

# Interest Rate Volatility And Macroeconomic Dynamics: A Cross-Country Analysis\*

Michael Curran<sup>†</sup>

Adnan Velic<sup>‡</sup>

Villanova University

Dublin Institute of Technology

October 15, 2017

## Abstract

We examine the relation between real interest rate volatility and aggregate fluctuations for 27 countries. Compiling a new dataset, we find that stochastic volatility outperforms Markov-switching in representing interest rates. Volatility is high and persistent. Internationally, however, we find substantial heterogeneity. While advanced countries are typically less volatile, some advanced economies are more volatile than emerging markets. Volatility increases with the level of spreads, correlating negatively with GDP, consumption and investment. We build and show how an equilibrium business cycle model with uncertainty shocks can generate these facts. Sample heterogeneity plays an important role in distinguishing the effects of volatility shocks.

**Keywords:** interest rates, stochastic volatility, macroeconomic dynamics, general equilibrium models, persistence.

**JEL:** C11, E13, E32, E43, E44, F41

---

\*We thank the Irish Research Council for financial support. We are grateful to Benjamin Born, Jesús Fernández-Villaverde, Philip Lane, Enrique Mendoza, Paul Scanlon, Frank Warnock, and Michael Wycherley for helpful comments and suggestions. A technical appendix can be found at [https://ae9e5d40-a-62cb3a1a-s-sites.googlegroups.com/site/adnvelic/research/Risk\\_App.pdf](https://ae9e5d40-a-62cb3a1a-s-sites.googlegroups.com/site/adnvelic/research/Risk_App.pdf)

<sup>†</sup>Corresponding author. Email: michael.curran@villanova.edu

Address: Economics Department, Villanova School of Business, Villanova University, 800 E Lancaster Ave, PA 19085, USA.

<sup>‡</sup>Email: adnan.velic@dit.ie

Address: College of Business, Dublin Institute of Technology, Aungier Street, Dublin 2, Ireland.

# 1 Introduction

We examine the relation between the volatility of real interest rates and aggregate economic performance for a diverse group of countries. Most research on the causes and consequences of country interest rate spreads focuses on movements in the level of these spreads (Neumeyer and Perri, 2005; Uribe and Yue, 2006; Ardagna *et al.*, 2007; Laubach, 2009; Von Hagen *et al.*, 2011; Favero and Missale, 2012; Mody and Sandri, 2012; Fahr *et al.*, 2013; Eijffinger *et al.*, 2015 ). Expectations concerning the volatility of interest rates are important in managing the debt of a country. It is therefore surprising that few studies explore facts about changes in interest rate volatility.<sup>1</sup>

In the first part of the paper, we compile data on 27 emerging and advanced economies and establish empirical facts on interest rate volatility using a stochastic volatility model. On a country-by-country basis, we conduct time series investigations, finding that the stochastic volatility model better represents time-varying volatility of interest rates than other models such as the discrete Markov-switching model. Our empirical study of sovereign interest rate volatility is the first to compare the performance of these models across countries. Comparing models is important because our results lend credence to the choice of modeling time-varying volatility of interest rates with stochastic volatility.

We find that stochastic volatility shocks to country spreads are large and persistent overall. Across countries, nevertheless, we observe substantial heterogeneity. For example, while emerging markets on average display a higher degree of stochastic volatility than advanced countries, some advanced countries are more volatile than many emerging markets. This result runs contrary to expectations. In particular, volatility can be considerable for some euro area members such as Ireland, but less so for certain emerging economies such as the Philippines. We also observe that volatility increases at higher levels of country spreads, while it correlates negatively with measures of macroeconomic performance such as output, consumption, and investment.

In the second part of our paper, we demonstrate that an equilibrium business cycle model with uncertainty shocks can account for the empirical results. Using the estimates from our empirical stochastic volatility model, we calibrate the process for real interest rates and feed it into an otherwise standard small open economy real business cycle model. Altering interest rate volatility has a quantitatively notable effect on the dynamics of real variables, even when the real interest rate remains constant. In contrast to previous work, we examine heterogeneity across a broad range of countries by relaxing the assumption that the cost of adjusting debt must be identical internationally. That is, the fees households pay to investment banks handling debt differ across countries. As a result, our model benefits from an extra degree of freedom in matching the data. We also update the computational procedures typically adopted in this literature, which leads to faster and more accurate estimation. Sample heterogeneity and improved computation alter results qualitatively. For instance, creditors acquire more debt assets following spread shocks and volatility shocks.

We can interpret higher volatility as capturing heightened uncertainty surrounding future events. Specifically, higher volatility can create financial uncertainty which has significant implications for

---

<sup>1</sup>In broader terms, until the last two decades, macroeconomists paid little attention to the impact of uncertainty and volatility on macroeconomic performance (Hamilton, 2008, p. 2).

business cycle fluctuations (Ludvigson *et al.*, 2015; Baker *et al.*, 2016; Leduc and Liu, 2016). Higher volatility in sovereign debt markets enters our empirical model through a larger variance of shocks to the real interest rate. The study of volatility is particularly relevant for the analysis of crisis episodes and debt sustainability. A better understanding of the implications of volatility should assist policymakers in formulating more effective macroeconomic interventions.

Our work is closest in spirit to that of Fernández-Villaverde *et al.* (2011) and García-Cicco *et al.* (2013).<sup>2</sup> Both of these studies also adopt stochastic volatility models of interest rates and feed the estimates into equilibrium business cycle models. Real interest rate volatility detrimentally affects macroeconomic performance for Argentina, Brazil, Ecuador, and Venezuela (Fernández-Villaverde *et al.*, 2011). Similar results hold for the case of Chile (García-Cicco *et al.*, 2013).

Our study differs from these works in several ways. First, rather than imposing the econometric model, we empirically test which model better represents time-varying volatility of country spreads – a question that has received no attention. We find that the stochastic volatility model outperforms the discrete Markov-switching model. Second, our paper compiles a new dataset on sovereign bond yields that comprises a broader range of countries and a wider time dimension including both the Great Recession and the European sovereign debt crisis. The analysis of a diverse range of advanced and emerging market economies means that our calibration distinguishes between debtor and creditor nations, thus enabling an assessment of the impact of risk on countries facing different international financial positions. Third, we allow countries to face different costs of adjusting debt. This yields an extra degree of freedom in matching model moments with those of the data. While analyzing relatively homogenous countries can produce qualitatively identical results, our sample heterogeneity distinguishes between the various effects of volatility shocks. Fourth, we update the computational methods. By doing so, we ultimately switch the signs of certain results. For instance, creditors now accumulate debt assets with spread and volatility shocks.

On computation, our paper benefits from recommendations proposed by Born and Pfeifer (2014). To further improve computational accuracy, we also apply new results on third-order “pruning” for state-space models and compute “generalized” impulse response functions at the true “ergodic” mean (Andreasen *et al.*, forthcoming). Moreover, we proceed a few steps further. Our paper employs “shell scripting” and exploits advances in high-performance computing which augment the efficiency with which computationally-intensive tasks are executed. With many repeated experiments, scripts enable the automation of labor intensive tasks. Scripts are useful in international macroeconomics since the cross-section dimension is normally large (Lane and Milesi-Ferretti, 2007) and issues can be specific to particular countries and different experiments. Consequently, we develop multiple scripts that make use of “algorithmic parallelism” across CPUs and clusters of computers.

Our paper assumes that real interest rate volatility is exogenous. To a large extent, interest rate volatility shocks can be viewed as being mostly exogenous to the country. For instance, events in Greece and Italy may affect interest rates on Belgian debt through regime uncertainty. By assuming exogenous volatility shocks, we follow the tradition of exogenous shocks to productivity (Kydland and Prescott, 1982), terms of trade (Mendoza, 1995), and country spreads (Neumeayer and Perri, 2005). The objective of our paper is not to explain *why* real interest rate volatility changes over

---

<sup>2</sup>On computation, Born and Pfeifer (2014) discuss technical issues arising from earlier work on this subject.

time, but rather *how* it changes. Longstaff *et al.* (2011) justify the empirical strategy of adopting an exogenous volatility process for real interest rate spreads on sovereign debt. The authors examine credit default swaps for sovereign debt across 26 economies and find that country spreads are driven much more by forces exogenous to the nation, such as global financial market variables and global risk premia, than by local forces. In a panel VAR study for 7 developing nations, Uribe and Yue (2006) show that innovations exogenous to domestic conditions account for at least two-thirds of movements in country spreads. In addition, the finance literature suggests that over 90 percent of spread movements in emerging markets can be ascribed to volatility shocks in the S&P 500.

The remainder of the paper is organized as follows. In Section 2, we empirically examine the dynamics of real interest rates. In Section 3, we estimate an equilibrium business cycle model augmented with stochastic volatility shocks, providing simulation results on the impact of interest rate volatility on macroeconomic outcomes. Section 4 contains additional experiments and sensitivity checks to investigate the mechanisms behind the results. Conclusions are summarized in Section 5.

## 2 Empirical Analysis of Real Interest Rates

In this section we first outline the data and methodology used to empirically examine real interest rates across countries. Subsequently, we discuss our findings.

### 2.1 Data

We consider two groups of countries based on interest rate availability: (i) 15 emerging markets using JP Morgan’s EMBI+ stripped spread (EMBIP) and (ii) 12 euro area members (EA). We list the countries together with the periods and types of bonds covered in table 1. Coverage depends on the availability of pricing data, international risk-free rates and country spreads. Periods start as early as 1993.12 for some countries. All periods end 2013.02. The effects of transition from centrally planned economies to market economies rule out a few years of data in the 1990s for some countries.

All bond maturities exceed one year and most bonds have a typical maturity of 10 years. We use monthly data as quarterly data smooth out too much of the volatility. We retrieve bond yields from Datastream. These data are available at daily frequencies and are converted to monthly figures by taking the end of period value.<sup>3</sup> Following a similar method to Fernández-Villaverde *et al.* (2011), we express the real interest rate at which countries borrow internationally as the sum of a real country spread and a real international risk free rate. We calculate the nominal country spread as the difference between the nominal yield on an EMBI+ or a sovereign bond and the nominal yield on a comparable international risk-free bond. We obtain real rates by adjusting for expected inflation. For emerging markets the international risk-free rate is given by the yield on the U.S. T-Bill (RINTEMBIP). For euro area members the international risk-free rate is given by the yield on the German Bund (GermanyRINT). Lastly, we source data on quarterly output, consumption and investment from the IMF’s IFS repository. In turn, we linearly interpolate corresponding monthly data to examine the relation between interest rate volatility and macroeconomic dynamics.<sup>4</sup>

<sup>3</sup>Taking the average during the month instead does not alter our findings.

<sup>4</sup>Alternative interpolation procedures, such as cubic spline approximations, do not significantly alter our results.

## 2.2 A Stochastic Volatility Model

Stochastic volatility models typically specify an autoregressive (AR) process for the logarithm of volatility, defining volatility as the standard deviation. Consistent with [Fernández-Villaverde \*et al.\* \(2011\)](#), we focus on a univariate stochastic volatility model in which country spreads and log volatility each follow an AR(1) process with drift. In the macroeconomic literature, other popular models of time-varying volatility include GARCH and Markov-switching models.<sup>5</sup> Level and volatility shocks cannot be isolated in the GARCH class of models as one shock drives both the level and volatility of interest rates. The choice between stochastic volatility and Markov-switching models is an empirical question as there are theoretical advantages and disadvantages to using each over the other. A review of the literature reveals that no study has considered this issue in the context of representing time-varying volatility for country spreads. Appealing to Bayesian log posterior odds, our stochastic volatility model outperforms a similar Markov-switching model in the data.<sup>6</sup>

As implied, we conduct exercises country-by-country. We decompose the real interest rate of a country at time  $t$  into the average real interest rate of the country over time,  $r$ , a time-demeaned country spread,  $\epsilon_{r,t}$ , and a time-demeaned international risk-free real rate,  $\epsilon_{tb,t}$ . So,

$$r_t = r + \epsilon_{r,t} + \epsilon_{tb,t}. \quad (1)$$

Let  $\{u_{i,t}\}_{i \in \{r,tb\}}$  and  $\{u_{\sigma_i,t}\}_{i \in \{r,tb\}}$  be standard Normal innovations. The innovation  $u_{\sigma_i,t}$  is called the stochastic volatility shock. The parameter  $\rho_i$  is the degree of persistence in the interest rate level, while  $\rho_{\sigma_i}$  is the degree of persistence in volatility. The parameter  $\sigma_i$  is the mean volatility and  $\eta_i$  influences the degree of stochastic volatility. The laws of motion for  $\epsilon_{r,t}$  and  $\epsilon_{tb,t}$  are

$$\epsilon_{r,t} = \rho_r \epsilon_{r,t-1} + e^{\sigma_{r,t}} u_{r,t}, \quad (2)$$

$$\epsilon_{tb,t} = \rho_{tb} \epsilon_{tb,t-1} + e^{\sigma_{tb,t}} u_{tb,t}, \quad (3)$$

$$\sigma_{r,t} = (1 - \rho_{\sigma_r}) \sigma_r + \rho_{\sigma_r} \sigma_{r,t-1} + \eta_r u_{\sigma_r,t}, \quad (4)$$

$$\sigma_{tb,t} = (1 - \rho_{\sigma_{tb}}) \sigma_{tb} + \rho_{\sigma_{tb}} \sigma_{tb,t-1} + \eta_{tb} u_{\sigma_{tb},t}. \quad (5)$$

Equations (2) and (4) describe the process for country spreads, while equations (3) and (5) describe the process for the real international risk-free rate.<sup>7</sup> Two shocks,  $u_{i,t}$  and  $u_{\sigma_i,t}$  hit  $\epsilon_{i,t}$ . The innovation  $u_{i,t}$  affects the level of the rate in question and the innovation  $u_{\sigma_i,t}$  affects the standard deviation of  $u_{i,t}$ . In the baseline version of the model, innovations to the level of the series,  $u_{i,t}$ , are independent to innovations to the volatility of the series,  $u_{\sigma_i,t}$ . That is, for each  $i \in \{r, tb\}$  and for each  $j \in \{r, tb\}$ ,  $u_{i,t}$  is independent of  $u_{\sigma_j,t}$ . Since country spread levels might be correlated with volatility, we also estimate the model under a correlation between  $u_{r,t}$  and  $u_{\sigma_r,t}$ .

We estimate our model using Bayesian techniques. Our estimation employs the bootstrap particle filter, which we nest within the Metropolis-Hastings algorithm. The estimates are subsequently fed into a DSGE model in the second part of our paper. Table 2 displays the priors employed. These priors are in line with [Fernández-Villaverde \*et al.\* \(2011\)](#).<sup>8</sup>

<sup>5</sup>We focus on parametric models since we feed parametric estimates into a DSGE model.

<sup>6</sup>Results are available in Section 4 of the [online appendix](#).

<sup>7</sup>With the international risk-free rate, we estimate one process for emerging markets and one for advanced nations.

<sup>8</sup>See [Fernández-Villaverde \*et al.\* \(2011, p. 2537-8\)](#) for a discussion on prior elicitation reflecting conservative choices.

## 2.3 Results

While we observe a non-negligible degree of heterogeneity in empirical results across countries, our analysis reveals a number of general patterns in the data. *First*, standard deviations of innovations to country spreads are large. *Second*, stochastic volatility of country spreads is substantial. *Third*, country spread levels and country spread volatility are highly persistent. *Fourth*, corresponding parameters for the real international risk-free rates are smaller in magnitude. *Fifth*, results are relatively robust to subsample analysis, in particular to the global financial crisis post September 2008. Results are also relatively robust to alternative selections of Bayesian priors for the parameters underlying the stochastic volatility processes. *Sixth*, contemporaneous correlations between country spread volatility and deviations of output, consumption and investment from respective trends reveal negative links. *Seventh*, country spread levels and volatilities are highly positively correlated.

We next discuss each of these results in detail. Tables 3-4 report the medians of the posteriors of the model parameters across countries and the corresponding 95 percent probability sets. In the benchmark model, the level and volatility of interest rates are uncorrelated. Table 3 displays the benchmark results. Table 4 provides results under a positive correlation between the level and volatility of country spreads. We refer to benchmark results unless otherwise noted.

### 2.3.1 Average Standard Deviation of Innovations to Country Spreads

The average standard deviation of an innovation to country spreads  $\sigma_r$  is generally large, although it varies across samples. In particular,  $\sigma_r$  is small for most non-peripheral members of the euro area. With the exception of peripheral euro area economies, especially Greece, on average  $\sigma_r$  is higher for emerging markets than for euro area countries. The parameter (in logs) ranges from  $-8.4$  in South Africa to  $-6.1$  and  $-6.0$  in Russia and Argentina versus  $-9.8$  in the Netherlands to  $-7.4$  and  $-6.4$  in Portugal and Greece. Given the sample periods, this is the distribution that one might expect for these countries. The numbers are indicative of a large degree of volatility in country spread data, though less than that in the four-country study of Fernández-Villaverde *et al.* (2011). In addition, our findings reveal heterogeneity in the degree of volatility in country spread data.

### 2.3.2 Stochastic Volatility and Concentration of 95 Percent Sets

Examining the 95 percent posterior probability sets, apart from the parameter governing the degree of stochastic volatility  $\eta_r$ , we witness mostly tightly concentrated posteriors. With the exception of the Philippines, which has a lower  $\eta_r$ , country spreads display a substantial presence of stochastic volatility (large  $\eta_r$ ). Notably the degree of  $\eta_r$  differs greatly across countries. While on average  $\eta_r$  is higher in emerging markets than the euro area, it is substantial for some euro area members, such as Greece, Finland and Slovenia. We note, however, that the sample period for Slovenia is shorter, which significantly magnifies its standard deviation and hence its probability set.

### 2.3.3 Persistence of Levels and Volatility

For the most part, interest rate levels and corresponding volatilities are persistent (large  $\rho_r$  and  $\rho_{\sigma_r}$ ). The standard deviations of the posterior of  $\rho_r$  are small (95 percent probability sets mostly lie

above approximately 0.9), while those for  $\rho_{\sigma_r}$  are larger. So, posterior medians for  $\rho_{\sigma_r}$  take a wider range of values. Most of these medians, nevertheless, are over 0.9, and even at the 2.5<sup>th</sup> percentile the persistence of the process is in range of 0.52 to 0.99 across countries. The typical posterior medians for  $\rho_r$  and  $\rho_{\sigma_r}$  across the full sample of countries are both 0.95, implying a half-life of about 14 months. Typical medians for  $\rho_r$  and  $\rho_{\sigma_r}$  in the euro area are 0.95 and 0.97, while the typical values in emerging markets are 0.95 and 0.93. The smaller value of 0.93 implies a half-life of about 10 months, while the bigger value of 0.97 implies a half-life of about 23 months.

