INTERNATIONAL MONETARY FUND

Spillovers from Large Emerging Economies: How Dominant Is China?

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WP/25/27

2025
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WORKING PAPER

 WP/25/27

IMF Working Paper
European Department

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Authorized for distribution by James Walsh
January 2025

ABSTRACT: This paper investigates the global economic spillovers emanating from G20 emerging markets (G20-EMs), with a particular emphasis on the comparative influence of China. Employing a Bayesian Global Vector Autoregression (GVAR) model, we assess the impacts of both demand-side and supply-side shocks across 63 countries, capturing the nuanced dynamics of global economic interactions. Our findings reveal that China's contribution to global economic spillovers significantly overshadows that of other G20-EMs. Specifically, China's domestic shocks have significantly larger and more pervasive spillover effects on global GDP, inflation and commodity prices compared to shocks from other G20-EMs. In contrast, spillovers from other G20-EMs are more regionally contained with modest global impacts. The study underscores China's outsized role in shaping global economic dynamics and the limited capacity of other G20-EMs to mitigate any potential negative implications from China's economic slowdown in the near term.

RECOMMENDED CITATION: Abdel-Latif, H., & Popescu, A. (2025). Spillovers from Large Emerging Economies: How Dominant Is China? (IMF Working Paper No. 25/27). International Monetary Fund.

JEL Classification Numbers:	F14, F43, O55, C32 , E32, O19
Keywords:	Emerging Economies; Growth Spillover; Global transmission; GVAR model
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WORKING PAPERS

Spillovers from Large Emerging Economies: How Dominant Is China?

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[1] The authors would like to thank Cristian Alonso, Nico Fernandez-Arias, Ashique Habib, Raju Huidrom, and Alberto Musso for their helpful comments on earlier drafts of this paper.

Spillovers from Large Emerging Economies: How Dominant Is China?[☆]

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Abstract

This paper investigates the global economic spillovers emanating from $G20$ emerging markets ($G20 - EMs$), with a particular emphasis on the comparative influence of China. Employing a Bayesian Global Vector Autoregression (GVAR) model, we assess the impacts of both demand-side and supply-side shocks across 63 countries, capturing the nuanced dynamics of global economic interactions. Our findings reveal that China's contribution to global economic spillovers significantly overshadows that of other $G20 - EMs$. Specifically, China's domestic shocks have significantly larger and more pervasive spillover effects on global GDP, inflation and commodity prices compared to shocks from other $G20 - EMs$. In contrast, spillovers from other $G20 - EMs$ are more regionally contained with modest global impacts. The study underscores China's outsized role in shaping global economic dynamics and the limited capacity of other $G20 - EMs$ to mitigate any potential negative implications from China's economic slowdown in the near term.

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1. Introduction

Over the last two decades, the global economic landscape has been significantly reshaped by the meteoric rise of the $G20$ large emerging economies ($G20 - EMs$), namely Argentina, Brazil, China, India, Indonesia, Mexico, Russia, Saudi Arabia, South Africa, Turkey. This shift has been characterized by a notable increase in these countries' contributions to global economic output and an expansion of their interactions with the global economy, primarily through international trade and cross-border financial linkages. For instance, the $G20 - EMs$ have experienced an average annual growth rate of nearly 6 percent, thereby significantly enhancing their contributions to approximately one-third of global economic activity and one-quarter of global trade (Abdel-Latif et al., 2024). This ascendancy has introduced complex economic spillovers, necessitating a deeper understanding for global policymakers.

☆ The views expressed here are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

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Historically, the focus of academic and policy-oriented research has been predominantly on China, given its significant stature and unprecedented integration into the global economy. Studies including Cesa-Bianchi et al. (2012), Dizioli et al. (2016), and Cashin et al. (2016) have extensively documented China's profound impact on global trade patterns, commodity markets, and its central role in global value chains. However, this emphasis on China, while justified, has inadvertently resulted in less attention being paid to other significant $G20-EMs$ and their contribution to global economic dynamics. This oversight becomes particularly relevant considering China's anticipated growth moderation, especially when contrasted with the dynamic growth potential of countries such as India, for which the IMF projects medium-term growth rates of 6.5 percent. This scenario posits that other $G20-EMs$ could increasingly serve as catalysts for future global growth, benefiting from demographic advantages and structural reforms aimed at enhancing their business environments, attracting investments, and improving productivity.

Given this backdrop, a cross-country comparative analysis seems crucial for unpacking possible growth spillovers emanating from all $G20-EMs$ economies. Such an analysis could provide a more comprehensive appraisal of the $G20-EMs$ global economic footprint, considering the diversity in their economic structures, policy frameworks, and developmental stages. While some studies, like Huidrom et al. (2020) and Ahmed et al. (2022), have ventured into this domain, there remains a significant gap in research, especially concerning the diverse channels through which these spillovers occur—including trade, commodities, and financial flows—and their broader implications.

This paper investigates the global diffusion of domestic growth shocks originating from the $G20-EMs$ utilizing a Bayesian Global Vector Autoregression (GVAR) model. This model, which follows the foundational approach by Pesaran et al. (2004), is enhanced with Bayesian estimation techniques to achieve more precise estimations over shorter horizons, including handling stochastic volatility, as demonstrated by Feldkircher and Huber (2016). By encompassing 63 countries, of which 30 are emerging economies, our research extends the geographical and temporal scope for analyzing the impact of emerging markets on the global stage, especially focusing on the period since the early 2000s.

Utilizing this comprehensive methodology, our study assesses the impact of developments in the $G20-EMs$ across all pertinent channels: direct trade linkages, regional effects, commodity price fluctuation, and financial integration. Our findings underscore the relatively larger spillovers from China, corroborating and expanding upon previous research by offering a more detailed examination of all spillover avenues to a broader set of emerging economies. Moreover, our study enriches the literature by estimating both demand-side and supply-side shocks within the $G20-EMs$, thereby allowing for a more nuanced understanding of the structural transmission mechanisms of external shocks originating from these economies.

2. Spillover Literature

A rich body of empirical literature has explored trade and financial spillovers from China to the rest of the world, revealing their significant global impact. However, estimates of China's influence on global growth vary widely, influenced by differences in methodology, sample size, and data quality. Generally, most studies indicate that a 1 percent decline in Chinese GDP growth could reduce world output by 0.2 to 0.5 percent (IMF, 2019; Cashin et al., 2016; Dizioli et al., 2016; Furceri et al., 2016). The magnitude of China's spillovers varies by region and the intensity of linkages, with estimates for specific countries reaching as high as 1.6 percent (Sznajderska and Kapuściński, 2020). Larger spillover effects are documented in Asian countries compared to economies with weaker trade links (Duval et al., 2014). Other studies highlight significant spillover effects from China to commodity exporters in emerging Asia (Dieppe et al., 2018; Gauvin and Rebillard, 2018) and Latin America (Ahmed et al., 2022; IMF, 2019), particularly to oil exporters (Dieppe et al., 2018).

Most studies indicate that China's spillovers to advanced economies (*AEs*), particularly the US, are generally small, although the reverse spillovers are substantial (Huang et al., 2018). This is because *AEs* often have limited direct trade or financial exposure to China. Nevertheless, Chinese growth can influence the global financial cycle through shifts in global risk sentiment (Barcelona et al., 2022), potentially resulting in larger negative spillovers to the US economy, especially under conditions of constrained US monetary policy (Ahmed et al., 2022).

Significantly less research has focused on examining spillovers from other major $G20 - EMs$, with findings generally pointing to more modest effects compared to those from China. Dabla-Norris et al. (2015) report expanding linkages between major *EMs* and low-income countries (*LICs*), primarily transmitted through terms-of-trade and demand shocks. More recently, Huidrom et al. (2020) identified substantial spillovers from major *EMs* to other emerging market and developing economies (*EMDEs*), with China identified as the principal contributor. Arezki and Liu (2020), examining cross-country aggregates, note that spillovers from *EMs* have increased over time as these economies became more integrated into the global economy, yet they remain significantly smaller than those from advanced economies (*AEs*).

