Global shocks, terms of trade and Small Open Economies business cycles

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Abstract

Terms of trade have been largely considered an important determinant of business cycles in Small Open Economies (SOEs). Current estimates of their contribution to fluctuations in real variables show a large variability and do not exploit the full information from global indicators to improve their reliability. In this paper, I propose a novel strategy that allows me to separately identify innovations in terms of trade and global variables by extending the news-identification approach. My results suggest that about 20 percent of the volatility of macro aggregates in SOEs are driven by terms of trade and more than one-third can be explained by *"global shocks"*. I also find that these innovations have different transmission mechanisms and asymmetric effects on countries in emerging and developed markets. Particularly, real interest rates respond in opposite directions, rising in the face of a global shock.

1 Introduction

The current literature recognizes the relevance of commodity price movements as a determinant of business cycles in Small Open Economies (SOEs). Drechsel and Tenreyro (2018) estimates that 39 percent of the variability in output growth is associated with commodities prices fluctuations, Ben Zeev et al. (2017) after considering anticipated information estimate it to be 50 percent. In contrast, Schmitt-Grohé and Uribe (2015) estimates that only 10 percent of real output fluctuations in emerging markets can be explained by terms of trade innovations. Differences in the assumptions, countries and data frequency across them could partly explained variation in their estimates. However, none of them take advantage of the endogenous nature of terms of trade, leaving out information that can help to improve the reliability of their results. In this paper, I provide a framework that allows me to disentangle the effect of terms of trade from common movements in world indicators in Small Open Economies. The result shows that terms of trade deviations drive approximately 20 percent of the long-run volatility in real variables in these markets.

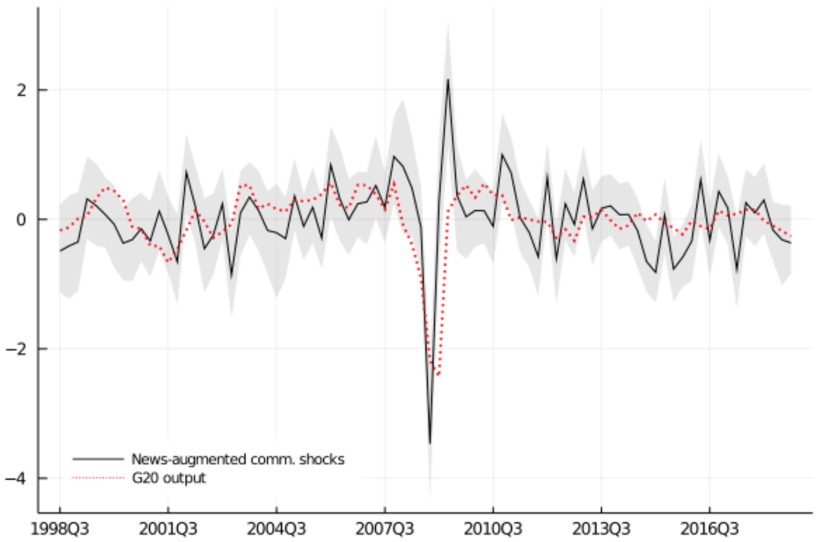
It is commonly assumed that terms of trade are exogenous to fluctuations in SOE domestic variables but they are endogenous in the world economy. However, markets are not perfect and thus fluctuations in terms of trade are not totally explained by real variables. Extending this logic, movements in terms of trade can be decomposed in two types: *a global* component which is driven by common fluctuations in global conditions and *an idiosyncratic* one. To illustrate the former, growth of Chinese real output during the last decade led to large volume of imports of mining and non-mining products from SOEs leading to better terms of trade. This triggered a rise in investment and a wealth effect in SOEs based on higher valuation of mining inventories. In contrast, an expectation-driven shock to relative prices is an example of the latter. It changes portfolio decisions and has a faster influence on financial variables.

There is evidence in the data showing a common global component in terms of trade movements across SOEs. Table 3 reports the simple correlation coefficients among terms of trade indexes for 6 emerging and 4 developed Small Open Economies. It shows that 80 percent of the pair by pair correlations are above 0.8 reflecting a possible common source of variation. Moreover, figure 1 reveals that anticipated terms of trade movements are correlated with global real output fluctuations. The solid line plots the innovation with largest contribution in fluctuations of terms of trade [recovered by applying the procedure in Ben Zeev et al. (2017)] while the dotted line show the evolution of the annual growth of the real GDP index for the G20 countries which is a proxy for world economic performance. These series have a correlation about 0.45 and even without considering the financial crisis (2007-2009) this coefficient only reduces to 0.38.

The presence of two sources of explanation for terms of trade fluctuations leads to question: *is it relevant to differentiate both from a policy perspective?* If these shocks present different transmission mechanisms with contrasting implications, policy makers have to consider the source of terms of trade fluctuations while making decisions. The scope of this paper is: first improve the understanding of the relation between business cycles fluctuations in Small Open Economies, terms of trade and global conditions by disentangling these shocks from each other, and then verifying whether these shocks have different implications at policy level.

To isolate the global component, I develop a novel identification procedure by extending the news-identification approach of Uhlig (2004) and apply it to a small open economy setting. In this framework, there are two types of economies, a Small Open Economy (SOE) and a foreign bloc (ROW) that represents the rest of the world economy. The ROW does not receive any feedback from the SOE. A global shock is defined as the innovation with the highest explanatory power in the joint variation of ROW variables. To control for the effect of common movements in the ROW and disentangle it from terms of trade idiosyncratic innovations I augment the Uhlig procedure to account for orthogonality to a pre-identified structural shock. The idiosyncratic part of terms trade [terms of trade deviations] is defined as the main determinant of commodities price volatility that orthogonal to the global shocks. Using this framework I run a country-specific SVAR for ten SOEs and the results show that global shocks explain more than one-third of business cycles movements.

Figure 1: News-augmented commodity shocks vs G20 output growth



The solid line represents the news-augmented terms of trade shock averaging across countries. This innovation is identified following Ben Zeev et al. (2017) and it is defined as the shock with highest contribution in the volatility of terms of trade. The shaded area is the confidence set of 68 percent. The dotted line is the growth rate of the real output index for the G20 group of countries.

The results suggest that both shocks are important determinants of the long-run volatility of terms trade, explaining two-thirds of their predictability. However, global shocks are relevant in the medium and long run while idiosyncratic terms of trade deviations drive short-term fluctuations of terms of trade and are responsible for more than half of their predictability during the first year. Moreover, these shocks also differ in their transmission mechanisms to small markets. An impulse-response analysis reveals that consumption and domestic output respond less to terms of trade deviations and the direction of movements of real interest rates is opposite. Besides, the appreciation of real exchange rates is more persistent when driven by terms of trade deviation.

In line with Shousha (2016), my results reveals an asymmetric response across emerging and advanced SOEs. The asymmetry is observed in the muted response of real variables in advanced markets, and the direction and shape of the impact of both shocks in consumption and net exports. Consumption in emerging countries report a positive and hump-shape response, while in advanced markets consumption reduces when facing a terms of trade deviations. On the other hand, net exports as ratio of the GDP increases in response to both shocks, while the effect is reverse in emerging markets.

2 Related Literature

The main scope of this paper is to enhance the knowledge about the role of terms of trade movements as a driver of SOEs' business cycles and their relation with global conditions. Roughly speaking, we could divide the theoretical framework of SOE modelling between Aguiar and Gopinath (2007), and García-Cicco et al. (2010). The former using a reliable calibration of the trend/cycle variance-ratio finds that standard RBCs fit well the data. The latter, using Bayesian techniques, suggests that basic models offer a poor explanation for business cycles in SOEs and concludes that the inclusion of additional departures as financial frictions, country-premium shocks, among others could improve the performance of these models. On the same line, Justiniano and Preston (2010) shows the difficulties of standard models to account for the effect of global fluctuations. Drechsel and Tenreyro (2018) builds a two-sector model that includes negative correlation of terms of trade with global interest rates, reporting that commodity price shocks drive around 22 percent of fluctuations in output and 34 percent on investment. In this regard, I find that orthogonal movements in terms of trade have a sizable contribution to real variables even after being controlled by global conditions.

This paper is also related to the literature of news shocks and its empirical estimation by maximizing the share of a cumulative forecast variance matrix. This method, developed by Uhlig (2004) has been widely used to identify anticipated TFP shocks[1]. Since terms of trade also have a financial asset role, the inclusion of future information is also relevant to account for the total effect of terms of trade, as is showed in Ben Zeev et al. (2017)

[1]Other seminal papers that explore news-driven business cycles are Beaudry and Portier (2006) that using a mixture of short and long identification supports the idea of business cycles news-driven, and Barsky and Sims (2011) that imposes a zero restriction besides with the standard maximum share approach

that after including anticipated information, term of trade explains around one-half of the forecastability for real variables in a sample of five commodity exporters LATAM countries. Although this approach is highly related to mine, I depart from it, by extending the current methodology in order to use the information of multiple varibale to improve the identification and disentangling the effect of pure terms of trade deviations from a global component. Additionally, I also include a set of developed markets to show the robustness of my approach.

