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Global drivers of inflation: The role of supply chain disruptions and commodity price shocks[☆]

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ABSTRACT

The determinants of inflation rates have been extensively studied with no clear consensus. Recent research highlights the growing influence of global supply factors, notably supply chain disruptions and commodity price shocks. This paper analyzes the changing impact of these global supply chain disruptions and commodity price shocks, compared to demand shocks, on inflation rates in Germany, Japan, the U.K., and the U.S. from 1998 to 2022. The findings reveal that since the mid-2010s, supply shocks have become the predominant drivers of inflation. After the Global Financial Crisis, commodity price shocks significantly affected inflation in Germany, the U.K., and the U.S., while the influence of global supply chain disruptions on inflation in all four countries surged following the COVID-19 pandemic.

1. Introduction

Supply chain bottlenecks suffered in the aftermath of the COVID-19 shock and the recent energy crisis that followed Russia's invasion of Ukraine have triggered significant increases in inflation rates worldwide. According to the global supply chain pressure index (GSCP) by Benigno et al. (2022), disruptions that began in April 2020 waned in October but remounted to a maximum peak by December 2021. On the other hand, the great dependence of EU countries on Russian energy and the EU decision to cut out Russian energy imports as much as possible, have been followed by pronounced rises in energy prices. By the end of the first quarter of 2022, crude oil prices had doubled, coal prices tripled, and natural gas prices increased more than five-fold relative to early 2021 (IMF, 2022). Other commodities also experienced price surges, particularly due to the standing of Ukraine as a major agricultural exporter. Following these events, annual inflation rates in the U.S., the U.K., and Germany rose to 8.1%, 9.1%, and 8.5% in October 2022, while inflation in Japan remained at 2% (OECD, 2022). In particular, inflation driven by global supply shocks, such as these, constitutes a great concern, given the increased risk of stagflation and the fact that monetary policy acts through demand channels to stabilize inflation. Moreover, the global nature of these shocks implies that their effects are more difficult to control with domestic policies.

This context of high and diverse inflation rates, therefore, begs several questions of interest; i.e., (i) have global supply shocks become more relevant for inflation rates in major economies? (ii) what is the magnitude and persistence of the effect of global supply chain disruptions and commodity price shocks on inflation?; (iii) which commodities present a prime concern for policymakers in terms of controlling inflation?; (iv) what explains such a diverse behavior of Japanese inflation given the global nature of these shocks? This paper addresses these questions by estimating the differential impact of global supply chain disruptions and commodity price shocks in Germany, Japan,

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the U.K., and the U.S. Not only can these countries be considered a geographically diverse representation of developed economies, but each country has its own currency and monetary policy stance for the stabilization of inflation. We, therefore, examine the magnitude and persistence of the inflationary effects of global supply shocks by means of a structural vector autoregressive (SVAR) model estimated for each economy over the period 1998–2022. The main contribution of this paper is, therefore, that it estimates the time-varying percentage of these four countries' inflation rates explained by these shocks, and does so for a long time span including major episodes, such as the Global Financial Crisis, the Brexit or the COVID-19 pandemic.

Regarding global supply chain disruptions, the literature has focused on bottlenecks generated in maritime transportation, due to the fact that 80% of international trade is conducted through sea transport. This has given rise to two main methods for identifying such shocks. Kilian et al. (2023) construct a monthly indicator of the volume of container trade to and from North America, the North American Container Trade Index (NACTI), and identify shocks to the global supply chain as changes in container trade that cannot be explained by shifts in U.S. aggregate domestic and foreign demand (measured through personal consumption and manufacturing industrial production). Diaz et al. (2023) employ this approach, extending the model by Kilian et al. (2023) to estimate the impact of both commodity price and global supply chain shocks on U.S. inflation rates, and find that inflation is significantly affected by both exogenous shocks. An alternative approach is presented by Benigno et al. (2022), who estimate the co-movement of several cross-country and global indicators of supply chain pressures, to propose a novel indicator, the Global Supply Chain Pressure (GSCP) index.[1] Based on this index, di Giovanni et al. (2022) find that global supply chain bottlenecks played a significant role in inflation rates in the U.S. and, especially, in the euro area, over 2020 and 2021. Also, Finck and Tillman (2022) estimate the impact of global supply chain shocks on the euro area business cycle and find that a global supply chain shock causes a drop in euro area real economic activity and an increase in consumer prices.[2] However, the global nature of the supply chain suggests that inflationary effects are likely to be transmitted worldwide, expecting similar effects for regions other than the euro area and the U.S., such as Japan and the U.K.

Moreover, a properly functioning supply chain relies not only on transportation but on the availability of input materials for the production process. In terms of a global supply chain, commodities are the main input for a wide range of industries across the globe. A supply shock in a commodity market, such as a geopolitical event, therefore, also represents a disruption to the distribution chain, where the resulting price increase will not only drive inflation higher but also depress economic activity. There is, in particular, vast literature documenting the significant impact of energy prices on inflation rates (i.e., Hooker, 2002; Blanchard and Gali, 2010; Kilian, 2009; Baumeister and Peersman, 2013; Baumeister and Kilian, 2016; Gelos and Ustyugova, 2017; Kilian, 2019; Garzon and Hierro, 2021; Kumar and Mallick, 2024). Additional empirical studies investigate the inflationary impact of other commodity prices (i.e., Mallick and Sousa, 2013; Chen et al., 2014; Furceri et al., 2016; Garratt and Petrella, 2022). It is, therefore, of interest for academics as well as policymakers, to identify the commodities that are the main drivers of imported stagflation in an economy. Particularly, as stated in Diaz et al. (2023), one must consider the time-varying importance of each commodity for inflation, given potential structural changes in an economy, including the introduction of policies for the energy transition. Moreover, despite the global nature of commodity markets, it is not clear whether this time-varying relevance is the same for all economies given the geographical and structural differences between countries. We, therefore, follow (Diaz et al., 2023) in estimating a time-varying Cost-Push Commodity (CPC) factor, and do so for each country, by recursively selecting, through a genetic algorithm, the combination of commodity prices that best explains domestic inflation over time. Notedly, each CPC factor will be constructed with commodity prices that generate inflation that is not pulled by demand, but rather pushed by supply.

We then estimate an SVAR model that includes the GSCP (Benigno et al., 2022), the CPC factor, and inflation for each country. Additionally, we account for demand shocks (industrial production, monetary policy, trade balance ratios, financial conditions), given the finding of Kabaca and Tuzcuoglu (2023) that, not only supply shocks but changes in demand were a main driver of inflation during the recovery of the COVID-19 pandemic. Finally, considering the nature of Germany, Japan, and the U.K. as small open economies, we also control for real exchange rate shocks. Do note that we focus on relative price changes (supply and demand shocks) that get counted into aggregate price level changes, and do not control for how monetary factors (inflation expectations and budget deficits), which also cause commodity price changes (Benk and Gillman, 2023), drive aggregate inflation over time.

The main contributions of the paper will, consequently, include the following. First, this paper considers a long time span, from 1998 to 2022, which will allow us to identify the average and time-varying impacts of commodity price shocks and supply chain pressures on each country's inflation rates over the entire period. Second, we construct a CPC factor for each of the countries with time-varying weights on commodities, which will allow us to determine the relative importance of the price of each commodity in explaining the inflation rates in each country. Third, we complement the recent study by Hall et al. (2023) where, instead of covering the drivers of the recent inflation in three currency areas (namely the U.S., the euro area, and the U.K.) we also add a fourth relevant Asian currency area represented by the Japanese economy. We also complement and extend previous very related empirical studies, such as those of di Giovanni et al. (2022), Finck and Tillman (2022), and Diaz et al. (2023). Moreover, we compare the time-varying percentage contribution of supply and demand shocks on each of these four countries' inflation rates. Finally, important policy implications will be derived from the results.

Our main results suggest that supply shocks, rather than demand shocks, have become the main drivers of inflation in these four economies since the mid-2010s, increasing the risk of stagflation. In particular, supply chain disruptions have had significant and permanent effects on inflation rates in the U.S., the U.K., and Germany after the COVID-19 pandemic, although not in Japan. In the case of Japan, demand shocks were the main drivers of inflation rates until the COVID-19 pandemic, while commodity price shocks were the key contributors to inflation after the pandemic. Furthermore, while commodity price shocks have only transitory effects on inflation rates, their increased importance for inflation, relative to demand shocks, suggests that global supply shocks are likely to continue to pose an inflationary risk for domestic economies.

The remainder of the paper is structured as follows. Section 2 describes the methodology to construct the CPC factor for each of the four economies. Section 3 presents the SVAR model used in the empirical analysis, Section 4 presents a discussion of the results, and Section 5 develops a series of robustness checks. Finally, Section 6 contains concluding comments and policy implications.

2. Estimation of the cost-push commodity factors

We begin by estimating the commodity factors that best explain supply-driven inflation in each of the four countries; that is, fluctuations

[1] This indicator contains information on 27 variables, including delays in shipments, the cost of shipping and air transportation, and country-level (including countries in the euro area, China, Japan, South Korea, Taiwan, the U.K., and the U.S.) manufacturing data.

[2] Also, recently, Isaacson and Rubintson (2023) studied the pass-through of shipping costs to U.S. import price inflation using variation across products in exposure to shipping price increases. However, their empirical findings suggest that the pass-through of shipping costs is small.

Table 1
Variable description and sources.

Name	Description	Source
Inflation	Year-to-year percentage change of CPI for all items, for each country	FRED Economic Data (Federal Reserve Bank of St. Louis)
Commodity prices	Real commodity prices (deflated by each country's CPI), log-linearly detrended	World Bank
GSCP	Global supply chain pressure index	Federal Reserve Bank of New York
Credit spread	Market yield on U.S. Treasury securities at 10-year constant maturity, quoted on an investment basis	FRED Economic Data (Federal Reserve Bank of St. Louis)
Economic activity	Industrial production index for each country, seasonally adjusted, log-linearly detrended	FRED Economic Data (Federal Reserve Bank of St. Louis)
Trade ratio	Net international trade, value in goods, in national currency, over industrial production	OECD
Real effective exchange rate	Real effective exchange rate, broad basket, for the euro area, Japan, and the U.K.	Bank for International Settlements
Shadow rate	Euro Area (Wu and Xia, 2016) shadow rate Japan (Ikeda et al., 2024) shadow rate U.K. Wu and Xia (2016) shadow rate U.S. Wu and Xia (2016) shadow rate	Author's personal website Author's personal website Author's personal website Author's personal website

in inflation rates, π, after accounting for changes in demand (measured through industrial production, IP; trade ratio, TR; monetary policy shadow rate, R; and the credit spread, CS), as well as controlling for global supply chain disruptions, $GSCP$, and the real effective exchange rate, $REER$.[3]

Table 1 shows a description of all variables and sources. We use the GSCP proposed by Benigno et al. (2022) to measure global supply chain disruptions. Notedly, while the NACTI (Kilian et al., 2023) is only available until April 2021 and is based on maritime trade activity in the U.S. and Canada, the GSCP is available for the full sample and constructed based on supply chain pressures across a wide variety of countries. Also, while industrial production serves as a monthly proxy for domestic economic activity in each country, the inclusion of the real effective exchange rate and the trade balance ratio becomes necessary due to the nature of Germany, Japan, and the U.K. as open economies. Additionally, given recent literature that shows that U.S. monetary policy and financial conditions are determinants of international macroeconomic fluctuations (Miranda-Agrippino and Rey, 2022), the shadow rates for each country as well as the U.S. credit spread are included as control variables.[4] However, we do not consider any measures of inflation expectations or budget deficits, as the paper focuses on supply and demand effects on inflation.

