Terms of Trade and Small Open Economies Business Cycles: The role of Global Shocks

Christian Velasquez

Banco Central de Reserva del Perú

Abstract

This paper proposes a new identification strategy to disentangle terms of trade movements due to global factors (global shocks) from country-specific fluctuations. This method is then applied to data on ten small open economies(SOEs) to show that global shocks contribute 33 percent of SOE business cycle. In contrast, idiosyncratic innovations account for around 80 percent of terms-of-trade volatility but are responsible for less than 10 percent of business cycle variability. The estimates suggest that developed economies are less sensitive to global shocks compared to emerging markets. The results help to reconcile current estimates on the importance of terms of trade for SOEs.

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

***JEL classification*—** E32, F41, F44

1 Introduction

It is widely accepted that terms-of-trade movements play a crucial role in shaping business cycles in Small Open Economies (SOEs).[1] However, empirical estimations have yet to establish a consensus on the quantitative impact of these shocks. Evidence from standard Structural Vector Autoregressive (SVAR) models suggests that terms-of-trade shocks contribute less than 10 percent to real output variability for emerging markets.[2] This contribution rises to approximately 30 percent when including multiple commodity prices in the estimation and further increases to roughly 50 percent when allowing households to have anticipated information about commodity prices.[3] In response to the ongoing debate, this paper argues that terms-of-trade fluctuations can be explained by two sources: *a global shock* and *a country-specific innovation*. The former describes shocks to global conditions, such as a tight United States monetary policy or a higher demand from China. These shocks not only affect terms of trade but also multiple economic variables. The latter is associated with commodity-specific deviations such as market frictions or animal spirits.

This paper proposes a novel strategy that allows us to identify global shocks and country-specific term-of-trade innovations. This strategy does not restrict global shocks to operate only through terms of trade but allows them to impact macroeconomic aggregates directly. Combining this approach with quarterly data from ten SOEs, I show that global shocks are the most important driver of business cycles in these countries. These shocks explain more than 30 percent of real output and consumption variability and 25 percent of investment variability over five years. In contrast, country-specific terms of trade shocks are responsible for less than 10 percent of the fluctuations in real output and consumption. The larger responses of domestic real variables to global shocks compared to country-specific terms-of-trade shocks reinforce their relevance for SOEs. For example, real output expands 0.2 percent on average immediately after a global shock, while only 0.02 percent after a country-specific terms-of-trade shock. The analysis also suggests that terms of trade are not the main channel through which global shocks are transmitted to SOEs. This conclusion is based on the observation that nearly 80 percent of the terms-of-trade fluctuations are driven by country-specific shocks, while around 18 percent are due to global shocks while approximately 18 percent are attributed to global shocks.

[1] Calibrated models suggest that terms-of-trade shocks explain approximately 30 percent of the macroeconomic variability in these countries. See Mendoza (1995) and Kose (2002)

[2] Schmitt-Grohé and Uribe (2015)

[3] Fernández, Schmitt-Grohé and Uribe (2017), Ben Zeev, Pappa and Vicondoa (2017)

I use a sequential strategy to disentangle global shocks and country-specific terms-of-trade shocks. Firstly, I identify global shocks by extending the so-called *"max-share"* identification approach proposed by Uhlig (2004). This approach finds the shock with the highest contribution to a single variable's [terms-of-trade] forecast error variance (FEV). Instead, my extension identifies the structural shock with the largest explanation power over a weighted sum of FEV of multiple variables. This is particularly attractive when dealing with data from SOEs that are highly dependent on commodities. For those countries, terms of trade - defined as the ratio between export and import prices- are assumed to be exogenous variables whose fluctuations are explained by the evolution of commodity prices. Since commodity prices are endogenous variables in the world market, some of their movements would result from global conditions rather than commodity-specific innovations.[4] Therefore, relying only on data from commodities does not allow us to discern between both components, leading to biased estimates of the importance of terms of trade for SOEs. This paper tackles this issue by exploiting information from global variables related to production, monetary conditions, and prices to identify global shocks. Secondly, the country-specific terms-of-trade shock is identified as the structural shock that satisfies (i) orthogonality to global shocks and (ii) maximum contribution to the remaining forecastability of terms-of-trade FEV.

This strategy was applied to ten small open economies for which country-specific two-block SVARs were estimated. In this setting, the first bloc represents the world's economy, which is composed of the G7 real gross output, the spread between the BAA bond and the Fed fund rate, and the IMF's commodity price index. The foreign block is assumed to be exogenous to domestic shocks and common to all countries, implying that each SOE is hit by the same global shock. Identified global shocks contribute, on average, to more than 50 percent of the variability of the foreign bloc during a five-year forecast horizon, reflecting the success of the identification strategy. The contemporaneous contribution of global shocks to terms-of-trade variability is less than 20 percent, increasing to 35 percent in the long run. In contrast, country-specific terms-of-trade shocks explain roughly 80 percent of terms-of-trade variability in the short-run, reducing to 60 percent in the long-run. On average, global shocks explain 40 percent of SOEs' real GDP fluctuations after one year and around 30 percent after five years. In comparison, the contribution of country-specific terms-of-trade shocks to this variability is roughly three and five percent for

[4]More than 40 percent of the selected SOEs' pairwise correlations among terms-of-trade movements are above 50 percent.

the same periods. An impulse-response analysis shows that consumption, output, and investment responses to global shocks are larger than their counterparts when country-specific terms-of-trade shocks hit the economy. Replicating this comparison at a country level reveals that the identified shocks have different impacts on real variables in both size and pattern. All these results suggest that most movements in terms of trade are due to idiosyncratic sources that have no significant effect on the domestic economy and that terms of trade are not the main channel through which global shocks propagate to SOEs.

A second dimension of analysis investigates whether there are asymmetries in the sensitivity to global shocks and country-specific terms of trade shocks across countries. To do so, I divide these ten economies into developed countries (four economies) and emerging markets (six economies). Then, I obtain the median response and contribution to forecast error variance of both shocks for each country group. Results suggest that, on average, real macroeconomic aggregates are more sensitive to global shocks in emerging markets than in developed economies. For example, while the maximum response of real output for emerging markets is 0.8 percent, developed markets' maximum expansion is around 0.3 percent. In terms of forecastability, almost 40 percent of the real GDP long-run variance in emerging markets is explained by global shocks while 25 percent in developed countries. On the other hand, there are small differences in the sensitivity to country-specific terms of trade shocks. The largest discrepancies are found in the explanation power of investment and real exchange rate. Country-specific terms-of-trade shocks account for roughly 13 percent of the investment volatility in emerging marker while 18 percent in developed countries. This difference is larger in the case of the real exchange rate, where this shock explains close to 10 percent for emerging market and 18.5 percent for developed economiezx. These results are robust to a country-level comparison for economies with similar trading structures. In contrast, the response of financial markets does not exhibit asymmetries between country groups. Interestingly, responses to country-specific terms of trade shocks do not exhibit these differences.

Finally, I conduct two comparison exercises to show what forces rule global shock dynamics. In the first exercise, I use Granger causality tests and a forecast error variance decomposition to verify whether some commonly used aggregate shocks can explain global shocks. Neither innovations on input-adjusted US-TFP, US monetary policy, and China activity explain global shocks' dynamics. In contrast, the proxy of the global financial cycle of risky assets proposed by Miranda-Agrippino and Rey (2022) drives around 45 percent of global shock variability while global shocks account for nearly 40 percent of their own predictability. In the second exercise, I combine long-run restrictions and data on the global production of twelve commodities to estimate an aggregate shock in the supply of commodities. These shocks correlate negatively with the global shocks and explain around one-third of their variability. These results reflect the tight connections between global economic activity, financial markets, and commodities. Further research that can shed light on these connections is required.

This paper is mainly related to two strands of the literature. First, papers that study and quantify the role of terms-of-trade movements in SOEs' economic dynamics. This literature can be broadly divided into theoretical studies and econometrics estimations. However, the evidence is mixed. Calibrated RBC models suggest that terms-of-trade shocks contribute to one-third of the variability of SOEs' business cycles (Mendoza, 1995; Kose, 2002). Schmitt-Grohé and Uribe (2015), on the other hand, find an average contribution of 10 percent using a three-sector model and data for 38 economies. Drechsel and Tenreyro (2018) build a two-sector model and observe a negative correlation of terms of trade with global interest rates. They find that commodity price shocks drive around 22 percent of output fluctuations and 34 percent of investment. In the econometric realm, Schmitt-Grohé and Uribe (2015) shows that an SVAR analysis supports the small contribution of terms-of-trade shocks. Fernández, Schmitt-Grohé and Uribe (2017) use country-specific two-block VARs with multiple commodity prices to conclude that commodity price shocks (referred to as global shocks) explain close to 30 percent of the macroeconomic volatility in SOEs. More closely related, Ben Zeev, Pappa and Vicondoa (2017) argue that the role of commodities as financial assets makes it relevant to include anticipated information unobserved by the econometrician to account for the total effect of terms-of-trade shocks. They show that an SVAR analysis combined with a "max-share" identification suggests that terms of trade explain around one-half of the forecastability of real variables in SOEs. Relative to this literature, this paper aims to reconcile previous estimates by decomposing terms of trade fluctuations into global and country-specific factors. This paper shows that country-specific terms of trade shocks have little impact on SOE business cycles, while large estimates also account for the impact of changes in global factors that can not be attributed to terms of trade alone.

The second strand is composed of studies exploring external shock's impact on SOEs. Finlay and Jääskelä (2014) explore the role of foreign credit supply shock on advanced SOEs. Özge Akıncı (2013) studies global risk's impact in emerging markets using a panel structural vector autoregressive model, finding that these shocks contribute to 20 percent of aggregate activity. Feldkircher and Huber (2016) use a Bayesian Global Vector Autoregressive model to estimate the transmission of shocks from the United States (demand, supply, and contractionary monetary policy) on 43 economies. They show that in the medium run, these shocks explain around 10 percent of the real GDP fluctuations in advanced economies while close to 50 percent in Latin America. More closely related, other studies suggest the existence of a global component to international fluctuations. Based on a multicountry dynamic factor, Kose, Otrok and Whiteman (2003) estimate that common global fluctuations explain around 30 percent of fluctuations in G7 real aggregates and 13 percent worldwide.[5] Guerron-Quintana (2013) estimates a DSGE model for advanced SOEs and finds a contribution of common disturbances on output predictability around 23 percent. Other articles explore asymmetric responses between advanced and emerging economies. In this line, Shousha (2016) and Kim, Lim and Sohn (2020) show that advanced economies are less sensitive to external fluctuations. Relative to this strand, my approach reaches similar estimates to Guerron-Quintana (2013) while also providing estimates for emerging markets. In addition, this paper finds a larger contribution of foreign shocks than previous estimates when accounting for both common and country-specific disturbances.

The rest of the paper is structured as follows: Section 2 details the method for identifying global shocks and idiosyncratic terms-of-trade innovations and describes the empirical strategy for estimating the country-specific SVARs. Section 3 analyzes the impulse-response functions and FEVs associated with both shocks. Section 4 explores which global factors can be associated with the identified global shock. Section 5 concludes.

2 Empirical Methodology

The identification strategy follows a two-step procedure to disentangle global shocks and country-specific terms-of-trade movements. In the first step, the global shock is identified as an underlying innovation that is exogenous to the domestic economy and induces contemporaneous and persistent comovement in global variables. In that way, this paper maintains an agnostic posture regarding the source of these fluctuations. In the second step, a country-specific shock to terms-of-trade is identified as a main driver of terms-of-trade variability, which is orthogonal to the global shock. Before identifying each shock, I describe the general vector autoregressive

[5] More details of global factors can be found in Miranda-Agrippino and Rey (2022)

setting used throughout the paper.