An opposite result is found by Schmitt-Grohé and Uribe (2015) that based on annual information for 38 countries reports, both theoretically and empirically a small contribution (10 percent) of terms of trade on real variable predictability. Their results are improved by Fernández et al. (2017) which shows that an enriched framework increases the relevance of the foreign bloc, concluding that global shocks (not only terms of trade) explain near to 30 percent of the volatility in small open economies. The impact of anticipated information on the domestic economy is also studied in Dupaigne et al. (2007) that estimates a VECM model with zeros restrictions to find that news-shock in large economies generates booms in smaller ones. On the same side, Kamber et al. (2017) estimates a contribution of TFP news-shocks on output fluctuations close to 20 percent. I take all these contributions to estimate the effect of global shocks including information about the future, but my treatment of the foreign block is different, I do not make any assumption about the TFP unobservable data and I include the terms of trade channel as well. Moreover, the effect of global risk is studied in Özge Akıncı (2013) which reports that these shocks contributes to 20 percent of output fluctuations. In contrast, I find that global shocks contribute by more than one-third of the predictability of domestic variables in the long run, even if both results are not incompatible, I show that the global economy (summing up both shocks) has a large contribution in SOEs cycles.

My analysis also states an asymmetric response between advanced and emerging economies, being in line with papers as Shousha (2016), and Kim et al. (2020). The former estimates a panel VAR showing that advanced economies respond weaker, while the later finds that emerging markets are more reactive to risk shocks while advanced are more focused in US policy. As in Shousha (2016), I find that not only real variables in advanced economies are less sensitive to global fluctuations in the short run, but also real interest rate and net exports exhibits different paths between them. Finally, and in line with Schmitt-Grohé and Uribe (2015) using a panel of 38 countries and annual data shows a disconnection between empirical SVARs and theoretical I find a high variance within groups.

3 Empirical Methodology

This paper focuses on analyzing how global conditions and terms of trade are transmitted into small open economies and their asymmetries across advanced and emerging markets. Current literature considers several sources for external shocks such as credit supply shocks, policy uncertainty, foreign TFP, among others. As my goal is not to disentangle all the possible external shocks or discuss their identification, I will assume an agnostic posture regarding the nature of these fluctuations and define a global shock in an all encompassing manner. For the scope of this paper, I will consider a global shock as an underlying innovation that induces a persistent comovement in all variables of the ROW and is not affected by domestic conditions. As global shocks are related to persistent conditions and under the assumption of forward-looking households I can exploit the framework of Uhlig (2004), by generalized it for a group of variables.

3.1 Identification of Global Shocks

Let $\mathbf{Y}_t = \begin{bmatrix} \mathbf{y}_{\text{ROW},t} \\ \mathbf{y}_{\text{SOE},t} \end{bmatrix}$ be a $N \times 1$ vector of variables from the foreign (y_{ROW}), and domestic economy (y_{SOE}). The reduce form of the VAR could be represented as:

$$\mathbf{Y}_t = \mathbf{F}\mathbf{Y}_{t-1} + \mathbf{u}_t \tag{1}$$

with $\mathbf{\Sigma} = \mathbb{E}[\mathbf{u}'\mathbf{u}]$ being the variance-covariance matrix. Let $\mathbf{C}$ be a orthogonalization matrix such that $\mathbf{u}_t = \mathbf{C}\mathbf{e}_t$, and $\mathbb{E}[\mathbf{e}'\mathbf{e}] = \mathbf{I}$. Then, the Wold representation of the reduced-form model will be:

$$\mathbf{Y}_t = \mathcal{R}(L)\mathbf{C}\mathbf{e}_t \tag{2}$$

where L is the backward operator, and $\mathcal{R}(L)$ is the polynomial of response matrices $\mathbf{R}$ such that $\mathcal{R}(L) = \sum_{i=0}^{\infty} \mathbf{R}_i L^i$. The matrix C controls any possible scale effect in the data. Let $\mathbf{D}$ be the matrix that maps the structural shocks ($\boldsymbol{\epsilon}$) to the residuals ($\mathbf{e}$) of the models, it implies that $\mathbf{e}_t = \mathbf{D}\epsilon_t$. In order to be observational equivalent to the reduced form, the identification matrix $\mathbf{D}$ should satisfy $\mathbf{D}'\mathbf{D} = \mathbf{I}$. Each column of $\mathbf{D}$ is called an identification vector. In my framework the partial identified system can be write as:

$$\mathbf{Y}_t = \mathcal{R}(L)\mathbf{C} \times [\boldsymbol{\gamma} \quad \boldsymbol{\psi} \quad d_{\text{N,N-2}}] \times \begin{bmatrix} \epsilon_t^{gs} \\ \epsilon_t^{tot} \\ \epsilon_{\text{N-2},t} \end{bmatrix} \tag{3}$$

In the equation above $\boldsymbol{\gamma}$, and $\boldsymbol{\psi}$ represent the contemporaneous effect of global shocks (ϵ^{gs}) and terms of trade deviations (ϵ^{tot}) on the endogenous variables. Let $S^i(\underline{\tau}, \overline{\tau})$ be the cumulative forecast error variance of the variable i over the interval $[\underline{\tau} : \overline{\tau}]$ and $S^i_j(\underline{\tau}, \overline{\tau})$ be the variance explained by shock j. In standard applications, the vector ψ has been identified using a recursive identification or as the innovation that explains the maximum forecast error variance of terms of trade. For example Schmitt-Grohé and Uribe (2015) uses a Cholesky identification, and Ben Zeev et al. (2017) using quarterly data identify $\boldsymbol{\psi}$ as $\hat{\psi} = argmax\ S^{tot}_{\psi}(0, 4)$. In a similar way, $\boldsymbol{\gamma}$ have been obtained mostly by exploiting the information of just one variable.

In contrast, I propose a sequential procedure that firstly identifies $\boldsymbol{\gamma}$, and then recovers $\boldsymbol{\psi}$ conditional on $\boldsymbol{\gamma}$. I define the global shock as the structural innovation with the highest explanatory power in the joint volatility of the variables belong to the ROW bloc. Then, the identification of $\boldsymbol{\gamma}$ involves the following maximization problem:

$$\begin{aligned} \max_{\gamma} \quad & \sum_{i \in ROW} \frac{S^i_{\gamma}(\underline{\tau}, \overline{\tau})}{S^i(\underline{\tau}, \overline{\tau})} \\ \text{s.t.} \quad & \gamma'\gamma = 1 \\ & \gamma(\text{GDP}_{\text{ROW}}) \geq 0 \end{aligned} \tag{4}$$

The objective function is the average share of the global shock on the cumulative forecast error variance of the variables belonging to the foreign economy. Since every contribution is expressed as a share, this procedure does not suffer of scale-invariance. I am assuming equal weights for each variable but it can be easily extended to the case with different ones. The first constraint ensures unique identification, while the second ensures that I am restricting the response of global real output to be non negative[2].

After some algebra this problem can be re-expressed as (for details see the appendix):

$$\begin{aligned} \max_{\gamma} \quad & \gamma' \xi \gamma \\ \text{s.t.} \quad & \gamma'\gamma = 1 \\ & \gamma(\text{GDP}_{\text{ROW}}) \geq 0 \end{aligned} \tag{5}$$

with $\boldsymbol{\xi} = \sum_{i \in \text{ROW}} \left(\prod_{j \in \text{ROW}, j \neq i} S^j(\underline{\tau}, \overline{\tau}) \right) \Lambda^{(i)}$ being a weighted sum of cumulative forecast error variance matrices, and $\Lambda^{(i)} = \sum_{h=0}^{H} (\overline{\tau} + 1 - max(\underline{\tau}, h)) R_h^{'(i)} R_h^{(i)}$, where $R_h^{(i)}$ is the i-row of the response matrix h-periods ahead. The solution to this system is the eigenvector related to the maximum eigenvalue of $\boldsymbol{\xi}$. This method is clearly related with the factor analysis. However, exploiting the forecast error variance with a large horizon permits: (i) including forward-looking behavior in the implicit households, and (ii) accounting for the persistence and feedback inside the system. Even though dynamic factor models allow some degree of persistence, the lower computational cost and simplicity makes this method appealing.

3.2 Identification of pure ToT deviations

I define idiosyncratic terms of trade deviations as the main driver of the volatility of terms of trade that is not explained by global shocks. As before, I use a modified version of the

[2] In practical terms, if the simulation give me a eigenvector with the relevant entrance negative I just multiply it by a factor -1

medium run identification approach that allows me account for orthogonality with respect to the pre-identified global shock by setting up the following maximization problem:

$$\begin{aligned} \max_{\psi} \quad & S_{\psi}^{tot}(\underline{\tau}, \overline{\tau}) \\ \text{s.t.} \quad & \psi'\psi = 1 \\ & \psi_{(tot)} \geq 0 \\ & \psi'\gamma = 0 \end{aligned} \tag{6}$$

Similar to equation 4 the first two constraints ensure well behaved identification. The last condition imposes orthogonality with respect to the global shock. The solution to this system takes the form (see details in the appendix):

$$\Lambda_{\Xi} \times \varphi = \lambda \Xi \varphi \tag{7}$$

where $\boldsymbol{\varphi}$ is a vector dependent on the entries of $\boldsymbol{\psi}$, Ξ is a matrix that incorporates the orthogonality condition, and Λ_{Ξ} is the cumulative forecast error variances matrix after controlling for $\boldsymbol{\psi}$. Since this is a generalized eigenvalue-eigenvector problem, $\hat{\varphi}$ is the eigenvector associated with the maximum generalized eigenvalue. Since $\boldsymbol{\psi} = g(\boldsymbol{\varphi}|\boldsymbol{\gamma})$, the identification vector $\hat{\psi}$ could be recovered conditional on $\hat{\gamma}$, and the estimated $\hat{\varphi}$.

