Commodity Price Shocks, Supply Chain Disruptions and Inflation Rates: Evidence for Four Big Economies

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Abstract

This paper estimates the differential impacts of both global supply chain disruptions and commodity price shocks on inflation rates in Germany, Japan, the U.K., and the U.S., and examines their persistence by means of a structural vector autoregressive (SVAR) model over the period from January 1998 to August 2022. With these objectives, we propose a cost-push commodity factor for each of the four economies built on the combination of commodity prices that best explain each country's inflation rates over time, selected through a genetic algorithm. The main results suggest that supply chain disruptions have significant and permanent effects on inflation rates in Germany, the U.K. and the U.S., although not in Japan. Furthermore, commodity price shocks have only transitory effects on inflation rates in Germany, Japan and the U.S., and a more permanent effect on the U.K. Important policy implications on energy and monetary policies can be derived from the results of the paper.

JEL Classification: E32, E37, F47, F62
Keywords: global supply disruptions; commodity price shocks; inflation rates; SVAR model

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. Notably, both supply chain disruptions and commodity price increases can be identified as stagflationary shocks of a global nature, presenting a challenge to policymakers who aim to mitigate the effects of these shocks on their domestic economies.

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). This context of high and diverse

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inflation rates begs several questions of interest; i.e., (i) what is the magnitude and persistence of the effect of global supply chain disruptions and commodity price shocks on inflation in major economies?; (ii) which commodities present a prime concern for policymakers in terms of controlling inflation?; (iii) 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, the U.K., and the U.S; countries that can be considered a geographically diverse representation of developed economies. We examine the magnitude and persistence of the stagflationary effects of these shocks by means of a structural vector autoregressive (SVAR) model estimated for each economy over the period 1998-2022.

Literature on global supply chain disruptions 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. (2022) employ this approach and extend 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. An alternative approach is presented by Benigno et al. (2022), who perform a principal component analysis based on several cross-country and global indicators of supply chain pressures, to propose a novel indicator, the GSCP index. 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. Based on this index, di Giovanni et al. (2022) find that global supply chain bottlenecks played a significant role in inflation rates, specially 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 with an SVAR model -identified using a combination of sign restrictions and narrative restriction-, and find that a global supply chain shock causes a drop-in euro area real economic activity and an increase in consumer prices.[1]

Nevertheless, 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 the 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 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, 2007; Kilian, 2009; Baumeister and Peersman, 2013; Baumeister and Kilian, 2016; Gelos and Ustyugova, 2017; Kilian, 2019). Additional empirical studies investigate the inflationary impact of other commodity prices (i.e., Chen et al., 2014; Furceri et al., 2015; 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. (2022), one must consider the time-varying importance of each commodity for inflation, given potential structural changes in an economy. We, therefore, follow Diaz et al. (2022) in estimating a Cost-Push Commodity (CPC) factor for each country through a genetic algorithm which allows to recursively select the combination of commodity prices that best explain domestic inflation over time. Notedly, the CPC factor will be constructed with commodity prices that generate inflation that is not pulled by demand, but rather pushed by supply.

Our SVAR model will include the GSCP (Benigno et al., 2022), the CPC factor, Industrial Production (IP) and inflation for each country in order to examine the stagflationary nature of these global shocks. Main contributions of the paper will, consequently, include the following. First, this paper considers a long time span and analyzes the impulse-response functions of global supply disruptions and commodity prices on inflation rates from 1998 to 2022 which will allow us to identify the average and time-varying impacts of

[1]Also, recently, Isaacson and Rubintson (2022) study 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.

commodity price and supply chain pressures to 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 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) and Finck and Tillman (2022). Finally, important energy and monetary policy implications will be derived from the results.

Our main results suggest that supply chain disruptions have significant and permanent effects on inflation rates in the U.S., the U.K., and Germany, although not in Japan. Furthermore, commodity price shocks have transitory effects on inflation rates in the U.S., Japan, and Germany, and a more permanent effect on the U.K. inflation rate.

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 time-varying SVAR model used in the empirical analysis and the main results based on the impulse response functions of inflation to a CPC shock and a global supply disruption. Finally, Section 4 contains some concluding comments and policy implications.

2. Estimation of the Cost-Push Commodity Factor

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

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

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. Equation 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 cost-push commodity prices.