[3] This is only considered for Germany, Japan, and the U.K. For the U.S., the real effective exchange rate is excluded given that commodity prices are already quoted in USD.

[4] Given the lack of availability of the GZ credit spread by Gilchrist and Zakrajšek (2012) for our spanned sample, we alternatively employ the market yield on 10-year U.S. Treasury securities. This variable is also implemented by Gordon and Clark (2023) as a control in examining the effects of global supply chain disruptions on inflation.

We define the CPC factor, f_t, for a given country, through the following factor model:

$$x_{it} = \lambda_i f_t + e_{it} \quad \forall\, i \ni \{1,\dots,n_s\} \tag{1}$$

where x_{it} is the log-level of the real price of commodity i at time t, λ_i is a loading factor, e_{it} is an error term, and n_s is the total number of commodities selected as determinants of each of the inflation rates. Eq. (1) is estimated using Principal Component Analysis (PCA), where f_t is the first principal component.

Note that, through PCA estimation, the CPC factor, f_t, is constructed as a weighted average of the selected commodities, where assigned weights (λ_i^2) are higher for those commodities i that drive most of the movements of all the selected commodity prices.

2.1. Selection of commodities

For the selection of commodities, as in Diaz and Perez-Quiros (2021) and Diaz et al. (2023), we begin by defining A_q as a binary vector of size $1 \times n$, where n is the total number of all available commodity price series, such that

$$A_q = (a_{1q}, a_{2q}, \dots, a_n) \tag{2}$$

whose elements a_{iq} take the value 1 when commodity i is selected for the estimation of the CPC factor, and 0, otherwise.

This implies that for any A_q, an original data set of all commodity price series of size $T \times n$ is reduced by eliminating all columns i, where $a_{iq} = 0$. We define the resulting data set as X_q, which is a matrix of size $T \times n_{sq}$, containing the standardized log-levels of the real prices of commodities i for which $a_{iq} = 1$, and where n_{sq} equals the total of all $a_{iq} = 1$. We then perform PCA on matrix X_q and define its first principal component as f_q. The commodity factor, f_q, is, therefore, a function of A_q such that $f_q(A_q)$.

We are searching for the commodity factor, f_q, that best explains inflation, π, in each of the four countries after accounting for changes in the control variables, such that

$$\pi_t = \mu + \sum_{j=1}^{p} \theta_j y_{qt-j} + \epsilon_t \tag{3}$$

where μ is a constant, θ_j represents the response of π_t, at time t, to y_{qt-j} at all p lags, $y_{qt} = [IP_t, f_{qt}(A_q), GSCP_t, TR_t, R_t, CS_t, REER_t, \pi_t]$, and ϵ_t is an error term. Eq. (3) is estimated through Ordinary Least Squares (OLS), allowing the error term to be defined as a function of A_q, such that $\epsilon_t(A_q)$. We therefore define our optimization problem as

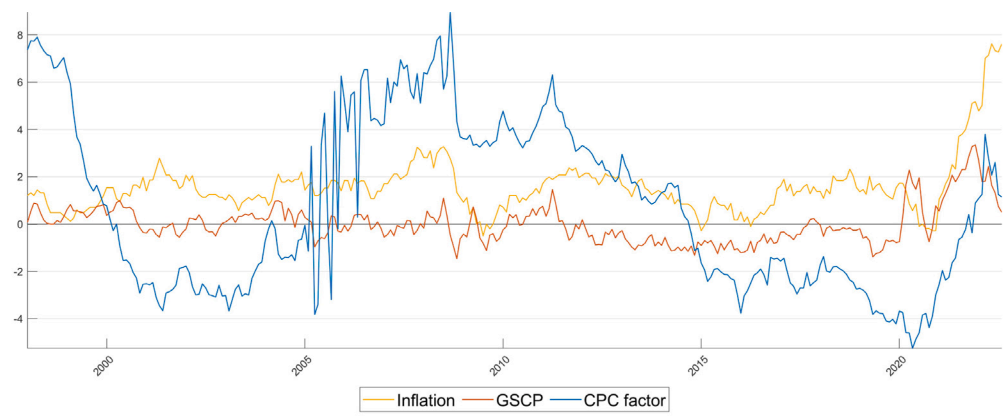
$$\min_{A_q} \quad \sum_t \epsilon_t^2(A_q) \tag{4}$$

where we minimize the sum of squared errors resulting from the estimation of Eq. (3), by selecting A_q.[5]

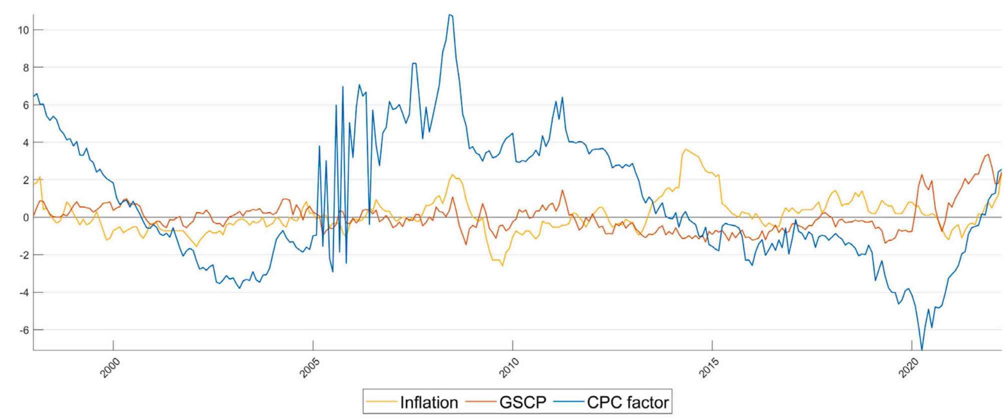
Following (Diaz and Perez-Quiros, 2021) and (Diaz et al., 2023), we solve this optimization problem through the use of the genetic algorithm. This nature-inspired optimization algorithm was developed by Holland (1975) and is based on evolutionary theory. Diaz and Perez-Quiros (2021) show that it is well suited for the selection of variables, given the binary nature of the solution variable, A_q. Please refer to the Appendix in Diaz and Perez-Quiros (2021) for a full description of the procedure for implementing the genetic algorithm in the selection of commodities.

The optimal solution for the optimization problem in Eq. (4) is then defined as A^*, and the CPC factor as $f \equiv f_q(A^*)$.

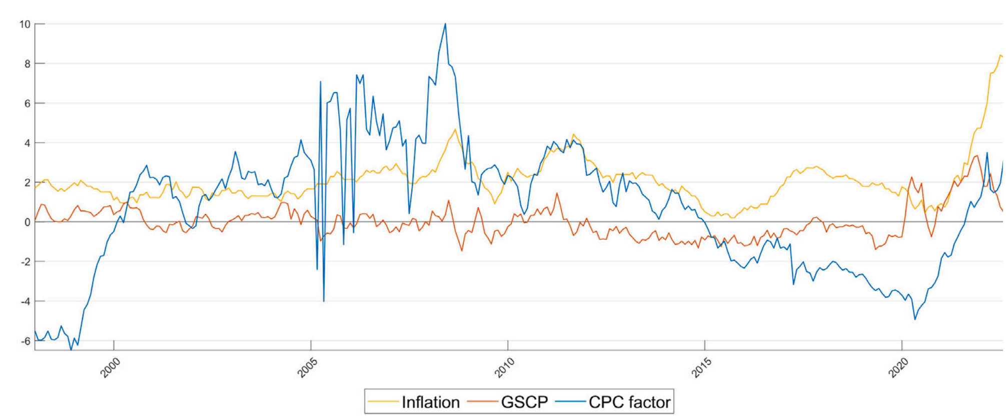
[5] Note that minimizing the sum of squared errors is equivalent to maximizing the R^2 statistic of the regression in Eq. (3), which was the approach adopted by Diaz and Perez-Quiros (2021) in their application. Additionally, like the authors, we restrict the algorithm to select a minimum of 3 commodities to avoid the PCA from degenerating.



(a) Germany

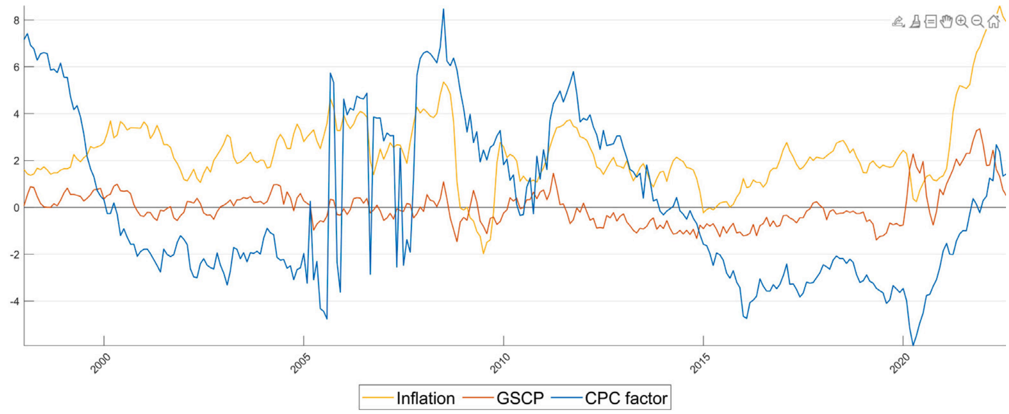


(b) Japan



(c) U.K.

Fig. 1. CPC Factors, GSCP, and Inflation Rates.
Notes: The figure above shows the year-to-year inflation rates for Germany, Japan, the U.K., and the U.S. along with their corresponding CPC factors and the GSCP index. All series are at a monthly frequency.



(d) U.S.

Fig. 1. (*continued*).

2.2. CPC factors

We perform a recursive estimation of the CPC factors, where the genetic algorithm is allowed to select the pool of commodities with the information available up to time t, in order to determine the time-varying relevance of commodities for inflation rates in each country.[6] This implies that the CPC factors, f_t, are constructed with the optimal combination of commodities, A_t^*, selected by the genetic algorithm, where A_t^* is generated by using a set of information available at time t, which we denote as I_t. In this sense, f_t can be defined as a function of $(A_t^* \mid I_t)$. We, therefore, create the series $\{f_1(A_1^* \mid I_1), f_2(A_2^* \mid I_1), \ldots, f_T(A_T^* \mid I_T)\}$ for each country. We use data starting in January 1998 and perform the recursive estimation from January 2005 until August 2022. We have a total of $n = 56$ commodity price series available from the World Bank. These include energy commodities, metals, raw materials, and agricultural products.

Fig. 1 shows the evolution of the inflation rate along with the GSCP index, and the recursively estimated CPC factor for each of the four countries. Between January 1998 and August 2022, prices increased only 4% in Japan compared to almost 49% in Germany, 78% in the U.K., and 78% in the U.S. We can observe a long-run relationship between the CPC factors and inflation rates, although especially during the most recent time, the post-COVID-19 period, and for Germany, the U.K., and the U.S. However, we cannot observe the same long-run relationship with the GSCP index. A relationship seems to arise only during the last portion of the sample, following the COVID-19 pandemic.