3. Data and Empirical Model

3.1. The GVAR Model

Our GVAR model allows to study dynamic relationships between the countries in our panel, while carefully incorporating multivariate transmission and feedback channels at both country and global levels. The GVAR model can be represented as follows:

$$\mathbf{x}_{it} = a_{i,0} + a_{i,1}t + \sum_{l=1}^{p_i} \mathbf{\Phi}_{il}\mathbf{x}_{i,t-l} + \sum_{l=1}^{q_i} \mathbf{A}_{il}\mathbf{x}^*_{i,t-l} + \epsilon_{it}, \tag{1}$$

where $i = 0, 1, 2, ..., N$ denotes the country and $t = 1, 2, ..., T$ represents the year. $a_{i,0}$ denotes the coefficient on the constant and $a_{i,1}$ is the coefficient on the deterministic time trend. $\mathbf{\Phi}_{il}$ and $\mathbf{A}_{il}$ are matrices of parameters to estimate, and ϵ_{it} denotes uncorrelated idiosyncratic shocks. The GVAR model includes two sets of lagged variables: domestic variables denoted by $\mathbf{x}$ and foreign variables denoted by $\mathbf{x}^*$. Lag orders of the two sets of variables for country i are denoted as p_i and q_i, respectively. The foreign variables are considered weakly exogenous and include country-specific foreign variables. The latter are computed as cross-sectional averages of domestic variables from other countries, using a fixed weights matrix $\{w_{ij}\}_{i,j=0}^{N}$ based on bilateral trade weights[1], namely:

$$\mathbf{x}^*_{it} = \sum_{j=0, j\neq i}^{N-1} w_{ij}\mathbf{x}_{jt}$$

The model includes as endogenous variables: real GDP, CPI inflation, the real exchange rate, the short-term rate and the long-term rate, while foreign variables are incorporated through predetermined bilateral trade weights to capture global influences. We use quarterly data from 2001Q1 to 2023Q2 for a sample of 63 countries, including 34 advanced economies and 29 emerging economies, which taken together account for over 90 percent of global output (see Table A.1 for a full list). All data were obtained from IMF databases, including Direction of Trade Statistics (DOTS) for the aforementioned trade weights and national authorities. Appendix A provides more details about the dataset.

Our model incorporates a dedicated commodity block that captures the dynamics within the oil market, including oil prices, production levels, oil inventories, and a measure of global demand. This approach stands in contrast to other methodologies found in the literature, which typically integrate oil prices as an endogenous variable within a single country model, usually the US. Our modeling framework allows us to underscore the significance of the commodity price channel in a unique manner. It enables the oil markets to exert influence across all country models, driven by empirical data, as demonstrated by Gauvin and Rebillard (2018). The GVAR model is then estimated individually for each country, with parameter estimates being stacked into a global model using a weight matrix. This consolidated model facilitates the simulation of shock propagation within the system, as elaborated by Chudik and Pesaran (2016).

[1] These are computed as the share of total trade (exports and imports) of country i with country j as a share of the total trade of country i, normalized to sum up to unity.

3.2. Bayesian GVAR: Priors and Model Selection

We utilize a Bayesian algorithm adept at handling stochastic volatility, effectively mitigating overfitting risks despite the comprehensive dataset used in our analysis. Notably, such Bayesian GVAR achieves enhanced forecasting precision across a wide array of variables and forecast intervals, markedly surpassing traditional cointegrated VAR models, as illustrated by Cuaresma et al. (2016). We tested various standard priors, which exhibited broadly similar performance, albeit with minor differences. Each prior inherently assumes that non-stationary variables tend toward a random walk process, differing primarily in their approach to introducing shrinkage.

The priors employed in this study include Minnesota (MN), Normal-Gamma (NG), and stochastic search variable selection (SSVS) priors. The MN prior nudges variables within country-specific VARs towards their unconditional stationary mean or towards a state with at least one unit root. It employs minimal hyperparameters and applies uniform shrinkage across all country VARs. We also explored the NG prior, which introduces both global and local shrinkage, effectively tightening each coefficient towards zero unless significant evidence suggests otherwise, while also favoring more substantial shrinkage for coefficients of higher lags.

The SSVS prior offers a more flexible solution that accounts for model uncertainty, while allowing for more country-specifity. This approach uses a stacked matrix of coefficients for country i, denoted as $\Xi_i = (a_{i,0}, a_{i,1}, \text{vec}(\phi_{i,1})', \text{vec}(A_{i,0})', \text{vec}(A_{i,1})')'$, assuming a mixture two normal prior on each coefficient, characteristic of 'spike and slab' priors. This setup pushes small coefficients towards zero while allowing significant coefficients more freedom, effectively managing the inclusion of variables in the model.

$$\Xi_{i,j} \,|\, \delta_{i,j} \sim \delta_{i,j}\mathcal{N}(0, \tau_{i,0}^2) + (1 - \delta_{i,j})\mathcal{N}(0, \tau_{i,1}^2), \delta_{ij} \sim \text{Bernoulli}(p)$$

where $\delta_{i,j}$ is a binary random variable which equals 1 if variable j is included in country model i and zero otherwise. We determine the prior variances semi-automatically, scaling the mixture normals with the OLS standard errors from the full model. The chosen parameters $\tau_{i,0} = 0.01$, $\tau_{i,1} = 3$, and a prior inclusion probability of 0.5, suggest an equal likelihood of covariate inclusion.

Overall, models produce closely comparable results, yet diagnostics favor the SSVS prior as the optimal choice. Diagnostics reveal modest serial correlation in most equations' residuals and minimal cross-unit correlation of (posterior median) residuals (see Appendix A). This is crucial since a fundamental assumption of the GVAR modeling approach is that idiosyncratic shocks in individual country models should exhibit weak cross-sectional correlation, thereby ensuring the weak exogeneity of foreign variables. Our selection aligns with previous research indicating the superior out-of-sample predictive performance of the SSVS prior in such contexts (Cuaresma et al., 2016), as it accommodates country-specific nuances by avoiding uniform shrinkage across all countries.

This model accommodates stochastic volatility, allowing residual variances to vary over time. This feature is particularly pertinent given that emerging economies constitute half of our sample and the period under study witnessed significant shocks. Accounting for temporal variation significantly enhances model fit (Dovern et al., 2016; Huber, 2016; Sims and Zha, 2006; Primiceri, 2005). For structural analysis, however, we utilize the variance-covariance matrix with median volatility (over the sample period) on its diagonal. Posterior results are based on $30,000$ draws following a $10,000$ iteration burn-in phase, using a thinning factor of 10 for efficiency, keeping the size of global posterior output manageable. Following Fry and Pagan (2011), we focus on the model yielding median impulse response values as our primary interpretative reference.

3.3. Structural Identification

The GVAR literature employs various strategies for identifying impulse responses, including generalized impulse response functions (GIRFs), orthogonalized impulse response functions via Cholesky decomposition, and structural impulse response functions defined by specific restrictions. Our study primarily uses GIRFs for consistency with existing literature, moving to structural identification thereafter. While GIRFs lack direct economic interpretation, they are useful for illustrating potential outcomes of a shock, a common practice in GVAR studies. Moreover, the GIRFs are invariant to the variables ordering, as they evaluate shocks to individual errors and neutralize the influence of concurrent shocks through the observed distribution of all shocks, eschewing any orthogonalization. Hence, GIRFs are notably theory-agnostic, not predicated on specific economic assumptions. The interpretation of shocks within the GIRF framework can be viewed as encompassing generic domestic growth shocks, encapsulating both demand and supply-side factors.

We further apply sign restrictions to discern structural shocks, distinguishing between demand and supply shocks. These shocks are identified locally within each country's model, following precedents set by the literature (Feldkircher and Huber, 2016; Eickmeier et al., 2015; Dees et al., 2007). Our approach, grounded in standard aggregate demand-and-supply frameworks and aligned with dynamic stochastic general equilibrium models, is notably rare in emerging market research, except for Copestake et al. (2023)'s study on China. We identify aggregate supply shocks as those reducing output and increasing inflation, whereas aggregate demand shocks result in positive comovement between output and prices (see Table 1). These restrictions are enforced over four quarters to enhance shock differentiation and exclude transient comovements. This approach follows Mountford and Uhlig (2009), who also applied four-quarter restrictions for better shock identification, excluding noise-like fluctuations. Other studies have varied the duration of sign restrictions, such as Feldkircher and Huber (2016), who identified U.S. aggregate supply shocks with restrictions binding for the first 10 quarters.

