

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

Christian Velasquez

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Boston College

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. Results show that the proposed method successfully identifies a global component and suggests that it explains about a half of output volatility in emerging countries and around one-third for developed commodity exporters, while terms of trade idiosyncratic movements are responsible only for 10 percent.

Keywords— Small open economies, global shocks, international business fluctuations

JEL classification— E32, F41, F44

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 more than 40 percent of the pair by pair correlations are above 0.5 reflecting a possible common source of variation.

The presence of two sources of explanation for terms of trade fluctuations leads to the 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.

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 shows 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.

To stress the relevance of commodities fluctuations in SOEs business cycles I run two exercises. The first considers a common shock in commodity prices orthogonal to the previously identified global shock while the second measured the effect of world-commodities supply shocks on the global component. Based on the former, a reduction [orthogonal to the global main factor] in commodities prices which is related with higher global production and worse monetary conditions causes an increase in domestic output and consumption for developed markets while emerging countries are not affected by it. Using the second exercise, I found that the world supply of commodities explains around 30 percent of the global shock fluctuations. This shows that although idiosyncratic movements in terms of trade are not a sizable explanation source of business cycles for Small Open Economies, global movements in commodities market [prices or quantities] have a relevant role to play.

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 \(2010b\)](#) 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 below what my estimates suggest.

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 shocks¹. 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. \(2017\)](#) 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 variable to improve the identification and disentangling the effect of pure terms of trade deviations from a global component.

On the other hand, I present additional evidence that show some relation between the identified global component and news about TFP (but not only related to them). Furthermore, my impulse response are qualitative similar to those found in [Jaimovich and Rebelo \(2008\)](#) after positive news in TFP. Similarly, [Guerron-Quintana \(2013\)](#) estimates a DSGE model for developed small open economies and finds a contribution of common disturbances on output predictability around 23 percent. Although my estimation reports a similar exposure of developed economies commodity exporter, the group of non commodity exporters are higher driven by global conditions.

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

¹Other 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

risk is studied in [Özge Akıncı \(2013\)](#) which reports that these shocks contribute 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 $\mathbf{Y}_t^{(d)} = \begin{bmatrix} \mathbf{y}_t^{(f)} \\ \mathbf{y}_t^{(d)} \end{bmatrix}$ be a column vector of $n = n_f + n_d$ entrances composed by n_f foreign variables and n_d domestic ones. The reduce form of the VAR is:

$$\mathbf{Y}_t = \mathbf{F}_1 \mathbf{Y}_{t-1} + \cdots + \mathbf{F}_p \mathbf{Y}_{t-p} + \mathbf{u}_t \quad (1)$$

with $\Sigma = \mathbb{E}[\mathbf{u}'\mathbf{u}]$ 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 is:

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

where L is the lag operator, and $\mathcal{R}(L)$ is the polynomial of response matrices \mathbf{R} such that $\mathcal{R}(L) = \sum_{h=0}^{\infty} \mathbf{R}_h L^h$.

Let \mathbf{D} be a matrix that maps the structural shocks (ϵ) to the residuals (\mathbf{e}) of the models, it implies that $\mathbf{e}_t = \mathbf{D}\epsilon_t$. Therefore, any matrix \mathbf{D} that satisfies $\mathbf{D}'\mathbf{D} = \mathbf{I}$ generates an observational equivalent reduced form. Each column of \mathbf{D} is called an identification vector. In my framework, the partial identified system can be written as:

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

In this equation γ , and ψ represent identification vector that map global shocks (ϵ^{gs}) and terms of trade innovations (τ) into the orthogonal residuals \mathbf{e}_t .

To recover these vectors, let $S^i(\underline{t}, \bar{t})$ be the cumulative forecast error variance of the variable i over the interval $[\underline{t} : \bar{t}]$ and $S_j^i(\underline{t}, \bar{t})$ be the variance explained by shock j in the same time span. 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, while [Ben Zeev et al. \(2017\)](#) using

quarterly data identify ψ as $\hat{\psi} = \text{argmax}_{\psi} S_{\psi}^{tot}(0, 4)$. In a similar way, γ have been obtained mostly by exploiting the information of just one global indicator.

In contrast, I propose a sequential procedure that firstly estimates $\hat{\gamma}$, and then recovers $\hat{\psi}$ conditional on $\hat{\gamma}$. I define the global shock as the structural innovation with the highest explanatory power in the joint volatility of the variables belong to the global economy bloc during the first 3 years ($[\underline{t}, \bar{t}] = [0, 13]$). Then, the identification of γ involves the following maximization problem:

$$\begin{aligned} \max_{\gamma} \quad & \sum_{i \in f} \frac{S_{\gamma}^i(\underline{t}, \bar{t})}{S^i(\underline{t}, \bar{t})} \\ \text{s.t.} \quad & \gamma' \gamma = 1 \end{aligned} \tag{4}$$

The objective function in 4 is the average share of the global shock on the cumulative forecast error variance that belong 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. Apart from the constraint $\gamma' \gamma = 1$ - that ensures unique identification - I impose that the contemporaneous response of global real output is not negative².

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

$$\begin{aligned} \max_{\gamma} \quad & \gamma' \xi \gamma \\ \text{s.t.} \quad & \gamma' \gamma = 1 \end{aligned} \tag{5}$$

with $\xi = \sum_{i \in f} \left(\prod_{j \in f, j \neq i} S^j(\underline{t}, \bar{t}) \right) \Lambda^{(i)}$ being a weighted sum of cumulative forecast error variance matrices, and $\Lambda^{(i)} = \sum_{h=0}^H (\bar{t} + 1 - \max(\underline{t}, h)) R_h'^{(i)} R_h^{(i)}$, 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 ξ . Although this method is related with common factor models, 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.

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

3.2 Identification of idiosyncratic Terms of Trade shocks

I define idiosyncratic terms of trade innovations as the main driver of terms of trade's volatility not explained by global shocks. As before, I use a modified version of the medium run identification approach that allows me to account for orthogonality with respect to the pre-identified global shock by setting the following maximization problem:

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

The last condition imposes orthogonality with respect to the global shock. In a similar way than before I include an additional constraint: the contemporaneous response of terms of trade after an idiosyncratic shock is non-negative. The solution to this system takes the form of a generalized eigenvalue-eigenvector problem (see appendix for details):

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

where φ is a vector dependent on the entries of ψ , Ξ is a matrix that incorporates the orthogonality condition, and Λ_{Ξ} is the cumulative forecast error variances matrix after controlling for ψ . Since $\psi = g(\varphi|\gamma)$, the identification vector $\hat{\psi}$ could be recovered conditional on $\hat{\gamma}$, and the estimated $\hat{\varphi}$.

3.3 Econometric Strategy

Let f represent the rest of the world (ROW) economy and i indexes the SOE economies. Under the assumption that domestic economies do not affect the global block, I can write the following

two lags VAR model:

$$\begin{bmatrix} p_t^f \\ y_t^f \\ \tau_t^i \\ y_t^i \end{bmatrix} = \begin{bmatrix} A_{11}^{(1)} & A_{12}^{(1)} & 0 & 0 \\ A_{21}^{(1)} & A_{22}^{(1)} & 0 & 0 \\ 0 & B_{i,11}^{(1)} & B_{i,12}^{(1)} & 0 \\ 0 & B_{i,21}^{(1)} & B_{i,22}^{(1)} & B_{i,23}^{(1)} \end{bmatrix} \begin{bmatrix} p_{t-1}^f \\ y_{t-1}^f \\ \tau_{t-1}^i \\ y_{t-1}^i \end{bmatrix} + \begin{bmatrix} A_{11}^{(2)} & A_{12}^{(2)} & 0 & 0 \\ A_{21}^{(2)} & A_{22}^{(2)} & 0 & 0 \\ 0 & B_{i,11}^{(2)} & B_{i,12}^{(2)} & 0 \\ 0 & B_{i,21}^{(2)} & B_{i,22}^{(2)} & B_{i,23}^{(2)} \end{bmatrix} \begin{bmatrix} p_{t-2}^f \\ y_{t-2}^f \\ \tau_{t-2}^i \\ y_{t-2}^i \end{bmatrix} + u_{it} \quad (8)$$

where p_t^f is the commodity price index, y_t^f is a vector of additional indicators of the foreign block, τ_t^i the country-specific terms of trade of the i small open economy and y_t^i a vector of complementary variables that embodies the dynamics of that economy.

In this VAR, terms of trade are assumed exogenous to the domestic economy, but I let them being explained by their own lags and affecting domestic variables, which leads the set of restrictions imposed in the domestic block. This particular setting allow us to extract a unique global component for all the countries.

The estimation process relies in frequentist techniques estimating the model in levels by restricted OLS, and then using a blocks-by-blocks bootstrapping approach to draw new samples³, keeping only those which satisfy stationarity conditions until I obtain 5000 simulations. Later, I identify γ and ψ from each simulated model and compute the impulse-response functions and forecast error variances. This procedure is repeated in each of the selected countries.

Following Shousha (2016), and Kamber et al. (2017), I distinguish between emerging and developed markets, however I consider three groups: (i) emerging commodity exporter, (ii) developed economies commodity exporters, and (iii) developed economies no commodity exporters. This gives me an idea of the relevance of being a developed market and being commodity exporter on the exposure to global shocks, separately.

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-

³I consider a new sample size twice larger than the original and 9 lags in the blocks. For details see, Killian, Lutkepohl (2016), chapter 12

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. The estimation algorithm is summarized as algorithm 1:

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 $g \in \{\text{Emerging, Advanced}\}$ **do**
 for c in countries **do**
 Obtain \hat{B} , and $\hat{\Sigma}$ by restricted OLS
 for $i = 1:N$ **do**
 1. Draw a new sample \tilde{Y} by a blocks-by-blocks bootstrap with 9 lags and a sample size twice larger than the original.
 2. Estimate $B^{(i)}$ and form the $\Phi^{(i)}$ matrix.
 3. **if** $\max(|\text{eigen}(\Phi^{(i)})|) < 1$, 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 world economy I include three variables in the exogenous block: (i) the real commodity prices index, obtained after deflate the IMF commodity price index by the US import price of manufactured goods, (ii) an indicator of real activity approximated by the real GDP of the G20 countries, and (iii) a proxy of monetary conditions constructed as the spread of the BAA corporate bonds yield with respect to the fed funds rate. The country-specific domestic block is composed of: (i) commodities terms of trade from the IMF⁴, (ii) real variables (production, consumption, and investment), (iii) net exports as ratio to GDP, (iv) the real effective exchange rate obtained from the BIS website, and (v) the real interest rate. In almost all cases domestic

⁴This index is already expressed in real terms.

variables were obtained from IMF, BIS, and Fed data sources, adjusted by seasonal factors⁵. The analysis we take into account the information of 13 Small Open Economies divided in three groups: a) emerging commodity-exporter markets - Argentina, Brazil, Chile, Colombia, Peru, and South Africa, b) developed commodity-exporter SOEs - Australia, Canada, New Zealand, and Norway, and c) developed non commodity exporter countries - Belgium, Spain, and Sweden. The frequency of the data is quarterly and covers the period 1998q1 to 2019q4⁶.

Real commodity prices: We consider the database from the IMF website which constructs country-specific term of trade measurements based on commodity prices (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.

4 Empirical results

4.1 Impact of Global component

Figure 1 reports the median impulse response and the contribution to forecastability of a global component innovation on the external variables by group of country inside one standard deviation confidence intervals for emerging markets in an horizon of 20 quarters. The upper panel shows that one standard positive shock deviation in global conditions causes an increase in commodity prices of around 4 percent, with a peak of 6 percent after two quarters, the global real activity also increases by around 0.26 percent contemporaneously touching its peak (approx. 0.67 percent) after 3 quarters, while monetary conditions are less tighten with a reduction in the spread of BAA

⁵In the cases when there is not seasonally adjusted data from central banks or other sources, we use ARIMA X13

⁶In the case to be required, the chained of different year-reference data was made using annual growth rates

bonds by 40 basic points achieving a maximum response of 56 basic points before the real activity reaches it.

