DOCUMENTOS DE TRABAJO

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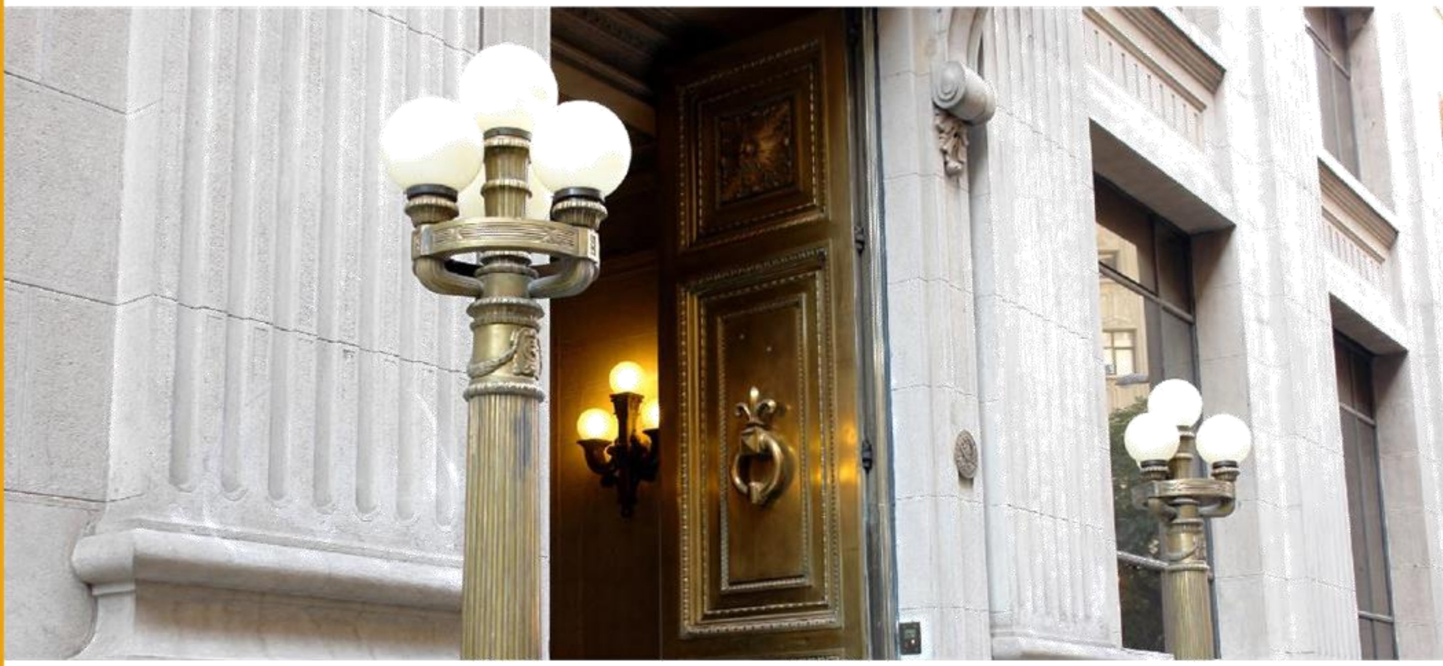
N° 1086 Agosto 2026
BANCO CENTRAL DE CHILE



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Working Papers of the Central Bank of Chile
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Documento de Trabajo N° 1086

Working Paper N° 1086

Structural Synchronicity: A Granular Analysis of China Shocks and Global Inflation*

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Resumen

Este documento cuantifica, en un panel de 56 países, el comovimiento entre los choques de China identificados y la inflación subyacente posterior. Empleamos una estrategia empírica en dos etapas: primero, identificamos innovaciones estructurales en la economía china utilizando un SVAR bayesiano con restricciones de signo junto con un índice mensual de actividad diseñado específicamente. Segundo, estimamos la respuesta al impulso de la inflación subyacente global ante los choques identificados mediante proyecciones locales. Metodológicamente, introducimos un marco inferencial robusto que utiliza imputación múltiple para propagar rigurosamente la incertidumbre de identificación del SVAR a las estimaciones del panel. Encontramos que los choques de oferta y demanda identificados en China tienen efectos similares: un choque positivo (negativo) de una desviación estándar se asocia con un aumento (disminución) acumulado de 0,2 puntos porcentuales en la inflación subyacente global en un horizonte de 18 meses. También encontramos que la respuesta es significativamente mayor en economías con mayor exposición importadora a China y en los bienes duraderos. Estos resultados subrayan la importancia de realizar un seguimiento de la actividad económica de China y de las condiciones de las cadenas de suministro para el pronóstico de la inflación global.

Abstract

This paper quantifies the cross-country comovement between identified China shocks and subsequent core inflation in a panel of 56 countries. We employ a two-step empirical strategy: first, we identify structural innovations in the Chinese economy using a sign-restricted Bayesian SVAR with a bespoke monthly activity index. Second, we estimate the impulse response of global core inflation to the identified shocks via local projections. Methodologically, we introduce a robust in-ferential framework that utilises multiple imputation to rigorously propagate SVAR identification uncertainty in the panel estimates. We find that both China-identified supply and demand shocks have similar responses: a one-standard-deviation posit-ive (negative) shock is associated with a cumulative 0.2 percentage point increase (decrease) in global core inflation over an 18-month horizon. We also find that the response is significantly larger in economies with higher import exposure to China and for durable goods. These results highlight the importance of monit-oring Chinese economic activity and supply-chain conditions for global inflation forecasting.

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* The views in this paper are those of the authors and do not necessarily reflect those of the Bank for International Settlements, the Central Bank of Chile or its board members, or any other institution with which the authors are affiliated.
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1 Introduction

China's deep integration into global value chains has reshaped international trade and production over the past two decades, enhancing its role as a central node in the global economy. As a result, shocks originating in China—whether they are due to domestic demand or supply conditions —have the potential to move in tandem with broader global inflation patterns.

A growing body of research shows that global forces play a central role in shaping domestic inflation. To capture these dynamics more precisely, we move beyond reduced-form fluctuations in prices or activity and instead identify structural shocks that reflect the broader state of the Chinese economy. These shocks are identified using sign restrictions, ensuring they represent specific co-movements across macroeconomic and supply-chain indicators rather than isolated price spikes. Within this framework, China's influence is multifaceted. In particular, a negative "local supply shock" is defined by a simultaneous rise in producer prices, a sharper contraction in domestic activity than observed in the rest of the world, and a tightening of supply-chain constraints, collectively signaling a broad shift in the economy.

Building on this structural identification approach, we operationalise the framework with a sign-restricted SVAR that uses a bespoke high-frequency index of Chinese activity, built via a bridge equation from multiple indicators. We use a two-step empirical strategy: first, we estimate a sign-restricted Bayesian SVAR to uncover distinct structural drivers; domestic demand, domestic supply, commodity prices, global demand and global supply. Second, we employ local projections in a panel of 56 countries to trace how these identified shocks affect harmonised inflation measures, leveraging the cross-country dimension to average out idiosyncratic disturbances and sharpen identification of the common response, with a particular focus on core prices and on the heterogeneity that arises from different levels of import exposure to China. Unlike prior two-step SVAR–LP applications, which typically treat the identified shock as observed data, we propagate the full SVAR posterior uncertainty into the panel estimates via Blackwell, Honaker and King (2017) multiple-imputation rules, yielding confidence bands that reflect both panel sampling variability and structural identification uncertainty.

Our key findings are threefold. First, structural demand and supply shocks originating in China are associated with a significant increase in global core inflation, with the response peaking at close to 0.2 percentage points after 18 months, for each shock. Second, the magnitude of this response is highly sensitive to trade intensity: a one-percentage-point increase in Chinese imports as a share of GDP is associated with an additional 0.02 percentage points increase in the cumulative co-movement between the shock and global core inflation, a result consistent with direct trade and input-linkage channels (Auer, Levchenko and Sauré (2019)). Finally, sectoral responses are heterogeneous, as services inflation remains notably more muted than tradable.

To ensure a comprehensive assessment, we extend the baseline analysis to account for global industrial production and producer price indices (PPI). These exercises demonstrate that the structural synchronicity observed in core inflation is mirrored in broader activity and production-side price dynamics.

These findings are consistent with a growing body of evidence linking global supply shocks to persistent inflationary spillovers. Studies examining shipping cost shocks, global value chain pressures, and supply chain disruptions—including Carrière-Swallow et al. (2023), Ascari, Bonam and Smadu (2024), De Santis (2024), and Cassinis, Ferrari Minesso and Van Robays (2025)—document comparable magnitudes and relation patterns across advanced and emerging economies, while Copestake et al. (2023), Abdel-Latif and Popescu (2025) and Eickmeier and Kühnlenz (2018) provide closest methodological benchmarks for China-specific structural shocks. We extend this literature by introducing a granular and robust inferential framework applied to a harmonised, large-scale panel of 56 economies. This approach explicitly propagates structural identification uncertainty while uncovering significant heterogeneity in the synchronicity between Chinese economic shocks and global inflation dynamics—an association that remains consistent when evaluating production-side measures and other price measures.

These results have clear policy implications. Monitoring developments in Chinese economic activity, prices, and supply conditions can enhance inflation forecasting in partner economies. Incorporating sectoral heterogeneity, global trade linkages, and the dynamic propagation of shocks into forecasting frameworks can help central banks and policymakers distinguish global from idiosyncratic drivers of inflation and calibrate appropriate responses.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 outlines the identification strategy and empirical methods. Section 5 presents the results, including heterogeneity by exposure and time variation. Finally, section 6 concludes.