3.3 Econometric Strategy

Let $y_{\text{ROW},t}$ and $y_{\text{SOE},t}$ be the vectors of foreign and domestic variables, respectively. I run the following two blocs VAR:

$$\begin{bmatrix} y_{\text{ROW},t} \\ y_{\text{SOE},t} \end{bmatrix} = \begin{bmatrix} B_{11,1} & B_{12,1} \\ B_{21,1} & B_{22,1} \end{bmatrix} \begin{bmatrix} y_{\text{ROW},t-1} \\ y_{\text{SOE},t-1} \end{bmatrix} + \begin{bmatrix} B_{11,2} & B_{12,2} \\ B_{21,2} & B_{22,2} \end{bmatrix} \begin{bmatrix} y_{\text{ROW},t-2} \\ y_{\text{SOE},t-2} \end{bmatrix} + u_t \tag{8}$$

Following the literature, I estimate the model with two lags. Based on the Small Open Economy assumption I restrict any parameter in the submatrices $B_{12,1}$ and $B_{12,2}$, that reflect the feedback from the small market to the ROW, to be zero. I estimate the model in levels by restricted OLS, and then use a diffuse inverse-Wishart prior to draw combinations of variance-covariance matrix and coefficients keeping only those which satisfy stationarity conditions until I obtain 5000 simulations. Later, I identity $\boldsymbol{\gamma}$ and $\boldsymbol{\psi}$ from each simulated model and compute the impulse-response functions and forecast error variances. This procedure is repeated in each of the ten selected countries.

Following Shousha (2016), and Kamber et al. (2017), I divide the SOEs into two groups: (i) Emerging commodity exporters, and (ii) Developed commodity exporters. An additional departure of my strategy is how I construct the average statistics. Standard approaches consider the representative IRF and FEVD as the average of the country-specific measures (IRF or FEVD) and construct their confidence bands based on a combination of country-specific variances. In contrast, I collect all the realizations of IRFs and FEVDs, reporting their median and percentiles as the average statistic and its confidence bands, respectively. It has two advantages over the standard method: (i) reporting the median can deal with extreme values, and (ii) the confidence set is not required to be symmetric which enriches our analysis.

Therefore, the estimation algorithm can be summarized as:

Algorithm 1 Estimation of Global Shocks and Terms of trade deviations

The model in VAR-1 form: $Y_t = \Phi Y_{t-1} + U_t$

for g $\in$ {Emerging, Advanced} **do**

  for c in countries **do**

    Obtain $\hat{B}$, and $\hat{\Sigma}$ by restricted OLS

    for i = 1:N **do**

      1. Draw $\Sigma^{(i)} \sim IW()$
      2. Draw $B^{(i)} \sim MN()$
      3. **if** $max(|eigen(\Phi^{(i)})|) < 1$, continue **else** redo 1-2 otherwise
      4. Calculate $\gamma^{(i)}$, and $\psi^{(i)}$
      5. Compute and save $IRF^{(i)}$, and $FEV^{(i)}$

    end for

    Country result: Report median and percentiles $16^{th} - 84^{(th)}$

  end for

  Group result: Collect simulations and report median, and percentiles

end for

3.3.1 Data

To define a well behaved exogenous bloc, in addition to real terms of trade (after being deflated by US import prices of manufacturing goods), I consider two extra variables: (i) a production indicator approximated by the real GDP of G20 countries, and (ii) proxy of monetary conditions constructed as the spread of BAA corporate bonds with respect to the fed funds rate. The country-specific domestic block is composed of: i) real variables (production, consumption, and investment) , ii) next exports as ratio to GDP, iii) the real effective exchange rate obtained from the BIS website, and iv) the real interest rate. In almost all cases domestic variables were obtained from IMF, BIS, and Fed datasources, adjusted by seasonal factors[3]. The analysis we take into account the information of 10 small open economies that are mainly commodity exporters: a) emerging markets - Argentina, Brazil,Chile, Colombia, Peru, and South Africa, and b) developed countries - Australia, Canada, New Zealand, and Norway. The frequency of the data is quarterly from 1998q1 to 2018q4[4].

Real commodity prices: We consider the database from the IMF website which constructs country-specific term of trade measurements based on exported commodities (Gruss and Kebhaj, 2019). Although the dataset has several measures for terms of trade, I choose the fixed-weights and the one weighted by the ratio of exports to total commodity exports. This has two advantages: i) the fixed-weight measure tends less to structural breaks and it can deal with misreporting, and ii) using commodity export participation as weights allows us to isolate explicitly the effect caused by their movements without relying on any identification assumption and avoiding any reverse effect of domestic variables on commodity prices.

[3]In the cases when there is not seasonal adjusted date from central banks u other sources, we use ARIMA X13

[4]In the case to be required, the chained of different year-reference data was made using annual growth rates

4 Empirical results

The impulse-response functions and FEV contributions of a global shock are reported in figures 5 and 6, jointly with their 16th and 84th percentiles. The left panel reports the result for emerging markets while the right one for developed countries. In the external bloc, a positive innovation in global conditions generates a rise in terms of trade and a fall in the BAA spread, in both cases exhibiting a hump shape path reaching their peak in the first year and achieving a stable level after 12 quarters.

After an improvement in global conditions we observe positive responses in domestic real variables for both group of countries. In the short run, the response of domestic output is highly similar between emerging and advanced markets, but the exposure level - measured as FEV contribution- is higher in emerging markets. The global shocks drive around 30 percent of the forecastability of domestic variables in the first year in comparison with 20 percent in advanced economies. The peak of the contribution is reached approximately in the second year with a share of 45 and 35 percent, respectively. However, this gap closes as the economies converges to a stable point in the long run, where global conditions explain around one third of the variance in domestic production. A larger difference is observed in investment, in which case emerging market reports a higher but less persistent response to global shocks. In terms of predictability, these innovations account for more than one third of the investment fluctuations in developing economies achieving its long run contribution after two years, while it takes nearly 5 years for advanced markets to reach its stationary level. Although the impact on consumption forecastability in the long-run global shocks is almost the same - one third- for both groups, advanced countries are less sensitive to global fluctuations in the short run. These shocks explain around 36 percent in the emerging groups after two years, while only 21 percent in developed countries. In particular, there is an asymmetry in the response of this aggregate between these groups - while emerging markets reports a hump shape with a higher response after one year, consumption growth in advanced countries decreases in the first quarters and then increase to a level comparable to the long run effect of the first group.

Table 1: Share of identified shocks: Emerging markets

(i) Global shocks

h	Global Output	Terms of trade	BAA spread	Production	Consumption	Investment	Trade Balance	REER	Interest rate
0	0.48	0.26	0.46	0.05	0.03	0.04	0.02	0.07	0.01
4	0.80	0.38	0.67	0.32	0.17	0.17	0.10	0.14	0.06
8	0.80	0.44	0.70	0.45	0.30	0.33	0.22	0.22	0.13
20	0.60	0.41	0.60	0.38	0.31	0.34	0.28	0.27	0.19
40	0.49	0.39	0.56	0.35	0.31	0.33	0.29	0.28	0.20

(ii) Terms of trade deviations

h	Global Output	Terms of trade	BAA spread	Production	Consumption	Investment	Trade Balance	REER	Interest rate
0	0.09	0.54	0.09	0.03	0.02	0.04	0.03	0.08	0.02
4	0.06	0.50	0.10	0.12	0.07	0.13	0.07	0.10	0.05
8	0.06	0.45	0.12	0.13	0.10	0.17	0.10	0.16	0.08
20	0.10	0.41	0.16	0.18	0.16	0.21	0.17	0.19	0.11
40	0.12	0.38	0.17	0.19	0.18	0.22	0.19	0.21	0.13

This table reports the share of the forecast error variances explained in average by global shocks and terms of trade deviations in emerging SOEs after h quarters. The results were based on the median of the share estimated after applying the recursive identification proposes in this paper for each country in the emerging group.

More remarkable differences, are observed in financial and trading variables. A positive shock in global conditions improves the trade balance as ratio of GDP in advanced economies, but it reduces in emerging markets denoting that real export grows by less than domestic demand. On the other hand, the effective exchange rate shows a higher appreciation in advanced economies possibly due to the better liquidity of their currencies driven by their higher market integration. Finally, the response of interest rate is also higher in developed countries. These two results suggest that financial conditions are more determined by global shock in advanced economies.

At country level, the dynamics within each group have similarities and differences, as it is summarized in table 4. For example, in the group of emerging markets, Colombia's gross product has the highest exposure to global shocks while Chile output is less explained in the short run. Even though exports in both economies are mainly composed by a unique commodity (cooper for Chile, and crude oil for Colombia), the asymmetry in their forecastability is dependent on the product. During the last years, a big portion of copper price movements was supported by the outstanding Chinese growth [Chilean commercial partner]. So, even though both these SOEs have concentrated trading patterns, global movements have accounted for less in Chile.

