Systemic Risk, Aggregate Demand, and Commodity Prices: An Application to Colombia

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Abstract

We embed a small open economy model for Colombia into the systemic risk model of Gómez, Guillaume, and Tanyeri (2015). The small open economy model is estimated by Bayesian methods and used for analysis and projections. Parameters estimates are constrained to yield an appropriate behavior to impulse responses, the evolution of latent variables, equation fit, error decompositions, and model forecast performance. The model enables us to give a consistent treatment of shocks to systemic risk, country risk, oil and commodity prices because rest-of-the-world variables are endogenous among themselves instead of exogenous rest-of-the-world variables for Colombia so that its economy responds to the reaction of these variables to the shocks of interest. Among other results we found that the identified episodes of retrenchment and buoyancy in

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systemic risk were transmitted to Colombia's country risk premium and that systemic risk shocks are important drivers of Colombia's output and unemployment gaps. Finally, aggregate demand-related shocks are unimportant drivers of noncore inflation in Colombia. This result contrasts with findings for other countries.

Keywords: global risk, financial linkages, commodity prices.

JEL classification: F32, F37, F41, F31, F47, E58.

1. INTRODUCTION

This paper studies the effect of systemic risk on Colombia, a small open developing economy. The systemic risk shock is dealt with consistently, meaning that the Colombian economy reacts directly to the systemic risk shock and indirectly via the reaction of world output, interest rates, inflation, and exchange rates to the shock under study. This contrasts sharply with the approach that appends an exogenous *rest-of-the-world* to a small open economy (SOE) model where *rest-of-the-world* variables are exogenous. The paper also deals with shocks to oil and commodity food prices in a consistent way.

In order to reap these benefits, the systemic risk global model in Gómez, Guillaume and Tanyeri (2015), hereafter GGT, is adapted to explain systemic risk transmission in a particular SOE (Colombia), instead of the average country in its region. As a matter of fact, GGT proposed a global model that explains the systemic risk transmission mechanisms across different regions of the world thus missing the idiosyncrasies of individually small countries within its region as is the case of Colombia. As a result, in this paper Colombia is treated as a new region that follows the same equations as any other region but with different parameter values. The soundness of this approach arises from the fact that the effect of the USA subprime crisis in Latin America seems to have been heterogeneous among its major economies. See Dufrénot et al. (2011) for instance.

In very general terms, GGT's model considers a world consisting of a series of regions: United States (US), European Union (EU), Japan (JA), East Asia (EA), and Latin America (LA); whose local behavior is similar except for its parameter values and variable's realized values. For each region, the model describes the behavior of macro variables measured as gaps over stochastic trends that is very similar to models used for inflation targeting. GGT propose to

1) Measure systemic risk as a common unobserved global factor encompassed by the global model;

2) Introduce an explicit channel, through which systemic risk transmits to country risk premiums;

3) Provide a transmission mechanism from systemic risk to global output and regional output gaps;

4) Include commodity prices and its effect on local inflation as well as real effects of commodity prices such as oil to global output; and,

5) "A treatment of the trade balance and a simple approximation to the current account" (Gómez et al., 2015, p. 5).

Colombia is an important case not only because it serves as an example on the implementation of the GGT model for specific needs, but also because of the unique effects the 2007-2009 global financial crisis and its medium-term aftermath had in this country. As a matter of fact, Dufrénot et al. (2011) found that "the financial stress in the USA markets is transmitted to these [Brazil, Chile, Colombia, Mexico, and Peru] countries' stock market volatility, but not in the same scale. Our findings support the idea of heterogeneity among the LAC markets, in the sense that the 2007/2008 subprime crisis did not equally affect all the countries, despite the fact that high volatility of the equity prices was observed everywhere". These results suggest that Latin American financial markets decoupled heterogeneously from USA as pointed out by Dooley and Hutchison (2009).

In the same vein, Julio et al. (2013) report a structural break in the relation between the appetite for risk of international investors and the Colombian component of the Emerging Markets Bond Index (EMBI)-Colombia, in the second half of the 2000s decade that lowered the financial cost of government debt. This sovereign risk break, according to these authors, is "apparently associated to [the aftermath of] the global financial crisis". However, these authors do not deeply explore the channels through which sovereign risk, which we explore further through the use of GGT's model.

As a result, the estimation of Colombian parameters is emphasized. In fact, provided that regions of GGT are identical except for their corresponding parameter values and their variables realizations, the key to model these responses lies on parameter estimates.

Furthermore, to our knowledge this is not the first time that a model of a SOE is embedded into a global model, but we are unaware of published papers on the topic as of now.

The paper has the following four sections in addition to this short introduction. The second briefly describes the model. The third deals with all the data aspects, namely, its sources as well as the model calibration and estimates. The fourth contains the impulse responses under the main shocks, the smoothing and error decomposition results, and the forecasting performance of the model. The fifth concludes and deals mainly with the role of systemic risk shocks in explaining local output gap, unemployment, and country energy and food prices.

2. THE MODEL

The model consists of a SOE model calibrated for Colombia embedded into the systemic risk model of Gómez et al. (2015). As in GGT, the model is built to incorporate three channels of transmission. First, systemic risk and its transmission to the country risk premium. Second, the transmission from country risk premiums to demand-related variables such as the output gap, the trade balance and unemployment. And third, the transmission from commodity prices to country inflation. With these features, the model can be operated to analyze financial booms and busts (low and high risk premium), and the effect of booms and boosts on output, unemployment, and the trade balance, as well as commodity-price shocks and their effect on inflation.

The model used in this paper draws extensively on GGT as the Colombian economy is modeled as one GGT block. Therefore, just as in GGT, the Colombian block is in the spirit a simple gap model of the type central banks use for their inflation targeting procedures.

That is, the model is based on two transmission channels: an aggregate demand channel and an exchange rate channel. The former describes the effect of interest rates on aggregate demand, inflation, and back again to the interest feedback rule, while the later establishes the effect of interest rates on the exchange rate, aggregate demand, inflation, and then to the interest rate feedback rule. These standard transmission channels, whose origin is the interest rate, may be extended to country risk premiums as follows. The *domestic aggregate demand channel* is the effect of a shock to the country risk premium on the country's output gap, inflation, and finally on the interest rate feedback rule. The *domestic exchange rate channel* comprises the effect of the country risk premium on output and trade balance gaps through the exchange rate; the interest rate feedback rule then takes the economy back to equilibrium.

The Colombian model also makes use of the three transmission channels incorporated in GGT, namely, the *systemic risk channel, the foreign aggregate demand channel, and the foreign exchange rate channel.* Further details on this matter may be found in Gómez et al. (2015, pp. 7-12).

The model consists of 22 core equations. These equations are, on one hand, behavioral equations for the following variables: risk premium, output gap, trade balance gap, capital flows, core inflation, energy prices, food prices, interest rates, unemployment, export prices, import prices, and real exchange rate. And on the other, identities for the variables foreign risk premiums, foreign real interest rates, real multilateral exchange rate, terms of trade, absorption, CPI inflation, nominal exchange rate, real interest rate, and a breakdown of the uncovered interest parity residual.[1]

The reader is referred to Gómez et al. (2015) for the model's details. Instead of transcribing the whole model in this paper, we describe the parameters of interest and refer the reader to the appropriate equations in GGT's paper.

Our interest lies on the estimation of 13 parameters that determine the responses to key shocks through the transmission channels described in GGT's model. The rest of parameters were either calibrated or estimated in GGT and taken here as given. A sample of those may be found in Tables A.1 and A.2. In turn, Table A.4 contains a list of the parameters we are interested in. The first parameter, $\alpha_{2,CO}$ determines the contemporary transmission of systemic risk shocks to the Colombian risk premium $\hat{\rho}_t$ in Gómez et al. (2015, Eq. 2, pp. 7). The second and the third, $\delta_{2,CO}$ and $\delta_{3,CO}$, determine the effect of the expected inflation gap $\pi_{t+5|t} - \bar{\pi}_{t+5|t}$, and the current output gap $\hat{y}_t$ on the current nominal interest rate i_t in the policy rule at Gómez et al. (2015, Eq. 56, pp. 15), respectively. The effect of the output gap $\hat{y}_t$ and the real exchange rate (RER) gap q_t^{RER} on the inflationary core π_t^C in the Phillips curve is determined by ν_2 and ν_3, respectively (Gómez et al., 2015, Eq. 39, pp. 13). The transmission from global food (commodity) prices $\hat{q}_t^{Food}$ to Colombian food prices $\hat{q}_t^f$ in Gómez et al. (2015, Eq. 34, pp. 12) depends on ν_4, and the effect of local prices $\hat{q}_t$ on local food prices depends on ν_5. In the same vein, the transmission from oil prices $\hat{q}_t^{Oil}$ and local prices $\hat{q}_t$ to domestic energy prices $\hat{q}_t^e$ are determined by ν_8 and ν_{12}, respectively, in Gómez et al. (2015, Eq. 33, pp. 12). The response of the NAIRU gap $(\hat{u}_t)$ to the output gap is $-\theta_2$ in $\hat{u}_t = \theta_1 \hat{u}_{t-1} - \theta_2 \hat{y}_t + \varepsilon_t^{\hat{u}}$. The last two parameters, $\sigma_{\rho,CO}$ and $\sigma_{rr,CO}$ correspond to the expanded version of the output gap equation which may be found

[1] The number of equations in the SOE model rises to 117 owing to the type of variables involved (in deviation and latent form), the several definitions used for growth and inflation, a set of equations for autocorrelated residuals, and another equation for exogenous interventions on the output gap.

in Gómez et al. (2015, Eq. 19-20, pp. 51), and represent the multiplicative inverse of the effect of the country risk and the real rate gap on the output gap, respectively.