2.1. Selection of Cost-Push Commodities

For the selection of commodities, as in Diaz and Perez-Quiros (2021) and Diaz et al. (2022), 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

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

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. Commodity factor, f_q, is, therefore, a function of A_q such that $f_q(A_q)$.

The objective is to search for a commodity factor, f_q, that best explains cost-push inflation in each of the four countries; that is, fluctuations in inflation rates, π, after accounting for changes in demand (measured through industrial production, ipm), as well as controlling for global supply disruptions, $GSCP$, 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, $y_{qt} = [ipm_t, f_{qt}(A_q), GSCP_t, \pi_t]$, and ϵ_t is an error term. Equation 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 Equation 3, by selecting A_q.[2]

Following Diaz and Perez-Quiros (2021) and Diaz et al. (2022), 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. They also provide a full description of the procedure for implementing the genetic algorithm in the selection of commodities.

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

2.2. CPC Factors

We perform a recursive estimation of the CPC factor, in which 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.[3] This implies that, the CPC factor, f_t, is 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 $\{f_1(A_1^* \mid I_1), f_2(A_2^* \mid I_1), ..., f_T(A_T^* \mid I_T)\}$. We use data starting in January 1995, 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. Prices are deflated with each country's consumer price index (CPI). CPI and IP indexes were obtained from Fred Economic Data, Federal Reserve Bank of St. Louis.

Figure 1 shows the recursively estimated CPC factor along with the inflation rate 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 factor 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. It is worth mentioning that the CPC factor estimated for Japan is not aligned with this country's inflation rate in that period. Related literature has provided different explanations for persistent 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 ageing 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 level of prices, as well as on potential output, labour market participation, and real interest rates. In addition, labour 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 tend to ask for wage increases considering observed inflation rather than expected or target inflation.

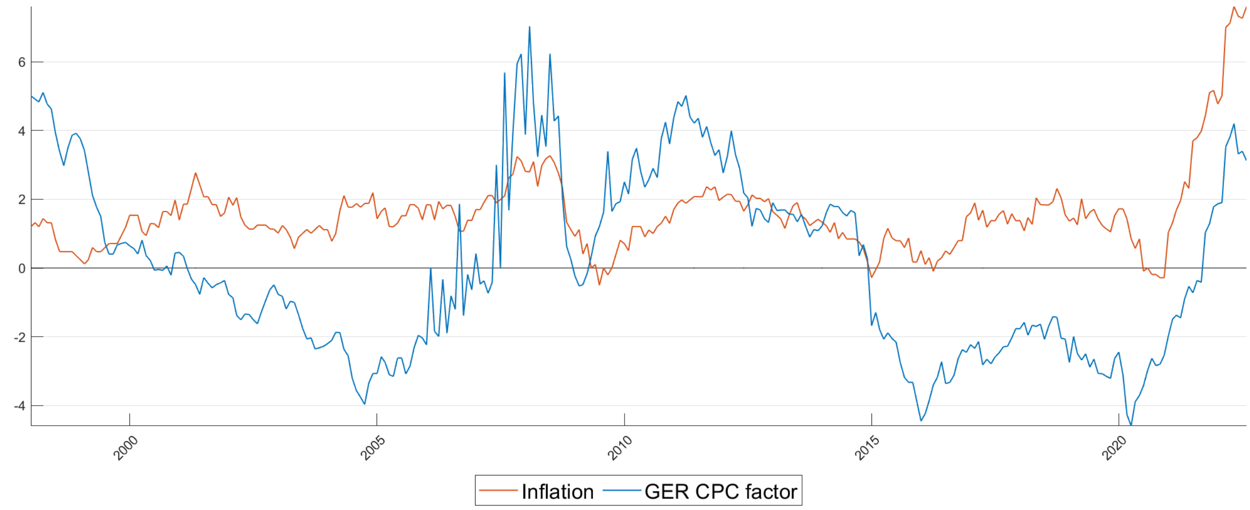
2.3. Cost-Push Commodities in each of the Four Countries

We can also examine which are the commodities that have induced cost-push inflation in each of the countries during the recursively estimated sample period. To do so, we present the aggregated weights assigned