### 2.3.4 Real International Risk-Free Rate and Country-Specific Interpretations

Relative to the real Bund (GermanyRINT), our risk-free rate for euro area members, all peripheral euro area countries exhibit more persistence in country spreads and volatility,  $\rho_r$  and  $\rho_{\sigma_r}$ . The spreads of these countries are also characterized by higher average volatility  $\sigma_r$  and stochastic volatility  $\eta_r$ . As for emerging markets, South Africa stands alone in displaying lower average volatility  $\sigma_r$  than that observed for the real U.S. T-Bill (RINTEMBIP), our international risk-free asset for the emerging sample. Meanwhile, compared to the real U.S. T-Bill, most nations have less persistent country spreads and volatility,  $\rho_r$  and  $\rho_{\sigma_r}$ , but higher degrees of stochastic volatility  $\eta_r$ .

Taking a country-specific approach to interpreting the results, let us consider Bulgaria and Spain. These economies represent median countries in their respective groups (emerging and euro area samples) with regard to the effects of standard deviation shocks to country spread levels and volatilities. Examining Bulgaria the posterior median of  $\sigma_r$  implies that an innovation to the spread has an average (annualized) standard deviation of  $120,000 \times \exp(\sigma_r) \approx 111$  basis points. We apply the loading factor of 120,000 to transform  $\sigma_r$  into annualized basis points. A one standard deviation positive volatility shock multiplies the standard deviation of the innovation to the spread by a factor of  $\exp(\eta_r) \approx 1.28$ . So, if both the level and volatility of spreads experienced positive shocks the Bulgarian spread would jump by  $120,000 \times \exp(\sigma_r + \eta_r) \approx 142$  points. In comparison, more volatile countries such as Ecuador and Russia have numbers that are as high as 253 and 363 points.

Focusing on Spain, one of the six euro area peripheral countries along with Cyprus, Greece, Ireland, Italy and Portugal, the posterior median of  $\sigma_r$  implies that the innovation to the spread has an average (annualized) standard deviation of 40 basis points. A one standard deviation positive volatility shock multiplies the standard deviation of the innovation to the spread by a factor of 1.17. Therefore, if both the level and volatility of spreads experienced simultaneous positive shocks, the Spanish spread would jump by 47 basis points. In comparison the corresponding figure is 94 basis points for Portugal, which is one of the most volatile countries in the euro area sample.

### 2.3.5 The Global Financial Crisis and Prior Sensitivity

Conducting further checks, we re-estimate the model for samples using data (i) up to 2008.08 ('PreSept08') and (ii) from 2008.09 to 2013.02 ('PostSept08').<sup>9</sup> 2008.08 is a good cut-off date for a

---

<sup>9</sup>When looking at different samples, for instance before September 2008 (pre-crisis), priors must be altered.

pre-crisis sample since spreads seem to increase around that month internationally.<sup>10</sup> Tables with the posterior medians from these estimations are available in Section 3.2 of the [technical appendix](#). As expected the 95 percent probability sets are wider for the PostSept08 samples as they have fewer observations.<sup>11</sup> Spreads for most euro area countries are more volatile on average since 2008.08 ( $\sigma_r$  rose), whereas the opposite appears to be true for many emerging countries. After 2008.08, stochastic volatility  $\eta_r$  rises in most countries. Some countries display more persistence in spreads  $\rho_r$  before 2008.08, while some display more persistence in spreads after 2008.08. Persistence in volatility  $\rho_{\sigma_r}$  increases in some countries since 2008.08, but declines in other countries.

In robustness checks, we loosen the priors for the means and standard deviations of  $\rho_r$  and  $\rho_{\sigma_r}$  to (0.5,0.1) and (0.5,0.2). In addition, we examine the effects of loosening the mean of the prior for  $\eta_r$  from 0.5 to 0.25 (less volatile). We re-estimate the model with this looser prior for  $\eta_r$  in combination with the looser priors for the means and standard deviations of  $\rho_r$  and  $\rho_{\sigma_r}$ . Tables with the posterior medians from these estimations are available in Section 3.2 of the [supplementary appendix](#). In particular, instead of  $\rho_r \sim \mathcal{B}(0.9, 0.02)$ ,  $\rho_{\sigma_r} \sim \mathcal{B}(0.9, 0.1)$  and  $\eta_r \sim \mathcal{N}^+(0.5, 0.3)$ , we have  $\rho_r \sim \mathcal{B}(0.5, 0.1)$ ,  $\rho_{\sigma_r} \sim \mathcal{B}(0.5, 0.2)$  and  $\eta_r \sim \mathcal{N}^+(0.25, 0.3)$ . Results are robust, although with looser priors for  $\rho_r$  and  $\rho_{\sigma_r}$ ,  $\rho_{\sigma_r}$  tends to be lower, i.e. volatility tends to be marginally less persistent. Likewise with looser priors for  $\eta_r$ , posterior medians for  $\eta_r$  tend to be lower. Both of these marginally ‘lower’ results arise from changing the means of priors for  $\rho_{\sigma_r}$  and  $\eta_r$  from 0.9 and 0.5 to 0.5 and 0.25. With looser priors for  $\rho_r$  and  $\rho_{\sigma_r}$ ,  $\eta_r$  appears to be higher, so there tends to be a stronger degree of stochastic volatility (occurs when we retain the higher mean prior for  $\eta_r$  of 0.5). Results are also relatively robust to loosening  $\rho_r$ ,  $\rho_{\sigma_r}$  and  $\eta_r$  simultaneously, although medians for  $\rho_{\sigma_r}$  are lower while medians for  $\eta_r$  are higher across countries in this case.

### 2.3.6 Countercyclical Country Spread Volatility

In section 5 of the [technical appendix](#), we plot country spread volatility against indicators of aggregate economic activity. To plot volatility  $\sigma_{r,t}$ , which is a latent variable, we require a smoother. The fixed-interval smoother we employ is a forward-filtering backward-smoothing algorithm based on [Godsill \*et al.\* \(2004\)](#) and [Fernández-Villaverde and Rubio-Ramírez \(2007\)](#). In our discussion, we refer to the average smoothed volatility conditional on the median of the posterior of the parameters as *country spread volatility*. We plot seasonally-adjusted (X-12 ARIMA), Hodrick-Prescott detrended, linearly interpolated real GDP (output) against country spread volatility. Similarly, we also graph consumption against volatility and investment against volatility over the sample period. Volatility correlates negatively with business cycle fluctuations, consistent with the notion that greater uncertainty has an adverse impact on economic activity.

Section 5 of the [technical appendix](#) contains plots of country spreads against detrended (HP filtered), seasonally adjusted macro aggregates such as output, consumption, investment and the trade balance. The median Pearson correlations in these four cases are  $-0.13$ ,  $-0.06$ ,  $-0.13$  and  $0.07$ .

<sup>10</sup>The VIX implied volatility of the S&P 500 index options spikes in September 2008, along with many other interest rates such as corporate rates. The median correlation between our measures of country spread volatility and the VIX is 0.36; the lower and upper quartiles for this correlation are 0.25 and 0.69 over 27 economies.

<sup>11</sup>Only a few years of monthly data are available before September 2008 for Indonesia, Malta and Slovenia, so their posterior 95 percent sets are tighter for PostSept08 samples than for PreSept08 samples.



Figures displaying macro aggregates against smoothed country spread volatility are also included in Section 5 of the [supplementary appendix](#). Corresponding median Pearson correlations are  $-0.27$ ,  $-0.2$ ,  $-0.18$  and  $0.07$ . Other than the trade balance, there tends to be a negative correlation between macro aggregates and country-spread levels, and a negative correlation between macro aggregates and country-spread volatility. Times of higher country spread volatility generally coincide with times of weaker macroeconomic performance and declining debt. To rationalize declining debt with higher interest rate spreads and volatility, first observe that the trade balance correlates positively with both interest rate spreads and their volatility. Trade surpluses export excess savings of a country, for instance an increase in foreign debt asset purchases relative to foreign debt liabilities.<sup>12</sup> These empirical results serve to further motivate the quantitative exploration in this paper.

### 2.3.7 Country Spread Levels vs. Country Spread Volatilities

We also plot country spreads levels against volatilities in section 5 of the [technical appendix](#). The graphs reveal a positive correlation between the two variables. So, when the country spread is high the country spread volatility is also high and *vice-versa*. This finding suggests that the assumption of a zero correlation between innovations to the country spread and innovations to the volatility of the spread should be relaxed.

In the baseline case,  $u_{tb,t}$ ,  $u_{r,t}$ ,  $u_{\sigma_{tb,t}}$  and  $u_{\sigma_r,t}$  are all independent of each other. While in the data  $u_{tb,t}$  and  $u_{r,t}$  are uncorrelated,  $u_{i,t}$  and  $u_{\sigma_{i,t}}$ ,  $i \in \{r, tb\}$  are correlated. We therefore re-estimate with a model that incorporates this correlation. To correct for the correlation, we assume innovations come from a multivariate normal distribution

$$\begin{pmatrix} u_{i,t} \\ u_{\sigma_{i,t}} \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \kappa \\ \kappa & 1 \end{pmatrix} \right) \quad (6)$$

in which  $i \in \{r, tb\}$  and  $\kappa$  is a parameter controlling the degree of correlation, i.e. the size of the leverage effect of the observed level shocks on the log volatility shocks. We also assume a uniform prior for  $\kappa \in (-1, 1)$ , expressing our prior view that any correlation is equally likely.

Table 4 presents the results from the more elaborate model. For each country the medians of the posteriors of the parameters  $\rho_r$ ,  $\sigma_r$ ,  $\rho_{\sigma_r}$  and  $\eta_r$  in the augmented model are similar to those values yielded in the benchmark model. Overall the correlation parameter  $\kappa$  tends to be rather high for country spreads, but it still exhibits a non-negligible degree of heterogeneity across countries. Apart from Finland, France and the Netherlands,  $\kappa$  is between 0.47 for Malta and 0.99 for Peru. Moreover, correlations are generally higher for emerging markets. Consequently, level and volatility innovations move and affect the economy in the same direction in causal analyses. Keeping the zero correlation case as the benchmark, nevertheless, we can still *isolate* the direct effects of changes in volatility while holding the level of interest rates constant.

<sup>12</sup>Using external debt and GDP data from the External Wealth of Nations dataset up to 2011, we plot country spread volatility against debt and the ratio of debt to GDP in section 5.1 of the [online appendix](#), where we define net foreign debt as debt liabilities net of debt assets. There are mixed results for signs and significance of correlations with interpolated debt (11 from 27 were statistically significantly positive, while 3 from 27 were statistically significantly negative), while all 14 of 27 correlations with interpolated debt-to-GDP are statistically significantly positive. With respect to debt and volatility, only one sample displayed significant correlation, which was negative, while for debt-to-GDP and volatility, two samples had a statistically significant correlation, which was positive in both cases.

### 3 A Quantitative-Theoretical Analysis

In this section we briefly present a real business cycle small open economy model augmented with stochastic volatility in country spreads and real international risk-free rates à la [Fernández-Villaverde \*et al.\* \(2011\)](#). Subsequently, we employ econometric estimates from Section 2 to examine the quantitative implications of our theoretical model.

#### 3.1 Theoretical Model

The representative household has expected lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t \left( \frac{C_t^{1-\nu}}{1-\nu} - \omega \frac{H_t^{1+\eta}}{1+\eta} \right) \quad (7)$$

where  $C_t$  is consumption,  $H_t$  is labor,  $\beta \in (0, 1)$  is the discount factor,  $\nu$  governs the intertemporal elasticity of substitution in consumption, and  $\eta$  mediates the Frisch elasticity of labor supply. The household faces a flow budget constraint in each period, namely,

$$\frac{D_{t+1}}{1+r_t} = D_t - W_t H_t - R_t K_t + C_t + I_t + \frac{\Phi_D}{2} (D_{t+1} - D)^2 \quad (8)$$

where  $D_t$  denotes debt holdings in the form of an internationally traded bond,  $D$  determines debt in the deterministic steady state,  $K_t$  is the stock of physical capital,  $I_t$  is gross capital investment,  $r_t$  is the real interest rate,  $W_t$  is the real wage,  $R_t$  is the rental rate on capital, and  $\Phi_D > 0$  mediates the cost of net external debt adjustment. Capital accumulates according to the equation

$$K_{t+1} = (1-\delta)K_t + \left( 1 - \frac{\phi}{2} \left( \frac{I_t}{I_{t-1}} - 1 \right)^2 \right) I_t \quad (9)$$

where  $\phi > 0$  influences the size of the capital adjustment costs and tempers the investment volatility in response to real interest rate changes for small open-economy models. The standard transversality condition holds for the maximization problem of the household.

On the production side, firms turn capital and labor into a final homogeneous good according to the production function

$$Y_t = K_t^\alpha (e^{X_t} H_t)^{1-\alpha} \quad (10)$$

in which labor-augmenting technology evolves according to

$$X_t = \rho_X X_{t-1} + \sigma_X u_{X,t} \quad u_{X,t} \sim \mathcal{N}(0, 1). \quad (11)$$

The parameter  $\alpha \in (0, 1)$  denotes the capital intensity. We note that the current account ( $CA_t$ ) is the change in the net external debt position

$$CA_t = D_t - D_{t+1} \quad (12)$$

and that the budget constraint in (8) can be rewritten to yield an expression for net exports ( $NX_t$ )

$$NX_t = Y_t - C_t - I_t = D_t - \frac{D_{t+1}}{1+r_t} + \frac{\Phi_D}{2} (D_{t+1} - D)^2. \quad (13)$$

Once again the dynamics of the real interest rate  $r_t$  faced by domestic residents in financial markets are governed by equations (1)-(5). We consider two versions of our model. The first version assumes a zero correlation between the level and volatility of interest rates, while the second version assumes a non-zero level-volatility correlation in interest rates of the form in equation (6).

### 3.2 Computation: Solution and Estimation

Our paper improves upon the computational procedures outlined in Fernández-Villaverde *et al.* (2011) and Born and Pfeifer (2014). To isolate the effect of volatility, we use a third-order perturbation solution method.<sup>13</sup> We apply a simulated method of moments procedure modifying Dynare codes from Born and Pfeifer (2014) on solution and Andreasen *et al.* (forthcoming) on pruning. Using analytic solutions for the theoretical ergodic mean from Andreasen *et al.* (forthcoming), we winsorize country spread level and volatility shocks, but leave technology shocks unwinsorized.<sup>14,15</sup> We then simulate the model from the ergodic mean using the perturbation approach of Andreasen *et al.* (forthcoming). This step improves upon the computations of Fernández-Villaverde *et al.* (2011) and Born and Pfeifer (2014) by using the ergodic mean rather than the ergodic mean in the absence of shocks to start the simulation in which *all* variables are subjected to pruning, and are pruned in the efficient manner proposed by Andreasen *et al.* (forthcoming).<sup>16, 17</sup>

We correct for time aggregation issues raised by Born and Pfeifer (2014). Dealing with mixed frequency data is common in international finance. As the simulated data is at monthly frequency, we must aggregate to quarterly frequency to match empirical moments. For variables that are expressed in percentage deviations from their ergodic means, the average rather than the summation is the correct transformation, as explained by Born and Pfeifer (2014), in turn correcting many of the transformations used in Fernández-Villaverde *et al.* (2011). Some measures, however, such as the net exports to output ratio, do not require any aggregation. We estimate model moments over 96 periods and obtain the mean over 3000 simulations, which yields the ergodic mean of each model moment. We find that 3000 periods is sufficient for convergence of model moments. Details on the grid search procedure are discussed in Section 7 of the [technical appendix](#).

As net exports can be negative, Correia *et al.* (1995) use the expression  $NX/|\overline{NX}| - 1$  for percentage growth deviations of net exports, which can be HP filtered.<sup>18</sup> The Correia *et al.* net export measure, however, is numerically unstable, especially when net exports are almost zero. We follow Born and Pfeifer (2014) by focusing on the net export share of output. So, rather than the ratio of the volatilities of net exports and output, and the correlation between net exports and

<sup>13</sup>Alternative methods include closed-form solutions and solutions involving lower-order approximations for incorporating stochastic volatility in DSGE models; see for instance de Groot (2015). To relate our results more closely to the work by Fernández-Villaverde *et al.* (2011) and Born and Pfeifer (2014), we do not adopt these techniques.

<sup>14</sup>We reduce computation time by avoiding unnecessarily computing the theoretical ergodic variance-covariance matrix, which takes five minutes. In contrast, computing the theoretical ergodic mean takes less than a second.

<sup>15</sup>Convergence of simulated moments toward corresponding ergodic means was improved by truncating shocks to be less than one in absolute value.

<sup>16</sup>This step addresses the issues raised by Born and Pfeifer (2014) in Section V of their technical appendix.

<sup>17</sup>We tested starting the simulations at the ergodic mean each time for 96 periods with various burn-in periods. Altering the number of burn-in periods made no significant difference to computed moments as draws already came from the ergodic distribution, negating the necessity of having a burn-in, thereby reducing the run-time.

<sup>18</sup>We get net export data from the IMF's IFS. We drop Panama since quarterly frequency data is unavailable.

output, we focus on the volatility of the net export share of output and the correlation between this ratio and output. We only HP filter the ratio of net exports to output  $NX/Y$  when computing the first-order autocorrelation between this ratio and output and the volatility of this ratio. We do not filter  $NX/Y$  when computing the mean of  $NX/Y$  used for moment matching in the calibration. We report empirical moments in table 5 along with the sample periods for each country.<sup>19</sup> The empirical and theoretical moments for net exports are under-reported by a factor of 100 in Fernández-Villaverde *et al.* (2011), but are corrected in our paper.