Table 1: Sign restrictions

Shock	y	Δp
Aggregate demand	↑	↑
Aggregate supply	↑	↓

Notes: The restrictions are imposed as ≥ / ≤. Constraints on output (y) and price dynamics (Δp) are binding for 4 quarters.

4. Empirical Results

This section presents results from the GIRFs and structural shocks (i.e., demand vs. supply) analysis, categorizing recipient countries by income level (advanced economies *AEs* vs. emerging economies *EMs*) and examining regional reactions to various shocks. Aggregated responses are based on individual countries GDP-PPP weights for the respective group (income or region). The section also explores empirical evidence on the impact of these shocks on commodity prices and investigates the evolving significance of growth spillovers from the $G20 - EMs$ and their global interconnectedness over time. The findings reported here focus on significant responses at the one-year horizon, determined by 90 percent credible intervals, with the shocks modeled as a 1 percent change in output.

4.1. Generalized Impulse Response Analysis

The analysis of the GIRFs (computed as in Pesaran and Shin (1998)), reveals that growth spillovers from China to the global economy are significantly larger than those originating from other $G20 - EMs$. As illustrated in Figure 1, the aggregate spillover effects from $G20 - EMs$ to both advanced economies (*AEs*) and emerging markets (*EMs*) are primarily attributed to China, markedly exceeding contributions from other $G20 - EMs$. Specifically, China's spillovers to *AEs* and *EMs* are 0.65 percent and 0.88 percent, respectively, while spillovers from other $G20 - EMs$ remain below 0.1 percent. On average, $G20 - EMs$ have a greater impact on other emerging economies than on advanced economies. Mexico stands out by exerting relatively larger spillovers to *AEs* (0.11 percent), reflecting its close economic ties with the United States. India and Brazil contribute spillovers nearing 0.1 percent to other emerging economies, whereas Russia, Indonesia, and Saudi Arabia generate spillovers around 0.05 percent. In contrast, Turkey, South Africa, and Argentina demonstrate minimal spillovers, falling below 0.025 percent.

Figure 2 shows aggregated spillover effects for four regions, as defined in Table A.1. China's spillovers to all regions significantly exceed those from other $G20 - EMs$. Notably, China's influence is most pronounced in the *MCD* region, with spillovers reaching 1.6 percent, largely due to its substantial impact on oil-producing countries within the region, such as Saudi Arabia. However, this figure, based on a limited sample of only four countries, may not fully represent the broader picture. Excluding *MCD*, China's largest spillovers are observed in Asian countries at 0.9 percent, while its influence on Europe and the Western Hemisphere is approximately 0.7 percent each. Shocks from other $G20 - EMs$ show significant regional spillovers: India and Indonesia to the *APD* region (0.08 percent and 0.12 percent, respectively), Mexico, Brazil, and Argentina to the *WHD* region (0.18 percent, 0.07 percent, and 0.02 percent, respectively), and Russia and Turkey to the *EUR* region (0.08 percent and 0.05 percent, respectively).

Exploring spillovers on a country-by-country basis reveals distinct patterns. For instance, the spillover effects from China to Hong Kong and Singapore are particularly noteworthy, both exceeding a magnitude of one. This is attributed not only to direct spillovers from China but also to the indirect boost these regional trade and financial centers receive due to enhanced activity in other nearby countries benefiting from China's growth. Among advanced economies (*AEs*), Japan receives exceptionally large spillovers from China, while the United States, with spillovers at 0.65, aligns with the average for the *AE* group. In *EMS*, China's influence is especially pronounced among commodity-producing nations, including those involved in oil and other commodities such as Argentina, Saudi Arabia, Russia, Kazakhstan, Brazil, and Chile. Additionally, Asian countries closely integrated with China through Global Value Chains (*GVCs*), like Thailand and the Philippines, experience significant spillovers. On average, the spillovers from China to *EMs* in our sample are around 0.8, surpassing those to advanced economies and are substantial in economic terms.

Within Asia, Singapore, Hong Kong, and Japan emerge as notable recipients of spillovers from Indonesia and India, albeit at levels significantly lower than those from China. For instance, Indonesia's spillovers to Singapore register at approximately 0.36, while India's reach about 0.17. In particular, India's spillovers to *EMs* prominently affect commodity producers, including a notable impact on oil demand with spillovers to Saudi Arabia at 0.36, as well as to other commodity-exporting countries like Argentina and South Africa, each around 0.18. Conversely, Indonesia's most significant spillovers to *EMs* are directed towards its regional partners closely integrated within Global Value Chains (*GVCs*)—namely Thailand, the Philippines, and Malaysia—with figures ranging from 0.17 to 0.14. Following this, Indonesia's influence extends to commodity exporters such as Argentina, South Africa, and Saudi Arabia.

In the Western Hemisphere, Mexico exhibits moderate spillovers to advanced economies, while Brazil's spillovers are smaller, and Argentina's are quite negligible. Among advanced economies, notable recipients include the US and Canada for Mexico, with spillovers around 0.19, and Portugal for Brazil at 0.06, showing the largest coefficients. Spillover patterns among *EMs* for these three countries are predominantly regional, including mutual interactions. Notably, Brazil's spillovers to Argentina are significantly larger (1.1) compared to the reverse (0.05). Argentina's most substantial spillovers to other *EMs* are directed towards Chile and Brazil, at approximately 0.07 and 0.05, respectively. Brazil's spillovers to Argentina are notably large (1.1), suggesting a considerable indirect influence on the region, with other significant spillovers directed towards Chile (0.25). Mexico has a notable impact on Argentina (0.18), Colombia (0.12), and Chile (0.09). Among these three Latin American nations, Brazil's spillover effects are more globally diversified, including to countries in Europe and Asia, likely reflecting its pivotal role in various commodity markets such as oil, metals, and food.

In the European region, Russia is distinguished by its significant spillovers to all European countries, particularly affecting its close neighbors among *EMs*. For advanced economies, the most substantial Russian spillovers are observed in Lithuania (0.25), Finland, and Greece (0.15 each). Among *EMs*, Kazakhstan (0.51), Belarus (0.47), and Moldova (0.46) are the most significantly impacted. Although Turkey's spillovers are somewhat smaller, they notably influence its trade and financial partners in Europe, especially Greece and several Eastern European countries, with spillovers ranging from 0.1 to 0.23. Saudi Arabia's spillovers are generally modest (with maximum bilateral spillovers around 0.11 percent) and do not exhibit a strong regional trend. The most affected countries include Singapore, India, South Africa, Greece, and Japan, potentially reflecting their reliance on oil imports from Saudi Arabia.

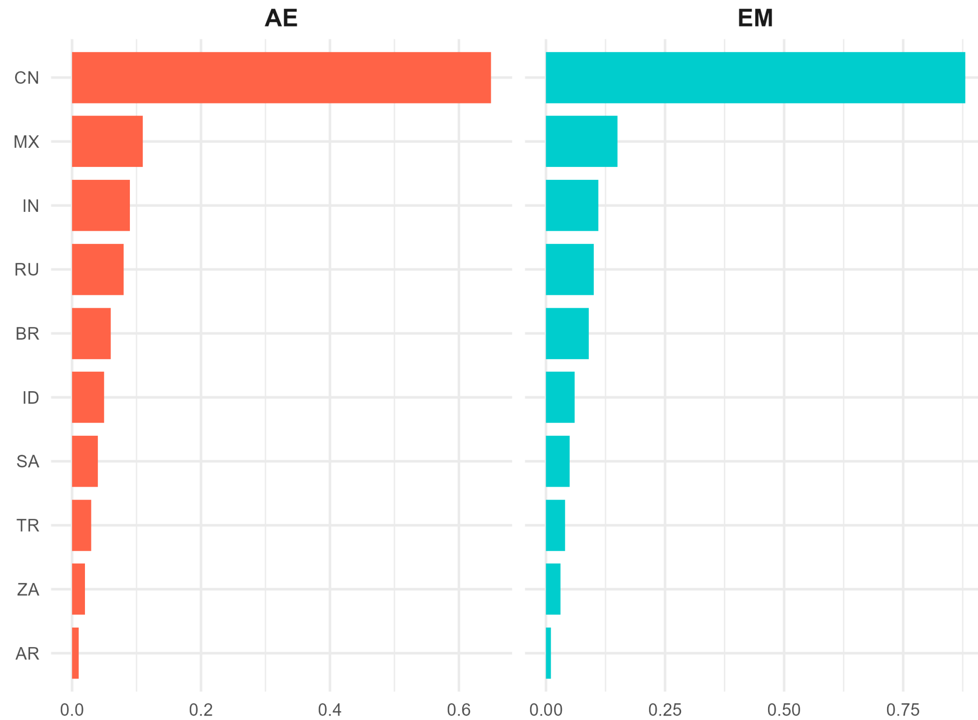
Within the countries analyzed, South Africa demonstrates minimal spillovers to European advanced economies and Singapore, as well as to commodity-producing emerging markets. Notably, the most significant spillovers are observed towards the UK (0.03), Singapore, and Germany (0.025 each). Among emerging economies, the largest impacts are on Saudi Arabia (0.07) and Argentina (0.05).

