Macroeconomic Dynamics (2025), **29**, e97, pp. 1–31
doi:10.1017/S1365100525000240

ARTICLE

Are inflation movements global in nature?

Zo Andriantomanga

University of Wisconsin - Milwaukee, Milwaukee, WI, USA
Corresponding author: Zo Andriantomanga; Email: andrian2@uwm.edu

Abstract

This paper adds to the literature on global inflation synchronization by distinguishing the traded and non-traded content of the consumption basket. Using a novel database of monthly CPI series of 40 countries from 2000, a dynamic factor model with stochastic volatility decomposes inflation into global, income-group, and idiosyncratic components. While synchronization has historically been prominent in tradable goods inflation, findings also reveal an increasing synchronization in non-tradable inflation. Second, I use a time-varying parameter vector autoregressive model to investigate the potential spillover effect. The results provide evidence of spillover from tradable to non-tradable inflation, while the reverse is mainly muted over the sample. Finally, results from local projections indicate that a tightening of US monetary policy causes a significant decline in global headline inflation, which is primarily driven by the heightened sensitivity of tradable goods.

Keywords: Inflation synchronization; tradable inflation; idiosyncratic inflation; bayesian estimation; dynamic factor models; stochastic volatility

JEL classifications: C11; E31; F44

1. Introduction

A large body of literature studying the determinants of inflation documents the effect of global inflation on domestic consumer prices. These studies traditionally model the behavior of inflation through the lens of a dynamic factor model, which measures the contribution of the global, regional, and idiosyncratic parts to the variability of national inflation (Hakkio, 2009; Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012; Förster and Tillmann, 2014; Parker, 2018; Auer et al. 2019; Ha et al. 2023). These studies, primarily focused on advanced economies, highlight a significant contribution of the global component to the overall variation in domestic inflation rates.

However, data availability constrains the study of global inflation across two dimensions. To begin with, most of the empirical evidence on global inflation focuses on measures of a headline or core inflation (e.g. Mumtaz and Surico, 2012; Förster and Tillmann, 2014; Szafranek, 2021). These papers fail to distinguish between traded goods, whose prices are determined in international markets, and non-traded goods, whose prices are determined by domestic markets. The distinction is important as traded goods, such as food and energy, drive global price synchronization (Förster and Tillmann, 2014; Ha et al. 2023). Subsequently, earlier studies of global inflation rely on homogeneous, advanced-economy, and low-frequency samples (e.g. Mumtaz and Surico, 2012; Ciccarelli and Mojon, 2010). This may lead to overestimating the share of variation attributed to global factors in the dynamics of national inflation rates (Szafranek, 2021).

This paper addresses these challenges in two main ways. First, I overcome the data availability issue by constructing a new dataset that breaks down national CPI components following the Harmonized Index of Consumer Prices (HICP) classification.[1] For each country, I collect data for sectoral price indexes with their associated weights from various sources including the IMF CPI database, Eurostat, and the Bureau of Labor Statistics.[2] This dataset allows me to analyze not only headline inflation but also the tradable (food, alcohol, clothing, household furnishings, and transportation) and nontradable components (health, communications, recreation, education, restaurants, and housing) of inflation. The sample includes a panel of monthly CPI series for 31 advanced economies and 9 emerging and developing economies from January 2000 to August 2022.[3] This heterogeneous and higher frequency sample allows me to estimate global inflation more accurately and provide robust conclusions about the relationship between global and domestic inflation. Additionally, this paper is, to the best of my knowledge, the first to examine the degree of synchronization across various components of the CPI basket.

Second, I depart from most of the literature on global inflation by introducing stochastic volatility to the standard dynamic factor model (DFM-SV henceforth).[4] This is an important contribution to the literature because previous studies do not account for the inherent volatility of inflation. The standard factor model rests on the assumption that the variance of the shocks is time-invariant. This poses a misspecification issue, which can lead to a substantial decline in fit. Additionally, previous studies only provide an estimate of the average contribution of the latent factors for a given sample period (e.g Ha et al. 2023; Szafranek, 2021). In contrast, my framework with stochastic volatility allows me to study the dynamic contributions of the common and idiosyncratic factors to national inflation rates.

I begin by estimating for a panel of 40 countries from January 2000 to August 2022 a dynamic factor model with stochastic volatility (DFM-SV). The goal is to disentangle changes in prices driven by external factors from changes in prices due to country-specific shocks. Thus, I decompose inflation into three factors, including (i) a global factor, that is shared to all countries in the sample, (ii) an income-group specific factor - distinguishing Advanced Economies and Emerging Markets and Developing Economies, (iii) and a country-specific idiosyncratic factor. The time variation in the shocks of the idiosyncratic and common factors allows me to examine their dynamic contributions to inflation.

The time-varying variance decomposition reveals three key results. First, inflation movements have become more internationally synchronized over time. The global inflation factor accounts, on average, for 22% of the variation in national inflation. I further find that over time, broad-based shocks exacerbate inflation synchronization. Notably, inflation synchronization has drastically increased during the Great Financial Crisis in 2008–09, the oil price plunge in 2014–16, and the COVID-19 pandemic. Second, by distinguishing the tradable content from the non-tradable content in the consumption basket, I find that inflation synchronization has become significant across traded and non-traded goods, whereas it was previously prominent only for tradable inflation. Third, inflation synchronization is now more present in emerging and developing economies, whereas it used to be an advanced economy phenomenon-only (Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012; Förster and Tillmann, 2014). The results remain robust over a series of checks.

Subsequently, I analyze the time-varying spillovers between tradable and non-tradable inflation. Following the methodology in Antonakakis (Chatziantoniou and Gabauer), I estimate a time-varying parameter vector autoregressive (TVP-VAR) model using the latent factors obtained from the DFM-SV. A key insight emerges from the analysis of the generalized forecast error variance decomposition (GFEVD). There is evidence of spillover of tradable inflation to non-tradable inflation, while the reverse effect is mainly muted over the sample. The spillover effect was most pronounced during three major events: the great financial crisis, the sharp decline in oil prices in 2015, and the COVID-19 pandemic. Generally, the global factor of tradable inflation drives this spillover, affecting the global, advanced economy (AE), and EMDE factors of non-tradable inflation. Interestingly, the pandemic period shows a shift in this pattern. During this time, the spillover effect is primarily driven by income-group factors (AE and EMDE) of tradable inflation rather than the global factor.

Finally, I assess the impact of US monetary policy on global inflation. Using Jordà (2005)'s local projection method, the results indicate that the global inflation factor responds negatively to a 25 bp increase in US interest rates. This impact is sizeable, statistically significant, and persistent. Following the initial shock, the global factor gradually declines to bottom out after 8 months and revert to zero in 20 months. It is also important to note that the persistent decline in global headline inflation is primarily driven by the heightened sensitivity of tradable goods, while non-tradable inflation remains unresponsive.

The remainder of this paper is organized as follows. Section 2 briefly discusses the related literature. Section 3 describes the data. Section 4 presents the dynamic factor model with stochastic volatility and its results. Section 5 studies the spillover effect between tradable and non-tradable inflation. Section 6 discusses the impact of US monetary policy on global inflation. Section 7 concludes.

2. Related literature

In this section, I briefly discuss the existing literature on three issues pertinent to my research question. The first relates to how global inflation has been modeled in the literature. The second concerns the literature on global spillover. Finally, I discuss the literature that discusses the role of US Monetary Policy on inflation.

While much of the literature has relied on dynamic factor models to quantify the global dimension of domestic inflation, there are alternative methodologies. A popular approach in the literature is to model the behavior of inflation through the lens of Phillips curve models (Jašová et al. 2020; Kabukçuoğlu and Martínez-García, 2018; Auer, et al. 2017; Szafranek, 2017). These papers highlight the pass-through of global inflation to domestic inflation. Another approach include vector autoregressions (Bobeica and Jarociński, 2019; Szafranek and Hałka, 2019), and local projections (Choi et al. 2018; Benigno et al. 2022; Carrière-Swallow et al. 2023). These studies highlight the sensitivity of inflation to global shocks including commodity price, exchange rate fluctuations, and supply chain disruptions (Choi et al. 2018; Bobeica and Jarociński, 2019; Szafranek and Hałka, 2019; Jašová et al. 2020; Andriantomanga et al. 2023; Benigno et al. 2022; Carrière-Swallow et al. 2023; Carrière-Swallow et al. 2023).

A considerable body of literature analyzing spillovers between diverse indicators, such as stock returns, oil prices, or house prices, has extensively employed the Diebold and Yilmaz (2012) methodology. These papers include Lovcha and Perez-Laborda (2020) who investigate the volatility connectedness between oil markets and the U.S. natural gas. Albulescu, et al. (2019) study the spillover effect between commodity currencies and oil prices. Additionally, Antonakakis (Chatziantoniou and Gabauer) extends the Diebold and Yilmaz (2012) methodology to analyze spillovers using time-varying parameter autoregressions. For example, Antonakakis, et al. (2018) study the dynamic connectedness of uncertainty across developed economies. André et al. (2021) study the time-varying spillover between housing sentiment and housing markets in the US.

Many papers have investigated the international impact of US monetary policy on domestic economic conditions (Bernanke and Blinder, 1992; Bauer and Swanson, 2023), global financial cycles and credit conditions (Obstfeld, et al. 2018; Brauning and Ivashina, 2020), foreign firms investment (Di Giovanni and Rogers, 2024), and its international spillover (Kim, 2001; Ehrmann and Fratzscher, 2009; Georgiadis, 2016; Özcan, 2019; Degasperi, et al. 2020; Ca'Zorzi et al. 2020; Brauning and Sheremirov, 2021). These papers demonstrate that U.S. monetary policy has wide-ranging impacts on both domestic and international economic conditions.

This paper builds on the existing literature by explicitly analyzing the dynamics of inflation synchronization for traded and nontraded goods and their potential spillover effects. Moreover, the approach allows me to examine time variation in the relative importance of latent common factors to the variation in inflation and account for global shocks. Additionally, this paper documents the impact of US monetary policy on global inflation.

Table 1. Summary statistics

	Obs.	Mean	Std. Dev.	Min	Max
Headline inflation	10,880	3.38	5.08	−5.41	69.71
Tradable inflation	10,880	3.26	5.36	−6.89	81.45
Non-tradable inflation	10,880	3.52	6.18	−6.89	99.73

Note: All variables are at monthly frequency.

3. Data

The data consists of a balanced panel of 40 countries for the period of January 2000 to August 2022 at a monthly frequency. Table 1 presents the summary statistics for the baseline sample. Table A1 lists countries included in the sample. Table A2 reports data sources.

The inflation measures are from the IMF CPI database and Haver Analytics. Each country is assigned twelve CPI components with their respective weights: alcohol, clothing, transport, furnishing, food, communication, health, housing, education, recreation, restaurants, and a residual. This breakdown is based on the Organization for Economic Cooperation and Development OECD)'s Harmonised Indices of Consumer Prices (henceforth, HICP).[5] For non-OECD countries, I match their reported national CPI series with the HICP classification.

For this analysis, I construct three inflation measures: (i) headline inflation, (ii) tradable inflation (alcohol, clothing, transport, furnishing, food), (iii) and non-tradable inflation (communication, health, housing, education, recreation, restaurants)..[6] The distinction between tradable and non-tradable inflation is important. In theory, goods that are traded on international markets, which include food and energy, drive global price synchronization. Empirical evidence found in Ha et al. (2023) suggests that global inflation is prominent for measures of inflation with higher tradable contents. Nonetheless, the authors proxied tradable inflation as the average of headline CPI, PPI, and import prices, and non-tradable inflation as the average of headline CPI, GDP deflator, and core CPI. I extend their work by focusing on CPI inflation and separating the tradable contents from the non-tradable ones in the basket.

The baseline sample contains monthly data from 2000m1 to 2022m8 covering 40 economies, of which 31 are classified as advanced economies and 9 as emerging and developing economies. The joint availability of country-month observations for the twelve CPI components determines the sample size. Doing so allows me to present comparable estimates of global inflation, but limits the ability to (i) study an extended time frame and (ii) include more low-income countries. Still, the sample is long and diverse enough to study the dynamic contributions of common and idiosyncratic factors to national inflation.

The price indexes and the associated weights for the US are obtained using the R-HICP series developed by the US Bureau of Labor Statistics (BLS) which follows the OECD's definition of the Harmonized Index of Consumer Prices (HICP).[7] It is worth noting that the construction of the official US CPI measure slightly differs from the OECD's HICP methodology. Lane (2006) explains that the main distinctions are in terms of aggregation and scope. First, to construct the "housing" component for the US, the BLS removed owners' equivalent rent measures since it is not considered in the HICP classification. Second, while the HICP includes the rural population in its scope, the US CPI only collects prices in urban areas. Despite these limitations, the R-HICP series allows me to obtain the twelve components to compute tradable and non-tradable inflation, and ultimately include the US in the sample.

The main variable of interest is the year-over-year percent change in the price index P_{ijt} for country i and component j at time t with weights $w_j > 0$ such that $\sum_{j=1}^{m} w_j = 1$ for all $j = 1, \ldots, m$:

$$\pi_{ijt} = 100 * \left[\left(\frac{(\sum_{j=1}^{m} w_j \cdot P_{ijt}) / \sum_{j=1}^{m} w_j)}{\sum_{j=1}^{m} w_j \cdot P_{ijt-12}) / \sum_{j=1}^{m} w_j)} \right) - 1 \right] \tag{1}$$

4. A latent dynamic factor model with stochastic volatility

In this section, I investigate the role of the common factors in explaining the movements of inflation.

4.1. Methodology

A dynamic factor model decomposes the movements in inflation to movements due to latent common factors and idiosyncratic factors. The standard factor models do not attempt to model the dynamics of the volatility and usually assume that the variance-covariance matrix is constant (e.g Ha et al. 2023). Not accounting for the inherent volatility of inflation poses a misspecification issue which can lead to a substantial decline in fit. Thus, I adopt a multivariate latent factor model with time-varying stochastic volatility (henceforth, DFM-SV).