As a result the most important parameters in the transmission of the shocks of interest are estimated based on sample information rather than calibrated.

3. MODEL ESTIMATION

In order to check the validity of preliminary prior parameters means (that is, the calibration) we compare the peak response of the output gap to country risk premium shocks in the model and in a global VAR model in Figure B.1.[2] The shock to the country risk premium is a unit and autocorrelated. Figure B.1 shows that the peak response of the output gap to the country risk premium shock is similar in the model and in the VAR. In like fashion, the peak response of the output gap to interest rate shocks is also similar in the model and in the VAR.

The hyperparameters of the a priori parameters distributions were obtained from the calibration of the model. The calibration covered 121 parameters, 41 of which are standard deviations; while the estimation covered 13 parameters. The calibration was obtained by analyzing impulse response functions, the evolution of latent variables, equation fit, error decompositions, and model forecast performance. As a result, calibration provides the mean, variance and limits for all 13 a priori parameter distributions.

The samples of calibrated parameters in Table A.1 and the estimated parameters in Table A.2 come directly from Gómez et al. (2015).[3]

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[2] To calibrate the effect of the country risk premium and real interest rate to the output gap GGT estimates a global VAR model that includes, for each region, the country risk premium gap, the local real interest rate gap, the local output gap and the output gap of the rest of the world. See Gómez et al. (2015, Eq. 63, pp. 17).

[3] The sources of the data are specified in Gómez et al. (2015). In the particular case of Colombia, the country risk premium was measured with Colombia's EMBI spread.

Once the a priori distributions are set, parameter estimation can be carried out by Bayesian methods. Under a zero-one loss function the 13 Bayesian parameter estimators correspond to the mode of the posterior distributions, while under mean squared error loss they correspond to posterior means. We chose Bayesian estimation as it helps tackle key estimation issues that arise when working with big and complicated models such as the one used in this paper, see Del-Negro and Schorfheide (2011).

However, because of the model's size and complexity the posterior distributions do not have closed form from which the modes and means could be derived. As a result, we have to rely on simulation. Simulation of the samples from the parameters posterior distributions was carried out by the adaptive version of the random walk Metropolis algorithm; see Haario et al. (1999). By design, this simulation technique guaranties an adequate degree of sample mixing when coupled with a *good* choice for the parameters of the proposal distribution, in particular its variance-covariance matrix. See Gelman et al. (2013).

In order to obtain an appropriate estimate of covariance matrix for the proposal distribution, the posterior distribution was maximized as follows. First, a good approximation to the posterior distribution mode [that is, the regularized likelihood maximum in Ljung (1999)] is found through the particle swarm algorithm.[4] And second, a Newton-Raphson

[4] The particle swarm algorithm is a time inexpensive maximization technique, see Johnston (2013). In this algorithm, a population (swarm) of particles climbs the log posterior at a number of arbitrary points. In every iteration, each particle knows its own altitude, its maximum historical altitude and the maximum altitude historically attained in the population. When coupled with a behavioral rule and some degree of persistence, this algorithm is a time inexpensive alternative to find a global maximum. Furthermore, since this algorithm computes the function only once for each particle in every iteration, it is able to solve the maximization problem very fast using parallel computing, which further enhances the time savings.

maximization algorithm is started at the result of the particle swarm in order to reach the posterior's maximum if it has not been attained already. Therefore, the use of the time expensive Newton-Raphson procedure is reduced and an estimate of the covariance matrix at the posterior mode is obtained.

The last generation of parameters in the particle swarm algorithm was fed to the Newton-Raphson procedure, which converged in just one step. This last procedure provided estimates of both the posterior mode as well as the covariance matrix at the maximum for the random walk Metropolis algorithm. After a burn sample of size 30,000, 100,000 samples were simulated in order to estimate the posterior distributions.

In order to check convergence to a maximum, Figure B.2 depicts the profiles of the negative log regularized likelihood along with the corresponding (maximum) achieved by the Newton-Raphson algorithm. These plots confirm that a mode was reached and thus we can confidently use the Hessian at the maximum to provide an estimate of the covariance matrix for the proposal distribution. Furthermore, a comparison of the posterior mode with the prior mean in Table A.4 shows important similarities among the values of all parameters, except v_3. Thus, at least from a 0-1 loss perspective the data seems to provide information about the value of some parameters.

Once this covariance matrix is fed into the random walk Metropolis algorithm, samples from the posterior distributions of the 13 parameters can be obtained. These simulations are used to estimate the 13 posterior densities and their corresponding moments. Table A.3 summarizes the simulation setup for the 13 parameters posterior distribution. The upper panel contains the setup for the maximization of the posterior, while the lower panel summarizes the setup of the random walk Metropolis simulator. Parameters a priori distributions were assumed to be independent normal, so that the regularized likelihood corresponds to the posterior mode. The particle swarm algorithm population ran in four parallel workers (processors) and contained a swarm of 80 members who were programed to climb the regularized log likelihood for up to

200 generations. Convergence, within a one in a millionth difference, was achieved after just 172 generations.

To check for convergence to the steady state distributions of the parameters posteriors, it is common to analyze the acceptance ratio of the proposed simulations, which in our case was 22.87%, a value close to the expected rate of acceptance in Gelman et al. (2013). The second criteria checks for changes in the variance at different intervals of the simulations. In our case the variance ratio of the first and second half of the marginal simulated samples is 1.09, which being close to one validates our simulations. Furthermore, Figure B.3 shows a small portion of the sample simulated path of four parameters. The upper left and right panels show that the marginal simulation of some parameters converge to a steady state distribution quite fast regardless of the starting point. In contrast, the lower panels show that the unconditional simulation of some parameters takes longer to explore different sets of their corresponding parameter spaces to achieve the required degree of mixing, regardless of the starting point also. In order to test for an adequate degree of mixing, a variance ratio among the two halves of the simulation was calculated, 1.09; which is close enough to one. This suggests that the simulations are adequate to infer the posterior densities and their moments.

Table A.4 summarizes the results of the Bayesian estimation. A priori distributions were assumed independent truncated normal with means and standard deviations displayed in the second and fifth columns, and truncation limits in columns three and four, respectively. The parameters of the a priori distributions arise from a very careful calibration of the impulse responses and historical decompositions of the model, and the standard deviation and truncation limits are set as wide as possible to reduce the amount information input to the estimation process. The final results of the estimation process, under square loss, are located at the right hand side panel of the table. Column seven contains the posterior means and columns eight and nine show the corresponding highest probability density confidence limits at 95%, respectively.

The estimated marginal posteriors and priors may be found in Figure B.4. From this figure it can be observed that the sample information does contain information about the parameters of interest as priors and posteriors tend to differ in their location (mean or mode) and their variance, or both, except for particular cases. These results, along with Table A.4 depict slight mean shifts from the prior to the posterior for δ_2 , ν_{12} , ν_2 , ν_1 , and σ_r; and in an important shift in the mean of ν_3 . Furthermore, the introduction of prior information reduced parameter uncertainty quite significantly for δ_3 , ν_{12} , ν_2 , ν_3 , ν_4 , ν_8 , θ_2 , and σ_r . Therefore, the sample data contains information about ν_3 (i.e., reduced uncertainty and shifted its mean), and contains some information about coefficients δ_3 , ν_{12} , ν_2 , ν_3 , ν_4 , ν_8 , θ_2 , and σ_r (i.e., sharply reduced uncertainty).

Once the parameters are estimated, these values are introduced in the model to further study the transmission channels of interest.

4. RESULTS

The results deal with the three main topics developed in the paper,

1) The transmission from systemic risk to the country risk premium;

2) The transmission from the country risk premium to aggregated demand–related variables such as the output gap, the trade balance gap, and unemployment; and

3) The transmission from commodity prices to country energy and food country prices.

In addition, impulse response analysis includes a shock to the policy interest rate, given that this shock is an explanation of the transmission mechanisms of monetary policy.

A Shock to Systemic Risk

Figure B.5, panel A, shows the behavior of the country variables in response to a shock to systemic risk. Global risk is shown to affect Colombia's country risk premium, output gap, and trade balance gap. The country risk premium and the output gap respond according to the strength of the systemic risk and aggregate demand channels.

The trade balance gap deteriorates owing primarily to the strength of the systemic risk channel. As loading factor α_2 is small, the country risk premium rises less than abroad, the country risk premium differential drops, and the trade balance deteriorates.

A Shock to the Country Risk Premium

Figure B.5, panel B, shows the response of the output gap to shocks to the country risk premiums. In response to an upward shock to the domestic risk premium, the output gap drops. Two channels are at work, the domestic aggregate demand and domestic exchange rate channels.

In response to an upward shock to a foreign risk premium, the output gap also drops. Both the foreign aggregate demand and foreign exchange rate channels help explain this response.