2 Literature review

A growing literature directly addresses the cross-country transmission of structural Chinese shocks, providing the closest benchmarks for our analysis. Eickmeier and Kühnlenz (2018) employ a structural dynamic factor model for 38 countries (2002–2011) to identify Chinese shocks and their transmission, finding that demand shocks are slightly more influential than supply shocks, that PPI responds more than CPI, and that Chinese shocks account for roughly 6% of the variance in foreign consumer prices in their baseline. More recently, Abdel-Latif and Popescu (2025) extend this analysis using a Bayesian GVAR for 63 countries (2001–2023) and separately identify demand versus supply innovations, reporting opposite-signed responses: demand shocks raise partner CPI by approximately 0.15 percentage points in advanced economies and 0.20 in emerging markets, while supply shocks reduce it by 0.10 and 0.20 percentage points, respectively. At business-cycle frequencies, Copestake et al. (2023) use a SVAR to separate Chinese supply versus demand shocks and local projections to estimate responses of partner-country GDP and global firms' sales, finding that both shock types depress partner activity but that supply shocks produce larger spillovers, with magnitudes scaling with trade exposure. These contributions establish the empirical relevance of Chinese structural shocks for international price and activity dynamics, but rely on quarterly data, smaller country samples, or reduced-form treatments of identification uncertainty—limitations our framework is designed to address.

The relevance of identifying drivers of global inflation co-movement is grounded in a broader literature documenting a strong common component in inflation across advanced economies. Ciccarelli and Mojon (2010), using CPI data for 22 OECD countries from 1960 to 2008, show that a single global component accounts for roughly 70% of the variance in national inflation at both low and business-cycle frequencies, with countries displaying error-correction behavior that re-anchors inflation to the global factor. Mumtaz and Surico (2012) complement this evidence with a time-varying framework, documenting a pronounced decline in inflation persistence since the late 1980s alongside a rising contribution of the global component. Taken together, these studies position global forces as first-order drivers of inflation co-movement and motivate the search for the specific structural sources behind it.

Several channels translate foreign shocks into domestic inflation. Auer, Levchenko and Sauré (2019) combine the World Input–Output Database with sector–country PPIs to recover underlying cost shocks and propagate them through the global Leontief inverse, finding that approximately half of the global component in producer-price co-movement is explained by input–output linkages. Therefore, global value chains synchronise and amplify sectoral cost shocks across borders, especially in PPIs, with implications for downstream CPI inflation depending on response and domestic margins. In the long-term integration margin, Amiti et al. (2020) study China's WTO entry and construct variety-adjusted price indexes, finding that from 2000 to 2006 China's accession reduced U.S. manufacturing price indexes—roughly one-third reflecting lower prices charged by incumbent Chinese exporters and two-thirds stemming from the entry of new exporters, with third-country suppliers also lowering prices in response. Earlier evidence on whether China "exported deflation" through direct trade in the early 2000s finds modest CPI effects in large advanced economies, consistent with limited import shares at the time: Kamin, Marazzi and Schindler (2004) estimate that China reduced annual import price inflation by about 0.25–0.33 percentage points since 1993, with small transmission to U.S. CPI and PPI. Together, these contributions identify the input–output, competition-and-variety, and direct-trade channels through which Chinese supply integration affects partner-country prices.

A parallel and now extensive literature documents the role of global supply-chain disruptions in shaping inflation, with particular emphasis on the post-2020 cycle. Carrière-Swallow et al. (2023), using panel local projections across up to 143 countries, show that global shipping-cost shocks transmit significantly into both headline and core inflation. Ascari, Bonam and Smadu (2024) and De Santis (2024) document that supply-chain pressure shocks were the dominant driver of the surge in euro-area core inflation during 2020–2022, with persistent effects extending beyond three years. Cassinis, Ferrari Minesso and Van Robays (2025) decompose inflationary contributions from global value chain disruptions in the United States using a mixed-frequency BVAR, finding that GVC shocks generate the most persistent and broad-based price pressures, with magnitudes markedly larger in the post-pandemic period than in earlier samples. di Giovanni et al. (2023) quantify that international supply-chain factors accounted for a substantial share of the post-2020 inflation surge across advanced economies, with effects amplified in countries more dependent on foreign inputs. Complementing these structural decompositions, Dao et al. (2024) decompose inflation across 21 advanced and emerging economies into core and headline shocks—encompassing food, energy, shipping, and supply-chain disturbances—and conclude that the synchronised post-2020 surge and subsequent disinflation were driven mainly by these headline shocks and their transmission into core prices, with domestic slack and expectations playing only secondary roles. This literature establishes that global supply disruptions generate economically significant and persistent inflationary responses that scale with trade and value-chain exposure—precisely the mechanism that motivates our focus on China's structural role in global price formation.

While the literature reviewed above establishes China as a central node in global value chains and identifies the channels through which its shocks propagate internationally, previous empirical assessments have traditionally relied on lower-frequency quarterly data or reduced-form specifications that often overlook critical dimensions of heterogeneity. Traditional models—such as large factor models or isolated country studies—frequently fail to account for state-dependence of the inflationary response, particularly the structural shift in dynamics between the pre- and post-2020 periods, and lack the granularity required to capture divergent responses across CPI sub-indices, such as the distinct patterns observed in tradable goods versus services. Our paper contributes along three dimensions.

First, we enhance the granularity of the analysis by combining a bespoke high-frequency activity index for China with a newly harmonised monthly CPI dataset covering a broad panel of 56 economies. By employing a bridge equation to construct a monthly proxy for Chinese activity, we are able to capture cyclical turning points and high-frequency innovations that quarterly or lower-frequency models typically overlook. This data framework, combined with CPI series harmonised to a common structure, allows for a precise examination of the sectoral heterogeneity and time-varying propagation of shocks across a globally representative sample.

Second, the paper provides novel empirical evidence on the post-2020 inflationary cycle, extending the sample through September 2025 to capture the unique dynamics of the pandemic recovery. Our findings demonstrate that the inflation relation is not uniform; rather, it scales significantly with a country's direct trade intensity—specifically, its import exposure to China. We document a marked sectoral asymmetry, where durable goods respond more strongly to Chinese supply innovations than services, reflecting the primacy of direct trade and global value chain linkages in the response of these structural shocks.

Finally, methodologically, this paper bridges two expanding strands of literature to provide a more 'honest' assessment of structural co-movements. We follow Montiel Olea and Plagborg-Møller (2021) in leveraging the flexibility of local projections for structural inference, but we extend this approach to address the classical generated-regressor problem (Pagan 1984)—recognising that Chinese structural shocks are estimated parameters rather than observed data. We apply the multiple-overimputation framework of Blackwell, Honaker and King (2017), which extends Rubin (1987) rules to settings with measurement error in regressors. This approach yields a formal decomposition of global inflation variance into sampling noise and identification ambiguity, providing a more conservative and robust benchmark for analysing the synchronicity of global price dynamics.

3 Data

To implement the empirical exercise, the data combine a comparable CPI index across all countries and a high frequency activity index for China. First, we use the CPI index from Bajraj, Carlomagno and Wlasiuk (2023) that is constructed by harmonising national indices to the EU HICP framework at the class level (93 categories) and applying a common set of Euro Area expenditure weights. This yields monthly, like-for-like measures for 56 economies (2007–2025) with consistent core, goods/services breakdowns; indices are aggregated with equal country weights to avoid size bias. Second, a high-frequency monthly activity index for China is developed via a bridge equation that aggregates multiple indicators (e.g., exports, electricity consumption, retail sales). The index closely tracks official benchmarks while exhibiting slightly higher short-run volatility, improving the capture of cyclical turning points and providing a timely proxy for shock identification.

3.1 CPI country data

The analysis utilises monthly data from January 2007 to September 2025 drawn from the Bajraj, Carlomagno and Wlasiuk (2023) database. Inflation measure is constructed as the logarithmic difference of an equally weighted cross-country price index. The primary dependent variable is monthly core inflation, which is widely regarded as a reliable indicator of underlying price pressures (e.g., Blinder 1997; Mishkin 2007; Wynne 2008). To examine heterogeneous responses, we also consider services and durable-goods inflation. The sample comprises 56 countries—34 advanced and 22 emerging—representing approximately 76% of global GDP (excluding China). All series are seasonally adjusted, and country-level indices are aggregated using equal weights to ensure balanced cross-country comparisons. Descriptive statistics are reported in the table below.

Table 1: Descriptive statistics

Variable	Mean	SD	P10	P25	Median	P75	P90	N
Core (m/m, %)	0.22	0.43	-0.09	0.04	0.17	0.34	0.59	11,925
Durable goods (m/m, %)	0.09	0.94	-0.41	-0.18	0.03	0.28	0.63	11,925
Services (m/m, %)	0.29	0.68	-0.04	0.09	0.22	0.40	0.68	11,925

Notes: CPI inflation is month-on-month percentage change. Sample covers 56 countries, monthly, 2007m1–2025m9.

For cross-country comparability, the consumer price indices are harmonised to a common structure and methodology following the EU Harmonised Index of Consumer Prices (HICP). The objective is to measure the cost of an identical basket of goods and services priced in different countries, thereby eliminating differences arising from national basket composition, index formulas, and weight updates.

This harmonised approach helps facilitate more consistent like-for-like comparisons across countries. It provides sufficient granularity to study sectoral patterns—including goods and services sub-sectors—and aims to mitigate discrepancies arising from national methodologies, such as index formulas, weight-updating frequencies, and scope.

3.2 China Economic Activity: Bridge Equation

To estimate annual China GDP at a monthly frequency, we employ a bridge equation using indicators such as exports, electricity consumption, and retail sales:

$$g_t^{\text{GDP}} = \alpha + \sum_{k=1}^{6} \beta_k \, g(A_{k,t}) + \rho \, g_{t-1}^{\text{GDP}} + \varepsilon_t \tag{1}$$

where $A_{k,t}$ represents the annual aggregator of monthly indicators.