4.2. Structural Shocks: Demand versus Supply

Our structural shock analysis confirms China's spillover effects significantly overshadow those from other $G20 - EMs$. Figure 3 illustrates the spillover effects on output and inflation from demand and supply shocks, aggregated for advanced and emerging economies, and assessed at 1 and 3 year horizons for output and at a 1 year horizon for inflation. We detail China's results separately and provide simple averages for other $G20 - EMs$, which uniformly exhibit smaller spillovers. These results are aggregated using GDP PPP weights to reflect the economic weight of the countries. As before, the shocks are normalized to trigger a 1 percent increase in source country output over 1 year.

Firstly, examining GDP responses, it's clear that spillovers from China, both in the short and medium term, greatly exceed those from other $G20 - EMs$. At the 1-year mark, China's demand-side shocks lead to 0.39 spillovers to emerging economies and 0.27 for supply-side shocks, in stark contrast to the 0.01 and 0.04,

Figure 1: Impact of GDP Growth Shocks on *AEs* and *EMs*: Results from Generalized Impulse Responses



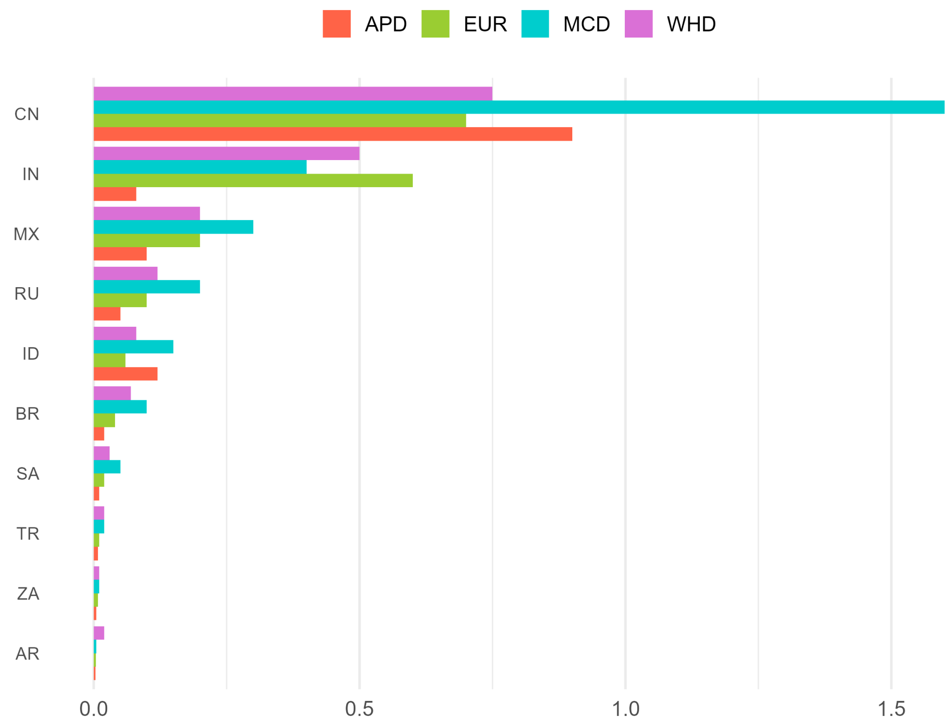
Notes: One-year, cumulative, GDP PPP weights

respectively, from other $G20 - EMs$. For advanced economies, China's demand and supply-side shocks result in 0.24 and 0.16 percent spillovers, respectively, compared to the much lower 0.02 and 0.015 from other $G20 - EMs$. It's noteworthy that our results indicate the magnitude of China's spillovers is quantitatively similar to those of the US. Specifically, US spillovers to advanced economies are 0.23 for demand shocks and 0.18 for supply shocks, while to emerging economies, they are 0.27 and 0.35, respectively.

China's spillovers through aggregate demand channels are notably larger than those from aggregate supply shocks, yet both hold substantial economic significance. This implies that China's aggregate demand shocks likely encompass a mix of policy measures, such as increased public investment and heightened demand from its expanding property sector, which in turn boosts demand for imports of raw materials. Positive supply shocks from China have become increasingly significant to global spillovers since its WTO entry, and negative supply shocks during the pandemic have further accentuated these trends.

In the medium term, China's impact on emerging economies amplifies to 0.8 for demand shocks and 0.39 for supply-side shocks, considerably more than the 0.04 and 0.05, respectively, from other $G20 - EMs$. To advanced economies, the spillovers from China reach 0.46 for demand and 0.4 for supply shocks, as opposed

Figure 2: Impact of GDP Growth Shock, by Region: Results from Generalized Impulse Responses



Notes: One-year, cumulative, GDP PPP weights

to 0.04 and 0.05 from other $G20 - EMs$. Overall, it is China's spillovers that demonstrate significant and sustained effects in the medium term, confirming the robustness of earlier findings (even under alternative specifications).

Further analysis at the country level (see Figure 4) reveals that most spillovers from other $G20 - EMs$ are below 0.05, except from Brazil, Mexico, Turkey, Russia, India, and Indonesia, primarily due to supply-side shocks. Russia is an anomaly with significant demand spillovers to advanced economies, likely due to its pre-war trade ties with Europe. The importance of supply-side spillovers from other $G20 - EMs$ underscores the roles of global value chain integration and commodity price impacts.

Regarding inflation, China's domestic shocks markedly influence global inflation rates, unlike the minor effects from other EMs (Figure 3). China's positive demand shocks elevate inflation by approximately 0.15 percentage points in advanced economies and 0.2 in emerging markets, while its supply shocks reduce inflation by -0.1 and -0.2 percentage points, respectively. In contrast, spillovers from other $G20 - EMs$ to inflation are minimal for both shock types.