Let $\mathbf{Y}_t^{(d)} = \begin{bmatrix} \mathbf{y}_t^{(f)} \\ \mathbf{y}_t^{(d)} \end{bmatrix}$ be a column vector of $n = n_f + n_d$ elements composed of n_f foreign variables and n_d domestic ones. The reduced-form VAR is:

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

with a variance-covariance matrix $\mathbf{\Sigma} = \mathbb{E}[\mathbf{u}'\mathbf{u}]$. 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 (1) is:

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

where L is the lag operator and $\mathcal{R}(L) = \sum_{h=0}^{\infty} \mathbf{R}_h L^h$ is the polynomial of reduced-form impulse-response matrices $\mathbf{R}_h$.[6] Let $\widetilde{\mathcal{R}}(L) = \mathcal{R}(L)\mathbf{C}$ be the orthogonalized impulse-response matrices. Now, Let $\mathbf{\Gamma}$ be a matrix mapping the structural shocks $\boldsymbol{\epsilon}$ to the orthogonalized residuals $\mathbf{e}$, i.e. $\mathbf{e}_t = \mathbf{\Gamma}\epsilon_t$. Then, the structural version of 2 is:

$$\mathbf{Y}_t = \widetilde{\mathcal{R}}(L) \cdot \mathbf{\Gamma} \cdot \epsilon_t \tag{3}$$

The h-step ahead forecast error of 1 conditional on the data until $t-1$ is

$$y_{t+h} - \mathbb{E}_{t-1}[y_{t+h}] = \sum_{l=0}^{h} \tilde{R}_l \mathbf{\Gamma} \epsilon_{t+h-l} \tag{4}$$

implying a $h - step$ forecast variance-covariance matrix $\Omega^{(h)} = \sum_{l=0}^{h} \tilde{R}_l \mathbf{\Gamma}\mathbf{\Gamma}' \tilde{R}_l'$ where the element $\Omega_{i,i}^{(h)}$ represents the forecast variance of the i-variable h-steps ahead. We can express $\Omega^{(h)}$ as the sum of each structural shock's contribution: $\Omega^{(h)} = \sum_{l=1}^{h} \sum_{j=1}^{n} \tilde{R}_l \boldsymbol{\gamma}_j \boldsymbol{\gamma}_j' \tilde{R}_l'$, with γ_j representing the j-column of $\mathbf{\Gamma}$. Now, we can define some objects for use in the next section. Let $S^i(\underline{t}, \bar{t})$ be the cumulative forecast error variance of the variable i over the interval $[\underline{t} : \bar{t}]$:

$$S^i(\underline{t}, \bar{t}) = \sum_{h=\underline{t}}^{\bar{t}} \Omega_{i,i}^{(h)} \tag{5}$$

and $S_j^i(\underline{t}, \bar{t})$ be the cumulative forecast error variance of variable i originating from the structural

[6] The elements of a reduced-form matrix are defined as: $(\mathbf{R}_h)_{ij} = \frac{\partial Y_{i,t+h}}{\partial Y_{j,t}}$

shock j during the same time span $[\underline{t} : \bar{t}]$

$$S_j^i(\underline{t}, \bar{t}) = \left(\sum_{h=\underline{t}}^{\bar{t}} \sum_{l=0}^{h} \tilde{R}_l \gamma_j \gamma_j' \tilde{R}_l' \right)_{i,i} = \gamma_j' \Lambda^{(i)}(\underline{t}, \bar{t}) \gamma_j \tag{6}$$

where $\Lambda^{(i)}(\underline{t}, \bar{t}) = \sum_l^h \left(\bar{t} + 1 - \max(\underline{t}, l) \right) \tilde{R}_l^{(i)\prime} \tilde{R}_l^{(i)}$ is the weighted sum of covariance matrices derived from the orthogonalized responses of the i-variable (corresponding to row i in the matrix $\tilde{R}$). Then, the share $s_j^i(\underline{t}, \bar{t}) = \frac{S_j^i(\underline{t}, \bar{t})}{S^i(\underline{t}, \bar{t})}$ quantifies the importance of the structural shock j as a determinant of unexpected fluctuations of the variable i.

2.1 Identification of Global and country-specific Terms-of-Trade Shocks

In standard applications, terms-of-trade shocks have been identified either using a recursive identification (Schmitt-Grohé and Uribe, 2015) or as the innovation that explains the maximum forecast error variance of terms of trade (Ben Zeev, Pappa and Vicondoa, 2017). A caveat of these applications is that they do not account for the fraction of terms-of-trade fluctuations explained by movements originating in the global market. Similarly, global shocks have been obtained by considering either information of only one global indicator or exploiting the contemporaneous correlations of multiple indicators (Miranda-Agrippino and Rey, 2022). As global shocks are associated with fluctuations that affect multiple variables and spread over time, both strategies leave out valuable information that can be used to identify these shocks. Therefore, this paper proposes a sequential strategy that firstly estimates the global shocks (ϵ^{gs}) and then recovers the country-specific component of terms of trade (ϵ^{τ}).

Let γ^{gs} and γ^{τ} two columns of $\mathbf{\Gamma}$ that map ϵ^{gs} and ϵ^{τ} respectively, to the orthogonal residuals $\mathbf{e}_t$. I define ϵ^{gs} as the structural innovation with the highest explanatory power over the joint volatility of variables belonging to the global economy bloc during the first three years. Then, the identification of γ^{gs} involves the following maximization problem:

$$\begin{aligned} \hat{\gamma}^{gs} = \underset{\gamma_j}{\operatorname{argmax}} \quad & \sum_{i \in \text{foreign}} s_j^i(\underline{t}, \bar{t}) \\ \text{s.t.} \quad & \gamma_j' \gamma_j = 1 \end{aligned} \tag{7}$$

from which $\hat{\gamma}^{gs}$ maximizes the average contribution of ϵ^{gs} to the cumulative forecast error variance of all foreign variables. The constraint $\gamma_j'\gamma_j = 1$ ensures unique identification.[7]. Since every contribution is expressed as a share, this procedure is not affected by differences in the scale. Although the maximization assumes equal weights for each foreign variable, it can be easily extended to the case with different ones.

After some algebra, this problem can be reexpressed as:

$$\begin{aligned} \hat{\gamma}^{gs} = \underset{\gamma_j}{\operatorname{argmax}} \quad & \gamma_j'\xi\gamma_j \\ \text{s.t.} \quad & \gamma_j'\gamma_j = 1 \end{aligned} \tag{8}$$

where $\xi = \sum_{i \in f} \frac{1}{S^{(i)}(\underline{\tau}, \overline{\tau})} \Lambda^{(i)}(\underline{\tau}, \overline{\tau})$ is the sum of the covariance matrices $\Lambda^{(i)}$ associated to foreign variables weighted by the inverse of their cumulative forecast error variance. To solve the system, we need to find the eigenvector related to the maximum eigenvalue of ξ. This technique is somewhat related to common-factors modeling, but exploiting the forecast error variance over a lengthy time allows it to differentiate from standard models by accounting for (i) forward-looking consumer behavior and (ii) the persistence of economic shocks.

The country-specific terms-of-trade shock is assumed to be the main driver of the forecastability of terms of trade (τ) not explained by ϵ^{gs} during the same time span. It implies the following maximization problem:

$$\begin{aligned} \hat{\gamma}^{\tau} = \underset{\gamma_j}{\operatorname{argmax}} \quad & s_j^{\tau}(\underline{t}, \overline{t}) \\ \text{s.t.} \quad & \gamma_j'\gamma_j = 1 \\ & \gamma_j'\gamma^{gs} = 0 \end{aligned} \tag{9}$$

As before, the first restriction ensures unique identification while the second condition guarantees that ϵ^{τ} is orthogonal to the global shock. This orthogonality condition implies that the first element of γ^{τ} satisfies:[8]

$$\gamma_1^{\tau} = -\frac{\sum_{k=2}^{n} \gamma_k^{\tau}\gamma_k^{gs}}{\gamma_1^{gs}} \tag{10}$$

[7]In addition, the structural shock is normalized to have a non-negative contemporaneous impact on commodities prices. In practical terms, if the simulation gives me an eigenvector with the relevant entrance negative, I just multiply it by a factor -1

[8]In addition, I normalize the contemporaneous response of commodities prices to a country-specific terms-of-trade shock to be non-negative.

Then, γ^{τ} can be expressed in function of the submatrix $\varphi' = \begin{bmatrix} \gamma_2^{\tau} & \cdots & \gamma_n^{\tau} \end{bmatrix}$ and elements of γ^{gs}:

$$(\gamma^{\tau})' = \begin{bmatrix} \gamma_2^{\tau} & \cdots & \gamma_n^{\tau} \end{bmatrix} \begin{bmatrix} -\frac{\gamma_2}{\gamma_1} & \\ \vdots & I \\ -\frac{\gamma_n}{\gamma_1} & \end{bmatrix} = \varphi' \chi' \tag{11}$$

and redefining 9 to:

$$\begin{aligned} \hat{\varphi} = \underset{\varphi}{\text{argmax}} \quad & \varphi' \chi' \Lambda^{(\tau)}(\underline{t}, \bar{t}) \chi \varphi \\ \text{s.t.} \quad & \varphi' \chi' \chi \varphi = 1 \end{aligned} \tag{12}$$

The solution of 12 implies the following generalized eigenvalue-eigenvector problem:

$$\Lambda_{\Xi}^{(\tau)} \varphi = \lambda \Xi \varphi \tag{13}$$

where $\Lambda_{\Xi}^{(\tau)} = \chi' \Lambda^{(\tau)}(\underline{t}, \bar{t}) \chi$ and $\Xi = \chi' \chi$. Then, $\hat{\psi}^{(\tau)}$ can be recovered indirectly from $\hat{\varphi}$ and $\hat{\gamma}^{gs}$.

2.2 Econometric Strategy and Data

This paper uses quarterly data on 10 SOEs highly dependent on commodities from 1998Q1 to 2019Q4.[9] These countries are divided into two groups: (i) emerging markets - Argentina, Brazil, Chile, Colombia, Peru, and South Africa and (ii) developed economies - Australia, Canada, New Zealand, and Norway. For each of these country, the two-bloc VAR with two lags is:[10]

$$\begin{bmatrix} y_t^f \\ \tau_t^d \\ y_t^d \end{bmatrix} = \mathbf{F}_1 \begin{bmatrix} y_{t-1}^f \\ \tau_{t-1}^d \\ y_{t-1}^d \end{bmatrix} + \mathbf{F}_2 \begin{bmatrix} y_{t-2}^f \\ \tau_{t-2}^d \\ y_{t-2}^d \end{bmatrix} + u_{it} \tag{14}$$

Here, y_t^f is a vector of global variables common to SOEs, τ_t^d is the terms-of-trade of the domestic economy d, and y_t^d is a vector of country-specific domestic variables. In this application, three variables characterize the global economy. First, the commodity price index obtained from the IMF is used to approximate the economy's price level, which is then deflated by the US import price index of manufactured goods. Second, the real GDP index of the G20 countries

[9]Data on domestic variables were obtained from the International Monetary Fund (IMF) and the Bank for International Settlements (BIS). When there is no seasonally adjusted data from central banks u other sources, I adjusted by seasonality using ARIMA X13. In the case to be required, the chained of different year-reference data was made using annual growth rates

[10]Two lags were selected based on the SIC criteria.

is included to serve as a proxy of global economic activity. Finally, the spread between the BAA corporate bonds yield and the Fed funds rate is added to account for changes in monetary conditions. The vector of domestic variables y_t^d consists of real output, real consumption, real investment, net exports-to-GDP ratio, real effective exchange rate (an increase/decrease reflects an appreciation/depreciation), and the real interest rate. Real terms of trade were obtained from (Gruss and Kebhaj, 2019). They construct country-specific terms-of-trade measurements based on commodity prices. Among the different measures of terms-of-trade provided by the authors, I choose the measurement that uses the share of the j-commodity to total commodity exports as weight.[11]

The matrices F_1 and F_2 have been restricted as follows:

$$(F_j)_{rc} = \begin{cases} 0, & \text{if } 1 \leq r \leq 3 \quad \& \quad c \geq 4 \\ 0, & \text{if } \quad r = 4 \quad \& \quad c > 4 \\ 0, & \text{if } \quad r \geq 4 \quad \& \quad c = 1 \\ (f_j)_{rc}, & \text{otherwise} \end{cases} \tag{15}$$

The first zero restrictions indicate the absence of feedback from domestic variables to foreign variables. This reflects a Small Open Economy (SOE) setup, where only information from variables common to all countries is included to identify the global shock. As a result, the estimated global shock will remain the same across SOEs. The second set of zeros is included to model the exogeneity of terms of trade to domestic variables. Finally, the last zero restrictions represent the assumption that commodity prices affect the domestic economy through terms of trade and that they are used only to provide information about the global shock.