In terms of volatility, the identified global shock explains - in average- almost two thirds (45 percent in prices, 60 percent in global output, and 56 percent in monetary conditions after 20 quarters) of foreign variables forecastability in the medium run (20 quarters) with peaks in the first year for real activity and monetary conditions and almost in the second year for commodity prices. The slower impact in short run volatility into commodities markets could be explained by the presence of futures in petroleum, copper, gold, and other commodities. The higher explanation power of global shocks in real activity and monetary conditions rather than in commodities relative price suggests that the isolated shock is originated in other sector aside the commodities markets.

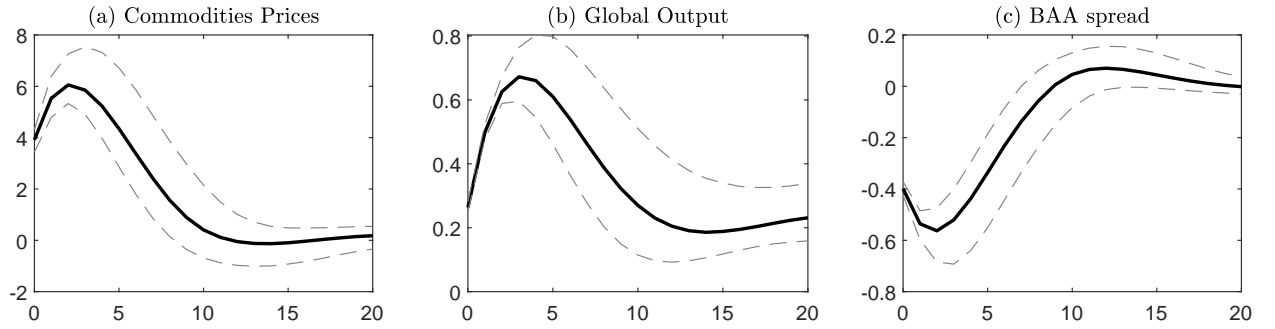
4.1.1 Impact on domestic variables

Figure 2 shows the response of domestic variables to movements in global conditions, while figure 3 plots the share of the forecast error variance explained by them, in both cases I present the confidence intervals of one standard deviation for the emerging market estimator. On the first hand, the impulse response analysis shows that the median response of commodity exporters after a global shock does not differ between emerging [*solid black line*] and developed countries [*marked blue line*], however developed SOEs no commodity exporters' median response [*red line with triangle markers*] displays a path in an opposite direction. Since the measure of terms of trade was constructed based on commodity prices, the previous result reflects the fact that this group of countries are mainly commodity importers.

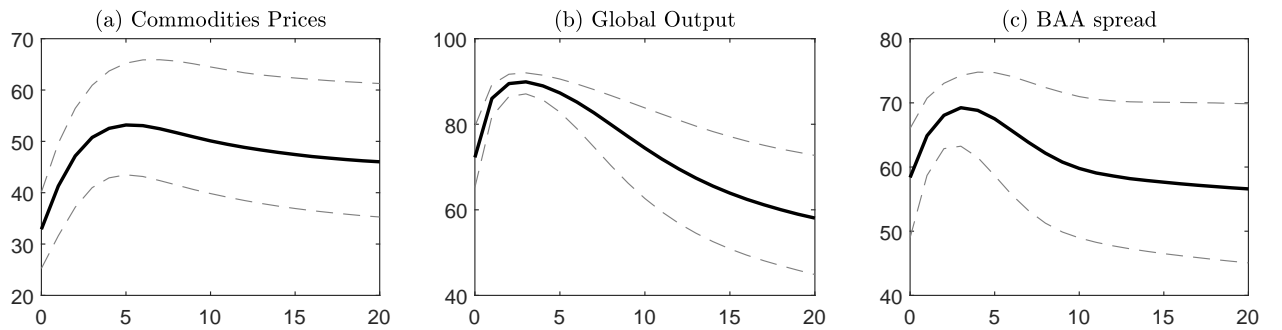
Aggregate variables (output, investment, and consumption) in emerging markets (ECXs) exhibit larger responses to global conditions with an initial increase of 0.4 percent in output, 0.9 percent in investment, and 0.5 percent in consumption. These reactions achieve their peak after four quarters in the case of output and investment and 6 quarters for consumption. In every variable, median responses of developed markets commodity exporters (DCXs) are located in below (or close) the lower bound of the confidence interval for the response of ECXs. Although, this is not a formal test, it gives us an idea of difference size between these groups of countries. An

Figure 1: Effect of Global Component innovations on external variables

i. Impulse-response functions



ii. Contribution to Forecast Error Variance

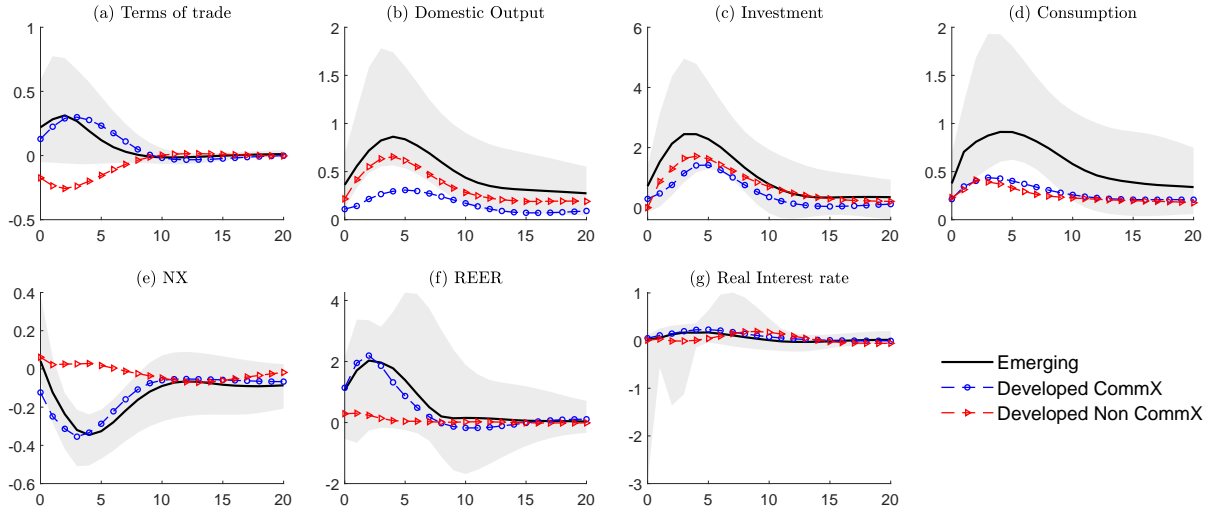


Note: The IRFs and FEVD were computed as the median response of all the simulated models for each group of countries. The gray shaded area is the 68 confidence interval for the impulse response/ contribution to FEV of emerging markets. The solid black line, circle-marked blue, and triangle-marked red lines are the median response of emerging, developed economies which export commodities, and non commodities exporter developed markets, respectively. Although, the global economy is composed by the same observations in each country specific VAR, since each model only admits the stationary replication there are few difference that are negligible.

interesting result is observed in the responses of developed not commodity exporters (DnCXs): while the patterns of its IRFs for output and investment looks more similar and are closes to the reported by ECXs, the response of consumption is almost the same that DCXs.

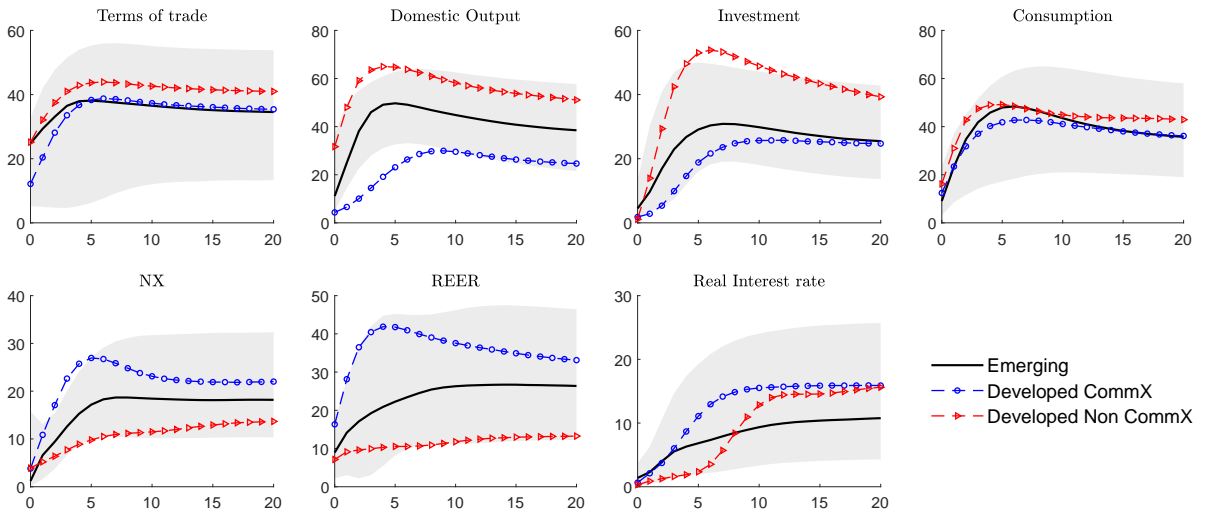
From the response of net export-to-GDP ratio and real effective exchange rate, we note that the trade channel can not explain the differences found a between ECXs and DCXs. Both group of countries experience a real appreciation, consistent with the theory, close to 2 percent in the short run while the participation of net trade in the economy reduces by 0.4 percent after one year with a faster response in DCXs countries. In contrast, we does not observe a significant response in these two variables for the group of developed no commodity exporters. I will come to interest rate

Figure 2: Response of domestic variables after a Global Component shock



Note: The IRFs were computed as the median response of all the simulated models for each group of countries. The gray shaded area is the 68 confidence interval for the impulse response/ contribution to FEV of emerging markets. The solid black line, circle-marked blue, and triangle-marked red lines are the median response of emerging, developed economies which export commodities, and non commodities exporter developed markets, respectively.

Figure 3: Contribution of global conditions to domestic forecastability



Note: The FEVDs were computed as the median response of all the simulated models for each group of countries. The gray shaded area is the 68 confidence interval for the impulse response/ contribution to FEV of emerging markets. The solid black line, circle-marked blue, and triangle-marked red lines are the median response of emerging, developed economies which export commodities, and non commodities exporter developed markets, respectively.

responses later. These results (ECXs and DCXs response) are similar to those found by [Jaimovich and Rebelo \(2008\)](#) for small open economies when households receive good news about future TFP, reinforcing the interpretation provided.