Specifically, the DFM-SV decomposes inflation in each country i into (i) a global inflation factor that is shared across all countries, (ii) an income-group factor that is shared within the respective groups (i.e, two group-specific inflation factors, one for advanced economies and one for EMDEs), and (iii) an idiosyncratic component that is unique to each country. The model is given by:

$$\pi_t = \beta \cdot f_t + \Sigma_t^{\frac{1}{2}} \varepsilon_t, \varepsilon_t \sim \mathcal{N}_m(0, I_m) \tag{2}$$

$$f_t = V_t^{\frac{1}{2}} \mu_t, \mu_t \sim \mathcal{N}_r(0, I_r) \tag{3}$$

where $\pi_t = (\pi_{1t}, \pi_{2t}, \ldots, \pi_{mt})'$ consists of m country-specific inflation measures. $\beta \in \mathbb{R}^{m\times r}$ is a matrix holding the factor loadings. $f_t = (f_t^W, f_{AE,t}^G, f_{EMDE,t}^G)'$ is a vector for the world factor, and the income group factors for AEs and EMDEs. The model has one global factor that accounts for the common movement across all countries and two income-group factors. The advanced economy factor has 31 members whereas the EMDE factor has 9 members. In the model, $m = 40$ and $r = 3$ which gives a 40×3 β matrix. The first column of this β matrix has all its elements unrestricted since it is shared by all the countries. The second column represents the AE factor, with the first thirty-one elements unrestricted corresponding to the member countries, and the remaining nine entries are restricted to be zero. Similarly, the third column of β represents the EMDE factor where the first thirty-one entries are restricted to zero and the next nine elements corresponding to the EMDE countries are unrestricted.

The covariance matrices Σ_t and V_t are both diagonals representing stochastic volatility processes such that

$$\begin{aligned} \Sigma_t &= diag(exp(h_{1t}), \ldots, exp(h_{mt})) \\ V_t &= diag(exp(h_{m+1,t}), \ldots, exp(h_{m+r,t})) \end{aligned} \tag{4}$$

The standard dynamic factor model assumes that the idiosyncratic innovations are homoscedastic. The DFM-SV relaxes the assumption of constant volatility. The idiosyncratic innovations and the latent factors are allowed to have time-varying variances, depending on $m + r$ latent volatilities. Following the broader literature on factor models, the shocks to the common and idiosyncratic components are orthogonal to each other. Both the latent factors and idiosyncratic factors follow different stochastic volatility processes:

$$h_{it} = \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \sigma_i \eta_{it}, \eta_{it} \sim \mathcal{N}(0, 1) \tag{5}$$

where h_{it} represents the log-variance process. The stochastic volatility parameters are referred to as $\vartheta = (\mu, \phi, \sigma)$: μ is the level, ϕ is the persistence, and σ is the standard deviation of the log-variance.

The DFM-SV allows the volatility of the factors to vary over time. Time variation in factor volatility can lead to dynamic changes in the contributions of various factors to inflation.

Therefore, the variance decomposition of inflation (conditional on knowing β) is given by:

$$Var(\pi_t) = \beta \cdot Var(f_t) \cdot \beta^T + \Sigma_t \tag{6}$$

4.1.1. Identification

There are two identification issues in the model shown in equations (1)–(5). The sign and the scale of the factor loadings and the factors are not separately identified. I follow the strategy in Kose, et al. (2003). To resolve the sign issue, I restrict the first factor loading to be positive for each of the factors. Specifically, I impose that the loadings on the first country on the global factor to be positive and restrict the loadings on the income-group factor for one country in each of the AE, and EMDE factors to be positive. Scales are identified by normalizing the variance of the common factors to a constant. Since the means of the common factors are not separately identifiable, I demean the data, component-wise, before estimation.

4.1.2. Priors

Prior distributions need to be specified for the factor loadings matrix β and the latent log-variance processes. For the factor loading matrix, I specify a normal prior such that $\beta_{ij} \sim N(0, \tau_{ij}^2)$ with $i \in \{1, \ldots, m\}$ and $j \in \{1, \ldots, r\}$. Each τ_{ij}^2 is fixed a priori and can be set not necessarily at the same value. Therefore, each independent element of the loading matrix follows a normal prior. For the log-variance, the level μ is unrestricted, and as such the common prior $\mu \sim N(b_\mu, B_\mu)$ can be applied. A restricted persistence $\phi \in (-1, 1)$ is needed to achieve stationarity in the variance process. Hence, it is assumed that $(\phi + 1)/2 \sim B(a_\phi, b_\phi)$ where $\mathcal{B}(a_\phi, b_\phi)$ is the beta distribution with shape parameters a_ϕ and b_ϕ. For σ, I apply the conjugate prior $\sigma^{-2} \sim \mathcal{G}(a_\sigma, b_\sigma)$, where $\mathcal{G}(a_\sigma, b_\sigma)$ is the gamma distribution with shape parameters a_σ and rate parameter b_σ.

4.1.3. Estimation

I estimate the model using a Bayesian Markov Chain Monte Carlo (MCMC) algorithm. The joint posterior distribution for the unknown parameters and the unobserved factors can be sampled by a Markov Chain Monte Carlo (MCMC) procedure on the full set of conditional distributions. The number of Monte Carlo draws is 20,000, and the number of initial draws to discard (burn-in replication) is 2000. As is usual in these estimations, I standardize inflation rates to a mean zero and a variance of one.

The importance of each factor in explaining inflation is measured by the fraction of the total variance of inflation due to the respective factor. For example, the degree of global inflation synchronization is measured by the share of the variance of national inflation attributable to the global factor:

$$\frac{(\beta_i^W)^2 \cdot Var(f_t^W)}{Var(\pi_{it})} \tag{7}$$

I employ a similar approach to calculate the variance share of the income-group and idiosyncratic factors. Since variance is time-varying, the contribution of each component to the overall variation in inflation also evolves with time.

4.2. Model selection

One of the contributions of this paper is to address the inherent volatility of inflation by introducing stochastic volatility into the standard dynamic factor model. While the basic DFM-SV model accomplishes this, it maintains constant factor loadings. More sophisticated models, such as the

Table 2. Deviance information criterion

Model	Headline	Tradable	Nontradable
DFM-SV	10,686	11,614	9,323
DFM-TVP-SV	18,010	17,410	16,859

Notes: This table presents the Deviance Information Criterion (DIC) values for two different Dynamic Factor Models with Stochastic Volatility (DFM-SV) applied to three measures of inflation: headline, tradable, and non-tradable. The DIC model selection criterion is used for Bayesian model comparison, where lower values indicate better model fit while accounting for model complexity.

DFM-TVP-SV model as specified in Del Negro and Otrok (2008), which allows for time-varying factor loadings, should also be considered. To identify the specific features of the DFM-SV model that best explain inflation dynamics, I compare the DFM-SV to a dynamic factor model with time-varying factor loadings and stochastic volatility (DFM-TVP-SV).

I use the Deviance Information Criterion (DIC) for model selection, following Spiegelhalter, et al. (2002) and Berg, et al. (2004). The DIC serves as a Bayesian model comparison metric that balances model fit with complexity, acting as a generalization of the widely-used Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Similar to the AIC and BIC, the DIC trades off a measure of model adequacy against a measure of complexity, and the best model has the lowest DIC value. In particular, the DIC model selection criterion consists of two key components. First, it includes a Bayesian measure of fit, defined as the posterior expectation of the deviance or the posterior distribution of the log-likelihood. Second, it incorporates a penalty term that represents model complexity, calculated as the effective number of parameters. This penalty term is determined by the difference between the posterior mean of the deviance and the deviance evaluated at the posterior mean of the parameters.

Following the methodology of Eo and Kim (2016), the DIC is calculated as follows:

$$DIC = -2E_{\frac{\Psi}{y}}\left[\log f\left(\frac{y}{\Psi}\right)\right] + 2\left\{\log f\left(\frac{y}{\bar{\Psi}}\right) - E_{\frac{\Psi}{y}}\left[\log f\left(\frac{y}{\Psi}\right)\right]\right\}$$

where y denotes headline, tradable, or non-tradable inflation. The first term characterizes the model fit, and the second term is the penalty factor for model complexity. Ψ represents model parameters and $\bar{\Psi}$ is its posterior mean. The posterior expectations of the log-likelihood or deviance are calculated as:

$$E_{\frac{\Psi}{y}}\left[\log f\left(\frac{y}{\Psi}\right)\right] = \frac{1}{M}\sum_{j=1}^{M}\log f\left(\frac{y}{\Psi_j}\right)$$

where M is the number of MCMC simulations. I calculate DIC for two sets of models for headline, tradable, and nontradable inflation. The results are shown in Table 2. The consistently lower DIC values for the DFM-SV model across all inflation measures indicate that it provides a better balance between model fit and complexity. This suggests that while accounting for stochastic volatility is important, the addition of time-varying parameters does not improve the model fit enough to justify the increased complexity.

4.3. Estimation results from the dynamic factor model

This section presents the estimation results of the dynamic factor stochastic model outlined above. The variance decomposition is presented in Figure 1. The estimated common factors are plotted in Figure 2. The estimated stochastic volatility is presented in Figure 3. Table A3 presents the posterior mean of the MCMC draws of the estimated factor loadings.

The findings of this section are as follows: (i) headline inflation rates have become more synchronized across countries: the common global factor accounts for 22 percent of the variation in

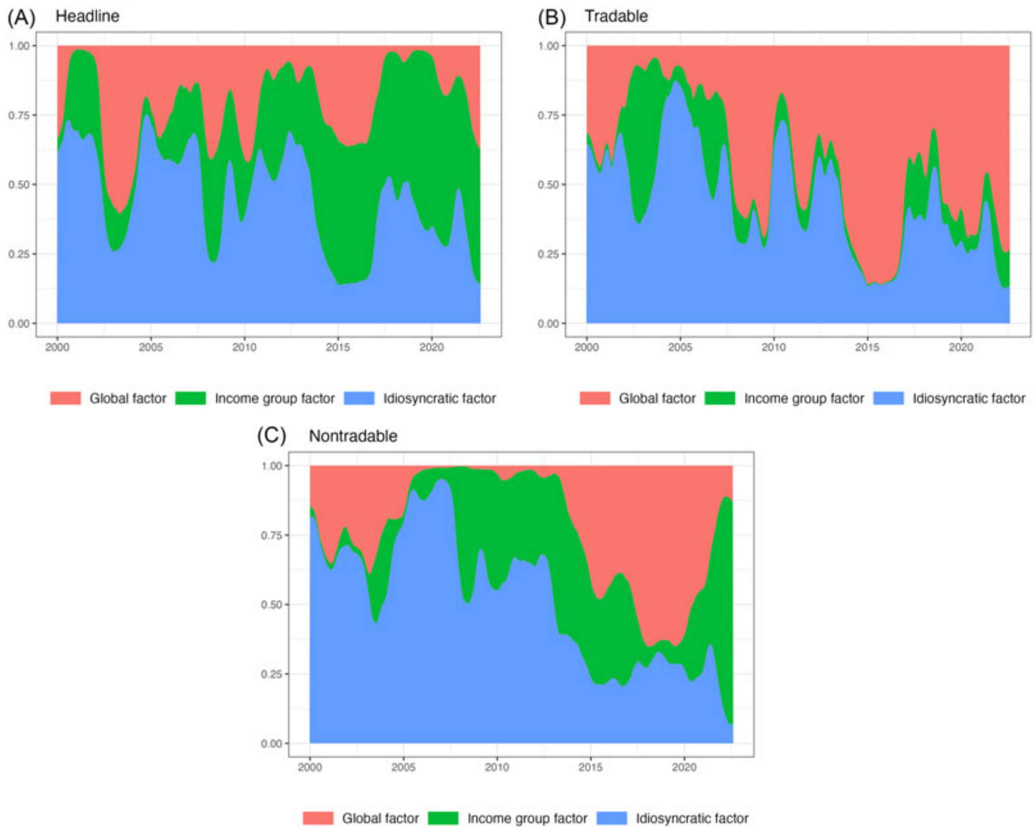

Figure 1. Average variance decomposition.
Notes: The figure plots the average variance decomposition of headline, tradable, and non-tradable inflation from 2000m1 to 2022m8 in a sample of 40 countries. The average time-varying contributions of the global, income-group, and idiosyncratic factors are respectively represented in red, green, and blue.

national inflation rates, (ii) inflation synchronization is significant across different inflation measures: the contribution of the global factor to the variations of tradable inflation is larger and more volatile compared to headline. Inflation synchronization is even present for non-traded goods, although the share of the global factor is smaller and less volatile.

4.3.1. Variance decomposition

Panel A of Figure 1 presents the variance decomposition of headline inflation over time. It allows me to investigate the relative contribution of each factor to the dynamics of inflation over time. Despite being an important driver of headline inflation, the share of the variance attributed to the idiosyncratic factor declines over time. The share of the variance explained by the idiosyncratic factor significantly lowered during the great financial crisis in 2008, the sharp decline in oil prices in 2015, and the COVID-19 pandemic in 2020. During these periods, the contributions of the global and income-group factors soared. Panel A of Figure 1 suggests that, on average, the global, income-group, and idiosyncratic factors contribute to 22, 33, and 45 percent of the variation of headline inflation. Figure 4 presents country-specific variance decomposition for headline inflation.