Estimates for $\hat{\gamma}^{gs}$ and $\hat{\gamma}^{\tau}$ are derived through simulation methods, as detailed subsequently. Firstly, let $\mathcal{Y}^{(d)}$ and $\mathcal{X}^{(d)}$ be country-specific matrices associated with the companion form of model 14: $\mathcal{Y}^{(d)} = \Phi^{(d)}\mathcal{X}^{(d)} + \mathcal{U}^{(d)}$. Secondly, estimate initial values for $\hat{\Phi}^{(d)}$, $\hat{\mathcal{U}}^{(d)}$, and the variance-covariance matrix $\hat{\Sigma}^{(d)}$ using restricted-OLS. Thirdly, simulate $\mathcal{Y}^{(s)}$ and $\mathcal{X}^{(s)}$ conditional on $\hat{\mathcal{U}}^{ols,(d)}$ and using a blocks-by-blocks bootstrapping with nine lags and a sample size twice larger than the original sample.[12] Then, estimate $\hat{\Phi}^{s,(d)}$ and $\hat{\Sigma}^{s,(d)}$ for the simulated sample, keeping it if $\hat{\Phi}^{s,(d)}$

[11]Since this measurement uses fixed-weights, it can deal with misreporting and structural breaks

[12]For details, see Killian, Lutkepohl (2016), chapter 12

describes a stationary model. Calculate $(\gamma^{gs})^s$ and $(\gamma^{\tau})^s$ for some predefined $(\underline{t}, \bar{t})$.[13] Compute the impulse-response functions $IRF^{(s,d)}$ and the forecast error variance contributions $FEV^{(s,d)}$. Repeat the previous steps until 5000 stationary estimates for each country are obtained. Finally, report the median IRF and FEV as the average statistics and percentiles 16^{th} and 84^{th} as confidence intervals. In contrast to the standard literature, I report the median since it is less affected by outliers. The pseudocode is summarized in Algorithm 1:

Algorithm 1 Estimation of γ^{gs} and γ^{τ}

```
The model in VAR-1 form: 𝒴 = Φ𝒳 + 𝒰
for c in SOEs do
  Obtain Φ̂ , and Σ̂ by restricted OLS
  for s = 1:N do
    1. Draw 𝒴^(s) and 𝒳^(s) from a blocks-by-blocks bootstrap with 9 lags and a sample
       size 2T.
    2. Estimate Φ̂^(s)
    3. if max(|eigen(Φ̂^(s))|) < 1, continue else redo 1-2
    4. Calculate γ̂^{gs,(s)}, and γ̂^{τ,(s)}
    5. Compute and save IRF^(s), and FEV^(s)
  end for
  Country result: Report median and percentiles 16th – 84th
end for
Group result: Collect simulations, report median, and percentiles 16th – 84th
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3 Empirical results

3.1 Impact of Global Shocks

A positive innovation of the global component by $\sigma_{\epsilon^{gs}}$ increases commodity prices and world economic activity and improves monetary conditions as shown by the impulse-response analysis displayed in panel (i) of Figure 1. This figure reports the median response (solid black line) and the 68th-probability confidence interval (dashed gray lines) of global variables to a positive global shock for a 20-quarter horizon. The results suggest that commodity prices increase approximately 4 percent during the quarter in which ϵ^{gs} is realized. This impact rises during the first two quarters, reaching a peak of 6 percent and vanishing after 12 quarters. Global economic activity also increases contemporaneously by roughly 0.3 percent. However, in contrast to the effect on

[13]Following Ben Zeev, Pappa and Vicondoa (2017), I set $\underline{t} = 0$ and $\bar{t} = 13$. In this way, I use information from around three years to identify global and country-specific shocks.

prices, this impact unfolds more gradually, taking four quarters to attain its maximum level (around 0.7 percent). Furthermore, this boost exhibits a higher persistence. The improvement in monetary conditions is characterized by a contemporaneous reduction of the BAA spread by 40 basic points, which increases to 56 basic points after two quarters.

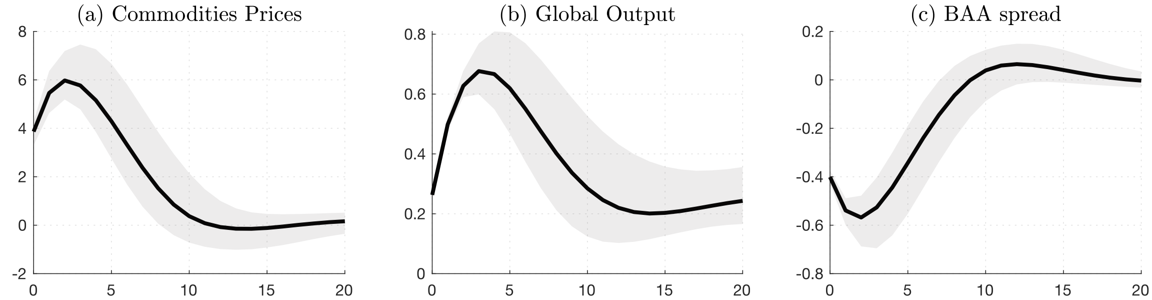
In terms of volatility, the identified global shock explains more than half of the forecastability of global variables being a major driver of real output and monetary conditions in the short run and for commodities prices in the medium run, as depicted in the second panel of Figure 1. The contemporaneous contribution of global shocks, measured as the share of the forecast error variance, is approximately 70 percent to output, 60 percent to monetary conditions, and 30 percent to commodities prices. These contributions follow a hump-shape pattern with peaks between the third and fourth quarters. After 20 quarters, the explanation power of global shocks to global economic activity and monetary conditions reduces to 60 percent and 55 percent, respectively. In contrast, global shocks appear to be more important drivers of commodities prices in the long run, explaining close to 45 percent of their fluctuations. The higher share of global shocks in real activity and monetary conditions rather than in commodities prices suggests that these shocks originated in sectors different from commodities markets.

3.1.1 Impact on domestic variables

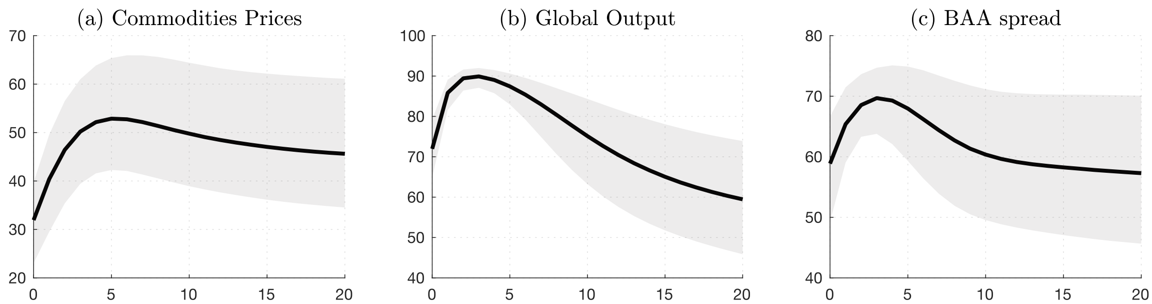
Domestic economies show an expansion of their economic activity mainly by increasing investment rather than international trade gains. Figure 2 shows the response of domestic variables to global shocks. Solid gray lines depict the median responses of the selected SOEs, while shaded gray areas comprise their 68th confidence interval. Median responses of real aggregates reveal a contemporaneous positive impact of global shocks, with output, consumption, and investment rising 0.20, 0.25, and 0.4 percent, respectively. All these responses exhibit a hump-shaped pattern peaking around the first year after the global shock is realized. Among them, investment presents the highest response, with a peak of 2 percent after four quarters, while output and consumption increased 0.65 and 0.70 percent, respectively. On the other hand, global shocks lead to a reduction in the net-export-to-GDP ratio, reflecting that the GDP increases by more than net international trade. This suggests that global shocks propagate to domestic economies mainly by capital inflows rather than a valuation effect caused by the increase in terms of trade. This argument is supported

Figure 1: Effect of Global Component innovations on external variables

i. Impulse-response functions



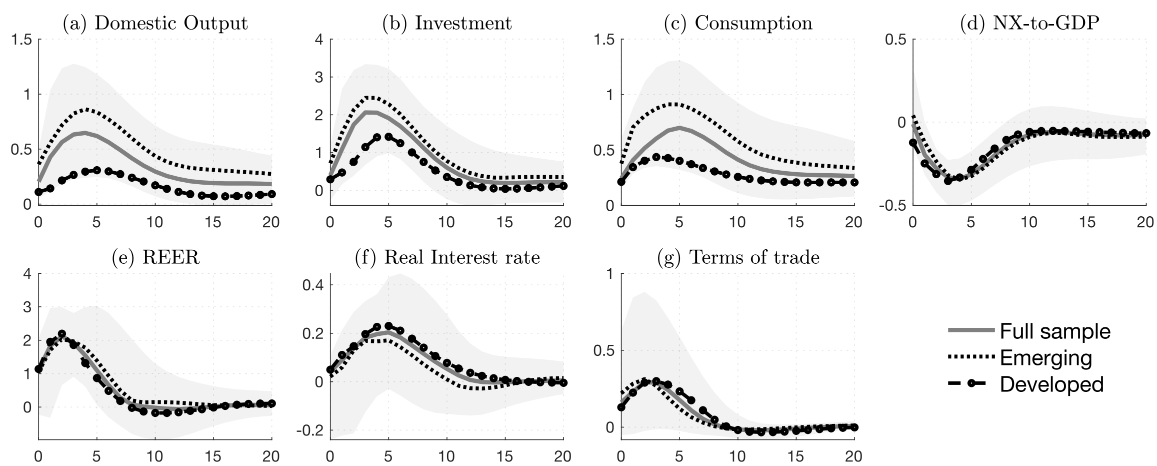
ii. Contribution to Forecast Error Variance



Note: Median response and contribution to forecast error variance are reported by solid black lines, while dashed gray lines display 68th confidence intervals

by the real appreciation of the effective exchange rate shown in panel (e).

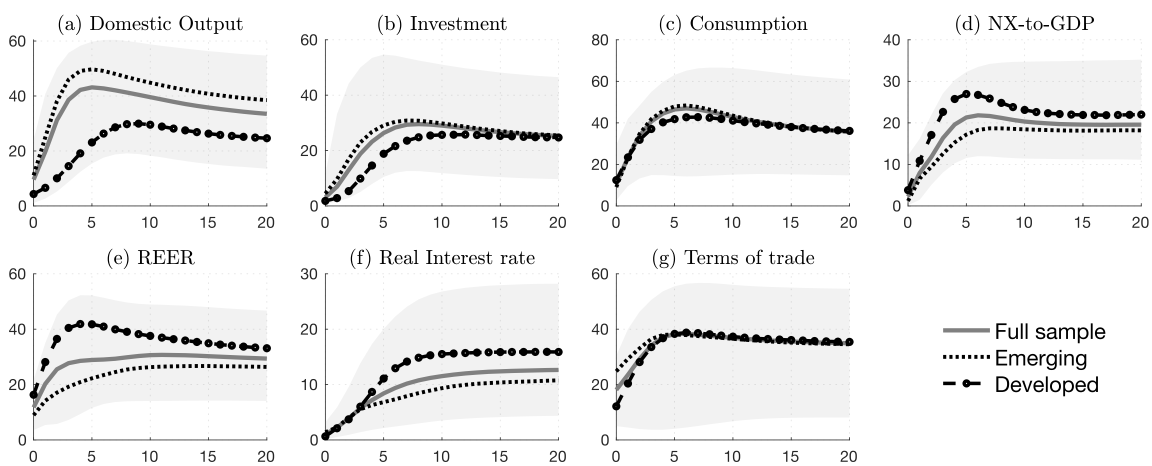
Figure 2: Response of domestic variables after a Global Component shock



Note: Solid gray line represents the median response of the full sample. Gray shaded area displays confidence intervals with 68th probability. The median response of emerging markets is depicted as dotted black lines. The dashed line with a circle maker shows the median response of developed economies