It is worth mentioning that the CPC factor estimated for Japan does not seem to align with this country's inflation rate for the sample period. No graphical relationship can be observed with the GSCP index, either. Related literature has provided different explanations for persistently low inflation rates (as well as expected inflation) in Japan (see, for example, Ikeda et al., 2022; Yagi et al., 2022 and references therein). Frequently, low inflation rates are explained by the deflationary effect of the aging of the population (see, for example, the recent study by Braun and Ikeda, 2022). Japan presents the highest proportion of seniors in the world, which places persistent downward pressure on the level of prices, as well as on potential output, labor market participation, and real interest rates. In addition, labor market conditions for full-time employees with a permanent contract also help to understand the low inflation rate dynamics in Japan. The collective bargaining of the trade unions of full-time workers tends to ask for wage increases considering observed inflation rather than expected or target inflation. Nevertheless, a more detailed analysis will provide further insights regarding the determinants of inflation for all economies.

2.3. Cost-push commodities in each of the four countries

First, we examine which are the commodities that have induced inflation in each of the countries during the recursively estimated sample period. To do so, we present the aggregated weights assigned to each commodity type (energy, raw materials, metal, agricultural commodities). These are defined in the following way:

$$\begin{aligned}
\lambda_{t,E}^2 &= \sum_i \lambda_{t,i}^2 \quad \forall\, i \ni \Omega_E \\
\lambda_{t,M}^2 &= \sum_i \lambda_{t,i}^2 \quad \forall\, i \ni \Omega_M \\
\lambda_{t,R}^2 &= \sum_i \lambda_{t,i}^2 \quad \forall\, i \ni \Omega_R \\
\lambda_{t,A}^2 &= \sum_i \lambda_{t,i}^2 \quad \forall\, i \ni \Omega_A
\end{aligned} \tag{5}$$

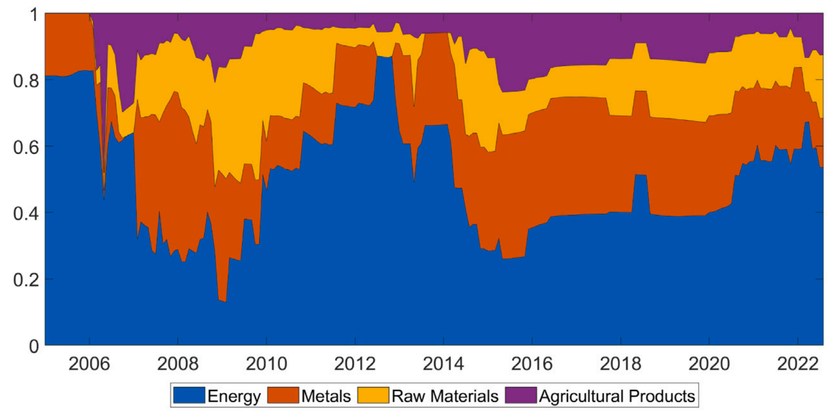
where $\lambda_{t,E}^2$, $\lambda_{t,M}^2$, $\lambda_{t,I}^2$, and $\lambda_{t,A}^2$ are the aggregated weights assigned at period t to energy commodities (Ω_E), metals (Ω_M), raw industrial commodities (e.g., fertilizers, raw materials, fats and oils and denoted Ω_R) and agricultural commodities (Ω_A), respectively, and $\lambda_{t,i}$ is defined as in Eq. (1).

Fig. 2 shows the weights for each commodity type. We can observe that these weights have varied significantly over time and that they are different for each of the countries. This shows that despite the global nature of commodity markets, the transmission of commodity price shocks into domestic economies is asymmetric. These results could be very useful for policymakers to understand which commodities present a prime concern in terms of controlling for inflation. In particular, the predominance of a certain commodity type calls for an improvement in the management of inventories and strategic reserves by firms and governments for short-term solutions. Moreover, long-term solutions require investments aimed at increasing the economy's resilience to these commodity price shocks, by either driving production away from the use of these commodities or by searching for alternative sources of supply.

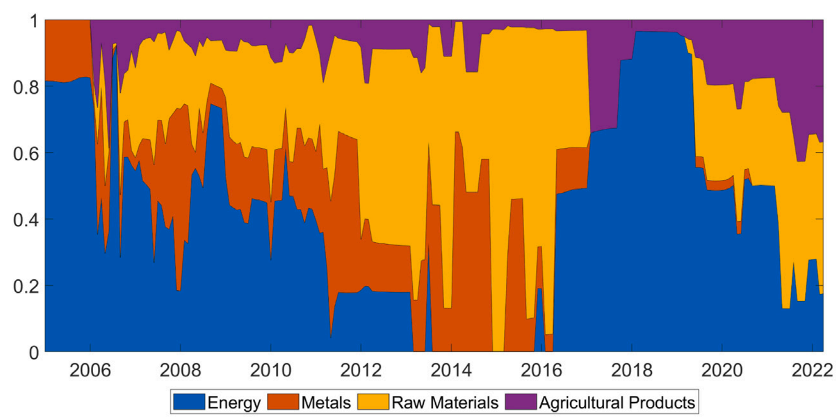
Note that, for most of the sample, weights are given primarily to crude oil, natural gas, iron ore, and fertilizers for all four countries.[7]

[6] This ensures that, for the spanned sample, one would have been able to construct this indicator in real time.

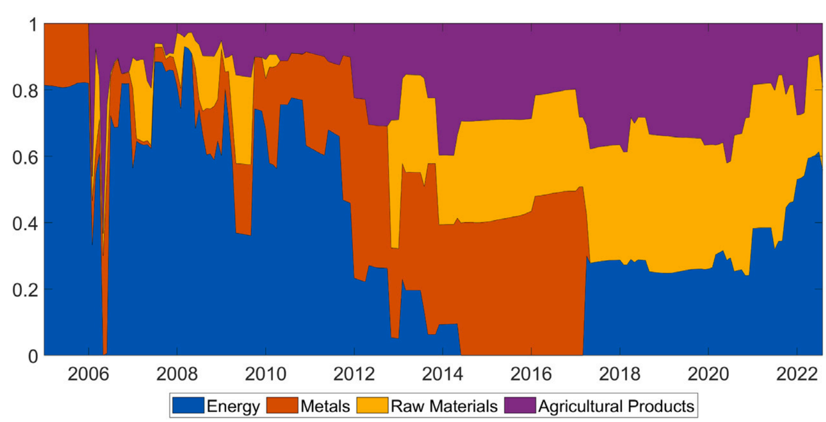
[7] Weights per commodity per country are available upon request.



(a) Germany



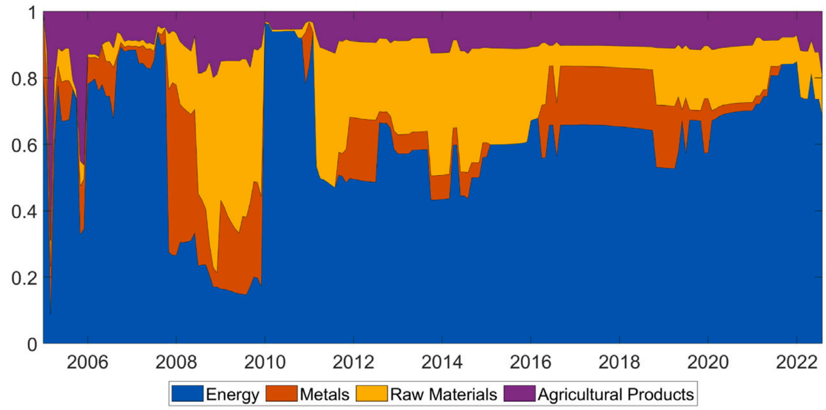
(b) Japan



(c) U.K.

Fig. 2. Time-varying Weights of Commodities for the Estimation of the CPC Factors.
Notes: The figure above shows the time-varying weights assigned by the genetic algorithm to each commodity type (energy, metals, raw material, and agricultural products) for the construction of the CPC factors for Germany, Japan, the U.K., and the U.S. The weights are estimated with the information available up to date.

Nevertheless, the relative importance of price shifts in these commodities varies across countries according to their economic structure. For example, as far as energy prices are concerned, their weights with respect to the inflation rates in Germany and the U.S. have been higher and more persistent than in Japan and the U.K. This is in line with Ikeda et al. (2022) who state that there are differences in how energy prices transmit across regions (U.S. vs Japan and Europe) due to variations across local energy market structures and in the rates of increase of



(d) U.S.

Fig. 2. (*continued*).

natural gas prices. Particularly, weights are higher for crude oil in Germany and the U.S., but it is natural gas prices that are a larger determinant of inflation rates in Japan and the U.K.

Furthermore, it is also worth mentioning that while the weight of energy prices was high in the four countries before the Global Financial Crisis (GFC), its weight gradually decreased in Japan and the U.K. until 2017. Note that there is virtually no weight assigned to energy commodities in either of these countries from close to 2012 until 2017. This coincides with fluctuations in natural gas prices, which continuously decreased reaching a decade-low in 2016. Also, while the weights in Japan shifted primarily to energy prices after this period, in the U.K. the shift was mainly to fertilizer prices. This is in line with the expected effects of Brexit on both the imports of fertilizers, which mainly proceed from the European Union or countries such as Morocco, Algeria, and Egypt. The energy mix in the U.K. is made up of roughly 40% of natural gas, 50% of which is imported. Thus, the lower dependence of the U.K. on the European Union for imports and exports of energy commodities explains the lower weights of energy prices, relative to agricultural products and raw materials, observed in this country after the Brexit referendum in June 2016. These results are in line with those in Pollit (2017, 2022).

Moreover, it is only in Japan that we observe a new decrease in the inflationary effects of energy prices, particularly after the COVID-19 pandemic. We could, thus, assume that inflation rates in Germany, the U.K., and the U.S. are now more vulnerable to energy prices than the Japanese inflation rate. Therefore, in the context of high energy prices, countries such as Germany, the U.K., and the U.S. will be more willing to shift away from fossil fuels to renewable energy sources, speeding up their energy transition.

3. SVAR for inflation rates: Modeling and empirical evidence

3.1. SVAR model

Following the estimation of the CPC factors, in order to examine the effect of global supply chain disruptions and cost-push commodity shocks on inflation rates, we estimate an SVAR model for each of the four economies, including industrial production, the trade ratio, the shadow rate, the credit spread, the real effective exchange rate, the GSCP proposed by Benigno et al. (2022), the CPC factor and the inflation rate. It is defined as follows:

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_j y_{t-j} + \epsilon_t \tag{6}$$

where p is the number of lags, $y_t = [f_t, GSCP_t, CS_t, IP_t, TR_t, \pi_t, R_t, REER_t]'$, β_j denotes the jth coefficient matrix for all lags $j \ \exists \ \{1, \dots, p\}$, and ϵ_t is an error term with a normal distribution $N \sim (0, \Sigma)$.

The structural shocks are identified as follows:

$$\begin{pmatrix} \epsilon_t^{f} \\ \epsilon_t^{GSCP} \\ \epsilon_t^{CS} \\ \epsilon_t^{IP} \\ \epsilon_t^{TR} \\ \epsilon_t^{\pi} \\ \epsilon_t^{R} \\ \epsilon_t^{REER} \end{pmatrix} = \begin{bmatrix} b_{11}^0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21}^0 & b_{22}^0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{31}^0 & b_{32}^0 & b_{33}^0 & b_{34}^0 & b_{35}^0 & 0 & 0 & 0 \\ b_{41}^0 & b_{42}^0 & b_{43}^0 & b_{44}^0 & b_{45}^0 & 0 & 0 & 0 \\ b_{51}^0 & b_{52}^0 & b_{53}^0 & b_{54}^0 & b_{55}^0 & 0 & 0 & 0 \\ b_{61}^0 & b_{62}^0 & b_{63}^0 & b_{64}^0 & b_{65}^0 & b_{66}^0 & 0 & 0 \\ b_{71}^0 & b_{72}^0 & b_{73}^0 & b_{74}^0 & b_{75}^0 & b_{76}^0 & b_{77}^0 & 0 \\ b_{81}^0 & b_{82}^0 & b_{83}^0 & b_{84}^0 & b_{85}^0 & b_{86}^0 & b_{87}^0 & b_{88}^0 \end{bmatrix} * \begin{pmatrix} \omega_t^{cost-push\ commodity\ shock} \\ \omega_t^{global\ supply\ disruption} \\ \omega_t^{financial\ shock} \\ \omega_t^{domestic\ demand\ shock} \\ \omega_t^{foreign\ demand\ shock} \\ \omega_t^{residual\ shock} \\ \omega_t^{monetary\ policy\ shock} \\ \omega_t^{currency\ shock} \end{pmatrix} \tag{7}$$

where the responses of the variables are freely estimated. Particularly, we assume that commodity shocks will impact domestic economies immediately, but commodity prices will respond with a delay to domestic shocks, given the global nature of commodity markets. This is in line with the conventional assumption that commodity prices are predetermined to domestic macroeconomic aggregates, as suggested by Kilian and Vega (2011), who using a wide range of U.S. macroeconomic news, find no evidence of feedback to crude oil prices at daily or monthly horizons.