Table 1: Contribution of global conditions to domestic forecastability

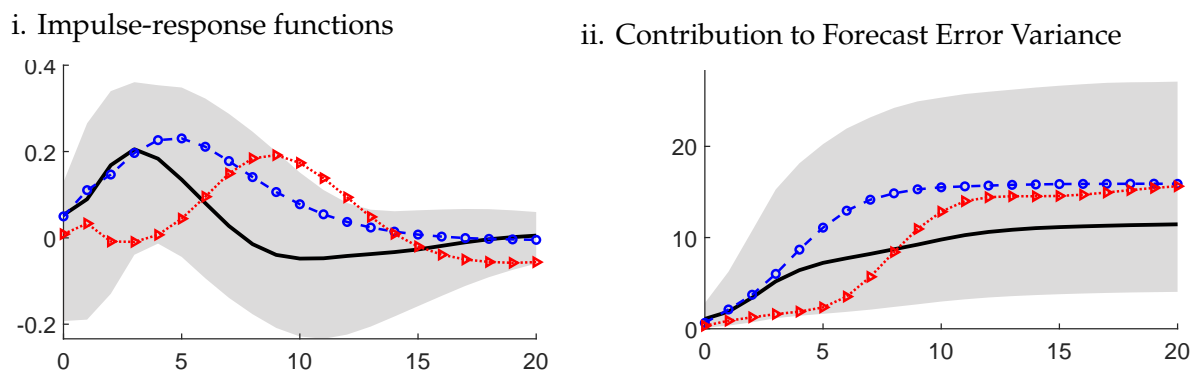
Country Group	H	Terms of Trade	Output	Investment	Consumption	NX/GDP	REER	Real interest rate
Emerging Markets	$h = 1$	24.5	12.3	4.4	8.9	1.1	10.7	1.3
	$h = 20$	34.6	39.3	26.0	37.4	19.4	26.6	11.1
	<i>maximum</i>	38.0	49.4	31.1	49.2	20.0	27.0	11.2
Developed Commodity exporters	$h = 1$	12.7	4.8	1.8	13.6	3.2	22.9	0.4
	$h = 20$	36.3	24.9	22.9	37.1	20.8	32.2	15.1
	<i>maximum</i>	39.7	30.5	23.5	43.3	25.8	41.2	15.2
Developed Non Commodity exporters	$h = 1$	25.7	31.9	1.1	16.8	4.1	6.8	0.3
	$h = 20$	41.7	52.0	40.2	42.9	14.1	13.6	15.0
	<i>maximum</i>	44.4	65.2	54.2	49.4	14.2	13.7	15.2

In terms of predictability, after 20 quarters the global component explains more than one-third of the fluctuations in terms of trade for all the groups (see table 1). Between commodity exporters output and investment in emerging economies show higher exposure being explained in the medium run by around 50 and 30 percent, respectively versus 30 and 24 percent for DCXs. On the other hand, we observe a larger explanation power of global shock on output and investment volatility in DnCXs while consumption is driven similarly among all the groups. These results suggest effectively that an increase in the global component could be rationalized as an improvement in the expectations about the global economy which is originated in developed markets (not modeled here), resulting in higher levels of investment and demand of intermediate goods (commodities) increasing commodity prices by more - since these are traded in more competitive markets - than final consumption goods implying a larger income effect in ECXs. Given that ECXs are more financially constrained the additional income will go mostly to finance new consumption in form of imports. On the other side, the better expectations and monetary conditions imply lower risk levels making that investors look for higher returns in ECXs rather than in DCXs bumping the effects over output, investment, and consumption.

After inspecting the response country by country (see figure 16) of interest rates we can confirm that Argentina results were increasing the size of the confidence intervals. Therefore, to control for any possible bias I plot the results without considering Argentina (figure 19). Since the conclusions reported until now are not changing, I only show the impulse response and contribution to the forecast error variance of global shocks to real interest rates in figure 4. The response of interest rates in commodity exporting countries is positive with higher persistence in developed markets

while the inverse path is followed for developed SOE no commodity exporters.

Figure 4: Effect of Global Component innovations on domestic interest rate



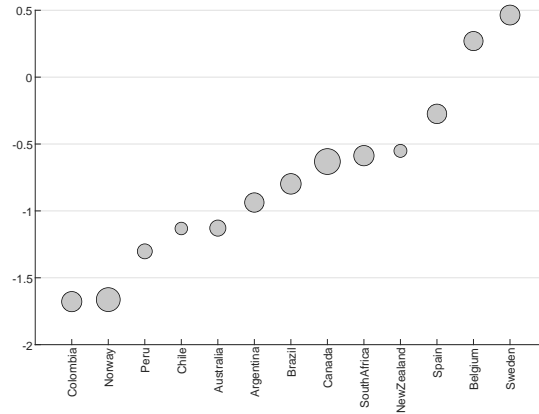
Note: Median response and FEV contribution of all the simulated models excepting Argentina. The gray shaded area is the 68 confidence interval for the impulse response/ contribution to FEV of emerging markets. The solid black line, circle-marked blue, and triangle-marked red lines are the median response of emerging, developed economies which export commodities, and non commodities exporter developed markets, respectively.

4.1.2 Country-specific comparison

Although a median analysis is robust to extreme values, maybe the within group variability would affect my conclusions. To avoid that, in this subsection I compare the results between similar ECXs and DCXs. I define two countries to be similar if the complexity of their exports basket are similar and their main export sector is the same. I calculated the aggregate complexity index based of the data from the Atlas of Economic Complexity reported at SITC 4 digits levels, weighting them by its average share in export during the last 20 years, and reported them in figure 5.

The chosen pair were Colombia- Norway and Chile-Australia. In the first case both countries have crude petroleum as their main exportable good (with a share of 37 and 42 percent , respectively) and have the less complex basket with indexes of -1.68 and -1.66. The second pair could be considered as mining exporters being copper the most important product for Chile (51 percent between alloys and concentrates), and iron ore (17) and gold (6 percent) the main mining exported goods for Australia, the calculated index for both is around -1.13.

Figure 5: Complexity index of Exported Goods



Note: The aggregate complexity index were calculated based on 4-digits STICs complexity reported by the Atlas of Economic Complexity weighed by the average share of each sector in their export basket since 1998. The size of the circle were adjusted by the relative variance of the serie.

Figure 6 shows the impulse response function comparison, reinforcing the conclusions from the aggregate level. Real variables in emerging markets are more exposed to global conditions in comparison with developed economies being output the variable where this differences are more noticeable. The latter is true even if the transmission into terms of trade is higher [panel (ii.)] or lower [panel (i.)] in emerging markets. Regarding the effect on global shocks on real exchange rates and real interest rates, figure 6 shows clearer an appreciation and an increase in real interest rates in the short run. In fact among all the analyzed commodity exporters only Peru reports a depreciation when there is an improve in global conditions.

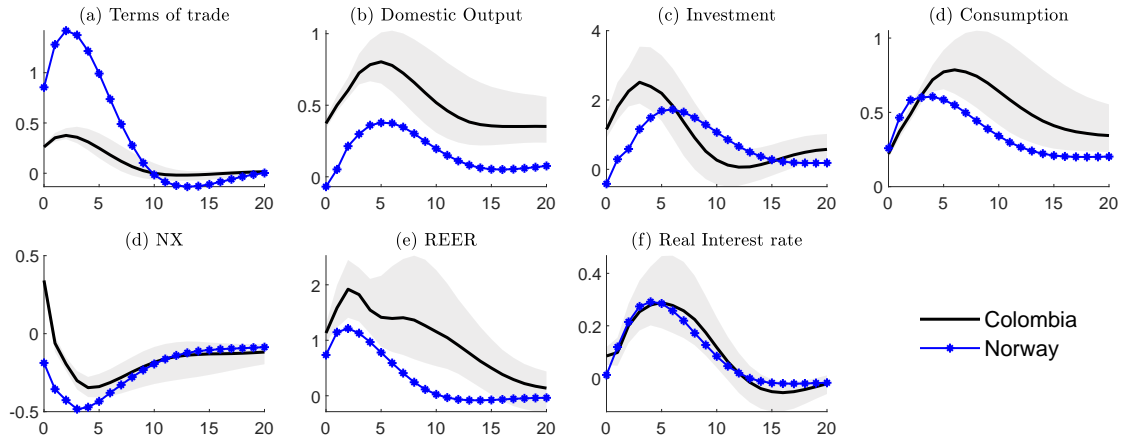
4.2 Impact of Terms of trade innovations

The proposed identification ensures that both shocks are orthogonal, which can be confirmed since the correlation coefficients between the global shocks and the terms of trade innovations are not statistically significant and lower, in absolute terms, than 7 percent.

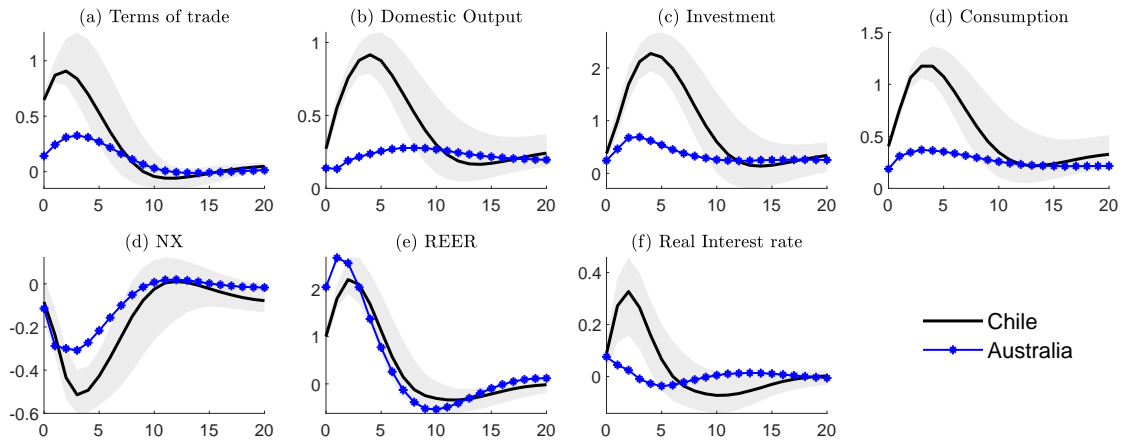
Figure 7 shows the effect of terms of trade deviations on the global variables. We can see that positive innovations in non commodity exporters are related with negative movements in the relative price of commodities, while the inverse is true for DCXs and ECXs. In the short run, when ECXs and DCXs' terms of trade increases we observed a raised in global output and tighter monetary conditions. In addition with the large confidence intervals, the explanation power of

Figure 6: Response of domestic variables to Global Shocks, by country

i. Fuel Exporters



ii. Mining exporters

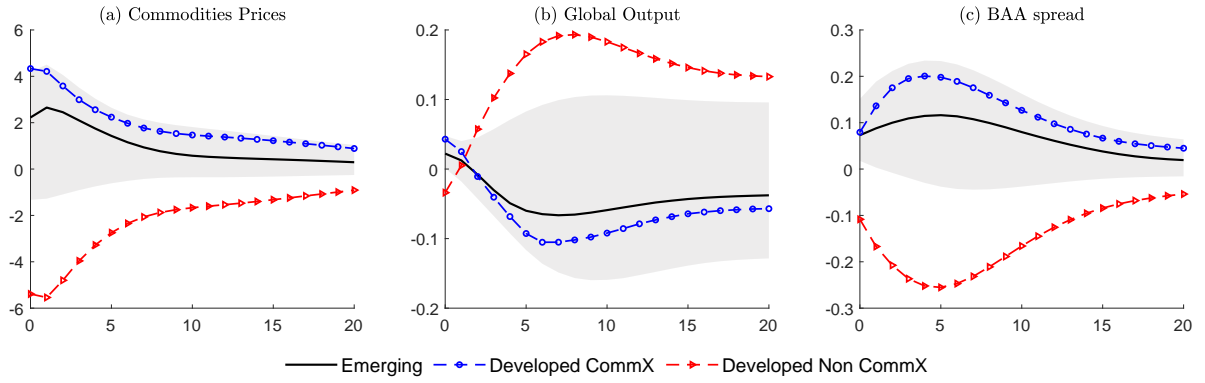


terms of trade shocks over global output is less than 10 percent.

Regarding its impact on the domestic variables, the impulse response functions exhibit a volatility level such that the median response is not significant. Without considering this fact, we can see that a terms of trade innovation leads to a raise in output, investment, and consumption. Furthermore, the median contribution of terms of trade on the forecast error variance of investment is less than 20 percent after 20 quarters for developed countries and around 10 percent for ECXs. The rest of country specific variables - excepting terms of trade - are lower: in example, less than 10 percent of consumption and output volatility is explained by them. Finally, the large fraction of the predictability on terms of trade suggests that the identification successfully filters terms of trade innovations.