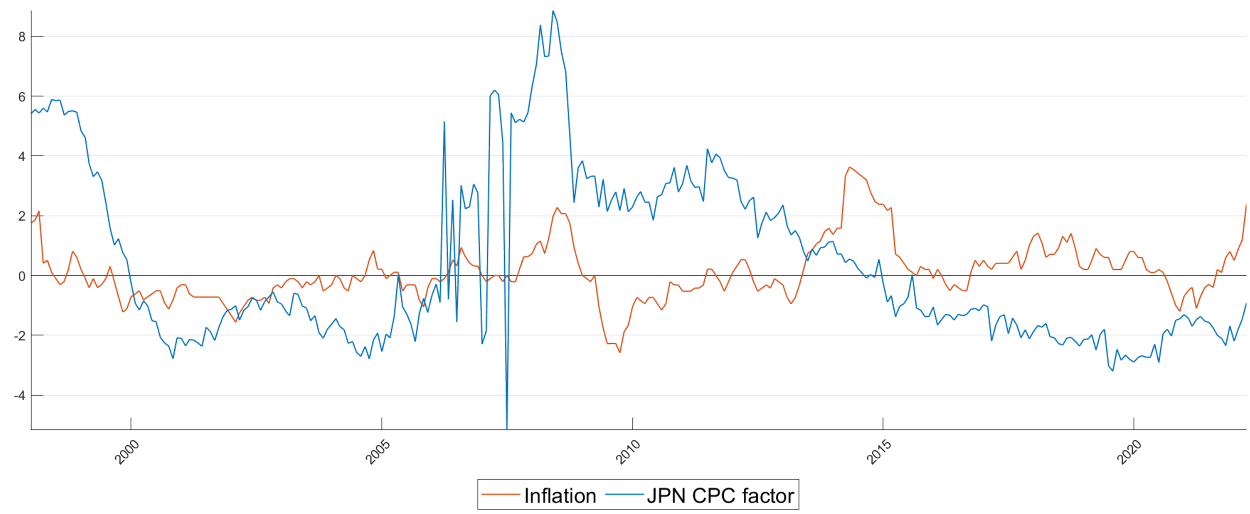
[2]Note that minimizing the sum of squared errors is equivalent to maximizing the R^2 statistic of the regression in Equation 3, which was the approach adopted by Diaz and Perez-Quiros (2021) in their application. Additionally, like the authors, we restrict the algorithm to select a minimum of 3 commodities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