Also, given that the nature of commodity shocks suggests shifts in the supply of commodities, these are allowed to immediately affect international trade; whereas, per Kilian et al. (2023), we assume that due to the presence of inventories, frictions in the global supply chain are expected to affect commodity markets with a delay.

Furthermore, Kilian and Vega (2011) also studied the response of the dollar-euro exchange rate to U.S. macroeconomic news and found a strong and statistically significant response. Therefore, there can be no indirect feedback from the exchange rate to commodity prices, or that would have resulted in a correlation with macroeconomic news as well. Thus we can treat commodity prices as predetermined to the exchange rate at the monthly frequency. An analogous assumption can be made for the response of commodity prices to interest rates. Because interest rates clearly respond to macroeconomic news instantaneously, the fact that commodity prices do not, allows us to assume that they are predetermined to changes in the shadow rate.

Additionally, given the equally global nature of the GSCP index, we instill the same assumptions as those made for the commodity factor and define it as predetermined to macroeconomic aggregates, interest rates, and exchange rate shocks.

Followingly, note, in Eq. (7), that there are not enough restrictions to differentiate between financial, domestic demand, or foreign demand shocks. It is not within the scope of this paper to disentangle the effects of these shocks. These will, therefore, simply be aggregated as "demand shocks".

Demand shocks are then distinguished from residual shocks to inflation by the assumption that the latter do not contemporaneously affect real output, and monetary policy shocks are identified as the residual of the shift in the shadow rate after accounting for the contemporaneous feedback of the global supply shocks and macroeconomic aggregates. Because events in the money market transmit to the real economy through medium and long-term loans provided to firms and households, it is reasonable to assume a sluggish reaction of the macroeconomy to a shift in monetary policy.

Also, as in Kilian and Zhou (2022), the assumption of sluggish inflation expectations in response to an exchange rate shock is based on findings by Mishkin (2008) that even large depreciations exert only small effects on consumer prices and real output in industrialized economies.

Finally, unexplained changes in inflation are termed residual shocks that cannot be explained by the other variables in the model. These include the role of inflation expectations and budget deficits, which have been found to cause aggregate inflation over time (Benk and Gillman, 2023). The identified supply and demand shocks, therefore, capture the effect on relative price changes and do not examine how fiscal deficits cause aggregate inflation across history and countries.

Note that, because demand shocks will be aggregated, we can proceed to estimate B_0^{-1} through the Cholesky decomposition of the variance–covariance matrix Σ, identify the shocks of interest, and aggregate the effects of demand shocks. For robustness, we also estimate all results considering the alternative that industrial production and the trade ratio are predetermined to CPC shocks and global supply chain disruptions. We find that altering the order of the variables in the structural VAR has no effect on the results, which provides further evidence of the CPC factor and the GSCP as measures of supply disruptions.[8]

3.2. Impulse response functions

This section reports the estimates of the impulse response functions of both a CPC shock and a global supply chain disruption. Figs. 3 and 4 show the average Impulse Response Functions (IRFs) to a CPC shock and a global supply chain disruption, respectively. These are shown with a 95% confidence interval, where f_t corresponds to the recursively estimated CPC factor for each country, and show the response of each variable to a one standard deviation shock.

It is interesting to compare the structural impulse response estimates for the selected four economies to an increase in commodity prices (Fig. 3). As expected, according to economic theory, the response of inflation rates to a CPC shock is positive and qualitatively similar in the short-run (from 1 to 6 months) for Germany, the U.K., and the U.S. However, CPC shocks generate significantly different impacts after 7 months. For example, the CPC shock has a much weaker impact on inflation rates in the U.S. than in Germany and the U.K., where inflation rates suffer the greatest impact in the long run. Furthermore, there is only a weak positive response of inflation rates in Japan in the 4th month after an increase in commodity prices.

Furthermore, when we focus on the impact of a global supply chain disruption shock on inflation rates (Fig. 4), we observe a long-run positive and significant effect in Germany, the U.K., and the U.S. The U.K. is affected the most, with a significant positive effect from the 2nd until the 16th month after impact. However, both for Germany and the U.S., the effect does not become statistically significant until after 9 and 6 months, respectively, which might be showing the delay caused by inventory management. Moreover, inflation rates in Japan, however, continue not to respond to a global supply shock, such as a supply chain disruption.

[8] Results are available upon request.

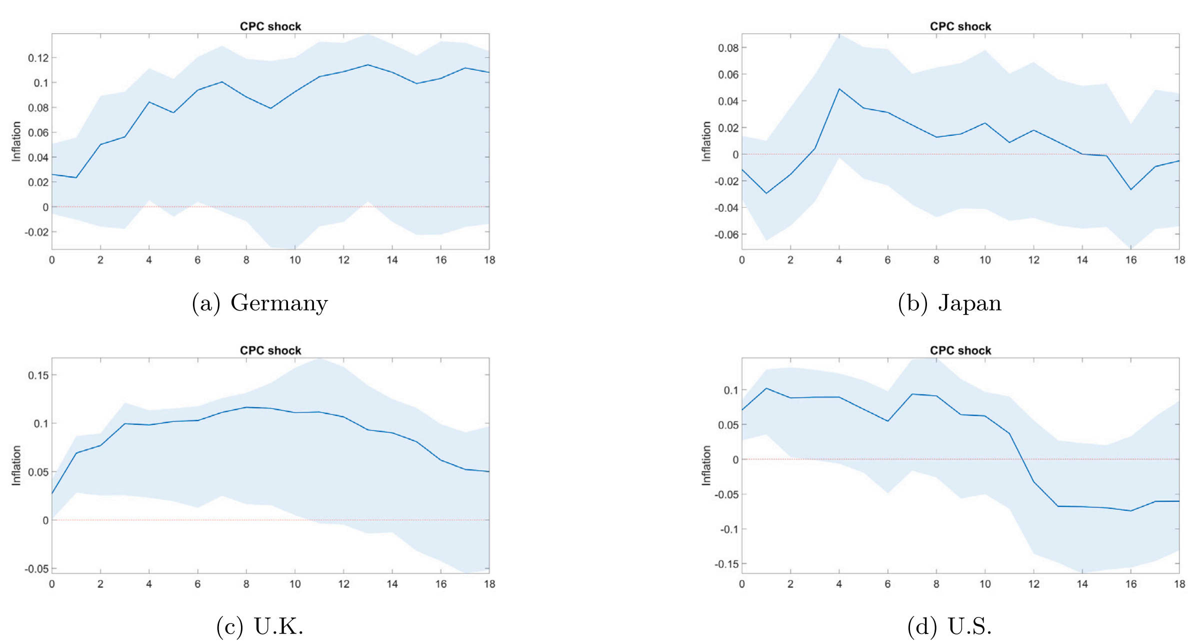


Fig. 3. Impulse Response Functions of Inflation to a CPC Shock.
Notes: The figure above shows the impulse response functions with a 95% confidence interval for Germany, Japan, the U.K., and the U.S., using the recursively estimated CPC factor for each country in the full sample.

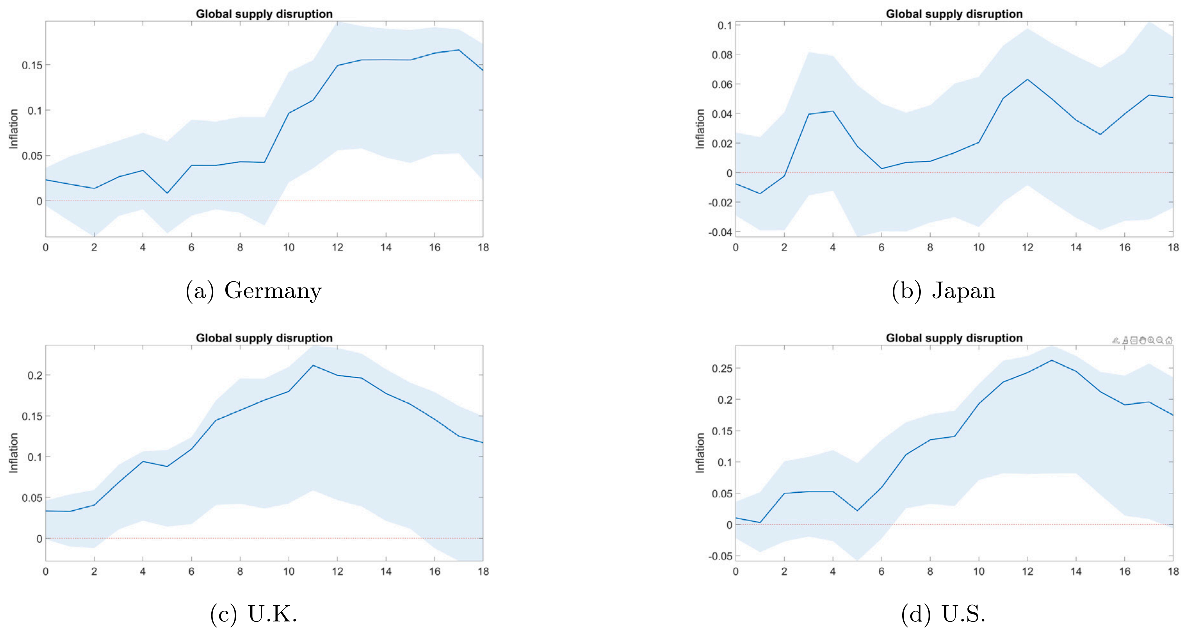


Fig. 4. Impulse Response Functions of Inflation to a Global Supply Chain Disruption.
Notes: The figure above shows the impulse response functions with a 95% confidence interval for Germany, Japan, the U.K., and the U.S., using the recursively estimated CPC factor for each country in the full sample.

Nevertheless, these impulse response functions do not account for possible structural changes in the way inflation rates respond to either of these shocks. Given that we have already observed a time-varying shift in the relevance of commodities for inflation (Fig. 2), we proceed to analyze the time-varying effects of both structural shocks of interest (CPC shock and global supply chain disruption).

Fig. 5 plots the recursively-estimated impulse responses of inflation for Germany, Japan, the U.K., and the U.S. to a commodity price shock, in three dimensions. All economies exhibit positive significant impact responses and hump-shaped medium-run responses for most of the sample. Note, however, that for all economies, the effect of a CPC shock is only significant until after the 2008 financial crisis. Moreover, in the case of Japan, this effect gradually increased in significance until the end of the sample. It is only in the case of the U.S. that one cannot observe a significant structural change throughout the sample after the financial crisis. Both for the U.K. and Germany, it is clear that after the COVID-19 pandemic, the effect of commodity price shocks on inflation has become more permanent rather than just medium-term. These results are qualitatively similar to Diaz et al. (2023) regarding the sign of the response of inflation rates to a CPC shock. In a recent study on the inflation rate in Japan during the COVID-19 shock, Ikeda et al. (2022) found an increasing cost-push pressure due in part to the effects of rising commodity prices with a positive short-run impact on the inflation rate.