Figure 7: Effect of Terms of Trade innovations on external variables

i. Impulse-response functions



ii. Contribution to Forecast Error Variance

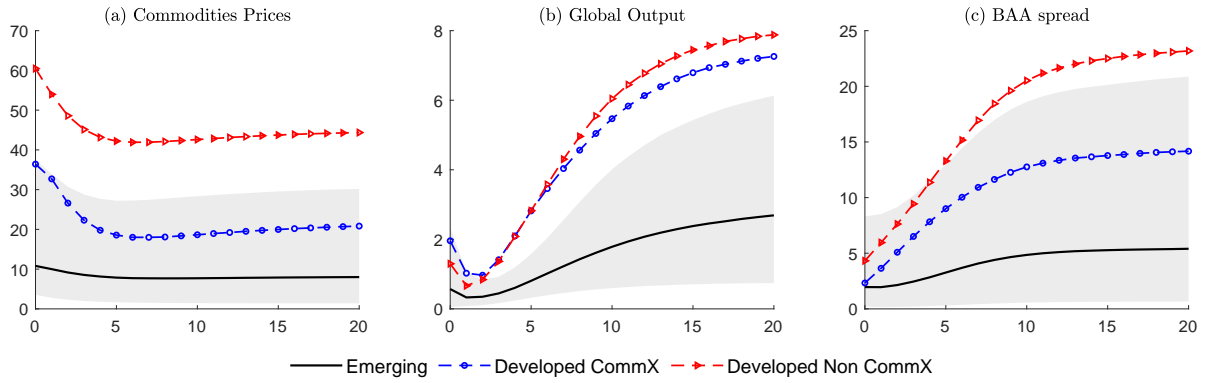
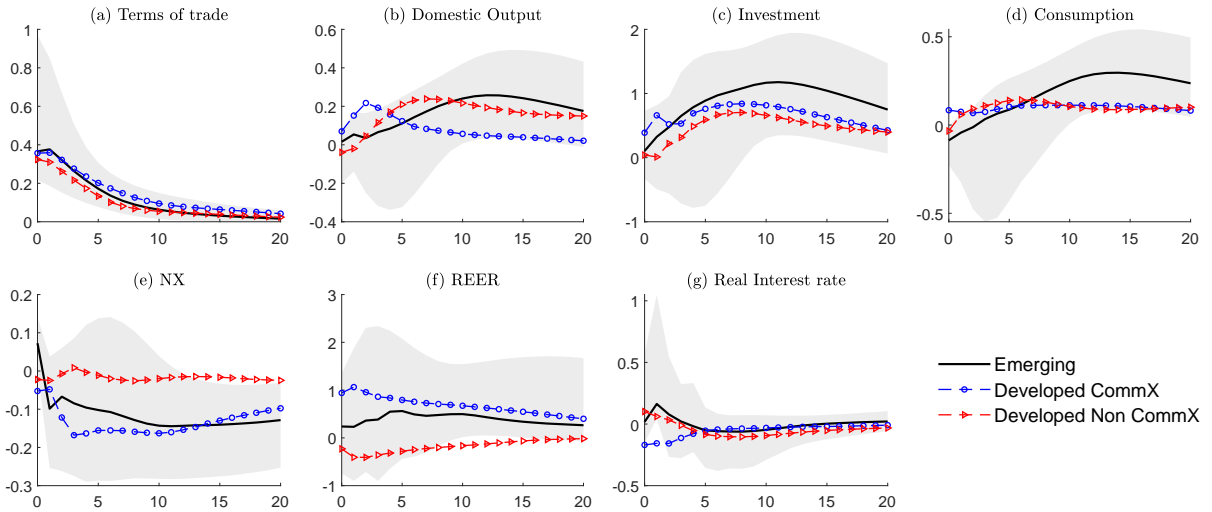


Table 2: Contribution of terms of trade innovation to domestic forecastability

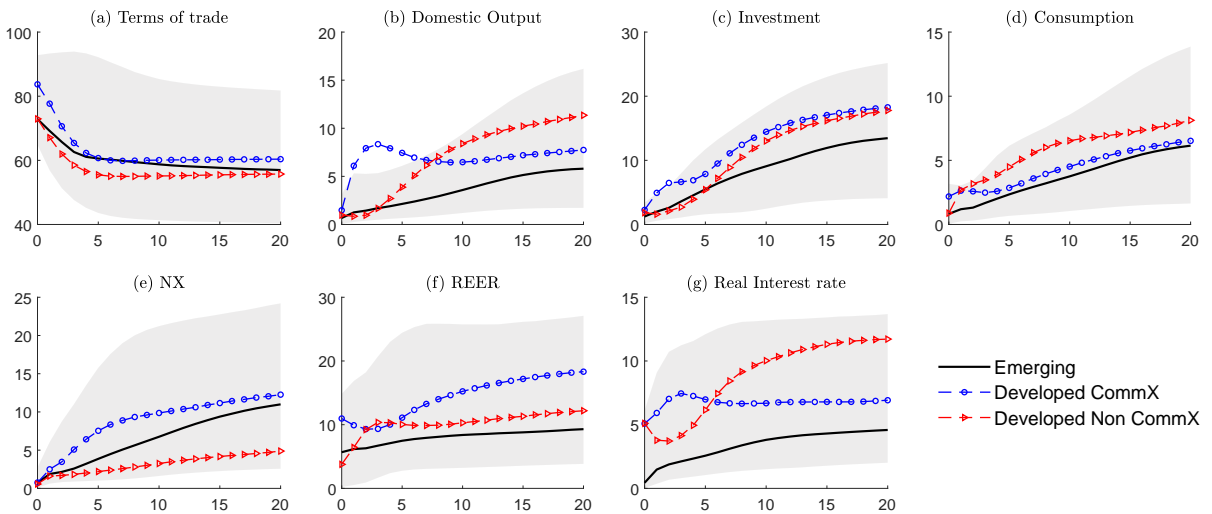
	H	Terms of trade	Output	Investment	Consumption	NX/GDP	REER	Real Interest rate
Emerging markets	$h=1$	73.1	0.7	1.4	0.8	0.9	3.6	0.5
	$h=20$	57.1	5.5	12.4	5.4	9.9	7.1	4.4
	<i>maximum</i>	73.1	5.6	12.6	5.5	10.1	7.2	4.5
Developed Commodity Exporters	$h=1$	83.0	1.5	2.2	1.7	0.6	13.2	6.7
	$h=20$	59.6	7.8	19.5	6.3	13.2	18.4	7.5
	<i>maximum</i>	83.0	8.3	19.8	6.4	13.5	18.6	8.3
Developed Non Commodity Exporters	$h=1$	72.4	0.9	1.8	1.1	0.6	4.9	5.5
	$h=20$	55.2	10.8	17.5	8.2	5.0	12.7	12.1
	<i>maximum</i>	72.4	11.0	17.8	8.4	5.2	12.9	12.2

Figure 8: Impact of Terms of Trade on domestic variables

i. Impulse-response functions



ii. Contribution to Forecast Error Variance



5 What is behind? Inspecting the Global Shock

5.1 Global shocks and commodities

In the previous section I show that idiosyncratic shocks to country specific terms of trade do not explain a large fraction of the variability of small open economies business cycles, independently from their degree of development. In contrast, common shocks to the whole economy appears as a major explanation source. However, the identification procedure does not take into consideration

shocks that are common to all commodities prices.

A first approach to isolate their relevance is to assume that part of terms of trade idiosyncratic shocks are actually explained by a common source. In this sense, we could exploit the remained variance in the foreign bloc to identify global movements in commodities prices (ϵ^ϑ). I identify them as the main source of variability in the commodity price index which is not correlated with the previously identified "global shock". It implies solving the following system

$$\begin{aligned} \max_{\vartheta} \quad & S_{\vartheta}^{p^f}(\underline{t}, \bar{t}) \\ \text{s.t.} \quad & \vartheta' \vartheta = 1 \\ & \vartheta' \gamma = 0 \end{aligned} \tag{9}$$

The solution is similar to the presented for ψ . However, for this case I estimate the model:

$$\begin{bmatrix} p_t^f \\ y_t^f \\ y_t^i \end{bmatrix} = A^{(1)} \begin{bmatrix} p_{t-1}^f \\ y_{t-1}^f \\ y_{t-1}^i \end{bmatrix} + A^{(2)} \begin{bmatrix} p_{t-2}^f \\ y_{t-2}^f \\ y_{t-2}^i \end{bmatrix} + u_{it} \tag{10}$$

with a small open economy restriction: $A_{13}^i, A_{23}^i = 0$ for $i = \{1, 2\}$. As it is noted, terms of trade were not included in order to exploit at maximum the variability and explanation power of common movements in commodities prices.

The contribution of ϵ^ϑ to the forecast error variance by countries group is plotted in figure 9. We can see an higher explanation power on output and consumption (solid lines) with respect to country idiosyncratic shocks (red dashed lines) for developed economies. Similar effects are not observed for emerging markets where both shocks explain roughly the same amount of variability. A contrasting story is found when we observed the explanation power on investment where common commodities prices shocks can not being considered as an explanation source. An impulse-response analysis shows that ϵ^ϑ is a shock such that global production increases while commodities prices decrease (see figure 10).

After inspecting the impulse responses in figure 11 we saw two main differences between the IRFs of emerging markets and developed commodity exporters economies: (i) output and

Figure 9: FEVD: Commodities prices shock vs idiosyncratic terms of trade shock

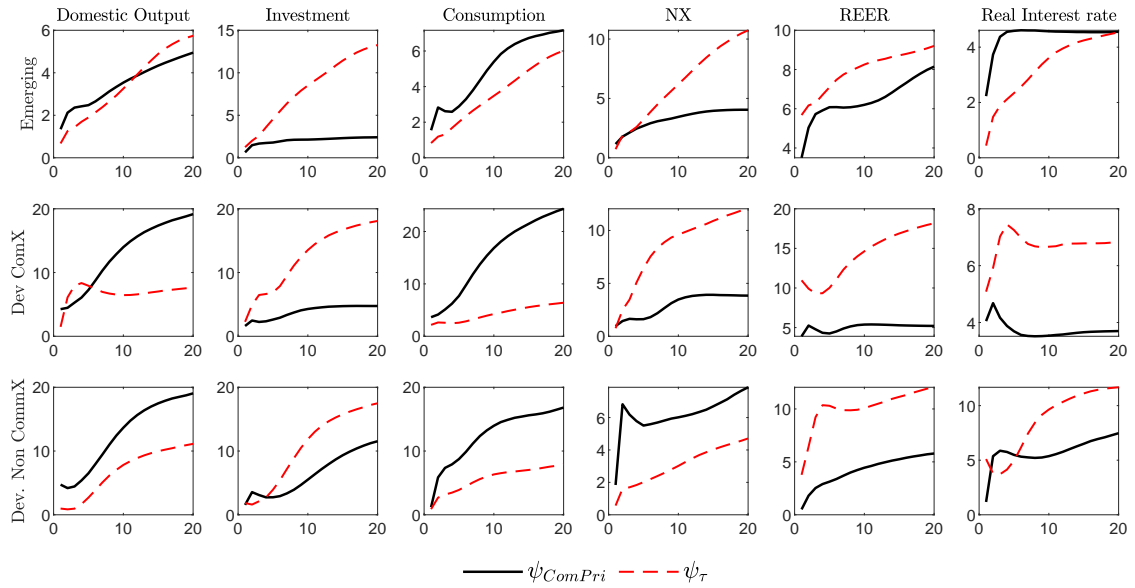
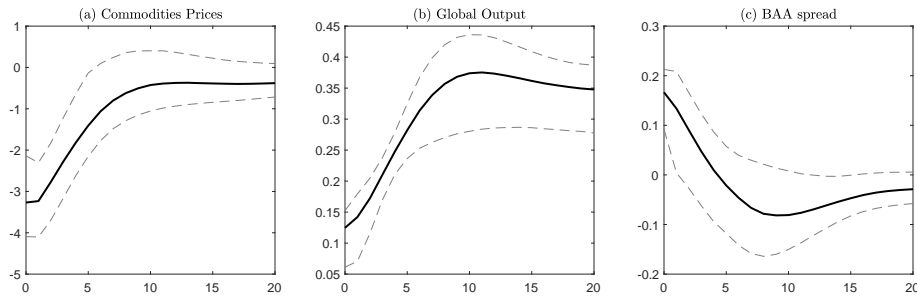