The output gap reacts to shocks to the domestic risk premium far more than to shocks to foreign risk premiums. In a relatively open economy, the output gap may react strongly to foreign risk premium shocks because the aggregate demand channel tends to be weak, while the foreign aggregate demand channel tends to be strong. But this is not the case of the country under study, Colombia.

Concerning the response of the trade balance gap to country risk premium shocks, Figure B.5, panel C, the trade balance gap improves with shocks to the domestic risk premium and drops with shocks to foreign risk premiums. The strength of the response of the trade balance gap to shocks to foreign risk premiums depends, mostly, on the export share of the country where the shock takes place.

Shock to Commodity Prices

The response of country variables to a shock to the price of oil appears in Figure B.5, panel D. The response involves higher inflation and interest rates. The monetary policy rules at home and abroad prescribe larger interest rate increases in Colombia; hence, Colombia's currency appreciates causing output gap to drop further.

Altogether, a shock to the price of oil has effects on inflation and the output gap that may be important, but quantitatively not as important as the effect of a one standard deviation shock to systemic risk.

A shock to the commodity price of food appears in Figure B.5, panel E. The response of the output gap and inflation is similar in kind and extent to that of a shock to the price of oil. Some differences do arise as to the extent of the response of the nominal interest rate and in the persistence of CPI inflation. These differences are explained by the higher persistence of the country food and energy prices under shocks to commodity food prices and to the price of oil, respectively.

An Interest Rate Shock

The focus here is on the effect of interest rate shocks on the country output and trade balance gaps. As expected, the relevant shocks are those to the own interest rates, while shocks to foreign interest rates are largely unimportant.

Consider first the response of the output gap to a shock to the domestic interest rate in Figure B.5, panel F. The response is standard with the domestic aggregate demand and exchange rate channels being involved.

Next, consider the effect of foreign interest rate shocks on the output gap, also in Figure B.5, panel F. The response of the output gap to a foreign interest rate shock is the result of transmission channels that work in opposite directions. In response to an increase in a foreign interest rate, the foreign aggregate demand channel causes a drop in the output gap; the foreign exchange rate channel causes a rise in it. Both effects offset each other to the extent that the response of the output gap to a foreign interest rate shock is trivial.

Next, consider the effect of an interest rate shock on the trade balance gap in Figure B.5, panel G. The response to an upward shock in the domestic interest rate is a drop in the trade balance gap. By the aggregate demand channel, a rise in the domestic interest rate decreases aggregate demand and hence imports. Consequently, the trade balance improves. Through the exchange rate channel, a rise in the domestic interest rate appreciates the exchange rate; thus, the trade balance deteriorates. The later effect predominates.

Finally, consider the effect of a foreign interest rate shock on the trade balance gap also in Figure B.5, panel G. As explained in GGT, the sign of the response of the trade balance gap to a foreign interest rate shock is opposite to that of a shock to the domestic interest rate. Thus, in response to an upward shock to a foreign interest rate the trade balance gap rises.

Smoothing Results

Reported smoothing results also deal with the three topics dealt with in the paper.

The first of the topics is presented in Figure B.6, panel A. The estimated, unobserved systemic risk marks periods of higher volatility during the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the eurozone crisis.

Figure B.6, panel B also shows the country risk premium. In deviation form, the country risk premium moves with global and idiosyncratic events. In latent form, the country risk premiums drops during the transition to lower inflation that started in the early 2000s.

The second of the topics appears in Figure B.6, panels C and D. Two of the three peaks in systemic risk and the country risk premium (the end of the century crisis and the global financial crisis) correspond with busts in output and increases in unemployment. During these episodes, the trade balance improved. Because the trade balance improved at the time the output gap dropped, absorption dropped more than output; in this light the trade balance is understood to be procyclical.

The third of the topics appears in Figure B.6, panels I and J. Country energy prices have low correlation with the price of oil, probably owing to the rule used to set gasoline prices in Colombia. Country food prices depict some correlation with commodity food prices.

Historical Decomposition Results

The historical decomposition of systemic risk, estimated with the model in Gómez et al. (2015), appears in Figure B.7, panel A. Global risk points at four episodes of retrenchment: The end-of-the-century crisis, the stock market downturn of 2002, the global financial crisis, and the eurozone crisis.

The historical decomposition of the Colombia's country risk premium gap appears in Figure B.7, panel B. Global risk shocks have a massive influence on the country risk premium. Peaks in the country risk premium are explained by systemic risk shocks in all episodes of global retrenchment. Note that the country risk premium is not explained by systemic risk during the burst of the dot-com bubble which is a USA event.

As to the historical decomposition of Colombia's output gap in Figure B.7, panel C, systemic risk shocks are important while own and foreign risk premium shocks are trivial. Other demand-related shocks, such as output and real interest rate shocks are also less important. Also, shocks to foreign variables are also trivial in explaining the output gap.

The decomposition of the unemployment gap also makes clear that systemic risk shocks are relevant and country risk premium shocks are trivial (Figure B.7, panel D). Global risk shocks help explain the rise in unemployment during the global financial crisis while interest rate shocks help explain the rise during the end of the century crisis. Again, foreign shocks are trivial.

The historical decomposition of the trade balance gap appears in Figure B.7, panel E. Recall that systemic risk shocks affect country risk premiums to different extents and that trade balance gaps depend on the country risk premium differential. In Colombia, an upward shock to systemic risk tends to cause a drop in the trade balance gap.

Country energy and food price gaps are broken down into the contributions from shocks in panels F and G. Demand related shocks play a role in explaining country energy prices and to a minor extent country food prices. The role of demand related variables in explaining the relative price of noncore inflation was emphasized in GGT. The same argument applies here to the relative price of energy.

However, the case is different regarding the aggregate of energy and food prices. Figure B.7, panel H, presents the decomposition of the aggregate of Colombia's energy and food prices. As noted in GGT, this aggregate is a measure of the deviation of CPI inflation from core inflation. The effect of demand related shocks is trivial on the aggregate. The reason is that while the effect of demand-related shocks on the country price of energy is large, the share of country energy prices in the CPI is small. In the aggregate, demand-related shocks are unimportant. Moreover, commodity food price shocks predominate.

Forecasting Properties

Table A.5 compares the model forecasts with the forecasts of analysts.[5] Model growth forecasts are better at one and four quarters ahead horizons[6] (Table A.5). As to inflation forecasts,

[5] The survey of analysts' forecasts is taken from Consensus Economics.

[6] Except for the four quarters ahead growth forecast for the United States.

model forecasts are better at one quarter horizon but worse at four and eight quarter horizons.

The relatively good performance of the model may in part be explained by the fact that analysts did not know the model, the shock, and the coefficients that we know after we set up, calibrate, and estimate the model throughout the sample. This is particularly relevant during the global financial crisis. The parameters do incorporate the effect of higher systemic risk on growth and inflation during the global financial crisis while it is fairly known that analysts performed quite poorly.

Figure B.8 shows the forecast variance of a handful of variables. The figure shows that systemic risk shocks are important in explaining the forecast variance of the country risk premium, output growth, trade balance, unemployment and energy and food price inflation.

5. CONCLUSIONS

The paper dealt with three main topics; first, the transmission of systemic risk to the Colombia's country risk premium; second, the effect of Colombia's country risk premium on aggregated demand-related variables such as the output gap, the trade balance gap, and unemployment; and third, the transmission from commodity prices to country energy and food prices.

On the first topic, systemic risk shocks were transmitted to Colombia's country risk premium in all events of global retrenchment. Although country risk premium shocks also mark some periods of idiosyncratic risk, the bulk of the country risk premium was explained by systemic risk shocks.

On the second topic, systemic risk was relevant at explaining Colombia's output gap, particularly during the global financial crisis. The historical decomposition of the country output and unemployment gaps showed the relevance of systemic risk shocks and the more trivial role of country risk premium shocks.

It was in the trade balance gap where country, domestic risk premium shocks played a more relevant role. The reason is that the trade balance gap is explained by the country risk premium differential. During retrenchment, systemic risk permeated with different intensity to country risk premiums. In Colombia, where the systemic risk channel is weaker, the risk differential dropped and the trade balance deteriorated.

On the third topic, the paper showed that in Colombia supply shocks were more relevant that demand-related shocks, given the higher weight of food in the CPI.

The model performed relatively well in forecasting, as compared to a survey of analysts' forecasts. Global risk shocks helped explain the variance of the forecasts for a handful of Colombian macroeconomic variables.

ANNEXES

Annex A

Table A.1

SOME CALIBRATED PARAMETERS

Parameter	*Value*	*Parameter*	*Value*	*Parameter*	*Value*	*Parameter*	*Value*
$1/\sigma_{\rho,\mathrm{CO}}$	0.333	$1/\sigma_{r,\mathrm{CO}}$	0.143	$\sigma_{1,\mathrm{CO}}$	0.040	$\sigma_{2,\mathrm{CO}}$	0.780
$\alpha_{1,\mathrm{CO}}$	0.630	$\delta_{1,\mathrm{CO}}$	0.200	$\nu_{1,\mathrm{CO}}$	0.850	$\vartheta_{1,\mathrm{CO}}$	0.780
$\nu_{7,\mathrm{CO}}$	0.550	$\sigma_{6,\mathrm{CO}}$	0.600	$\sigma_{11,\mathrm{CO}}$	0.600	β_1	0.500
λ_{CO}	0.005	$\bar{x}_{\mathrm{CO}}$	0.171	$\bar{m}_{\mathrm{CO}}$	0.194	β_4	0.700

Source: Authors' calculations.