Additionally, in Fig. 6 we can observe the time-varying IRFs of inflation rates to a global supply chain disruption. Similar to Fig. 5, these IRFs are plotted in three dimensions. For global supply chain disruptions, we can observe significant structural changes in the way

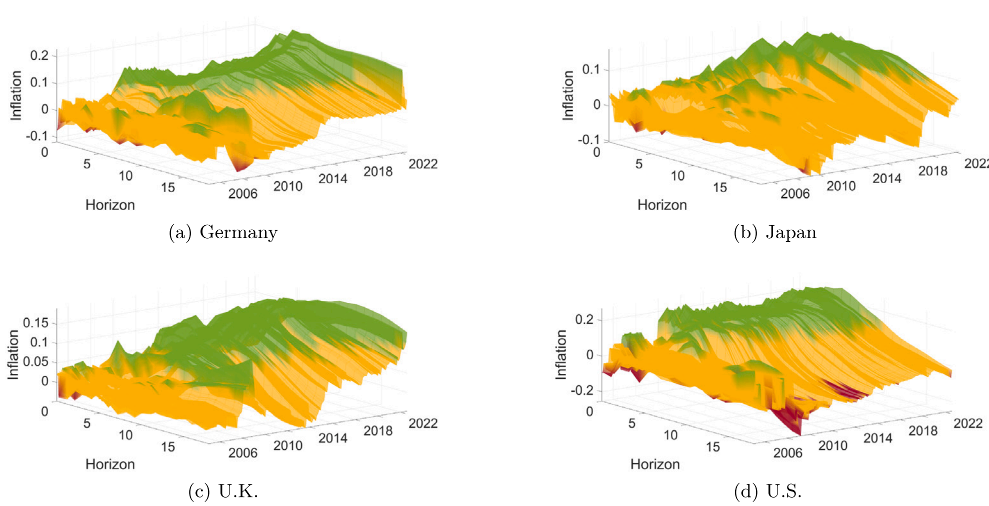


Fig. 5. Time-Varying Impulse Response Functions of Inflation to a CPC Shock.
Notes: The 3-D figure above shows the recursively estimated impulse response functions of inflation to a CPC shock for Germany, Japan, the U.K., and the U.S. The sample period is from January 2005 to August 2022 and the model is estimated with 12 lags. Green values denote a significantly positive response within a 95% confidence interval. Red values denote a significantly negative response within a 95% confidence interval. Yellow values denote insignificant values within a 95% confidence interval. x-axis: months after shock; y-axis: magnitude of response; z-axis: sample date.

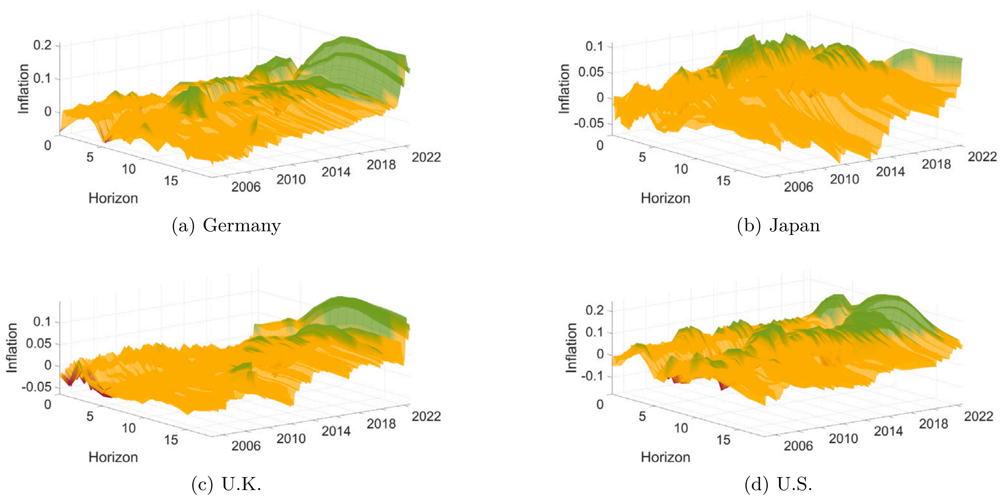


Fig. 6. Time-Varying Impulse Response Functions of Inflation to a Global Supply Chain Disruption.
Notes: The 3-D figure above shows the recursively estimated impulse response functions of inflation to a global supply chain disruption for Germany, Japan, the U.K., and the U.S. The sample period is from January 2005 to August 2022 and the model is estimated with 12 lags. Green values denote a significantly positive response within a 95% confidence interval. Red values denote a significantly negative response within a 95% confidence interval. Yellow values denote insignificant values within a 95% confidence interval. x-axis: months after shock; y-axis: magnitude of response; z-axis: sample date.

inflation rates respond to these shocks, in all economies. The effect becomes statistically significant after the COVID-19 pandemic. One can observe short-term effects before the pandemic, in Germany, Japan, and the U.S., although for the latter, this effect is delayed (probably due to inventory management). More importantly, the inflation rates of Germany and the U.K. have a permanent long-term effect in response to global supply chain disruptions since the COVID-19 crisis, whereas it is humped-shaped for the U.S., and unclear for Japan. Overall, our main results are in line with the recent related literature that studies supply drivers of inflation during the COVID-19 shock (see, for example, Benigno et al., 2022; and Finck and Tillman, 2022).

4. Discussion of the results

This paper empirically estimates the time-varying impact of commodity price shocks and supply chain disruptions, while controlling for demand shocks, on inflation rates in Germany, Japan, the U.K., and the U.S. over the period from January 1998 to August 2022. Interesting results and policy implications can be derived from the main findings of the paper. To facilitate the interpretation and discussion of the results, we calculate now the percentage of contribution of each shock on inflation by observing the average forecast error variance decomposition (FEVD). Given the structural changes we have observed in the time-varying impulse responses in the previous subsection, we proceed to plot the average FEVD for each recursively estimated IRF. The averages are taken over the 18-month horizon, and the effect of demand shocks is aggregated for innovations on the credit spread, industrial production, and trade ratio. Fig. 7 shows the results for each country.

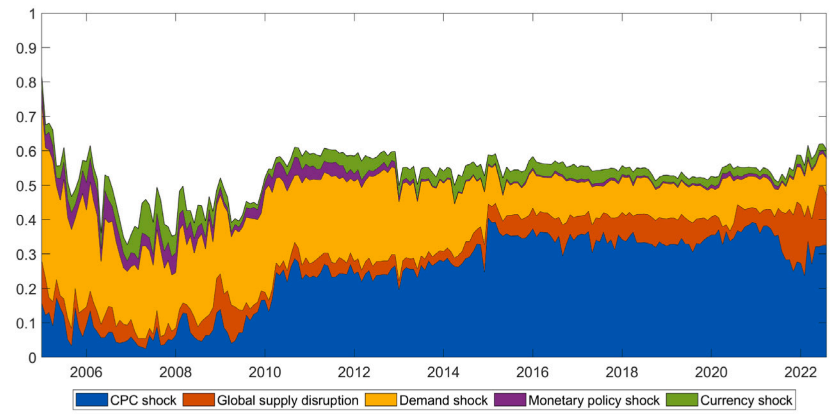
We can observe that, on average, the variables included in the model explain around 60% of innovations in inflation for Germany, the U.K., and the U.S., while we can only explain around 40% of innovations in Japanese inflation rates. Note also, that, after the 2008 financial crisis, shifts in commodity prices explain around 30% of unexpected shifts in inflation in Germany, the U.K., and the U.S., while global supply chain disruptions only explained between 5 and 10% throughout most of the sample for Germany and the U.S., with an even smaller percentage for the U.K. and Japan. These results suggest that the Japanese economy has been less vulnerable to those two supply shocks, which explains the lower inflation rates in this country in recent moments of high commodity prices and global supply chain disruptions.

Nonetheless, global supply chain disruptions become much more relevant after the COVID-19 pandemic, explaining around 20% of inflation innovations in Germany and the U.S., and 10% of innovations in the U.K. during 2022. This is not the case, however, for Japan, where global supply chain disruptions explain an even lower percentage of shifts in inflation than it does throughout the sample.

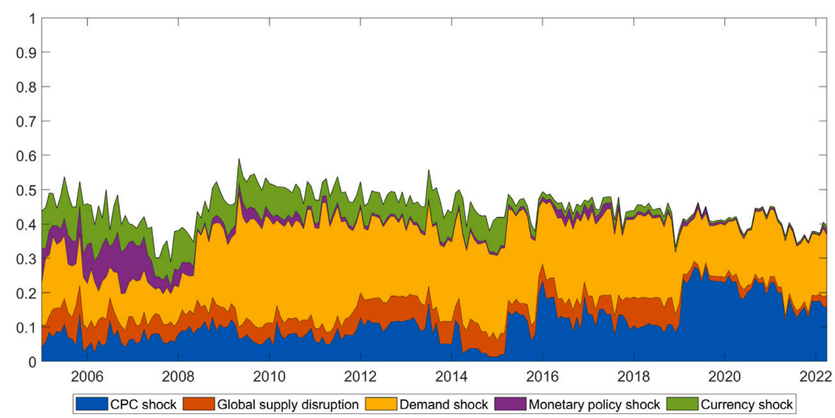
Moreover, it is important to note the importance of demand shocks on inflation. Particularly in Japan, 30% of inflation innovations, throughout most of the sample, can be explained by changes in demand. This decreases to about 20% after 2019 when commodity price shocks go from explaining 10% to 20% of unexpected movements in inflation. In the case of Germany, the U.K., and the U.S., the importance of demand shocks decreases gradually over time, from an initial 40%, 30%, and 30% of inflation innovations explained by changes in demand to only 10%, 5%, and 15% by the end of the sample, respectively.

Results also show that monetary policy has not been effective in driving inflation. For Germany, the introduction of unconventional monetary policy by the European Central Bank was not successful in stimulating the euro area economies and increasing inflation after the Euro Sovereign debt crisis. Moreover, we need to consider the long-lasting liquidity trap in Japan, which has also hindered the ability of monetary policy to translate into the real economy, as evidenced in Fig. 7b. We can observe a relatively higher efficacy of monetary policy actions undertaken by the Bank of England and the Federal Reserve throughout the sample. Particularly, monetary policy shocks explain between 5 and 10% of innovations in inflation in the U.K. between 2014 and 2020, during which developed economies faced risks of deflation. Likewise, from 2014 to 2022, changes in the value of the British pound explain between 10 and 15% of unexpected shifts in inflation. For the U.S., on the other hand, the effectiveness of monetary policy has been more stable throughout the sample, but only able to explain around 5% of innovations in inflation, on average. However, the percentage of fluctuations in inflation that cannot be explained by any of the variables in the model does suggest a heightened importance of the residual term, which includes the effect of inflation expectations and fiscal budgets on inflation. This is left for further research.