Next, I discuss the results of the variance decomposition for tradable and nontradable inflation. Panel B of Figure 1 presents the variance decomposition for tradable inflation. Tradable inflation includes the components of inflation that are being traded internationally: alcohol, clothing,

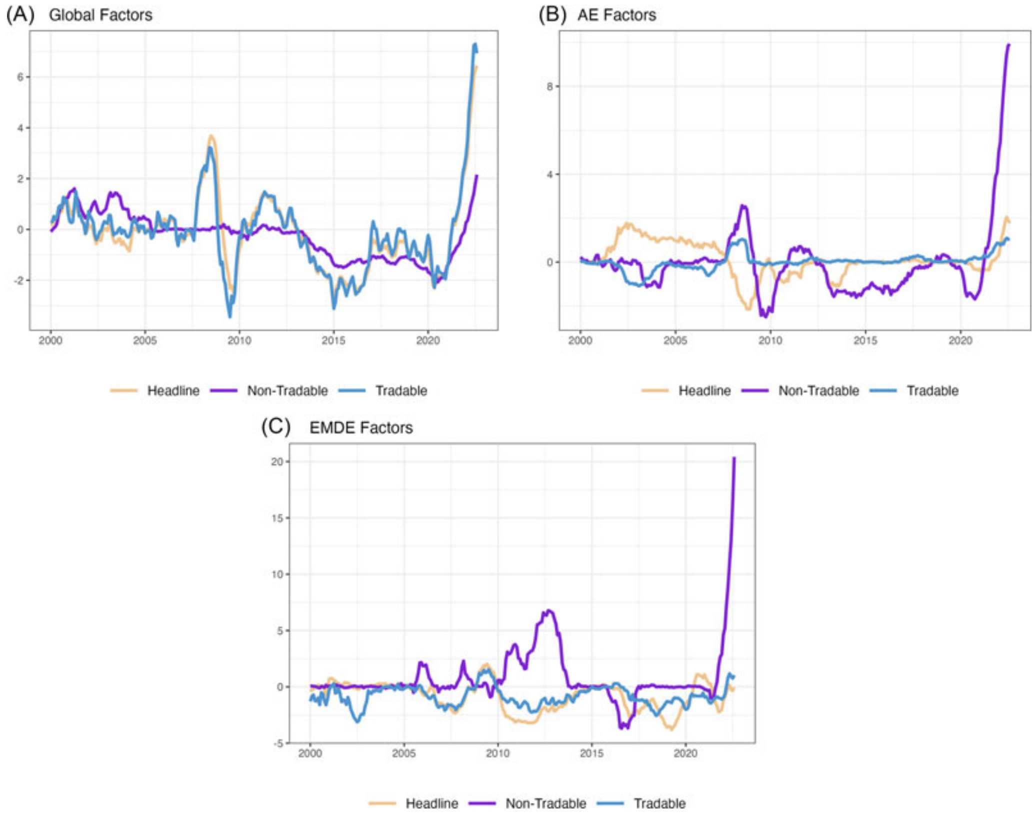

Figure 2. Estimated latent factors.
Notes: Each figure presents the posterior mean of the MCMC draws of the estimated factors for three different measures of inflation: headline (orange line), nontradable (purple line), and tradable (blue line). Panel A plots the global factors. The income-group factors are plotted in Panel B and C, respectively, for advanced economies (AE) and emerging markets and developing economies (EMDE). Factors are estimated with the dynamic factor model with stochastic volatility outlined in the text.

transport, furnishing, and food. I see a more pronounced presence of the global factor over time. Both the global and income-group factors dominate the variation of tradable inflation. Panel B of Figure 1 shows that the global factor and the income-group factor contribute, respectively, to 43% and 13% of the variation of tradable inflation on average. While the idiosyncratic factor contributes as much as 44% of the variation, it is the lowest share. Figure 5 shows the country-specific variance decomposition for tradable inflation.

Panel C of Figure 1 illustrates the variance decomposition results for nontradable inflation. As expected, the idiosyncratic factor dominates most of the variation in nontradable inflation. On average the share of inflation explained by the global, income-group, and idiosyncratic factors are, respectively, 24, 25, and 51 percent. However, the dynamics of non-traded goods are affected by the external factors. The shares of the global and income-group factors have become more and more sizeable in the later part of the sample. In particular, the share of the external factors in the variation of nontradable inflation has become larger during the COVID-19 pandemic period. This can be due to the second-round effects of supply chain disruptions. Andriantomanga et al. (2023) document the impact of supply chain shocks to inflation. Unlike commodity price shocks, supply chain shocks have a direct and outsized effect on tradable inflation; and a smaller but non-negligible effect on non-tradable inflation.

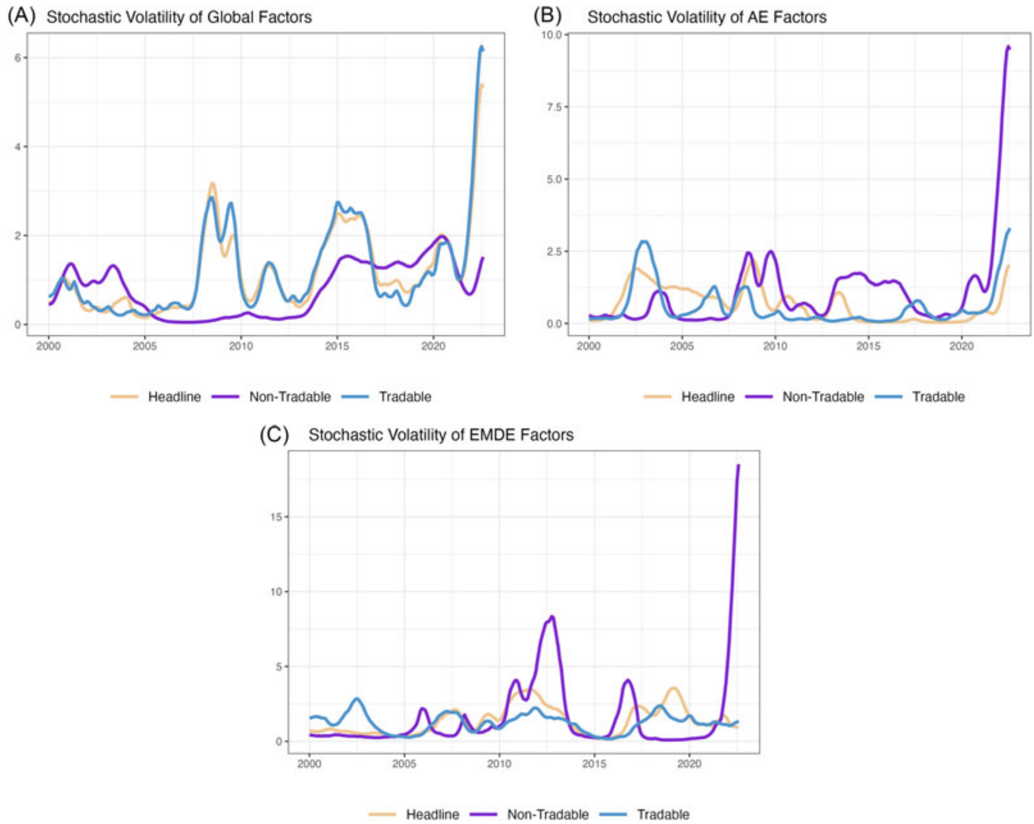

Figure 3. Estimated stochastic volatility.
Notes: Each figure presents the estimated stochastic volatility of the latent factors for three different measures of inflation: headline (orange line), non-tradable (purple line), and tradable (blue line). Panel A plots the stochastic volatility of the global factors. The stochastic volatility of the income-group factors are plotted in Panel B and C, respectively, for advanced economies (AE) and emerging markets and developing economies (EMDE). Factors are estimated with the dynamic factor model with stochastic volatility outlined in the text.

The extent of synchronization also depends on the specific non-tradable good. Some non-tradables might be more susceptible to global influences, while others may be more affected by local factors. In Section 4.4.1, I disentangle the movements of non-tradable inflation by looking at its individual components. Additionally, business cycle synchronization and monetary policy coordination also contribute to price synchronization across countries (Ha et al. 2023). Figure 6 plots the variance decomposition for non-tradable inflation by country.

4.3.2. Estimated common factors

The findings from the variance decomposition are supported by the evolution of the different factors. Figure 2 presents the posterior mean of the estimated factors. There are three main takeaways from these graphs. First, there has been a decline in headline inflation during the great financial crisis of 2008–09, the fall in oil prices in 2015, and a sharp increase during the pandemic crisis of 2020. Second, the variations in tradable inflation are more pronounced. While tradable inflation closely follows the path of headline inflation, the common factor for nontradable inflation remains flat. Also, the decline for tradable inflation was deeper during the great financial crisis of 2008–09, and the fall in oil prices in 2015, and faster and higher over the pandemic. Third, there is some notable heterogeneity across income groups. For example, the peak inflation in the EMDE

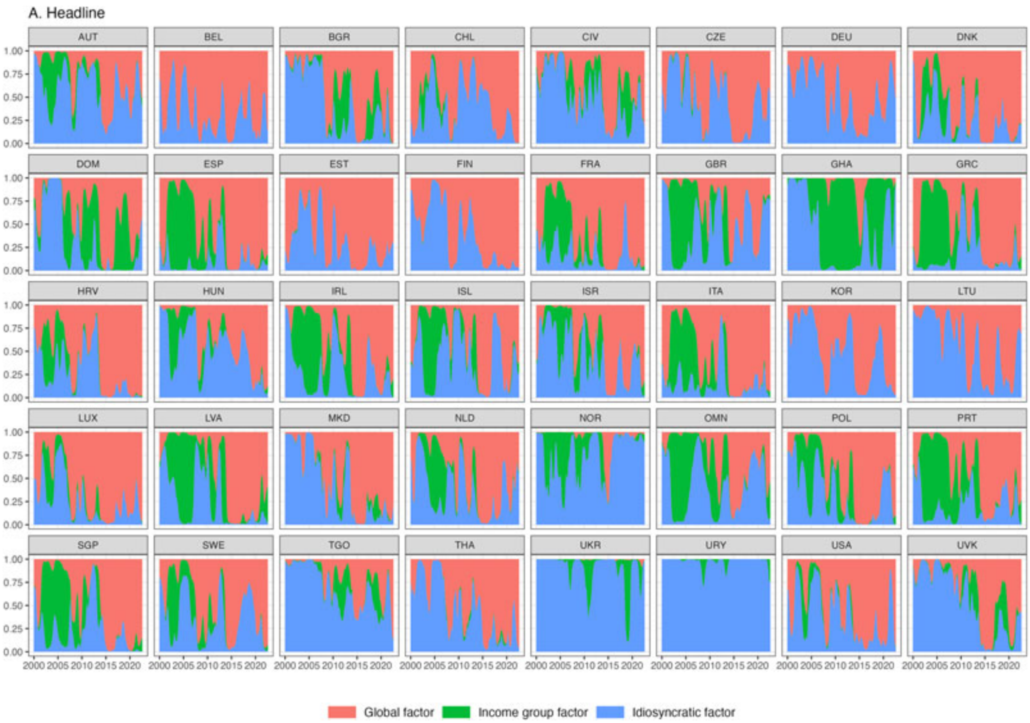

Figure 4. Variance decomposition of headline inflation.
Note: The figure plots the average variance decomposition of the disaggregated components of CPI from 2000m1 to 2022m8 in a sample of 40 countries. The average time-varying contributions of the global, regional, and idiosyncratic factors are respectively represented in red, green, and blue.

common factor for non-tradable inflation may be driven by inflation in Latin American countries, including Argentina, Brazil, Venezuela, and Bolivia. A commodity price boom, weakening currencies, and the El Niño weather phenomenon in the region have led prices to rise. Finally, variations in the global factor are small compared to the AE and EMDE factors.

4.3.3. Estimated stochastic volatility

Figure 3 presents the estimated stochastic volatility for the estimated factors. The results are in line with the findings of the variance decomposition exercise. In Panel A of Figure 3, I see that the peaks in volatility happened during the great financial crisis of 2008–09, the fall in oil prices in 2015, and the pandemic of 2020. Tradable inflation is more volatile than headline while nontradable inflation fluctuates less. There is also a certain degree of heterogeneity when comparing the evolution of stochastic volatility across different factors. The global factor fluctuates less than the AE and EMDE factors. There was a volatility peak in the EMDE factor around 2012, which was driven by inflation in Latin America.