Emerging markets' real aggregates are more sensitive to global shocks than developed economies. Figure 2 also reports the median response for emerging markets (dotted lines) and developed economies (dashed lines with circle marker). There are no visible differences in the response of the net-export-to-GDP ratio, real exchange rates, real interest rates, and terms of trade. This result suggests that the exposure to global shocks through the trade channel is similar for emerging and developed economies. On the other hand, there are evident differences in the short-run and medium-run responses of output, consumption, and investment. The contemporaneous impact of global shocks on output is 0.4 percent, with a peak of 0.8 percent for emerging markets and 0.10 percent, with a peak of 0.3 for advanced economies. In terms of consumption, the response of emerging economies is 0.90 percent higher in its peak, which is reached after five quarters. Differences in investment are smaller, happening mostly during the first four quarters, after which both emerging and developed economies converge quickly. These results suggest that identified global shocks can be associated with better expectations of the global economy. The better expectations cause higher incentives to invest and rising demand for raw materials. A similar increase in external capital flows to SOEs will be more important for emerging markets since they are financially constrained, leading to a higher income effect.

Figure 3: Contribution of global conditions to domestic forecastability



Note: Solid gray line represents the median contribution of global shocks to the FEV in the full sample. Gray shaded area displays confidence intervals with 68th probability. The median contribution of global shocks for emerging markets is depicted as dotted black lines. The dashed line with a circle maker shows the median contribution of global shocks for developed economies

In terms of forecastability, global shocks are important determinants of the variation of domestic variables with an approximate explanation power of 30 percent in the long run. Figure 3 shows the median contribution of global shocks to the forecast error variance of domestic variables for the whole sample (gray line), emerging markets (dotted line), and developed economies

Table 1: Contribution of global conditions to domestic forecastability

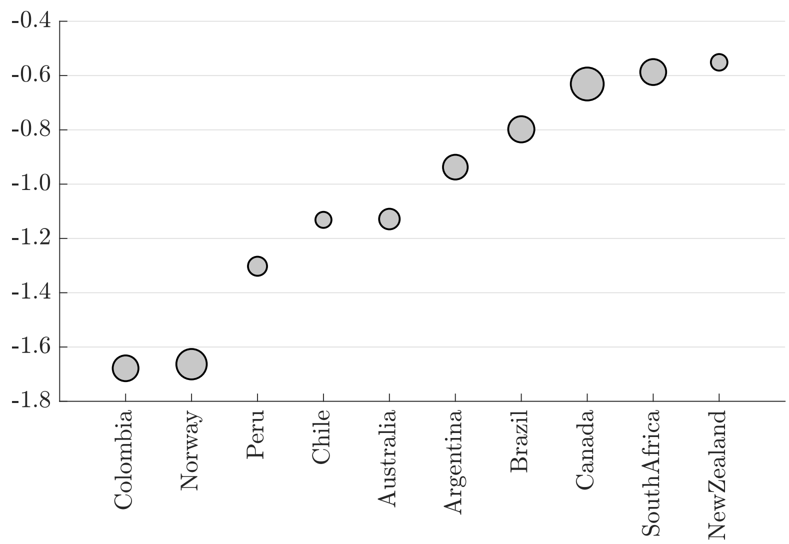
Country Group	horizon	Terms of trade	Production	Investment	Consumption	Net Exports to GDP ratio	Real Exchange Rate	i^{real}
Full Sample	$h = 0$	17.9	9.6	3.1	10.7	2.2	11.7	1.0
	$h = 4$	37.0	42.0	23.2	44.5	19.5	28.6	7.1
	$h = 12$	36.2	38.0	28.0	40.7	19.8	30.6	12.0
	$h = 20$	34.8	33.5	25.3	36.0	19.5	29.4	12.6
Emerging	$h = 0$	24.7	11.2	4.4	9.1	1.2	8.9	1.4
	$h = 4$	37.9	49.0	26.7	45.7	15.3	20.8	6.3
	$h = 12$	35.8	43.0	28.6	40.9	18.1	26.5	10.0
	$h = 20$	34.5	38.5	25.5	35.8	18.0	26.1	10.7
Developed	$h = 0$	12.1	4.4	1.8	12.4	3.7	16.3	0.6
	$h = 4$	36.7	19.2	14.6	40.2	25.7	41.7	8.6
	$h = 12$	36.6	28.5	25.5	40.1	22.3	36.3	15.5
	$h = 20$	35.3	25.0	24.4	36.6	22.0	33.0	15.7

(marked dashed line). Additionally, Table 1 reports these values for specific horizons. Among the domestic variables, global shocks explain more than 40 percent of the forecastability of real output and consumption after four quarters and more than one-third after 20 quarters. The variables less explained by global factors are the net exports-to-GDP ratio (around 20 percent) and real interest rates (around 13 percent). Contrary to the impulse-response analysis, international trade is a channel that explains differences in the global shocks' contribution to real output's forecastability between emerging and developed economies. Global shocks explain 40 percent of output variability after 20 quarters in emerging markets while 25 in developed economies. After the forecast horizon (20 quarters), we do not observe significant differences in the explanation power of global shocks in terms of trade (35 percent), investment (25 percent), and consumption (36 percent). In contrast, the volatility of exchange rates, net exports, and interest rates are more affected by global shocks in developed economies.

3.1.2 Country-specific comparison

Although a median analysis is robust to extreme values, differences in international trade patterns between developed and emerging markets may influence the domestic impact of global shocks. This section presents country-level comparisons between similar emerging and developed economies to handle this possibility. This paper considers two countries to be similar if their exports are mostly based on the same commodity and have a comparable aggregate product complexity index. Hausmann et al. (2014) define *'complexity'* as a measure of the knowledge required to produce certain goods. It depends on *diversity*, which is how many goods a country can produce, and *ubiquity*, which is how many other countries produce similar goods. The country-level index was calculated as the weighted average of product complexity indices for goods at the SITC 4-digit level, weighted by their share in the country's total exports since 1998. Data was obtained from the Atlas of Economic Complexity. If two countries have similar complexity indexes and their trade is based on a similar commodity, then global shocks should affect them similarly.

Figure 4: Complexity index of Exported Goods



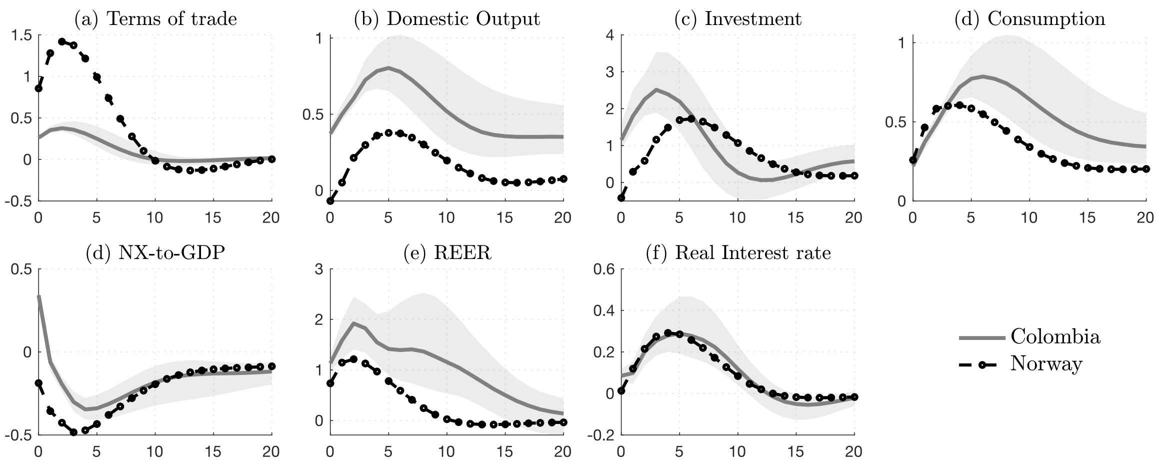
Note: Aggregate complexity index based on 4-digits STICs complexity from the Atlas of Economic Complexity weighted by the average share of each sector in their export basket since 1998.

Figure 4 shows the calculated index for each country in my sample. The first chosen pair of countries were Colombia and Norway. These countries have their exports based on crude petroleum, with shares around 37 and 42 percent, respectively, and complexity indexes of -1.68 and -1.66. The second pair were mining exporters, specifically Chile and Australia. Although South Africa and New Zealand have similar complexity indexes, I do not include them in the comparison due to their differences in export structure. While South Africa's exports are mainly crude and manufacturing materials, New Zealand relies on food-related commodities. Figure 4 depicts the reaction of domestic variables to global shocks for different countries. Panel (i) displays the response of fuel exporting countries, whereas panel (ii) shows the response of mining exporting countries.