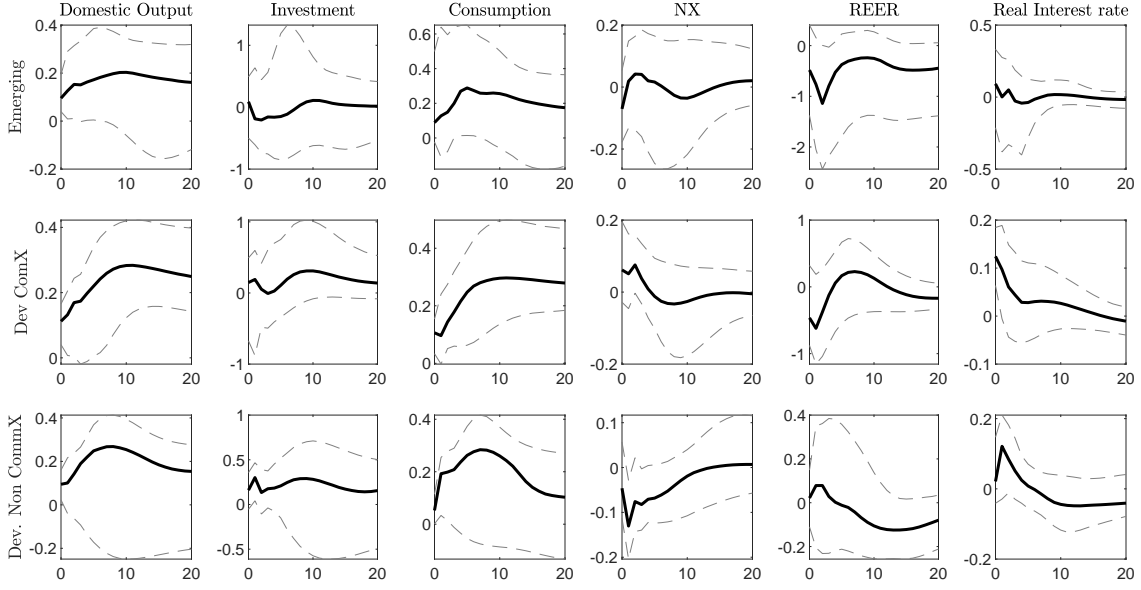
Figure 10: Impact of commodities prices shock on foreign variables



consumption are more responsive in developed SOE which are commodities exporters (emerging markets are not highly impacted by that), and (ii) monetary policy in developed markets is reacting to this shock. Given the impulse-responses in figure 9 a possible interpretation of this shock is a commodity supply innovation, however the trade pattern and/or export complexity (see figure 5) do not support a different response between developed and emerging markets. On the other hand, the null response of real investment and the difference in sensitivity of real interest rates could suggest that this shock is related with the international financial markets or others non-capital based sectors.

To complement this analysis, I also investigated to which extent the identified global shocks can be explained by common movements in commodities markets. A main assumption in my

Figure 11: Impact of commodities prices shock on domestic variables



baseline identification is that any quarterly fluctuation which affects [largely] contemporaneously the whole foreign block can not being properly associated with a unique source of variation I will need to move to a different model. Following [Stuerner \(2018\)](#) I use along-run identification approach to isolate supply shocks in each commodity market under the model:

$$\begin{bmatrix} \Delta y_t^f \\ \Delta q_t^{(j)} \\ \Delta p_t^{(j)} \end{bmatrix} = A^{(1)} \begin{bmatrix} \Delta y_{t-1}^f \\ \Delta q_{t-1}^{(j)} \\ \Delta p_{t-1}^{(j)} \end{bmatrix} + U_{jt} \quad (11)$$

where y_t^f is the real global GDP, $q_t^{(j)}$ represents the world production of the commodity j at the year t being $p_t^{(j)}$ its international price. The operator Δ represents the first log-difference. Data runs from 1900 in an annual frequency. The identification assumes a long-run impact matrix of the way:

$$\begin{bmatrix} \Delta y_{t+\infty}^f \\ \Delta q_{t+\infty}^{(j)} \\ \Delta p_{t+\infty}^{(j)} \end{bmatrix} = \begin{bmatrix} * & 0 & 0 \\ * & * & 0 \\ * & * & * \end{bmatrix} * \begin{bmatrix} e_1 \\ e^{j,supply} \\ e^{j,demand} \end{bmatrix} \quad (12)$$

it implies that world supply [and demand] shocks in the commodity j are mean to have no long run effect in the global production, while nominal shocks have only a transitory effect in the global production of commodities.

After recovering $e^{j,supply}$ for each of the selected commodities⁷(5 related with food, 4 from the mining sector, cotton and crude oil) I proceed to summarize global supply pressures as their first principal component. Since this data is only available in annual frequency, a direct incorporation into the baseline model is not possible. Moreover, the small sample size of the latter (after being converted from quarterly to annual data) makes unfeasible employs a VAR analysis, then I calculates a correlation coefficient which is close to -0.7 significant at 1 percent and with an R^2 of 32 percent. The latter can be interpret as the percentage from global shocks explained by world commodity supply shocks.

5.2 Relation with other variables

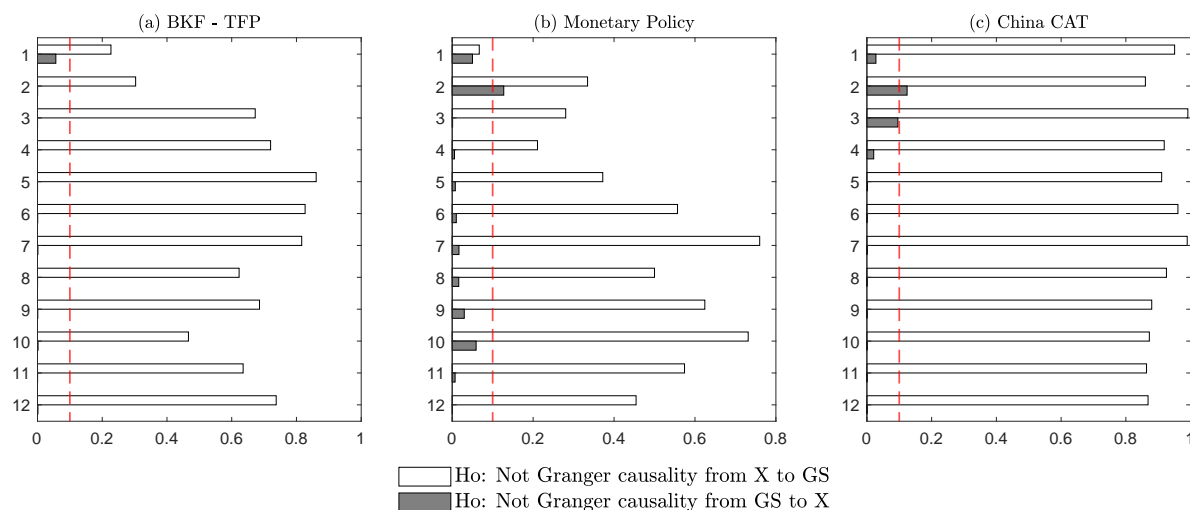
Near two-thirds of the global-shocks variability are not explained by activity in commodities markets. To evaluate in which extend other sources can explain these fluctuations I will use some shocks commonly used in the literature and see whether exist any relationship between them and the global innovation. I select three variables: (a) the US total factor productivity calculated by the Federal Reserve Bank and adjusted by capital utilization (BKF-TFP) as proposed by Basu, Fernald, and Kimball (2006), (b) a measure of monetary policy shocks suggested by Bu, Rogers, and Wu (2019), and (c) the China activity indicator proposed by Fernald, Hsu, and Spiegel (2020) and computed by the San Francisco Federal Reserve.

Firstly, I run Granger causality tests in pairs under different lags structures and then I perform a impulse-response analysis based on the order suggested by these tests. The results for the former are displayed in the figure 12, where the black outline bars represent the pvalue associated to the null hypothesis of global shocks do not causes *à la* Granger to the variable X, while the simple bars show the significance level for the null hypothesis for Granger causality from X to global shocks. The results suggest the existence of a unidirectional Granger causality that comes from the global component to the previously defined indicators. It does not necessarily indicate any causation relationship but instead a forward looking behave of my identified shock consistent with

⁷I include in this analysis the following commodities: barley, rice, wheat, coffee, sugar, copper, lead, tin, zinc, cotton, and crude

expectations. Similar to what we observe between stock prices and dividends, where the former moves based on anticipated changes in the latter, my identified shock would reflect expectations about the performance of the global economy and its positive movements would be related with optimism periods.

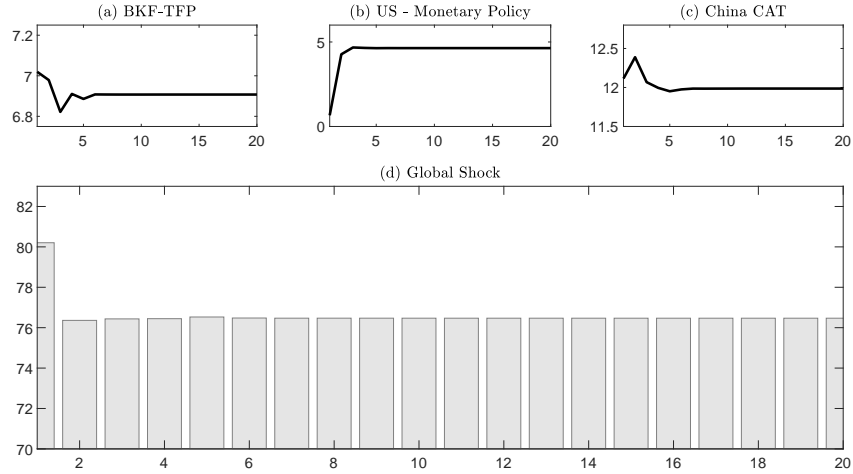
Figure 12: Granger Causality Test



Note: The Granger causality tests were conducted for bivariate models under different lag structures. Under the null hypothesis, all the coefficients associated to lags of the other variable are equal to zero. The black outline bars are the significance levels of the null hypothesis under which global-shocks lags are not helpful to predict movements in TFP/ Monetary shocks. The skyblue bars are the significance level for the null hypothesis of TFP/MP lags are not helpful for predict global shocks. The dotted red line are the pvalue of 10 percent.

In addition with the Granger causality test, I included a forecast error variance analysis by running a VAR with two lags which was identified by a Cholesky decomposition being global-shocks the more endogeneous variable. Figure 13 shows the global-shocks forecast error variance decomposition. The selected variables can explain around one quarter of fluctuations in the global shock, with China activity being the more relevant among them (close to 12 percent). It means that near to half of the volatility of global-shocks, after including the effect of commodity supply shocks- remains for further analysis.