It is also important to note the difference in dynamics between the global factors for tradable and nontradable inflation specifically during the pandemic of 2020. Figure 2 and Figure 3 show that the global inflation factors for both tradable and non-tradable tradable inflation have reached historically high levels. This suggests that tradable and non-tradable inflation are affected by some unobservable common international factors. Nonetheless, the global factor for tradable inflation reaches a higher peak and is more volatile. This more pronounced effect might be due to the direct impact that lockdowns, supply chain disruptions, shipping costs, and port congestion had

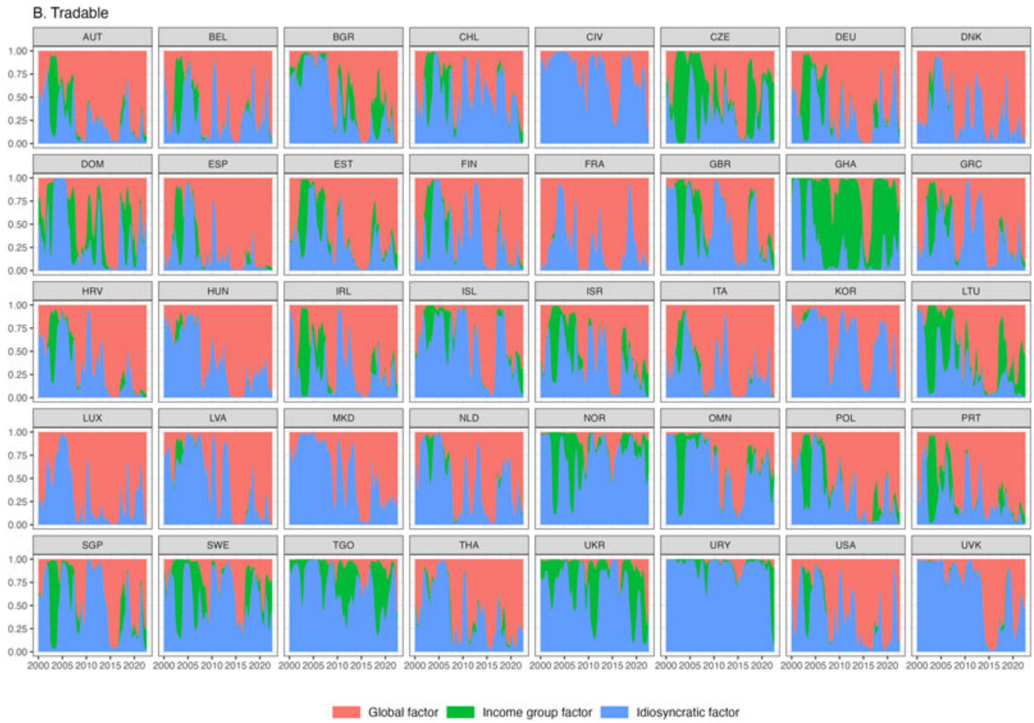

Figure 5. Variance decomposition of tradable inflation.
Notes: The figure plots the average variance decomposition of headline, tradable and non-tradable inflation from 2000m1 to 2022m8. The DFM-SV model is re-estimated separately for the sample of advanced (AE) and emerging (EMDE) economies. The average time-varying contributions of the global, and idiosyncratic factors are respectively represented in red and blue. The AE sample contains 31 countries (left panel), while the EMDE sample has 8 countries (right panel). AE = Advanced economies; EMDE = Emerging markets and developing economies.

on goods that are traded internationally. Papers that discuss the inflationary effects of these different events include Benigno et al. (2022); Carrière-Swallow et al. (2023); LaBelle and Santacreu (2022); Finck and Tillmann (2022); Komaromi, et al. (2022). The more interesting part is the comparatively lower peak in the global factor for nontradable inflation. This shows that the variations in prices of non-traded goods are to some extent affected by some international common factor.

4.3.4. Factor loadings

The factor loadings β are reported in Table A3 for headline, tradable and nontradable inflation. They represent the correlation between each observed inflation series and the underlying latent factors. In other words, they highlight how sensitive national inflation is to the global and income-group factors. Analyzing this table allows me to identify which common factors are the most important in driving national inflation. Overall, the results show that the factor loadings for the global and income-group factors are relatively larger in magnitude for tradable inflation compared to non-tradable inflation. This indicates that the higher pass-through of the latent factors also influences the variations in the dynamics of tradable inflation. It is noteworthy, however, that while non-tradable inflation exhibits smaller factor loadings, its dynamics are still influenced by the latent factors, albeit with a more pronounced contribution from the idiosyncratic factor.

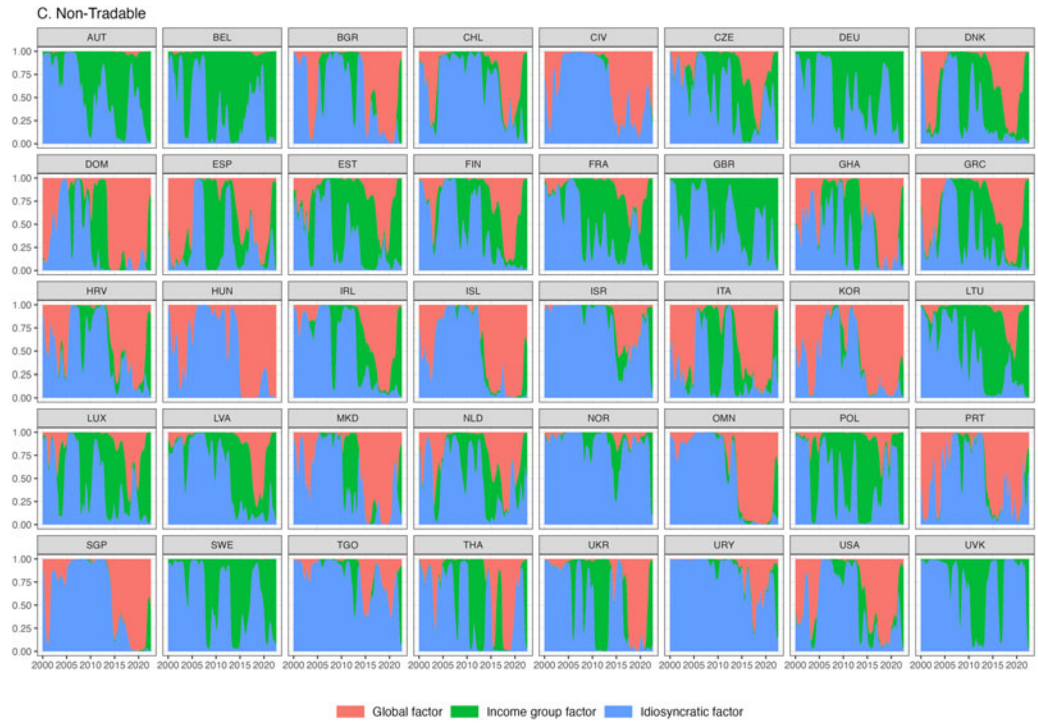

Figure 6. Variance decomposition of non-tradable inflation.
Notes: The figure plots the average variance decomposition of headline, tradable, and non-tradable inflation from 2000m1 to 2022m8 in a sample of 40 countries. The average time-varying contributions of the global, regional, and idiosyncratic factors are respectively represented in red, green, and blue. Regions include Europe, Asia, Central and Eastern Europe and West Asia, Latina America, Middle East and North Africa, and Sub-Saharan Africa.

4.4. Further analysis

4.4.1. Digging deeper with disaggregated CPI series

Section 4.3 analyzes global inflation by looking at three measures of inflation: headline, tradable, and non-tradable. The uniqueness of this dataset allows me to explore further by breaking down the degree of inflation synchronization for each component of the CPI basket. The twelve CPI components include food, alcohol, clothing, household furnishings, transportation, health, communications, recreation, education, restaurants, and housing. Except for the residual, I individually estimate the DFM-SV for each of these components.[8]

Examining each component of the CPI basket allows me to have a deeper understanding of global inflation. In particular, my aim is to disentangle the movements of inflation and explain the increased synchronization in the price of non-traded goods. Moreover, breaking down the CPI basket allows me to see beyond the headline figures and identify significant trends in specific areas. Furthermore, the results of this exercise can be used to draw specific policy recommendations. By closely tracking component prices, policymakers can provide tailored recommendations for various groups and sectors. The variance decomposition for each CPI item is reported in Figure 7.

One interesting result from the previous section is the increasing synchronization in the prices of tradable goods. Breaking down the contribution of the global factor to each non-traded CPI yields the following: communication 26%, housing 34%, health 35%, education 29%, restaurants 35%, and recreation 17%. It is clear that the presence of global inflation is more prominent for items affected by the fluctuations in commodity prices such as food and energy. There is a broad literature on inflation that attributes synchronization to the variations in commodity prices including food and energy (e.g Choi et al. 2018). For example, fluctuations in global energy prices

Figure 7. Average variance decomposition - disaggregated CPI.
Notes: The figure plots the impact of a 25bp shock to a US monetary policy shock on the global factors (Panel A) and their stochastic volatility (Panel B) for headline, tradable and non-tradable inflation from 2000m1 to 2019m12. The monetary policy shock measure is based on the work of Bauer and Swanson (2023). The solid blue line is the impulse response function (IRF); the gray-shaded region represents the 90 percent confidence band. $t = 0$ indicates the month of the shock.

are reflected in housing prices, and similarly, a surge in global food prices will affect the price of meals at restaurants.[9]

As expected, the CPI items that are traded on international markets are more synchronized. On average, the contribution of the global factor to the overall variation of each traded CPI item is as follows: alcohol 32%, clothing 16%, food 38%, furnishing 25%, transportation 61%. Again, I see the pass-through of global energy prices to transportation driving the synchronization in prices. Nonetheless, it must be noted that these average contributions mask the dynamics of each

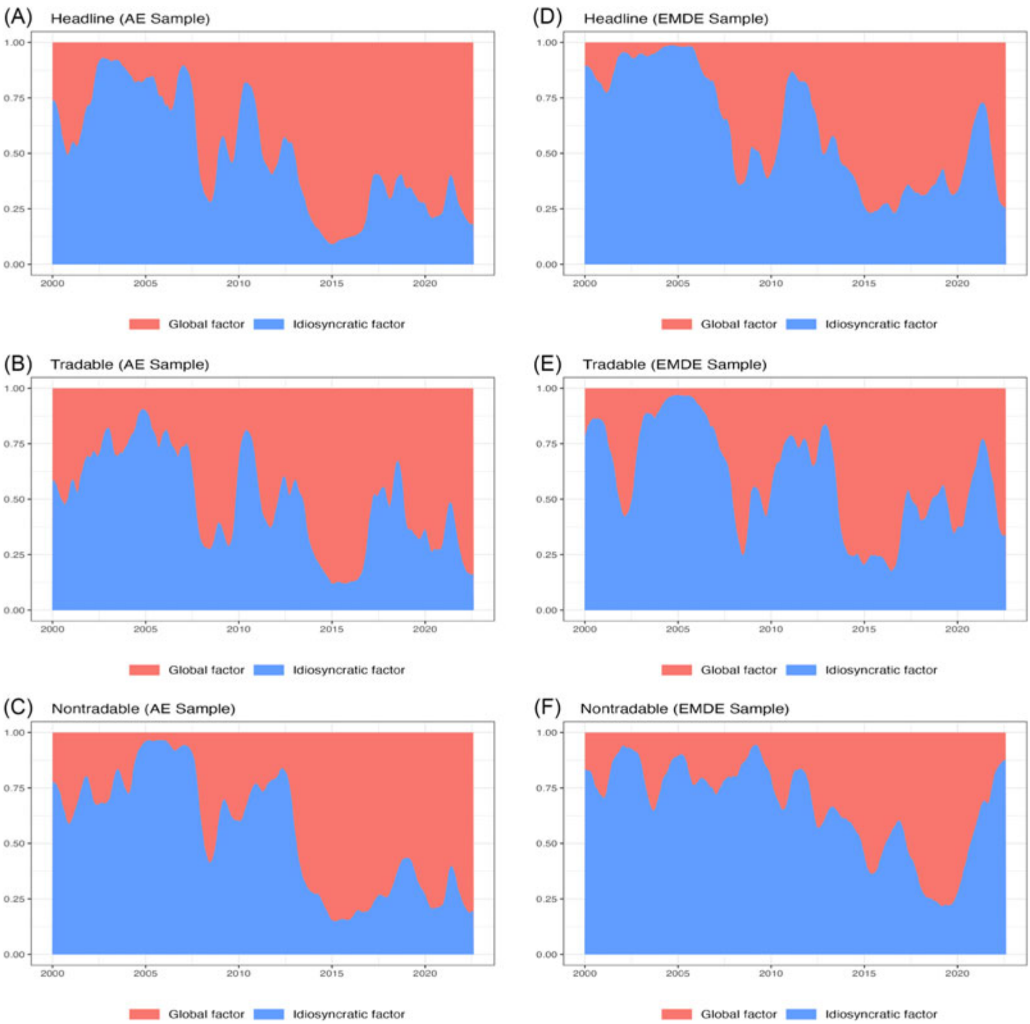

Figure 8. Average variance decomposition - AE vs EMDE.
Notes: This figure shows the Total Connectedness Index (TCI) over the full sample. It indicates the average impact one variable has on all others or all others have on one. High (low) values indicate high (low) levels of spillover. TCI metrics are based on the 12-step-ahead GFEVD of a TVP VAR model.

CPI item. For example, as seen in Figure 7, the global factor for food is very cyclical reflecting the volatile nature of food prices.

To sum up the findings, by disentangling the movements of inflation, I can explain the increasing synchronization in the price of non-tradables. I find that this phenomenon can be attributed to the pass-through of global commodity prices, including food and energy, to housing and restaurant prices (both non-traded). This pass-through is also observed for tradable inflation as the global energy prices strongly drive the synchronization of transportation prices.

4.4.2. Comparing inflation synchronization across income groups

In Section 4.3, the DFM-SV model is estimated on a pooled sample of 31 advanced economies and 9 emerging and developing economies. In this section, I separately re-estimate the model for the sample of advanced and emerging economies. This variation of the DFM-SV model only has two factors: the global factor and the idiosyncratic factors. This specification allows me to compare the dynamic contributions of the global factor to inflation in advanced economies and emerging and developing economies.

Figure 8 reports the variance decomposition. The main takeaway from this graph is that global inflation has become increasingly present in advanced and emerging economies over time. In particular, prior to the great financial crisis, global inflation was more prominent for advanced economies. Following the GFC, inflation has become increasingly synchronized in emerging market economies. To sum up, previously global inflation has been more prominent in advanced economies, now it is present in both advanced and emerging market economies.

I begin the discussion by looking at headline inflation. Abstracting from income-group factors, global inflation accounts for almost half of the variation in inflation for both advanced (AEs) and emerging economies (EMDEs). The global factor's contribution to inflation variation was 48 percent on average for the sample of advanced economies, compared to 41 percent for the emerging and developing economies from 200m1 to 2022m8. However, it must be noted that the degree of inflation synchronization has drastically increased after the Great Financial Crisis. Prior to the great financial crisis, inflation synchronization was minimal in emerging and developing economies (see Figure 8, panel D). In contrast, advanced economies already experienced inflation synchronization to some degree - possibly due to the resemblance in monetary policy frameworks, and exchange rate regimes. Following the great financial crisis, inflation has become increasingly synchronized for both groups, especially during times when the global economy is hit by broad shocks like the great financial crisis in 2007–08, the oil price plunge in 2015, and the COVID-19 pandemic in 2020.