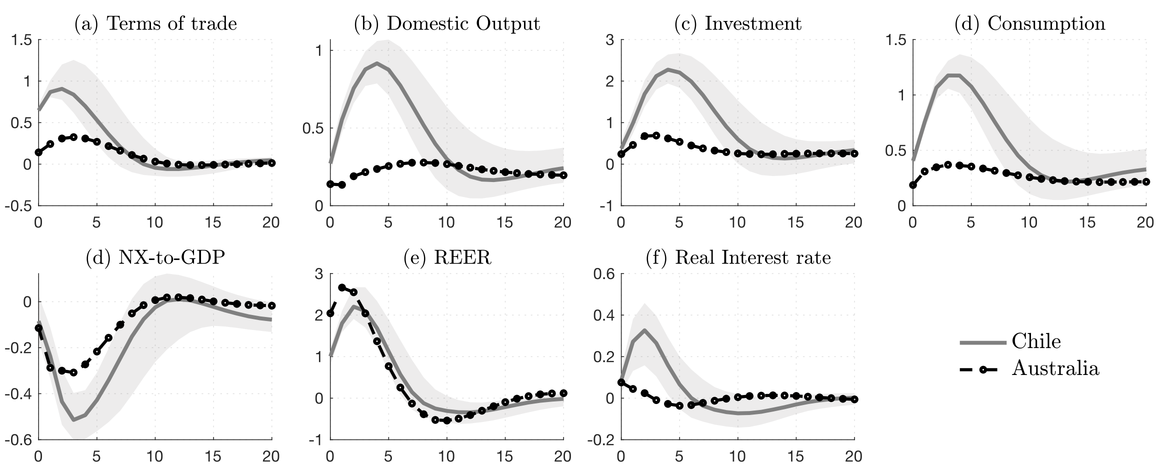
The country-by-country analysis reinforces the lower sensitivity of real variables to global shocks in developed economies compared to emerging markets. For example, it takes six quarters for Colombia to respond to global shocks, and its response reaches a maximum of 0.80 percent. On the other hand, Norway's output increment is half the size of Colombia's, at 0.38 percent, during the same period. This pattern is also observed in mining exporters. Following a global shock, Chile's output increased by 0.90 percent after four quarters, outpacing the maximum impact on Australia's production, which is only 0.30 percent. As before, differences in net exports, exchange rates, and real interest rates are less pronounced.

Figure 5: Response of domestic variables to Global Shocks, by country

i. Fuel Exporters



ii. Mining exporters



3.2 Impact of country-specific Terms of Trade shock

In this section, I show how identified country-specific terms of trade shocks are related to global and domestic variables. First, each vector γ^{τ} was normalized to positively impact commodity prices and then be comparable to the results from global shocks. Second, the shocks were constructed to be orthogonal to global shocks, which is reflected in the low correlation between both shocks, averaging around 7 percent. Each figure displays the median response and a 68 probability confidence interval.

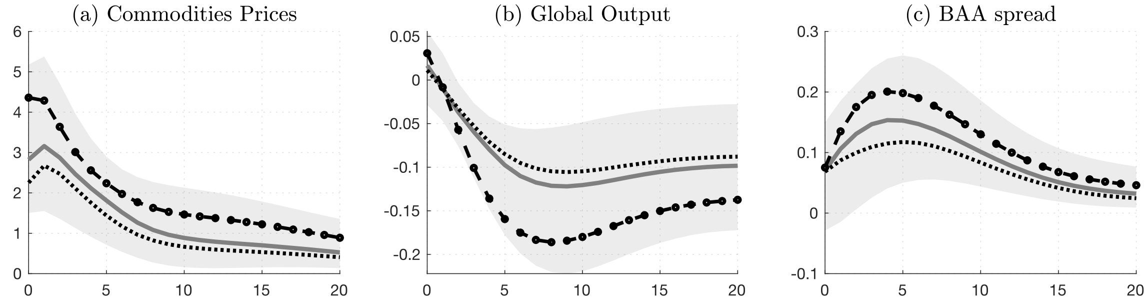
Country-specific terms-of-trade shocks explain a small fraction of the variation of global output and monetary conditions while a sizable fraction of commodity price variability. Panel (i) of Figure 6 shows the impulse-response function of terms-of-trade shocks to global variables, while panel (ii) displays its contribution to the forecast error variance. The identified country-specific terms-of-trade shocks cause a reduction in global output and a tightening of monetary conditions. The contribution of country-specific terms-of-trade shocks to global output's forecastability is lower than 5 percent after 20 periods with minimal explanation over the short run. Similarly, the contribution to monetary conditions is small (< 8%). In contrast, these shocks explain roughly 15% for the whole analysis horizon. In all the cases, the impact and explanation power is higher for developed economies (marked dashed black lines).

Regarding country-specific variables, country-specific terms-of-trade shocks are the main driver of country-specific terms-of-trade variability, but they lack a clear impact on other domestic variables at the aggregate level due to the high variability across countries. Panel (i) of Figure 7 shows the impulse-response function of domestic variables to a country-specific terms-of-trade shock. Results show that the median response is not significant for any country group (see panel (i) of Figure 7 and Figure 18 in the appendix). A disaggregated analysis reveals that there is high volatility across the country-specific impulse-response functions (Figure 16 and Figure 17). For example, a positive country-specific terms-of-trade shock leads to a contraction in Peru's consumption but an expansion in Chile. Regarding volatility, in the short-run, country-specific terms-of-trade shocks contribute less than 10 percent to the forecast error variance of domestic variables, as reported in Table 2. After 20 quarters, these shocks drive around 20 percent of investment and real exchange rate variability.

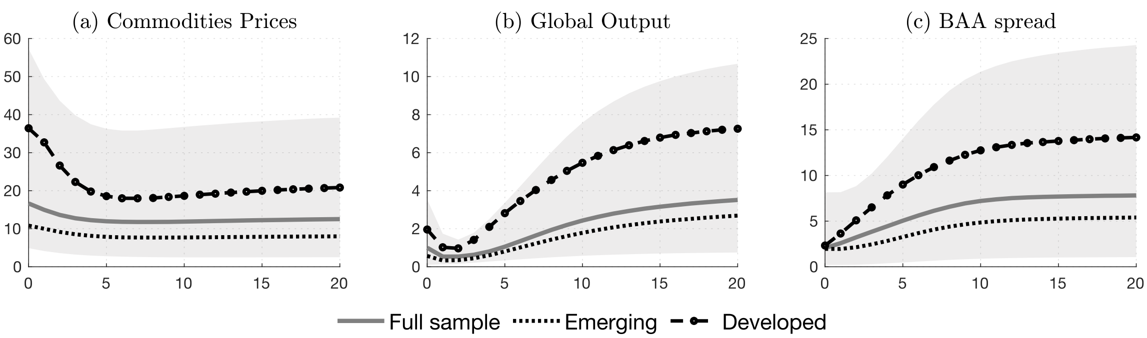
In the short run, about 80% of the variation in terms of trade can be explained by country-specific terms-of-trade shocks. This effect is more pronounced in developed economies (84%) as compared to emerging markets (73%), as shown in panel (ii) of Figure 7 and in Table 2. However, after 4 quarters, this contribution decreases to 62% and drops to 59% after 5 years, and no significant differences were observed between emerging and developed economies during this period. On the

Figure 6: Effect country-specific Terms of Trade shock to external variables

i. Impulse-response functions



ii. Contribution to Forecast Error Variance



Note: Solid gray line represents the median contribution of country-specific terms-of-trade shocks to the FEV in the full sample. Gray shaded area displays confidence intervals with 68th probability. Contribution to emerging markets is depicted as dotted black and as a dashed line with a circle maker for developed economies

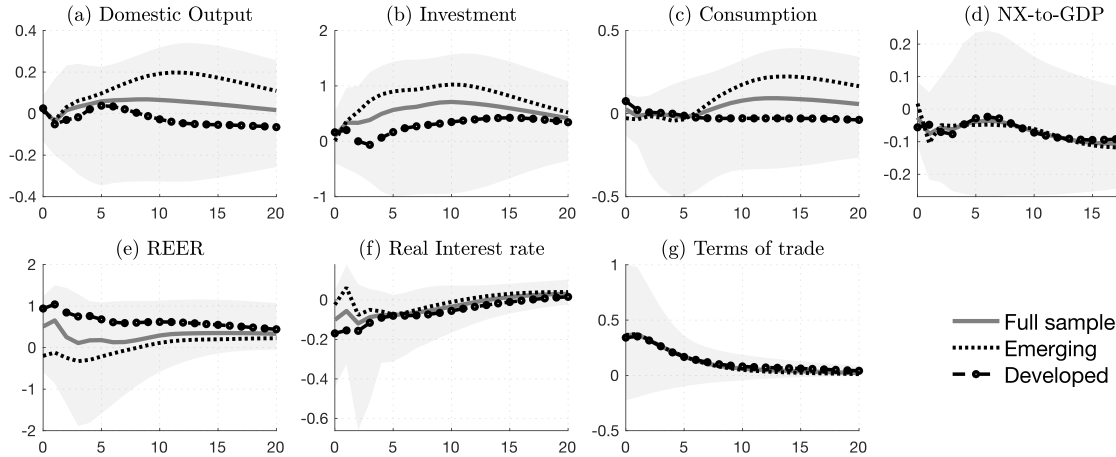
other hand, these shocks can explain less than 7% of real production and consumption variability. Similarly, country-specific terms-of-trade shocks account for about 1% of the contemporaneous real interest rate variability and 6% after 20 quarters. The shocks are also responsible for around 15%, 11.5%, and 12% of the forecastability of investment, net export, and real exchange rates, respectively. These results show that most movements of terms of trade have no real effects on SOEs business cycles after controlling by global shocks.

3.3 Comparing Global and country-specific Terms-of-trade shocks

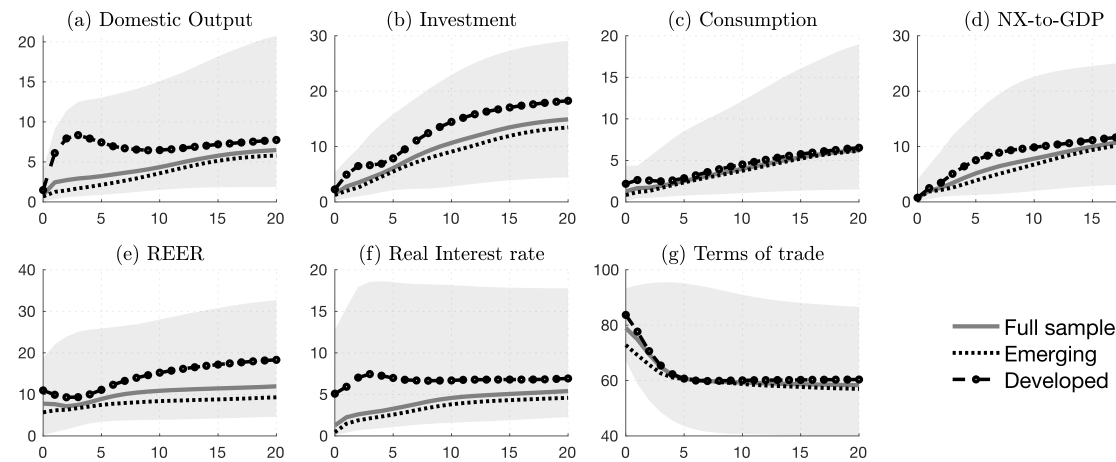