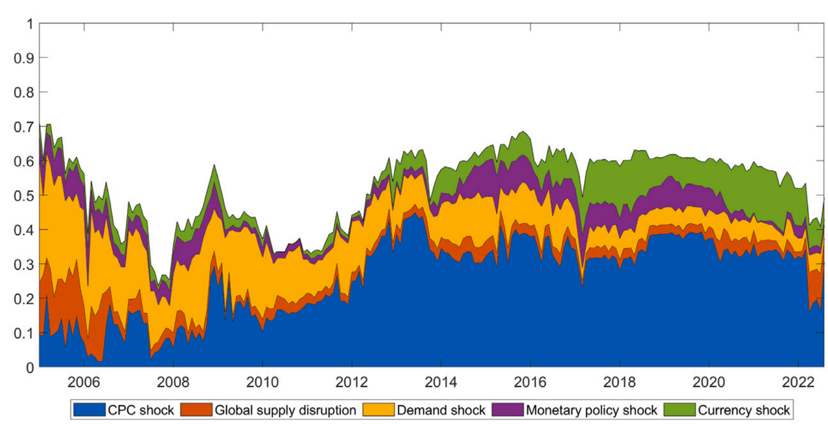
Overall, results suggest that the relevance of global supply shocks has not increased merely as a result of the COVID-19 pandemic. While this may hold for global supply chain disruptions, commodity price shocks have incrementally explained unexpected changes in inflation rates since after the financial crisis for Germany, the U.K., and the U.S., and since 2019 for Japan. While domestic demand shocks remain



(a) Germany



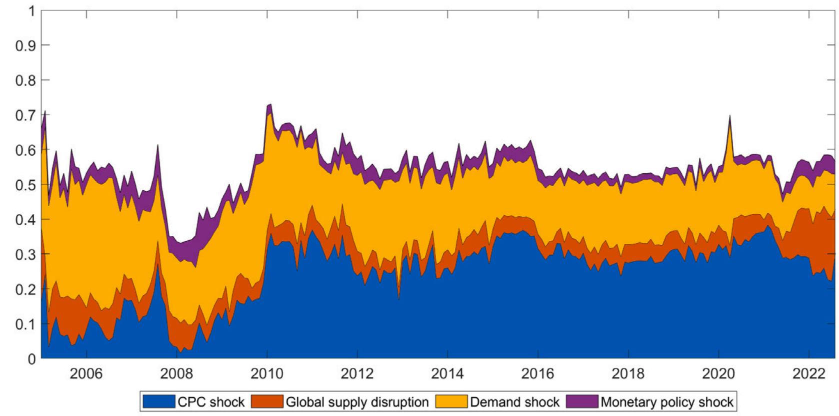
(b) Japan



(c) U.K.

Fig. 7. Time-Varying Forecast Error Variance Decompositions.
Notes: The figure above shows the time-varying forecast error variance decompositions. These correspond to the recursively estimated IRFs, averaged across the 18-month horizon.

relevant in understanding inflation, our study suggests that given the global nature of raw materials and the supply chain, supply shocks are likely to continue to pose inflationary risks for domestic economies. In particular, given the sluggish global economic growth since 2010, our results show that demand shocks have been relatively less responsible for fluctuations in inflation, while scarcity, in the form of tightness in



(d) U.S.

Fig. 7. (*continued*).

supply, constitutes an increased risk of stagflationary shocks stemming from commodity markets and the supply chain. This is a primary concern for policymakers, given that monetary policy may become ineffective as it works through demand channels. Rather, the results suggest a growing need for strategic management of inventories and reserves to accommodate short-term supply shocks and important investments for finding alternative sources for the supply of commodities.

5. Robustness checks

We perform two robustness checks to assert the validity of our results. First, we examine the importance of having an individual and time-varying CPC factor for each economy. To do so, we study how our results compare to: (i) estimating a constant CPC factor that is common to all four economies and (ii) estimating a time-varying CPC factor that is common to all four economies. Second, we investigate whether using the NACTI (Kilian et al., 2023) as an alternative to the GSCP (Benigno et al., 2022) significantly alters our results.

5.1. Constant and time-varying common CPC factor

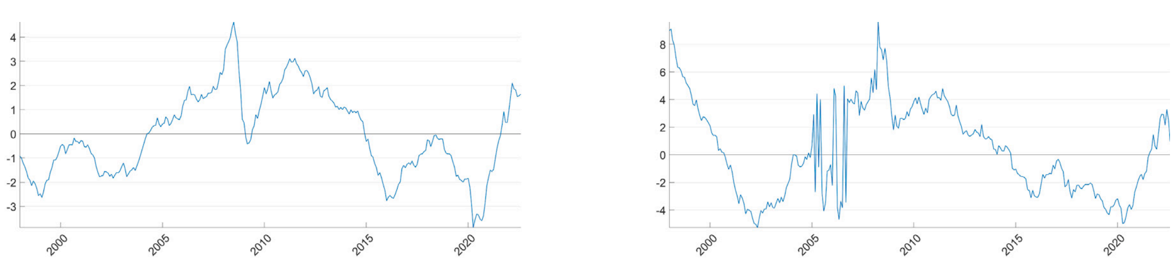
In order to consider a common factor, the genetic algorithm is set to maximize the sum of the R^2 statistics of the regressions for all four economies (Eq. (3)), simultaneously. For the constant CPC factor, there is a single optimization using the full sample, while for the time-varying, the CPC factor is estimated recursively.

Fig. 8 shows a significant difference between a constant and a recursively estimated CPC factor. Notably, by construction, the constant CPC factor will correlate most with inflation, given that the selection of commodities is performed looking to best fit the entire sample. However, this would question the selection of the sample. When performing a recursive selection, the CPC factor changes significantly, which would make us expect further changes with the income of new information (that is, a change in sample).

Smaller changes can be observed between the common (Fig. 8) and the individual time-varying CPC factors (Fig. 1). However, a close look will show that differences arise at several periods. Firstly, the in-sample portion shows that British inflation did not have the same increase as the one observed in Germany and the U.S. Moreover, larger contrasts are found during the commodity boom in the mid-2000s for all economies. Note also, that individual CPC factors suggest a lagged increase of inflation during the 2008 financial crisis for Japan and the U.K. relative to Germany and the U.S. Also, while the individual CPC factors all show deflationary pressures in the years following the 2008 crisis, these seem to occur at different rates. Finally, for the COVID-19 crisis, the Japanese CPC factor suggests stronger deflationary pressures stemming from commodity prices than in the other three countries.

Note also, in Fig. 9, the difference in the weights that are optimally assigned by the genetic algorithm for the different model specifications. Notably, a constant-weighted CPC factor discards the relevance of metal prices for the entire sample. This is not the case for a time-varying CPC factor in which some periods denote the inflationary relevance of metal prices. Additionally, in the mid-2010s, while energy prices remained relevant in Germany and the U.S., this was not the case for Japan and the U.K. (Fig. 2). Nevertheless, a common CPC factor discounts the continuing relevance of energy prices in Germany and the U.S. during this period.

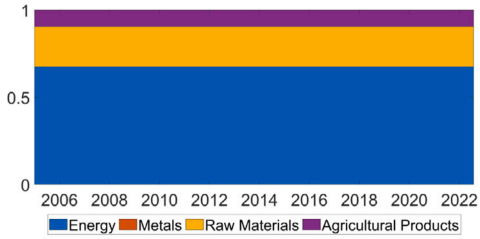
Furthermore, Fig. 10 shows that, by construction, IRFs have a stronger statistical significance when the CPC is constantly weighted. This is expected as these IRFs are estimated for the full sample. However, when the CPC factor is recursively estimated, we observe that



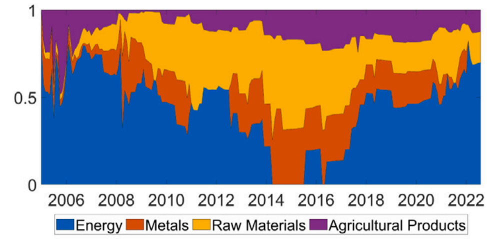
(a) Common and Constant CPC factor

(b) Common and Time-Varying CPC factor

Fig. 8. Constant and Time-Varying Common CPC Factors.
Notes: The figure above shows the constant and time-varying common CPC factors for Germany, Japan, the U.K. and the U.S.

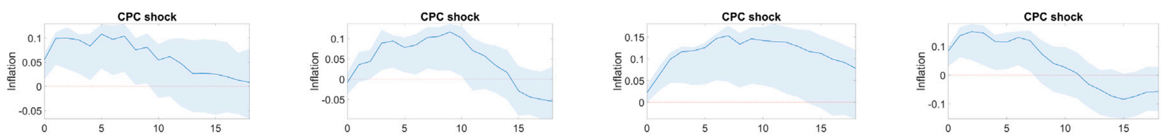


(a) Common and Constant CPC Factor

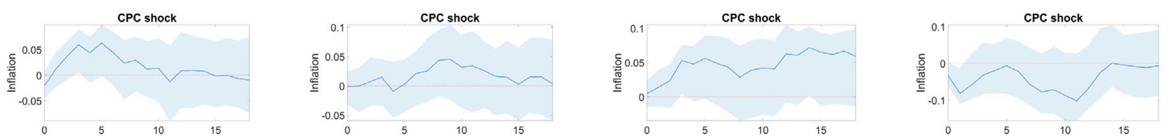


(b) Common and Time-Varying CPC Factor

Fig. 9. Weights of Commodities for the Estimation of Common CPC Factors.
Notes: The figure above shows the time-varying weights assigned by the genetic algorithm to each commodity type (energy, metals, raw material, and agricultural products) for the construction of the common CPC factors for Germany, Japan, the U.K., and the U.S.



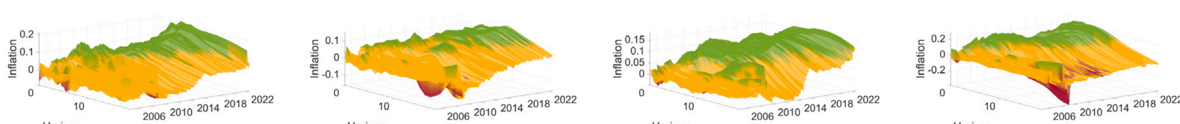
(a) Germany. Common and Constant CPC Factor (b) Japan. Common and Constant CPC Factor (c) U.K. Common and Constant CPC Factor (d) U.S. Common and Constant CPC Factor



(e) Germany. Common and Time-Varying CPC Factor (f) Japan. Common and Time-Varying CPC Factor (g) U.K. Common and Time-Varying CPC Factor (h) U.S. Common and Time-Varying CPC Factor

Fig. 10. Impulse Response Functions of Inflation to a CPC Shock with Common CPC Factors.
Notes: The figure above shows the impulse response functions with a 95% confidence interval for Germany, Japan, the U.K. and the U.S. with the two alternative measures of a common CPC factor.