Table A.2

SOME ESTIMATED PARAMETERS

Parameter	*Prior mode*	*Posterior mode*	*Parameter*	*Prior mode*	*Posterior mode*
$\alpha_{2,US}$	0.495	0.267	$\delta_{2,US}$	0.082	0.084
$\delta_{3,US}$	0.275	0.304	$\vartheta_{2,US}$	0.266	0.215
$\nu_{2,US}$	0.082	0.084	$\nu_{3,US}$	0.020	0.028
$\nu_{5,US}$	0.624	0.119	$\nu_{8,US}$	0.486	0.643
$\nu_{4,EU}$	0.040	0.038	$\nu_{12,EU}$	0.040	0.042
ν_{US}	0.200	0.000	β_2	6.959	7.373

Source: Authors' calculations.

Table A.3

PARAMETERS FOR POSTERIORS SIMULATIONS

Process	*Feature*	*Value*
Maximizing the posterior	Parameters	13
	Population size	80
	Generations	200
	Generations to convergence	172
	Parallel workers	4
	Newton-Raphson iterations	1
Adaptive Metropolis	Iterations	100,000
	Burn in sample	30%
	Acceptance ratio	22.87%
	Average variance ratio	1.0941

Note: Iris Toolbox 20120121, Benes and Johnston (2014); particle swarm algorithm, Johnston (2013).
Source: Authors' calculations.

Table A.4

PARAMETERS PRIOR AND POSTERIOR DISTRIBUTIONS FEATURES

	Prior				**Posterior**			
Parameter	*Mean*	*Min*	*Max*	*Std*	*Mode*	*Mean*	*HPDI_05*	*HPDI_95*
$\sigma_{2,CO}$	0.8000	0.0000	1.6000	0.0800	0.8000	0.7939	0.6635	0.9302
$\delta_{2,CO}$	1.0000	0.0000	2.0000	0.1000	1.0836	1.0835	0.9199	1.2286
$\delta_{3,CO}$	0.5000	0.0000	1.0000	0.0500	0.5137	0.5170	0.5157	0.5192
$v_{12,CO}$	0.0400	0.0000	0.0800	0.0040	0.0400	0.0409	0.0385	0.0429
$v_{2,CO}$	0.1000	0.0000	0.2000	0.0100	0.1013	0.0922	0.0860	0.0995
$v_{3,CO}$	0.0400	0.0000	0.0800	0.0040	0.0503	0.0502	0.0476	0.0520
$v_{4,CO}$	0.0400	0.0000	0.0800	0.0040	0.0400	0.0394	0.0384	0.0409

$\nu_{5,CO}$	0.0800	0.0000	0.1600	0.0080	0.0800	0.0798	0.0668	0.0930
$\nu_{8,CO}$	0.0500	0.0000	0.1000	0.0050	0.0500	0.0548	0.0530	0.0569
ν_{CO}	0.2000	0.0000	0.4000	0.0200	0.2039	0.2038	0.1718	0.2371
$\sigma_{\rho,CO}$	4.8000	0.0000	9.6000	0.4800	4.8246	4.8089	4.0555	5.5593
$\sigma_{rr,CO}$	15.0000	0.0000	30.0000	1.5000	14.6967	14.7293	14.6764	14.7802
$\theta_{2,CO}$	0.2000	0.0000	0.4000	0.0200	0.1999	0.1964	0.1895	0.2023

Note: Adaptive version of the random walk Metropolis algorithm.
Source: Authors' calculations.

Table A.5

GOODNESS OF FIT

Root mean squared errors in percentage points

	One quarter ahead		*Four quarters ahead*		*Eight quarters ahead*	
	Consensus Forecast	*Global risk model*	*Consensus Forecast*	*Global risk model*	*Consensus Forecast*	*Global risk model*
Colombia's growth	1.019	0.28	2.273	1.887	1.902	2.72
Colombia's inflation	0.943	0.875	2.292	3.615	1.596	3.987

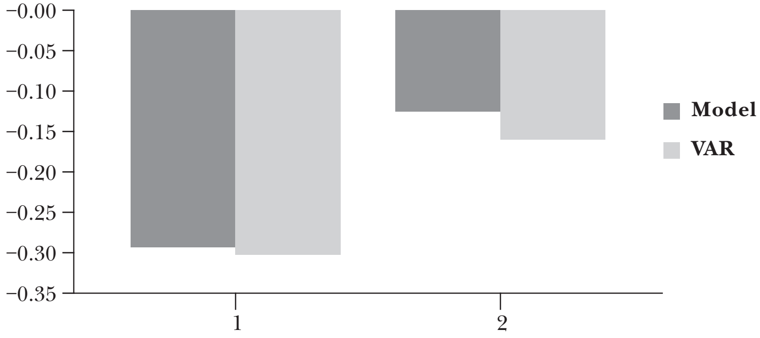
Note: To make Consensus Forecast (CF) and global risk model forecasts (GR) broadly comparable we approximated the CF and GR forecasts as follows. The one quarter ahead forecast is the October forecast for the end of the year; the four quarters ahead forecast is the October forecast for the end of the following year; and the eight quarters ahead forecasts is the October forecast two years ahead. The sample is 1996-2013.
Source: Authors' calculations.

Annex B

Figure B.1

MODEL CALIBRATION

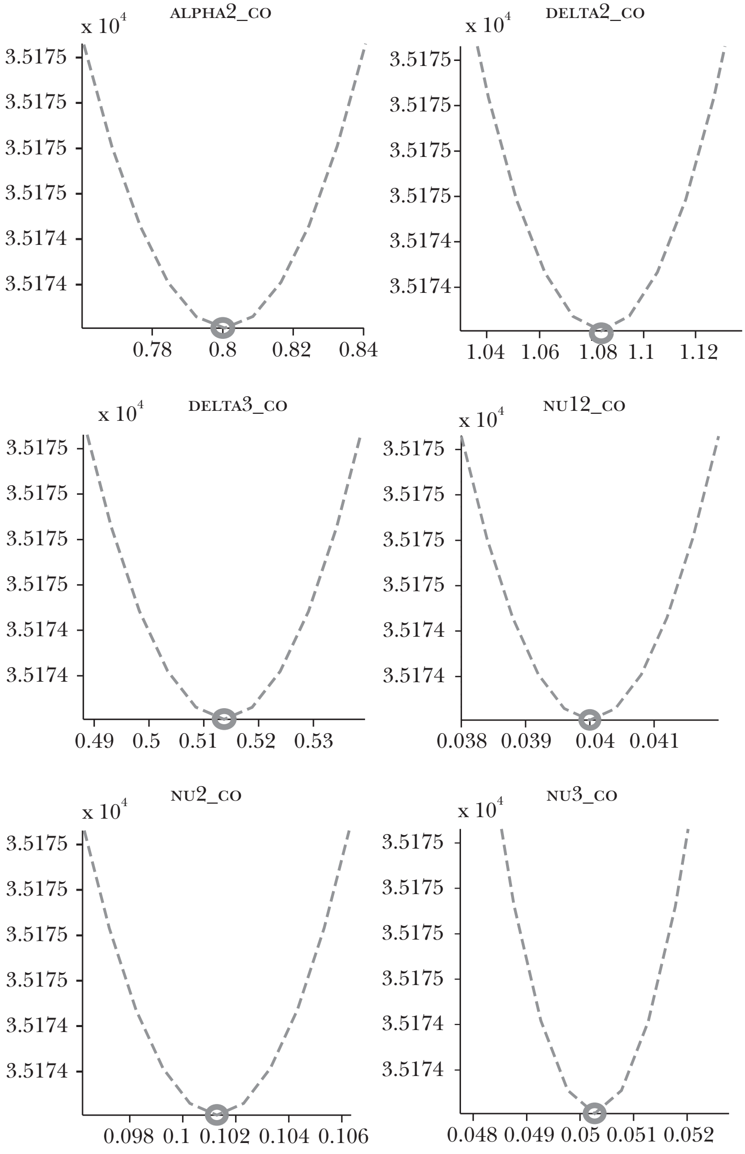
Peak response to a unit shock to the country risk premium (1) and the interest rate (2)



Source: Authors' calculations.