To bridge the frequency gap between official quarterly GDP and our monthly activity measure, we follow a two-step estimation procedure. First, we estimate the parameters $\{\beta_k\}$ at the quarterly frequency by regressing official year-on-year GDP growth on quarterly-aggregated versions of our high-frequency indicators. Second, we apply these estimated coefficients to the monthly year-on-year growth rates of the indicators to derive the high-frequency 'Nowcast' series. This approach ensures that the structural relationship is grounded in official benchmarks while preserving the high-frequency signals—such as rapid cyclical turning points—necessary for robust shock identification.

The reliance on this high-frequency activity index is motivated by the inherent limitations of official Chinese GDP data, which are published only at a quarterly frequency and are often characterised by a high degree of 'smoothing' that may obscure underlying economic volatility. Building on the logic established by Barcelona et al. (2022), we argue that such smoothing can hinder the precise identification of structural shocks and the detection of rapid cyclical turning points. We therefore construct a monthly proxy that aggregates a broad set of real-economy indicators—including exports, imports, electricity consumption, credit impulse, retail sales and Cement production—to provide a timely gauge of China's business cycle.

The resulting index exhibits a correlation of 0.86 with the official series and 0.82 with the 'China Now' index developed by Barcelona et al. (2022). Notably, our index records a standard deviation of 3.91, which is higher than the official index (3.47) and aligns closely with the 'China Now' measure (3.65). The fact that our index moves in such close synchronicity with both official benchmarks and established third-party measures suggests that the bridge equation effectively captures a broad, representative signal of the Chinese business cycle rather than reflecting the idiosyncratic noise of any single indicator.

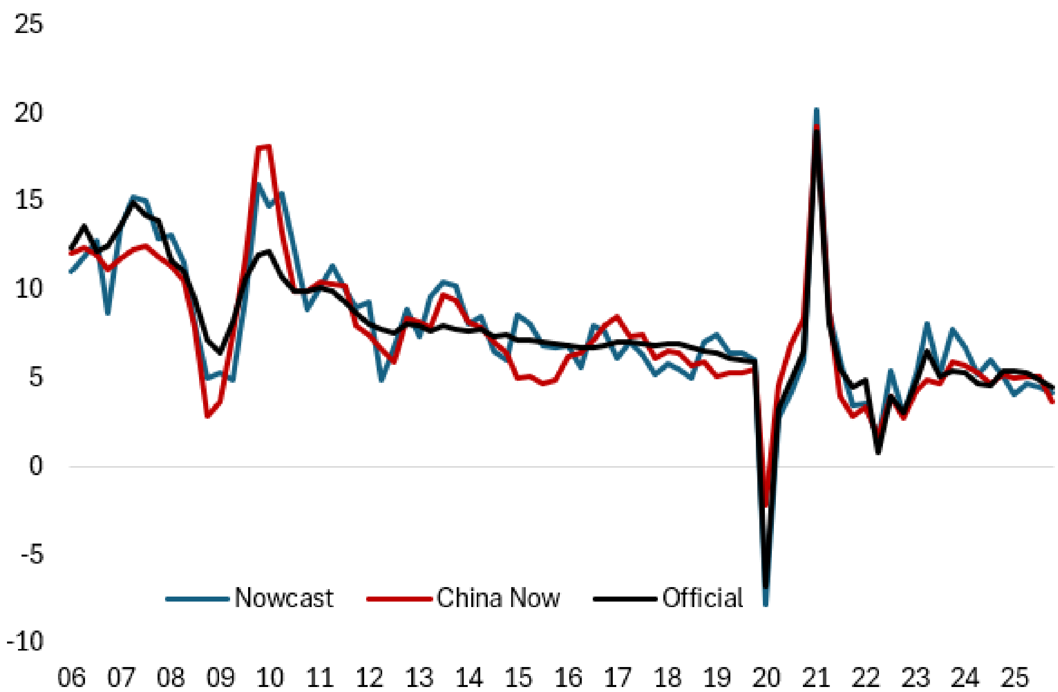

Figure 1: China activity indices. *Note: All series are shown at quarterly frequency. "China Now" refers to the index in Barcelona et al. 2022; Official" denotes the official GDP series; and "Nowcast" denotes the activity index developed in this paper. Source: Authors' calculation.*

4 Methodology

We adopt a two-step empirical identification strategy. First we employ a structural Bayesian VAR to obtain the structural shocks of the Chinese economy, then we use those shocks to estimate the response of global prices using local projections.

4.1 Step 1: Structural Bayesian VAR

To capture the structural decomposition of the Chinese economy, we employ a Bayesian Structural Vector Autoregression (SVAR). The model uses monthly data with twelve lags spanning from the first month of 2006 through September 2025 and is specified as follows:

$$A_0 y_t = \mu + \sum_{i=1}^{12} A_i y_{t-i} + \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0, \Sigma), \qquad t = 1, ..., T \tag{2}$$

Where y_t is a vector of the following observed variables: (i) *China Economic Activity*, that is the logarithm difference of an activity index elaborated in this paper; (ii) *China Producer Price Index (PPI)* , as the logarithm difference of the producer prices of China; (iii) *Commodity prices*, constructed as the logarithm difference of the IMF commodity prices index for all commodities minus the logarithm difference of the China PPI; (iv)

Supply PMI, the simple average of supply delivery time, finished good inventories and input prices; (v) *World Economic Activity*, constructed from the logarithm difference of the industrial production indexes of the world excluding China weighted by gross domestic product minus the logarithm difference of the local Economic Activity Index of China; and (vi) *GSCPI / China Supply PMI Index*, is ratio between the Global Supply Chain Pressure Index from Benigno et al. (2022) and the China Supply PMI Index. The A_i are fixed 6×6 coefficient matrices with A_0 invertible, μ is a 6×1 fixed vector of constants, and ϵ_t represents the structural shocks with zero mean and a covariance matrix equal to the identity matrix. The reduced-form VAR model obtained from 2 can be written as:

$$y_t = c + \sum_{i=1}^{12} B_i y_{t-i} + \nu_t, \qquad \nu_t \sim \mathcal{N}(0, \phi), \qquad t = 1, ..., T \tag{3}$$

where $B_i = A_0^{-1} A_i, \quad c = A_0^{-1}\mu \quad and \quad \nu_t = A_0^{-1}\epsilon_t, \quad thus \quad E(\nu_t'\nu_t) = \Omega = (A_0' A_0)^{-1}$.

We estimate a Bayesian VAR using the Minnesota prior for the coefficients, following Litterman (1986). Posterior draws of the reduced-form parameters and the residual covariance matrix are obtained via a Gibbs sampler as described in Koop and Korobilis (2010). While structural identification is then implemented by imposing sign restrictions on the impulse responses, following the methodology of Arias, Rubio-Ramírez and Waggoner (2018), which is detailed in the next section.

We identify five structural shocks. These shocks are recovered from the reduced-form residuals using the following equation:

$$\epsilon_t = A_0 \nu_t \tag{4}$$

where A_0 denotes the matrix of contemporaneous relationships among prices and quantities, with $Var(\nu_t) = \Omega$ and $Var(\epsilon_t) = I_{6\times6}$. Structural shocks are identified using sign restrictions on impulse response functions (IRFs). For each posterior draw of the reduced-form parameters, we generate a random orthogonal matrix Q, uniformly distributed over the space of orthogonal matrices, and compute the candidate structural impact matrix as $A^* = A_0 Q$. We then derive IRFs and verify compliance with the imposed sign restrictions. If the restrictions hold, the candidate draw is retained; otherwise, a new rotation is generated. For each posterior draw, we store 500 valid rotations to construct the posterior distribution of structural parameters. This procedure ensures identification without relying on recursive ordering and provides a robust framework for inference under sign and zero restrictions. The specific sign restrictions for each structural shock are detailed in Section 4.1.1.

4.1.1 Structural shocks

We identify five structural shocks that drive the dynamics of the Chinese economy by utilising economic activity, supply indices, local indicators, and commodity prices. Each shock is characterised by distinct response patterns, as specified below; meanwhile, the remaining residual component is left unidentified.

- *Demand:* identified as an increase in China's producer price index (PPI) positively correlated with China's economic activity; and with the China supply PMI (indicating tighter local supply-chain conditions); negatively correlated with the ratio of rest-of-world growth to China's growth (consistent with China growing faster than the rest of the world); and with the ratio of global supply chain conditions to the China supply PMI (indicating local supply chains tightening more than global conditions).

- *Supply:* [1] identified as an increase in China's producer price index (PPI) negatively correlated with China's economic activity; positively correlated with the China supply PMI (indicating tighter local supply-chain conditions); positively correlated with the ratio of rest-of-world growth to China's growth (implying a larger domestic slowdown than abroad); and negatively correlated with the ratio of global supply chain conditions to the China supply PMI (indicating local supply chains tightening more than global conditions).

- *Commodities:* identified as an increase in China's producer price index (PPI) positively correlated with the commodity-to-PPI price ratio (indicating commodity prices rising faster than general producer prices); negatively correlated with economic activity (as higher commodity prices weigh on growth in a net commodity-importing economy); and negatively correlated with the PMI supply index (since weaker activity tends to loosen supply-chain conditions).

- *World Demand:* identified as an increase in China's producer price index (PPI) positively correlated with local economic activity; with the ratio of rest-of-world economic activity to local activity (consistent with stronger external than domestic growth); and with the ratio of global supply chain conditions to the local supply index (indicating tighter global than local supply conditions).

- *World Supply:* identified as an increase in China's producer price index (PPI) positively correlated with the local supply index (as local conditions tighten); and with

[1] Our supply shock is defined as an adverse, inflationary disturbance, so a positive realisation yields a positive estimated response of global core inflation. Abdel-Latif and Popescu (2025) normalise the supply shock as a favourable improvement that lowers producer prices. Aligning normalisations reconciles the sign difference.

global supply chain ratio shocks (as global supply conditions tighten more than local conditions); negatively correlated with local economic activity; and with the ratio of rest-of-world growth to China's economic growth (reflecting a larger impact abroad than domestically).

