Figure A6: High versus Low Debt

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