Figure B.2

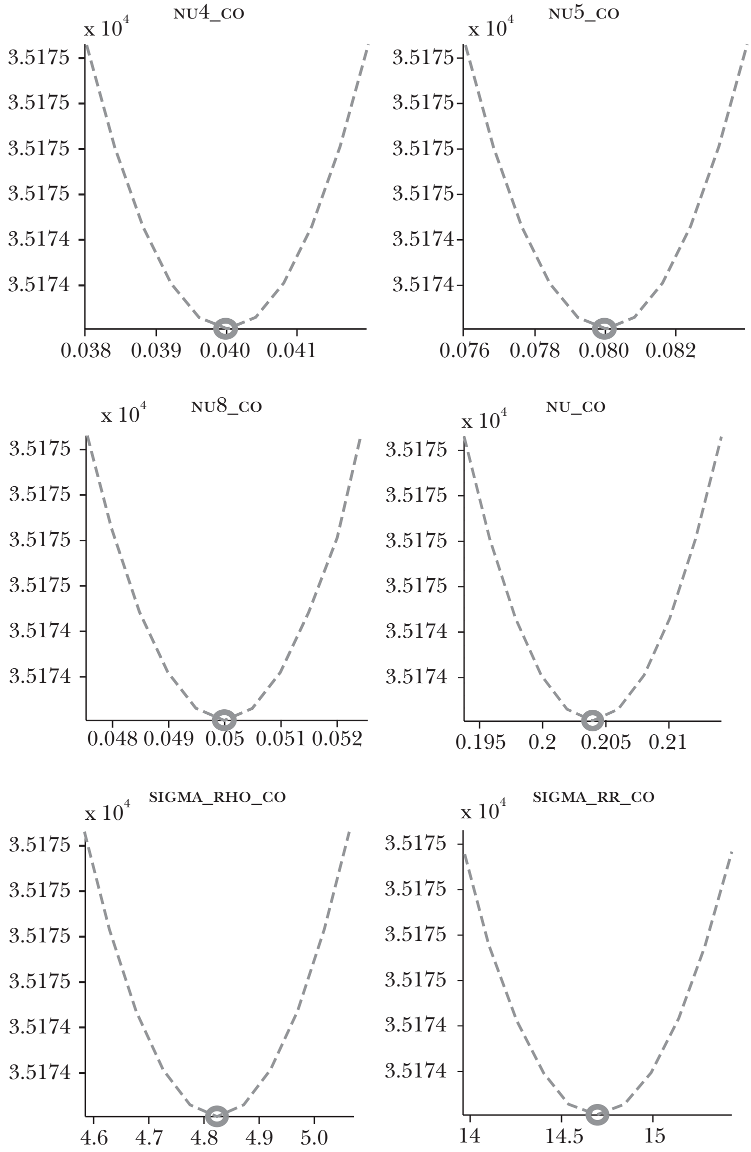
CHECKING CONVERGENCE TO THE MAXIMUM OF THE REGULARIZED LIKELIHOOD FUNCTION



Source: Authors' calculation.

Figure B.2 (cont.)

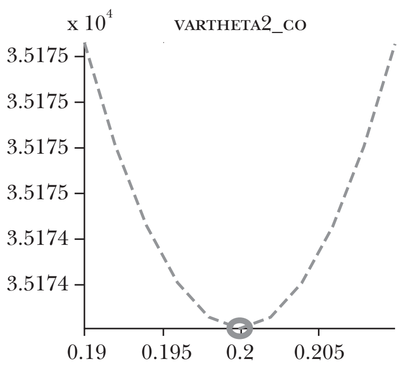
CHECKING CONVERGENCE TO THE MAXIMUM OF THE REGULARIZED LIKELIHOOD FUNCTION



Source: Authors' calculation.

Figure B.2 (cont.)

CHECKING CONVERGENCE TO THE MAXIMUM OF THE REGULARIZED LIKELIHOOD FUNCTION

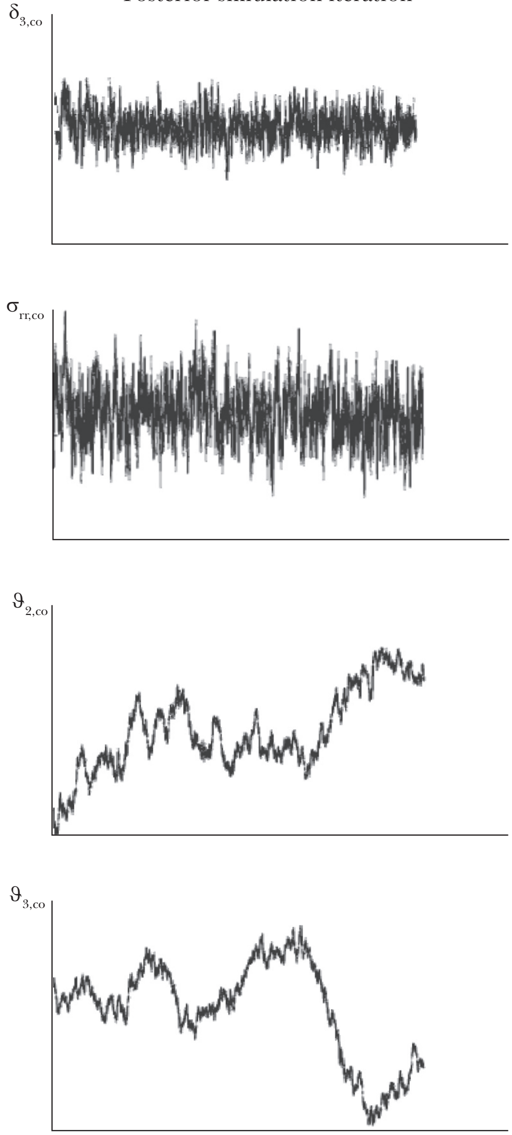


Source: Authors' calculation.

Figure B.3

SIMULATION PATHS OF FOUR SELECTED PARAMETERS

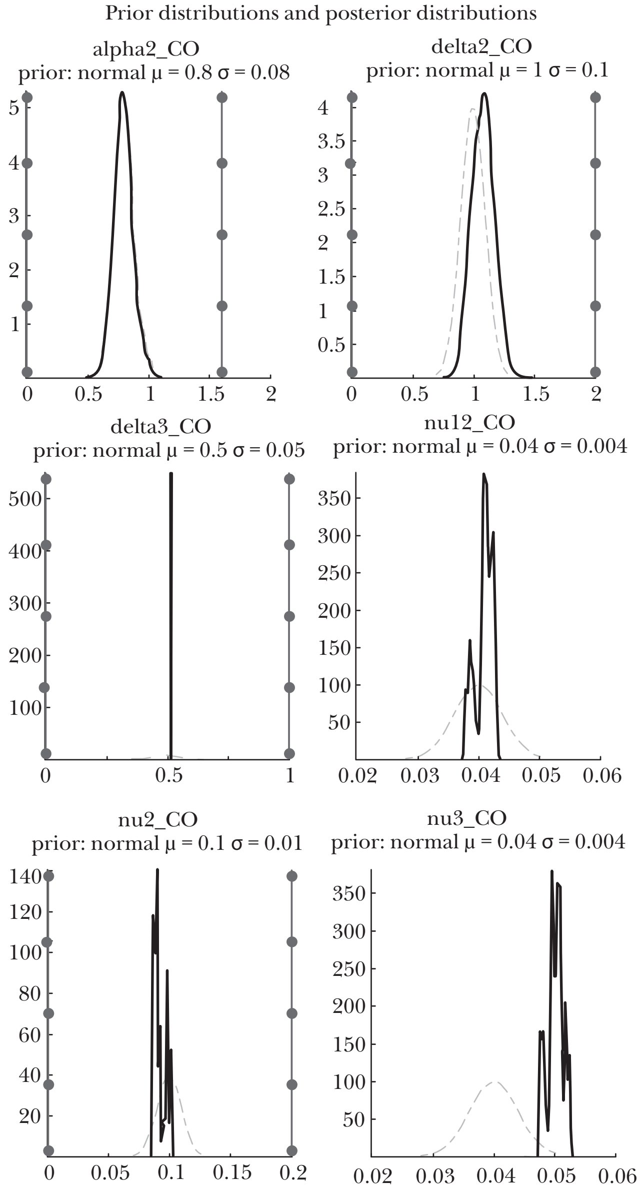
Posterior simulation iteration



Source: Authors' calculation.

Figure B.4

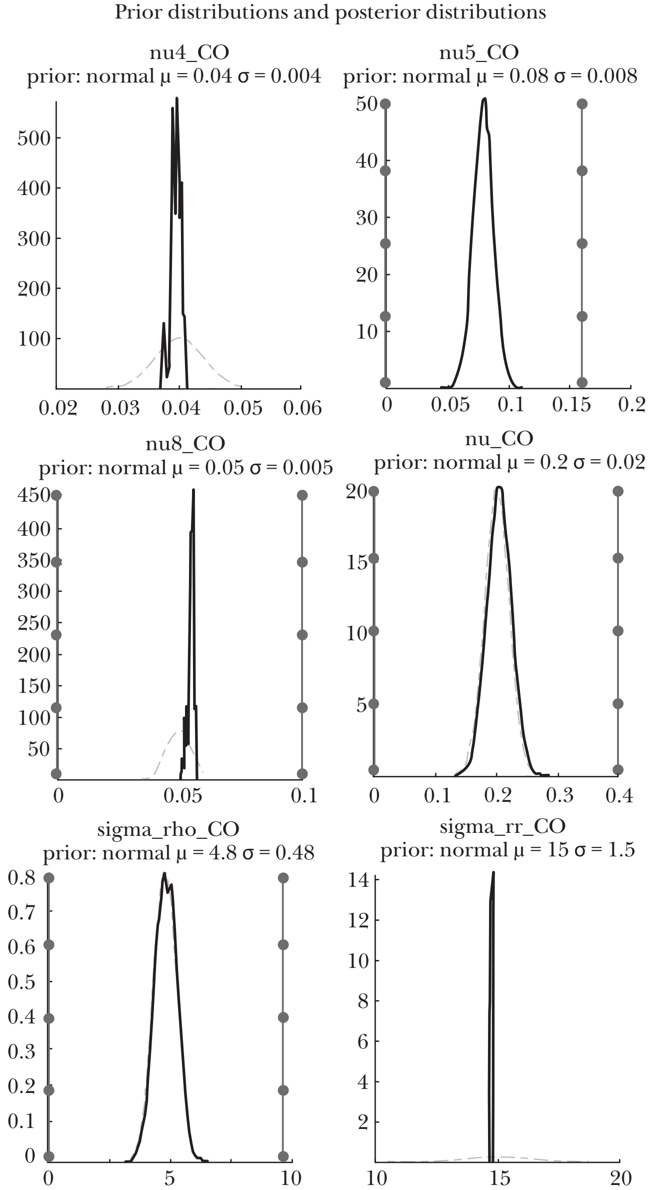
PARAMETERS MARGINAL A-PRIORI AND A-POSTERIORI DENSITIES



Source: Authors' calculations.