	Demand	Supply	Commodities	World Demand	World Supply
China Activity	+	-	-	+	-
China PPI	+	+	+	+	+
Commodity prices / PPI China			+		
China supply PMI Index	+	+	-		+
RoW Activity / China Activity	-	+		+	-
GSCPI / China supply PMI Index	-	-		+	+

Table 2: Sign restrictions. *i) China Economic Activity refers to the economic activity index developed in this paper, expressed in logarithmic differences. ii) China PPI represents the Producer Price Index for China. iii) Commodity Prices / China PPI is calculated as the logarithmic difference of the IMF's all-commodity price index minus the China Producer Price Index. iv) China Supply PMI Index is the average of three supply-related sub-indexes from the official PMI index. v) Rest of the World Economic Activity is the logarithmic difference of an index of global industrial production (excluding China) minus the logarithmic difference of the economic activity index for China developed in this paper. vi) GSCPI / China Supply PMI Index is ratio between the Global Supply Chain Index from Benigno et al. (2022) and China Supply PMI Index.*

To further validate the idiosyncratic nature of the identified innovations, we conduct a robustness exercise by applying a parallel structural identification framework to the United States economy. Following an identical sign-restriction logic, we identify a set of US structural shocks using industrial production as the local activity index, US producer prices (PPI), and a local PMI supply index[2]. The model also incorporates the baseline commodity price index, world activity excluding the United States, and the Global Supply Chain Pressure Index (GSCPI).

When comparing the results of the China and United States Bayesian SVAR models, we find that the correlation between the two sets of structural shocks is near zero (Figure 2). This suggests that the identified innovations are uniquely characteristic of the Chinese domestic environment rather than reflections of a generic global component common to all large economies.

We acknowledge that this exercise primarily validates our shocks against US-centric signals and does not exhaustively rule out every regional innovation, such as those originating in the Euro-area. Due to data availability constraints—specifically the absence of comparable local supply-chain indicators for other major economic blocks—we refrain

[2] This is constructed as the simple average of supplier delivery times, customer inventories, and backlog orders from the Institute for Supply Management (ISM).

from performing additional regional structural identifications. However, because our baseline identification (Section 4.1.1) already explicitly accounts for global commodity cycles and international demand/supply shifts, the recovered China-specific shocks are orthogonal to broad global factors by construction. Ultimately, this lack of synchronicity with US structural cycles reinforces the validity of our approach in isolating idiosyncratic Chinese signals that subsequently move in tandem with global price dynamics.

This classification facilitates a structural decomposition of the shocks impacting the Chinese economy, providing a clearer understanding of their historical evolution. By distinguishing between domestic innovations and broader international shifts, the framework captures the varying drivers of key economic episodes. Such alignment with observed narrative evidence reinforces the model's capacity to isolate the specific structural signals.

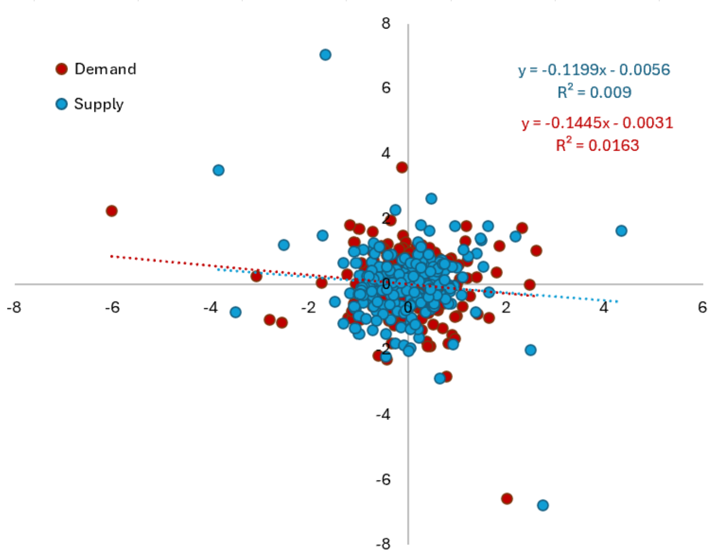

Figure 2: Lack of systematic co-movement between China and U.S. structural shocks. *Note: The x-axis reports structural shocks for the United States (in standard-deviation units); the y-axis reports structural shocks for China (in standard-deviation units). Structural shocks for both countries are obtained from a Bayesian VAR estimated with 12 lags. Endogenous variables include the producer price index (PPI) for each country; a constructed local economic activity index for China; industrial production for the United States; a local supply chain index; commodity prices; global economic activity excluding the country in question; and the Global Supply Chain Pressure Index (GSCPI). Source: Authors' calculation.*

4.1.2 Historical decomposition

Figure 3 presents the historical decomposition of cumulative changes in the Chinese Producer Price Index (PPI) from January 2007 to September 2025. The decomposition illustrates distinct phases in China's inflationary narrative. During the 2008–09 Global Financial Crisis, the decline in prices was considerably affected by global shocks. Conversely, during the 2014–16 period, when several local real estate companies were facing difficulties [3], the influence of global factors was more contained, with local demand and supply shocks emerging as the dominant drivers of price volatility.

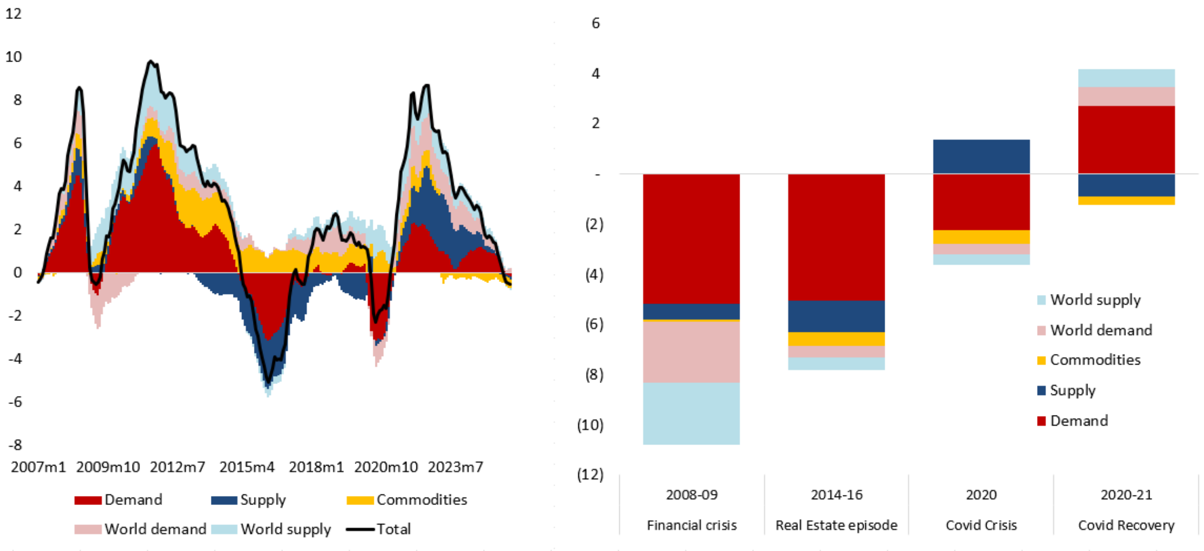

Figure 3: China SVAR. *Note: Historical decomposition from a Bayesian VAR estimated with 12 lags. The endogenous variables include China Producer Price Index, Local Economic Activity Index, local Supply Chain index, commodity prices, world economic activity excluding China and the Global Supply Chain Pressure Index. The figure shows the contribution of each shock to the percentage deviation of Producer Prices for China. Source: Authors' calculation.*

The model captures a unique dynamic during the COVID-19 crisis: an adverse supply shock —coinciding with documented logistical bottlenecks— drove prices upward. This was offset by a simultaneous negative demand shock that exerted downward pressure on prices. In the subsequent recovery phase, we find evidence of a reversal of these trends as supply-chain constraints began to ease and demand to recover.

This alignment between the model's historical decomposition and observed narrative evidence—such as the 2020 industrial disruptions and lockdowns—reinforces the structural validity of the shocks utilised in the subsequent local projection analysis. [4]

4.2 Step 2: Panel Local Projections with Shock-Draw Integration

Having identified structural innovations within the Chinese economy, we move to quantify their international propagation. We employ a panel local projections (LP) framework following Jordà (2005) to estimate the dynamic response of inflation across $i = 1, \ldots, N$ eco-

[3] Significant real estate shocks during this period include the March 2014 collapse of Zhejiang Xingrun and the January 2015 Kaisa Group default. The former signaled a reduction in implicit domestic guarantees, while the latter represented the first offshore bond failure by a Chinese developer; both episodes triggered substantial volatility in property-linked equity and the broader local stock market.

[4] The Forecast Error Variance Decomposition is provided in the appendix.

nomies over horizons $h = 0, ..., H$. This two-step strategy—identifying structural shocks in a VAR and subsequently projecting them through LP—follows a growing literature that takes advantage of the flexibility of local projections while maintaining structural identification, as formalised by Montiel Olea and Plagborg-Møller (2021).

We estimate the cumulative response of inflation in economy i at horizon h using the following specification:

$$y_{i,t+h} = \alpha_i + \sum_{l=0}^{12} \beta_{h,l} \epsilon_{t-l} + \sum_{j=1}^{J} \sum_{l=1}^{12} \gamma_{h,j,l} X_{i,t-l}^{(j)} + u_{i,t+h} \tag{5}$$

where $\beta_{h,0}$ identifies the impulse response at horizon h, denoted as $IRF(h)$. The Cumulative Impulse Response Function over a horizon H is then defined as the sum of these marginal effects:

$$\text{CIRF}(H) \;=\; \sum_{h=0}^{H} \text{IRF}(h) \;=\; \sum_{h=0}^{H} \beta_{h,0}. \tag{6}$$

where $y_{i,t}$ denotes monthly inflation—with a primary focus on core CPI to capture persistent, policy-relevant price dynamics. The term α_i accounts for unit fixed effects, while ϵ_t represents the common Chinese structural shock derived from the Step 1 SVAR. To ensure the estimated spillovers are not confounded by broader macroeconomic shifts, $X_{i,t}$ includes a suite of baseline controls: the lagged dependent variable, local USD exchange-rate fluctuations, and the Global Financial Conditions Index (GFCI) [5].