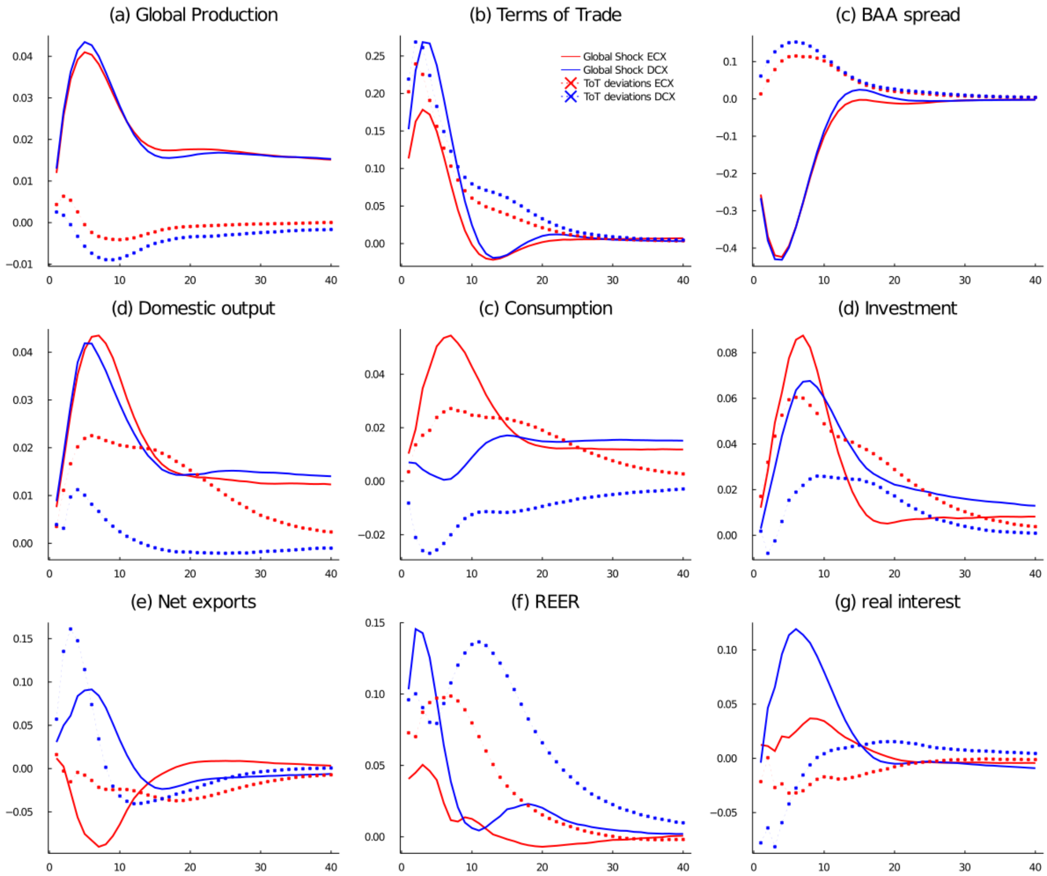
Among the analyzed advanced economies, with exception of New Zealand, the contribution of global shocks to the predictability of domestic production exhibits a hump shape. It is steeper for Norway and Canada both main exporters of crude oil. On par with Colombian results, the exposure of Norway's trade balance fluctuations to global shocks is the highest among the developed economies with a long run contribution close to 40 percent.

In line with Schmitt-Grohé and Uribe (2015) although the median response is different between groups of countries and the effects of global shocks are similar in the foreign block, the country-specific results for countries that belongs to the same group show high dispersion suggesting that country-specific conditions are required to improve our analysis (see figure 9).

4.1 Pure ToT deviations

The identified shock to terms of trade looks to be the main driver of terms of trade in the short run, explaining more than half of its contemporaneous fluctuations. A different picture is seen in the rest of components of the external economy in which it explains less than 10 percent of the instantaneous variance. Although, not at the same level as global shocks, terms of trade innovations explain a sizable fraction of the predictability of domestic real variables, accounting for 20 percent of their volatility. Regarding production and investment, the response are lower than those caused by global conditions, and their asymmetry between advanced and emerging markets are more pronounced. A slightly different story is observed in consumption where the impact of terms of trade movement increases the consumption in developing economies, while reducing consumption in advanced countries.

Figure 2: Comparison of shocks: Impulse response functions



The figure above plots the impulse response functions for the identified shocks divided between emerging and developed SOEs. The blue color represents the results for developed markets while the red color is associated with emerging countries. The response to global shocks is plotted in solid lines while the dotted one are related with terms of trade deviations. The estimations are based on 5000 draws of stationary country-specific SVAR models and computed as the median response by group.

The response of financial variables are a good source to verify the assumption of different transmission mechanism. On one hand, although both shocks appreciate the domestic currency, a persistent misalignment in commodity prices generates a continuous appreciation with a longer half-life. On the other hand, while global conditions cause an increase in real interest rates, idiosyncratic innovations generates a fall in them that is consistent with the response of global financial conditions (BAA spread). For instance, although it is not a pure terms of trade shock, I can conjecture a hike in commodities prices by an expected rise in the risk of substitute financial assets. This shock impacts positively on investment through a substitution effect among SOEs and rest of the world, but at the same time improvements in relative productivity appreciates the domestic currency, leading to a decreases in domestic real interest rate. In terms of predictability,

Table 2: Share of identified shocks: Developed markets

(i) Global shocks

h	Global Output	Terms of trade	BAA spread	Production	Consumption	Investment	Trade Balance	REER	Interest rate
0	0.56	0.24	0.49	0.04	0.04	0.02	0.02	0.11	0.02
4	0.83	0.43	0.67	0.20	0.12	0.11	0.10	0.17	0.08
8	0.82	0.46	0.67	0.35	0.18	0.18	0.16	0.19	0.16
20	0.59	0.42	0.56	0.37	0.26	0.29	0.23	0.25	0.22
40	0.47	0.40	0.53	0.36	0.29	0.29	0.25	0.26	0.24

(ii) Terms of trade deviations

h	Global Output	Terms of trade	BAA spread	Production	Consumption	Investment	Trade Balance	REER	Interest rate
0	0.04	0.56	0.07	0.02	0.04	0.02	0.04	0.1	0.04
4	0.03	0.49	0.09	0.05	0.13	0.05	0.12	0.1	0.07
8	0.05	0.43	0.12	0.06	0.16	0.08	0.14	0.14	0.09
20	0.08	0.38	0.16	0.10	0.20	0.14	0.19	0.22	0.12
40	0.10	0.36	0.17	0.12	0.20	0.16	0.20	0.22	0.14

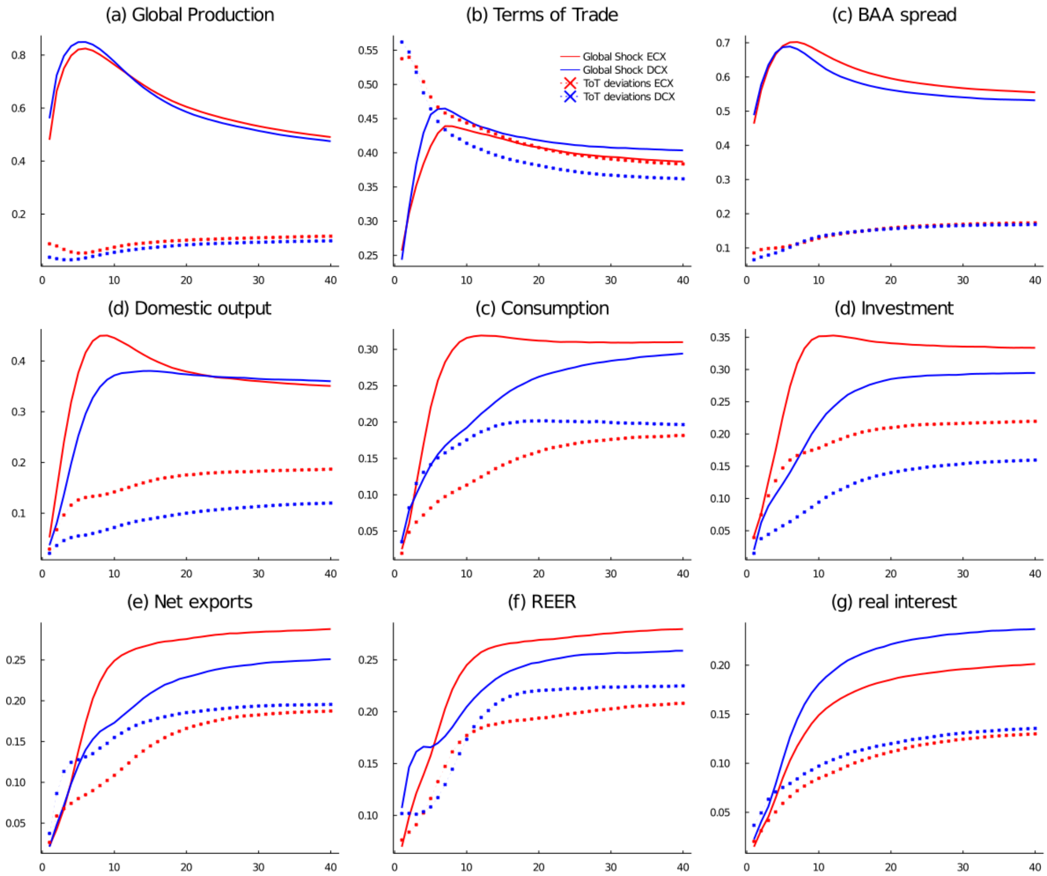
This table reports the share of the forecast error variances explained in average by global shocks and terms of trade deviations in developed SOEs after h quarters. The results were based on the median of the share estimated after applying the recursive identification proposes in this paper for each country in the developed group.

although global shocks have more explanatory power, the differences with respect to terms of trade deviations are not as large as in real variables, explaining on average 7-8 percent less than global conditions.