Figure B.4 (cont.)

PARAMETERS MARGINAL A-PRIORI AND A-POSTERIORI DENSITIES

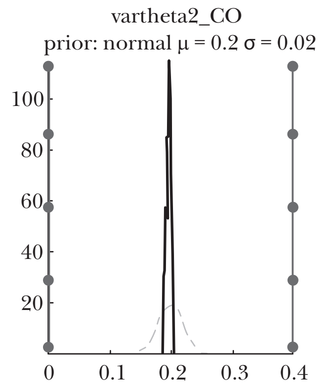


Source: Authors' calculations.

Figure B.4 (cont.)

PARAMETERS MARGINAL A-PRIOR AND A-POSTERIORI DENSITIES

Prior distributions and posterior distributions



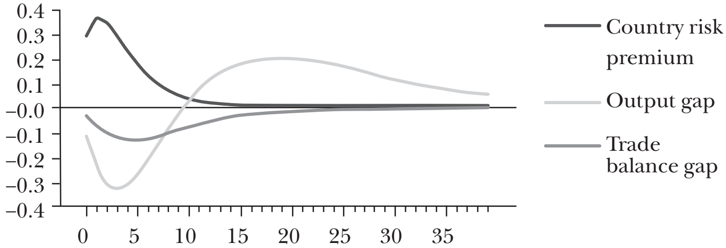
Source: Authors' calculations.

Figure B.5

IMPULSE RESPONSES

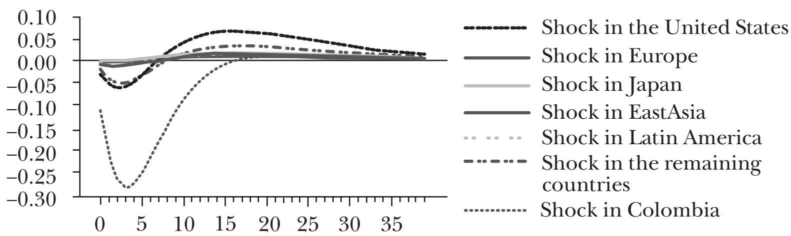
PANEL A

RESPONSE TO A ONE STANDARD DEVIATION SHOCK TO GLOBAL RISK



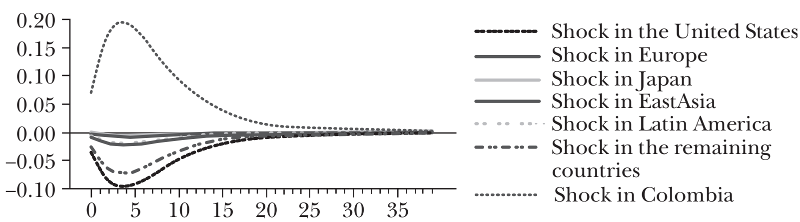
PANEL B: OUTPUT GAP

RESPONSE TO A ONE STANDARD DEVIATION SHOCK TO THE COUNTRY RISK PREMIUM



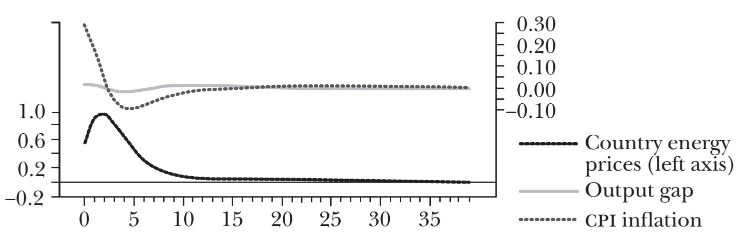
PANEL C: TRADE BALANCE GAP

RESPONSE TO A ONE STANDARD DEVIATION SHOCK TO THE COUNTRY RISK PREMIUM



PANEL D

RESPONSE TO A ONE STANDARD DEVIATION SHOCK TO THE PRICE OF OIL



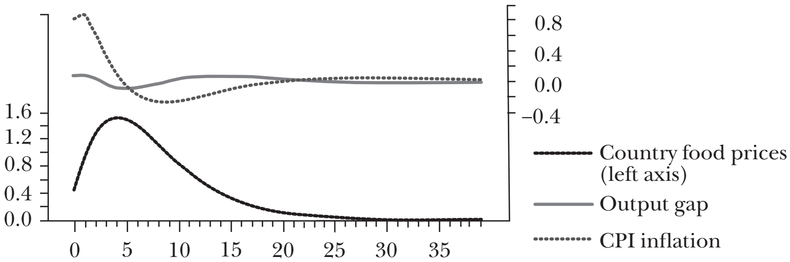
Source: Authors' calculations.

Figure B.5

IMPULSE RESPONSES

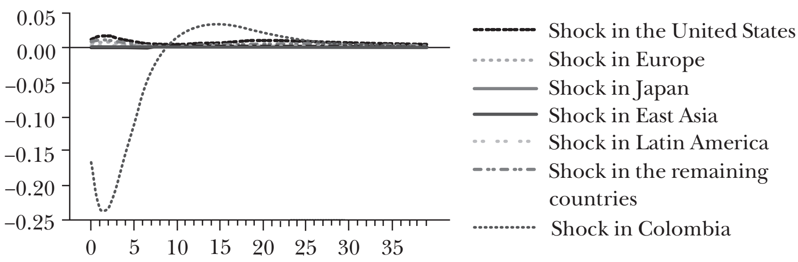
PANEL E

RESPONSE TO A ONE STANDARD DEVIATION SHOCK TO COMMODITY FOOD PRICES



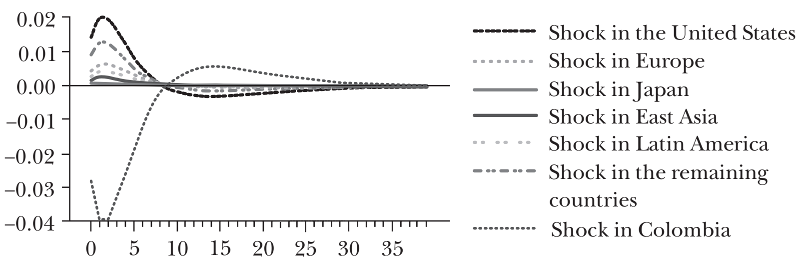
PANEL F: OUTPUT GAP

RESPONSE TO A UNIT SHOCK TO THE INTEREST RATE



PANEL G: TRADE BALANCE GAP

RESPONSE TO A UNIT SHOCK TO THE INTEREST RATE



Source: Authors' calculations.