Figure 13: Explanation power of extraneous shock on Global fluctuations



6 Comparison with news identification

In this work I extend the identification approach of Uhlig to isolate the main driver of the global economy and then contrast the impact of terms of trade with other results in the literature. Therefore, my work is closely related to [Ben Zeev et al. \(2017\)](#) since it also incorporates anticipated information to accounting for the impact of terms of trade in small open economies. Then, a natural question is to verify if whether both procedures map different structural errors. In order to show the difference, I recover the identification vector that maximizes the forecast error variances of terms of trade without controlling for common movements. It means I recover a vector τ that solves:

$$\begin{aligned} \max_{\tau} \quad & S_{\epsilon}^{tot}(\underline{t}, \bar{t}) \\ \text{s.t.} \quad & \tau' \tau = 1 \end{aligned} \tag{13}$$

This identification is made in every simulated sample to avoid any possible difference based on the randomness of the bootstrapped procedure. Since the estimated model is a two block VAR,

the orthogonalized impulse response h -periods ahead matrix takes the form:

$$\mathbf{R}_h = \begin{bmatrix} * & 0 & 0 & 0 & \cdots & 0 \\ * & * & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ * & * & * & * & \cdots & 0 \\ * & * & * & * & \cdots & * \end{bmatrix}$$

given that I defined γ based on the orthogonalized impulse response functions for the first three variables, the matrix ξ is:

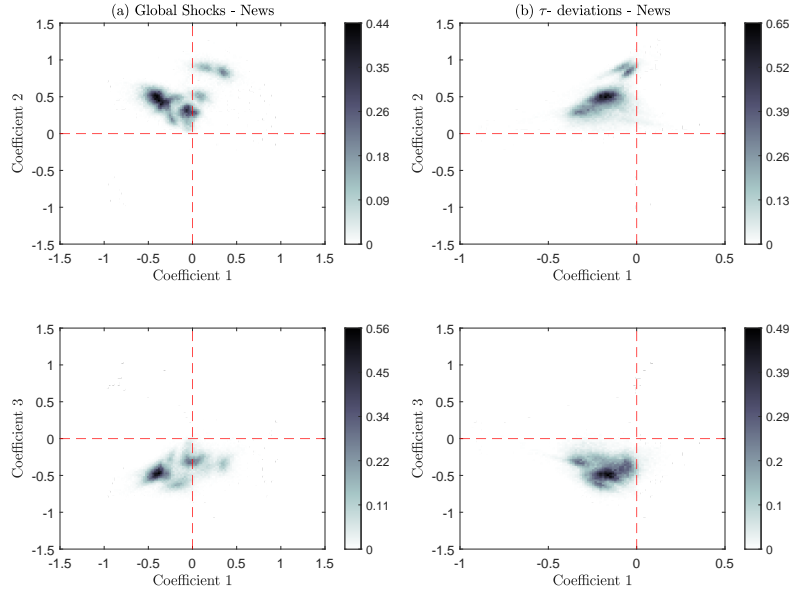
$$\xi = \begin{bmatrix} * & * & * & 0 & \cdots & 0 \\ * & * & * & 0 & \cdots & 0 \\ * & * & * & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 \end{bmatrix}$$

a reduced rank matrix with only the upper square submatrix being different from 0. It implies that the identification vector γ^* will have only the 3 coefficients different from zero. Considering that terms of trade are also independent from any feedback of the other domestic variables ψ^* will have also 4 entries different from 0, as well τ^* .

Since the identification of γ , ψ , and τ relies in the same simulated sample the matrices \mathbf{R}_h , with $i \in [0 : 20]$ are common, thereby I only need to make a direct comparison of the first entries of my identified vectors and τ^* . To stress it, I set the first entrance of each vector to be non negative.

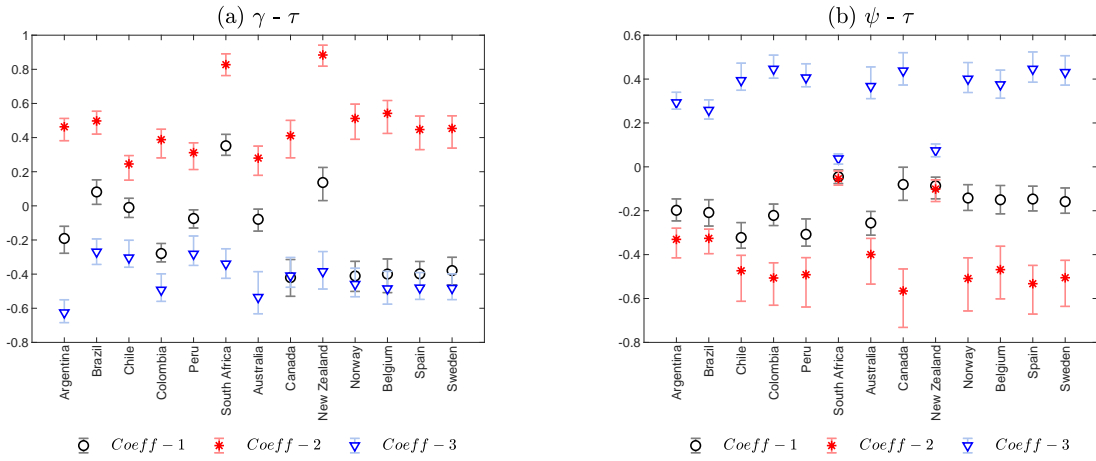
Let define the vectors $d_1 = \gamma^* - \tau^*$, and $d_2 = \psi^* - \tau^*$ as the distance vectors. Figure 14 reports scatter plots with computed differences. Panel (a) shows the results for d_1 with the x -axis being its first entrance, while panel (b) reports the same for d_2 . The color intensity were adjusted to reflect their relative frequency. In each panel, we can see that the probabilistic mass is not close to zero demonstrating that my approach identified two shocks statistically different from a news-augmented terms or trade innovation. Moreover, in figure 15 I plot the median difference for each

Figure 14: Methodology comparison



coefficient and a one standard deviation confidence interval by each country. This shows that country-by-country in the majority of cases the differences lies far from zero.

Figure 15: Methodology comparison, by country



7 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 around than one-third of real variable fluctuations in the medium run for developed market which relies in commodities prices, around a half in emerging market and more than a half in developed markets non commodity exporters, while terms of trade deviations contribution is only close to 10 percent. Even though my identification strategy ensures that both shocks are orthogonal to each other, an impulse-response analysis gives more evidence of these differences by exhibiting different size and persistence degree. Additionally, I find an asymmetric response across advanced and emerging markets, with a higher difference in output, investment and consumption.

Appendices

A Figures and tables

Table 3: Correlation table, terms of trade

	Argentina	Brazil	Chile	Colombia	Peru	SouthAfrica	Australia	Canada	NewZealand	Norway	Belgium	Spain
Brazil	0.02											
Chile	0.25	0.07										
Colombia	0.49	-0.43	0.21									
Peru	0.29	-0.08	0.88	0.49								
SouthAfrica	-0.16	0.71	0.27	-0.32	0.10							
Australia	0.41	0.29	0.48	0.45	0.52	0.59						
Canada	0.58	-0.35	0.31	0.70	0.47	-0.20	0.53					
NewZealand	-0.19	0.51	0.18	-0.41	0.01	0.64	0.21	-0.20				
Norway	0.52	-0.62	0.17	0.83	0.41	-0.53	0.30	0.86	-0.51			
Belgium	-0.57	0.50	-0.19	-0.83	-0.43	0.40	-0.43	-0.88	0.48	-0.98		
Spain	-0.59	0.54	-0.20	-0.89	-0.44	0.50	-0.37	-0.82	0.54	-0.97	0.96	
Sweden	-0.54	0.64	-0.18	-0.83	-0.42	0.56	-0.24	-0.62	0.59	-0.89	0.85	0.90

Figure 16: Response of domestic variables after a Global Component shock

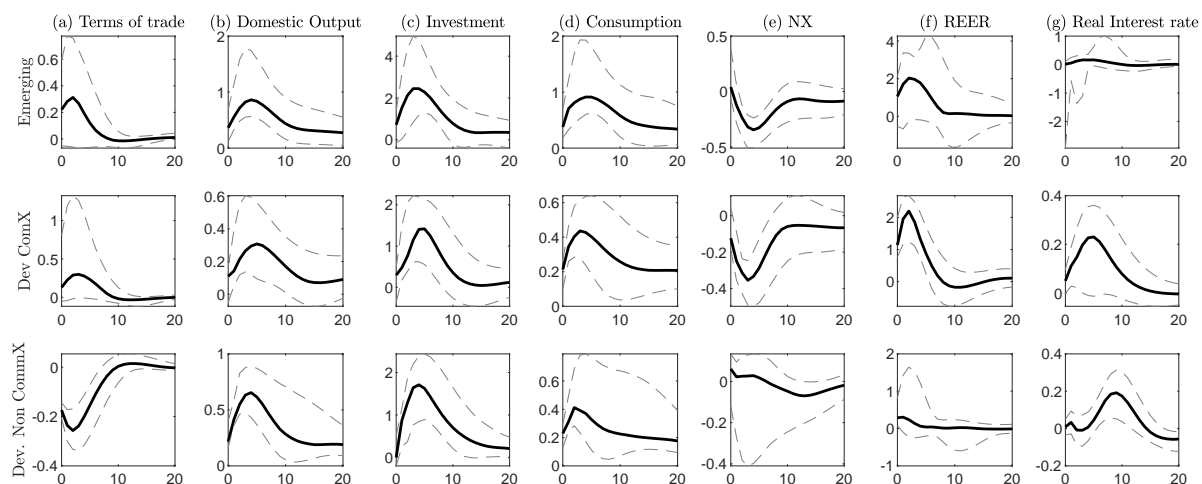


Table 4: Contribution of global conditions to domestic forecastability by country

Country Group	H	Terms of Trade	Output	Investment	Consumption	NX/GDP	REER	Real interest rate
Argentina	$h = 1$	22.6	14.0	9.9	3.7	0.2	2.6	4.0
	$h = 20$	23.7	42.5	39.2	39.2	15.8	15.2	9.2
	<i>maximum</i>	24.1	59.1	56.1	50.5	16.3	15.2	9.3
Brazil	$h = 1$	7.1	48.0	21.6	35.7	0.3	16.2	1.6
	$h = 20$	27.5	36.1	26.4	35.3	16.7	19.8	7.1
	<i>maximum</i>	27.8	58.5	42.2	44.9	16.7	20.1	7.2
Chile	$h = 1$	28.5	10.2	2.0	15.4	0.7	26.4	1.9
	$h = 20$	48.1	40.8	23.6	39.1	20.9	45.0	16.5
	<i>maximum</i>	50.2	50.2	28.9	55.0	25.4	50.3	16.5
Colombia	$h = 1$	27.5	24.4	4.9	13.1	20.6	7.8	1.0
	$h = 20$	43.2	54.4	27.2	57.3	27.3	20.2	27.7
	<i>maximum</i>	47.8	62.9	30.2	64.6	27.9	22.1	27.7
Peru	$h = 1$	34.2	8.5	1.2	4.2	12.2	4.6	0.1
	$h = 20$	46.1	38.2	27.3	18.9	13.5	15.9	8.3
	<i>maximum</i>	51.6	39.1	32.1	19.0	13.5	15.9	8.4
South Africa	$h = 1$	4.3	3.5	3.5	5.1	0.5	33.5	1.3
	$h = 20$	3.5	19.1	11.6	33.4	21.9	42.6	7.5
	<i>maximum</i>	4.3	41.1	16.9	50.5	22.7	43.4	7.6
Australia	$h = 1$	11.1	12.4	1.4	17.6	5.2	43.1	0.7
	$h = 20$	34.7	39.8	9.6	30.2	17.7	37.5	4.0
	<i>maximum</i>	40.6	40.9	11.4	35.8	36.2	53.5	4.0
Canada	$h = 1$	17.7	14.9	10.9	31.3	6.4	31.5	0.6
	$h = 20$	48.7	29.6	47.3	58.7	21.5	45.3	20.4
	<i>maximum</i>	50.9	52.4	65.2	67.6	26.1	55.2	20.5
New Zealand	$h = 1$	4.2	0.3	0.8	0.8	1.1	14.2	0.3
	$h = 20$	5.6	3.0	7.1	4.9	15.7	17.6	16.3
	<i>maximum</i>	5.6	3.1	7.2	11.2	17.2	22.7	16.4
Norway	$h = 1$	23.3	0.6	1.6	9.0	2.2	15.7	0.2
	$h = 20$	41.1	24.6	30.1	47.8	30.1	18.6	18.2
	<i>maximum</i>	43.5	25.6	31.0	53.1	31.8	23.2	18.2
Belgium	$h = 1$	20.8	29.7	0.4	16.3	4.2	0.7	0.4
	$h = 20$	38.1	49.5	27.7	40.2	8.7	6.4	15.4
	<i>maximum</i>	39.2	66.3	29.5	45.7	8.7	6.4	15.6
Spain	$h = 1$	26.0	35.3	16.7	14.5	7.0	6.7	0.3
	$h = 20$	43.0	53.1	44.1	49.9	39.4	11.7	24.5
	<i>maximum</i>	47.9	65.4	67.1	61.1	52.3	11.7	24.7
Sweeden	$h = 1$	31.0	31.4	0.4	18.9	2.0	26.5	0.3
	$h = 20$	43.3	53.0	46.9	40.9	9.9	32.8	7.0
	<i>maximum</i>	45.3	64.8	56.0	42.9	10.0	35.8	7.3
Emerging Markets	$h = 1$	24.5	12.3	4.4	8.9	1.1	10.7	1.3
	$h = 20$	34.6	39.3	26.0	37.4	19.4	26.6	11.1
	<i>maximum</i>	38.0	49.4	31.1	49.2	20.0	27.0	11.2
Developed Commodity exporters	$h = 1$	12.7	4.8	1.8	13.6	3.2	22.9	0.4
	$h = 20$	36.3	24.9	22.9	37.1	20.8	32.2	15.1
	<i>maximum</i>	39.7	30.5	23.5	43.3	25.8	41.2	15.2
Developed Non Commodity exporters	$h = 1$	25.7	31.9	1.1	16.8	4.1	6.8	0.3
	$h = 20$	41.7	52.0	40.2	42.9	14.1	13.6	15.0
	<i>maximum</i>	44.4	65.2	54.2	49.4	14.2	13.7	15.2