While Montiel Olea and Plagborg-Møller (2021) establish the validity of leveraging local projections for structural inference, a critical challenge in this two-step strategy remains: the Chinese structural shocks (ϵ_t) are estimated parameters rather than observed data. Treating these identified shocks as known systematically understates the uncertainty of global response estimates—the classical generated-regressor problem first formalised by Pagan (1984), in which conventional standard errors fail to account for sampling variability in first-stage estimates—a concern that traditional two-step SVAR-LP applications often overlook. We address this issue by adopting the Multiple Over-imputation (MO) framework of Blackwell, Honaker and King (2017). Although Rubin (1987) rules are traditionally associated with missing-data inference, the MO framework generalises this machinery to address measurement error by treating variables observed with uncertainty as a specific form of missingness.

Formally, we define the unobserved "truth" (Y^*) as the latent structural shock series ϵ_t, while our observed data consists of the reduced-form residuals ν_t conditioned on the manifold of valid sign restrictions. By treating each of the M draws from the SVAR posterior as an imputation of this latent truth, we move beyond the "non-standard" mapping

[5] Federal Reserve Bank of Chicago, Chicago Fed National Financial Conditions Index [NFCI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NFCI, May 9, 2026.

of missing-data tools to structural shocks. This framework allows us to propagate the structural identification ambiguity—the fact that multiple rotation matrices satisfy our imposed restrictions—directly into the panel estimates. The resulting procedure yields a formal decomposition of global inflation variance into sampling noise and identification uncertainty, providing a more "honest," conservative, and robust benchmark for analysing the structural synchronicity of global price dynamics.

We favor this Multiple Overimputation approach over alternatives such as a fully Bayesian joint estimation (Plagborg-Møller (2019)) or a frequentist refit-bootstrap (Plagborg-Møller and Wolf (2021)). While joint Bayesian sampling is theoretically appealing, it is computationally demanding given our panel of 56 economies and monthly frequency. Conversely, the MO framework allows for a direct, formal decomposition of global inflation variance into sampling noise and identification ambiguity—providing the 'honest' and conservative benchmark necessary for analysing structural synchronicity.

In practice, this procedure begins by drawing M realisations (500) of the shock series, $\{\epsilon_t^{(m)}\}_{m=1}^{M}$, from the SVAR posterior that satisfy the imposed sign restrictions. For each individual posterior draw m, we estimate the LP equation across all horizons h, yielding a distribution of coefficients and their associated country-clustered variances. Finally, we aggregate these results using Rubin's rules to produce a final point estimate ($\overline{\beta}_{h,l}$) and a total variance ($T_{h,l}$) that incorporates both the sampling uncertainty of the panel and the identification uncertainty of the structural shock. [6]

By leveraging a panel of 56 economies, this framework effectively averages out idiosyncratic disturbances—such as localised supply shocks or specific policy shifts. To assess robustness, we estimated several alternative specifications, including testing the impact on Producer Price Indexes, industrial production, official CPI benchmarks, incorporating additional controls for monetary policy, economic activity, and varying country aggregations. We also conducted tests on trimmed samples to mitigate the influence of outliers. Although these expanded specifications reduce the available sample size, the resulting impulse responses remain qualitatively and quantitatively consistent with our baseline estimates, confirming the robustness of the identified response.[7]

We interpret the reported point impact as an aggregate response resulting from at least four primary transmission channels: direct trade in final goods from China (Kamin, Marazzi and Schindler 2004); input-output transmission of Chinese value-added embedded in third-country inputs (Auer, Levchenko and Sauré 2019; di Giovanni et al. 2023); competition and variety effects on tradable prices (Amiti et al. 2020); and commodity-price response (Hamilton 2009; Jacks and Stuermer 2020), given China's role as a marginal buyer in several commodity markets. It is important to clarify that the current empirical design is not intended to decompose these constituent channels; instead, the

[6]Details of the estimation are provided in the Appendix.

[7]Full results for these alternative specifications are provided in Appendix.

results provide a holistic measure of the total transmission of these structural shocks to global inflation.

5 Results

The baseline cumulative impulse responses suggest that shocks originating in China are associated with a persistent increase in global core CPI inflation (Figure 4). The cumulative response of a shock of one standard deviation peaks at around 0.2 percentage points approximately 18 months after impact and remains positive over the two-year horizon. Confidence bands exclude zero over most horizons, indicating statistical significance of the response. The observed patterns suggest a gradual increase in prices after the Chinese shock.[8]

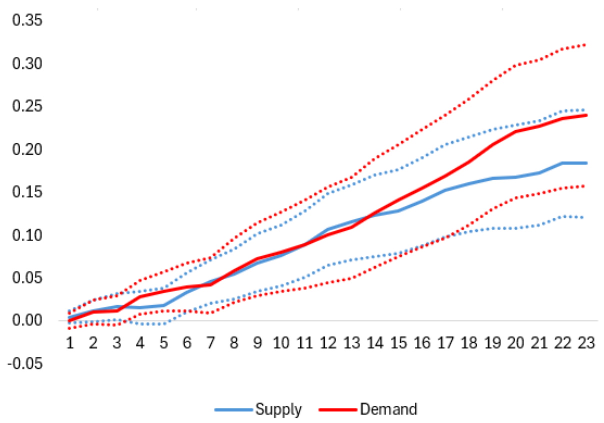

Figure 4: Cumulative impulse responses of core CPI inflation to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Disaggregation shows that the co-movement is concentrated in tradable segments: the estimated response of durable-goods inflation is larger than that of services. (Figure 5). This pattern is consistent with durables' greater exposure to imported inputs and international competition, while the higher local-cost share in services dampens the response of external shocks.

[8] In what follows, we focus on the responses to supply and demand shocks; results for the remaining shocks (commodities, world demand and supply) are reported in Appendix.

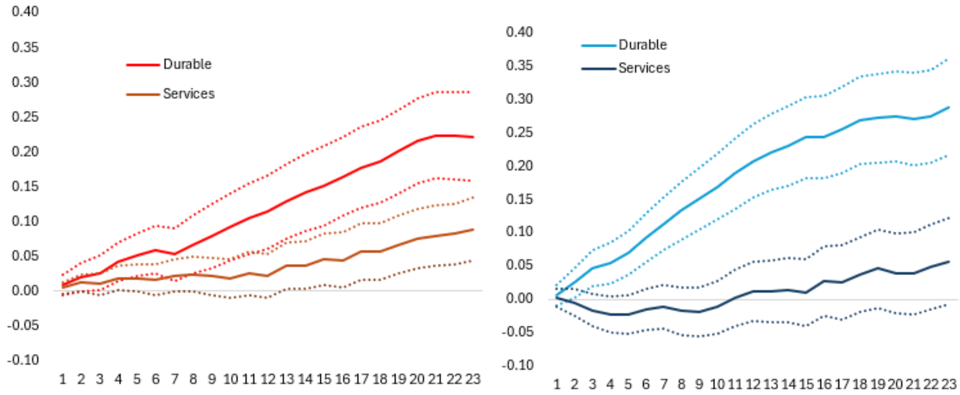

Figure 5: Cumulative impulse responses of durable and services inflation to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. Durable denotes the durable goods inflation index; Services denotes the services inflation index. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Split-sample estimates provide suggestive—though not definitive—evidence of increasing comovement between Chinese shocks and global inflation. Comparing a pre-period (January 2007–December 2015) with a post-period (January 2016–September 2025), the latter exhibits a larger and more persistent response (Figure 6). However, the post-period spans only nine years, and the supply-shock responses are only marginally significant (90% confidence). We therefore refrain from drawing strong conclusions about a stronger role in recent years. Instead, we view these patterns as preliminary and plan to reassess them as additional data become available, allowing for longer split samples and greater statistical power.

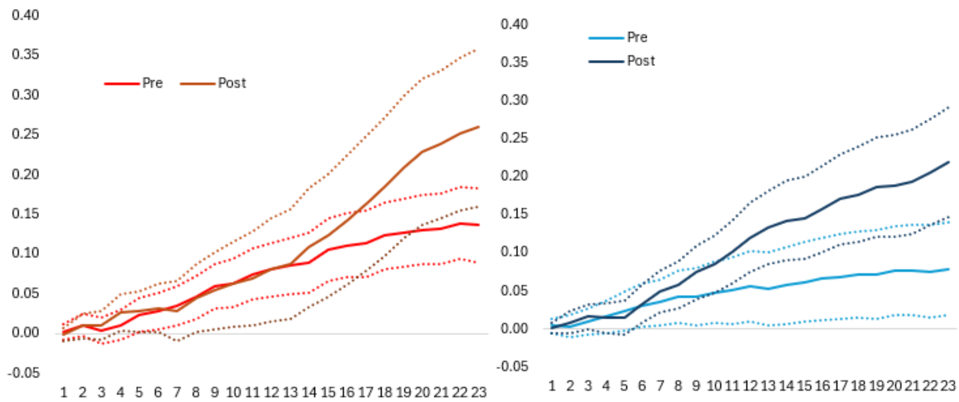

Figure 6: Cumulative impulse responses of core CPI inflation to Chinese supply and demand shocks for different periods. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. "Pre" represent the sample since January 2007 until December 2015 and "Post" since January 2016 until September 2025. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

In the following exercise we examine how the co-movement varies with countries' import exposure to China. We estimate local projections with country α_i and time γ_t fixed effects, interacting the China shock with each country's imports from China as a share of GDP ($share_i$):

$$y_{i,t+h} = \gamma_t + \alpha_i + \beta_h(\varepsilon_t^{\text{shock}} \times \text{share}_i) + \mathbf{X}'_{i,t}\Gamma_h + \epsilon_{i,t+h} \tag{7}$$

The cross-country dimension reveals systematic heterogeneity: the response is significantly more pronounced in economies with greater import exposure to China (Figure 7). This is consistent with a response that scales with trade exposure, though we do not attempt to disentangle direct-trade effects from input-linkage components. Quantitatively, a one-percentage-point increase in imports from China (as a share of GDP) is associated with an estimated cumulative response larger by about 0.02 pp.