5 Conclusions

In this paper, I focus on the role of anticipated information to identify common components in global variables and trade of terms fluctuations. My procedure allows to disentangle both innovations. The results show that global shocks are more related to medium and large run fluctuations in terms of trade, while commodities prices have a small role in the determination of global real and financial conditions, but both shocks have sizable effects in domestic variables. Global shocks are the main driver in SOEs business cycles explaining more than one-third of real variable fluctuations in the long run, while terms of trade deviations are responsible by near 20 percent. Even though my identification strategy ensures that both shocks are orthogonal to each other, and impulse-response

Figure 3: Comparison of shocks: Forecast Error Variance contribution



The figure above plots the contribution to the forecast error variance of the identified shocks divided into emerging and developed SOEs. The blue color represents the results for developed markets while the red color is associated with emerging countries. The impact of global shocks is plotted in solid lines while the dotted ones are related with terms of trade deviations. The estimations are based on 5000 draws of stationary country-specific SVAR models and computed as the median share by group

analysis gives more evidence of these differences by exhibiting different transmission mechanisms. In particular, consumption is less responsive to terms of trade innovations, and interest rates respond positively to better global conditions, and negative to terms of trade deviations. Additionally, I find an asymmetric response across advanced and emerging markets, with a higher difference in consumption, trade balance, and exchange rates.

Appendices

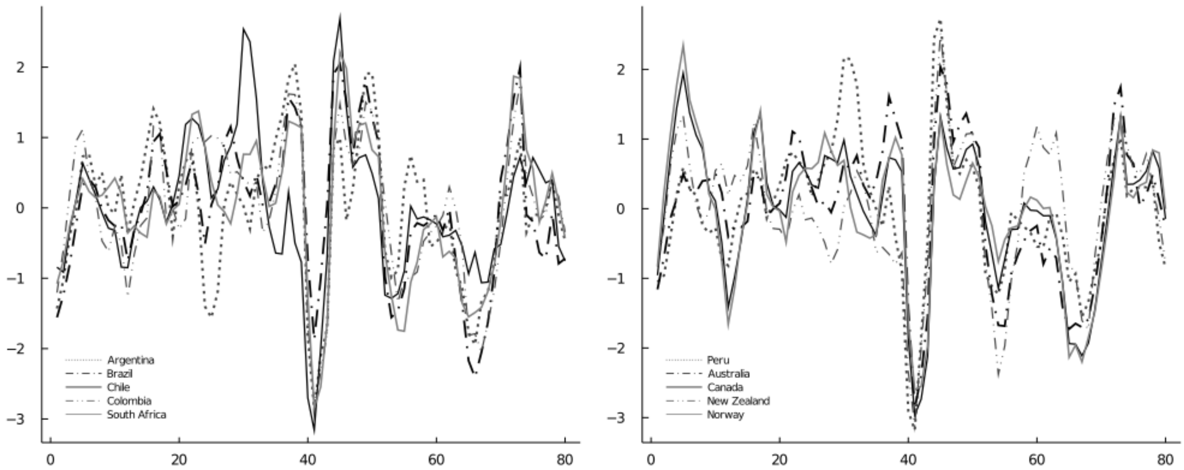
A Figures and tables

Table 3: Terms of Trade: Pair Correlation

	Argentina	Brazil	Chile	Colombia	Peru	South Africa	Australia	Canada	New Zealand
Brazil	0.911								
Chile	0.823	0.901							
Colombia	0.898	0.952	0.946						
Peru	0.888	0.952	0.951	0.975					
South Africa	0.853	0.938	0.99	0.956	0.962				
Australia	0.912	0.964	0.945	0.976	0.995	0.963			
Canada	0.862	0.809	0.886	0.913	0.893	0.868	0.899		
New Zealand	0.275	0.141	0.305	0.245	0.298	0.27	0.281	0.436	
Norway	0.826	0.76	0.831	0.876	0.841	0.811	0.851	0.99	0.417

This table shows the correlation between the country-specific terms of trade for the analyzed sample.

Figure 4: Country specific terms of trade



The plotted series are the standardized terms of trade (zero-mean and divided over its standard deviation).

Table 4: Share of Global shocks on FEV by country

	Global Output					Terms of trade					BAA spread				
	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40
Emerging	**0.48**	**0.798**	**0.801**	**0.605**	**0.491**	**0.257**	**0.384**	**0.439**	**0.408**	**0.387**	**0.464**	**0.666**	**0.697**	**0.596**	**0.555**
Argentina	0.144	0.395	0.617	0.535	0.434	0.32	0.401	0.422	0.413	0.399	0.29	0.589	0.706	0.626	0.573
Brazil	0.488	0.796	0.817	0.629	0.522	0.123	0.197	0.246	0.305	0.311	0.505	0.706	0.734	0.635	0.597
Chile	0.345	0.65	0.763	0.616	0.497	0.342	0.396	0.513	0.448	0.419	0.349	0.603	0.699	0.579	0.53
Colombia	0.549	0.844	0.822	0.611	0.502	0.218	0.368	0.4	0.383	0.376	0.513	0.683	0.688	0.604	0.574
Peru	0.562	0.848	0.84	0.623	0.517	0.136	0.293	0.351	0.375	0.372	0.482	0.67	0.674	0.597	0.568
South Africa	0.546	0.854	0.847	0.612	0.473	0.503	0.654	0.636	0.502	0.434	0.533	0.709	0.68	0.537	0.478
Advanced	**0.561**	**0.834**	**0.822**	**0.585**	**0.475**	**0.243**	**0.429**	**0.46**	**0.418**	**0.404**	**0.488**	**0.671**	**0.669**	**0.562**	**0.532**
Australia	0.568	0.832	0.831	0.614	0.516	0.165	0.335	0.389	0.356	0.35	0.44	0.627	0.632	0.538	0.513
Canada	0.545	0.814	0.808	0.563	0.455	0.29	0.485	0.522	0.443	0.414	0.469	0.667	0.672	0.553	0.514
New Zealand	0.569	0.854	0.85	0.628	0.507	0.265	0.428	0.417	0.418	0.41	0.533	0.707	0.715	0.611	0.582
Norway	0.563	0.83	0.797	0.524	0.412	0.265	0.464	0.504	0.445	0.431	0.498	0.675	0.643	0.545	0.52

	Domestic Production					Consumption					Investment				
	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40
Emerging	**0.052**	**0.319**	**0.45**	**0.379**	**0.351**	**0.025**	**0.169**	**0.299**	**0.312**	**0.31**	**0.042**	**0.174**	**0.333**	**0.341**	**0.334**
Argentina	0.023	0.239	0.39	0.321	0.321	0.014	0.131	0.333	0.297	0.3	0.024	0.234	0.387	0.342	0.34
Brazil	0.22	0.325	0.3	0.297	0.309	0.087	0.265	0.305	0.296	0.31	0.067	0.131	0.183	0.262	0.28
Chile	0.03	0.17	0.347	0.37	0.367	0.069	0.229	0.273	0.317	0.34	0.037	0.145	0.201	0.285	0.306
Colombia	0.086	0.436	0.585	0.519	0.447	0.012	0.176	0.313	0.309	0.31	0.087	0.346	0.543	0.492	0.464
Peru	0.059	0.26	0.445	0.419	0.387	0.014	0.045	0.126	0.279	0.293	0.015	0.225	0.387	0.354	0.341
South Africa	0.019	0.451	0.549	0.375	0.295	0.021	0.289	0.493	0.375	0.318	0.057	0.094	0.354	0.307	0.255
Advanced	**0.037**	**0.197**	**0.349**	**0.374**	**0.36**	**0.037**	**0.122**	**0.177**	**0.262**	**0.294**	**0.02**	**0.106**	**0.18**	**0.285**	**0.295**
Australia	0.114	0.185	0.319	0.434	0.401	0.029	0.087	0.142	0.3	0.334	0.014	0.05	0.087	0.193	0.224
Canada	0.041	0.292	0.428	0.384	0.366	0.031	0.072	0.122	0.194	0.235	0.016	0.467	0.612	0.485	0.435
New Zealand	0.028	0.175	0.26	0.323	0.336	0.046	0.136	0.161	0.221	0.273	0.019	0.072	0.165	0.229	0.252
Norway	0.013	0.163	0.381	0.364	0.345	0.045	0.256	0.339	0.328	0.329	0.035	0.081	0.135	0.253	0.271

	Trade Balance					REER					Real interest rate				
	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40
Emerging	**0.022**	**0.1**	**0.223**	**0.276**	**0.288**	**0.07**	**0.139**	**0.221**	**0.269**	**0.28**	**0.015**	**0.065**	**0.13**	**0.185**	**0.201**
Argentina	0.019	0.086	0.334	0.333	0.321	0.044	0.06	0.192	0.232	0.253	0.015	0.086	0.105	0.131	0.138
Brazil	0.021	0.047	0.085	0.175	0.218	0.065	0.115	0.179	0.256	0.275	0.016	0.045	0.082	0.143	0.171
Chile	0.119	0.218	0.262	0.302	0.316	0.045	0.242	0.367	0.382	0.374	0.023	0.098	0.189	0.246	0.264
Colombia	0.015	0.284	0.49	0.439	0.416	0.05	0.091	0.13	0.205	0.228	0.008	0.041	0.156	0.263	0.272
Peru	0.016	0.105	0.214	0.265	0.284	0.065	0.126	0.18	0.277	0.291	0.014	0.056	0.144	0.219	0.239
South Africa	0.014	0.07	0.157	0.192	0.198	0.169	0.314	0.333	0.284	0.277	0.018	0.071	0.143	0.169	0.173
Advanced	**0.021**	**0.098**	**0.162**	**0.229**	**0.251**	**0.107**	**0.166**	**0.185**	**0.248**	**0.259**	**0.022**	**0.078**	**0.16**	**0.221**	**0.237**
Australia	0.013	0.081	0.167	0.217	0.233	0.199	0.262	0.219	0.256	0.264	0.042	0.078	0.118	0.191	0.212
Canada	0.02	0.1	0.157	0.218	0.241	0.188	0.282	0.297	0.29	0.29	0.016	0.1	0.268	0.312	0.307
New Zealand	0.012	0.047	0.072	0.143	0.173	0.068	0.099	0.149	0.256	0.269	0.015	0.065	0.126	0.201	0.219
Norway	0.061	0.308	0.395	0.375	0.37	0.042	0.094	0.126	0.196	0.214	0.025	0.074	0.151	0.197	0.213

This table reports the median share in the forecast error variances explained by global shocks by country. The results were based on 5000 stationary draws.