(a) Germany. Common and Constant CPC Factor (b) Japan. Common and Constant CPC Factor (c) U.K. Common and Constant CPC Factor (d) U.S. Common and Constant CPC Factor



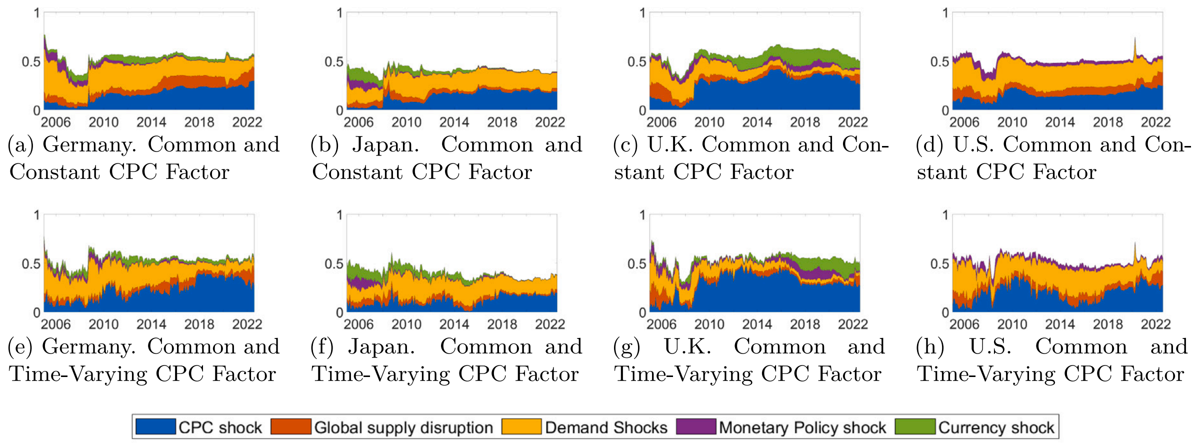
(e) Germany. Common and Time-Varying CPC Factor (f) Japan. Common and Time-Varying CPC Factor (g) U.K. Common and Time-Varying CPC Factor (h) U.S. Common and Time-Varying CPC Factor

Fig. 11. Time-Varying Impulse Response Functions of Inflation to a CPC Shock with Common CPC Factors.
Notes: The 3-D figures above show the recursively estimated impulse response functions of inflation to a CPC shock for Germany, Japan, the U.K., and the U.S. The sample period is from January 2005 to August 2022 and the model is estimated with 12 lags. Green values denote a significantly positive response within a 95% confidence interval. Red values denote a significantly negative response within a 95% confidence interval. Yellow values denote insignificant values within a 95% confidence interval. x-axis: months after shock; y-axis: magnitude of response; z-axis: sample date.

almost no statistical significance can be obtained when this is a common CPC factor. For the U.S., one even observes a deflationary pressure of increasing commodity prices as the economy transitions back to equilibrium.

Concerning recursively estimated IRFs (Fig. 11), we can observe an increasing statistical significance through time when the CPC factor is time-varying. This is most noticeable in Germany and the U.S., where the statistical significance of CPC shocks gradually decreases for a shorter sample when using a constant CPC factor. Furthermore, the individual German CPC factor better captures the inflationary effect of CPC shocks during the commodity boom (Fig. 5) than does a common factor. Also, stronger inflationary effects are captured for Japan for the 2010–2020 decade when the CPC is individually constructed (Fig. 5). Fewer differences can be observed for the U.K., suggesting that this country may be driving the optimization of the common CPC factor. Finally, a common CPC factor suggests a lower inflationary effect of commodity prices in the mid-2010s for the U.S. This is the case because the common factor is not weighting energy prices, which were strongly relevant for the U.S. during this period.

These results are confirmed by the forecast error variance decompositions in Fig. 12. A lower percentage of fluctuations in inflation can be explained for Germany during most of the decade between 2010



(a) Germany. Common and Constant CPC Factor (b) Japan. Common and Constant CPC Factor (c) U.K. Common and Constant CPC Factor (d) U.S. Common and Constant CPC Factor

(e) Germany. Common and Time-Varying CPC Factor (f) Japan. Common and Time-Varying CPC Factor (g) U.K. Common and Time-Varying CPC Factor (h) U.S. Common and Time-Varying CPC Factor

Fig. 12. Time-Varying Forecast Error Variance Decompositions with Common CPC Factors.
Notes: The figure above shows the time-varying forecast error variance decompositions. These correspond to the recursively estimated IRFs, averaged across the 18-month horizon.

and 2020 with a common CPC factor. Also, a higher percentage of Japanese inflation is explained since 2019 with an individual factor (Fig. 7). Finally, while similar results are obtained for the U.K., a lower percentage of U.S. inflation can be explained with a common CPC factor for the mid-2010s.

We also found no significant changes in the estimated effects of global supply chain disruptions on inflation in any of the countries, showing the robustness of these results concerning the different specifications of the CPC factor.[9]

Overall, results are in line with Diaz et al. (2023), who argue that the relevance of commodity prices for inflation may shift over time. While oil prices are typically considered the most relevant for price levels, one might consider the recent increase in natural gas prices after the sanctions imposed on Russia for the invasion of Ukraine, as well as the increase of agricultural prices, such as those of wheat and corn. One would also expect an increase in the relevance of natural gas prices after the Fukushima accident in 2011, for Japanese inflation. Moreover, we have viewed recent periods when increases in the prices of fertilizers became topical. The same could be said about prices of metals related to the production of microchips. The lack of materials in recent years also created inflationary issues which begs the question of whether the issue behind was only related to global supply chain disruptions or to the price of the materials themselves. All in all, structural changes in economies, including the introduction of policies for the energy transition, are expected to change the relevance of certain commodities for inflation. Moreover, despite the global nature of commodity markets, it is not clear whether this time-varying relevance is the same for all economies given the geographical and structural differences between countries. Note also, that the construction of a common CPC factor requires a simultaneous optimization of the four regression models. For the robustness check, the four countries were equally weighted. However, constructing a global CPC factor would require not only more countries but would also question the weight that should be assigned to each one. All in all, we find that both time-variance and an individual estimation of the CPC factors allow for a better explanation of fluctuations in inflation in all four economies.

5.2. Alternative measure for global supply chain disruptions: NACTI

To examine the use of the NACTI (Kilian et al., 2023) as an alternative to the GSCP (Benigno et al., 2022), we are required to modify the order of the variables in the structural VAR. In line with Kilian et al. (2023), demand shocks are considered to be predetermined to container trade, and a global supply chain disruption is identified as a change in NACTI that demand shocks cannot explain.

We estimate an SVAR model for the four economies, where $y_t = [f_t, CS_t, IP_t, TR_t, GSCP_t, \pi_t, R_t, REER_t]'$ and the structural shocks are identified as follows:

$$\begin{pmatrix} \varepsilon_t^{f} \\ \varepsilon_t^{CS} \\ \varepsilon_t^{IP} \\ \varepsilon_t^{TR} \\ \varepsilon_t^{GSCP} \\ \varepsilon_t^{\pi} \\ \varepsilon_t^{R} \\ \varepsilon_t^{REER} \end{pmatrix} = \begin{bmatrix} b_{11}^0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21}^0 & b_{22}^0 & b_{23}^0 & b_{24}^0 & 0 & 0 & 0 & 0 \\ b_{31}^0 & b_{32}^0 & b_{33}^0 & b_{34}^0 & 0 & 0 & 0 & 0 \\ b_{41}^0 & b_{42}^0 & b_{43}^0 & b_{44}^0 & 0 & 0 & 0 & 0 \\ b_{51}^0 & b_{52}^0 & b_{53}^0 & b_{54}^0 & b_{55}^0 & 0 & 0 & 0 \\ b_{61}^0 & b_{62}^0 & b_{63}^0 & b_{64}^0 & b_{65}^0 & b_{66}^0 & 0 & 0 \\ b_{71}^0 & b_{72}^0 & b_{73}^0 & b_{74}^0 & b_{75}^0 & b_{76}^0 & b_{77}^0 & 0 \\ b_{81}^0 & b_{82}^0 & b_{83}^0 & b_{84}^0 & b_{85}^0 & b_{86}^0 & b_{87}^0 & b_{88}^0 \end{bmatrix} * \begin{pmatrix} \omega_t^{cost-push\ commodity\ shock} \\ \omega_t^{financial\ shock} \\ \omega_t^{domestic\ demand\ shock} \\ \omega_t^{foreign\ demand\ shock} \\ \omega_t^{global\ supply\ disruption} \\ \omega_t^{residual\ shock} \\ \omega_t^{monetary\ policy\ shock} \\ \omega_t^{currency\ shock} \end{pmatrix} \quad (8)$$

The responses of the variables are freely estimated. However, the sample is limited until April 2021, given the availability of the NACTI.

Notably, from Figs. 1 and 13, the NACTI and the GSCP are quite different. For NACTI, demand and supply shocks need to be disentangled; while this has already been done for the GSCP. Note that the estimated CPC factors for each country remain similar whether the estimation is controlled for GSCP or NACTI. A few significant differences can be observed for Germany and the U.K. during the in-sample estimation until 2005, which could be explained by the difficulty of filtering out demand shocks from NACTI using those countries' demand indexes. Nevertheless, results show, in general, that the estimated CPC factors remain quite similar for the sample spanned until April 2021.

Furthermore, notice that the weights assigned to each commodity type remain similar, particularly for the U.S. and Germany (Figs. 2 and 14). We do observe a large difference for Japan starting in 2016. Nevertheless, the impulse response functions in Fig. 15 show no significant differences in the effects on inflation of the corresponding CPC shocks for Japan. This is also the case for Germany and the U.S. However, the difference in weights assigned for commodities in the

[9] Results are available upon request.

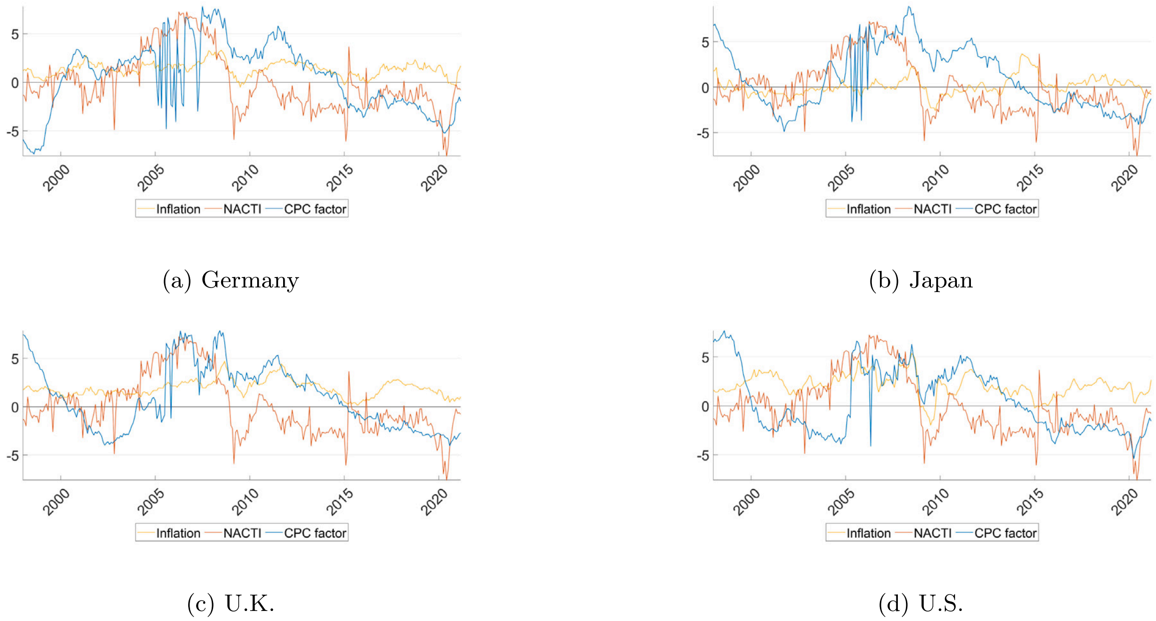


Fig. 13. CPC Factors, NACTI, and Inflation Rates.
Notes: The figure above shows the year-to-year inflation rates for Germany, Japan, the U.K., and the U.S., their estimated CPC factors, and the NACTI, which has been scaled for a better visualization. All series are at a monthly frequency.