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

Figure 1: CPC Factors and Inflation Rates



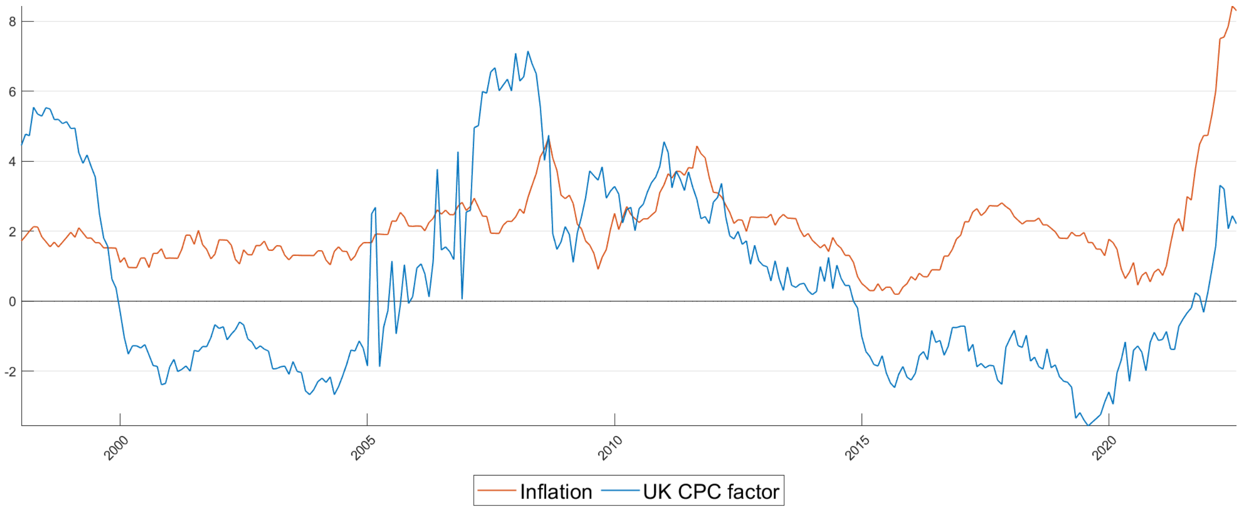
(a) Germany



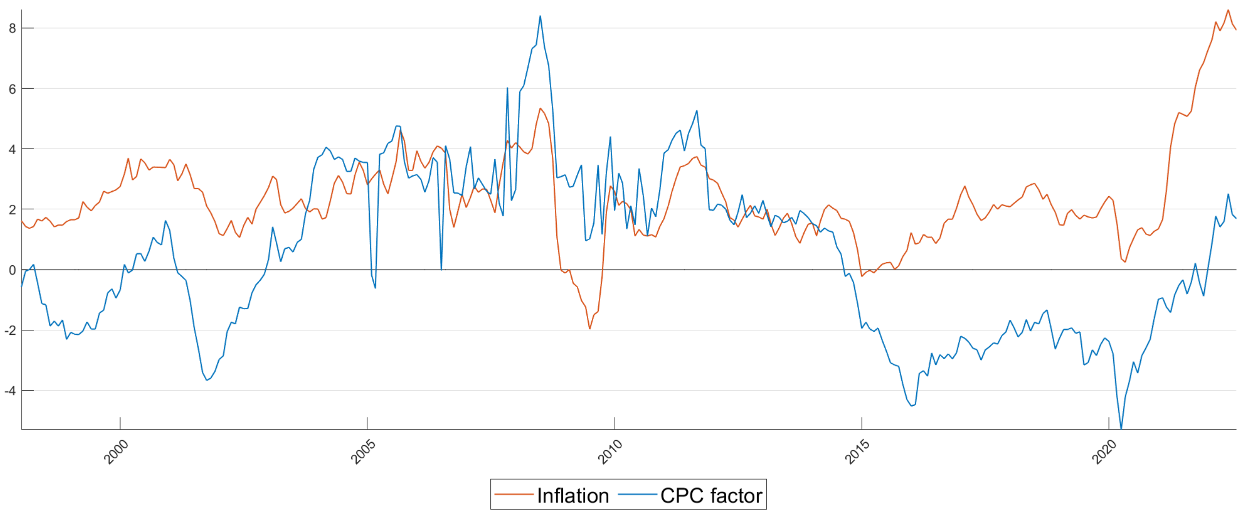
(b) Japan

to each commodity type (energy, raw materials, metal, agricultural commodities). These are defined in the following way:

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



(c) U.K.



(d) U.S.

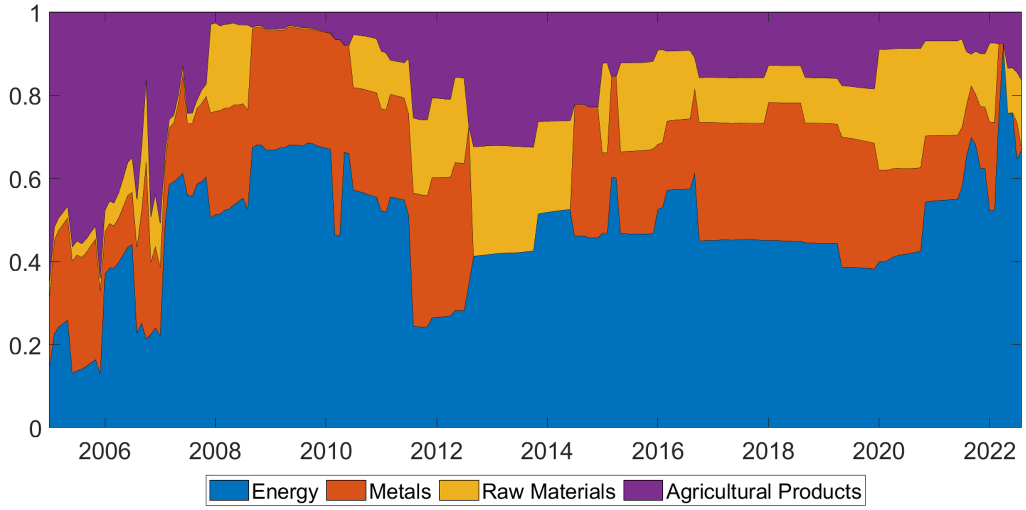
Notes: The figure above shows the year-to-year inflation rates for Germany, Japan, the U.K. and the U.S. along with their corresponding CPC factors. Both series are at a monthly frequency.

where $\lambda^2_{t,E}$, $\lambda^2_{t,M}$, $\lambda^2_{t,I}$, and $\lambda^2_{t,A}$ 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 Equation 1.