Table 5: Contribution of terms of trade shocks to domestic forecastability by country

	H	Terms of trade	Output	Investment	Consumption	NX/GDP	REER	Real Interest rate
Argentina	$h=1$	74.8	3.2	2.8	1.3	0.2	1.3	0.3
	$h=20$	72.7	7.8	8.0	6.8	10.5	6.2	3.7
	<i>maximum</i>	75.7	8.2	8.3	7.2	10.7	6.7	3.7
Brazil	$h=1$	91.1	0.6	0.4	0.6	2.7	0.7	11.0
	$h=20$	61.2	3.0	3.6	1.4	1.7	8.0	18.5
	<i>maximum</i>	91.1	3.0	3.8	1.5	2.7	8.4	20.8
Chile	$h=1$	69.8	0.3	1.7	0.1	0.5	11.2	2.1
	$h=20$	46.0	3.5	12.2	4.6	9.6	7.3	4.8
	<i>maximum</i>	69.8	3.6	12.3	4.7	9.7	11.2	4.8
Colombia	$h=1$	69.5	0.5	4.5	3.5	1.4	20.0	0.1
	$h=20$	52.2	6.6	18.5	6.4	28.2	42.7	2.2
	<i>maximum</i>	69.5	6.7	18.5	6.5	28.4	43.2	2.2
Peru	$h=1$	64.5	0.2	0.2	0.2	0.5	7.8	0.6
	$h=20$	46.1	4.7	24.4	7.0	15.1	6.0	3.3
	<i>maximum</i>	64.5	4.7	24.7	7.1	15.8	7.8	3.4
South Africa	$h=1$	94.0	1.5	1.4	1.5	1.0	0.3	0.1
	$h=20$	92.2	14.4	14.5	8.2	3.3	1.7	5.8
	<i>maximum</i>	96.7	14.5	14.5	8.3	3.4	1.7	5.9
Australia	$h=1$	83.8	0.4	0.3	1.8	1.8	6.9	11.3
	$h=20$	59.5	2.2	18.3	3.8	27.5	18.5	7.4
	<i>maximum</i>	83.8	5.8	18.7	3.8	27.9	18.9	12.7
Canada	$h=1$	79.3	4.3	11.0	4.5	5.7	24.7	35.1
	$h=20$	47.1	8.8	22.4	4.4	5.9	18.2	34.1
	<i>maximum</i>	79.3	16.0	22.5	4.6	6.1	24.7	41.2
New Zealand	$h=1$	95.2	2.7	4.3	1.0	0.1	1.1	0.1
	$h=20$	92.8	49.2	35.4	50.6	22.4	11.2	4.3
	<i>maximum</i>	97.1	49.2	36.7	50.6	23.2	12.0	4.6
Norway	$h=1$	74.9	0.4	0.7	1.2	0.1	24.7	4.8
	$h=20$	56.1	5.9	5.9	3.3	7.3	33.8	5.6
	<i>maximum</i>	74.9	6.1	6.1	3.4	7.6	34.1	5.7
Belgium	$h=1$	77.8	1.6	2.5	8.2	0.3	7.6	1.3
	$h=20$	58.4	10.6	22.4	7.2	4.3	8.1	7.6
	<i>maximum</i>	77.8	10.7	22.5	8.2	4.3	13.3	7.7
Spain	$h=1$	71.3	0.5	2.6	0.4	0.3	1.2	20.0
	$h=20$	53.4	6.8	6.3	4.6	4.1	21.1	14.9
	<i>maximum</i>	71.3	7.3	7.3	5.0	4.4	22.3	20.0
Sweeden	$h=1$	67.6	1.0	0.6	0.3	1.9	5.2	5.5
	$h=20$	54.2	14.3	20.1	13.7	7.9	12.1	13.8
	<i>maximum</i>	67.6	14.6	20.4	13.8	8.1	12.4	13.9
Emerging markets	$h=1$	73.1	0.7	1.4	0.8	0.9	3.6	0.5
	$h=20$	57.1	5.5	12.4	5.4	9.9	7.1	4.4
	<i>maximum</i>	73.1	5.6	12.6	5.5	10.1	7.2	4.5
Developed Commodity Exporters	$h=1$	83.0	1.5	2.2	1.7	0.6	13.2	6.7
	$h=20$	59.6	7.8	19.5	6.3	13.2	18.4	7.5
	<i>maximum</i>	83.0	8.3	19.8	6.4	13.5	18.6	8.3
Developed Non Commodity Exporters	$h=1$	72.4	0.9	1.8	1.1	0.6	4.9	5.5
	$h=20$	55.2	10.8	17.5	8.2	5.0	12.7	12.1
	<i>maximum</i>	72.4	11.0	17.8	8.4	5.2	12.9	12.2

Figure 17: Response of domestic variables after a Global Component shock

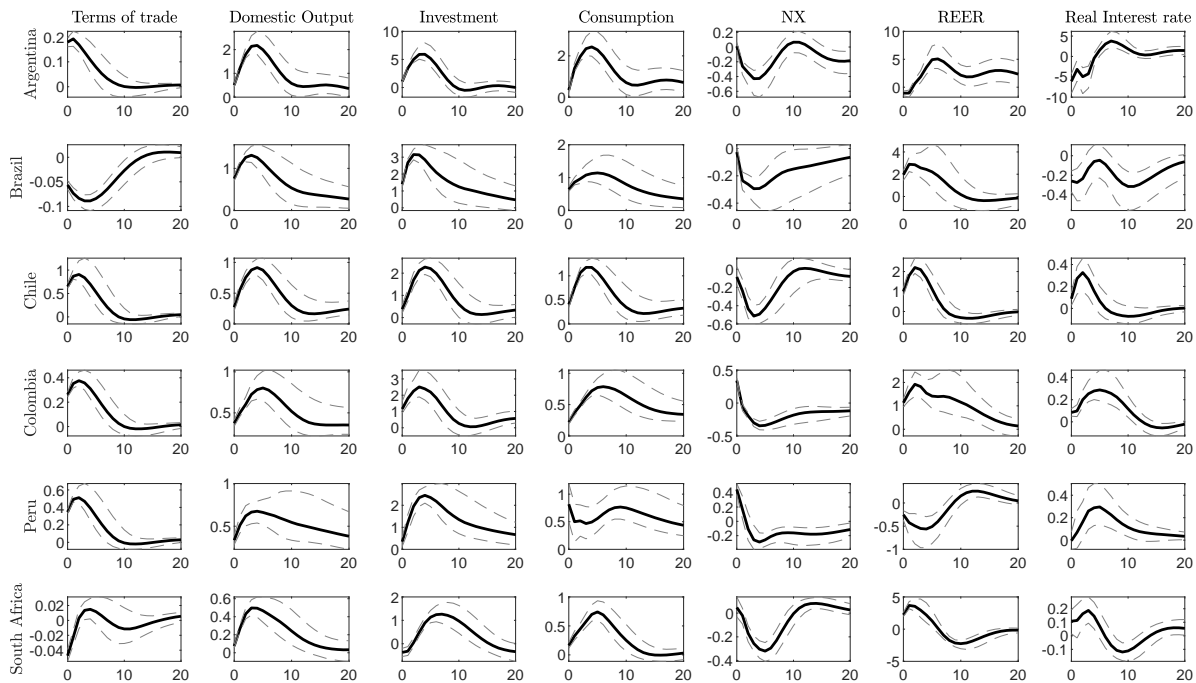
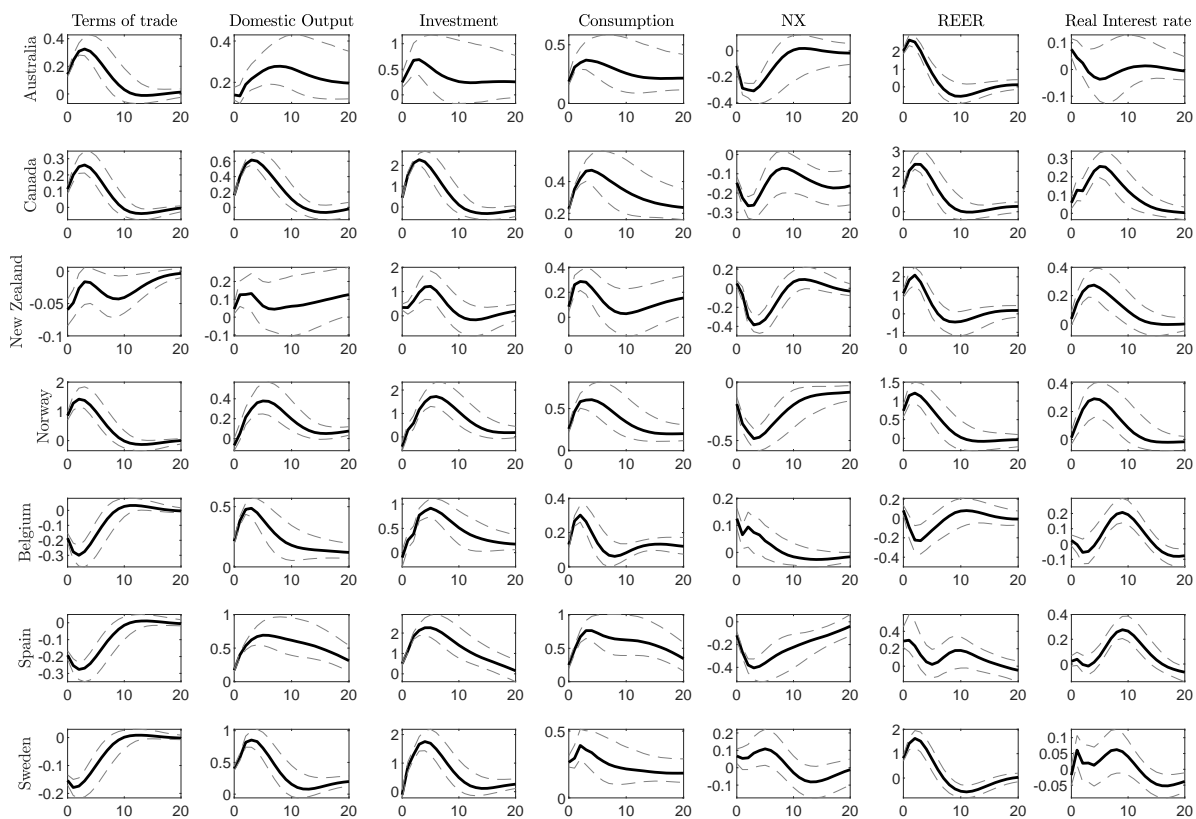