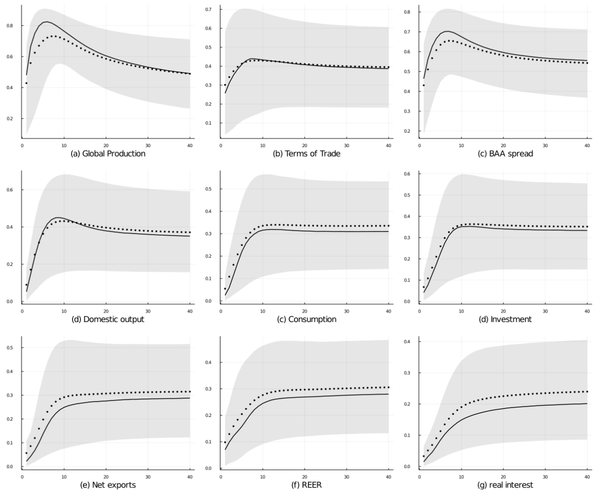
Table 5: Share of ToT deviations on FEV by country

	Global Output					Terms of trade					BAA spread				
	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40
Emerging	**0.088**	**0.057**	**0.064**	**0.102**	**0.117**	**0.538**	**0.504**	**0.453**	**0.408**	**0.384**	**0.085**	**0.1**	**0.117**	**0.159**	**0.173**
Argentina	0.452	0.388	0.201	0.129	0.112	0.535	0.532	0.472	0.393	0.359	0.153	0.128	0.1	0.117	0.121
Brazil	0.105	0.07	0.054	0.081	0.1	0.665	0.711	0.662	0.533	0.48	0.069	0.079	0.092	0.132	0.151
Chile	0.106	0.103	0.086	0.113	0.132	0.234	0.268	0.308	0.3	0.279	0.103	0.089	0.086	0.141	0.16
Colombia	0.069	0.033	0.055	0.1	0.115	0.625	0.572	0.509	0.449	0.428	0.082	0.106	0.137	0.171	0.185
Peru	0.084	0.037	0.045	0.084	0.104	0.687	0.643	0.566	0.469	0.444	0.051	0.111	0.15	0.181	0.196
South Africa	0.025	0.021	0.038	0.107	0.141	0.357	0.286	0.29	0.332	0.332	0.086	0.089	0.141	0.217	0.241
Advanced	**0.037**	**0.028**	**0.046**	**0.084**	**0.099**	**0.562**	**0.488**	**0.426**	**0.382**	**0.362**	**0.065**	**0.085**	**0.12**	**0.156**	**0.169**
Australia	0.051	0.033	0.044	0.088	0.114	0.612	0.57	0.517	0.459	0.433	0.059	0.121	0.157	0.192	0.204
Canada	0.038	0.035	0.055	0.103	0.12	0.489	0.408	0.357	0.34	0.331	0.061	0.069	0.108	0.155	0.178
New Zealand	0.037	0.02	0.034	0.06	0.069	0.575	0.501	0.444	0.372	0.351	0.064	0.078	0.099	0.119	0.123
Norway	0.027	0.028	0.054	0.093	0.103	0.557	0.46	0.404	0.372	0.35	0.077	0.083	0.127	0.17	0.178
	Domestic Production					**Consumption**					**Investment**				
	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40
Emerging	**0.029**	**0.116**	**0.135**	**0.175**	**0.187**	**0.02**	**0.072**	**0.103**	**0.159**	**0.182**	**0.039**	**0.128**	**0.171**	**0.21**	**0.22**
Argentina	0.024	0.139	0.115	0.122	0.127	0.016	0.063	0.076	0.099	0.11	0.025	0.133	0.113	0.126	0.127
Brazil	0.086	0.319	0.409	0.393	0.351	0.019	0.078	0.224	0.362	0.322	0.047	0.255	0.384	0.398	0.361
Chile	0.088	0.158	0.175	0.202	0.195	0.161	0.207	0.214	0.201	0.202	0.036	0.079	0.161	0.216	0.22
Colombia	0.015	0.046	0.071	0.112	0.142	0.009	0.127	0.175	0.211	0.221	0.089	0.169	0.148	0.176	0.189
Peru	0.023	0.093	0.109	0.168	0.182	0.011	0.034	0.046	0.103	0.135	0.04	0.14	0.198	0.301	0.294
South Africa	0.013	0.065	0.084	0.143	0.187	0.022	0.053	0.048	0.112	0.166	0.02	0.073	0.109	0.152	0.21
Advanced	**0.021**	**0.052**	**0.064**	**0.1**	**0.12**	**0.035**	**0.131**	**0.164**	**0.202**	**0.197**	**0.015**	**0.051**	**0.079**	**0.14**	**0.16**
Australia	0.031	0.051	0.061	0.083	0.115	0.02	0.255	0.306	0.247	0.217	0.013	0.047	0.095	0.222	0.237
Canada	0.017	0.04	0.058	0.118	0.142	0.024	0.064	0.088	0.172	0.182	0.015	0.04	0.047	0.124	0.16
New Zealand	0.028	0.068	0.091	0.1	0.105	0.018	0.039	0.061	0.09	0.096	0.026	0.058	0.098	0.123	0.127
Norway	0.013	0.053	0.054	0.1	0.116	0.182	0.359	0.344	0.327	0.305	0.011	0.061	0.083	0.113	0.134
	Trade Balance					**REER**					**Real interest rate**				
	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40	t=0	t=4	t=8	t=20	t=40
Emerging	**0.026**	**0.074**	**0.096**	**0.166**	**0.187**	**0.076**	**0.102**	**0.161**	**0.194**	**0.208**	**0.02**	**0.05**	**0.077**	**0.112**	**0.13**
Argentina	0.04	0.047	0.061	0.087	0.1	0.062	0.063	0.089	0.103	0.107	0.017	0.048	0.059	0.07	0.074
Brazil	0.024	0.05	0.07	0.165	0.196	0.159	0.291	0.35	0.347	0.327	0.036	0.064	0.086	0.113	0.132
Chile	0.225	0.2	0.213	0.22	0.218	0.06	0.105	0.137	0.182	0.192	0.047	0.091	0.129	0.16	0.172
Colombia	0.012	0.203	0.177	0.213	0.215	0.121	0.174	0.26	0.288	0.284	0.008	0.031	0.055	0.097	0.116
Peru	0.012	0.06	0.074	0.212	0.241	0.076	0.07	0.133	0.165	0.188	0.036	0.057	0.114	0.152	0.17
South Africa	0.018	0.05	0.07	0.127	0.174	0.023	0.05	0.118	0.165	0.196	0.01	0.038	0.054	0.109	0.153
Advanced	**0.037**	**0.125**	**0.142**	**0.185**	**0.196**	**0.102**	**0.104**	**0.145**	**0.22**	**0.225**	**0.037**	**0.071**	**0.089**	**0.12**	**0.136**
Australia	0.028	0.2	0.184	0.196	0.208	0.122	0.115	0.18	0.307	0.304	0.03	0.056	0.083	0.137	0.154
Canada	0.027	0.059	0.087	0.153	0.175	0.138	0.104	0.146	0.237	0.253	0.058	0.107	0.119	0.147	0.171
New Zealand	0.014	0.063	0.086	0.12	0.127	0.019	0.046	0.079	0.112	0.119	0.027	0.066	0.084	0.108	0.114
Norway	0.16	0.33	0.319	0.302	0.289	0.207	0.171	0.177	0.247	0.244	0.037	0.06	0.076	0.097	0.109

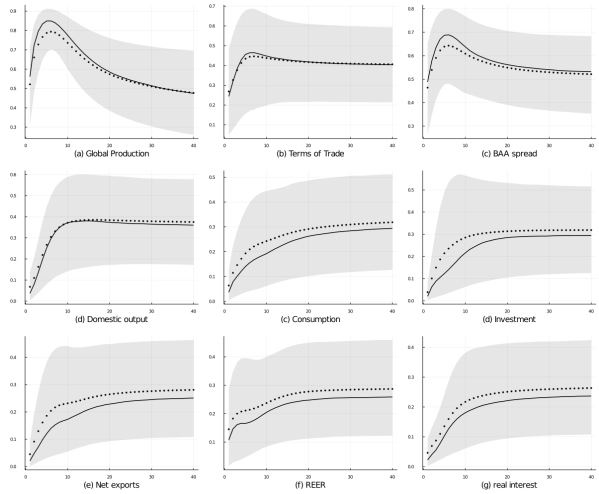
This table reports the median share in the forecast error variances explained by terms of trade deviations by country. The results were based on 5000 stationary draws.