Figure 3: Aggregate Spillovers to Output and Inflation: China versus the Other G20 EMs

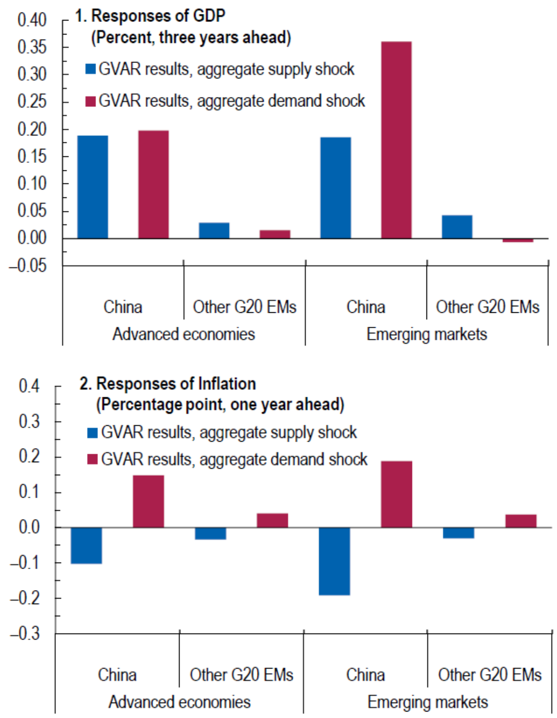
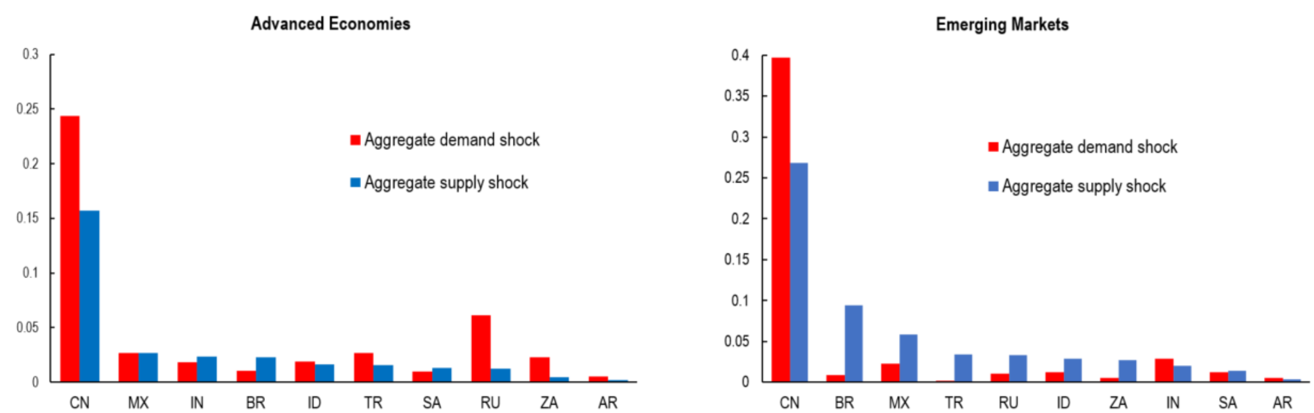


Figure 4: Aggregate Output Spillovers by Income Group after 1 Year



Notes: Reported results are cross-country aggregates using PPP GDP weights of impulse responses which are significant on the basis of 68 percent credible intervals.

4.3. *Regional Spillovers*

We also explore the spillovers from *G*20 – *EMs* to four geographical regions: Europe, Asia, the Western Hemisphere, and the Middle East and Central Asia. Figure 5 illustrates the effects of demand and supply shocks from each of the *G*20 – *EMs* across these regions. The bars indicate median impulse responses at the 1-year horizon for each region, with whiskers showing the lower and upper quartiles, based solely on significant responses (using a 68% threshold).

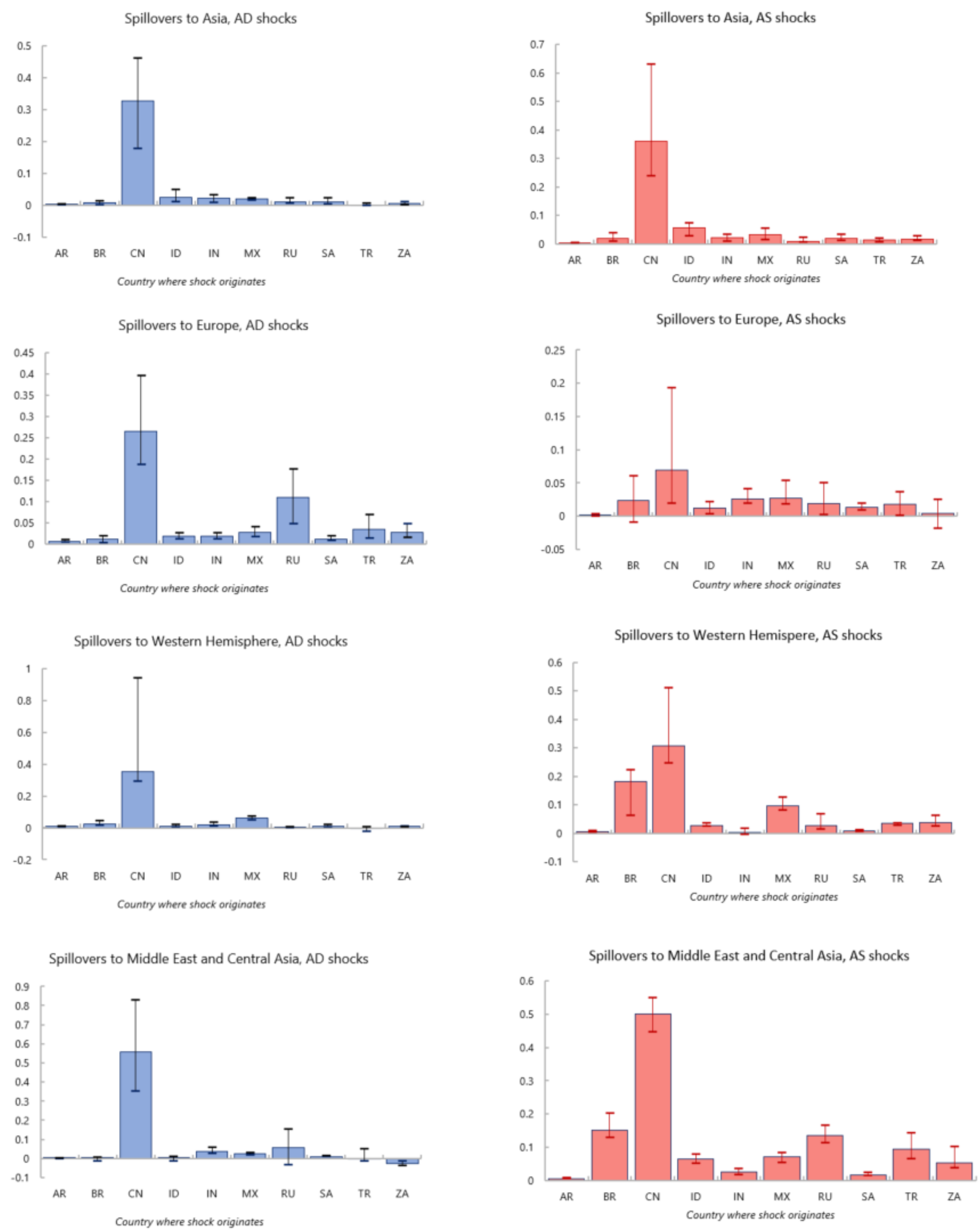
Our analysis reveals that China's spillovers, resulting from both demand and supply shocks, have a global reach, underscoring China's extensive global influence. However, other large emerging markets (*EMs*) tend to have a more pronounced impact within their own geographical areas. In Asia, for instance, China's spillovers are 0.32 from demand-side shocks and 0.36 from supply-side shocks, reflecting China's role in boosting regional exports and its significant participation in global value chains. In contrast, demand and supply side shocks from Indonesia and India have much smaller effects in Asia, with medians up to 0.05 and 0.02 percent, respectively. This may be related to India's relatively closed economy and Indonesia's growing importance as a commodity producer for the green transition.

In the Middle East and Central Asia, China exhibits substantial spillovers from both demand and supply shocks, approximately 0.15 percent each, largely attributable to its pronounced influence on commodity producers within the region. China's significant spillover effect is chiefly driven by its impact on Saudi Arabia through oil markets, approximately 0.55. Other commodity exporters such as Russia and Brazil, alongside regional trade partners like Turkey, also exert considerable impacts on this region, a result of both their geographical proximity and their importance in global commodity markets.

In Europe, China's spillovers are notably significant, especially from the demand side (0.26 percent), but considerably smaller from the supply side (0.07 percent). This highlights the critical role of Chinese demand for European exporters. Russia's spillovers in Europe are also noteworthy, with demand-side impacts at 0.10 percent, whereas supply side shocks have a more modest effect of only 0.02 percent. However, it's important to recognize that the Russia-Ukraine conflict and the subsequent shift in trade patterns between Russia and Europe—occurring towards the end of our sample period—represent a significant structural change, making such estimates largely reflective of past dynamics. Turkey, as expected, also exhibits somewhat larger spillovers to European countries, predominantly through demand-side channels (0.03 percent).