In estimating the response functions of control variables, standard orthogonalized impulse response functions (IRFs) are inappropriate because of the nonlinearities in the model (Koop *et al.*, 1996). We improve upon Fernández-Villaverde *et al.* (2011) and Born and Pfeifer (2014) by estimating generalized IRFs (GIRFs) at the true ergodic mean.<sup>20</sup> In particular, we employ the second version of GIRFs from the technical appendix of Andreasen *et al.* (forthcoming, p. 182) defined as  $GIRF_{\text{var}}(l, v_i, \mathbf{w}_t) = \mathbb{E}_t[\text{var}_{t+l}|v_i] - \mathbb{E}_t[\text{var}_{t+l}]$  for a disturbance to innovation  $i$ .<sup>21</sup> From this definition, we can see that these GIRFs are expressed as absolute deviations from the ergodic means.

When a variable is logarithmically transformed, multiplying the GIRF by 100 will result in a GIRF that can be interpreted in percentage deviations from the ergodic mean. We convert GIRFs for the country interest rate spread  $\epsilon_{r,t}$  into annualized basis points by multiplying the GIRF by the loading factor of  $12 \times 100 \times 100$ . As the ergodic mean for the country interest rate spread is zero, we can interpret impulse responses for country interest rate spreads in annualized basis points. The variable will depart from zero following interest spread level shocks for instance before gradually returning back toward zero, with duration depending positively on the persistence of the country interest rate. We express the GIRF for each other variable as the percentage deviation from its ergodic mean. To express the response of debt in percentage deviations from its ergodic mean we need to adjust the GIRF for debt (a level variable) by dividing it by the ergodic mean for debt and multiplying it by 100. Once adjusted, all resulting GIRFs are aggregated to quarterly frequency by averaging the adjusted monthly GIRFs.

Regarding computational efficiency gains, we use `bash` and `SLURM` scripting for algorithmic, high-level parallelism over 16 threads with hyperthreading and make use of multiple remote systems simultaneously on high-performance clusters. For the main computation, we run on 8 cores simultaneously per node, making use of multiple batch submission over many nodes. Running time per sample is approximately 140 hours on 8-core Opteron 2.30GHz nodes. We run 104 samples

---

<sup>19</sup>The ratio of investment volatility to output volatility for Russia is 105.8 (due to the financial crisis), while the ratio across all countries lies in the interval [2.73, 12.56]. The ratio for Russia would only be 4.29 if we impute the value for investment in 1998Q4 as an average of the quarters immediately preceding and succeeding 1998Q4. To minimize the effect of investment volatility exerting too great an influence on parameter calibration, we use 4.29 hereafter.

<sup>20</sup>In contrast to our approach, computing the GIRFs at the ergodic mean in the absence of shocks only captures part of the economic effects of risk shocks – in particular the risk adjustment channel (through the constant term and time-varying risk-adjustment), but not the difference in amplification effects brought through risk shocks and rooted in other higher-order terms. When making decisions, furthermore, households will account for the past and future absence of shocks. Taken together, households will hold higher levels of debt than they may otherwise.

<sup>21</sup>We can use this definition and the formulae derived from this definition to explore the joint effects of more than one shock. For instance, defining  $\kappa$  as the correlation parameter between levels and volatility, we can study a one standard deviation disturbance to country spread level shocks along with a  $\kappa$  standard deviation innovation to country spread volatility shocks. Shocking disturbances  $i$  and  $j$  simultaneously:  $GIRF_{\text{var}}(l, v_i, v_j, \mathbf{w}_t) = E_t[\text{var}_{t+l}|v_i, v_j] - E_t[\text{var}_{t+l}]$ .

(26 countries  $\times$  two models  $\times$  two grids for debt (negative and positive)) in parallel simultaneously, eight per node across 13 nodes. The novel use of the `bash xargs` command and the submission of multiple jobs simultaneously over a cluster by slicing grids and controlling timing and memory through modified SLURM scripts help reduce the runtime.<sup>22</sup>

### 3.3 Parameter Calibration

We calibrate two versions of the model for each of the 26 countries: the baseline and augmented cases, denoted by M1 and M2. In line with the data, we calibrate the parameters at monthly frequency. We subsequently convert model data in simulations from monthly to quarterly frequency so that all results are reported on a quarterly basis. In comparison to [Fernández-Villaverde \*et al.\* \(2011\)](#), we recalibrate parameters according to the broader, longer samples of our paper and following the improvements suggested by [Born and Pfeifer \(2014\)](#). Table 6 shows the values of the six parameters  $\nu, \eta, \delta, \alpha, \rho_X$  and  $\omega$  that are fixed across countries. Meanwhile, table 7 lists the country-specific calibrations. In addition,  $\beta = (1 + r)^{-1}$  is country-specific, where  $r$  is the mean net real interest rate for each country and is reported in table 1. The parameters for the laws of motion for country spread deviations and real international risk-free rate deviations along with their volatilities, including the level-volatility correlation parameter  $\kappa$  in the augmented model, are taken from the medians of the posterior distributions estimated in Section 2.

We chose the final four parameters  $\sigma_X, \phi, D, \Phi_D$  to match the ergodic distribution of the model moments with the four empirical moments  $\sigma_Y, \frac{\sigma_C}{\sigma_Y}, \frac{\sigma_I}{\sigma_Y}, \frac{NX}{Y}$ . We select these four parameters through a simulated method of moments procedure to minimize an equally-weighted quadratic form of the distance between the model moments and those of the data. The moments of the model correspond to those of the ergodic distribution of the model as described in Subsection 3.2. Since higher-order approximations shift the ergodic mean of endogenous variables away from the deterministic steady states, we calibrate parameters according to ergodic moments rather than those in steady state. Empirical moments correspond to quarterly data which were converted to real values, seasonally adjusted with the U.S. Census Bureau’s X12-ARIMA program, and HP filtered. Similarly, we adjust simulated series by applying the HP filter.<sup>23,24</sup>

### 3.4 Moments

Tables 8 and 9 report model moments and repeat the data moments of table 5 for comparison.<sup>25</sup> The ratio of net exports to output influences higher values of  $D$ , with a higher ratio indicating a higher level of foreign debt. The external debt adjustment cost parameter  $\Phi_D$  is higher in this model for most countries than the typical values reported by [Fernández-Villaverde \*et al.\* \(2011\)](#), [Born and Pfeifer \(2014\)](#) and [Uribe and Yue \(2006\)](#). In general,  $\Phi_D$  is proportional to the volatility of consumption with higher values of  $\Phi_D$  appearing with higher consumption volatility. In contrast

<sup>22</sup>The `bash xargs` command allows for built in scheduling and automation of procedures over multiple cores with enhanced control.

<sup>23</sup>Results from using other filtering methods such as the bandpass filter were almost identical to results from using the HP filter with a tuning parameter of  $\lambda = 1600$ .

<sup>24</sup>Further details on parameter calibration by grid search are relegated to Section 7 of the [online appendix](#).

<sup>25</sup>Variance decompositions are relegated to Section 8 of the [supplementary appendix](#).

to [Fernández-Villaverde \*et al.\* \(2011\)](#), we allow  $\Phi_D$  to move freely to narrow the gap between model moments and empirical moments. While in [Fernández-Villaverde \*et al.\* \(2011\)](#) higher  $\Phi_D$  and  $\sigma_X$  appear with higher consumption and output volatility, we find no strong relation.

With a linear model, it would be easy to vary each parameter in the set  $\{D, \Phi_D, \phi, \sigma_X\}$  to match corresponding moments, e.g.  $\sigma_X$  for  $\sigma_Y$  and  $D$  for  $\frac{NX}{Y}$ . With a third-order solution, however, moments in the ergodic distribution may be shifted away because of the presence of higher-order terms, with moments affected by a nonlinear combination of parameters. For example the ergodic mean may not match the steady state mean and adjusting one parameter to improve the fit of the model with respect to one moment may deteriorate the fit of the model with respect to another moment. We address this problem by minimizing an equally-weighted quadratic distance function as described earlier.

While for most samples the model performs well in matching the volatility of output, the relative volatilities of investment and output, and the ratio of net exports to output, it tends to underpredict the relative volatilities of consumption and output. As an alternative, we conduct the same grid search with weights proportional to the relative magnitude of each moment and summing to one. Minimizing this proportionally-weighted loss function typically improves the ability of the model to match output volatility and relative consumption volatility to output volatility moments at the cost of failing to match relative investment volatility to output volatility and the ratio of net exports to output. Nevertheless, rather than incur the substantial loss in the ability of the model to match the net export to output ratio, which is related to the debt held by an economy, and since [Fernández-Villaverde \*et al.\* \(2011\)](#) use equal weights in their loss function, we use an equally weighted loss function. Both the baseline (M1) and augmented (M2) models do a good job of matching the moments in the data, with only a couple of exceptions. Regardless of the choice of parameter values, standard small open economy models have difficulties in accounting for the data.

As a caveat the final two columns in tables 8 and 9 report two untargeted moments, namely the volatility of the net export share of output,  $\sigma_{NX/Y}$ , and the first-order autocorrelation between the net export share of output and output,  $\rho_{NX/Y,Y}$ . Net trade tends to be countercyclical in the data but the standard real business cycle model generates procyclical net exports ([García-Cicco \*et al.\*, 2010](#)). The literature attempting to deal with this issue incorporates permanent technology shocks or financial frictions. Additionally, in line with [Born and Pfeifer \(2014\)](#), almost all countries in our study tend to observe overpredicted net export share volatility relative to the data.

### 3.5 Generalized Impulse Response Functions

We plot GIRFs in figure 1. Columns 1-6 represent the dynamic responses of consumption, investment, output, labor hours, real interest rates and debt. We express interest rates in annualized basis points, while every other variable is in percentage deviation from the mean of its ergodic distribution. For each country the graphs provide variable responses to (i) level shocks (row 1), (ii) volatility shocks (row 2), and (iii) combined level and volatility shocks (third row). Level shocks are one standard deviation spread shocks (one standard deviation shock to  $u_{r,t}$  in the M1 model). Volatility shocks are one standard deviation volatility shocks (one standard deviation shock to  $u_{\sigma_r,t}$  in the M1 model). The last row plots GIRFs in the M2 model after a one standard deviation

country spread level shock combined with a  $\kappa$  standard deviation shock to country spread volatility, where  $\kappa$  is the estimated correlation between the innovation to country spread deviations and the innovation to the volatility of country spreads.

### 3.5.1 Level Shocks

A one-standard deviation shock to  $u_{r,t}$  varies from 283 annualized basis points for Argentina to 6 annualized basis points for the Netherlands. These annualized figures correspond to about 24 and 0.5 basis points at a monthly rate.

Consumption drops upon impact for most countries before returning to its ergodic mean. For many countries the decline in consumption is persistent, although the magnitude of the percentage decline differs across countries, in addition to the size of persistence. In a few instances, however, consumption rises upon impact and then returns to its ergodic mean. We refer to these countries as “group two” (Greece, Mexico, Turkey and Venezuela). “Group two” countries are creditors who have the largest net external debt adjustment costs. Creditors are countries for whom the mean of debt in the ergodic distribution is negative. That is, creditors are countries in which on average the net external debt of the country is negative with external debt assets exceeding liabilities.

Investment falls for several quarters before reverting to its ergodic mean in many countries. For “group two” countries, investment rises for several quarters before falling back to its ergodic mean. This persistence arises since in many cases the model requires a moderate degree of adjustment costs in investment,  $\phi$ , to match the second moments found in the data. Indeed, countries observing lower persistence in investment have lower capital adjustment costs.

In a number of economies, output declines persistently and only after many quarters begins to rise. For “group two” countries, output rises persistently and eventually declines. The persistence (or lack thereof) of the declines in consumption and investment will tend to impact the persistence of the declines in output.

Labor marginally increases initially (due to the negative wealth effects) but later converges to its original level in most countries. For “group two” countries, labor displays a small decrease initially (due to the labor-leisure optimality condition) but later also converges to its original level. While we truncate the maximum length of the GIRF plots at 32 quarters, labor falls later in many countries (by a very small margin given preferences) because of the reduction in investment and the resulting decline in marginal productivity. For “group two” countries, labor eventually rises because of the expansion in investment and the consequent rise in marginal productivity.

In some cases debt falls while in others debt appears to rise. Debt rises for all creditors. In our calibration, creditors want to increase their exposure to higher interest rates, so they increase assets, which contrasts with the interpretation in [Fernández-Villaverde \*et al.\* \(2011\)](#). Their study omitted creditor countries and did not divide by any measure of debt, hence interpreted absolute deviations as percentage deviations. They interpret the household as reducing its holding of assets because it fears a negative spread shock tomorrow may drive down the return of their foreign debt asset positions. The opposite is true, however. Facing spread shocks, creditors accumulate debt assets. Debtors mostly reduce their exposure to higher interest rates, but the largest debtors increase their exposure. All but one of these large debtors display high adjustment costs of debt

and the one with a moderate debt adjustment cost exhibits a high capital adjustment cost. Debt falls persistently for most countries, although this persistence is influenced by the cost of net foreign debt adjustment,  $\Phi_D$ , with smaller values of  $\Phi_D$  leading to more persistent reductions in percentage terms of the original value of the liability. Additionally, higher capital adjustment costs contribute to lengthening the period for debt adjustment.

Our heterogeneous sample benefits in identifying nuances and our updated computation helps to improve economic interpretations. The drop in consumption, investment, output, and debt can be explained as follows. Higher  $r_t$  increases the service payment of the debt, reduces consumption and decreases the level of the debt since it is now more costly to finance debt. Higher  $r_t$  lowers investment through a non-arbitrage condition between the returns to physical capital and foreign debt that makes investment more expensive. The results for “group two” countries differ from [Fernández-Villaverde \*et al.\* \(2011\)](#). Intuitively, when households experience a rise in interest rates on assets owned the direction of consumption changes (rises) as does that of the labor supply (falls) because of positive wealth effects initially. Labor supply eventually rises because of the increasing marginal product of labor from rising investment and declining labor supply. Investment rises because of a non-arbitrage relation between the return to financial assets and the return to physical assets. Output also rises. Creditors earning interest on their assets want to accumulate more debt.

The persistence of output depends on the cost of adjusting investment. The adjustment cost is necessary to account for the volatility of investment. In our paper, however, most countries have lower calibrations for the adjustment cost relative to those of [Fernández-Villaverde \*et al.\* \(2011\)](#) because investment volatility tends to be marginally higher for most cases. Output is less persistent on average, with evidence of an intermediate persistence level between that of [Fernández-Villaverde \*et al.\* \(2011\)](#) and [Uribe and Yue \(2006\)](#).

### 3.5.2 Volatility Shocks

The level shocks depicted in the first rows put into context the size of GIRFs to volatility shocks in the second row for each country. The domestic interest rate faced by the country and its expected value are fixed. In response to the volatility shock, we observe (i) a fall (mostly) in consumption, (ii) a decline (mostly) in investment with a longer period until investment stops falling associated with higher adjustment costs of capital, (iii) a decrease (mostly) in output, (iv) a small rise (mostly) in labor initially that falls later and (v) a contraction (mostly) of debt (or positive assets) upon impact that declines persistently before rising, although this persistence in debt reduction tends to be higher for countries with lower costs of net foreign debt adjustment  $\Phi_D$  and is also influenced positively by capital adjustment costs  $\phi$ . Some countries exhibit expansions in investment and output following a volatility shock, which contrasts with the results from [Fernández-Villaverde \*et al.\* \(2011\)](#).<sup>26</sup> The GIRFs highlight how increases in risk have real effects on the economy, even when the interest rate

---

<sup>26</sup>[Basu and Bundick \(2017\)](#) show that the New Keynesian model is necessary for volatility to always generate recessions. With flexible prices as in the standard real business cycle model, uncertainty shocks are incapable of generating business-cycle comovements among key macroeconomic variables. With sticky prices as in the standard New Keynesian model, uncertainty shocks can produce fluctuations consistent with business cycles. Moreover, monetary policy typically offsets the detrimental impact of uncertainty shocks. At the zero lower bound, however, monetary policy can not stabilize the economy, so the effects of higher uncertainty are amplified.



is held constant. We note that qualitatively the GIRFs in the third rows are largely the same as those in the first rows across countries. Thus, our results are robust to allowing for a correlation between level and volatility innovations.<sup>27</sup>

For the study of Argentina, Brazil, Ecuador and Venezuela pre-2008.02, the authors use the first-order condition with respect to  $D_{t+1}$  to dissect the economic logic of the precautionary behavior mechanism behind the effects of country spread volatility shocks (Fernández-Villaverde *et al.*, 2011). In particular, this condition can be rewritten as

$$\frac{1}{1+r_t} - \beta \mathbb{E}_t \frac{\lambda_{t+1}}{\lambda_t} = \Phi_D(D_{t+1} - D) \quad (14)$$

In contrast to that study, while volatility shocks do not affect  $r_t$ , it is not necessarily the case that  $\mathbb{E}_t \frac{\lambda_{t+1}}{\lambda_t}$  always increases. To understand this implication, consider the following argument. The marginal utility of consumption, i.e. the Lagrange multiplier  $\lambda_t$  is convex because third-order terms are determined by the fourth derivative of the utility function that has to be positive for households to lower debt in response to volatility shocks. Higher real interest rate volatility will increase the future volatility of consumption. With more uncertainty regarding future consumption, convex marginal utility will then imply, graphically or by Jensen's inequality, that  $\mathbb{E}_t \lambda_{t+1}$  rises. When consumption falls upon impact, calibration will determine which effect dominates: the rise in  $\mathbb{E}_t \lambda_{t+1}$  or the rise in  $\lambda_t$ . The calibration of Fernández-Villaverde *et al.* (2011) always implies that the rise in  $\mathbb{E}_t \lambda_{t+1}$  dominates the rise in  $\lambda_t$ . In contrast, we find some countries where consumption rises upon impact, in particular for certain creditors, which unambiguously raises  $\mathbb{E}_t \lambda_{t+1} / \lambda_t$ . Furthermore, GIRFs for debt in our paper are expressed as percentage deviations from its ergodic mean by dividing by the ergodic mean for debt.<sup>28</sup> So, we distinguish between the following cases. If consumption rises upon impact, creditors will take on more debt assets (relative to liabilities) whereas debtors will reduce their debt liabilities (relative to assets). The results will be the same if consumption falls upon impact and the  $\mathbb{E}_t \lambda_{t+1}$  effect dominates. When calibration suggests that the  $\lambda_t$  effect dominates, creditors will reduce their debt assets (relative to liabilities) whereas debtors will take on more debt liabilities (relative to assets).<sup>29</sup>

## 4 Understanding Volatility

In this section we perform sensitivity checks on the benchmark model to enhance our understanding of volatility shocks. We will not discuss model version M2, except to report that the results are relatively robust qualitatively. We detail our experiments, along with graphs and tables, in Sections 9 through 12 of the [technical appendix](#).<sup>30</sup>

<sup>27</sup>Differences reflect both the interaction of level and volatility shocks as well as the calibration for M2 being distinct to that for M1. Quadratic moment matching implies parameter values that are sometimes different for M1 and M2.