Figure 5: Global Shock share in FEV

(a) Emerging markets



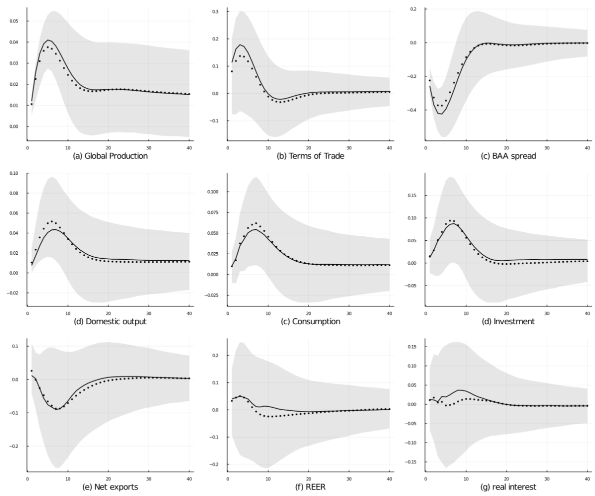
(b) Developed markets



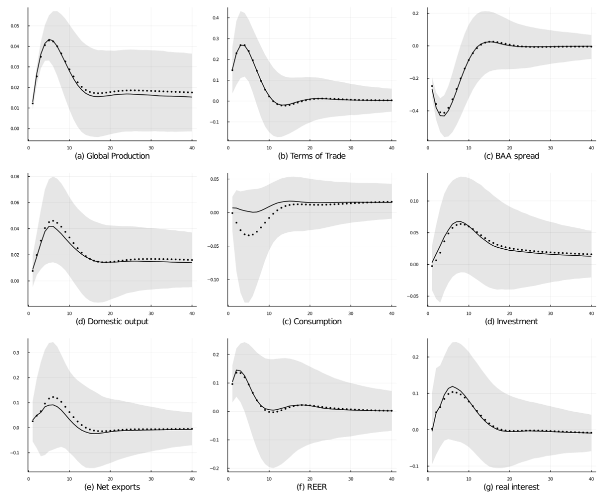
The figure plots the share of global shock in the forecast error variance by group of country. Panel (a) shows the results for emerging SOE, and panel (b) for developed countries. The calculations were based on 5000 stationary draw by each country and computed as the median (solid line) and the average (dotted lines) of all the simulations.The shaded area represents the confidence set for a 68% of probability

Figure 6: IRF to a Global shock

(a) Emerging markets



(b) Developed markets

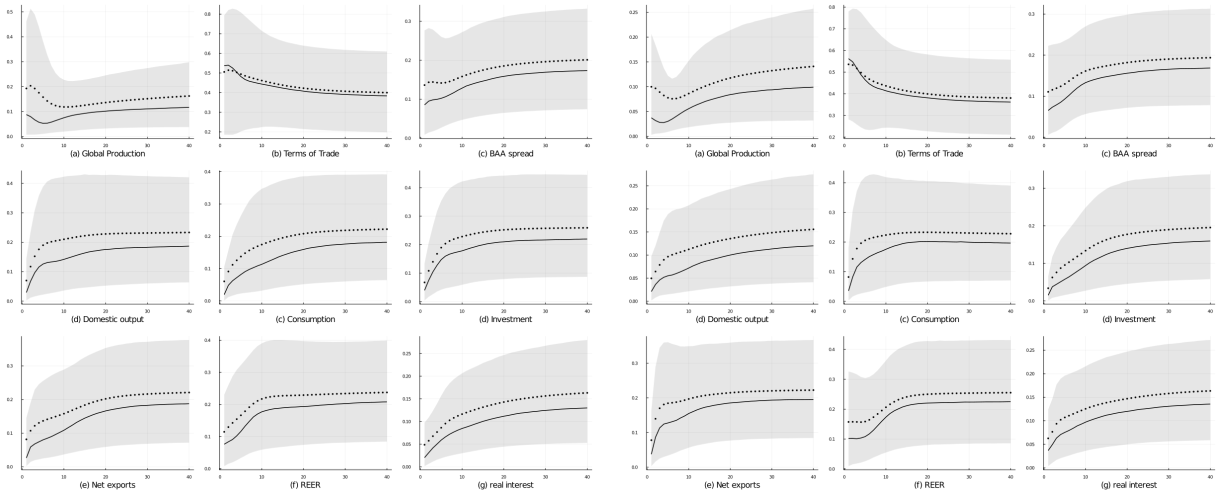


The figure plots the impulse response function to global shocks. Panel (a) shows the results for emerging SOE, and panel (b) for developed countries. The calculations were based on 5000 stationary draw by each country and computed as the median (solid line) and the average (dotted lines) of all the simulations.The shaded area represents the confidence set for a 68% of probability

Figure 7: ToT deviations share in FEV

(a) Emerging markets

(b) Developed markets

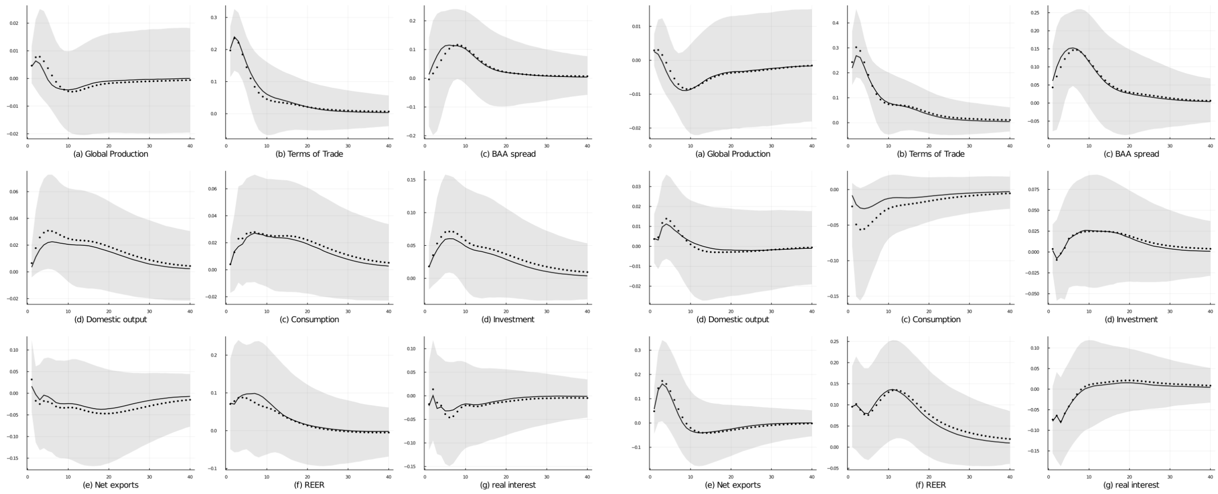


The figure plots the share of terms of trade deviations in the forecast error variance by group of country. Panel (a) shows the results for emerging SOE, and panel (b) for developed countries. The calculations were based on 5000 stationary draw by each country and computed as the median (solid line) and the average (dotted lines) of all the simulations.The shaded area represents the confidence set for a 68% of probability