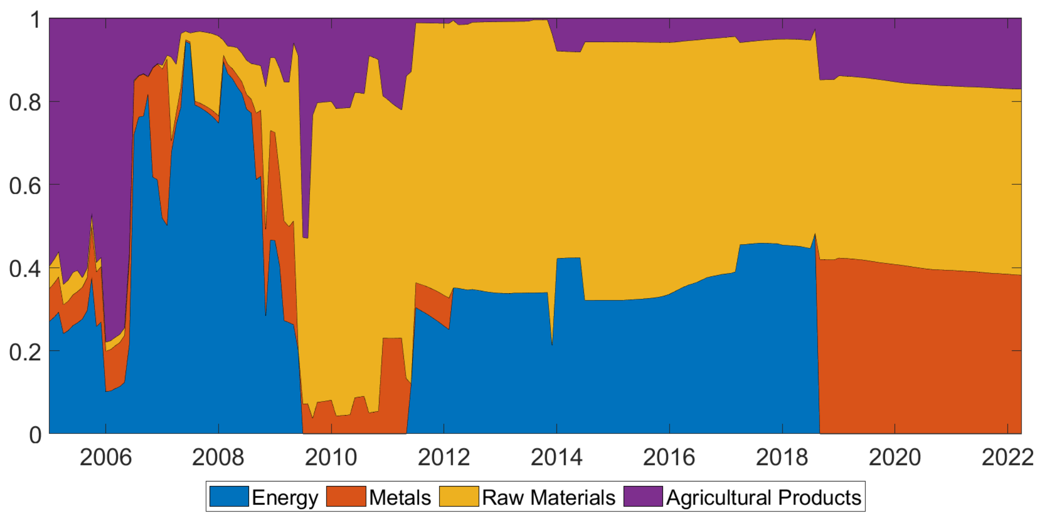
Figure 2 shows the weights for each commodity type. We can observe that these weights have varied significantly over time and that they are different for each of the countries. For example, and as far as energy prices are concerned, their weights with respect to the inflation rates in Germany and the U.S. are higher than in Japan and the U.K. For example, Ikeda et al. (2022) state that there are differences in how energy prices increase across regions (U.S. vs. Japan and Europe) due to differences in local energy market structures and in the rates of increase of natural gas prices.

Furthermore, it is also worth mentioning that while the weight of this commodity type was high in the four countries before the Global Financial Crisis (GFC), its weight decreased significantly in the U.K. until the recent post COVID-19 period. We could, thus, assume that inflation rates in Germany and the U.S. are

Figure 2: Time-varying Weights of Commodities for the Estimation of the CPC Factors