<sup>28</sup>Tables 60-85 in section 13.3 of the [online appendix](#) show that steady states and ergodic means share the same sign for our sample.

<sup>29</sup>Positive GIRFs mean taking on relatively more debt (assets for creditors, liabilities for debtors) and *vice-versa*.

<sup>30</sup>In Section 13 of the [online appendix](#), we compare our results with those found in Fernández-Villaverde *et al.* (2011) and Born and Pfeifer (2014). We also carry out a subset of these experiments using the computational methods of both papers. The exercises confirm that the results from this paper arise from the difference in the samples studied and from the differences in methodology employed in estimating the DSGE model.

While the experiments were conducted for all 26 economies, we will occasionally provide country-specific interpretations for the case of Ireland. Ireland, as a peripheral euro area member, offers itself as a good case study given its exposure to sizable interest rate volatility, especially throughout the financial crisis and European sovereign debt crisis, unlike Belgium or Canada. Ireland has displayed sufficient interest rate volatility to make third-order approximations to policy functions matter, allowing us to observe significant interest rate volatility effects in the augmented DSGE model. Indeed, Ireland's share of debt to GDP grew from 24.8 percent in 2007 to 123.2 percent in 2014 and was one of the first euro area countries to receive external financial assistance. Finally, the estimates from the stochastic volatility model show Ireland to be less volatile than other bail-out countries. So, in drawing lessons from the exercises that apply to Ireland the results may be viewed as a lower bound case for other peripheral euro area countries and emerging markets.

#### 4.1 Extensions and Sensitivity Analysis

We first conduct two experiments designed to improve our understanding of volatility. The first experiment illustrates the impact of volatility shocks on the evolution of debt, current accounts and net exports, indicating that volatility has notable implications for movements in variables like the current account and net exports. This experiment also serves to quantify the mechanism by which debt changes following a volatility shock. The second experiment highlights the non-trivial effects of higher-order terms on responses.

In the first experiment, we graph the evolution of the debt-to-output ratio, along with the current account-to-output and net exports-to-output ratios where the last two quotients are expressed in absolute deviations from their ergodic means. Responses are non-monotonic. Looking at Ireland for example, times until trough for  $D/Y$ ,  $CA/Y$  and  $NX/Y$  are three, four and five quarters. After a one standard deviation volatility shock the debt-to-output ratio falls by 0.35 percent after three quarters while the current account improves by 0.36 percent of output on impact to finance the deleveraging. As for net exports, the model indicates that output rises for Ireland in response to a volatility shock, which would put downward pressure on the net export-to-output ratio: net exports decrease by about 7.8 percent of quarterly output.

Regarding the second experiment, we plot GIRFs for level and volatility shocks where first-, second- and third-order approximations are used. GIRFs to level shocks at first and second orders are mostly identical. Some differences in GIRFs are evident, particularly further out at later horizons, which arise from the third-order approximation since only in third order will risk depend on the state of the economy (i.e. risk will be time-varying). The responses to volatility shocks make it clear that GIRFs must be approximated to at least order three in order for volatility to make a distinct impression. Impulses are flat at orders less than three since volatility does not enter the system in the first-order approximation (second moments require taking second derivatives) and volatility only enters the system through a multiplicative interaction term with level shocks at second order (level shocks are zero in this experiment so the interaction will be zero). In the first order, households will behave as if there is no uncertainty, i.e. certainty equivalence will hold, thus households will not respond to shocks since they do not feature in their model. At second order, volatility is constant and so are risk premia: the only way households respond to risk is if we turn

on both level and risk shocks or employ the M2 version of the model that allows for correlation between level and risk shocks so that one shock endogenously affects the other. This correlation complicates interpretation and identification of the separate effects of risk shocks. This extension clarifies that to isolate the effects of risk, we need to go at least as far as third-order approximations.

We consider further extensions and robustness checks along the following lines: (i) working capital, (ii) high debt versus low debt, (iii) negative debt versus positive debt, (iv) higher adjustment cost of capital  $\phi$ , (v) lower persistence of country spread volatility  $\rho_{\sigma_r}$ , (vi) higher standard deviation of volatility shocks (one versus two standard deviations), (vii) lower and higher values of risk aversion  $\nu$ , (viii) adjusting Frisch elasticity  $\eta$ , depreciation  $\delta$ , technological persistence  $\rho_X$  and capital share of income  $\alpha$ , and (ix) priors (pre-September 2008, post-September 2008, loose priors for persistence  $(\rho_r, \rho_{\sigma_r})$ , conservative prior for stochastic volatility  $\eta_r$  and combinations of these priors).

Exploring the results, (i) the model is largely robust to the inclusion of working capital. For the vast majority of countries the GIRFs are identical regardless of whether or not working capital is part of the model. (ii) Holding less debt typically magnifies the response of consumption, output, labor and debt for creditor countries. For debtor countries, responses are muted with the exception of the response of debt, which is weaker upon impact but can be weaker or stronger as the horizon increases.<sup>31</sup> (iii) Reversing the sign on net external debt debt, as given by the mean in the ergodic distribution, debtors become creditors and responses are mostly dampened. Results are mixed when creditors become debtors.

(iv) GIRFs differ marginally when we alter the adjustment cost of capital. Raising investment adjustment costs depresses consumption and output. Consumption and output tend to fall more and rise less than before; more adjustment takes place through labor and debt. Investment responds less and is more sluggish. Output is also more sluggish owing to the response of investment. The reverse is true for the case of lowering investment adjustment costs. The response of debt is mostly magnified, however, since it depends on the adjustment costs of capital and debt. Raising the cost of adjusting investment means that more adjustment should take place through debt, but lowering the cost of adjusting investment makes it easier to change debt by altering domestic absorption.

(v) When we reduce the persistence of the volatility shock from the normal (high) values estimated as posterior medians to 0.75, most of the effects of a one-standard-deviation shock to volatility disappear. Households know that volatility will quickly revert to its mean, and so are less keen on paying back the debt. In light of the empirical results, country spread volatility being highly persistent (most posterior medians for  $\rho_{\sigma_r}$  are over 0.9) is crucial in justifying the quantitative importance of the impulse responses. This experiment elucidates the significance of persistence in accounting for the magnitude of the responses of households to volatility.

(vi) Higher volatility (two-standard deviation rather than one-standard deviation) amplifies the magnitudes of the GIRFs. (vii) Qualitatively the patterns in the GIRFs from lowering risk aversion are the same as in the benchmark case except that responses are generally dampened for investment, output and labor, in particular, but mostly amplified for consumption: lower risk aversion tends to

---

<sup>31</sup> *Ceteris paribus*, a higher debt-to-output ratio (net exports-to-output ratio) will result in stronger effects of interest rate level and volatility shocks. Facing a less austere environment, however, can mean that GIRFs are dampened. That is, lower average volatility,  $\sigma_r$  reduces the size of the GIRFs. Similarly, a smaller standard deviation of the innovation to volatility shocks,  $\eta$  reduces the size of the GIRFs.

dampen declines in debt but amplify increases. Responses are still substantial, however, in most cases between 25 percent and 50 percent of their original responses. As households become more risk averse, dynamics are mostly stronger than in the benchmark case other than for consumption.

(viii) Higher capital shares are mostly associated with dampened GIRFs, in contrast to lower capital shares that amplify GIRFs. Raising the Frisch elasticity of labor increases the responsiveness of labor to volatility shocks. Consequently, investment and output are marginally more responsive, while consumption and debt are mainly marginally less responsive. Low rates of capital depreciation are associated with marginally dampened GIRFs, other than that for investment and debt. Investment rises less and falls more. Households know that capital depreciates less, so reducing investment will be less costly for the household *via* future output. Thus, most of the adjustment by increasing net exports to finance the deleveraging of debt occurs through reducing investment. Overall, with lower depreciation the costs of altering investment on future output are lower, borrowing is less important, and so shocks to the volatility of interest rates matter less for households.

GIRFs for volatility shocks are invariant to the persistence of technology shocks, at least within the interval  $\rho_X \in (0.90, 0.99)$ . With extremely persistent technology shocks (0.99), however, debt can sometimes become marginally more responsive for net external debtor countries and marginally less responsive for net external creditor countries. Persistent shocks have larger effects on variables according to the permanent income hypothesis. Risk (volatility) shocks matter more for countries that are debtors and so they reduce their debt more in response to volatility shocks. Debtor countries are also less keen on changing their asset holdings when technology shocks are more persistent. With less persistent technology shocks, debt tends to become marginally less volatile for net external debtors. The dampening of the debt response is almost negligible for the technology autoregressive values examined, however.

(ix) GIRFs are dampened when we lower the prior persistence of levels and volatility. When volatility shocks do not last long, households are less eager to pay back debt and will respond less. Results are robust to lowering the prior for stochastic volatility. GIRFs are almost identical with ever so modestly amplified results. The reason behind the marginal amplification of GIRFs is that the only parameter to have changed is  $\sigma_r$ , which is now marginally higher indicating that volatility is marginally higher on average. Hence households will want to pay more attention to debt reduction following a volatility shock as they live in a slightly more uncertain environment on average with respect to the country spread.

Combining low priors for stochastic volatility with low priors for persistence of levels and volatility, the second set of priors tend to dampen the GIRFs to magnitudes between the benchmark case and the case with low priors for persistence. Responses are dampened for both the post-September 2008 and pre-September 2008 subsamples and are qualitatively identical. There is, nevertheless, some heterogeneity quantitatively. In some cases the amplification effects from higher average volatility and stochastic volatility dominate the opposite effects from lower volatility persistence.

Nonlinearities become evident when exploring the role of the global financial crisis. For instance, Ireland displays dampened responses for both pre- and post-September 2008 subsamples, relative to its benchmark. What drives the calm responses pre-September 2008 in euro area peripheral countries such as Ireland is lower average country spread volatility ( $-9.01$  and  $-7.71$  before and after 2008.08

relative to  $-7.94$  for the complete sample period). Nevertheless, the pre-September 2008 sample displays strong persistence of country spread volatility with  $\rho_{\sigma_r} = 0.99$ . Lower persistence of country spread volatility ( $\rho_{\sigma_r} = 0.87$ ) dampens responses post-September 2008 (households are less keen on paying back debt since times of high volatility are not expected to last long). On the other hand the post-September 2008 sample displays strong average country spread volatility.

While individually the pre- and post-September 2008 samples may be characterized by dampened responses, the full sample displays amplified responses relative to both of these subsamples. This counterintuitive finding is explained by the combined effect of volatility persistence and average volatility being raised by the result of combining pre- and post-September 2008 time periods. Nonlinearity is inherent in that the linear combination of both parameters arising from the influence of both time periods produces a strictly concave result.

## 5 Conclusion

This paper investigates the relation between real interest rate volatility and macroeconomic performance for a diverse set of countries. We find the stochastic volatility model to be a better representative of time-varying volatility of spreads than a discrete Markov-switching model. Decomposing the real interest rate into an international risk-free rate and a country spread component, we obtain unequivocal evidence indicating that stochastic volatility shocks to real interest rate spreads are rather large and persistent overall, with estimates exhibiting non-negligible cross-country heterogeneity. Moreover, we emphasize that volatility increases at higher levels of interest rate spreads and that it moves countercyclically with measures of aggregate economic outcomes.

We subsequently demonstrate that the observed empirical regularities can be reproduced by a standard equilibrium business cycle model augmented with stochastic interest rate volatility shocks. Our heterogeneous sample and improved computational procedures enable us to identify new nuances in analyzing and interpreting how risk shocks can affect the macroeconomy. Computationally, our paper makes advances in performance and accuracy through the use of shell scripting, high-level parallelism, new results on third-order pruning in state-space models, and recommendations proposed by [Born and Pfeifer \(2014\)](#).

Indeed, quantifying changes in real interest rate volatility and its interaction with business cycle fluctuations further enhances our understanding of the international financial macroeconomy. In particular, our analysis of the impact of interest rate volatility shocks on aggregate economic outcomes should assist policymakers in the formulation of more effective macroeconomic interventions. In addition, the wealth of empirical findings in this paper across a wide-ranging sample of countries will be of interest to academics aiming to incorporate interest rate uncertainty in alternative stochastic frameworks of the macroeconomy.

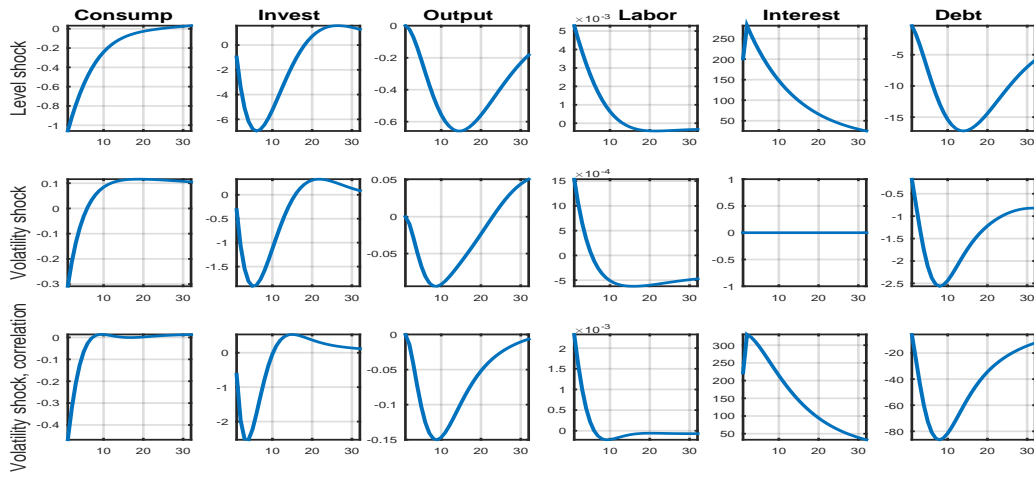
## References

- ANDREASEN, M. M., FERNÁNDEZ-VILLAVÉRDE, J. and RUBIO-RAMÍREZ, J. (forthcoming). The Pruned State-Space System for Non-Linear DSGE Models: Theory and Empirical Applications. *Review of Economic Studies*.
- ARDAGNA, S., CASELLI, F. and LANE, T. (2007). Fiscal Discipline and the Cost of Public Debt Service: Some Estimates for OECD Countries. *The B.E. Journal of Macroeconomics*, **7**, 1–35.
- BAKER, S. R., BLOOM, N. and DAVIS, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, **131** (4), 1593–1636.
- BASU, S. and BUNDICK, B. (2017). Uncertainty Shocks in a Model of Effective Demand. *Econometrica*, **85** (3), 937–958.
- BORN, B. and PFEIFER, J. (2014). Risk Matters: The Real Effects of Volatility Shocks: Comment. *American Economic Review*, **104** (12), 4231–39.
- CORREIA, I., NEVES, J. C. and REBELO, S. (1995). Business Cycles in a Small Open Economy. *European Economic Review*, **39** (6), 1089–113.
- DE GROOT, O. (2015). Solving Asset Pricing Models with Stochastic Volatility. *Journal of Economic Dynamics and Control*, **52** (C), 308 – 21.
- EIJFFINGER, S. C., KOBIELARZ, M. L. and URAS, B. (2015). *Sovereign Debt, Bail-Outs and Contagion in a Monetary Union*. Tech. Rep. No. 10459, CEPR Discussion Papers.
- FAHR, S., MOTTO, R., ROSTAGNO, M., SMETS, F. and TRISTANI, O. (2013). A Monetary Policy Strategy In Good And Bad Times: Lessons From The Recent Past. *Economic Policy*, **28** (74), 243–288.
- FAVERO, C. and MISSALE, A. (2012). Sovereign Spreads In The Eurozone: Which Prospects For A Eurobond? *Economic Policy*, **27** (70), 231–273.
- FERNÁNDEZ-VILLAVÉRDE, J., GUERRÓN-QUINTANA, P., RUBIO-RAMÍREZ, J. and URIBE, M. (2011). Risk Matters: The Real Effects of Volatility Shocks. *American Economic Review*, **101** (6), 2530–61.
- and RUBIO-RAMÍREZ, J. (2007). Estimating Macroeconomic Models: A Likelihood Approach. *Review of Economic Studies*, **74** (4), 1059–1087.
- GARCÍA-CICCO, J., NAUDON, A. and HERESI, R. (2013). *The Real Effects of Global Risk Shocks in Small Open Economies*. Tech. rep., Central Bank of Chile Working Paper.
- , PANCAZI, R. and URIBE, M. (2010). Real Business Cycles in Emerging Countries? *American Economic Review*, **100** (5), 2510–31.
- GODSILL, S., DOUCET, A. and WEST, M. (2004). Monte Carlo Smoothing for Nonlinear Time Series. *Journal of the American Statistical Association*, **99** (465), 156–168.
- HAMILTON, J. (2008). *Macroeconomics and ARCH*. NBER Working Papers 14151, NBER Working Papers.
- KOOP, G., PESARAN, H. and POTTER, S. (1996). Impulse Response Analysis in Nonlinear Multivariate Models. *Journal of Econometrics*, **74** (1), 119–47.
- KYDLAND, F. and PRESCOTT, E. (1982). Time to Build and Aggregate Fluctuations. *Econometrica*, **50** (6), 1345–70.
- LANE, P. R. and MILESI-FERRETTI, G. M. (2007). The External Wealth of Nations Mark II. *Journal of International Economics*, **73** (2), 223–50.
- LAUBACH, T. (2009). New Evidence on the Interest Rate Effects of Budget Deficits and Debt. *Journal of the European Economic Association*, **7** (4), 858–885.
- LEDUC, S. and LIU, Z. (2016). Uncertainty Shocks Are Aggregate Demand Shocks. *Journal of Monetary Economics*, **82**, 20–35.