In the Western Hemisphere, China's spillovers are notably substantial, reaching 0.35 and 0.30, primarily due to significant impacts on the US and commodity-exporting countries in Latin America. Following China, the largest regional spillovers stem from Brazil (0.18) and Mexico (0.10), attributed to supply-side shocks. Mexico's spillovers are linked to its integration into global value chains with the United States, which also generates notable demand-side effects. Brazil's spillovers, on the other hand, are tied to its status as a commodity exporter, playing a crucial role in the region's dynamics. As anticipated, Argentina's contributions to regional spillovers are relatively minor.

Figure 5: Regional Spillovers from Aggregate Demand and Aggregate Supply Shocks after 1 Year



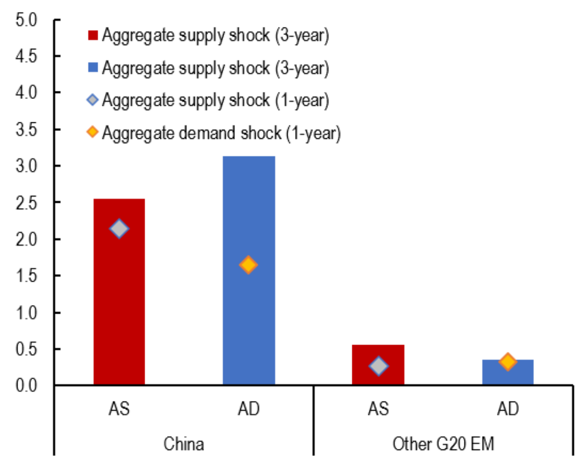
Notes: The bars denote the country median response and the markers represent the interquartile range of responses among countries.

4.4. Spillovers to Commodity Prices

China's expanding influence in the global economy also enhances its ability to impact global commodity prices. Our analysis reveals that aggregate demand shocks from China lead to approximately a 2.2 percent increase in oil prices after one year, while aggregate supply shocks contribute to a 1.6 percent rise (escalating to 3.1 percent and 2.5 percent at the three-year mark, with these effects remaining significant only for China during this period). In contrast, spillovers from shocks in other $G20 - EMs$ are minimal, around 0.25 percent, aligning with their overall lesser spillover effects (refer to Figure 7). Notably, aggregate demand shocks from India demonstrate a more pronounced impact, around 1 percent at the one-year horizon. For context, similar shocks in the United States result in a 2.5 percent increase in oil prices after one year.

Furthermore, we observe that oil production reacts to both demand and supply shocks from China, increasing by approximately 0.5 to 0.6 percent after one year. This response in oil production is significantly more pronounced than reactions to shocks from other $G20 - EMs$. Additionally, both aggregate demand and supply shocks from China increment metal prices by about 0.25-0.3 percent after one year, a phenomenon largely non-existent for other $G20 - EMs$. These findings underscore the particular potency of the commodity price channel in the case of China, indicating that both demand and supply shocks from China notably affect commodity exporters as well as global prices and production.

Figure 6: Response of Oil Prices to Aggregate Demand and Supply Shocks



Notes: Impulse responses to a 1pp per year positive domestic AD and AS shocks in each G20 EM on the price of oil.

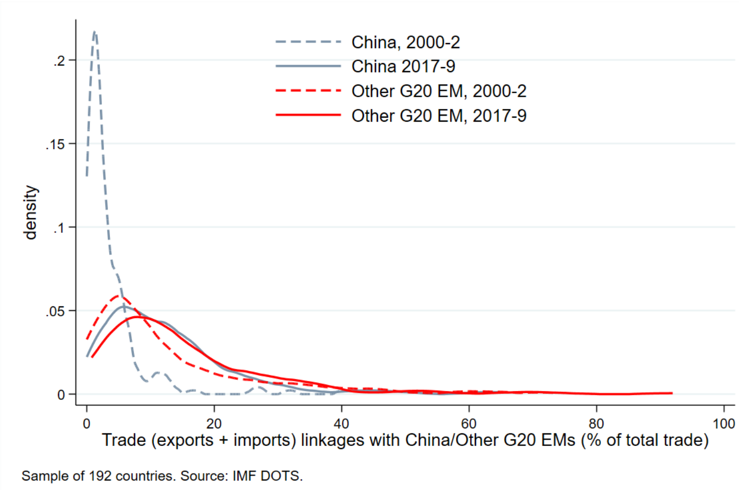
4.5. Changes in the Size of Spillovers over Time

The analysis reported so far utilized trade weights for the period from 2017 to 2019. However, it's crucial to examine the effects of variations in trade weights throughout the sample on the extent of spillovers. The early 2000s marked a significant milestone with China's entry into the World Trade Organization (WTO), profoundly influencing both the nation's economic dynamics and the landscape of global trade. It's plausible to suggest that the magnitude of spillovers at the onset of our sample period might have markedly differed.

Over the last two decades, China's trade connections with the global community have notably intensified. From the early 2000s to the present, China's contribution to global merchandise exports has dramatically increased from approximately 4% to over 14%, while its import share has ascended from around 4% to 11%, primarily driven by its dominance in manufacturing. China has ascended to become the world's manufacturing hub, accounting for 35% of global manufacturing gross production (and 29% of value-added), equating to the combined total of the next eight economies. Although the United States remains China's most significant economic partner, its influence has been widespread across the globe. China stands as the largest export destination for 33 countries and the primary source of imports for 65 countries.

In contrast to China's rapid rise, other $G20 - EMs$ have seen a more modest expansion in their trade shares. Figure 8 illustrates the evolution of trade share distributions for China versus the $G20 - EMs$ (based on simple averages) over time. While China's distribution has undergone a substantial shift, the distribution for the other $G20 - EMs$ has experienced a more gradual rightward movement. Delving into the bilateral trade matrices reveals that China has augmented its trade share with the majority of its partners. Conversely, among the other $G20 - EMs$, some nations like India, Indonesia, and Mexico have seen a slight increase in their trade shares, whereas others, including Argentina and Russia, have witnessed a decline over the past two decades.

Figure 8: Trade Linkage: Change in the Distribution Over Time



To assess how the global influence of major emerging economies has evolved over the last two decades, we re-estimated our model to contrast trade weight estimates at the outset of our analysis period (averages from 2001 to 2003) against those just before the pandemic (averages from 2017 to 2019). Figure 9depicts the findings for Advanced Economies (*AEs*) and Emerging Markets (*EMs*) based on GDP-PPP weighted aggregates, considering both demand and supply-side shocks.

Our findings reveal a clear pattern, especially after China's integration into the global trade system following its WTO accession. Spillover effects originating from China have significantly intensified over the last twenty years, in stark contrast to the more subtle changes observed among other $G20 - EMs$. Specifically, spillovers from China—attributable to both demand and supply fluctuations—have roughly doubled in the period leading up to the COVID-19 pandemic. For instance, the impact of aggregate supply shocks on advanced economies surged from 0.19 to 0.4, while the effect of aggregate demand shocks escalated from 0.25 to 0.46. In the context of emerging economies, the impact from supply shocks grew from 0.15 to 0.39 and from 0.23 to 0.79 for demand shocks.

Such dramatic shifts were not observed among the other $G20-EMs$. Notably, spillovers from certain $G20-EMs$ (e.g., Turkey and Saudi Arabia for supply-side impacts, Mexico and Brazil for demand-side effects), especially to other emerging markets, have modestly increased. This could be due to their enhanced connections through Global Value Chains (GVCs) and commodities markets. Conversely, spillovers from some countries, particularly Russia, have markedly declined, affecting both advanced and emerging economies.