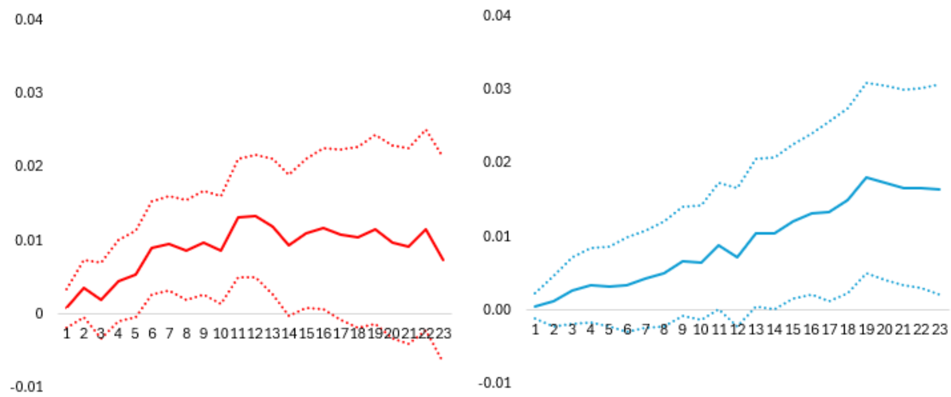

Figure 7: Cumulative Impulse Response Function of China demand shock, weighted by the share of imports Chinese goods as a percentage of GDP, on core inflation. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country and time fixed effects. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Our estimates are broadly consistent with the related empirical literature on supply shock response, while also reflecting the particular features of China's structural role in global value chains. Eickmeier and Kühnlenz (2018) find that Chinese shocks account for roughly 6 percent of the variance in foreign consumer prices across 38 countries, and Copestake et al. (2023) document that supply shocks from China produce larger and faster spillovers than demand shocks, scaling with trade exposure in a manner directly analogous to our heterogeneity results. In terms of CPI magnitudes, Carrière-Swallow et al. (2023) estimate that a one-standard-deviation shipping cost shock raises headline inflation by approximately 0.15 percentage points across a broad country panel. Abdel-Latif and Popescu (2025) find that supply shocks from China reduce CPI inflation in partner economies by approximately 0.1 percentage points in advanced economies and 0.2 percentage points in emerging markets.

A clarification is warranted regarding the apparent contrast with Abdel-Latif and Popescu (2025), who report that Chinese supply shocks reduce partner-country CPI, whereas in our framework the supply shock raises global core inflation by an amount comparable to the demand shock. The difference is one of sign convention rather than substance. Our identification (Section 4.1.1) defines the supply shock as inflationary by construction – an adverse disturbance that raises China's PPI while contracting domestic activity and tightening supply-chain conditions – so that by design its inflationary realization shares the sign of the demand shock. Abdel-Latif and Popescu (2025) instead normalise the supply innovation as a favourable expansion that lowers producer prices and operates through the "China-exporting-deflation" channel. Once the normalisation is aligned the two sets of estimates are mutually consistent: a favourable supply shock in their setup corresponds to a negative realisation of ours, which would lower global core inflation by a roughly symmetric magnitude.

Cassinis, Ferrari Minesso and Van Robays (2025) provide the closest quantitative benchmark, finding that GVC shocks raise U.S. core CPI by approximately 0.4 percentage points over two years in their full sample, but by only around 0.05 percentage points in the pre-pandemic subsample—a pattern that closely parallels our own split-sample finding of an intensified pass-through in the post-2020 period and corroborates the view that the pandemic era represents a structural break in supply-chain transmission dynamics. The sectoral asymmetry we document—where durable goods respond significantly more than services—aligns with De Santis (2024) and Ascari, Bonam and Smadu (2024), who show that supply chain disruptions generate strong and persistent responses on goods prices while services respond with a lag.

Three implications follow. First, the magnitude and persistence of global core CPI response underscore the importance of China-origin supply and demand innovations, even after controlling for global conditions and exchange rates. Finally, sectoral asymmetry points to import exposure and tradability as key characteristics.

As an example, we can see the accumulated responses during different episodes. Structural shocks are mean-zero by construction, but they can deviate significantly during specific episodes. During the 2014 real-estate episode (Section 4.1.2), China experienced on average a negative demand shock of 1.3 standard deviations and a supply shock of about 0.3 standard deviations. Based on our IRFs, these realisations are consistent with a cumulative estimated response of roughly 0.2–0.4 percentage points over the following 12 to 24 months. Economies with higher import exposure to China as a share of GDP by one standard deviation could experience an additional between 0.03 to 0.08 percentage points relative to the average response.

6 Conclusion

This paper quantifies the cross-country comovement between identified Chinese structural shocks and global core inflation, using a two-step empirical strategy that bridges sign-restricted SVAR identification with panel local projections across 56 economies. Two design choices distinguish the exercise from the existing literature. First, we combine a bespoke monthly activity index for China—built via a bridge equation that aggregates a diverse set of real-economy indicators—with a harmonised CPI dataset that places all 56 economies on a like-for-like HICP-style basis. Second, we treat the Chinese structural shocks as estimated parameters rather than observed data and propagate the full SVAR posterior uncertainty into the panel estimates via the multiple-overimputation framework of Blackwell, Honaker and King (2017), generalising Rubin (1987) rules to the SVAR–LP setting. The resulting confidence bands reflect both panel sampling variability and structural identification ambiguity.

We find that one-standard-deviation Chinese structural demand and supply shocks are each associated with a cumulative increase in global core inflation of approximately 0.2 percentage points, peaking 18 months after impact. We provide a specific empirical benchmark: for every 1 percentage point increase in a country's Chinese imports as a share of GDP, the estimated cumulative response increases by about 0.02 percentage points. The fact that durable-goods inflation responds significantly more than services suggests a role for direct trade, providing a potential explanation for why the response scales with import exposure.

These magnitudes sit comfortably within the range documented by adjacent literature—Eickmeier and Kühnlenz (2018) attribute roughly six percent of the variance in foreign consumer prices to Chinese shocks, Abdel-Latif and Popescu (2025) report supply-shock responses of 0.10 to 0.20 percentage points, and Cassinis, Ferrari Minesso and Van Robays (2025) document GVC effects of similar order. The contribution of our exercise is less in the magnitudes themselves than in the cross-country granularity, the explicit treatment of structural identification uncertainty, and the documented heterogeneity along the import-exposure margin.

The headline results are robust to alternative outcomes (producer prices and industrial production), to using official rather than harmonised CPI series, to a 5 percent trim of the inflation distribution, to splitting the sample by income level, and to controlling for local industrial production and policy rates.

For policymakers and central banks, these findings have immediate implications for inflation forecasting and for the design and calibration of macroeconomic policy responses. In light of the inflationary comovements documented in this study—amplified by import exposure and concentrated in tradable goods—the influence of external structural conditions warrants closer consideration within standard inflation-monitoring frameworks.

Given China's growing role in the world economy, future research should monitor the evolving influence of China-identified shocks. The post-2020 sample is short, and a more decisive test of state dependence will require the next several years of data. The exercise reports an aggregate transmission rather than separately identifying the direct-trade, input–output, competition, and commodity channels—a decomposition that microdata on bilateral trade in value added would make tractable.

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A Appendix

A.1 Country details table

Table 3: Country coverage and characteristics

Country name	Income	Activity	CPI	Trim.	Rates	PPI	GDP	Imports
Switzerland	Dev	-	-	-	-	X	0.42	1.45
Australia	Dev	-	-	X	-	-	0.96	4.44
Taiwan	Dev	-	-	X	-	-	0.94	6.78
New Zealand	Dev	-	-	X	-	-	0.14	3.42
Greece	Dev	X	X	-	X	X	0.22	0.21
Ireland	Dev	X	X	-	X	X	0.56	1.29
Israel	Dev	X	X	-	X	-	0.27	0.85
Austria	Dev	X	-	X	X	X	0.36	0.91
Belgium	Dev	X	X	X	X	X	0.44	1.18
Canada	Dev	X	X	X	X	-	1.28	0.90
Cyprus	Dev	X	X	X	-	X	0.03	0.11
Czechia	Dev	X	-	X	-	X	0.31	0.76
Germany	Dev	X	X	X	X	X	2.89	2.16
Denmark	Dev	X	X	X	X	X	0.24	0.81
Spain	Dev	X	X	X	X	X	1.34	0.39
Finland	Dev	X	-	X	X	X	0.18	1.26
France	Dev	X	X	X	X	-	2.12	0.70
Great Britain	Dev	X	X	X	X	-	2.10	0.50
Croatia	Dev	X	-	X	-	X	0.10	0.12
Iceland	Dev	X	-	X	-	-	0.02	0.41
Italy	Dev	X	X	X	X	X	1.74	0.59
Japan	Dev	X	X	X	X	-	3.16	2.58
Korea	Dev	X	X	X	X	X	1.59	8.32
Luxembourg	Dev	X	X	X	X	-	0.05	0.35
Latvia	Dev	X	-	X	-	X	0.04	0.35
Malta	Dev	X	-	X	-	X	0.02	0.45
Netherlands	Dev	X	X	X	X	X	0.71	1.18
Norway	Dev	X	X	X	X	X	0.28	0.73
Portugal	Dev	X	X	X	X	X	0.25	0.27
Sweden	Dev	X	X	X	X	X	0.37	1.07
Singapore	Dev	X	X	X	X	-	0.45	14.51
Slovenia	Dev	X	X	X	X	X	0.06	0.40
Slovakia	Dev	X	-	X	-	X	0.12	1.52
United States	Dev	X	X	X	X	-	14.52	0.52
Ecuador	Eme	-	-	-	-	-	0.14	1.55
Albania	Eme	-	-	X	-	-	0.19	0.40
Saudi Arabia	Eme	-	-	X	-	-	1.30	0.77
Brazil	Eme	X	X	-	X	-	2.4	2.46
India	Eme	X	X	-	X	-	8.27	0.68
Russia	Eme	X	-	-	-	X	3.35	2.06
Turkey	Eme	X	-	-	-	-	1.81	0.29
Uruguay	Eme	X	-	-	-	-	0.06	1.78
Bulgaria	Eme	X	-	X	-	X	0.13	0.93
Chile	Eme	X	X	X	X	X	0.34	7.86
Colombia	Eme	X	X	X	X	-	0.56	0.74
Costa Rica	Eme	X	X	X	-	X	0.08	0.85
Hungary	Eme	X	X	X	X	X	0.22	1.15
Montenegro	Eme	X	-	X	-	X	0.01	1.14