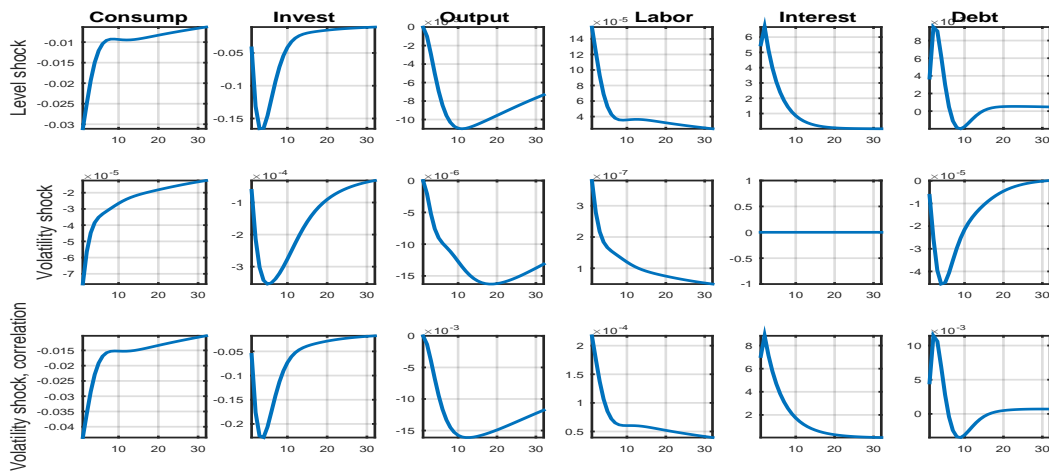
- LONGSTAFF, F. A., PAN, J., PEDERSEN, L. H. and SINGLETON, K. J. (2011). How Sovereign Is Sovereign Credit Risk? *American Economic Journal: Macroeconomics*, **3** (2), 75–103.
- LUDVIGSON, S. C., MA, S. and NG, S. (2015). *Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?* Tech. Rep. 21803, NBER Working Paper.
- MENDOZA, E. (1995). The Terms of Trade, the Real Exchange Rate, and Economic Fluctuations. *International Economic Review*, **36** (1), 101–37.
- MODY, A. and SANDRI, D. (2012). The Eurozone Crisis: How Banks And Sovereigns Came To Be Joined At The Hip. *Economic Policy*, **27** (70), 199–230.
- NEUMEYER, P. and PERRI, F. (2005). Business Cycles in Emerging Economies: the Role of Interest Rates. *Journal of Monetary Economics*, **52** (2), 345–80.
- URIBE, M. and YUE, V. (2006). Country Spreads and Emerging Countries: Who Drives Whom? *Journal of International Economics*, **69** (1), 6–36.
- VON HAGEN, J., SCHUKNECHT, L. and WOLSWIJK, G. (2011). Government Bond Risk Premiums in the EU Revisited: The Impact of the Financial Crisis. *European Journal of Political Economy*, **27** (1), 36–43.

Figure 1: Generalized Impulse Response Functions

*Argentina*



*Austria*



*Belgium*

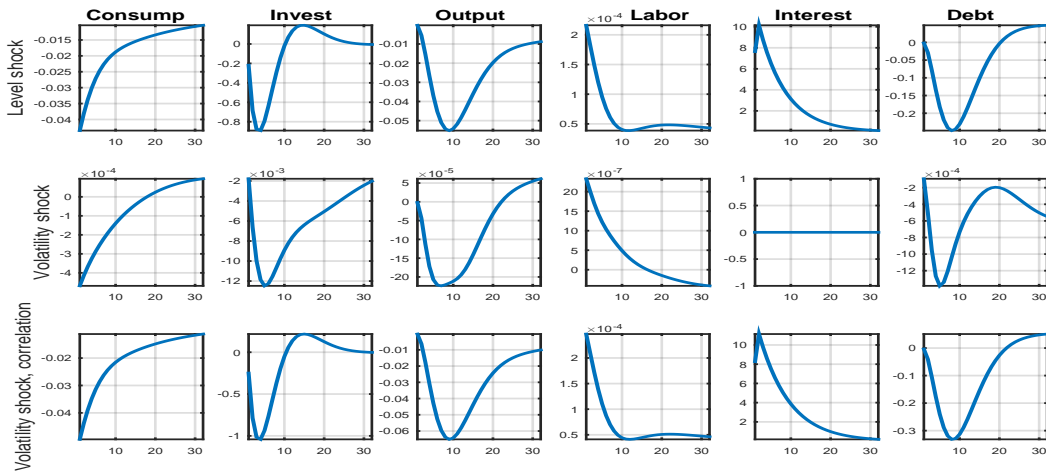
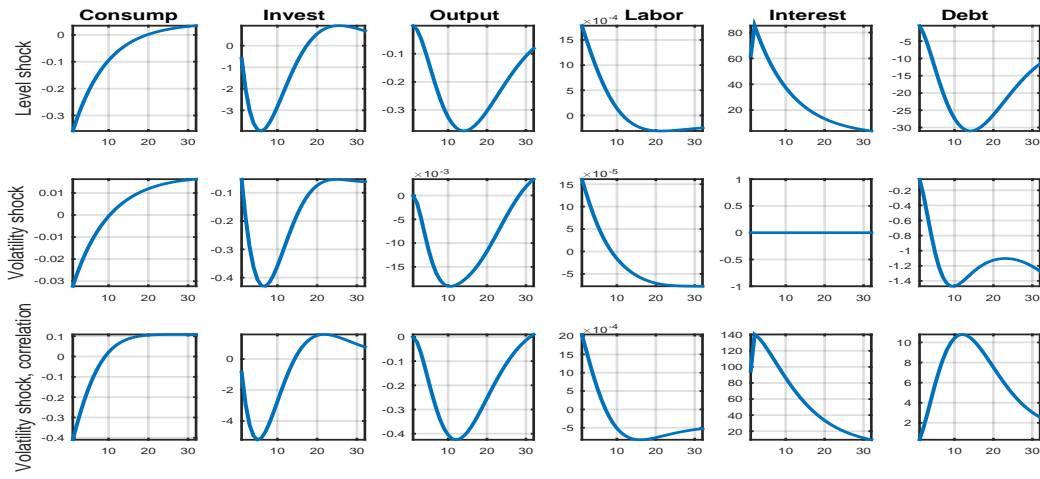


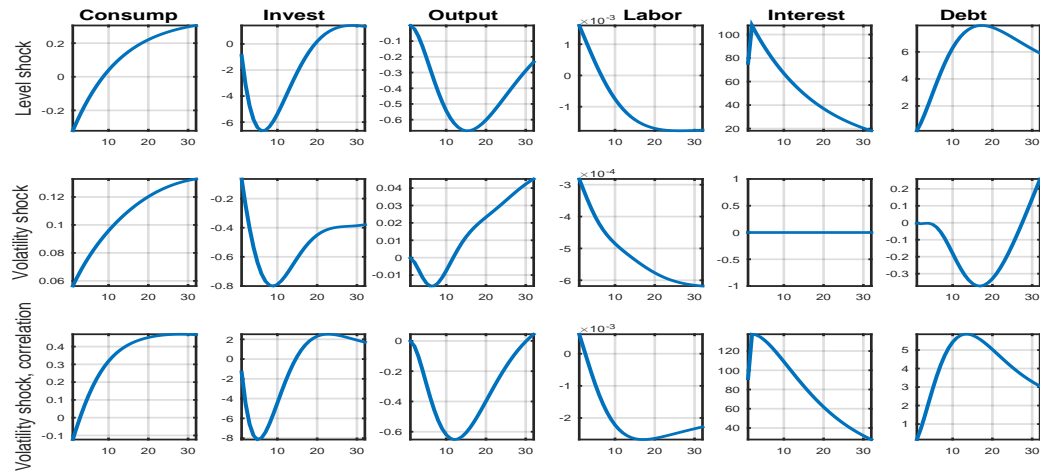


Figure 1: Generalized Impulse Response Functions (continued)

*Brazil*



*Bulgaria*



*Colombia*

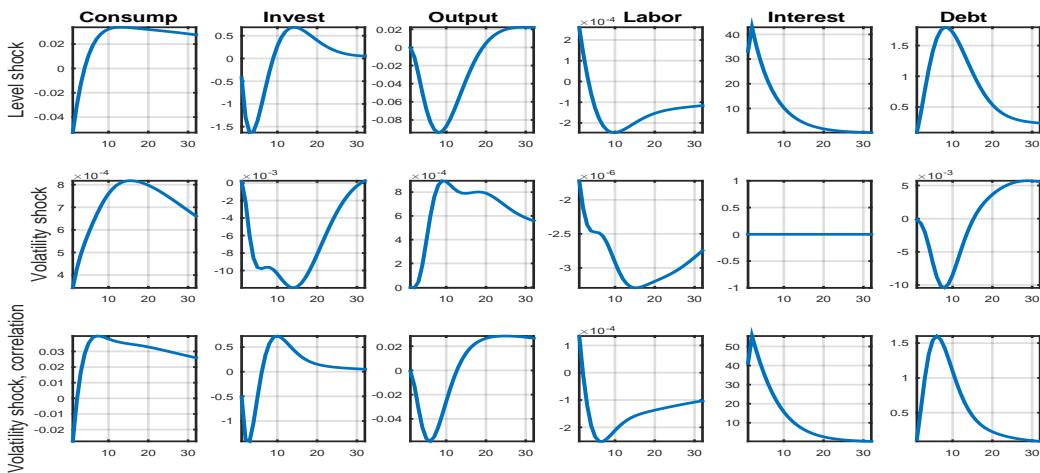
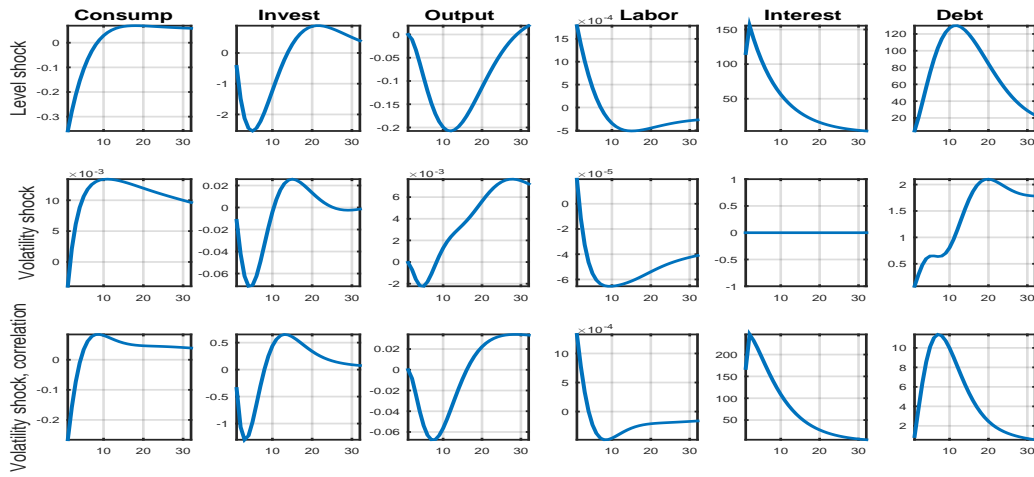
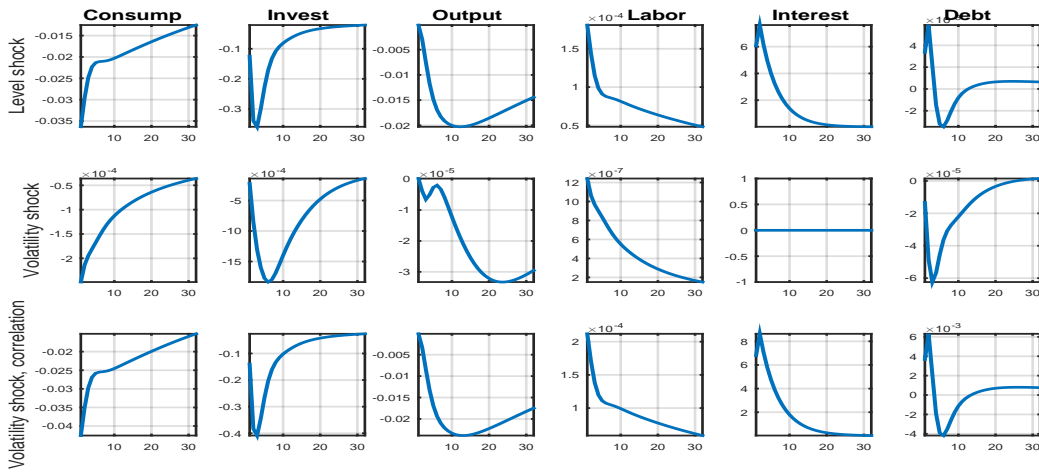


Figure 3: Generalized Impulse Response Functions (continued)

*Ecuador*



*Finland*



*France*

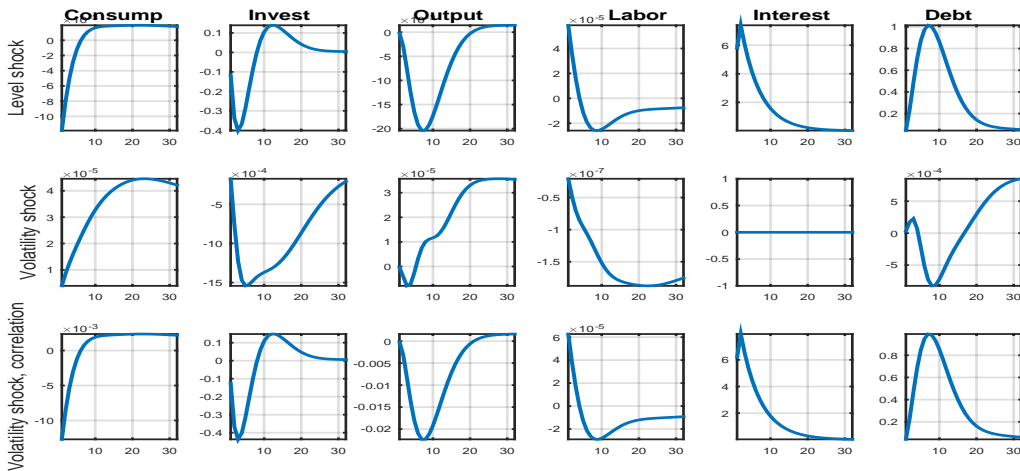
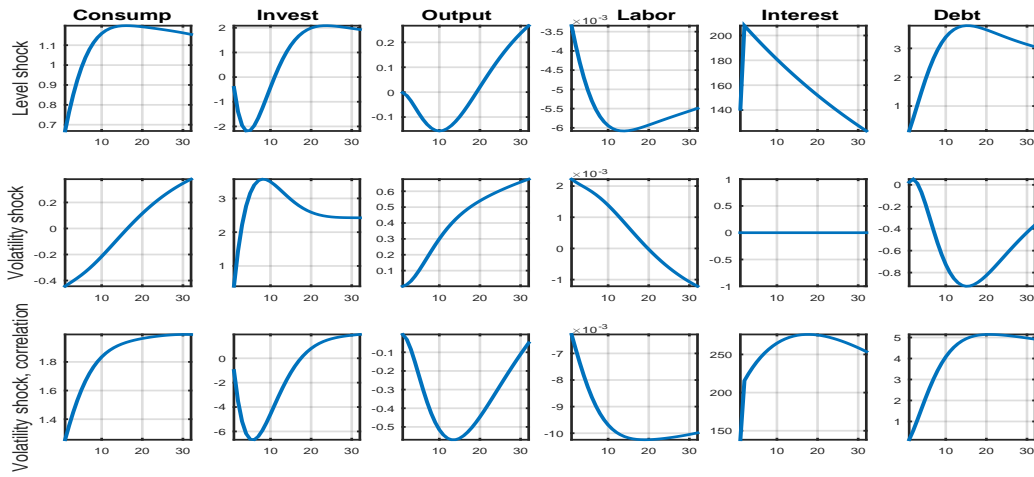
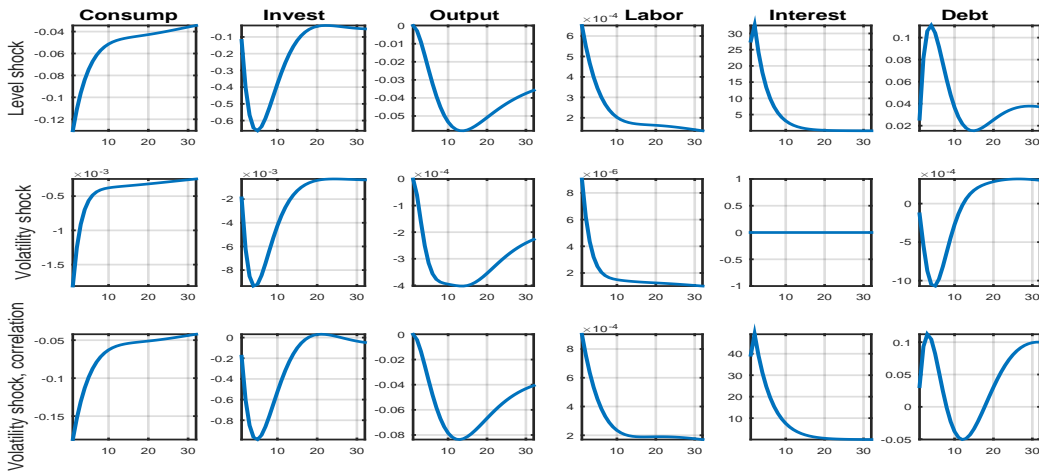


Figure 4: Generalized Impulse Response Functions (continued)