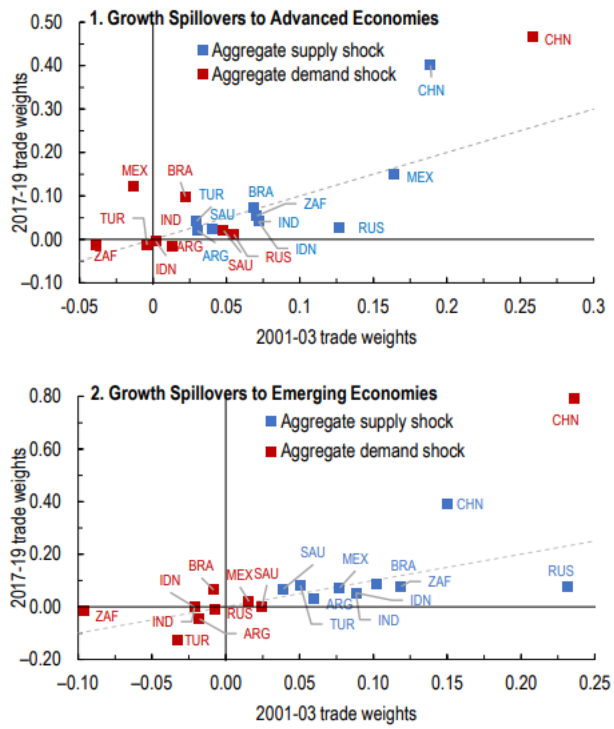
4.6. Robustness and Comparison with Previous Studies

For robustness, we estimated the model using various prior specifications, lag lengths, and both with and without time trends and stochastic volatility. We also experimented with different approaches to identifying structural demand and supply shocks, adjusting the restrictions used and the duration of their application. Additionally, a traditional GVAR model (excluding Bayesian estimation) encompassing a smaller set of countries and variables was analyzed. Although some quantitative variations exist among the different specifications, the core conclusions of this study—namely, the significant magnitude of spillovers originating from China and their notable escalation over the last two decades—remain consistently robust.

Overall, our findings on China's spillovers align with prior estimates, albeit on the higher end, likely due to utilizing the most recent data sample. In particular, previous studies that did not use structural identification of shocks have documented a significant global impact from China's growth shocks. These studies suggest a range of 0.15 to 0.5 percent decrease in global output for a 1 percent reduction in Chinese GDP growth over one to three years (Cashin et al., 2016; Dizioli et al., 2016; Furceri et al., 2016; Cesa-Bianchi et al., 2012). Our results based on the GIRFs indicate a global impact of about 0.75 percent at the one-year horizon.

A more recent study by Copestake et al. (2023), which does use structural shocks, presents a slightly different perspective on the relative impact of these shocks. They report that supply shocks result in a cumulative 0.6 percent decrease in GDP in other countries after two years, while demand shocks lead to a smaller decline

Figure 9: Variation of Growth Spillovers over Time



Notes: The chart shows the cross-country aggregate responses of output to aggregate demand and supply shocks in the $G20 - EMs$, when applying different weighting schemes, namely using 2001-2003 and respectively 2017-2019 average trade weights. The dots represent PPP GDP weighted impulse responses three year ahead, based on responses which are significant on the basis of 68 percent credible intervals.

of 0.4 percent even after four years. In contrast, our analysis reveals that demand-side shocks from China have larger spillovers than supply-side shocks (0.3 percent versus 0.2 percent at the one-year horizon on global output), a finding consistent across different country groups and between the one and three-year horizons. For instance, at the three-year mark, China's demand-side shocks cumulatively affect world output by 0.6 percent, compared to 0.4 percent from supply-side shocks. While pinpointing the exact reason for these differences is challenging, it is worth noting that Copestake et al. (2023) used a simpler 4-variable VAR model compared to our more comprehensive dataset. Additionally, they relied on the China Cyclical Activity Tracker by Fernald et al. (2021) as a proxy for GDP, whereas our study is based on official GDP figures.

Previous research has highlighted regional variations in China's spillovers, with some estimates indicating impacts as substantial as 1.6 percent for certain countries, particularly in Asia, and more pronounced effects observed in economies with robust value-added trade connections (Sznajderska and Kapuściński, 2020; Duval et al., 2014). Notably, significant spillover effects have also been identified for commodity exporters in emerging Asia and Latin America, especially among oil-exporting nations (Ahmed et al., 2022; Dieppe et al., 2018). Our study contributes additional detail and more recent findings, demonstrating that geographically, China's spillovers have grown increasingly widespread and influential across all regions, paralleling its dramatically expanded trade relationships with areas like Africa and Latin America. Furthermore, we provide a more comprehensive analysis of China's impact on a broader spectrum of emerging economies, elucidating spillovers from Chinese demand-side shocks to global commodity producers, as well as from supply-side shocks to countries integrated with China in global supply chains.

Regarding China's influence on commodity markets, our study demonstrates a notable impact of China's demand and supply side shocks on both oil and metal prices. These findings are consistent with the research of Cashin et al. (2016), who discovered that a one standard deviation decrease in China's GDP results in a 2.8 percent reduction in commodity prices after three years. Similarly, Gauvin and Rebillard (2018) identified significant effects on oil and metal markets, though direct comparisons of magnitudes are more challenging.

Among the limited studies that assess spillovers from seven major emerging markets (EMs) beyond China alone, Huidrom et al. (2020) found that a 1 percentage point increase in the growth of these EM7 (comprising China, India, Brazil, Russia, Mexico, Indonesia, and Turkey) leads to a 0.9 percentage point increase in growth in other emerging and frontier markets, and a 0.6 percentage point increase in global growth over three years. Spillovers from China were identified as the most substantial and globally pervasive. Their findings closely align with ours, offering the added benefit that our Global Vector Autoregression (GVAR) methodology provides more detailed insights into country-specific effects, unlike the aggregate EM and G7 measures used by Huidrom et al. (2020).

5. Conclusion

This paper examines global spillovers emanating from growth shocks in the $G20$ emerging market economies ($G20 - EMs$), with a special emphasis on delineating China's influence relative to other prominent EMs. Through the application of a Bayesian Global Vector Autoregression (GVAR) model, which encompasses 63 countries, we estimate both generalized and structurally identified demand and supply shocks.

Our findings vividly highlights China's prominent and extensive impact on the global economic landscape, an influence that is markedly more pronounced when contrasted with other G20 emerging markets. The spillover effects from China not only exhibit significant statistical and economic magnitude but also have witnessed a substantial amplification over the preceding two decades. Specifically, our findings indicate that a one percentage point uptick in China's GDP growth elicits an approximate increase in the output of advanced economies by $0.2 - 0.4$ percentage points and in other emerging economies by $0.3 - 0.8$ percentage points, with the effects stemming from demand shocks surpassing those originating from supply-side disturbances. Conversely, the spillover impacts from other $G20 - EMs$ are discernibly more modest, generally below 0.1 percentage points.

While China's influence permeates globally, our research also uncovers that other $G20 - EMs$ tend to exert influence that is more geographically localized. Notably, significant commodity exporters like Russia and Saudi Arabia are identified to trigger substantial and sustained impacts across a broader spectrum of countries, especially within their respective regions. The pivotal roles of global value chains and commodity markets in the transmission of these shocks are unmistakably evident. Moreover, our study sheds light on China's escalating prominence in the global economy and its consequential substantial capacity to sway global commodity prices. We observe that both demand and supply disruptions originating from China exert a far-reaching impact on oil prices, production, and metal prices, significantly exceeding the effects of shocks from other $G20 - EMs$.

These insights contribute to the existing body of literature by offering a more holistic examination of spillovers from several large emerging economies, rather than centering exclusively on China. Furthermore, our findings underscore the criticality of accounting for both demand and supply shocks and tracking the temporal evolution of these spillover effects. Crucially, our results signal the potential for extensive and far-reaching adverse global ramifications stemming from China's ongoing economic deceleration, ramifications that are unlikely to be adequately mitigated by other emerging markets in the foreseeable future. This underscores the imperative for policymakers globally to remain vigilant and proactively respond to economic developments in China.

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Appendix A. Data, Diagnostics, and Additional Results

Data Sources, Definitions and Transformations

The dataset contains quarterly observations from 2001Q1 to 2023Q2 and for 63 countries (see Table A.1). While we use the definitions and transformations from previously published GVAR datasets, we reconstruct the dataset entirely using IFS, Haver and in a few cases with missing data, national authorities (see Figure A.2). The key difference compared to other GVAR datasets is the inclusion of significantly more emerging economies, which is achieved by focusing on a shorter time span to increase the cross-sectional dimension.