Continued on next page...

Table 3: Country coverage and characteristics (continued)

Country name	Income	Activity	CPI	Trim.	Rates	PPI	GDP	Imports
North Macedonia	Eme	X	-	X	-	X	0.03	0.69
Mexico	Eme	X	X	X	X	X	1.62	0.44
Peru	Eme	X	X	X	-	-	0.31	4.82
Philippines	Eme	X	X	X	-	-	0.73	2.65
Poland	Eme	X	X	X	X	X	0.97	0.37
Paraguay	Eme	X	-	X	-	-	0.07	0.14
Romania	Eme	X	X	X	X	X	0.43	0.29
Serbia	Eme	X	-	X	-	X	0.10	0.46

Note: Income denotes the income-level classification by the IMF; Activity indicates whether the country is included in the robust regressions that control for a monthly economic activity indicator; CPI indicates whether the country is included in the robust regressions that compare the harmonised CPI with the official CPI; Rates indicates whether the country is included in the robust regressions that control for the monetary policy reference rate; PPI indicates whether the country is included in the robust regressions of Producer Price Index; GDP is the country's share of world gross domestic product at purchasing power parity (PPP); Imports is imports from China as a share of the country's GDP.

A.2 SVAR Forecast Error Variance Decomposition

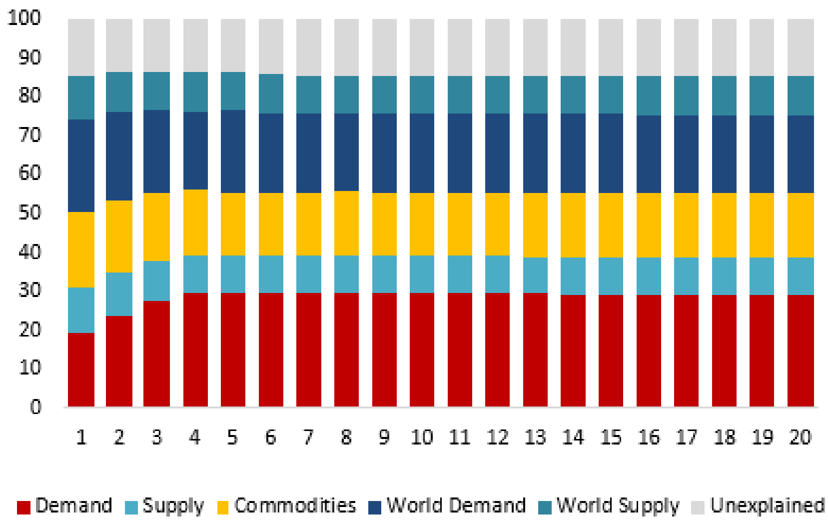

Figure 8: China SVAR FEVD - PPI. *Note: Forecast Error Variance Decomposition from a Bayesian VAR estimated with 12 lags. The endogenous variables include China Producer Price Index, Local Economic Activity Index, local Supply Chain index, commodity prices, world economic activity excluding China and the Global Supply Chain Pressure Index. The figure shows the contribution of each shock to the percentage deviation of Producer Prices for China. Source: Authors' calculation.*

A.3 Robustness exercises

This section presents several exercises to assess the robustness of our results. Figure 9 repeats the analysis using industrial production and the producer price index (PPI) for each country, rather than core CPI inflation. For industrial production, each shock is associated with an increase in global industrial production, but the response is short-lived and dissipates within six months. For PPI, the response is persistent—similar to core CPI—but larger in magnitude, consistent with PPI's greater volatility.

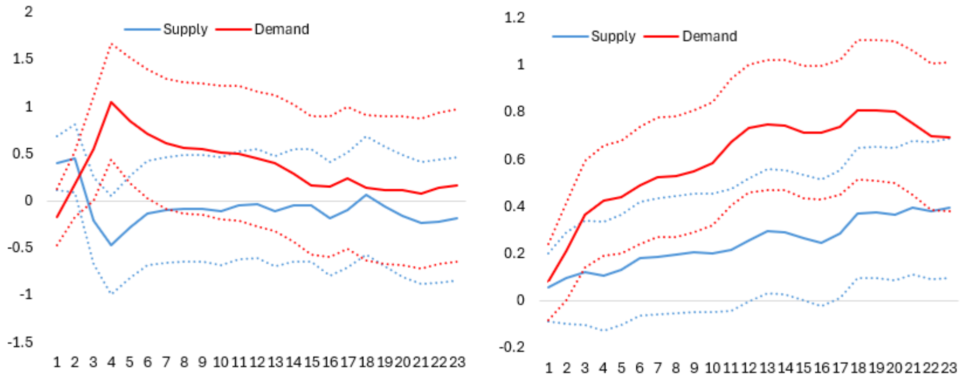

Figure 9: Cumulative impulse responses of industrial production and PPI inflation to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Figure 10 compares estimates obtained using the harmonised core CPI of Bajraj, Carlomagno and Wlasiuk (2023) with those based on the official core CPI for the same set of 35 countries. The results are broadly similar. However, the Bajraj, Carlomagno and Wlasiuk (2023) index offers important advantages: it helps eliminate biases stemming from differences in national weighting schemes, provides a larger sample for the main regression, and is disaggregated into subitems, allowing us to examine heterogeneous responses.

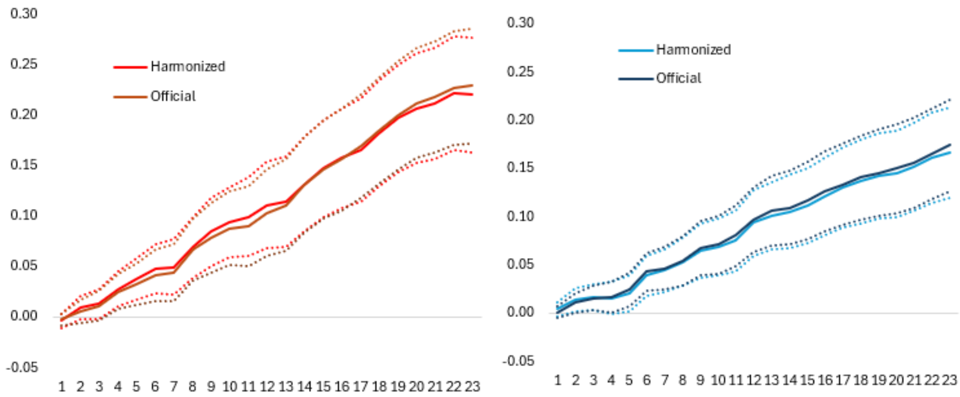

Figure 10: Cumulative impulse responses of core CPI inflation to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 35 countries with country fixed effects. Harmonised denotes the Bajraj, Carlomagno and Wlasiuk (2023) harmonised core CPI, whereas Official denotes the official core CPI. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Figure 11 compares the full-sample results with those from a trimmed sample that excludes the top 5% and bottom 5% of inflation observations. As shown, the results do not change materially.

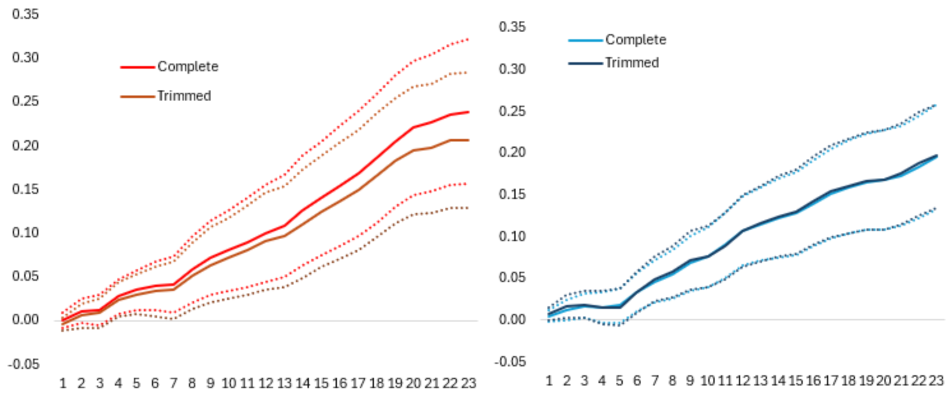

Figure 11: Cumulative impulse responses of core CPI inflation to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. Complete denotes the whole-sample results, whereas Trimmed denotes the results obtained after excluding the 5% of observations with the highest and lowest inflation. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Figure 12 compares the results for 22 emerging and 34 advanced economies, as classified by the IMF. The findings show a higher result for emerging market in the point estimate as for supply and demand, however the confidence intervals overlaps substantially.