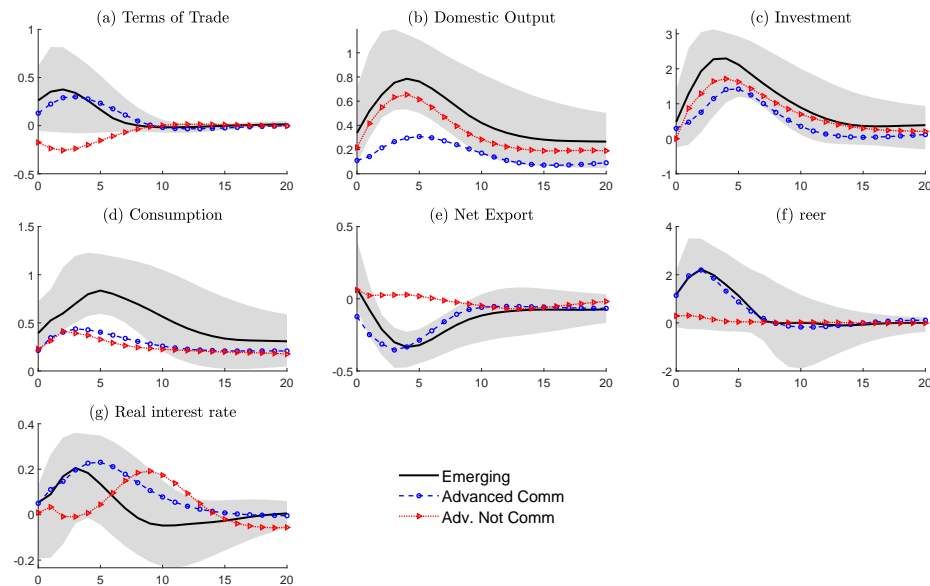
Figure 18: Response of domestic variables after a Global Component shock



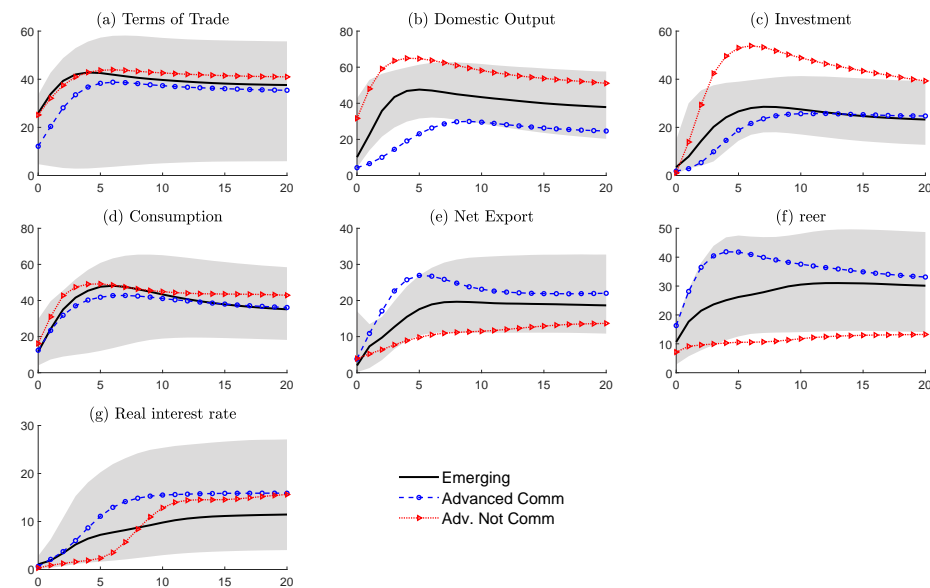
B Robustness Analysis

Figure 19: Effect of Global Component innovations on country-specific variables without Argentina

i. Impulse-response functions



ii. Contribution to Forecast Error Variance



C 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 an 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.

C.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:

$$\Omega^{(h)} = \sum_{i=0}^h \sum_{j=1}^N R_i \gamma_j \gamma_j' R_i' \quad (14)$$

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 $[\underline{\tau}, \bar{\tau}]$. Let be

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

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

$$\begin{aligned} \gamma^* &= \underset{\gamma}{\operatorname{argmax}} \left(\sum_{h=\underline{\tau}}^{\bar{\tau}} \sum_{i=0}^h R_i \gamma \gamma' R_i' \right)_{kk} \\ \text{s.t.} \quad &\gamma' \gamma = 1 \end{aligned} \tag{15}$$

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

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

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

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

Finally:

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

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

D 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 $S^i(\underline{\tau}, \bar{\tau}|j)$ the forecast variance of the i -variable explained by the j structural shock over the time span $[\underline{\tau} : \bar{\tau}]$, the

maximization problem is:

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

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:

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

The maximization problem becomes into:

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

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

D.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:

$$\begin{aligned} \psi^* &= \underset{\psi}{\operatorname{argmax}} \quad \psi' \Lambda^{(tot)} \psi \\ \text{s.t.} \quad &\psi' \psi = 1 \\ &\psi' \gamma = 0 \end{aligned}$$

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:

$$\begin{bmatrix} \psi_1 & \psi_2 & \dots & \psi_n \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_n \end{bmatrix} = 0$$

$$\psi_1 = -\frac{\sum_{k=2}^n \psi_k \gamma_k}{\gamma_1}$$

Hence, we can rewrite the vector ψ as

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

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 $\psi = \chi \varphi$.

References

- M. Aguiar and G. Gopinath. Emerging market business cycles: The cycle is the trend. *Journal of Political Economy*, 115(1):69–102, 2007.
- O. Akinci. Financial Frictions and Macroeconomic Fluctuations in Emerging Economies. International Finance Discussion Papers 1120, Board of Governors of the Federal Reserve System (U.S.), Oct. 2014.
- H. Armelius, I. Hull, and H. Stenbacka Köhler. The timing of uncertainty shocks in a small open economy. *Economics Letters*, 155:31 – 34, 2017.
- D. K. Backus, P. J. Kehoe, and F. E. Kydland. International real business cycles. *Journal of Political Economy*, 100(4):745–775, 1992. ISSN 00223808, 1537534X. URL <http://www.jstor.org/stable/2138686>.
- R. B. Barsky and E. R. Sims. News shocks and business cycles. *Journal of Monetary Economics*, 58(3):273 – 289, 2011.
- R. B. Barsky and E. R. Sims. Information, animal spirits, and the meaning of innovations in consumer confidence. *The American Economic Review*, 102(4):1343–1377, 2012.
- P. Beaudry and F. Portier. Stock prices, news, and economic fluctuations. *The American Economic Review*, 96(4):1293–1307, 2006.
- N. Ben Zeev. Global credit supply shocks and exchange rate regimes. *Journal of International Economics*, 116:1 – 32, 2019.
- N. Ben Zeev, E. Pappa, and A. Viccondoa. Emerging economies business cycles: The role of commodity terms of trade news. *Journal of International Economics*, 108:368 – 376, 2017.
- V. Charnavoki and J. J. Dolado. The effects of global shocks on small commodity-exporting economies: Lessons from canada. *American Economic Journal: Macroeconomics*, 6(2):207–37, April 2014.
- K. Chen and M. J. Crucini. Trends and Cycles in Small Open Economies: Making The Case For A General Equilibrium Approach. CAMA Working Papers 2014-76, Centre for Applied

- Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University, Dec. 2014.
- M. D. Chinn and O. Coibion. The Predictive Content of Commodity Futures. *Journal of Futures Markets*, 34(7):607–636, 2014.
- M. J. Crucini and M. Shintani. Measuring business cycles by saving for a rainy day. Working Paper 16075, National Bureau of Economic Research, June 2010.
- S. Dees. The role of confidence shocks in business cycles and their global dimension. *International Economics*, 151:48 – 65, 2017. ISSN 2110-7017.
- T. Drechsel and S. Tenreyro. Commodity booms and busts in emerging economies. *Journal of International Economics*, 112:200 – 218, 2018.
- M. Dupaigne, F. Portier, and P. Beaudry. The International Propagation of News Shocks. 2007 Meeting Papers 251, Society for Economic Dynamics, 2007.
- M. Feldkircher and F. Huber. The international transmission of us shocks—evidence from bayesian global vector autoregressions. *European Economic Review*, 81:167 – 188, 2016. Model Uncertainty in Economics.
- A. Fernández, S. Schmitt-Grohé, and M. Uribe. World shocks, world prices, and business cycles: An empirical investigation. *Journal of International Economics*, 108:S2 – S14, 2017. 39th Annual NBER International Seminar on Macroeconomics.
- R. Finlay and J. P. Jääskelä. Credit supply shocks and the global financial crisis in three small open economies. *Journal of Macroeconomics*, 40:270 – 276, 2014.
- J. García-Cicco, R. Pancrazi, and M. Uribe. Real business cycles in emerging countries? *American Economic Review*, 100(5):2510–31, December 2010.
- F. Grigoli, A. Herman, and K. Schmidt-Hebbel. The impact of terms of trade and macroeconomic regimes on private saving. *Economics Letters*, 145:172 – 175, 2016.
- B. Gruss and S. Kebhaj. Commodity Terms of Trade; A New Database. IMF Working Papers 2019/021, International Monetary Fund, Jan. 2019.

- P. A. Guerron-Quintana. Common and idiosyncratic disturbances in developed small open economies. *Journal of International Economics*, 90(1):33–49, 2013.
- N. Jaimovich and S. Rebelo. News and business cycles in open economies. *Journal of Money, Credit and Banking*, 40(8):1699–1711, 2008.
- A. Justiniano and B. Preston. Monetary policy and uncertainty in an empirical small open-economy model. *Journal of Applied Econometrics*, 25(1):93–128, 2010a.
- A. Justiniano and B. Preston. Can structural small open-economy models account for the influence of foreign disturbances? *Journal of International Economics*, 81(1):61 – 74, 2010b.
- G. Kamber, K. Theodoridis, and C. Thoenissen. News-driven business cycles in small open economies. *Journal of International Economics*, 105:77 – 89, 2017.
- T. J. Kehoe and K. J. Ruhl. Are Shocks to the Terms of Trade Shocks to Productivity? *Review of Economic Dynamics*, 11(4):804–819, October 2008.
- Y. Kim, H. Lim, and W. Sohn. Which external shock matters in small open economies? global risk aversion vs. us economic policy uncertainty. *Japan and the World Economy*, 54:101011, 2020.
- A. Kose. Explaining business cycles in small open economies: ‘how much do world prices matter?’. *Journal of International Economics*, 56(2):299–327, 2002.
- G. Lorenzoni. A theory of demand shocks. *American Economic Review*, 99(5):2050–84, December 2009.
- E. G. Mendoza. Real business cycles in a small open economy. *The American Economic Review*, 81(4):797–818, 1991. ISSN 00028282. URL <http://www.jstor.org/stable/2006643>.
- P. A. Neumeyer and F. Perri. Business cycles in emerging economies: The role of interest rates. Working Paper 10387, National Bureau of Economic Research, March 2004.
- S. Schmitt-Grohé and M. Uribe. How important are terms of trade shocks? Working Paper 21253, National Bureau of Economic Research, June 2015.
- S. Shousha. Macroeconomic effects of commodity booms and busts : The role of financial frictions job market paper. 2016.

- K. Souki and W. Enders. Assessing the importance of global shocks versus country-specific shocks. *Journal of International Money and Finance*, 27(8):1420 – 1429, 2008.
- M. Stuermer. 150 years of boom and bust: What drives mineral commodity prices? *Macroeconomic Dynamics*, 22(3):702–717, 2018. doi: 10.1017/S136510051600050X.
- H. Uhlig. Do Technology Shocks Lead to a Fall in Total Hours Worked? *Journal of the European Economic Association*, 2(2-3):361–371, 04/05 2004.
- M. Uribe and V. Z. Yue. Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, 69(1):6 – 36, 2006a. Emerging Markets.
- M. Uribe and V. Z. Yue. Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, 69(1):6–36, June 2006b.
- K. Walentin. Expectation driven business cycles with limited enforcement. *Economics Letters*, 124(2):300 – 303, 2014.
- Özge Akıncı. Global financial conditions, country spreads and macroeconomic fluctuations in emerging countries. *Journal of International Economics*, 91(2):358 – 371, 2013.