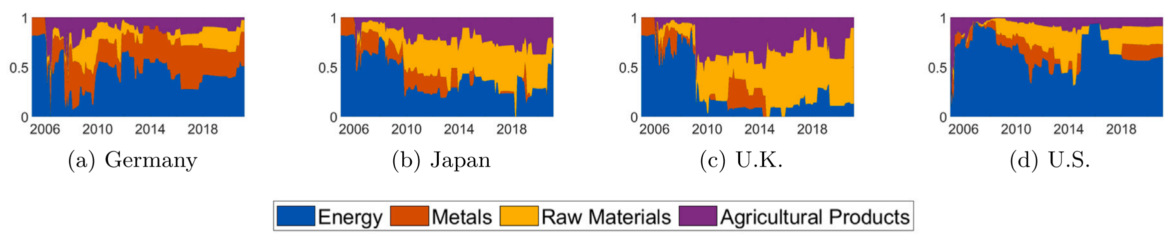


Fig. 14. Time-varying Weights of Commodities for the Estimation of the CPC Factors (using NACTI).
Notes: The figure above shows the time-varying weights assigned by the genetic algorithm to each commodity type (energy, metals, raw material, and agricultural products) for the construction of the CPC factors for Germany, Japan, the U.K., and the U.S. using the NACTI to account for global supply chain disruptions. The weights are estimated with the information available up to date.

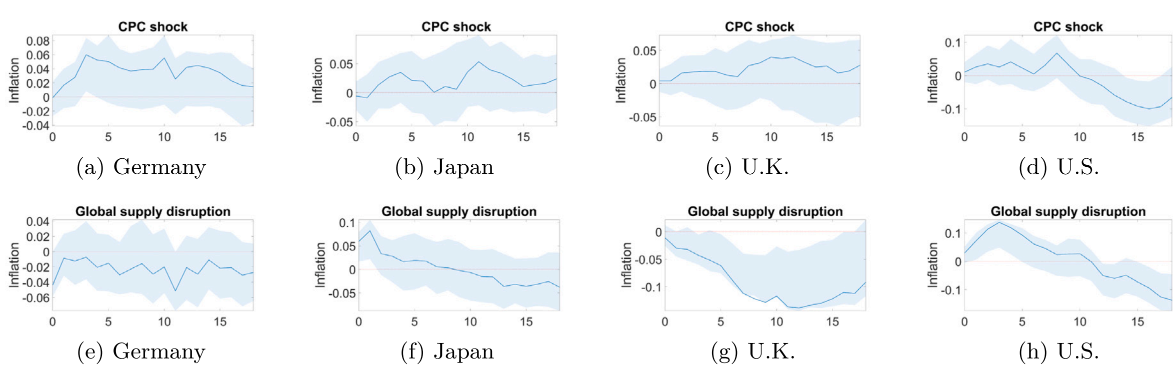
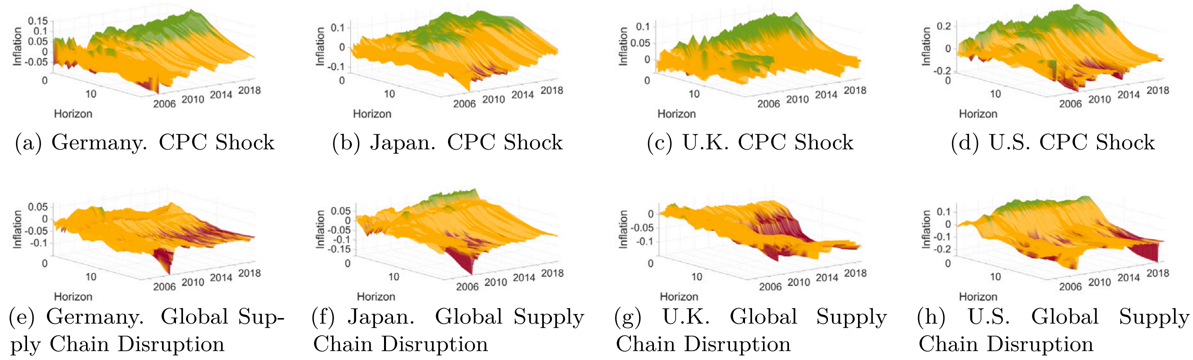


Fig. 15. Impulse Response Functions of Inflation (using NACTI).
Notes: The figure above shows the impulse response functions with a 95% confidence interval for Germany, Japan, the U.K. and the U.S. with the NACTI for global supply chain disruptions.

U.K. (particularly after 2017), does reduce the statistical significance of the CPC shocks to British inflation. Yet, the recursively estimated IRFs (Fig. 16) for responses of inflation to CPC shocks remain consistent, whether estimations are performed controlling for GSCP or NACTI.

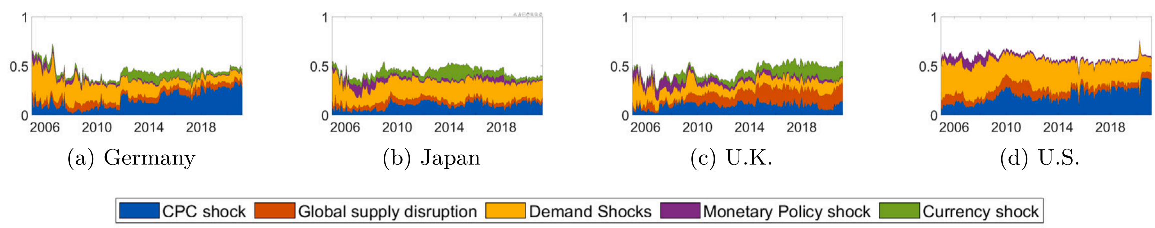
More importantly, concerning the impulse response functions to global supply chain disruptions, Fig. 15 shows an appropriate shape for the IRFs in the case of the U.S. and Japan. The shocks only have a short-term effect, though, as opposed to what is shown with the GSCP (Fig. 4). Moreover, the NACTI does not seem to capture inflationary effects for Germany, while the GSCP does. Note that while NACTI only accounts for maritime container trade, the GSCP is built with delays in different transportation methods. Germany's imports and exports are also frequently traded by land. Moreover, for the U.K., a deflationary effect of supply chain disruptions is obtained. This does bring into



(a) Germany. CPC Shock (b) Japan. CPC Shock (c) U.K. CPC Shock (d) U.S. CPC Shock

(e) Germany. Global Supply Chain Disruption (f) Japan. Global Supply Chain Disruption (g) U.K. Global Supply Chain Disruption (h) U.S. Global Supply Chain Disruption

Fig. 16. Time-Varying Impulse Response Functions of Inflation (using NACTI).
Notes: The 3-D figure above shows the recursively estimated impulse response functions of inflation to a CPC shock and a global supply chain disruption for Germany, Japan, the U.K., and the U.S. The sample period is from January 2005 to August 2022 and the model is estimated with 12 lags. Green values denote a significantly positive response within a 95% confidence interval. Red values denote a significantly negative response within a 95% confidence interval. Yellow values denote insignificant values within a 95% confidence interval. x-axis: months after shock; y-axis: magnitude of response; z-axis: sample date.



(a) Germany (b) Japan (c) U.K. (d) U.S.

Fig. 17. Time-Varying Forecast Error Variance Decompositions (using NACTI).
Notes: The figure above shows the time-varying forecast error variance decompositions. These correspond to the recursively estimated IRFs, averaged across the 18-month horizon.

question whether the use of the NACTI index can be easily extrapolated to regions besides North America. Particularly in Fig. 16, regarding the time-varying IRFs for the effect of global supply chain disruptions on inflation, we can still observe coherent results for Japan and the U.S. in the short term. However, IRFs suggest a long-term deflationary effect of global supply chain disruptions for these countries, no statistical significance for Germany, and a counter-intuitive result for the U.K.

Finally, results given by the Forecast Error Variance Decompositions remain consistent with the use of the GSCP or NACTI (Figs. 7 and 17). Results are slightly better with the GSCP than with NACTI, except for the U.K. Overall results suggest that the NACTI index is capturing more of a demand shock for the U.K. than a supply shock, which suggests that a different identification scheme would be necessary to use the NACTI to measure supply disruptions for the U.K. This is left for further research.

Overall, results remain consistent, proving the robustness of empirical analysis in the paper, and confirming that, for an international analysis, the GSCP measure is preferred.

6. Conclusions

This paper examines the differential impacts of both commodity price shocks and global supply chain disruptions while controlling for demand shocks, on the inflation rates of Germany, Japan, the U.K., and the U.S. This is performed through a structural model with monthly data from 1998 to 2022. Based on the idea that the inflationary effect of particular commodities is time-varying, we calculate a CPC factor through a genetic algorithm which allows us to recursively select the combination of commodity prices that best explain each country's inflation rate over time. To account for global supply chain disruptions, we use the GSCP index proposed by Benigno et al. (2022). We also control for demand shocks through shifts in industrial production and the trade balance ratio, and for financial conditions, monetary policy shocks, and the real effective exchange rate. This allows us to focus on relative price changes stemming from supply and demand shocks, rather than on the monetary aspect that drives aggregate inflation.

The main results of the paper can be summarized as follows. First, the estimation of the CPC factors shows the varying relevance of each of the commodities for each of the country's inflation rates. For example, we observe that inflation rates in Germany, the U.K., and the U.S. are very sensitive to energy prices. In contrast, in the case of Japan, while the weight of energy prices on inflation rates varies throughout the period of analysis, it remains low for the last part of the sample, and inflation rates currently respond mainly to raw materials and agricultural products. Second, average impulse response functions calculated from the model suggest that CPC shocks have a medium-term effect on inflation rates in Germany, the U.S., and the U.K., but a weaker effect on the Japanese inflation rate. Regarding energy policy implications, these results suggest that, since their inflation rates are currently more vulnerable to energy price shocks, countries such as Germany, the U.K., and the U.S. have a higher need to shift away from fossil fuels to renewable energy in order to reduce stagflationary risks stemming from high energy prices.

IRFs also indicate that global supply chain pressures have a significant and permanent impact on inflation rates in Germany, the U.K., and the U.S., suggesting that current inflation rate increases in these countries are mainly driven by recent supply chain disruptions suffered in the aftermath of the COVID-19 pandemic. However, the inflation rate in Japan has not significantly responded to these supply chain shocks. Such results call for a strategic management of inventories and reserves not only for commodities but across the entire supply chain.

Finally, forecast error variance decompositions show that global supply shocks have incrementally explained unexpected changes in inflation since 2010, showing that scarcity in supply constitutes a continuously increasing risk of stagflation. Overall, while demand shocks remain relevant in understanding inflation, global supply shocks, mainly commodity price shocks, have become the main drivers of international inflation.

We believe our results are useful for all agents concerned with inflation rates. For example, they allow us to understand to which extent inflation rates can be explained by supply or demand factors. Since monetary policies to control inflation rates work through demand channels, identifying when inflation rates are mainly supply-driven invites the use of other measures to contain inflation. In particular, there is a growing need for strategic management of inventories and reserves to accommodate short-term supply shocks and important investments for finding alternative sources for the supply of commodities. Knowing the relevance of each commodity allows for a more efficient allocation of such policies. Particularly, regarding energy transition policies, our results allow us to further understand the vulnerability of each domestic economy to energy price shocks and the need for each country to invest in renewable energy sources.

Declaration of competing interest

None of the authors hold any paid or unpaid positions as officer, director, or board member of relevant non-profit organizations or profit-making entities, whose policy positions, goals, or financial interests relate to the article.

This declaration applies also to the close relatives and partners of the authors. Finally, no other party had the right to review the paper prior to its circulation.

The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of the affiliated institutions.

Data availability

All data and replications codes are available in the following link:

Replication Folder. Global Drivers of Inflation: The Role of Supply Cha in Disruptions and Commodity Price Shocks (Original data) (Mendeley Data)

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