*Greece*



*Indonesia*



*Ireland*

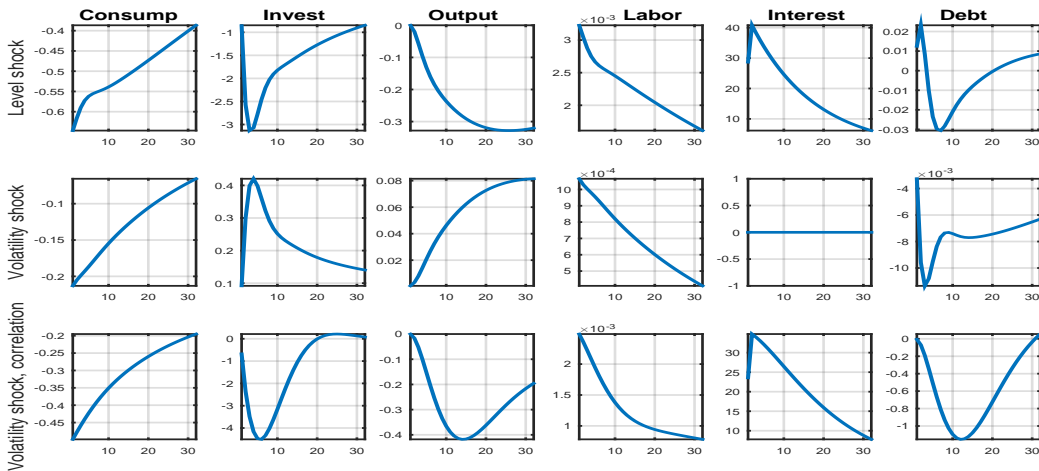
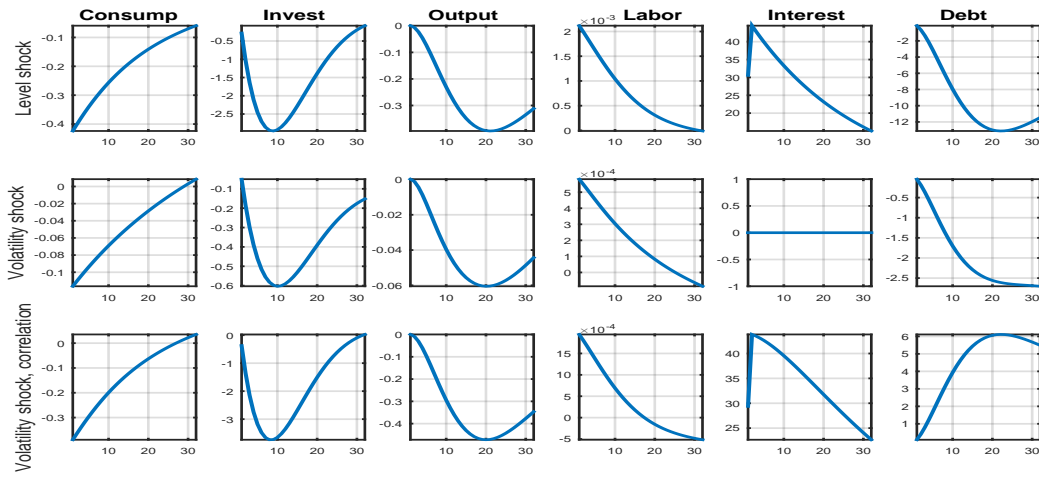
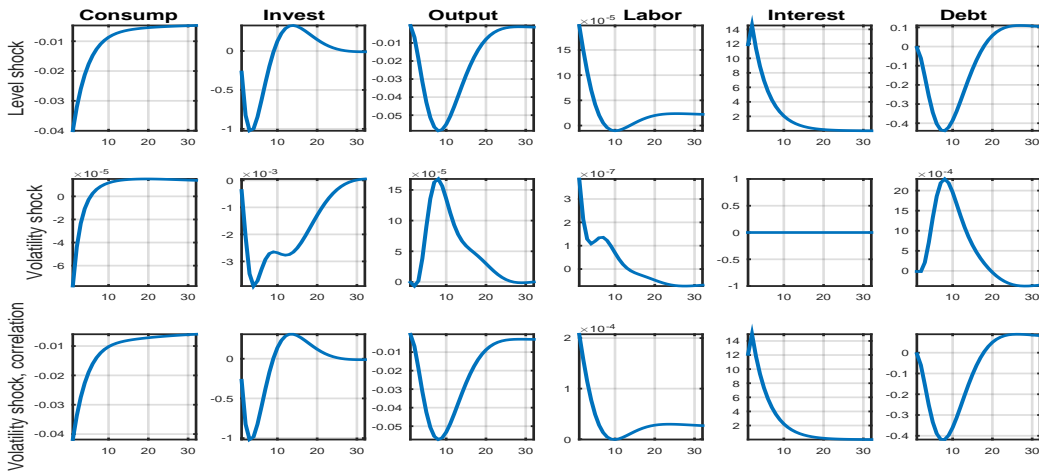


Figure 5: Generalized Impulse Response Functions (continued)

*Italy*



*Malta*



*Mexico*

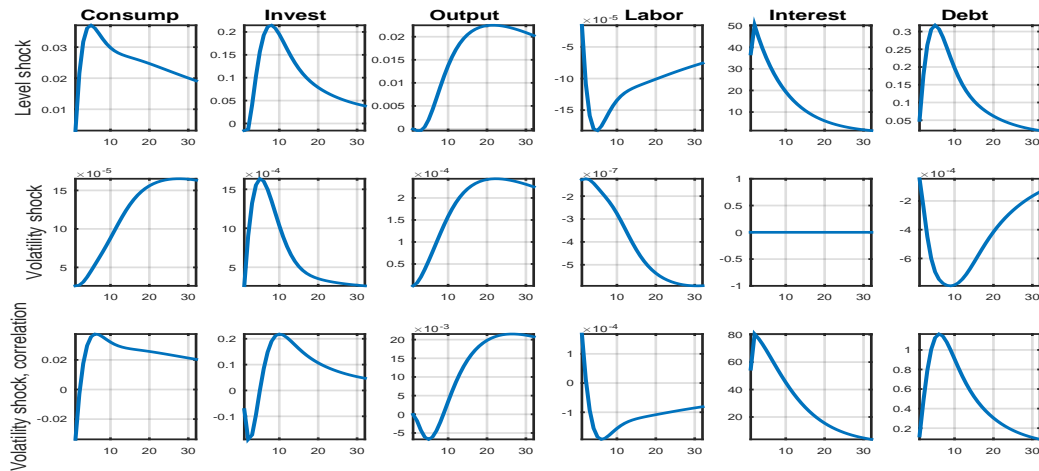
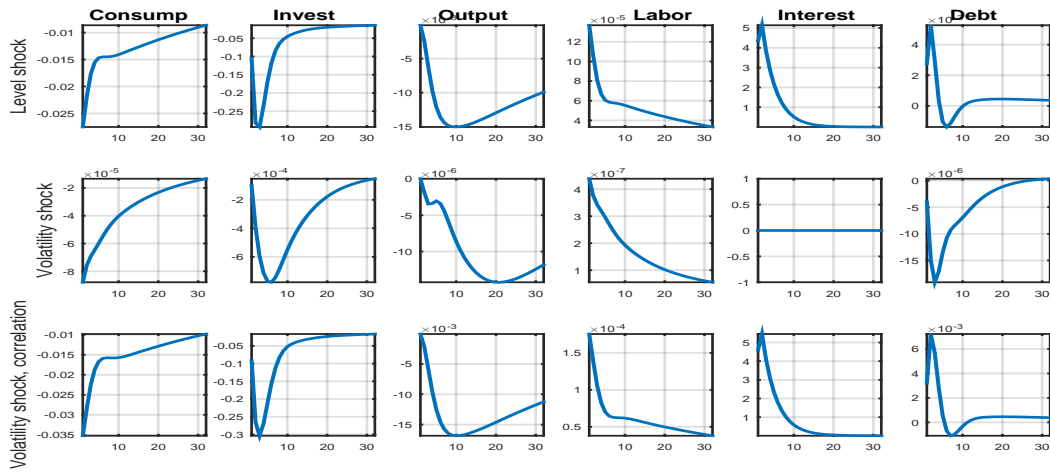
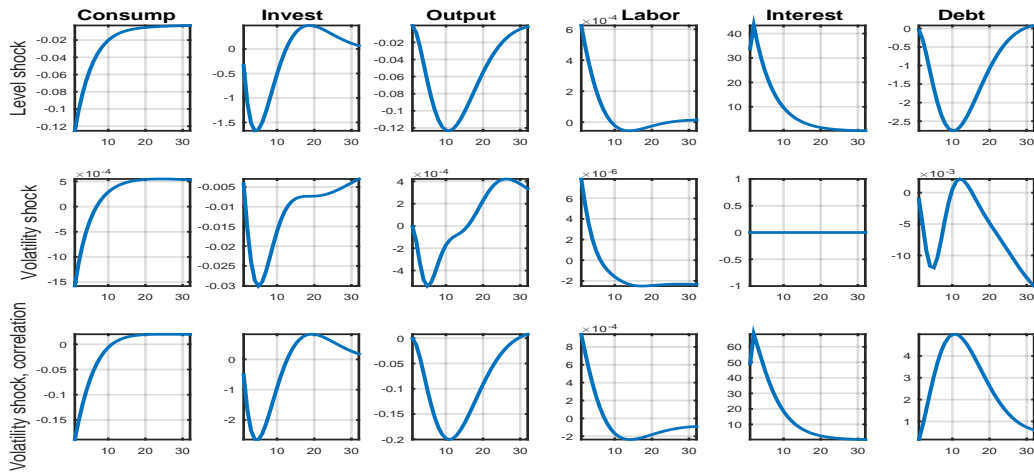


Figure 6: Generalized Impulse Response Functions (continued)

*Netherlands*



*Peru*



*Philippines*

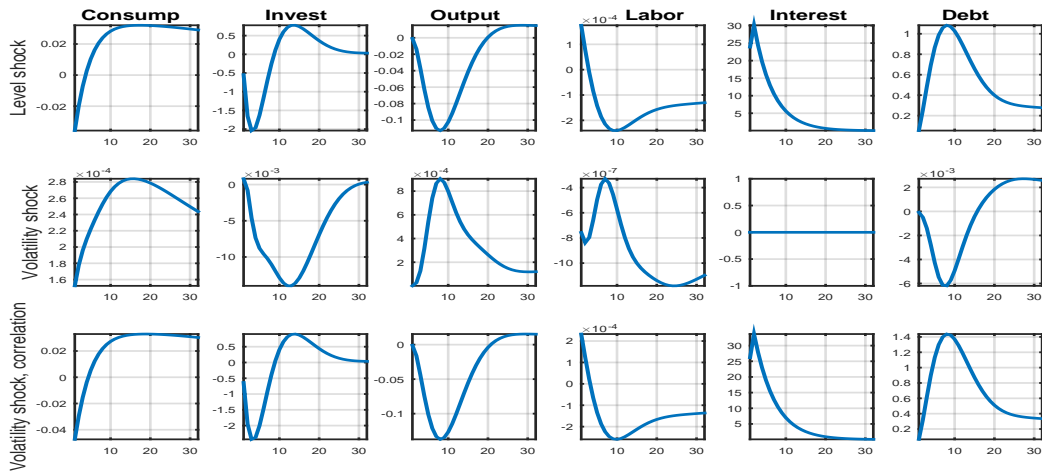
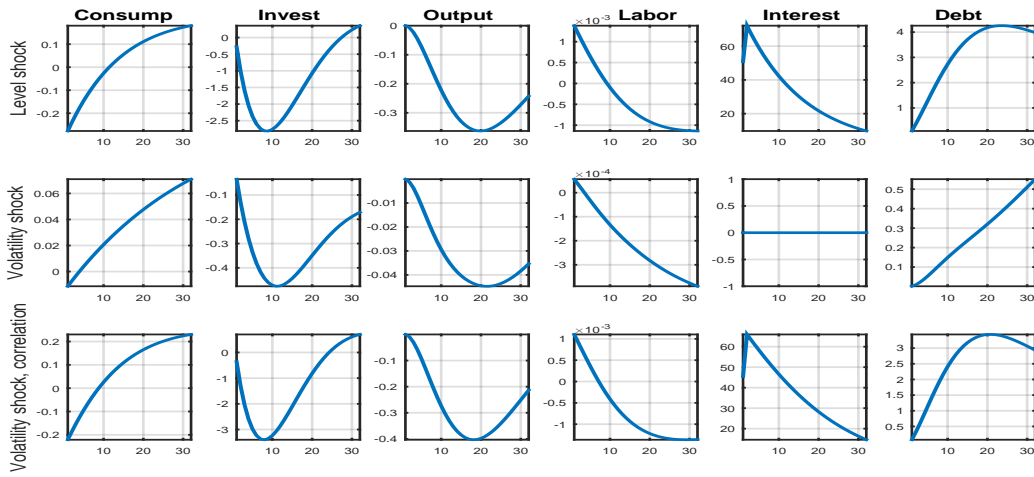
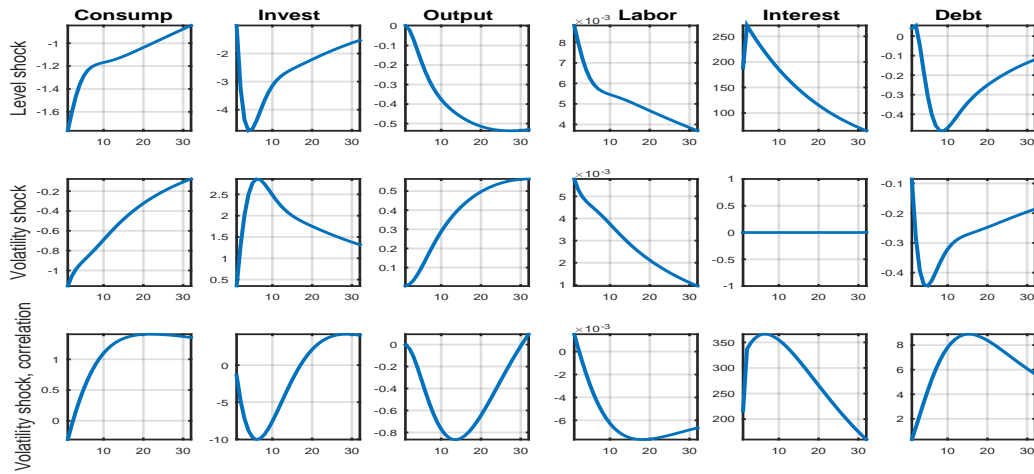


Figure 7: Generalized Impulse Response Functions (continued)

*Portugal*



*Russia*



*South Africa*

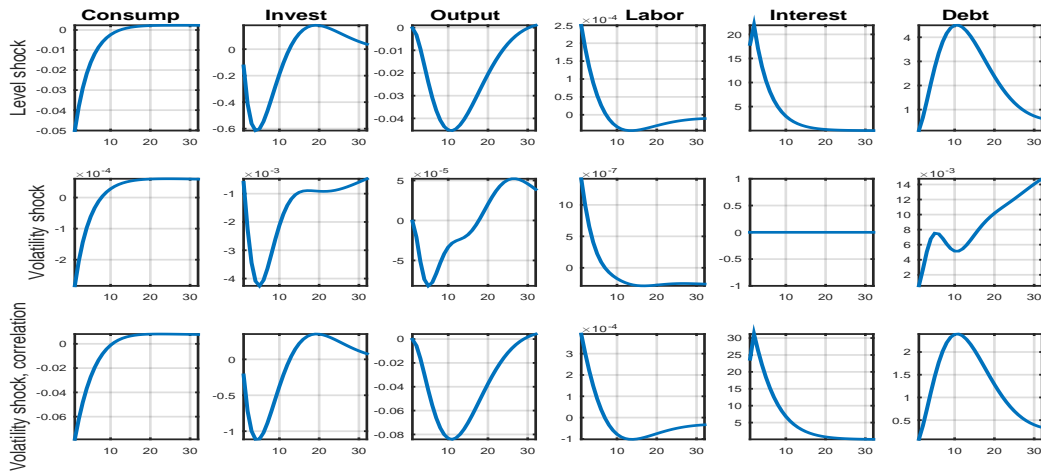
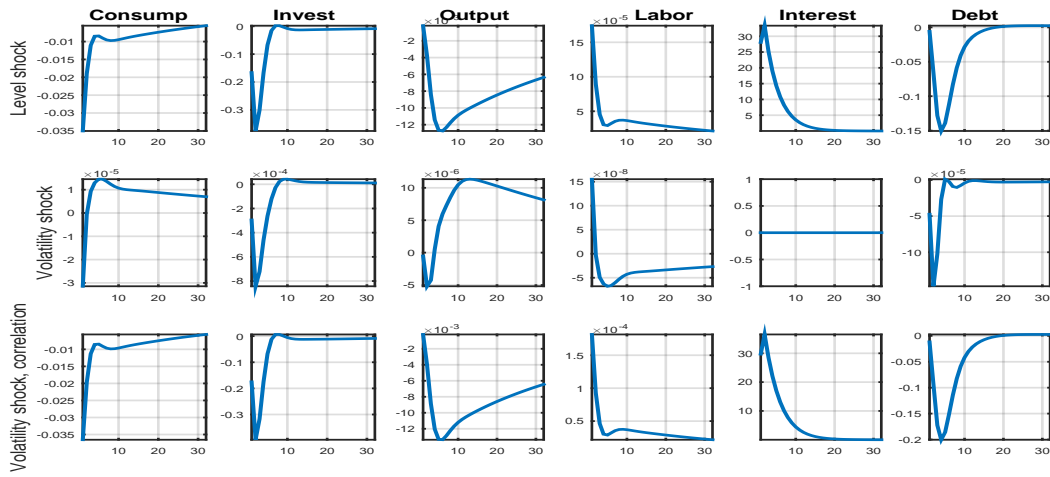
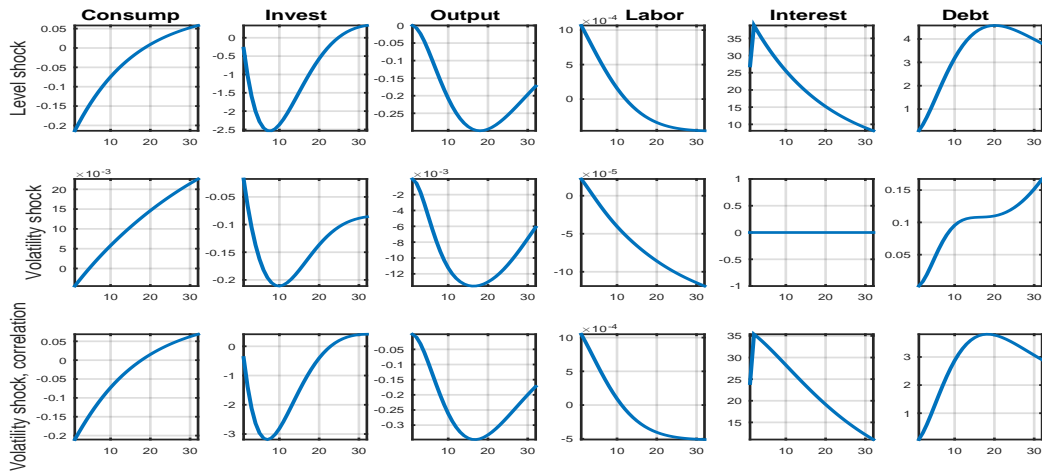