A similar pattern of increasing degree of inflation synchronization is also observed for both tradable inflation and non-tradable inflation in both advanced (AEs) and emerging economies (EMDEs). As expected, the prices of goods that are traded on international markets are more synchronized in contrast to their non-traded counterpart. Also, it appears that the global factor for tradable inflation is similarly sensitive to shocks for both groups of countries.

4.5. Robustness check: alternative DFM-SV specification

In Section 4.3, the DFM-SV is specified using income-group factors - contrasting advanced versus emerging and developing economies. In this section, I re-estimate the baseline model using regional factors. The countries in the sample are found across 6 regions of the world: Europe (18), Asia (3), CEEWA (11), Latina America (3), Middle East and North Africa (2), and Sub-Saharan Africa (3).

Exploring this alternative specification, will not only serve as a robustness check to the previous findings but also allow me to get a comprehensive understanding of the nature of the external and domestic drivers of inflation. I aim to uncover the underlying factors driving inflation at the geographical level. By specifying regional factors, I can capture regional synergies in inflation movements that were hidden in the baseline specification. This approach has been implemented in the global inflation literature (e.g Ha et al. 2023).

Under this alternative specification, the results corroborate previous findings that about half of the variation in inflation is driven by external factors, and only the remaining half is explained by idiosyncratic factors. Nonetheless, there are slight nuances in the contributions of the global and regional factors to the total variation. Panel A of Figure 9 presents the results for headline inflation. On average the global, regional, and idiosyncratic factors contribute to 44, 17, and 48 percent of the overall variation of inflation. Contrasting these results to the baseline specification, the contribution of global of the global factor doubled (was 22 percent in the baseline). This is mainly because the regional factor only explains 17 percent of the total variation in inflation (33 percent in the baseline). The idiosyncratic factor explains, on average, 38 percent of the variation in inflation, which is slightly below the 45 percent reported in the baseline.

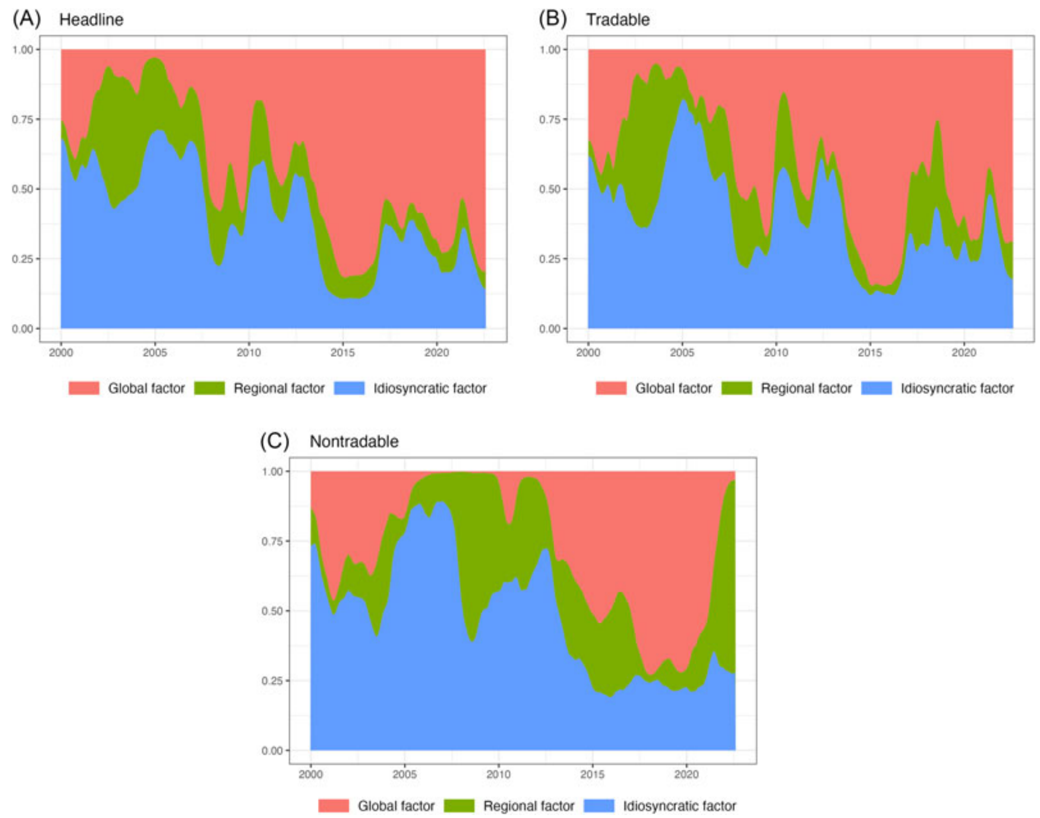

Figure 9. Average variance decomposition: alternative specification with regional factors.
Notes: This figure shows the Net Total Directional Connectedness (NET) over the full sample. Positive (negative) NET values indicate that a variable is a net transmitter (receiver) of shocks. NET metrics are based on the 12-step-ahead GFEVD of a TVP VAR model.

Panel B of Figure 9 shows the variance decomposition of tradable inflation. On average, the global, regional, and idiosyncratic factors contribute, respectively, to 44%, 17%, and 39% of the total variation in inflation. Panel C of Figure 9 illustrates the contributions of the global, regional, and idiosyncratic factors to the variation of non-tradable inflation which are, respectively, 45%, 17%, and 38%. Overall, these results indicate that domestic factors remain an important driver of national inflation.

Under two alternative specifications, the DFM-SV produces different estimates of global inflation - depending on whether regional or income-group factors are considered. Nonetheless, one finding remains robust: about half of the variation in inflation is driven by external factors, and the remaining half is explained by idiosyncratic factors. I further observe that the share of inflation explained by the idiosyncratic factors declines over time (see Figure 9).

5. Spillovers between tradable and non-tradable inflation

In this section, I analyze the time-varying spillovers between tradable and non-tradable inflation. The previous section highlighted that a significant portion of inflation is driven by international common factors, and these factors are present in the dynamics of both traded and non-traded goods. However, a key concern is the potential comovement between the dynamics of tradable and non-tradable inflation, which was not captured previously. This analysis can reveal important transmission mechanisms and spillover effects, enabling more effective and targeted policy responses.

The interconnectedness of tradable and non-tradable inflation across advanced economies, emerging markets, and globally can manifest through various channels. Changes in global commodity prices, typically tradable goods, can spill over into non-tradable sectors (Choi et al. 2018). The complexity of global value chains means price changes in one country's tradable sector can affect both tradable and non-tradable inflation elsewhere (Andriantomanga et al. 2023; Finck and Tillmann, 2022; Carrière-Swallow et al. 2023). Exchange rate fluctuations can affect tradable goods prices directly and non-tradable goods prices indirectly through input costs and wage adjustments (Carrière-Swallow et al. 2023). Understanding these interconnections is crucial for policymakers to anticipate how global economic developments and policy decisions might affect domestic inflation dynamics.

5.1. Methodology: A TVP VAR

Diebold and Yilmaz (2012) propose a framework to study economic spillovers. This methodology has gained significant traction in economics and finance research. Its popularity stems from its straightforward yet powerful framework, which offers an intuitive way to quantify interconnectedness through the analysis of spillover effects (e.g. Antonakakis et al. 2020, 2022; Lovcha and Perez-Laborda, 2020). To analyze spillovers, I follow the methodology in Antonakakis (Chatziantoniou and Gabauer), which extends the framework proposed by Diebold and Yilmaz (2012).[10] In particular, I estimate a TVP-VAR of length one as suggested by the Bayesian information criterion (BIC) as follows:

$$y_t = A_t y_{t-1} + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_t\right) \tag{8}$$

$$\text{vec}\left(A_t\right) = \text{vec}\left(A_{t-1}\right) + \nu_t \qquad \nu_t \sim N\left(\mathbf{0}, R_t\right) \tag{9}$$

where y_t denotes an $N \times 1$ dimensional vector, while $y_{t-\mathbf{1}}$ represents its lagged counterpart. $y_t = (f^{Trad}_{W,t}, f^{Trad}_{AE,t}, f^{Trad}_{EMDE,t}, f^{NTrad}_{W,t}, f^{NTrad}_{AE,t}, f^{NTrad}_{EMDE,t})'$ is a vector of the world, the AE and EMDE factors for both tradable and non-tradable inflation derived from the DFM-SV in Section 4.1. The time-varying coefficient matrix A_t has dimensions $N \times N$. The error term ε_t is an $N \times 1$ dimensional vector with a time-varying variance-covariance matrix Σ_t of size $N \times N$. The vectorized form of A_t, denoted as vec (A_t), depends on its past values vec $(A_{t-\mathbf{1}})$ and an $N^2 \times 1$ dimensional error vector ν_t with an $N^2 \times N^2$ variance-covariance matrix, R_t.

Multiple measures of connectedness can be derived from the GFEVD. These metrics offer diverse perspectives on system interdependencies:

$$TO_{jt} = \sum_{j=1, i\neq j}^{N} \tilde{\phi}_{ij,t}(H) \tag{10}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{N} \tilde{\phi}_{ij,t}(H) \tag{11}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{12}$$

$$TCI_t = \frac{1}{N}\sum_{j=1}^{N} TO_{jt} \equiv \frac{1}{N}\sum_{j=1}^{N} FROM_{jt} \tag{13}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H) \tag{14}$$

First, TO_{jt} represents the aggregated impact a shock in variable j has on all other variables, defined as the *total directional connectedness to others*. $FROM_{jt}$ demonstrates the aggregated influence all other variables have on variable j that is defined as the *total directional connectedness*

Table 3. Averaged connectedness table

	$f^{T}_{W,t}$	$f^{NT}_{W,t}$	$f^{T}_{AE,t}$	$f^{NT}_{AE,t}$	$f^{T}_{EM,t}$	$f^{NT}_{EM,t}$	FROM
Global Factor Tradable $f^{T}_{W,t}$	54.14	6.24	14.34	12.86	9.81	2.61	45.86
Global Factor Non-Tradable $f^{NT}_{W,t}$	26.86	42.14	6.24	10.78	7.04	6.95	57.86
AE Factor Tradable $f^{T}_{AE,t}$	15.76	1.37	59.56	8.61	7.23	7.47	40.44
AE Factor Non-Tradable $f^{NT}_{AE,t}$	38.98	1.69	13.12	28.04	14.13	4.03	71.96
EMDE Factor Tradable $f^{T}_{EMDE,t}$	14.34	5.45	6.11	5.3	63.57	5.24	36.43
EMDE Factor Non-Tradable $f^{NT}_{EMDE,t}$	14.05	3.83	4.68	4.47	5.55	67.42	32.58
Contribution TO others	109.99	18.58	44.49	42.01	43.77	26.3	285.1
NET directional connectedness	64.13	−39.28	4.05	−29.95	7.34	−6.29	TCI

Note: $y_t = (f^{Tr}_{W,t}, f^{Tr}_{AE,t}, f^{Tr}_{EM,t}, f^{NT}_{W,t}, f^{NT}_{AE,t}, f^{NT}_{EM,t})'$ are latent factors derived from a dynamic factor model with stochastic volatility. Spillover metrics are based on the 12-step-ahead generalized forecast error variance decomposition of a TVP VAR model.

from others. NET_{jt} defined as the *net total directional connectedness* determines whether a variable is predominantly a net transmitter or a net receiver of shocks. If variable j is a net transmitter (receiver) of shocks - and hence driving (driven by) the network - it means that the impact of variable j on others is larger (smaller) than the influence all others have on variable j, $NET_{jt} > 0$ ($NET_{jt} < 0$).

TCI_t represents the average impact one variable has on all *others* or all others have on one, defined as the *total connectedness index*. If this measure is relatively high (low) it indicates that the spillover effect is high (low). Finally, $NPDC_{ij,t}$, offers insights at the bilateral level, specifically between variables j and i. The *net pairwise directional connectedness*, $NPDC_{ij,t}$, measures whether variable j is driving variable i or vice versa. If $NPDC_{ij,t} > 0$ ($NPDC_{ij,t} < 0$), variable j is dominating (dominated by) variable i.

5.2. Results

A key insight emerges from this analysis: There is evidence of spillover of tradable inflation to non-tradable inflation, while the reverse effect is mainly muted over the sample. The spillover effect was most pronounced during three major events: the great financial crisis, the sharp decline in oil prices in 2015, and the COVID-19 pandemic. Generally, the global factor of tradable inflation drives this spillover, affecting the global, advanced economy (AE), and EMDE factors of non-tradable inflation. Interestingly, the pandemic period shows a shift in this pattern. During this time, the spillover effect is primarily driven by income-group factors (AE and EMDE) of tradable inflation rather than the global factor. This change indicates a more dispersed and less localized transmission of inflation spillover over time, suggesting a broader and more complex impact of lockdowns, supply chain disruptions, and port congestion.

Table 3 shows the average connectedness over the sample. The results provide evidence of spillover of tradable inflation to non-tradable inflation, while the reverse is muted on average. The main source of spillover is the global factor of tradable inflation, and the main receivers are the global, AE, and EMDE factors of non-tradable inflation. The global factor of tradable inflation substantially contributes to the forecast error variance decomposition of the global, AE, and EMDE factors of non-tradable, respectively, by 26.86%, 38.98%, and 14.05% on average. Conversely, the global factor of non-tradable inflation contributes, on average, by 6.24%, 1.37%, and 5.45% to the variations of the global, AE, and EMDE factors of tradable.

Now, I investigate the dynamics of the spillovers. Figure 10 shows that the TCI index was fairly stable over the sample period. Spillovers account, on average, for 47.5% of the variation in the system. Nonetheless, I observe upward fluctuations in the early 2000s, around the great financial crisis and the oil decline in 2015, but the highest variation occurred over the COVID-19 pandemic, reaching a high of 78% period.