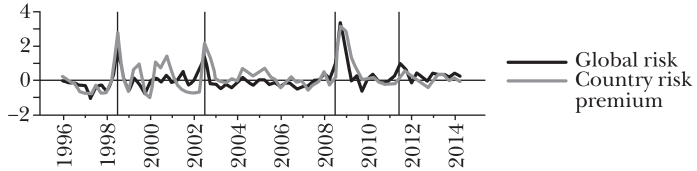
Figure B.6

SMOOTHING RESULTS

PANEL A

GLOBAL RISK AND COUNTRY RISK PREMIUM

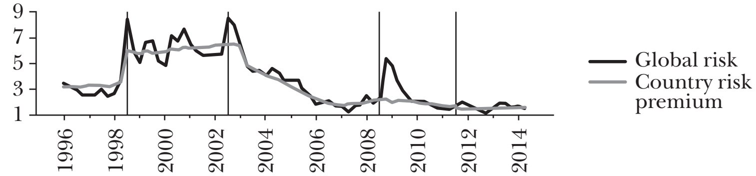
IN PERCENT



PANEL B

COUNTRY RISK PREMIUM AND LATENT COUNTRY RISK PREMIUM

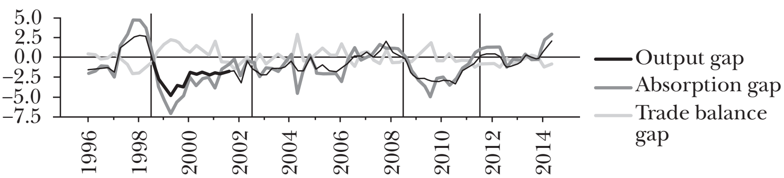
IN DEVIATION FROM LATENT VALUES



PANEL C

OUTPUT, ABSORPTION, AND TRADE BALANCE GAPS

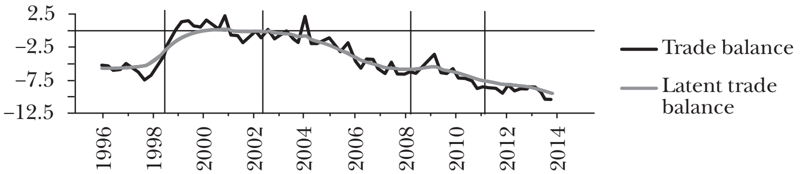
LOG PERCENT DEVIATION FROM LATENT VALUES



PANEL D

THE TRADE BALANCE

LOG PERCENT OF GDP

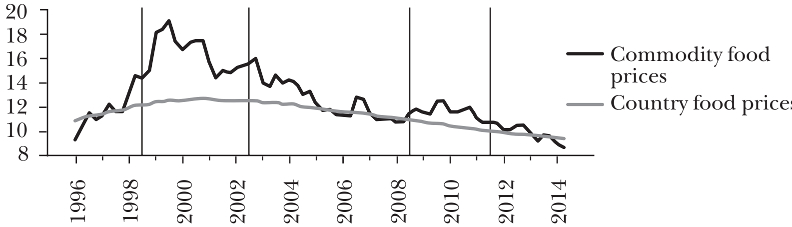


Note: The grid indicates the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the financial crisis, and the eurozone crisis.
Source: Authors' calculations.

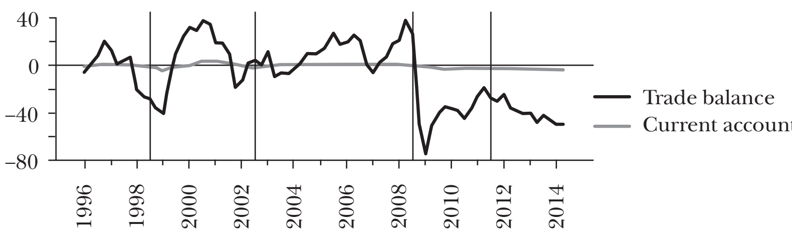
Figure B.6 (cont.)

SMOOTHING RESULTS

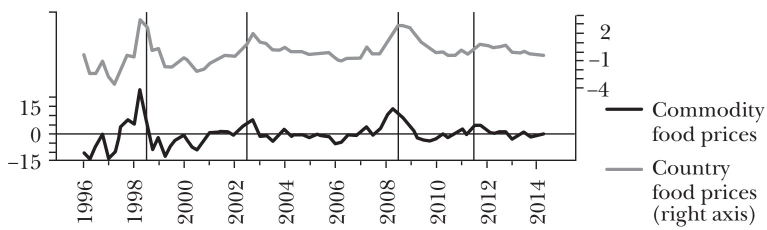
PANEL E
UNEMPLOYMENT AND LATENT UNEMPLOYMENT
PERCENT DEVIATION FROM LATENT VALUES



PANEL F
THE PRICE OF OIL AND COUNTRY ENERGY PRICES
IN PERCENT OF GDP



PANEL G
COMMODITY FOOD PRICES AND COUNTRY FOOD PRICES
PERCENT DEVIATION FROM LATENT VALUES

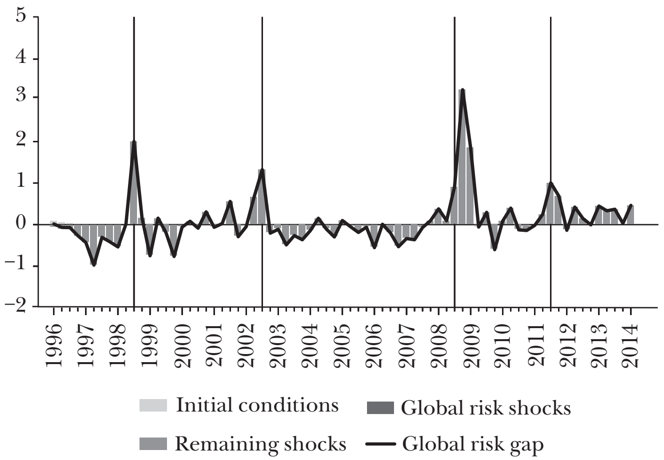


Note: The grid indicates the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the financial crisis, and the eurozone crisis.
Source: Authors' calculations.

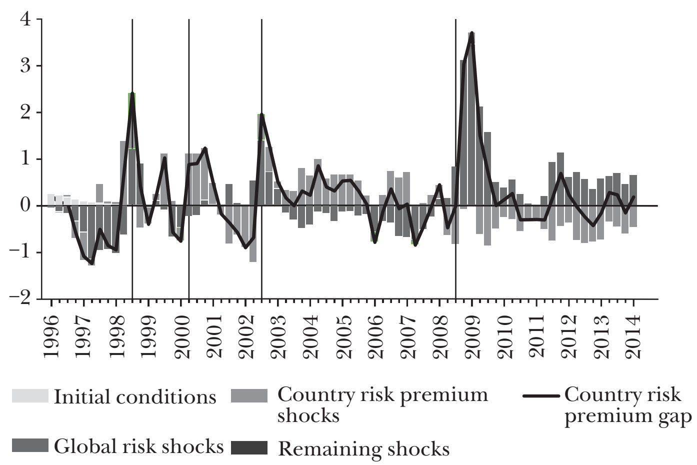
Figure B.7

HISTORICAL DECOMPOSITIONS

PANEL A. WORLD: GLOBAL RISK GAP
HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS



PANEL B. COLOMBIA: COUNTRY RISK PREMIUM GAP
HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS

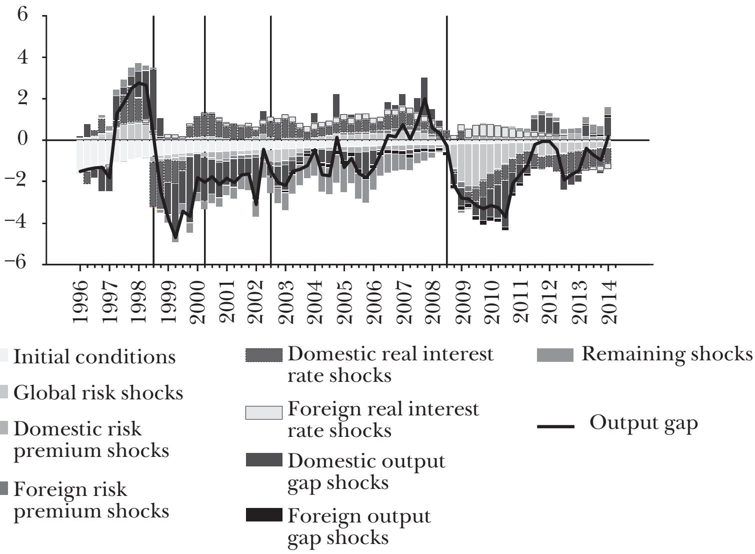


The grid indicates the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the financial crisis, and the eurozone crisis.
Source: Authors' calculation.

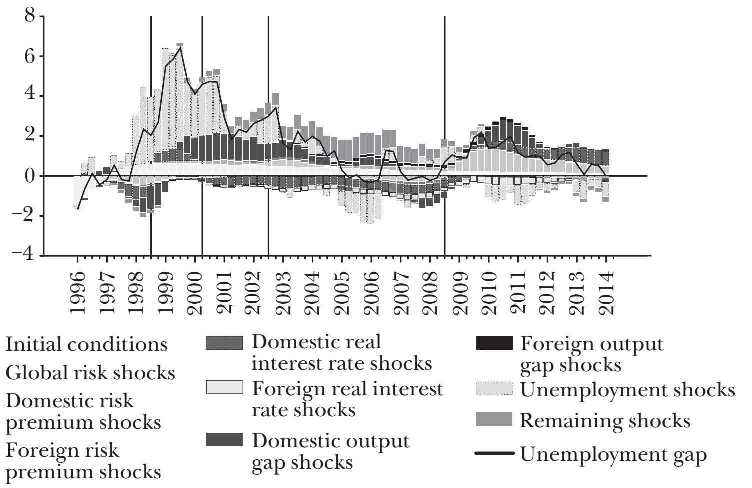
Figure B.7 (cont.)

HISTORICAL DECOMPOSITIONS

PANEL C. OUTPUT GAP
HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS



PANEL D. UNEMPLOYMENT GAP
HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS

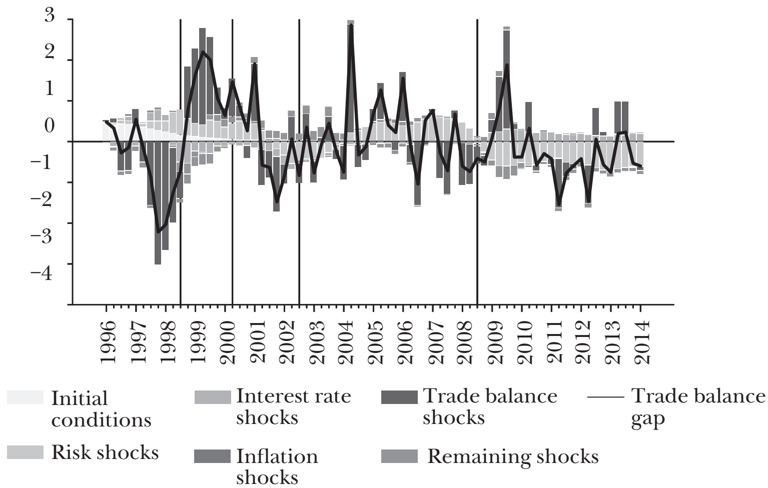


The grid indicates the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the financial crisis, and the eurozone crisis.
Source: Authors' calculation.