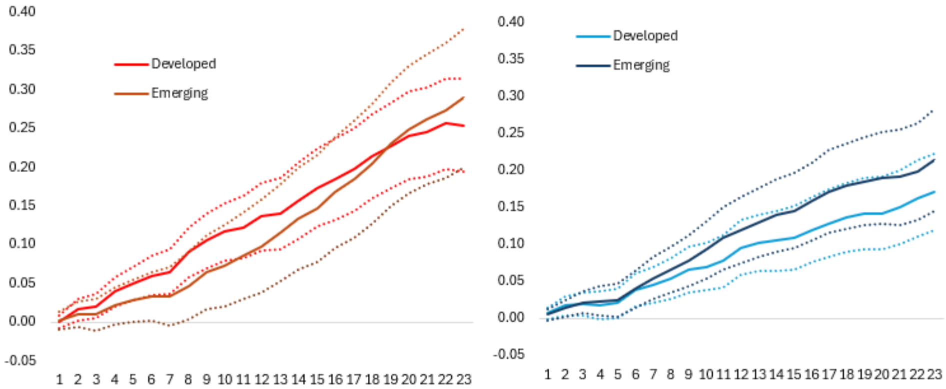

Figure 12: Cumulative impulse responses of core CPI inflation by country income level to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. The terms 'Emerging' and 'Developed' align with the IMF's classification of emerging market and advanced economies, respectively. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Figure 13 evaluates the robustness of the baseline results by augmenting the specification with controls of local industrial production and monetary policy reference rates. While the inclusion of these variables reduces the available sample to 38 countries, the impulse responses remain qualitatively and quantitatively consistent with the baseline. For comparability, both the main and control-augmented specifications are estimated on the same set of 38 countries.

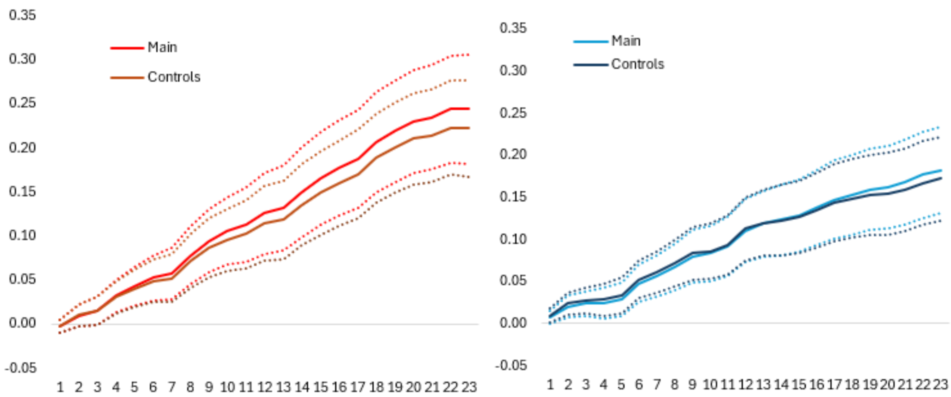

Figure 13: Cumulative impulse responses of core CPI inflation to Chinese supply and demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. The 'Main' specification represents the results of the equations presented in this work, while 'Controls' includes additional reference rates and industrial production indices. Confidence intervals at 90%. See Section 4.2 for controls and inference. Source: Authors' calculation.*

Lastly, Figure 14 reports results for the commodity, global demand, and global supply shocks identified in Section 4.1. Estimating these shocks helps verify that the spillovers attributed to China are not merely reflections of broader macroeconomic shifts or global commodity cycles. As shown, these shocks are less relevant for the Chinese economy than the supply and demand shocks and are estimated with greater uncertainty, with confidence intervals roughly three times wider.

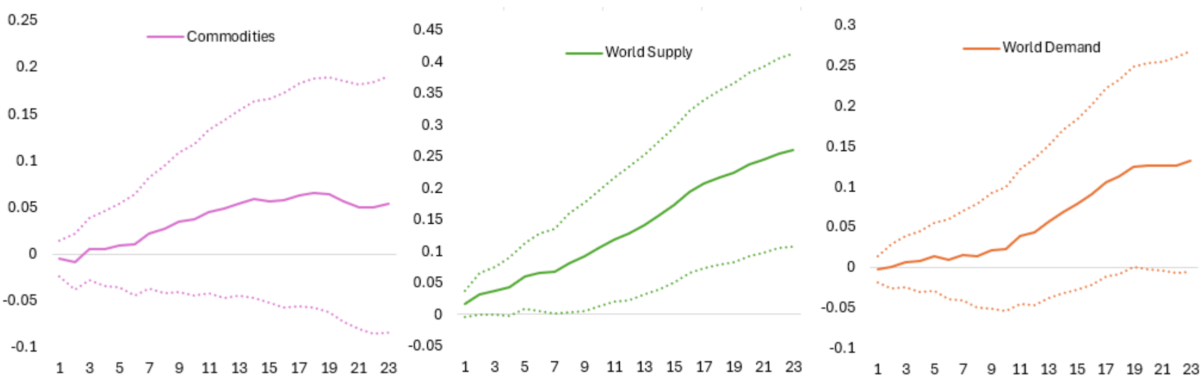

Figure 14: Cumulative responses to one-standard-deviation commodity, world supply, and world demand shocks. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. See Section 4.2 for controls and inference. Source: Authors' calculation.*

A.4 Technical notes on multiple imputation

Following the methodology of Rubin (1987), let M be the number of posterior draws of the Chinese structural shock series $\{\epsilon_t^{(m)}\}_{m=1}^M$ that satisfy the sign restrictions described in Section 4.1.1. For each horizon h and lag l, the pooled results are calculated as follows:

1. The final impulse response coefficient is defined as the arithmetic mean of the coefficients estimated across all M draws:

$$\overline{\beta}_{h,l} = \frac{1}{M}\sum_{m=1}^{M}\hat{\beta}_{h,l}^{(m)}$$

2. The total variance of the estimate consists of two distinct components:

Within-draw variance ($W_{h,l}$): This represents the average sampling uncertainty of the panel estimation across all draws:

$$W_{h,l} = \frac{1}{M}\sum_{m=1}^{M}\widehat{Var}^{(m)}(\hat{\beta}_{h,l}^{(m)})$$

where $\widehat{Var}^{(m)}$ is the country-clustered variance from the m-th estimation.

Between-draw variance ($B_{h,l}$): This captures the uncertainty stemming from the structural identification process itself (i.e., how much the IRF varies across different valid rotations of the SVAR):

$$B_{h,l} = \frac{1}{M-1} \sum_{m=1}^{M} (\hat{\beta}_{h,l}^{(m)} - \overline{\beta}_{h,l})^2$$

3. The total variance ($T_{h,l}$) is the weighted sum of these components, incorporating a correction factor $(1 + 1/M)$ for the finite number of draws:

$$T_{h,l} = W_{h,l} + \left(1 + \frac{1}{M}\right) B_{h,l}$$

The final standard error used for constructing confidence intervals is $SE_{h,l} = \sqrt{T_{h,l}}$.

4. For hypothesis testing, we calculate the relative increase in variance due to identification uncertainty:

$$r_{h,l} = \frac{(1 + 1/M)B_{h,l}}{W_{h,l}}$$

The adjusted degrees of freedom ($\nu_{h,l}$) used for t-based inference are defined as:

$$\nu_{h,l} = (M-1)\left[1 + \frac{1}{r_{h,l}}\right]^2$$

This adjustment ensures that our confidence bands remain robust even when the number of structural draws M is finite. By accounting for both the sampling variability of the panel estimates and the structural identification uncertainty of the Chinese shocks, this procedure yields conservative and reliable inference.

Figure 15 illustrates the difference between estimation using multiple imputations and estimation based solely on the median. As shown, the median tends to overestimate the impact compared to multiple imputations. Additionally, it exhibits a significantly lower standard deviation, approximately half that of the multiple imputations.

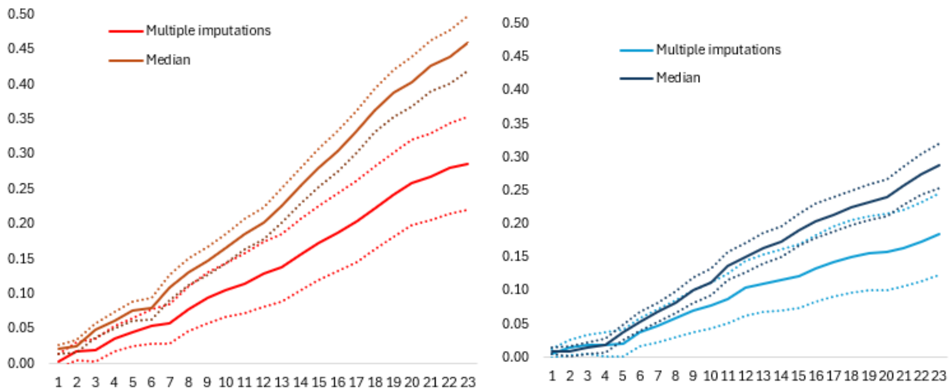

Figure 15: Cumulative impulse responses of core CPI inflation to Chinese supply and demand shocks with different estimation methods. *Sample: January 2007–September 2025. Responses to a one–standard-deviation China shock; horizon in months after impact; units: percentage points (pp). Estimated via panel local projections on 56 countries with country fixed effects. The median represents the estimation based solely on the median, whereas multiple imputations refer to the method introduced by Rubin (1987). See Section 4.2 for controls and inference. Source: Authors' calculation.*

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