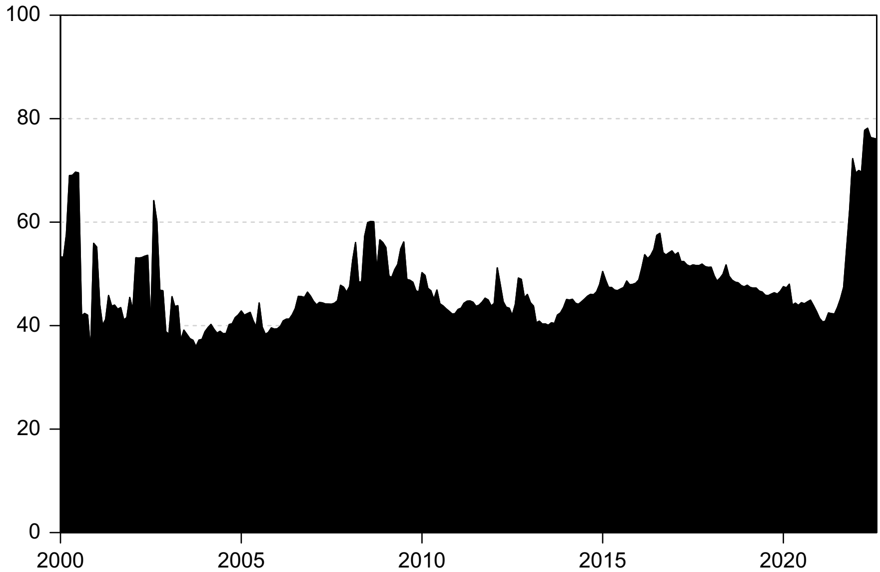

Figure 10. Dynamic total connectedness.
Notes: This figure shows the Net Pairwise Directional Connectedness (NPDC) over the full sample. It examines the bilateral relationship between two variables variables *i* and *j*. Positive (negative) values indicate that variable *i* is driving (being driven) by variable *j*. NPDC metrics are based on the 12-step-ahead generalized forecast error variance decomposition of a TVP VAR model.

Next, I look at the evolution of the Net Total Directional Connectedness. Figure 11 shows that the main source of spillover is the global factor of tradable inflation. Its dynamic shows an increase in spillover after the great financial crisis to peak a few years after the sharp decline in oil prices of 2015 and to gradually decline in the subsequent months. The main receiver, the global factor of non-tradable inflation, displays a notable increase over the pandemic while remaining fairly steady over the whole sample. To further examine such development, it is necessary to look at the Net Pairwise Directional Connectedness of the variables.

The Net Pairwise Directional Connectedness in Figure 12 shows that the global factor of tradable strongly affects the global, AE, and EMDE factor of non-tradable. First, the spillover of the global factor to tradable inflation to the global factor of non-tradable occurs mainly around the great financial crisis and the sharp decline in oil prices, while it seems to be more muted over the pandemic period. Nonetheless, the TCI index suggests that the total spillover in the system was at the highest over the pandemic (see Figure 10). A closer look at Figure 12 reveals that the income group factors have increasingly contributed to the total spillover in the system over the pandemic. The AE and EMDE factors of tradable have influenced the AE and EMDE factors of non-tradable.

6. Effects of us monetary policy on global inflation

This section investigates the influence of an exogenous global financial tightening on global inflation. I use changes in US monetary policy as a proxy for a global financial tightening. First, thanks to highly interconnected financial markets, tightening actions by the US Federal Reserve can influence global interest rates and risk premiums. These adjustments directly impact the cost of borrowing internationally, potentially dampening aggregate demand and inflationary pressures across economies (Miranda-Agrippino and Rey, 2020; Azad and Serletis, 2022; Brauning and Ivashina, 2020; Tillmann, et al. 2019; Georgiadis, 2016). Second, US monetary policy actions can serve as a signal regarding the global economic and inflationary outlook. Consequently, other central banks may implement similar tightening measures, leading to a global financial tightening (Gokmenoglu and Hadood, 2020; Degasperi, et al. 2020; Melosi, 2017).

6.1. Methodology

I estimate the response of global inflation after US monetary policy shocks, following local projections specification in Jordà (2005):

$$y_{t+h} = \alpha^h + \sum_{j=0}^{J} \beta_{hj} mps_{t-j} + \sum_{j=0}^{J} \theta_{hj} x_{t-j} + \sum_{j=0}^{J} \gamma_{hj} y_{t-j} + \epsilon_{t+h} \quad \text{, for} \quad h = 0, \ldots, H, \tag{15}$$

where h is the response horizon in months, y_{t+h} is the global factor for either headline, tradable, or non-tradable inflation from period t to $t+h$. The measure of US monetary policy shock mps_{t-j}, adapted from the work of Bauer and Swanson (2023), is a series of monetary policy surprises identified via high-frequency changes in interest rates around the Federal Open Market Committee (FOMC) announcements. x_{t-j} is a set of controls that account for global factors, including the year-over-year log change in global food and oil prices.

I estimate the local projections for a 25 basis point US monetary policy shock across $h = 0, \ldots, H$ monthly horizons, with $H = 20$, using the ordinary least squares estimator. To control for potential seasonality in the global factor series, the number of lags j is set to 12. I construct the 90 percent confidence intervals for the impulse response functions (IRFs) using the Newey and West (1986) standard errors of the β_{hj} coefficients estimated for each horizon. The estimation sample excludes the COVID-19 pandemic as the monetary policy shock measure adapted from Bauer and Swanson (2023) ends in 20019m12. Nonetheless, the sample is long enough to provide accurate estimates of the impact of US monetary policy on global inflation.

6.2. Results

Panel A of Figure 13 plots the impact of a 25bp increase in US monetary policy on the global inflation factor estimated from a DFM-SV in a sample of 40 countries that excludes the US. For each global inflation factor, including headline, tradable, and non-tradable, I report the impulse

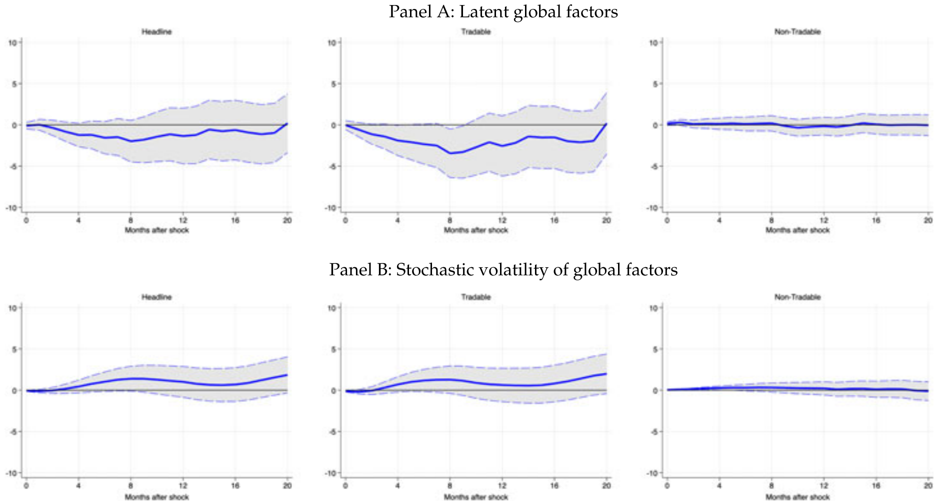

Figure 13. Effects of US monetary policy on global inflation.
Notes: The figure plots the variance decomposition of tradable inflation from 2000m1 to 2022m8 in a sample of 40 countries. The time-varying contributions of the global, income-group, and idiosyncratic factors are respectively represented in red, green, and blue.

response function while controlling for global oil and food prices. I find that US monetary policy has a sizeable, statistically significant, and persistent impact on global inflation. The key finding is that a 25bp shock to US monetary policy causes a persistent decline in global headline inflation, which is primarily driven by the heightened sensitivity of tradable goods, while non-tradable inflation remains unresponsive.

Following a 25bp shock to US monetary policy, the global factor for headline inflation gradually declines from zero to bottom out at −2.5 (equivalent to about 139 percent of the standard deviation of headline inflation's global factor) after 8 months. This impact is persistent as the global factor remains depressed for the next four months before gradually reverting to zero 20 months after the initial shock. The impact on tradable inflation is similar to headline inflation, with a steeper decrease from zero to −3.7 (equivalent to 218 percent of the standard deviation of tradable inflation's global factor) 8 months following the initial shock. Tradable inflation's global factor remains persistently negative in the subsequent months and reverts to zero after 20 months. It must be noted that the magnitude of the impact is larger for tradable inflation suggesting a higher sensitivity of goods traded on the international markets to US monetary policy. Finally, non-tradable inflation is insensitive to US monetary policy as the coefficients are not statistically significant.

Panel B of Figure 13 illustrates the effect of a US monetary policy shock on the volatility of the global factors. In this exercise, I employ the estimated stochastic volatility of the global factor as the dependent variable, consistent with Equation 15. The results show that an increase in US monetary policy will exacerbate the volatility of the global factor. To sum up, while a global financial tightening depresses the global inflation factor, it also increases its volatility.

7. Conclusions

Understanding inflation dynamics across countries and sectors has become crucial in an increasingly interconnected global economy. This paper presents a comprehensive analysis of global inflation, focusing on three interrelated aspects: the synchronization of inflation across countries, the spillover effects from tradable to non-tradable inflation, and the impact of U.S. monetary policy. The study leverages a novel dataset to construct measures of headline, tradable, and nontradable inflation for a panel of 40 countries.

The analysis begins by examining the degree of inflation synchronization across countries. The findings reveal that inflation movements have become more synchronized internationally over time, with a common global factor accounting for about 22 percent of changes in headline inflation rates. This synchronization is increasingly pronounced for non-traded contents, whereas it was previously prominent only for internationally traded goods. The study attributes this shift primarily to the pass-through of global commodity prices, including food and energy, to the prices of goods and services in domestic sectors such as restaurants and housing. Moreover, the degree of synchronization has become more significant among emerging market and developing economies, while it was previously only prominent for advanced economies.

Building on these observations, the analysis then explores the spillover effects between tradable and non-tradable inflation. The study finds evidence of spillover from tradable inflation to non-tradable inflation, while the reverse effect is mainly muted over the sample. This spillover effect was most pronounced during three major events: the Great Financial Crisis, the sharp decline in oil prices in 2015, and the COVID-19 pandemic. Generally, the global factor of tradable inflation drives this spillover, affecting the global, advanced economy (AE), and EMDE factors of non-tradable inflation. Interestingly, the pandemic period shows a shift in this pattern. During this time, the spillover effect is primarily driven by income-group factors (AE and EMDE) of tradable inflation, rather than the global factor.

The final component of the analysis focuses on the impact of U.S. monetary policy on global inflation. The study finds that the impact is sizeable, statistically significant, and persistent.

Specifically, a 25bp shock to US monetary policy causes a persistent decline in global headline inflation, primarily driven by the heightened sensitivity of tradable goods, while non-tradable inflation remains unresponsive. This finding underscores the importance of U.S. monetary policy in shaping global inflation dynamics, particularly through its significant impact on tradable goods.

These results have important policy implications. While individual central banks may have limited scope to address global inflation on their own, a coordinated approach to monetary policy can be more effective. In practice, it requires central banks to align their monetary policies with the shared goal of price stability. By working together, central banks can reduce the risk of their policies having unintended consequences for other countries and the global economy as a whole. For example, if one country raises interest rates too quickly, it could lead to a recession in that country and a slowdown in global economic growth. By coordinating their actions, central banks can avoid this type of outcome by gradually raising interest rates in a synchronized manner.

Additionally, these findings also highlight that policymakers must consider the global context when formulating policies. The high degree of inflation synchronization in traded goods suggests that domestic policies alone may be insufficient to manage inflation effectively. Furthermore, the spillover effects to non-tradable inflation show the need for a comprehensive approach that accounts for both domestic and international factors. Policymakers should also be mindful of the potential global repercussions of U.S. monetary policy decisions, particularly in economies with a high degree of trade and financial integration.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1365100525000240.

Acknowledgments. I am very grateful to Kundan Kishor for his guidance, encouragement, and support throughout this project. I also would like to thank Andrew Lee Smith, Brent Bundick, Amaze Lusompa, Taeyoung Doh, and seminar participants at the Federal Reserve Bank of Kansas City for useful comments and suggestions. I want to express my sincere gratitude to the two anonymous referees for their invaluable insights.

Funding statement. No funding was received to assist with the preparation of this manuscript.

Competing interests. The author declares that there is no conflict of interest.

Data availability. Raw data were generated from the IMF CPI database, Bureau of Labor Statistics website, and Eurostat. Derived data supporting the findings of this study are available from the author on request.

Notes

1 The HICP methodology is used to monitor inflation and compare inflation in the Eurozone. HICP is broken down by goods and services aggregates derived from the European Classification of Individual Consumption according to Purpose (ECOICOP).

2 The twelve CPI components include food, alcohol, clothing, household furnishings, transportation, health, communications, recreation, education, restaurants, and housing. A residual component captures the remaining share of the consumption basket.

3 See Table A1 for the list of countries.

4 Application of Bayesian estimation to dynamic factor models with stochastic volatility in finance and economics include Aguilar and West (2000); Pitt and Shephard (1999); Chib, et al. (2006); Han (2006); Hosszejni and Kastner (2021); Bhatt and Kishor (2022).

5 Countries report to the International Monetary Fund (IMF) and the Organization for Economic Cooperation and Development (OECD) the aggregate all-items index and more detailed indexes and weights for 12 subgroups of consumption expenditure.