Previous sections show the effects of each identified shock on domestic variables and demonstrate the higher importance of global shocks as drivers of business cycles in small open economies. Then, we show that most trade fluctuations are unrelated to global shocks and have no significant impact on average. While these insights are valuable for policymakers, a more detailed comparison between the two shocks can assist in distinguishing between them. In this section, I proceed to compare both shocks. This comparison is made at the country level due to the heterogeneity across

Figure 7: Effect of country-specific Terms-of-trade shocks on domestic variables

i. Impulse responses



ii. Contribution to FEV



Note: Solid gray line represents the median contribution of country-specific terms-of-trade shocks to the FEV in the full sample. Gray shaded area displays confidence intervals with 68th probability. Estimates for emerging markets and developed economies are plotted in dotted black lines and dashed lines, respectively.

economies. Figure 8 plots the impulse response of domestic variables in emerging markets to a one-standard-deviation shock of each kind. Figure 9 presents the same for developed economies. Each impulse response is accompanied by its 68 probability confidence interval. Gray lines and gray-shaded areas depict the responses to country-specific terms-of-trade shocks, while black dashed and dotted lines show the responses to global shocks.

As shown by the comparison of impulse responses, the proposed strategy has identified two orthogonal shocks with different implications in the dynamic of domestic variables for both emerging and developed markets. The clearest difference is observed in the response of real interest rates, where these shocks have opposite patterns for all countries. While global shocks are

Table 2: Contribution of terms of trade to domestic forecastability

Country Group	horizon	Terms of trade	Production	Investment	Consumption	Net Exports to GDP ratio	Real Exchange Rate	i^{real}
Full Sample	$h = 0$	79.2	0.9	1.5	1.3	0.7	7.8	1.3
	$h = 4$	62.4	3.1	5.2	2.2	4.4	8.2	3.1
	$h = 12$	59.3	5.0	11.9	4.6	8.8	11.2	4.9
	$h = 20$	58.6	6.5	14.9	6.2	11.5	12.0	5.5
Emerging	$h = 0$	72.9	0.7	1.2	0.8	0.7	5.7	0.4
	$h = 4$	61.4	1.9	4.6	2.0	3.3	7.1	2.3
	$h = 12$	58.5	4.3	10.3	4.4	8.0	8.5	4.1
	$h = 20$	57.2	5.8	13.5	6.1	11.1	9.4	4.7
Developed	$h = 0$	83.9	1.5	2.3	2.2	0.8	11.0	5.1
	$h = 4$	62.9	7.9	6.8	2.6	6.4	10.1	7.3
	$h = 12$	60.6	6.8	15.7	5.2	10.4	16.3	6.8
	$h = 20$	60.9	7.9	18.2	6.5	12.3	18.5	7.0

related to increases in interest rates, a country-specific terms-of-trade shock mostly reduces them. Although responses of real variables are not always opposing, global shocks cause larger impacts than country-specific terms-of-trade shocks. For example, while real output in all countries rises after a global shock is realized, real output reacts negatively after a country-specific terms-of-trade shock in some countries like Argentina, South Africa, Australia, and New Zealand.

Figure 8: Impulse response by country- Emerging markets

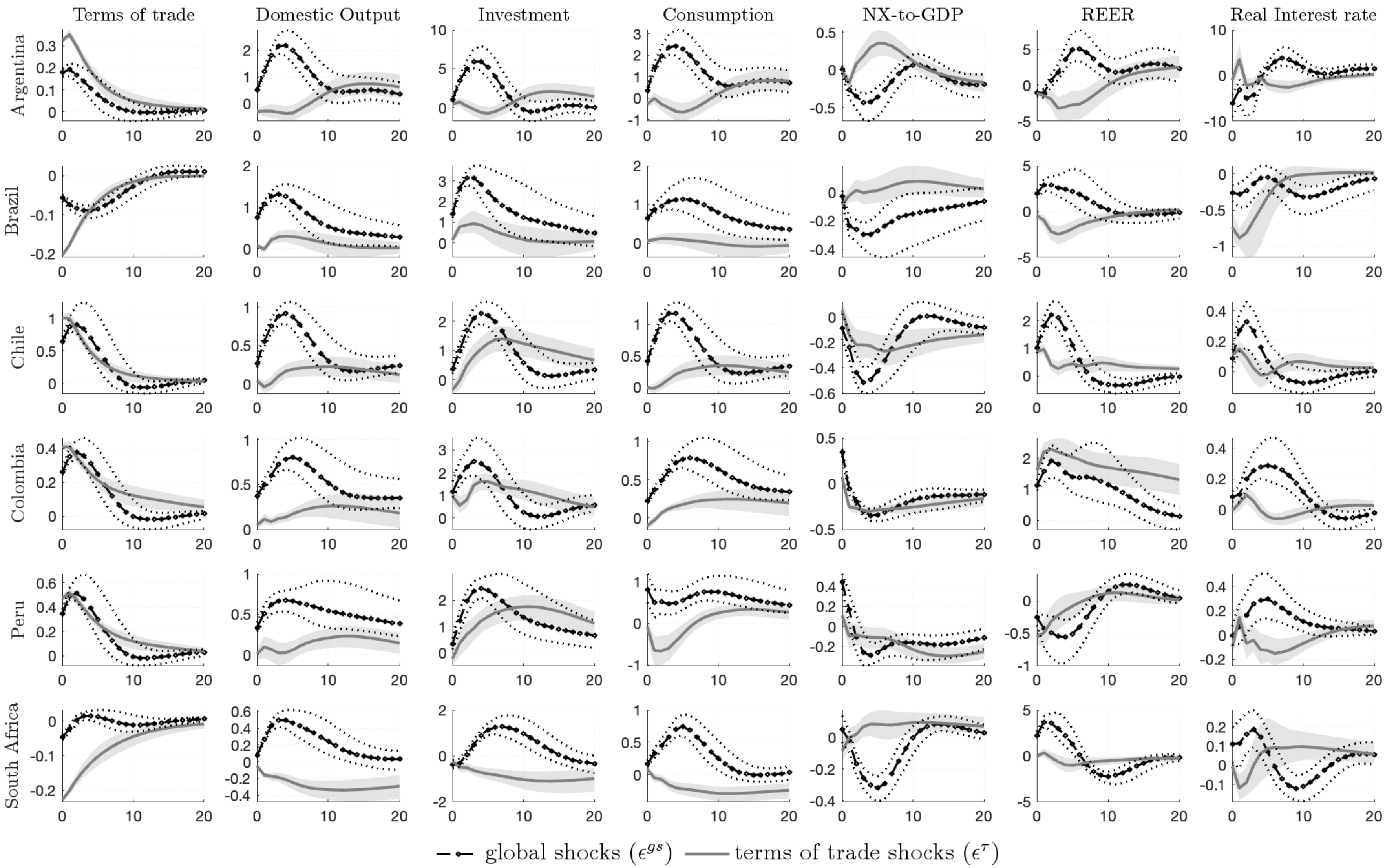
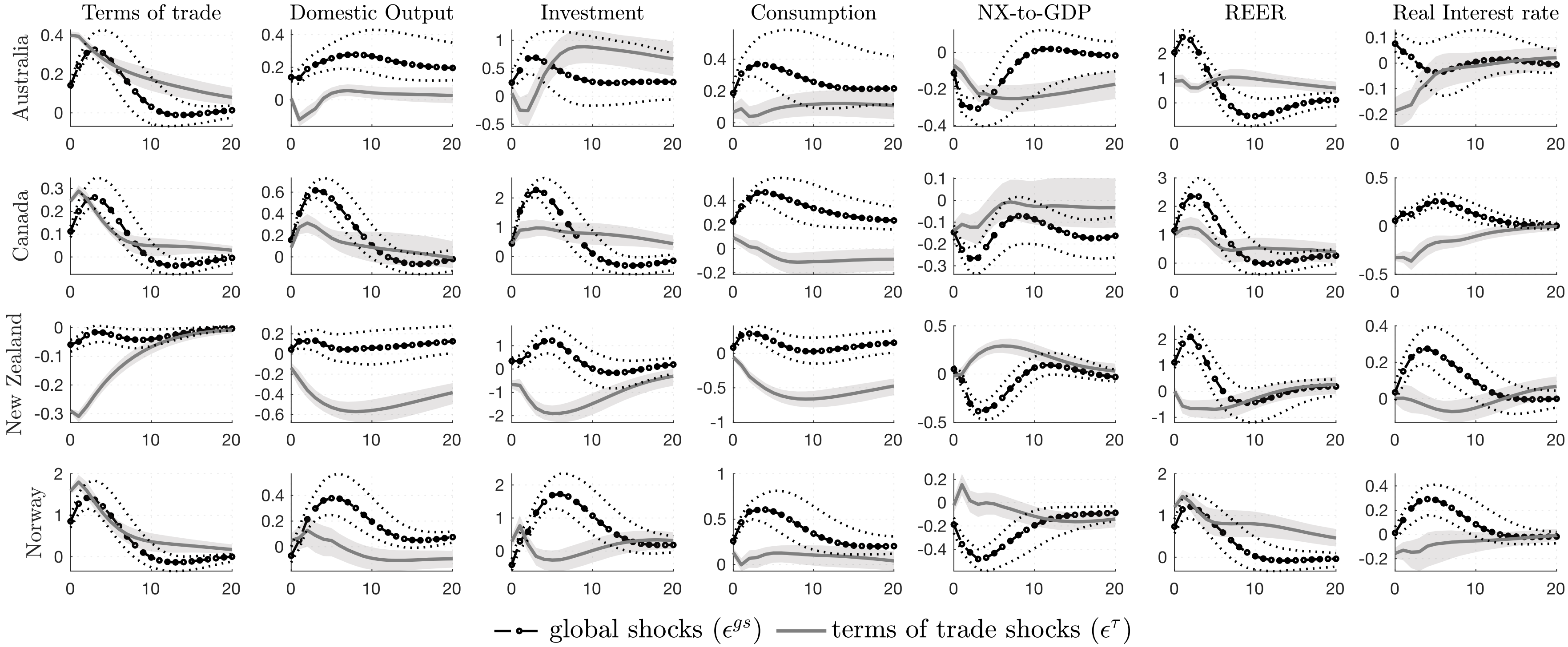


Figure 9: Impulse response by country- Developed economies



4 Relation with other aggregate shocks

As discussed above, my identification strategy is based on the assumption that any quarterly fluctuation that has a significant impact on all foreign block variables at the same time cannot be attributed to a single source of variation. In that sense, my identification strategy lacks of an underlying narrative and could encompass many other aggregate shocks. To shed light on this regard, this section analyzes the relation of the identified global shock with other aggregate shocks used by the literature. The first shock is a measurement of US total factor productivity adjusted (TFP) by input utilization. The TFP was calculated by the Federal Reserve Bank based on Basu, Fernald and Kimball (2006). As commented by the authors, controlling input utilization is crucial to identifying TFP innovations, given their negative correlation. The second variable is a proxy for monetary policy shocks proposed by Bu, Rogers and Wu (2021). The advantages of this proxy can be summarized in: (i) dealing with periods of zero-lower bound and unconventional monetary policy, (ii) longer time-series, and (iii) unpredictability and no information effect. The third series included in this analysis was an indicator of China's economic activity developed by Fernald, Gerstein and Spiegel (2019) and called Cyclical Activity Tracker. This indicator is computed as the first principal component of eight non-GDP indicators. Including China's real activity is crucial since commodities prices (mainly copper and food) could be impacted by the rapid growth in China's demand. I also include a proxy of the global financial cycle called global factor in risky assets. This proxy is calculated by Miranda-Agrippino and Rey (2022) as the principal component of more than 800 risky asset price series.

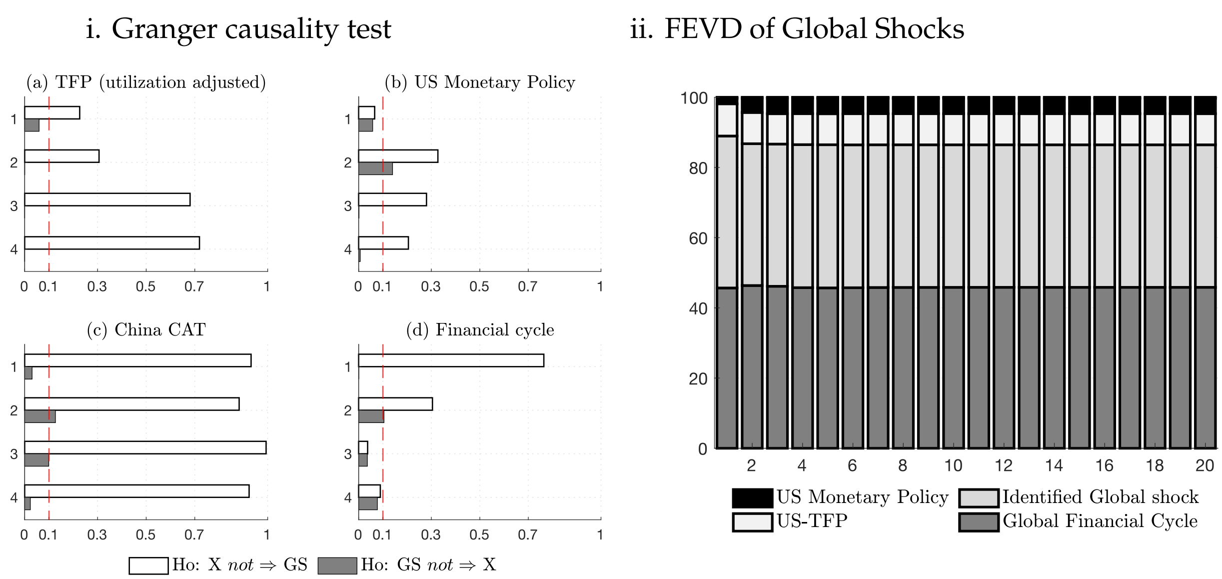
A Granger causality test suggests that lags of global shocks explain each of the previously mentioned variables. In contrast, only US monetary policy appears to drive global shocks. The null hypothesis of a Granger test shows whether the coefficients associated with lags of a variable **X** are jointly not different from zero. If the test is rejected, past information of **X** is a predictor of [and "cause"] global shocks. These tests were conducted using bivariate VARs. Panel (i) of Figure 10 displays the p-values of the null hypothesis. The y-axis in each subpanel represents the number of lags of the VAR (up to 4), while the x-axis shows the p-value. Gray bars indicate whether the null hypothesis of Granger causality from global shocks to each aggregate shock is rejected, while white bars do the same from aggregate shocks to global shocks. Dashed red lines indicate the 10 percent threshold for hypothesis testing. If a bar exceeds this threshold, the hypothesis of no Granger causality cannot be rejected. Results show that only US monetary policy has prediction power on global shocks. Although this test is not informative about actual causality, it gives us a sense of the unpredictability of global shocks.