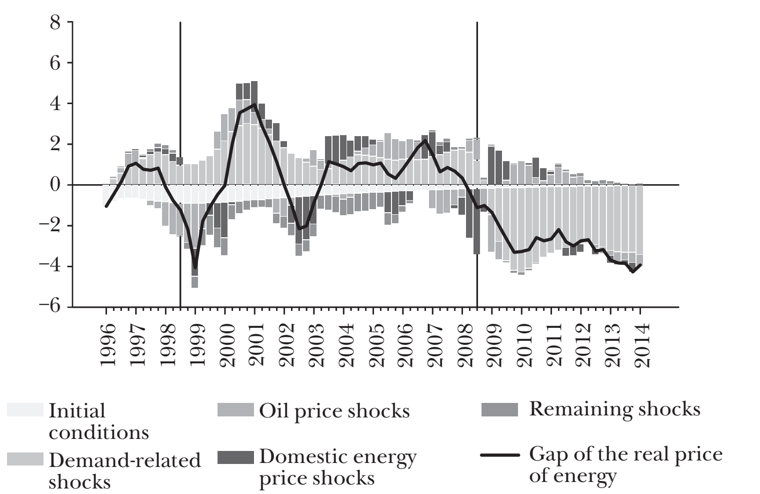
Figure B.7 (cont.)

HISTORICAL DECOMPOSITIONS

PANEL E. TRADE BALANCE GAP
HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS



PANEL F. GAP OF COUNTRY ENERGY PRICES
HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS



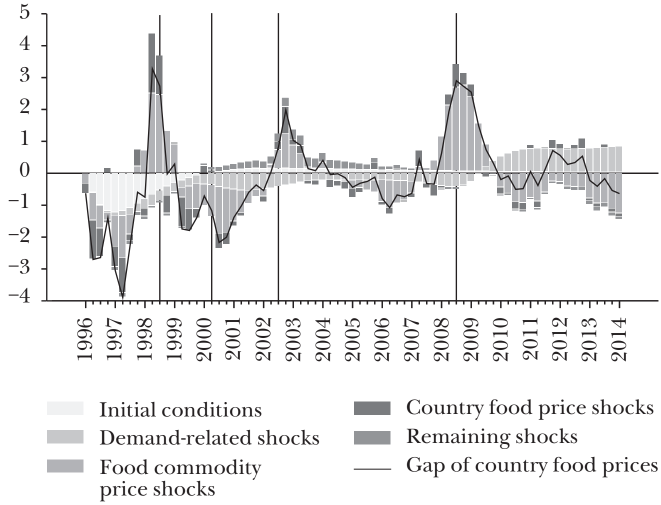
The grid indicates the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the financial crisis, and the eurozone crisis.
Source: Authors' calculation.

Figure B.7 (Cont.)

HISTORICAL DECOMPOSITIONS

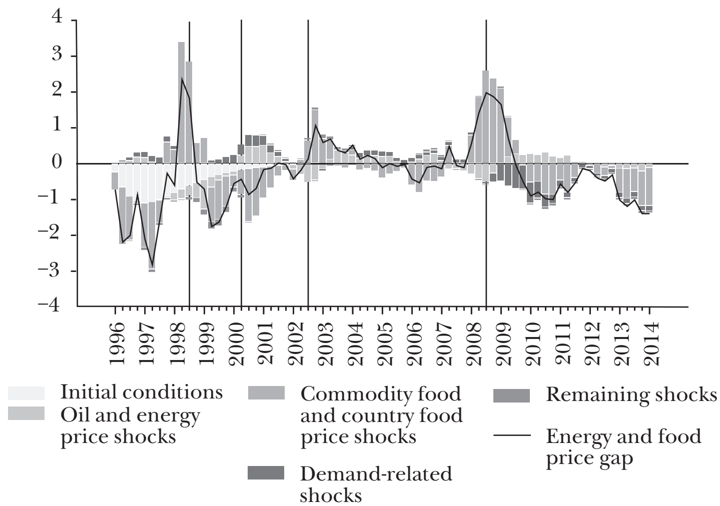
PANEL G. GAP OF COUNTRY FOOD PRICES

HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS



PANEL H. ENERGY AND FOOD PRICE GAP

HISTORICAL DECOMPOSITION INTO PERCENT CONTRIBUTIONS FROM SHOCKS

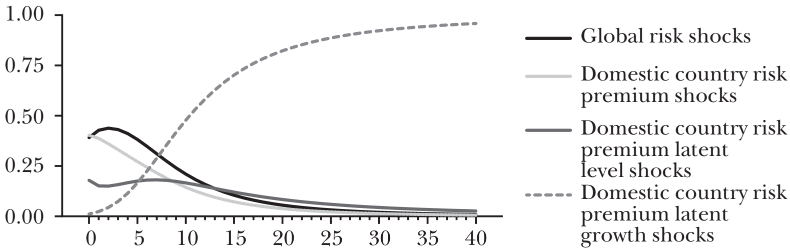


Note: the grid indicates the end of the century crisis, the stock market downturn of 2002, the global financial crisis, and the financial crisis, and the eurozone crisis.
Source: Authors' calculation.

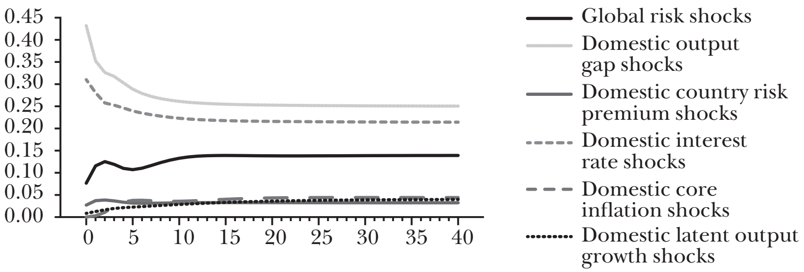
Figure B.8

FORECAST ERROR VARIANCE DECOMPOSITION

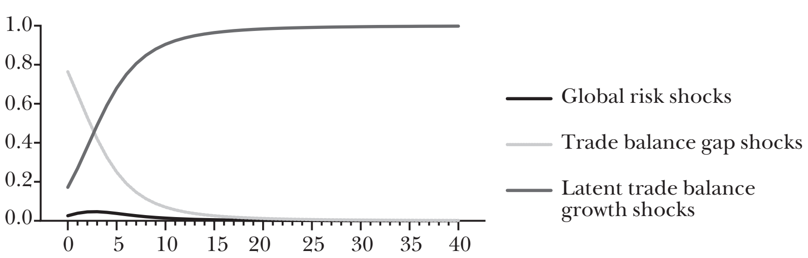
PANEL A. COUNTRY RISK PREMIUM
FORECAST ERROR VARIANCE DECOMPOSITION



PANEL B. OUTPUT GROWTH
FORECAST ERROR VARIANCE DECOMPOSITION



PANEL C. TRADE BALANCE
FORECAST ERROR VARIANCE DECOMPOSITION

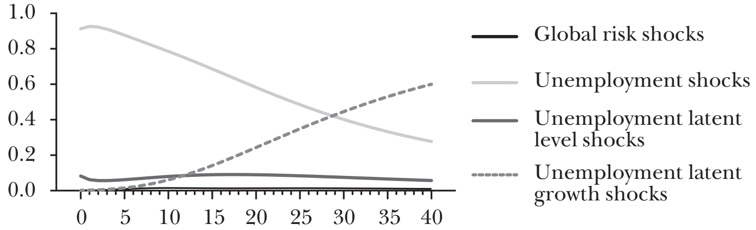


Source: Authors' calculation.

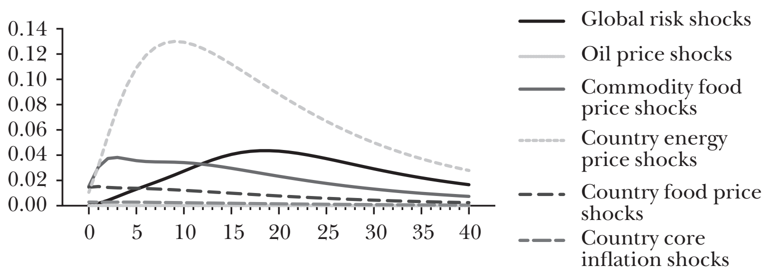
Figure B.8 (cont.)

FORECAST ERROR VARIANCE DECOMPOSITION

PANEL D. UNEMPLOYMENT
FORECAST ERROR VARIANCE DECOMPOSITION



PANEL E. ENERGY AND FOOD PRICE INFLATION
FORECAST ERROR VARIANCE DECOMPOSITION



Source: Authors' calculation.

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