6 These measures are calculated following Equation 1. Note that headline inflation is, thus, the weighted average of tradable and non-tradable inflation.
7 For more information on the R-HICP, visit the US Bureau of Labor Statistics website at https://www.bls.gov/cpi/research-series/r-hicp-home.htm. Note that the weights for the years before 2022 are obtained from the Eurostat database.
8 As outlined in Equation 1, each CPI component is the linear combination of a weight and a price series. Although the weights vary over time, I show in a separate exercise that variations in the price series - which are larger than variations in the CPI weights over time - drive inflation synchronization. These results are not included in the paper and are available upon request.
9 In the appendix, I formally quantify the pass-through of global commodity prices to the non-traded components of the consumption basket. In particular, a standard deviation shock to global oil prices increases housing prices by 2.1 percentage points after 16 months. Similarly, a standard deviation shock to global food prices increases restaurant prices by about 1 percentage point after 16 months (See bottom panel of Figure 14).
10 The full methodology is presented in the supplementary material accompanying this paper.

References

Aguilar, O. and M. West. (2000). Bayesian dynamic factor models and portfolio allocation. *Journal of Business & Economic Statistics* 18(3), 338–357.

Albulescu, C. T., R. Demirer, I. D. Raheem and A. K. Tiwari. (2019). Does the US economic policy uncertainty connect financial markets? Evidence from oil and commodity currencies. *Energy Economics* 83, 375–388.

André, C., D. Gabauer and R. Gupta. (2021). Time-varying spillovers between housing sentiment and housing market in the united states. *Finance Research Letters* 42, 101925.

Andriantomanga, Z., M. Bolhuis and S. Hakobyan. (2023). The global supply chain disruptions: Implications for inflation and monetary policy. International Monetary Fund Working Paper.

Antonakakis, N., O. Adekoya, A. Akinseye, I. Chatziantoniou, D. Gabauer and J. A. Oliyide. (2022). Crude oil and Islamic sectoral stocks: asymmetric tvp- var connectedness and investment strategies. Available at SSRN: 4064817.

Antonakakis, N., I. Chatziantoniou, and D. Gabauer. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management* 13(4), 84.

Antonakakis, N., D. Gabauer, R. Gupta and V. Plakandaras. (2018). Dynamic connectedness of uncertainty across developed economies: A time-varying approach. *Economics Letters* 166, 63–75.

Auer, R., C. E. Borio and A. J. Filardo. (2017). The globalisation of inflation: The growing importance of global value chains. CEPR Discussion Paper No. DP11905.

Auer, R. A., A. A. Levchenko and P. Sauré. (2019). International inflation spillovers through input linkages. *Review of Economics and Statistics* 101(3), 507–521.

Azad, N. F. and A. Serletis. (2022). Spillovers of US monetary policy uncertainty on inflation targeting emerging economies. *Emerging Markets Review* 51, 100875.

Bauer, M. D. and E. T. Swanson. (2023). A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual* 37(1), 87–155.

Benigno, G., J. Di Giovanni, J. J. Groen and A. I. Noble. (2022). *The gscpi: A new barometer of global supply chain pressures*. FRB of New York Staff Report no. 1017.

Berg, A., R. Meyer and J. Yu. (2004). Deviance information criterion for comparing stochastic volatility models. *Journal of Business & Economic Statistics* 22(1), 107–120.

Bernanke, B. and A. S. Blinder. (1992). The federal funds rate and the channel of monetary transmission. *The American Economic Review* 82(4), 901–921.

Bhatt, V. and N. K. Kishor. (2022). (a) synchronous housing markets of global cities. *The Journal of Real Estate Finance and Economics*, 1–31. https://link.springer.com/article/10.1007/s11146-022-09903-2#citeas

Bobeica, E. and M. Jarociński. (2019). Missing disinflation and missing inflation: A var perspective. 57th issue (March 2019) of the International Journal of Central Banking.

Brauning, F. and V. Ivashina. (2020). US monetary policy and emerging market credit cycles. *Journal of Monetary Economics* 112, 57–76.

Brauning, F. and V. Sheremirov. (2021). US monetary policy and international risk spillovers. *Journal of International Economics* 133, 103541.

Ca'Zorzi, M., L. Dedola, G. Georgiadis, M. Jarocinski, L. Stracca and G. Strasser. (2020). Monetary policy and its transmission in a globalised world.

Carrière-Swallow, Y., M. Firat, D. Furceri and D. Jiménez. (2023). State-dependent exchange rate pass-through. IMF Working Paper.

Chib, S., F. Nardari and N. Shephard. (2006). Analysis of high dimensional multi- variate stochastic volatility models. *Journal of Econometrics* 134(2), 341–371.

Choi, S., D. Furceri, P. Loungani, S. Mishra and M. Poplawski-Ribeiro. (2018). Oil prices and inflation dynamics: Evidence from advanced and developing economies. *Journal of International Money and Finance* 82, 71–96.

Ciccarelli, M. and B. Mojon. (2010). Global inflation. *The Review of Economics and Statistics* 92(3), 524–535.

Degasperi, R., S. Hong and G. Ricco. (2020). The global transmission of US monetary policy. CEPR Discussion Paper No. DP14533.

Del Negro, M. and C. Otrok. (2008). Dynamic factor models with time-varying parameters: Measuring changes in international business cycles. FRB of New York Staff Report (326).

Di Giovanni, J. and J. Rogers. (2024). The impact of US monetary policy on foreign firms. *IMF Economic Review* 72(1), 58–115.

Diebold, F. X. and K. Yilmaz. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting* 28(1), 57–66.

Ehrmann, M. and M. Fratzscher. (2009). Global financial transmission of monetary policy shocks. *Oxford Bulletin of Economics and Statistics* 71(6), 739–759.

Eo, Y. and C.-J. Kim. (2016). Markov-switching models with evolving regime- specific parameters: are postwar booms or recessions all alike? *Review of Economics and Statistics* 98(5), 940–949.

Finck, D. and P. Tillmann. (2022). The macroeconomic effects of global supply chain disruptions. BOFIT Discussion Papers.

Förster, M. and P. Tillmann. (2014). Reconsidering the international comovement of inflation. *Open Economies Review* 25(5), 841–863.

Georgiadis, G. (2016). Determinants of global spillovers from US monetary policy. *Journal of international Money and Finance* 67, 41–61.

Gokmenoglu, K. K. and A. A. A. Hadood. (2020). Impact of US unconventional monetary policy on dynamic stock-bond correlations: Portfolio rebalancing and signalling channel effects. *Finance Research Letters* 33, 101185.

Ha, J., M. A. Kose and F. Ohnsorge. (2023). One-stop source: A global database of inflation. *Journal of International Money and Finance* 137, 102896.

Hakkio, C. S. (2009). Global inflation dynamics. Federal Reserve Bank of Kansas City Working Paper (09-01).

Han, Y. (2006). Asset allocation with a high dimensional latent factor stochastic volatility model. *The Review of Financial Studies* 19(1), 237–271.

Hosszejni, D. and G. Kastner. (2021). Modeling univariate and multivariate stochastic volatility in R with stochvol and factorstochvol. *Journal of Statistical Software* 100, 1–34.

Jašová, M., R. Moessner and E. Takáts. (2020). Domestic and global output gaps as inflation drivers: What does the Phillips curve tell? *Economic Modelling* 87, 238–253.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review* 95(1), 161–182.

Kabukçuoğlu, A. and E. Martínez-García. (2018). Inflation as a global phenomenon—some implications for inflation modeling and forecasting. *Journal of Economic Dynamics and Control* 87, 46–73.

Kalemli-Özcan, S. (2019). *US monetary policy and international risk spillovers*, National Bureau of Economic Research.

Kim, S. (2001). International transmission of US monetary policy shocks: Evidence from VAR's. *Journal of monetary Economics* 48(2), 339–372.

Komaromi, A., M. D. A. Cerdeiro and Y. Liu. (2022). *Supply chains and port congestion around the world*. International Monetary Fund.

Kose, M. A., C. Otrok and C. H. Whiteman. (2003). International business cycles: World, region, and country-specific factors. *american economic review* 93(4), 1216–1239.

LaBelle, J. and A. M. Santacreu. (2022). Global supply chain disruptions and inflation during the COVID-19 pandemic. Federal Reserve Bank of St. Louis Review.

Lane, W. (2006). Comparing us and european inflation: The CPI and the HICP. *Monthly Labor Review* 129, 20.

Lovcha, Y. and A. Perez-Laborda. (2020). Dynamic frequency connectedness between oil and natural gas volatilities. *Economic Modelling* 84, 181–189.

Melosi, L. (2017). Signalling effects of monetary policy. *The Review of Economic Studies* 84(2), 853–884.

Miranda-Agrippino, S. and H. Rey. (2020). US monetary policy and the global financial cycle. *The Review of Economic Studies* 87(6), 2754–2776.

Mumtaz, H. and P. Surico. (2012). Evolving international inflation dynamics: World and country-specific factors. *Journal of the European Economic Association* 10(4), 716–734.

Newey, W. K. and K. D. West. (1986). A simple, positive semi-definite, heteroskedas- ticity and autocorrelation consistent covariance matrix. National Bureau of Economic Research Cambridge, MA.

Obstfeld, M., J. D. Ostry and M. S. Qureshi. (2018). Global financial cycles and the exchange rate regime: A perspective from emerging markets. *AEA Papers and Proceedings* 108, 499–504.

Parker, M. (2018). How global is "global inflation"? *Journal of Macroeconomics* 58, 174–197.

Rey, H. (2015). *Dilemma not trilemma: the global financial cycle and monetary policy independence*, National Bureau of Economic Research.

Spiegelhalter, D. J., N. G. Best, B. P. Carlin and A. Van Der Linde. (2002). Bayesian measures of model complexity and fit. *Journal of the royal statistical society: Series b (statistical methodology)* 64(4), 583–639.

Szafranek, K. (2017). Flattening of the New Keynesian Phillips curve: Evidence for an emerging, small open economy. *Economic Modelling* 63, 334–348.
Szafranek, K. (2021). Evidence on time-varying inflation synchronization. *Economic modelling* 94, 1–13.
Szafranek, K. and A. Hałka. (2019). Determinants of low inflation in an emerging, small open economy through the lens of aggregated and disaggregated approach. *Emerging Markets Finance and Trade* 55(13), 3094–3111.
Tillmann, P., G.-Y. Kim and H. Park. (2019). The spillover effects of US monetary policy on emerging market economies. *International Journal of Finance & Economics* 24(3), 1313–1332.

Appendix A.

A.1. Appendix graphs

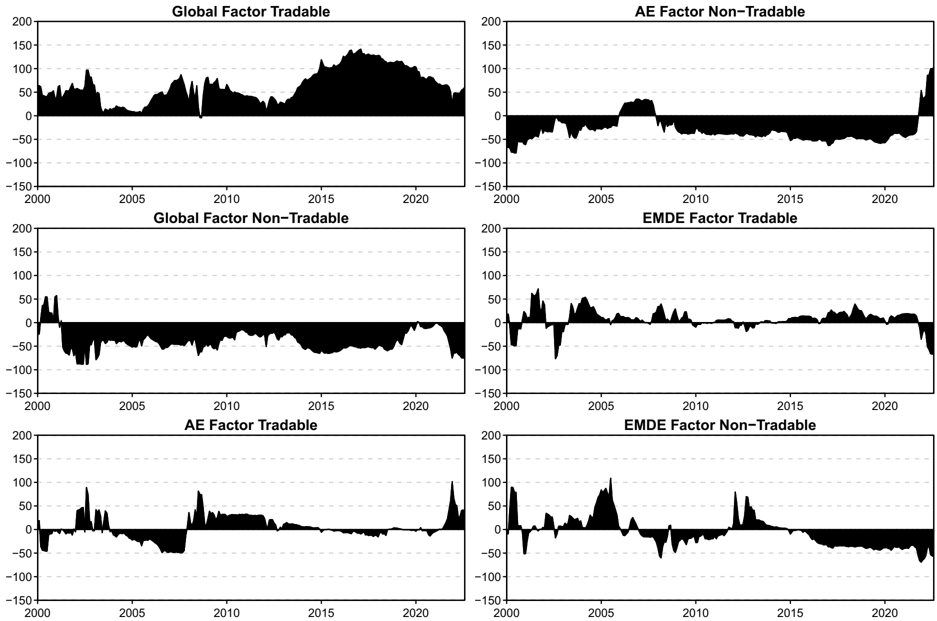

Figure 11. Net total directional connectedness.
Note: The figure plots the impact of a one standard deviation shock to global oil (solid blue) and food (dashed red) prices on disaggregated components of CPI. The solid blue line is the impulse response function (IRF); the gray-shaded region represents the 90 percent confidence band. The impulse response functions are obtained following Jordà (2005)'s local projection methods. The sample consists of 40 countries from 2000m1 to 2022m8. t=0 indicates the month of the shock.