In addition to the Granger tests, I conduct an FEV decomposition of global shocks to account for contemporaneous correlations. The model for this analysis is a VAR with two lags, including the four aggregate shocks and the global shocks. The identification assumes a recursive identification with the following order (more exogenous to more endogenous):

$$\text{TFP} \longrightarrow \text{Financial cycle} \longrightarrow \text{US monetary policy} \longrightarrow \text{China's CAT} \longrightarrow \text{Global shocks}$$

Although this identification stresses the prediction power of global shocks on themselves, global shocks are still responsible for 40 percent of their own volatility in the long run, as shown by the panel (ii) of Figure 10. The other variables, except for the global financial cycle, explain less than 10 percent of global shocks' forecastability. The global financial cycle contributes to 46 percent of the variability of global shocks.

Figure 10: Global shocks vs foreign structural shocks



Note: Granger causality tests were conducted from bivariate models. Under the null hypothesis, all the coefficients associated with the lags of the other variable are equal to zero. Gray bars are the significance levels of the null hypothesis under which global shock lags are not helpful in predicting the movements of the other aggregate shocks. White bars are the significance level for the null hypothesis of aggregate shocks being not helpful in predicting global shocks. Dashed red lines are set at 10 percent.

Lastly, I complement this analysis by exploring the relationship between the identified global shock and aggregate disruptions in the aggregate supply of commodities. I consider annual data on the global production of barley, rice, wheat, coffee, sugar, copper, lead, tin, zinc, cotton, and crude since 1900. For each commodity j, I estimate the following VAR.

$$\begin{bmatrix} \Delta y_t^f \\ \Delta q_t^{(j)} \\ \Delta p_t^{(j)} \end{bmatrix} = A^{(j)} \begin{bmatrix} \Delta y_{t-1}^f \\ \Delta q_{t-1}^{(j)} \\ \Delta p_{t-1}^{(j)} \end{bmatrix} = +U_{jt} \tag{16}$$

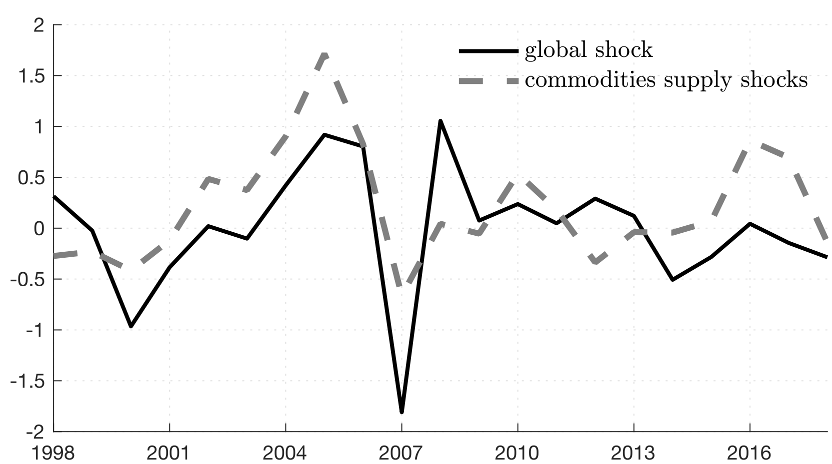
where y_t^f is the real global GDP, $q_t^{(j)}$ denotes the world production of the commodity j at the year t being $p_t^{(j)}$ its international price. The operator Δ represents the first log-difference.

Following Stuermer (2018), I use long-run restrictions to identify supply shocks in each market. The set of restrictions imply that commodity production can be affected in the long run by supply shocks but not by changes in demand:

$$\begin{bmatrix} \Delta y_{t+\infty}^f \\ \Delta q_{t+\infty}^{(j)} \\ \Delta p_{t+\infty}^{(j)} \end{bmatrix} = \begin{bmatrix} * & 0 & 0 \\ * & * & 0 \\ * & * & * \end{bmatrix} * \begin{bmatrix} e_1 \\ e^{j,supply} \\ e^{j,demand} \end{bmatrix} \tag{17}$$

The aggregate commodity supply shock is derived as the first principal component of the set of individual supply shocks $\{e^{j,supply}\}_j$. Global shocks were annualized using a simple mean to compare them with the commodity supply shocks. Since the small sample size makes it unfeasible to employ a VAR analysis, only a correlation analysis was performed by an OLS estimation. The estimated correlation was -0.7, which was significant at 1 percent. The percentage of global shock variability explained by the supply shocks was 32 percent.

Figure 11: Global shocks and aggregate commodity supply shock



The high correlation between global shocks, financial cycles, and supply shocks reflects the tight connections between economic activity, financial markets, and commodities. Further analysis is required to gain deeper insights regarding these strong correlations.

5 Conclusions

In this paper, I combine a novel identification with data on ten small open economies to show that business cycles in small open economies are driven mainly by common fluctuations in the global market, which I called *global shocks*. On the other hand, movements in terms of trade are largely explained by country-specific shocks, but these are only responsible for less than 10 percent of the SOEs' business cycle fluctuations. A country-level analysis reveals that responses to both identified shocks do not only differ in size but also in sign and pattern. I find an asymmetric response across advanced and emerging markets, with higher differences in output, investment, and consumption. The results indicate that policymakers must identify the source of fluctuations in terms of trade prior to implementing any policy response.

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Appendices

A Figures and tables

Figure 12: Response of Domestic Variables to a Global Shock, Emerging Markets

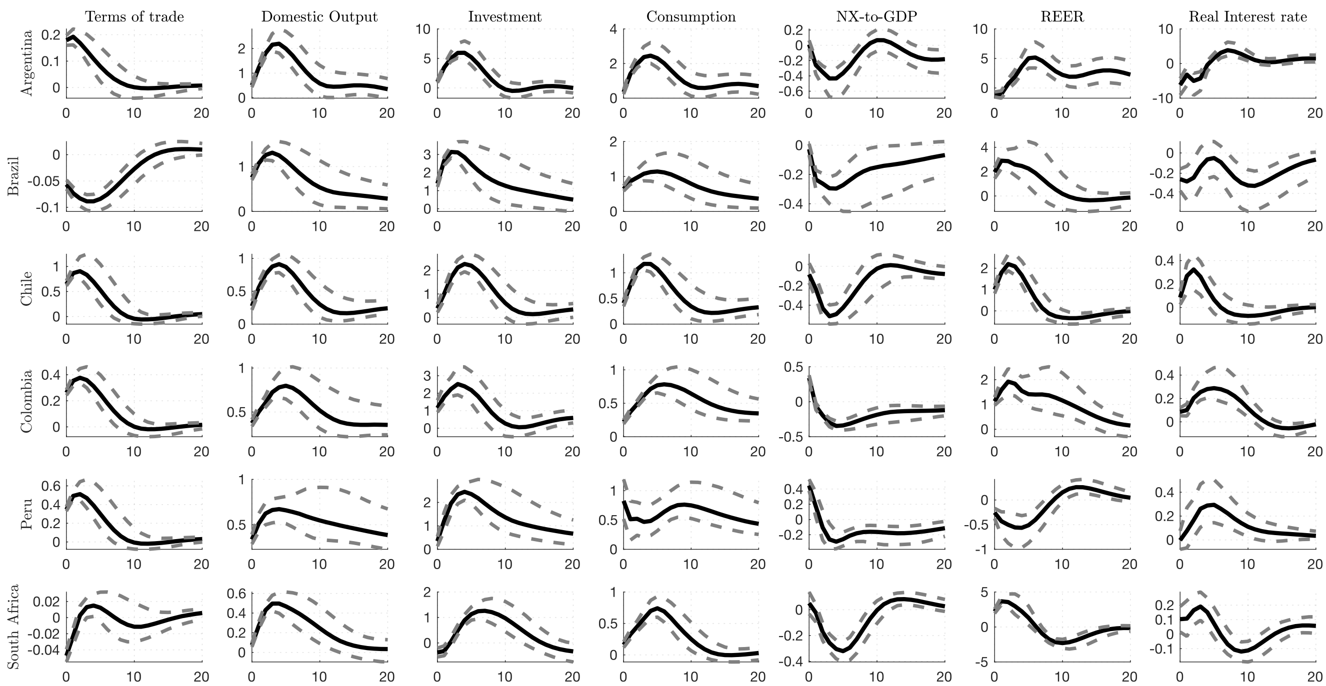

Figure 13: Response of Domestic Variables to a Global Shock, Developed Economies

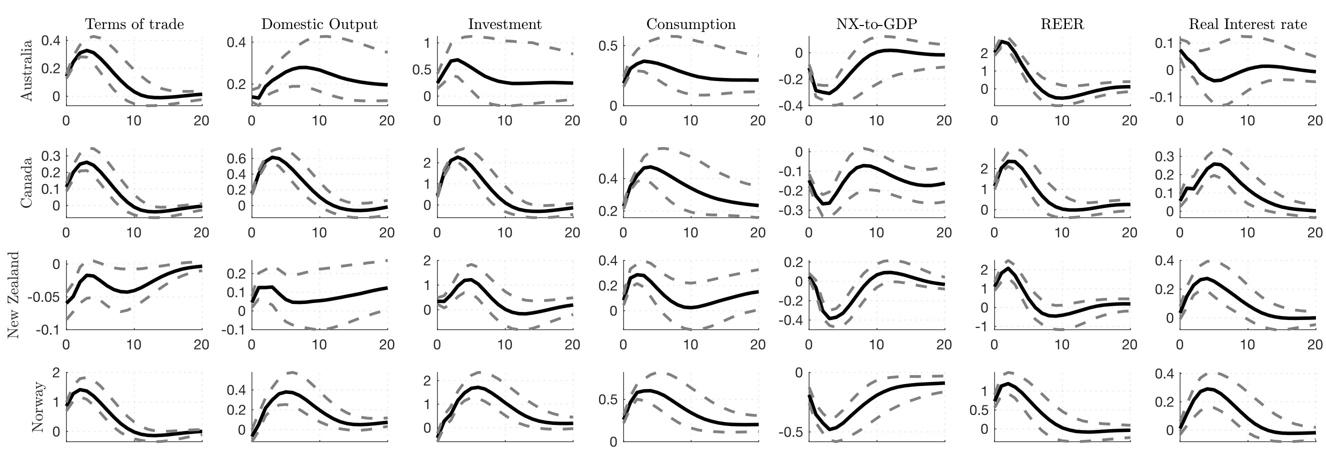

Figure 14: Global Shock Contribution to FEV for domestic variables, Emerging Markets

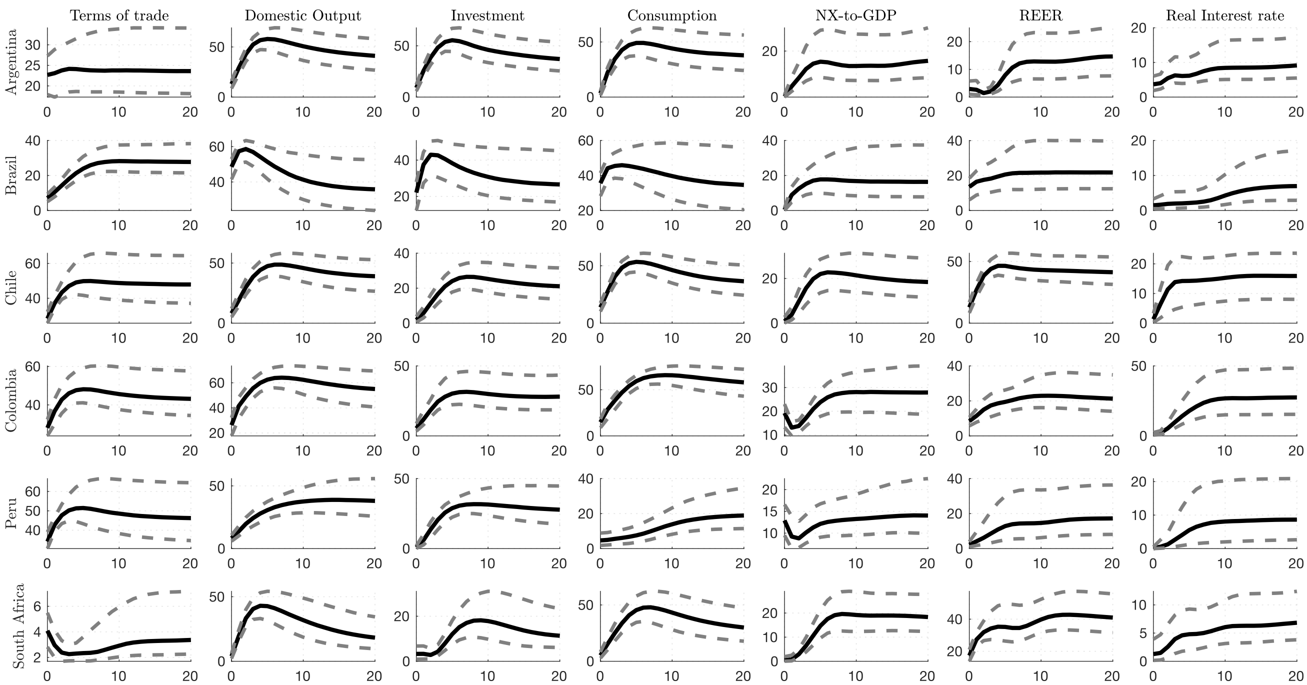

Figure 15: Global Shock Contribution to FEV for domestic variables, Developed Economies

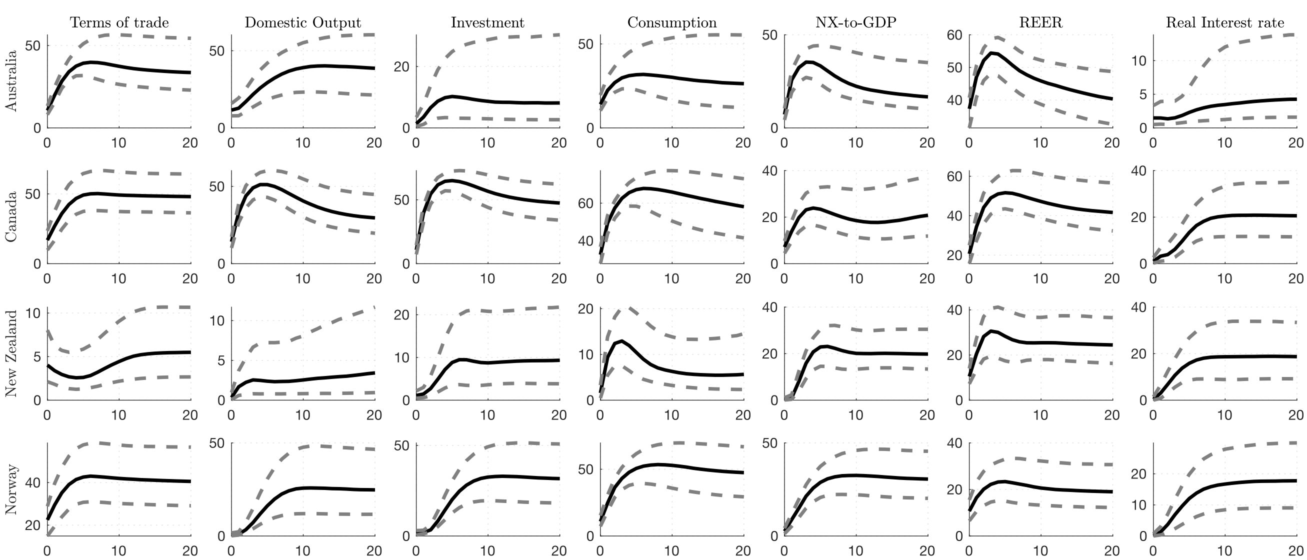

Figure 16: Response of Domestic Variables to a Global Shock, Emerging Markets

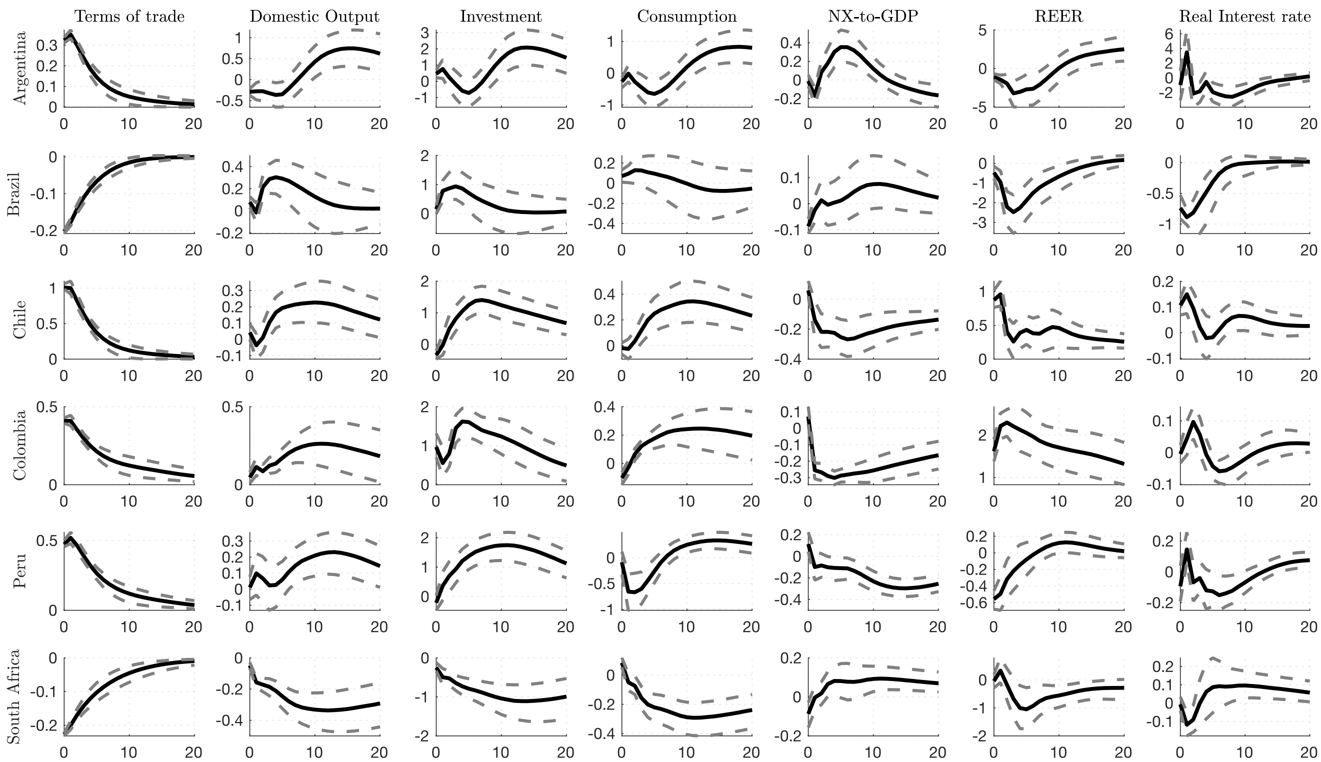

Figure 17: Response of Domestic Variables to a Global Shock, Developed Economies

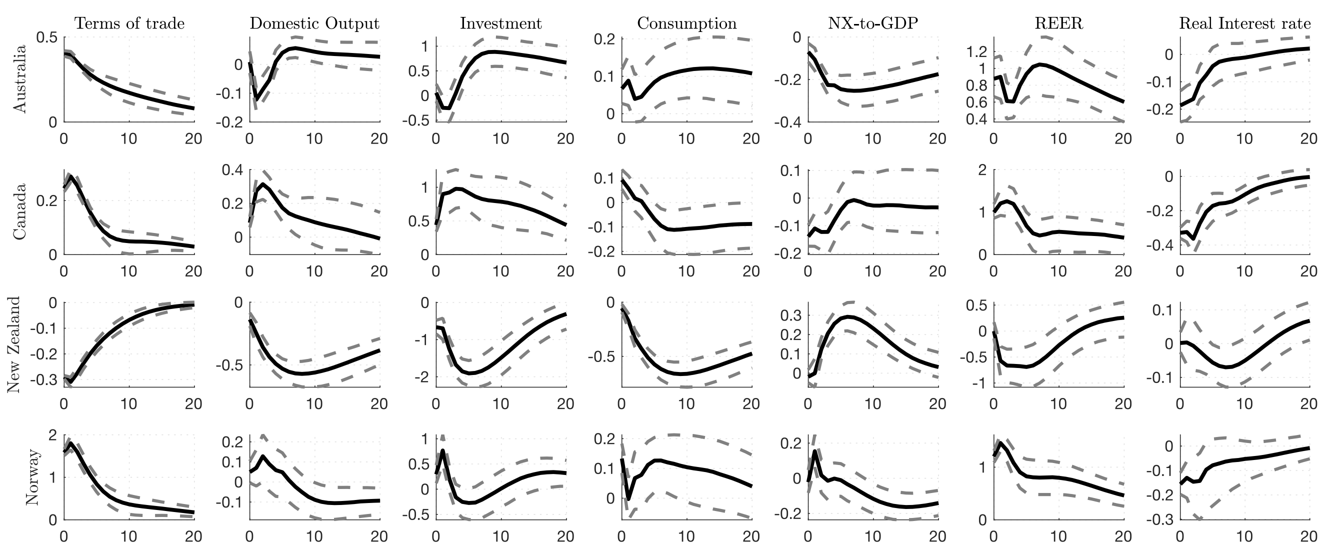

Figure 18: Response to Terms-of-trade shocks, by country group