Figure 8: Generalized Impulse Response Functions (continued)

*Slovenia*



*Spain*



*Turkey*

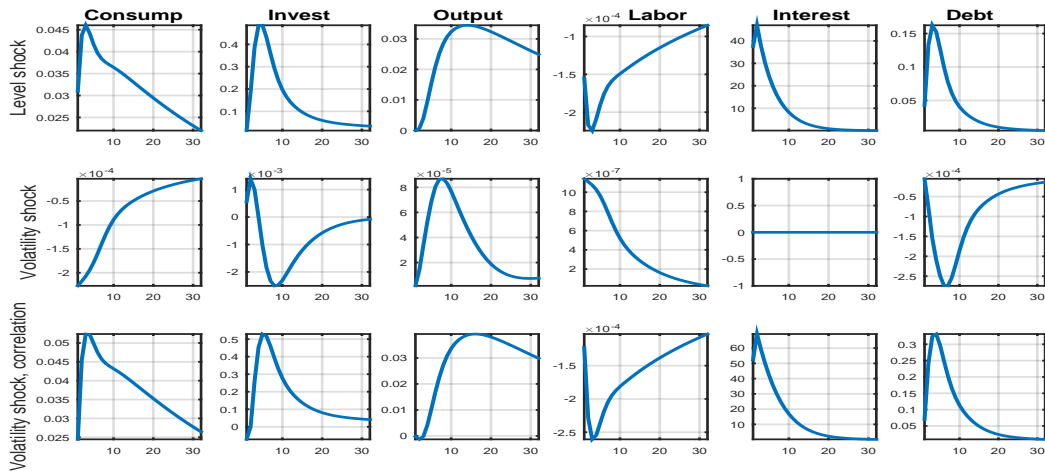
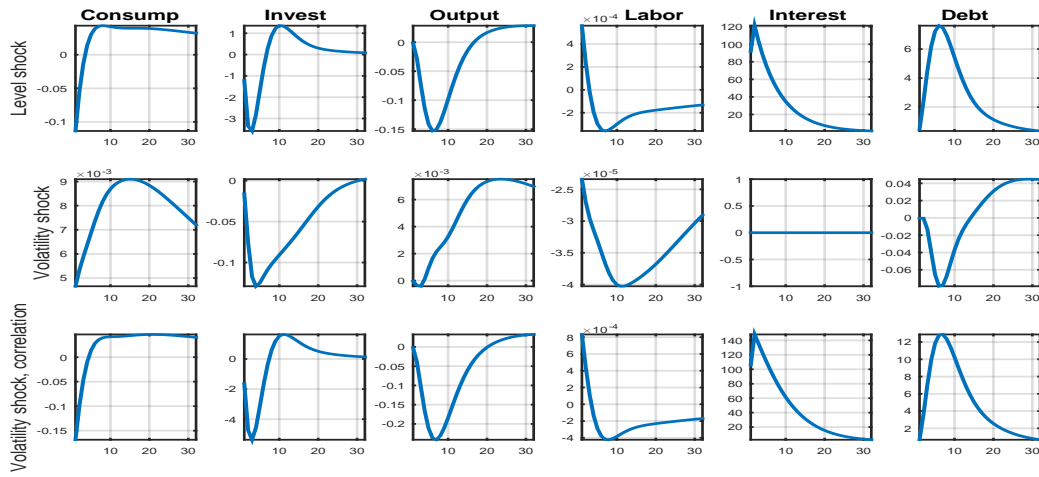


Figure 9: Generalized Impulse Response Functions (continued)

*Ukraine*



*Venezuela*

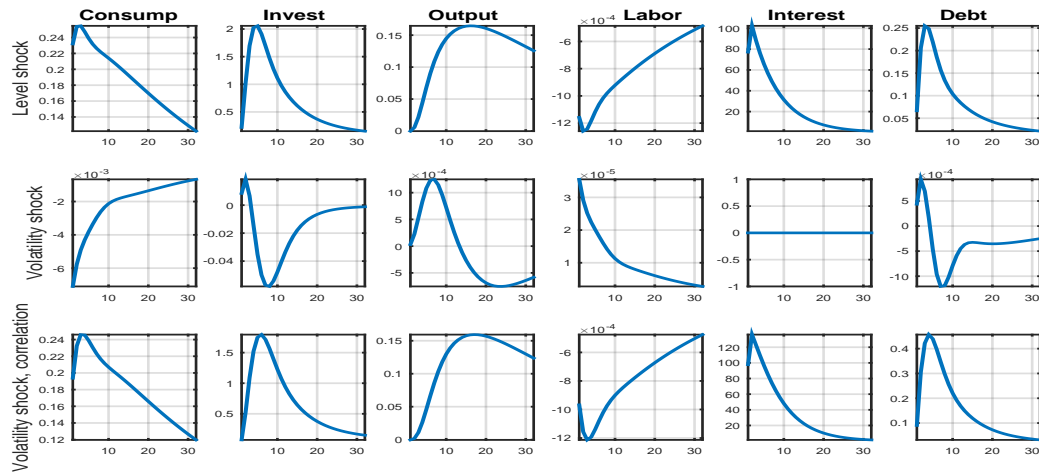




Table 1: Country Interest Rate Coverage and Mean of Real Interest Rates

<i>EMBIP Sample</i>	Time Period	$r$	Real T-Bill
Argentina	1993.12-2013.02	16.7	0.5
Brazil	1994.04-2013.02	6.4	0.5
Bulgaria	1994.08-2013.02	5.8	0.4
Colombia	1999.05-2013.02	3.5	-0.3
Ecuador	1995.02-2013.02	13.0	0.4
Indonesia	2006.10-2013.02	1.7	-1.2
Mexico	1993.12-2013.02	4.0	0.5
Panama	1996.07-2013.02	3.3	0.2
Peru	1997.03-2013.02	3.7	0.1
Philippines	1999.04-2013.02	3.2	-0.3
Russia	1997.08-2013.02	7.7	0.1
South Africa	2002.04-2013.02	1.0	-0.8
Turkey	1999.07-2013.02	3.8	-0.3
Ukraine	2001.07-2013.02	5.2	-0.8
Venezuela	1993.12-2013.02	9.6	0.5
<i>EA Sample</i>	Time Period	$r$	Real Bund
Austria	1997.12-2013.02	2.1	1.9
Belgium	1997.12-2013.02	2.3	1.9
Finland	1997.12-2013.02	2.0	1.9
France	1997.12-2013.02	2.1	1.9
Greece	1998.08-2013.02	5.6	1.9
Ireland	1997.12-2013.02	3.1	1.9
Italy	1997.12-2013.02	2.7	1.9
Malta	2008.02-2013.02	2.3	0.7
Netherlands	1997.12-2013.02	2.0	1.9
Portugal	1997.12-2013.02	3.4	1.9
Slovenia	2007.04-2013.02	2.9	1.0
Spain	1997.12-2013.02	2.7	1.9

*Notes:* EMBIP sample: yield difference of JP Morgan EMBI+ bond over a 3-month U.S. T-Bill; loans are denominated in U.S. dollars. EA sample: 3rd polynomial, constant maturity, stored yield curves on 10 year government bonds for loans denominated in Euros. Available in frequencies from daily downwards (monthly, quarterly, etc.). *Source:* Datastream. RINTEMBIP is the real international risk-free rate described in Section 2.1 and in Section 2 of the [technical appendix](#). We chose periods based on the availability of bond yield data. For spreads (all are nominal), we could go back further to 1990.09 (except for Finland (1996.01), Greece (1998.08), Malta (2008.02), Portugal (1995.01) and Slovenia (2007.04)). GermanyRINT is the real (inflation expectations adjusted) German 10-year government benchmark bid yield – it is the nominal version of this (dating back to 1990.09) for which spreads are relative to, for the EA sample. The HICP index used to compute expected inflation dates from 1997.12. We multiply average rates by 100 to be in percentages.

Table 2: Priors for Parameters of the Stochastic Volatility Model

Country	$\rho_r$	$\sigma_r$	$\rho_{\sigma_r}$	$\eta_r$
Argentina	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-5.3, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Austria	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-9.5, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Belgium	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-8.9, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Brazil	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-6.8, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Bulgaria	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-6.7, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Colombia	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.5, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Ecuador	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-6.1, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Finland	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-9.3, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
France	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-9.3, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
GermanyRINT	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.9, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Greece	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-6.2, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Indonesia	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.8, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Ireland	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.7, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Italy	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.7, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Malta	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-8.6, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Mexico	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.3, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Netherlands	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-9.9, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Panama	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-8, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Peru	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.5, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Philippines	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.9, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Portugal	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.2, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
RINTEMBIP	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.6, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Russia	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-5.8, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
South Africa	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-8.2, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Spain	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.8, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Turkey	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-7.4, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Ukraine	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-6.5, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$
Venezuela	$\mathcal{B}(0.9, 0.02)$	$\mathcal{N}(-6.7, 0.4)$	$\mathcal{B}(0.9, 0.1)$	$\mathcal{N}^+(0.5, 0.3)$

*Notes:* Prior means and standard deviations are in parentheses, where  $\mathcal{B}$ ,  $\mathcal{N}$  and  $\mathcal{N}^+$  denote Beta, Normal and truncated Normal distributions. RINTEMBIP is the real (inflation expectations adjusted) 3 Month U.S. T-Bill – it is the nominal version of this for which EMBI+ spreads are relative to. Sensitivity of priors was checked with respect to the following: (i) changing mean of  $\eta_r$  prior from 0.5 to 0.25; (ii) changing mean and standard deviation of  $\rho_r$  and  $\rho_{\sigma_r}$  priors from (0.9, 0.02) to (0.5, 0.1) and from (0.9, 0.1) to (0.5, 0.2); (iii) combining (i) and (ii). These checks were also conducted for pre- and post-September 2008 samples.

Table 3: Posterior Medians

Sample	$\rho_r$	$\sigma_r$	$\rho_{\sigma_r}$	$\eta_r$	Sample	$\rho_r$	$\sigma_r$	$\rho_{\sigma_r}$	$\eta_r$
Austria	0.92 [0.89,0.94]	-9.56 [-10.03,-9.07]	0.95 [0.88,0.99]	0.19 [0.12,0.30]	Argentina	0.97 [0.96,0.98]	-6.05 [-6.64,-5.05]	0.93 [0.83,0.99]	0.39 [0.29,0.52]
Belgium	0.95 [0.94,0.97]	-9.25 [-9.80,-8.48]	0.97 [0.92,0.99]	0.20 [0.13,0.30]	Brazil	0.97 [0.95,0.98]	-7.17 [-7.69,-6.42]	0.97 [0.90,0.99]	0.23 [0.17,0.33]
Finland	0.93 [0.91,0.95]	-9.49 [-10.00,-8.78]	0.96 [0.87,0.99]	0.28 [0.18,0.42]	Bulgaria	0.98 [0.97,0.99]	-6.99 [-7.66,-6.14]	0.98 [0.92,0.99]	0.25 [0.16,0.38]
France	0.94 [0.92,0.96]	-9.52 [-10.01,-8.81]	0.97 [0.90,0.99]	0.21 [0.13,0.33]	Colombia	0.94 [0.92,0.96]	-7.78 [-8.16,-7.28]	0.92 [0.76,0.99]	0.20 [0.11,0.34]
Germany	0.95 [0.93,0.96]	-8.42 [-8.71,-7.56]	0.96 [0.77,0.99]	0.11 [0.04,0.24]	Ecuador	0.96 [0.94,0.97]	-6.62 [-7.07,-6.03]	0.89 [0.78,0.97]	0.46 [0.35,0.62]
RINT	0.99 [0.99,0.99]	-6.38 [-7.12,-5.62]	0.99 [0.98,0.99]	0.30 [0.22,0.42]	Indonesia	0.91 [0.87,0.94]	-7.98 [-8.47,-7.43]	0.87 [0.63,0.98]	0.34 [0.18,0.58]
Greece	0.98 [0.97,0.99]	-7.94 [-8.71,-7.19]	0.99 [0.97,0.99]	0.17 [0.11,0.25]	Mexico	0.96 [0.95,0.97]	-7.68 [-8.23,-6.86]	0.97 [0.92,0.99]	0.20 [0.13,0.30]
Ireland	0.99 [0.98,0.99]	-7.88 [-8.59,-7.08]	0.99 [0.98,0.99]	0.18 [0.13,0.25]	Panama	0.93 [0.90,0.95]	-8.13 [-8.39,-7.83]	0.83 [0.54,0.97]	0.27 [0.13,0.47]
Italy	0.92 [0.89,0.95]	-8.80 [-9.20,-8.31]	0.85 [0.55,0.99]	0.20 [0.02,0.58]	Peru	0.94 [0.92,0.96]	-7.76 [-8.14,-7.25]	0.93 [0.74,0.99]	0.21 [0.12,0.37]
Malta	0.91 [0.87,0.94]	-9.79 [-10.23,-9.35]	0.96 [0.88,0.99]	0.17 [0.10,0.26]	Philippines	0.93 [0.91,0.95]	-8.09 [-8.36,-7.80]	0.90 [0.63,0.99]	0.14 [0.05,0.30]
Netherlands	0.98 [0.97,0.98]	-7.38 [-8.14,-6.57]	0.99 [0.97,0.99]	0.23 [0.15,0.35]	RINTEMBIP	0.97 [0.96,0.98]	-8.37 [-8.88,-7.25]	0.97 [0.86,0.99]	0.21 [0.14,0.30]
Portugal	0.91 [0.88,0.94]	-7.96 [-8.37,-7.46]	0.82 [0.52,0.98]	0.31 [0.14,0.54]	Russia	0.98 [0.98,0.99]	-6.08 [-6.90,-5.20]	0.99 [0.96,0.99]	0.28 [0.20,0.39]
Slovenia	0.98 [0.98,0.99]	-8.00 [-8.72,-7.24]	0.99 [0.97,0.99]	0.16 [0.11,0.24]	SouthAfrica	0.92 [0.89,0.95]	-8.39 [-8.79,-7.93]	0.92 [0.73,0.99]	0.24 [0.14,0.39]
Spain					Turkey	0.93 [0.90,0.95]	-7.65 [-8.10,-7.12]	0.95 [0.81,0.99]	0.19 [0.11,0.32]
					Ukraine	0.95 [0.93,0.97]	-6.79 [-7.42,-6.03]	0.95 [0.85,0.99]	0.31 [0.21,0.46]
					Venezuela	0.95 [0.93,0.97]	-6.97 [-7.31,-6.56]	0.89 [0.78,0.97]	0.31 [0.21,0.43]

Notes: The euro area (EA) sample is on the left, while the emerging market (EMBIP) sample is on the right. 95% probability sets in brackets.  $\rho_r$  is the persistence of the interest rate level,  $\sigma_r$  is the mean (log) volatility of the interest rate,  $\rho_{\sigma_r}$  is the persistence of the (log) volatility and  $\eta_r$  is the parameter influencing the degree of stochastic volatility.

Table 4: Posterior Medians with Level-Volatility Correlation

Sample	$\rho_r$	$\sigma_r$	$\rho_{\sigma_r}$	$\eta_r$	$\kappa$	Sample	$\rho_r$	$\sigma_r$	$\rho_{\sigma_r}$	$\eta_r$	$\kappa$
Austria	0.92 [0.89,0.94]	-9.31 [-9.69,-8.90]	0.95 [0.89,0.98]	0.17 [0.12,0.26]	0.67 [0.35,0.88]	Argentina	0.97 [0.96,0.98]	-5.94 [-6.45,-5.21]	0.92 [0.84,0.97]	0.38 [0.29,0.50]	0.49 [0.27,0.65]
Belgium	0.95 [0.93,0.96]	-9.17 [-9.55,-8.67]	0.95 [0.90,0.98]	0.17 [0.12,0.26]	0.60 [0.25,0.84]	Brazil	0.96 [0.95,0.98]	-6.74 [-7.07,-6.37]	0.93 [0.89,0.96]	0.22 [0.17,0.29]	0.88 [0.70,0.97]
Finland	0.93 [0.91,0.95]	-9.38 [-9.88,-8.75]	0.95 [0.87,0.99]	0.29 [0.19,0.43]	0.26 [-0.07,0.54]	Bulgaria	0.98 [0.97,0.98]	-6.79 [-7.21,-6.33]	0.95 [0.90,0.97]	0.21 [0.16,0.31]	0.79 [0.54,0.93]
France	0.94 [0.91,0.95]	-9.45 [-9.92,-8.83]	0.96 [0.89,0.99]	0.21 [0.13,0.31]	0.30 [-0.04,0.58]	Colombia	0.94 [0.92,0.96]	-7.55 [-7.80,-7.31]	0.90 [0.79,0.95]	0.17 [0.11,0.27]	0.87 [0.52,0.99]
GermanyRINT	0.95 [0.93,0.96]	-8.32 [-8.69,-7.60]	0.98 [0.82,0.99]	0.08 [0.03,0.20]	-0.31 [-0.86,0.12]	Ecuador	0.95 [0.94,0.97]	-6.21 [-6.66,-5.67]	0.89 [0.81,0.95]	0.39 [0.30,0.53]	0.57 [0.32,0.75]
Greece	0.99 [0.99,0.99]	-6.39 [-7.11,-5.64]	0.98 [0.96,0.99]	0.27 [0.20,0.37]	0.58 [0.28,0.79]	Indonesia	0.90 [0.86,0.93]	-7.59 [-7.99,-7.17]	0.92 [0.81,0.98]	0.20 [0.12,0.33]	0.92 [0.42,0.99]
Ireland	0.98 [0.97,0.98]	-8.13 [-8.53,-7.53]	0.96 [0.93,0.99]	0.17 [0.12,0.25]	0.77 [0.49,0.95]	Mexico	0.96 [0.94,0.97]	-7.29 [-7.58,-6.93]	0.93 [0.89,0.96]	0.21 [0.16,0.29]	0.91 [0.77,0.97]
Italy	0.97 [0.98,0.99]	-7.92 [-8.51,-7.21]	0.98 [0.96,0.99]	0.18 [0.13,0.24]	0.62 [0.32,0.82]	Panama	0.93 [0.91,0.95]	-7.93 [-8.14,-7.69]	0.85 [0.69,0.94]	0.23 [0.15,0.34]	0.69 [0.41,0.86]
Malta	0.92 [0.89,0.95]	-8.76 [-9.09,-8.22]	0.90 [0.60,0.99]	0.13 [0.02,0.47]	0.47 [-0.17,0.96]	Peru	0.94 [0.91,0.95]	-7.39 [-7.57,-7.19]	0.86 [0.79,0.91]	0.22 [0.17,0.28]	0.99 [0.91,0.99]
Netherlands	0.91 [0.87,0.94]	-9.73 [-10.25,-9.30]	0.96 [0.88,0.99]	0.16 [0.10,0.26]	0.23 [-0.17,0.56]	Philippines	0.93 [0.91,0.96]	-8.00 [-8.19,-7.82]	0.85 [0.64,0.95]	0.13 [0.06,0.24]	0.71 [0.28,0.97]
Portugal	0.98 [0.97,0.98]	-7.48 [-8.10,-6.73]	0.98 [0.95,0.99]	0.20 [0.14,0.30]	0.55 [0.11,0.84]	RINTEMBIP	0.97 [0.96,0.98]	-8.41 [-8.87,-7.29]	0.96 [0.84,0.99]	0.21 [0.13,0.31]	-0.02 [-0.27,0.25]
Slovenia	0.91 [0.88,0.94]	-7.88 [-8.23,-7.44]	0.85 [0.62,0.98]	0.23 [0.10,0.44]	0.54 [0.03,0.93]	Russia	0.98 [0.97,0.99]	-5.94 [-6.56,-5.29]	0.96 [0.93,0.98]	0.25 [0.19,0.33]	0.79 [0.58,0.92]
Spain	0.98 [0.97,0.99]	-8.11 [-8.59,-7.56]	0.97 [0.95,0.99]	0.15 [0.11,0.21]	0.77 [0.44,0.96]	SouthAfrica	0.92 [0.89,0.95]	-8.11 [-8.41,-7.72]	0.91 [0.81,0.96]	0.21 [0.14,0.32]	0.82 [0.54,0.94]
						Turkey	0.93 [0.90,0.95]	-7.31 [-7.54,-7.04]	0.91 [0.84,0.95]	0.17 [0.12,0.25]	0.95 [0.77,0.99]
						Ukraine	0.95 [0.92,0.96]	-6.63 [-7.08,-6.09]	0.93 [0.86,0.97]	0.25 [0.19,0.36]	0.70 [0.40,0.87]
						Venezuela	0.95 [0.93,0.96]	-6.72 [-7.01,-6.35]	0.89 [0.81,0.95]	0.27 [0.19,0.37]	0.63 [0.41,0.79]