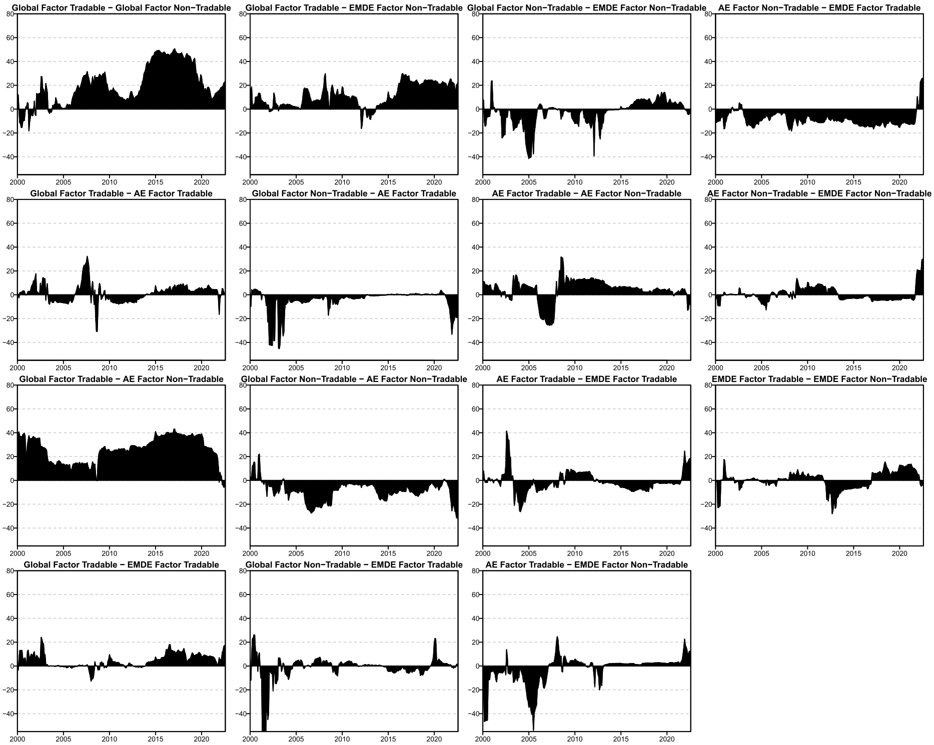

Figure 12. Net pairwise directional connectedness.
Notes: The figure plots the variance decomposition of headline inflation from 2000m1 to 2022m8 in a sample of 40 countries. The time-varying contributions of the global, income-group, and idiosyncratic factors are respectively represented in red, green, and blue.

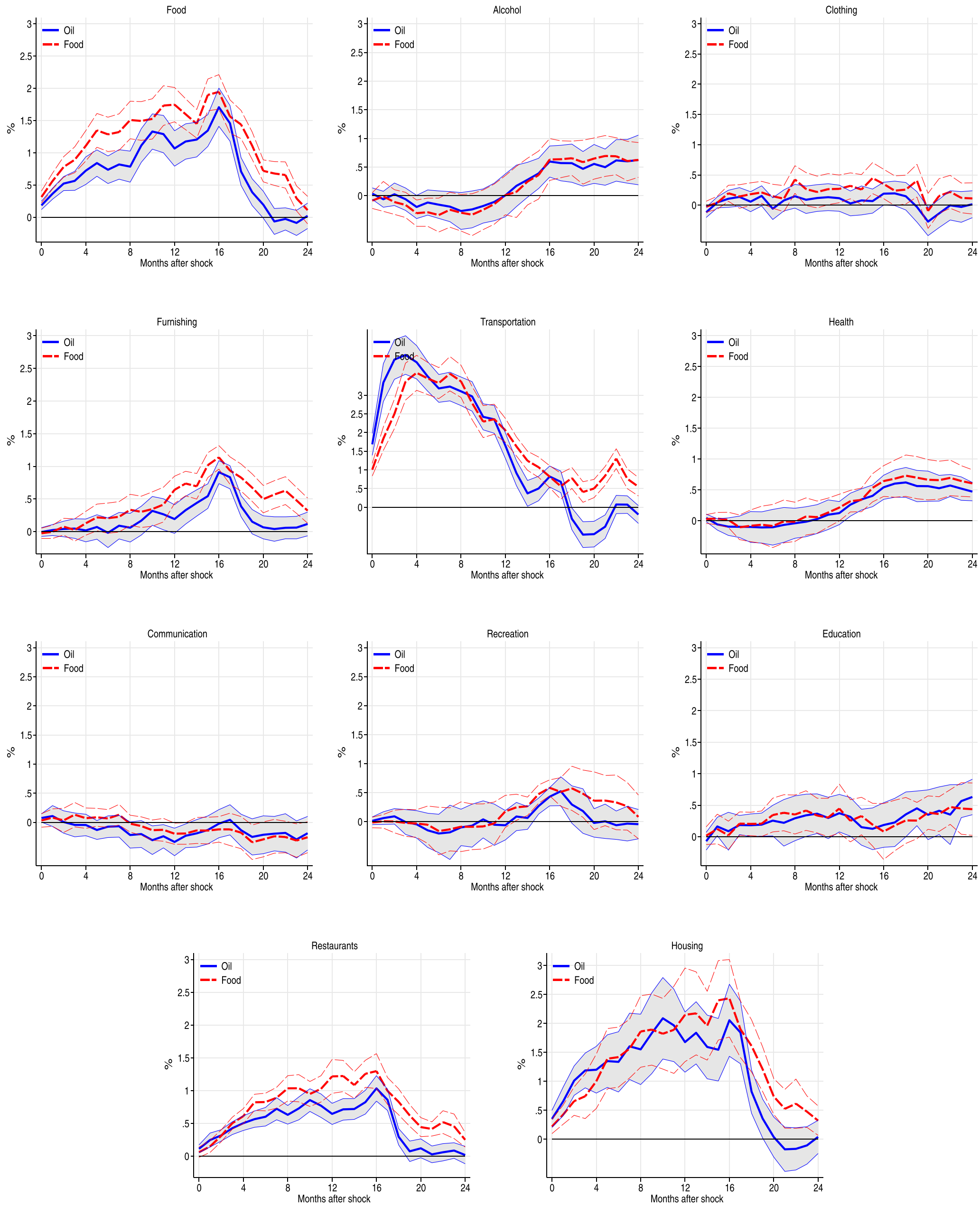

Figure 14. Passthrough of global commodity prices to disaggregated CPI.
Notes: The figure plots the variance decomposition of non-tradable inflation from 2000m1 to 2022m8 in a sample of 40 countries. The time-varying contributions of the global, income-group, and idiosyncratic factors are respectively represented in red, green, and blue.

A.2. Appendix tables

Table A1. Economies

Country	N	Start	End	Country	N	Start	End
Austria	272	2000m1	2022m8	Korea, Rep.	272	2000m1	2022m8
Belgium	272	2000m1	2022m8	Kosovo	272	2000m1	2022m8
Bulgaria	272	2000m1	2022m8	Latvia	272	2000m1	2022m8
Chile	272	2000m1	2022m8	Lithuania	272	2000m1	2022m8
Croatia	272	2000m1	2022m8	Luxembourg	272	2000m1	2022m8
Czech Republic	272	2000m1	2022m8	Netherlands	272	2000m1	2022m8
Côte d'Ivoire	272	2000m1	2022m8	North Macedonia	272	2000m1	2022m8
Denmark	272	2000m1	2022m8	Norway	272	2000m1	2022m8
Dominican Republic	272	2000m1	2022m8	Oman	272	2000m1	2022m8
Estonia	272	2000m1	2022m8	Poland	272	2000m1	2022m8
Finland	272	2000m1	2022m8	Portugal	272	2000m1	2022m8
France	272	2000m1	2022m8	Singapore	272	2000m1	2022m8
Germany	272	2000m1	2022m8	Spain	272	2000m1	2022m8
Ghana	272	2000m1	2022m8	Sweden	272	2000m1	2022m8
Greece	272	2000m1	2022m8	Thailand	272	2000m1	2022m8
Hungary	272	2000m1	2022m8	Togo	272	2000m1	2022m8
Iceland	272	2000m1	2022m8	Ukraine	272	2000m1	2022m8
Ireland	272	2000m1	2022m8	United Kingdom	272	2000m1	2022m8
Israel	272	2000m1	2022m8	United States	272	2000m1	2022m8
Italy	272	2000m1	2022m8	Uruguay	272	2000m1	2022m8

Note: Total = 40 countries.

Table A2. Data sources

IMF CPI Database ID	Description	Sources
PCPIFBT_IX	Alcohol, Price Index	IMF CPI Database
PCPIFBT_WT	Alcohol, Weight	IMF CPI Database
PCPIA_IX	Clothing, Price Index	IMF CPI Database
PCPIA_WT	Clothing Weight	IMF CPI Database
PCPIEC_IX	Communication, Price Index	IMF CPI Database
PCPIEC_WT	Communication, Weight	IMF CPI Database
PCPIED_IX	Education, Price Index	IMF CPI Database
PCPIED_WT	Education, Weight	IMF CPI Database
PCPIF_IX	Food, Price Index	IMF CPI Database
PCPIF_WT	Food, Weight	IMF CPI Database
PCPIHO_IX	Furnishings, Price Index	IMF CPI Database
PCPIHO_WT	Furnishings, Weight	IMF CPI Database

Table A2. (Continued)

IMF CPI Database ID	Description	Sources
PCPIM_IX	Health, Price Index	IMF CPI Database
PCPIM_WT	Health, Weight	IMF CPI Database
PCPIH_IX	Housing, Price Index	IMF CPI Database
PCPIH_WT	Housing, Weight	IMF CPI Database
PCPIO_IX	Miscellaneous, Price Index	IMF CPI Database
PCPIO_WT	Miscellaneous, Other	IMF CPI Database
PCPIR_IX	Recreation, Price Index	IMF CPI Database
PCPIR_WT	Recreation, Weight	IMF CPI Database
PCPIRE_IX	Restaurants, Price Index	IMF CPI Database
PCPIRE_WT	Restaurants and hotels, Weight	IMF CPI Database
PCPIT_IX	Transport, Price Index	IMF CPI Database
PCPIT_WT	Transport, Weight	IMF CPI Database

Notes: Price Index for the USA available on the BLS website at https://www.bls.gov/cpi/research-series/r-hicp-home.htm Weights for the USA available on the Eurostat data browser at https://ec.europa.eu/eurostat/databrowser/view/prc_hicp_inwcustom_13308022/default/table?lang=en.

Table A3. Factor loadings (Full sample)

	Headline			Tradable			Non-tradable		
Code	Global	AE	EMDE	Global	AE	EMDE	Global	AE	EMDE
AUT	0.47	0.49	0.00	0.56	0.28	0.00	0.04	0.57	0.00
BEL	0.57	0.00	0.00	0.62	0.24	0.00	0.04	0.69	0.00
BGR	0.52	0.00	0.18	0.46	0.00	0.17	0.45	0.00	0.13
CHL	0.75	−0.14	0.00	0.51	0.36	0.00	0.30	0.29	0.00
CIV	0.50	0.00	0.22	0.32	0.00	0.01	0.54	0.00	−0.02
HRV	0.67	0.23	0.00	0.57	0.22	0.00	0.62	0.27	0.00
CZE	0.44	−0.06	0.00	0.34	0.91	0.00	0.33	0.48	0.00
DNK	0.55	0.21	0.00	0.60	−0.07	0.00	0.41	0.50	0.00
DOM	0.26	0.00	0.15	0.25	0.00	0.13	0.69	0.00	−0.12
EST	0.52	0.02	0.00	0.49	0.43	0.00	0.26	0.53	0.00
FIN	0.60	−0.02	0.00	0.55	0.21	0.00	0.35	0.47	0.00
FRA	0.67	0.42	0.00	0.69	0.02	0.00	0.27	0.55	0.00
DEU	0.41	0.01	0.00	0.50	0.32	0.00	0.00	0.60	0.00
GHA	0.05	0.00	0.28	0.07	0.00	0.31	0.81	0.00	−0.22
GRC	0.61	0.66	0.00	0.59	−0.29	0.00	0.49	0.47	0.00
HUN	0.40	0.31	0.00	0.74	−0.11	0.00	0.80	0.00	0.00

Table A3. (Continued)

	Headline			Tradable			Non-tradable		
ISL	0.38	−0.45	0.00	0.36	−0.44	0.00	0.61	−0.10	0.00
IRL	0.44	0.58	0.00	0.58	−0.38	0.00	0.37	0.31	0.00
ISR	0.41	−0.48	0.00	0.59	−0.65	0.00	0.13	0.10	0.00
ITA	0.62	0.45	0.00	0.65	−0.14	0.00	0.61	0.30	0.00
KOR	0.56	−0.01	0.00	0.50	−0.07	0.00	0.93	0.10	0.00
UVK	0.31	0.00	−0.11	0.23	0.00	0.03	0.00	0.00	0.35
LVA	0.42	0.92	0.00	0.46	0.10	0.00	0.17	0.45	0.00
LTU	0.33	0.00	0.00	0.38	0.70	0.00	0.15	0.55	0.00
LUX	0.63	0.21	0.00	0.58	0.00	0.00	0.26	0.56	0.00
NLD	0.48	−0.33	0.00	0.48	0.16	0.00	0.28	0.27	0.00
MKD	0.40	0.00	0.06	0.37	0.00	−0.01	0.65	0.00	0.13
NOR	0.09	−0.48	0.00	−0.16	0.70	0.00	0.12	0.20	0.00
OMN	0.28	−0.64	0.00	0.27	0.34	0.00	0.52	−0.10	0.00
POL	0.64	0.57	0.00	0.57	0.42	0.00	0.16	0.59	0.00
PRT	0.53	0.84	0.00	0.65	−0.41	0.00	0.74	0.12	0.00
SGP	0.56	−0.62	0.00	0.39	0.41	0.00	0.46	0.07	0.00
ESP	0.70	0.71	0.00	0.67	−0.23	0.00	0.63	0.40	0.00
SWE	0.67	0.44	0.00	0.23	0.56	0.00	0.01	0.63	0.00
THA	0.55	0.00	−0.04	0.65	0.00	0.08	−0.39	0.00	0.36
TGO	0.32	0.00	0.14	0.15	0.00	0.25	0.27	0.00	0.08
UKR	0.02	0.00	0.05	0.11	0.00	0.22	0.32	0.00	−0.21
GBR	0.32	−0.47	0.00	0.45	0.42	0.00	0.01	0.63	0.00
USA	0.51	0.17	0.00	0.52	0.14	0.00	0.57	0.27	0.00
URY	0.00	0.05	0.00	−0.03	0.20	0.00	0.10	−0.05	0.00

Notes: This table presents the posterior mean of the factor loadings β for headline, tradable and non-tradable inflation.

Cite this article: Andriantomanga Z (2025). "Are inflation movements global in nature?." *Macroeconomic Dynamics* **29**(e97), 1–31. https://doi.org/10.1017/S1365100525000240