The dataset comprise a good balance between advanced and emerging economies and world regions (with the exception of Africa, where quarterly data was not available). Overall, most countries in the sample are located in Europe (out of which 26 are advanced and 10 emerging economies). In the Asia-Pacific region, the sample covers 13 countries (6 advanced and 7 emerging economies). From the Western Hemisphere region, 9 countries are included (2 advanced and 7 emerging), while the least coverage pertains to countries from the Middle East and Central Asia (5 emerging economies).

Table A.1: List of Countries Included in the Analysis

Advanced Economies				**Emerging Economies**			
Country	**Region**	**Country**	**Region**	**Country**	**Region**	**Country**	**Region**
Australia	APD	Hong Kong	APD	China	APD	Indonesia	APD
Japan	APD	South Korea	APD	India	APD	Malaysia	APD
New Zealand	APD	Singapore	APD	Philippines	APD	Thailand	APD
Austria	EUR	Belgium	EUR	Vietnam	APD	Bulgaria	EUR
Switzerland	EUR	Cyprus	EUR	Belarus	EUR	Croatia	EUR
Czech Republic	EUR	Germany	EUR	Hungary	EUR	Moldova	EUR
Denmark	EUR	Estonia	EUR	Poland	EUR	Romania	EUR
Spain	EUR	Finland	EUR	Russia	EUR	Turkey	EUR
France	EUR	United Kingdom	EUR	Ukraine	EUR	Georgia	MCD
Greece	EUR	Ireland	EUR	Kazakhstan	MCD	Saudi Arabia	MCD
Israel	EUR	Italy	EUR	Tunisia	MCD	South Africa	AFR
Lithuania	EUR	Luxembourg	EUR	Argentina	WHD	Brazil	WHD
Latvia	EUR	Malta	EUR	Chile	WHD	Colombia	WHD
Netherlands	EUR	Norway	EUR	Ecuador	WHD	Mexico	WHD
Portugal	EUR	Sweden	EUR	Peru	WHD		
Slovenia	EUR	Slovakia	EUR				
Canada	WHD	United States	WHD				

The variables covered in the data set comprise real GDP, consumer price inflation, short- and long-term interest rates, the real exchange rate against the US dollar, and equity prices. All variables except interest rates are in logarithmic form. The exchange rate is deflated using consumer prices with an increase implying a real depreciation of the local currency against the dollar. Short-term interest rates are transformed as $0.25 \times \log(1 + R_{it}/100)$, with R_{it} denoting 3-months money market rates. A similar transformation is used for long-term rates, with the underlying interest rates corresponding to 10-year government bond yields.

All country models at least contain data on output, inflation, and one other financial variable, given that some data in particular on long-term yields and equity prices, are missing for some emerging economies. Last, we need to consider a weight matrix that links the country models. Here, the baseline specification uses a matrix is based on annual bilateral trade flows averaged over the period 2017 to 2019, to limit distortions due to the pandemic.

Table A.2: Data Definitions and Sources

Variable	**Description**	**Sources**
GDP	Logarithm of real GDP	World Economic Outlook Database
Inflation	The rate of inflation, calculated as difference of the logarithm of CPI	World Economic Outlook Database
Short-term interest	Nominal short-term interest rate per quarter, in percent	World Economic Outlook Database
Long-term interest	Nominal long-term interest rate per quarter, in percent	World Economic Outlook Database
Equity price	Logarithm of the nominal equity price index deflated by CPI	World Economic Outlook Database
Exchange rate	Logarithm of the real exchange rate expressed in US dollars	World Economic Outlook Database
Oil price	Logarithm of the nominal price of oil in US dollars	Haver Analytics
Oil production	Logarithm of oil production (mil. Barrels/Day)	Haver Analytics
Oil inventories	Logarithm of forward consumption in OECD (in days)	Haver Analytics
Global activity proxy	Global real economic activity index in industrial countries	Haver Analytics
Trade flows	Bilateral goods trade in US dollars, annual	IMF Direction of Trade Statistics

Model Selection and Diagnostics

This research evaluates multiple model specifications, varying in lag length and prior assumptions. In particular, we have conducted estimations with models that incorporate lags ranging from one to four. As discussed previously, we have explored three distinct alternative priors: the Minnesota (MN) prior, the Stochastic Search Variable Selection (SSVS) prior, and the Normal-Gamma (NG) prior. The model diagnostics indicate that the model employing the SSVS prior with a two-lag structure exhibits enhanced performance, particularly concerning residual autocorrelation and cross-country residual correlation. High levels of cross-country correlation can impede the analysis of structural dynamics and spillover effects. This section presents the diagnostics for the preferred model.

Convergence Diagnostics. We use the Geweke's Convergence Diagnostic (CD) assesses the performance of a Markov Chain Monte Carlo (MCMC) algorithm by comparing the means of different segments of the chain. If the chain is in its stationary distribution, these means should be comparable, resulting in a Z-score statistic, adjusted for autocorrelation, that adheres to a standard normal distribution. A low Z-score suggests effective convergence of most coeffcients, indicating a well-functioning MCMC algorithm. The Geweke statistic for the selected model shows that out of 218460 variables, 25169 (11.52%) have Z-values exceeding the 1.96 threshold.

Table A.3: Correlation of Country Models' Residuals

	y	Dp	real_er	pequity	stir	ltir	invent
<0.1	59 (93.65%)	63 (100%)	52 (82.54%)	54 (98.18%)	17 (34.69%)	6 (19.35%)	2 (100%)
0.1-0.2	4 (6.35%)	0 (0%)	11 (17.46%)	1 (1.82%)	7 (14.29%)	5 (16.13%)	0 (0%)
0.2-0.5	0 (0%)	0 (0%)	0 (0%)	0 (0%)	25 (51.02%)	3 (9.68%)	0 (0%)
>0.5	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	17 (54.84%)	0 (0%)

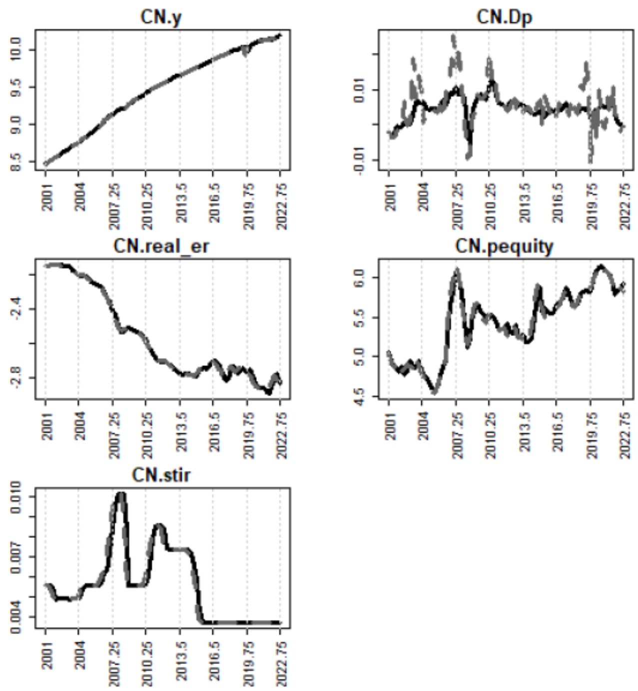
Average Pairwise Cross-Country Residual Correlation. Table A.4 examines the cross-country correlation of posterior median residuals within the GVAR framework. A fundamental assumption of the GVAR model is the minimal cross-country correlation of residuals, as significant correlations can hinder structural and spillover analyses (Dees et al. (2007). The results presented in the Table A.4 indicate that the correlation levels are acceptably low.

Table A.4: Residual Autocorrelation Tests

	# p-values	in %
>0.1	232	70.3%
0.05-0.1	21	6.36%
0.01-0.05	36	10.91%
<0.01	41	12.42%

In-Sample Fit. We can also examine the in-sample fit using the posterior median of the country models' residuals. Figure 1 shows the in-sample fit for China. While not shows here for brevity, the fit is similarly good for all the G20 EM country models.

Figure A.1: In-sample Fit, China



PUBLICATIONS

Spillovers from Large Emerging Economies: How Dominant Is China?

Working Paper No. WP/2025/027