Notes: The euro area (EA) sample is on the left, while the emerging market (EMBI) sample is on the right. 95% probability sets in brackets.  $\rho_r$  is the persistence of the interest rate level,  $\sigma_r$  is the mean (log) volatility of the interest rate,  $\rho_{\sigma_r}$  is the persistence of the (log) volatility,  $\eta_r$  is the parameter influencing the degree of stochastic volatility and  $\kappa$  is the correlation parameter between the level shocks and the (log) volatility shocks.

Table 5: Empirical Moments of Output, Consumption, Investment and Net Exports

Country	Period	$\sigma_Y$	$\frac{\sigma_C}{\sigma_Y}$	$\frac{\sigma_I}{\sigma_Y}$	$\frac{\sigma_{NX}}{\sigma_Y}$	$\rho_{NX,Y}$	$\frac{NX}{Y}$ (%)	$\sigma_{NX/Y}$	$\rho_{NX/Y,Y}$
Argentina	1993Q1:2012Q3	4.76	1.23	3.19	15.05	-0.64	1.47	1.37	-0.67
Austria	1999Q1:2012Q4	1.62	0.66	2.73	12.5	0.53	2.09	0.41	0.38
Belgium	1999Q1:2012Q4	1.37	0.79	4.99	22.45	-0.28	1.88	0.57	-0.35
Brazil	1995Q1:2011Q4	2.16	1.02	3.66	163.1	-0.073	0.08	0.47	-0.05
Bulgaria	1999Q1:2012Q3	2.32	1.49	5.85	17.41	-0.70	-5.45	1.88	-0.70
Colombia	2000Q1:2010Q4	1.58	0.94	3.68	23.63	0.07	-1.37	0.52	0.15
Ecuador	1994Q1:2012Q3	2.07	2.25	8.17	520.8	-0.42	-0.01	2.13	-0.53
Finland	1999Q1:2012Q3	2.75	0.54	3.56	10.47	0.37	2.85	0.74	0.30
France	1999Q1:2012Q3	1.36	0.64	4.03	53.77	-0.51	-0.29	0.24	-0.48
Greece	2001Q1:2012Q4	1.86	1.27	5.18	8.93	-0.58	-6.06	0.93	-0.48
Indonesia	2001Q1:2012Q4	1.29	1.75	6.20	31.12	0.32	1.95	0.67	-0.18
Ireland	1999Q1:2012Q3	2.52	1.10	4.46	4.76	-0.40	8.15	1.01	-0.56
Italy	1999Q1:2012Q4	1.63	0.86	2.88	425.1	-0.12	0.07	0.39	-0.16
Malta	2008Q1:2012Q3	1.55	0.80	12.56	130.5	-0.00	0.78	1.63	-0.02
Mexico	1993Q1:2012Q4	3.43	1.34	2.85	25.79	-0.53	-0.75	0.77	-0.58
Netherlands	1990Q1:2012Q3	1.48	0.73	3.36	7.51	0.30	3.57	0.39	0.01
Peru	1997Q1:2012Q3	1.81	1.39	4.94	70.46	-0.18	0.67	1.07	-0.20
Philippines	1997Q1:2012Q3	1.18	0.95	10.11	45.67	0.14	-2.59	1.46	-0.01
Portugal	1999Q1:2011Q4	1.36	1.17	3.53	11.15	-0.34	-4.73	0.70	-0.38
Russia	1995Q1:2012Q1	3.57	0.95	105.8	8.59	0.26	5.43	2.00	0.03
Slovenia	2007Q1:2012Q4	2.71	0.81	3.99	62.39	-0.84	0.53	0.80	-0.84
SouthAfrica	2001Q1:2012Q4	1.55	1.22	3.76	130.6	-0.45	-0.19	0.61	-0.50
Spain	1999Q1:2012Q3	1.41	1.16	3.41	23.1	-0.78	-1.79	0.54	-0.74
Turkey	1997Q1:2012Q3	3.87	1.09	4.15	18.3	-0.68	-1.47	1.21	-0.60
Ukraine	2001Q1:2012Q3	4.61	0.84	3.97	38.28	-0.52	-0.70	1.58	-0.47
Venezuela	1998Q1:2013Q2	5.88	0.94	3.79	6.71	-0.51	-6.51	2.83	-0.48

Notes:  $\sigma_Y$  is output volatility,  $\frac{\sigma_C}{\sigma_Y}$  is the ratio of consumption volatility to output volatility,  $\frac{\sigma_I}{\sigma_Y}$  is the ratio of investment volatility to output volatility,  $\frac{\sigma_{NX}}{\sigma_Y}$  is the ratio of net export volatility to output volatility,  $\rho_{NX,Y}$  is the correlation between net exports and output,  $\frac{NX}{Y}$  is the ratio of net exports to output in percent,  $\sigma_{NX/Y}$  is the volatility of the ratio of net exports to output and  $\rho_{NX/Y,Y}$  is the correlation of the net export share of output and output.

Table 6: Calibration for Parameters Fixed across Countries

$\nu$	$\eta$	$\delta$	$\alpha$	$\rho_X$	$\omega$
5	1000	0.014	0.32	0.95	1

Notes:  $\nu$  is the inverse of the elasticity of intertemporal substitution,  $\eta$  is the inverse of the Frisch elasticity of labor supply to wages,  $\delta$  is the depreciation rate,  $\alpha$  is the capital income share,  $\rho_X$  is the persistence of productivity and  $\omega$  measures the disutility of labor.

Table 7: Country-Specific Parameter Calibrations Based on Fine Grid Search

	M1	M1	M1	M1	M2	M2	M2	M2
Countries	D	$\Phi_D$	$\phi$	$\sigma_X$	D	$\Phi_D$	$\phi$	$\sigma_X$
Argentina	15	0.0004	30	0.04	3	0.007	16	0.0425
Austria	50	0.01	12	0.015	50	0.01	12	0.015
Belgium	42	0.0001	2	0.0075	40	0.0001	2	0.0075
Brazil	12	0.00003	16	0.0175	11	0.0003	16	0.0175
Bulgaria	-25	0.00004	16	0.0175	2	0.0002	10	0.0175
Colombia	-18	0.0002	4	0.0125	-12	0.001	2	0.0125
Ecuador	0	0.0005	26	0.005	0	0.006	20	0.0025
Finland	72	0.01	2	0.0225	72	0.01	2	0.0225
France	-6	0.0002	2	0.0075	-7	0.0002	2	0.0075
Greece	-36	0.001	34	0.015	4	0.0007	20	0.0175
Indonesia	64	0.0005	20	0.0025	48	0.0003	20	0.0025
Ireland	130	0.005	2	0.0175	102	0.0001	6	0.0125
Italy	20	0.00003	40	0.0125	30	0.0001	30	0.0125
Malta	28	0.00002	2	0.0025	28	0.0001	2	0.0025
Mexico	-9	0.01	14	0.03	-4	0.01	14	0.03
Netherlands	90	0.01	2	0.0125	95	0.01	4	0.0125
Peru	11	0.0001	8	0.0075	31	0.0001	10	0.0075
Philippines	-38	0.0001	2	0.005	-24	0.0001	2	0.005
Portugal	-36	0.00001	60	0.01	1	0	40	0.01
Russia	33	0.01	14	0.0325	20	0.0005	40	0.03
Slovenia	9	0.01	2	0.0225	8	0.01	2	0.0225
South Africa	-1	0.00001	10	0.0075	10	0	10	0.0075
Spain	-24	0.00002	26	0.01	8	0	16	0.01
Turkey	-19	0.01	2	0.0325	-13	0.01	2	0.0325
Ukraine	-5	0.001	2	0.04	0	0.001	2	0.04
Venezuela	-30	0.01	2	0.0475	-20	0.01	4	0.0475

*Notes:* M1 is the benchmark model without correlation between level shocks and volatility shocks. M2 is the augmented model with non-zero correlation between level shocks and volatility shocks.  $D$  determines debt in the deterministic steady state,  $\Phi_D$  is the cost of net external debt adjustment,  $\phi$  is the capital adjustment cost and  $\sigma_X$  is the volatility of productivity.

Table 8: Matched Moments from Fine Grid Search (1 of 2)

		$\sigma_Y$	$\frac{\sigma_C}{\sigma_Y}$	$\frac{\sigma_I}{\sigma_Y}$	$\frac{NX}{Y}$	$\sigma_{NX/Y}$	$\rho_{NX/Y,Y}$
Argentina	Data	4.76	1.23	3.19	1.48	1.37	-0.67
	M1	4.66	0.61	3.23	1.39	4.78	0.59
	M2	4.87	0.52	3.11	1.49	2.63	0.44
Austria	Data	1.62	0.66	2.73	2.10	0.41	0.38
	M1	1.74	0.37	2.66	2.10	0.88	0.30
	M2	1.74	0.37	2.67	2.12	0.90	0.30
Belgium	Data	1.37	0.79	4.99	1.88	0.57	-0.35
	M1	0.89	0.23	4.98	1.92	1.25	0.22
	M2	0.90	0.24	5.15	1.87	1.31	0.21
Brazil	Data	2.16	1.02	3.65	0.08	0.47	-0.05
	M1	2.08	0.36	3.65	0.10	2.63	0.59
	M2	2.05	0.38	3.71	0.06	2.51	0.49
Bulgaria	Data	2.32	1.49	5.85	-5.50	1.89	-0.70
	M1	2.17	0.38	5.80	-5.44	3.79	0.48
	M2	2.11	0.32	5.61	-5.40	3.59	0.36
Colombia	Data	1.59	0.94	3.68	-1.37	0.52	0.15
	M1	1.46	0.22	3.73	-1.37	1.52	0.43
	M2	1.46	0.24	3.66	-1.35	1.11	0.25
Ecuador	Data	2.07	2.25	8.17	-0.01	2.13	-0.53
	M1	0.64	1.05	8.31	-0.27	1.39	0.32
	M2	0.30	1.37	8.38	-0.53	0.70	0.20
Finland	Data	2.75	0.54	3.56	2.85	0.74	0.30
	M1	2.66	0.26	3.13	2.88	1.12	0.04
	M2	2.66	0.26	3.14	2.83	1.15	0.04
France	Data	1.36	0.64	4.03	-0.29	0.24	-0.48
	M1	0.88	0.20	4.01	-0.27	0.93	0.28
	M2	0.88	0.20	4.19	-0.30	0.98	0.26
Greece	Data	1.86	1.27	5.18	-6.06	0.93	-0.48
	M1	1.81	1.29	5.06	-6.10	2.75	0.55
	M2	2.09	1.26	5.19	-6.02	3.49	0.51
Indonesia	Data	1.29	1.75	6.20	1.95	0.67	-0.18
	M1	0.30	1.14	6.56	2.17	0.77	0.23
	M2	0.30	0.98	6.33	2.54	0.74	0.26
Ireland	Data	2.52	1.10	4.46	8.15	1.01	-0.56
	M1	2.08	0.64	4.41	8.21	2.54	0.00
	M2	1.49	0.44	4.38	8.18	2.32	0.34
Italy	Data	1.63	0.86	2.88	0.07	0.39	-0.16
	M1	1.49	0.56	2.92	0.04	2.07	0.63
	M2	1.48	0.44	2.87	0.04	1.97	0.62

*Notes:* M1 is the benchmark model without correlation between level shocks and volatility shocks. M2 is the augmented model with non-zero correlation between level shocks and volatility shocks.  $\sigma_Y$  is output volatility,  $\frac{\sigma_C}{\sigma_Y}$  is the ratio of consumption volatility to output volatility,  $\frac{\sigma_I}{\sigma_Y}$  is the ratio of investment volatility to output volatility,  $\frac{NX}{Y}$  is the ratio of net exports to output in percent,  $\frac{\sigma_{NX}}{\sigma_Y}$  is the ratio of net export volatility to output volatility and  $\rho_{NX/Y,Y}$  is the correlation of the net export share of output and output.

Table 9: Matched Moments from Fine Grid Search (2 of 2)

		$\sigma_Y$	$\frac{\sigma_C}{\sigma_Y}$	$\frac{\sigma_I}{\sigma_Y}$	$\frac{NX}{Y}$	$\sigma_{NX/Y}$	$\rho_{NX/Y,Y}$
Malta	Data	1.55	0.81	12.56	0.78	1.63	-0.02
	M1	0.35	0.37	12.71	1.25	1.31	0.08
	M2	0.35	0.40	12.74	1.26	1.30	0.08
Mexico	Data	3.44	1.34	2.85	-0.75	0.77	-0.58
	M1	3.47	0.39	2.65	-0.75	1.62	0.42
	M2	3.47	0.39	2.66	-0.69	1.62	0.41
Netherlands	Data	1.48	0.73	3.36	3.57	0.39	0.01
	M1	1.48	0.28	3.34	3.60	0.87	0.02
	M2	1.47	0.33	3.29	3.59	0.96	0.09
Peru	Data	1.81	1.39	4.94	0.67	1.07	-0.20
	M1	0.90	0.33	5.00	0.71	1.42	0.40
	M2	0.90	0.34	5.14	0.67	1.52	0.39
Philippines	Data	1.18	0.95	10.11	-2.59	1.46	-0.01
	M1	0.66	0.21	10.52	-2.58	1.89	0.13
	M2	0.66	0.22	10.63	-2.51	1.95	0.12
Portugal	Data	1.36	1.17	3.53	-4.73	0.70	-0.38
	M1	1.22	0.51	3.79	-4.34	1.91	0.63
	M2	1.20	0.40	3.52	-4.65	1.71	0.61
Russia	Data	3.57	0.95	4.29	5.43	2.00	0.03
	M1	3.81	1.19	4.26	5.39	5.48	0.13
	M2	3.57	0.90	4.36	5.43	6.03	0.39
Slovenia	Data	2.71	0.81	3.99	0.53	0.80	-0.84
	M1	2.65	0.26	3.16	0.53	0.97	0.10
	M2	2.65	0.26	3.15	0.55	0.97	0.11
SouthAfrica	Data	1.55	1.22	3.77	-0.19	0.61	-0.50
	M1	0.90	0.25	3.89	-0.14	1.32	0.51
	M2	0.89	0.23	3.74	-0.15	1.26	0.50
Spain	Data	1.41	1.16	3.41	-1.79	0.54	-0.74
	M1	1.20	0.35	3.36	-1.87	1.65	0.62
	M2	1.19	0.28	3.37	-1.81	1.59	0.58
Turkey	Data	3.87	1.09	4.15	-1.47	1.21	-0.60
	M1	3.83	0.27	3.26	-1.49	1.39	0.16
	M2	3.83	0.27	3.30	-1.53	1.39	0.16
Ukraine	Data	4.61	0.84	3.97	-0.70	1.58	-0.47
	M1	4.68	0.26	3.75	-0.72	3.30	0.27
	M2	4.69	0.27	3.76	-0.67	3.42	0.24
Venezuela	Data	5.88	0.94	3.79	-6.51	2.83	-0.48
	M1	5.61	0.33	3.86	-6.40	2.25	0.28
	M2	5.56	0.36	3.76	-6.59	2.35	0.34

Notes: M1 is the benchmark model without correlation between level shocks and volatility shocks. M2 is the augmented model with non-zero correlation between level shocks and volatility shocks.  $\sigma_Y$  is output volatility,  $\frac{\sigma_C}{\sigma_Y}$  is the ratio of consumption volatility to output volatility,  $\frac{\sigma_I}{\sigma_Y}$  is the ratio of investment volatility to output volatility,  $\frac{NX}{Y}$  is the ratio of net exports to output in percent,  $\frac{\sigma_{NX}}{\sigma_Y}$  is the ratio of net export volatility to output volatility and  $\rho_{NX/Y,Y}$  is the correlation of the net export share of output and output.