Figure 8: IRF to a ToT deviation

(a) Emerging markets

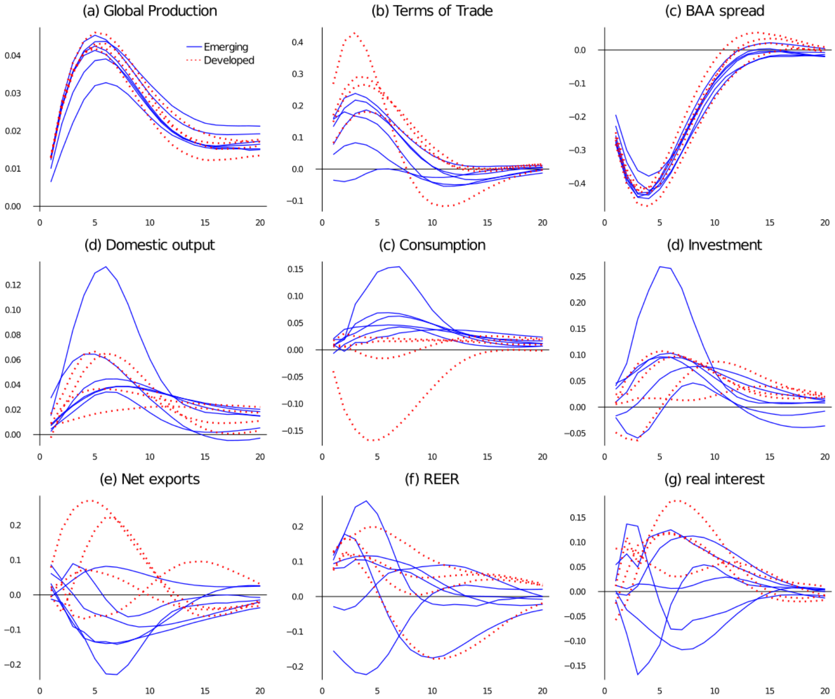
(b) Developed markets



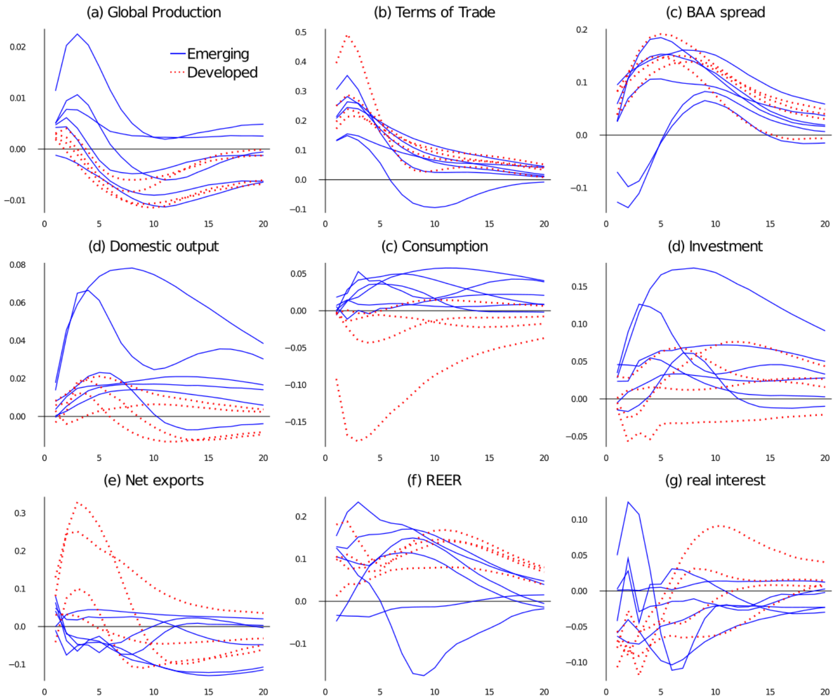
The figure plots the impulse response function to a terms of trade deviation. Panel (a) shows the results for emerging SOE, and panel (b) for developed countries. The calculations were based on 5000 stationary draw by each country and computed as the median (solid line) and the average (dotted lines) of all the simulations.The shaded area represents the confidence set for a 68% of probability

Figure 9: IRF by country

(a) Impulse Response Functions Global shocks



(b) Impulse Response Functions Pure ToT deviations



The figure plots the median of the impulse response functions to identified shocks by country. Panel (a) plots the response to global shocks and panel (b) to terms of trade deviations.Blue solid lines represents emerging markets and red dotted lines to advanced economies.

B Medium Run identification

Let be the reduced form of the VAR:

$$Y_t = FY_{t-1} + Ce_t$$

where Y is a vector of N variables with f indexing the foreign ones, while d the domestic ones, C is am orthogonalization matrix such that the $\mathbb{E}[e'e] = I$. Then, the forecast error after H period is:

$$Y_{t+H} - E[Y_{t+H}|t] = \sum_{h=0}^{H} F^h C e_{t+h-i} = \sum_{h=0}^{H} R_h e_{t+H-h}$$

with R_h being the reduce-form impulse-response matrix h periods ahead.

B.1 Identification of *augmented*-anticipated shock

We can write the forecast error variance matrix as:

$$\Omega^{(h)} = \sum_{i=0}^{h} R_i D D' R_i'$$

The diagonal of Ω registers the forecast error variance $h - step$ ahead for each variable of the system. Any matrix D will be observationally equivalent to the base model as it satisfies the condition $D'D = I$. We can decompose Ω into the contribution of each structural shock γ_j as follow:

$$\Omega^{(h)} = \sum_{i=0}^{h} \sum_{j=1}^{N} R_i \gamma_j \gamma_j' R_i' \tag{9}$$

The standard approach finds an identification vector γ that allows to recover an structural shock with maximum contribution to the cumulative forecast error variance (S) of the variable k between the periods $[\underline{\tau}, \overline{\tau}]$. Let be

$$S(\underline{\tau}, \overline{\tau}|j) = \sum_{h=\underline{\tau}}^{\overline{\tau}} \sum_{i=0}^{h} R_i \gamma_j \gamma_j' R_i'$$

the FEV explained by the $j-$shock. Then,, the problem will be equivalent to:

$$\begin{aligned} \gamma^* \quad &= \underset{\gamma}{\operatorname{argmax}} \left(\sum_{h=\underline{\tau}}^{\overline{\tau}} \sum_{i=0}^{h} R_i \gamma \gamma' R_i' \right)_{kxk} \\ \text{s.t.} \quad & \qquad \gamma'\gamma = 1 \end{aligned} \tag{10}$$

It could be rewritten by defining a matrix G_{NxN} of zeros with 1 in the kxk position, and using the trace operator, then:

$$\left(\sum_{h=\underline{\tau}}^{\overline{\tau}}\sum_{i=0}^{h} R_i\gamma\gamma' R_i'\right)_{kk} = \sum_{h=\underline{\tau}}^{\overline{\tau}}\sum_{i=0}^{h} tr(GR_i\gamma\gamma' R_i' G') = \gamma'\left(\sum_{h=\underline{\tau}}^{\overline{\tau}}\sum_{i=0}^{h}(GR_i)'(GR_i)\right)\gamma$$

Defining $R^{(k)}$ as the k-row of matrix R_i.

$$\begin{aligned}\gamma'\left(\sum_{h=\underline{\tau}}^{\overline{\tau}}\sum_{i=0}^{h}(GR_i)'(GR_i)\right)\gamma &= \gamma'\left(\sum_{h=\underline{\tau}}^{\overline{\tau}}\sum_{i=0}^{h} R_i^{'(k)} R_i^{(k)}\right)\gamma \\ &= \gamma' \underbrace{\left(\sum_{i=0}^{H}(\overline{\tau}+1-max(\underline{\tau},i))R_i^{'(k)}R_i^{(k)}\right)\gamma}_{\Lambda}\end{aligned}$$

Finally:

$$\begin{aligned}\gamma^* \quad &= \underset{\gamma}{\text{argmax}} \quad \gamma'\Lambda\gamma \\ \text{s.t.} \quad & \qquad\qquad \gamma'\gamma = 1\end{aligned}$$

Therefore, the optimal γ is the eigenvector related to the maximum eigenvalue of Λ.

C Global Shocks identification

I extend the previous methodology to obtain a vector γ that maps a structural shock which explains at maximum the forecastability in a group of variables (the external ones). Defining $S^i(\underline{\tau},\overline{\tau}|j)$ the forecast variance of the i-variable explained by the j structural shock over the time span $[\underline{\tau}:\overline{\tau}]$, the maximization problem is:

$$\begin{aligned}\gamma^* \quad &= \underset{\gamma}{\text{argmax}} \quad \sum_{i\in f}\frac{S^i(\underline{\tau},\overline{\tau}|\gamma)}{S^i(\underline{\tau},\overline{\tau})} \\ \text{s.t.} \quad & \qquad\qquad \gamma'\gamma = 1\end{aligned}$$

In this case, γ is an underlying shock that has a maximum average explanation power in the predictability of the foreign variables. I am labeling γ as the identification vector for the global shock. Developing the expression:

$$\sum_{i\in f}\frac{S^i(\underline{\tau},\overline{\tau}|\gamma)}{S^i(\underline{\tau},\overline{\tau})} = \sum_{i\in f}\frac{\gamma'\Lambda^{(i)}\gamma}{S^i(\underline{\tau},\overline{\tau})} = \frac{\overbrace{\sum_{i\in f}\left(\prod_{j=1,j\neq i}^{n^*} S^i(\underline{\tau},\overline{\tau})\right)\left(\gamma'\Lambda^{(i)}\gamma\right)}^{\gamma'\xi\gamma}}{\underbrace{\prod_{i\in f} S^i(\underline{\tau},\overline{\tau})}_{constant}} \propto \gamma'\xi\gamma$$

The maximization problem becomes into:

$$\gamma^* = \underset{\gamma_j}{\text{argmax}} \quad \gamma'\xi\gamma$$
$$\text{s.t.} \qquad \gamma'\gamma = 1$$

Finally, γ^* is the eigenvector related to the maximum eigenvalue of ξ.

C.1 Identifying a non-fundamental shocks

In order to identify a second shock mostly related with term of trade movements I define $\Lambda^{(i)}$ as the cumulative FEV matrix of the terms of trade, and I solve the problem:

$$\psi* = \underset{\psi}{\text{argmax}} \quad \psi'\Lambda^{(tot)}\psi$$
$$\text{s.t.} \qquad \psi'\psi = 1$$
$$\psi'\gamma = 0$$

The new restriction $\psi'\gamma = 0$ is imposed to ensure that the second identification vector will be orthogonal to the global shock, it implies that:

$$\begin{bmatrix} \psi_1 & \psi_2 & ... & \psi_n \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_n \end{bmatrix} = 0$$
$$\psi_1 = -\frac{\sum_{k=2}^{n} \psi_k \gamma_k}{\gamma_k}$$

Hence, we can rewrite the vector ψ as

$$\psi = \psi_2 \begin{bmatrix} -\frac{\gamma_2}{\gamma_1} \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + ... + \psi_n \begin{bmatrix} -\frac{\gamma_n}{\gamma_1} \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \rightarrow \psi' = \begin{bmatrix} \psi_2 & ... & \psi_n \end{bmatrix} \begin{bmatrix} -\frac{\gamma_2}{\gamma_1} & \\ \vdots & I \\ -\frac{\gamma_n}{\gamma_1} & \end{bmatrix} = \varphi'\chi'$$

From the first constraint:

$$\varphi'\chi'\chi\varphi = 1$$
$$\varphi'\Xi\varphi = 1$$

The Lagrangian is:

$$\mathcal{L} = \varphi'\chi'\Lambda^{(tot)}\chi\varphi + \lambda(1 - \varphi'\Xi\varphi) = \varphi'\Lambda_{\Xi}\varphi + \lambda(1 - \varphi'\Xi\varphi)$$

with the FOC:

$$\Lambda_{\Xi} * \varphi = \lambda B\varphi$$

Which is a generalized eigenvalue-eigenvector problem. Therefore, φ will be the vector associated with the larger generalized eigenvalue, and $\psi = \chi\varphi$.

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