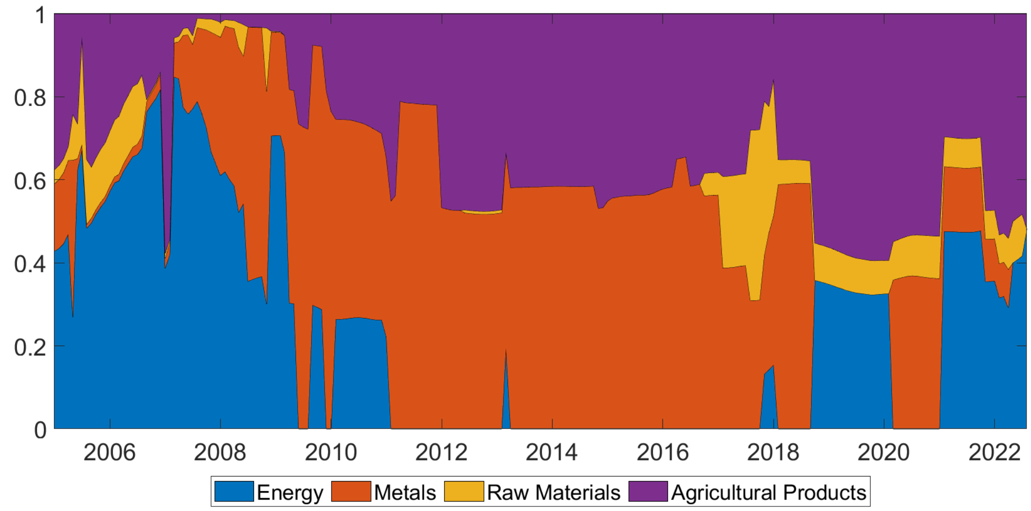


(a) Germany

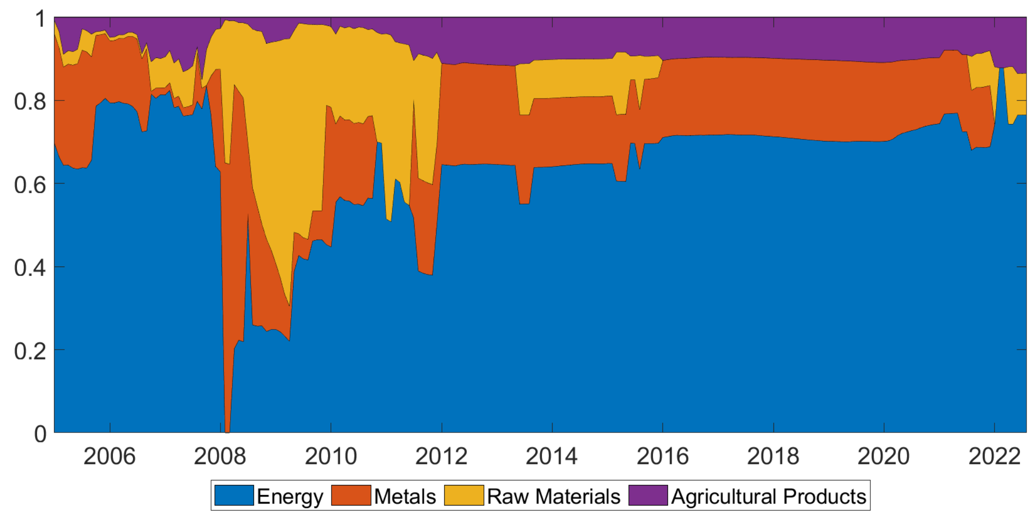


(b) Japan

now more vulnerable to energy prices than the Japanese inflation rate. Therefore, in a context of high energy prices, countries such as Germany and the U.S. will be more willing to shift away from fossil fuels to renewable energy sources, speeding up their energy transition.



(c) U.K.



(d) U.S.

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.

3. SVAR for Inflation Rates: Model and Empirical Evidence

3.1. SVAR model

In order to examine the effect of global supply disruptions and cost-push commodity shocks on inflation rates, we estimate an SVAR model for each of the four economies, including industrial production, the GSCP proposed by Benigno et al. (2022), the CPC factor calculated above and the inflation rate. It is defined as follows:

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

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

The structural shocks are identified as follows:

$$\begin{pmatrix} \varepsilon_t^{IP} \\ \varepsilon_t^{f} \\ \varepsilon_t^{GSCP} \\ \varepsilon_t^{\pi} \end{pmatrix} = \begin{bmatrix} b_{11}^0 & 0 & 0 & 0 \\ b_{21}^0 & b_{22}^0 & 0 & 0 \\ b_{31}^0 & b_{32}^0 & b_{33}^0 & 0 \\ b_{41}^0 & b_{42}^0 & b_{43}^0 & b_{44}^0 \end{bmatrix} * \begin{pmatrix} \omega_t^{domestic\ demand\ shock} \\ \omega_t^{cost-push\ commodity\ shock} \\ \omega_t^{global\ supply\ disruption} \\ \omega_t^{monetary\ shock} \end{pmatrix} \tag{7}$$

where the responses of the four variables are freely estimated. Particularly, we allow for higher domestic demand to have an instantaneous impact commodity prices, pressures on the global supply distribution, as well as on inflation.

Moreover, we identify a cost-push commodity shock, as a shift in the CPC factor that is not explained by the change in domestic demand. Given that the nature of this shock suggests a shift of supply in commodity markets, this is allowed to immediately affect international trade as well as inflation. Followingly, as shown in Kilian et al. (2023), given the presence of inventories, frictions in the global supply chain are expected to affect domestic demand and commodity markets with a delay. Finally, unexplained changes in inflation are termed monetary shocks as they may include monetary policy actions by the Federal Reserve, exchange rates shocks and others.

Such identification of shocks allows us to define B_0^{-1} as the Cholesky decomposition of the variance-covariance matrix Σ.

3.2. Impulse Response Functions

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

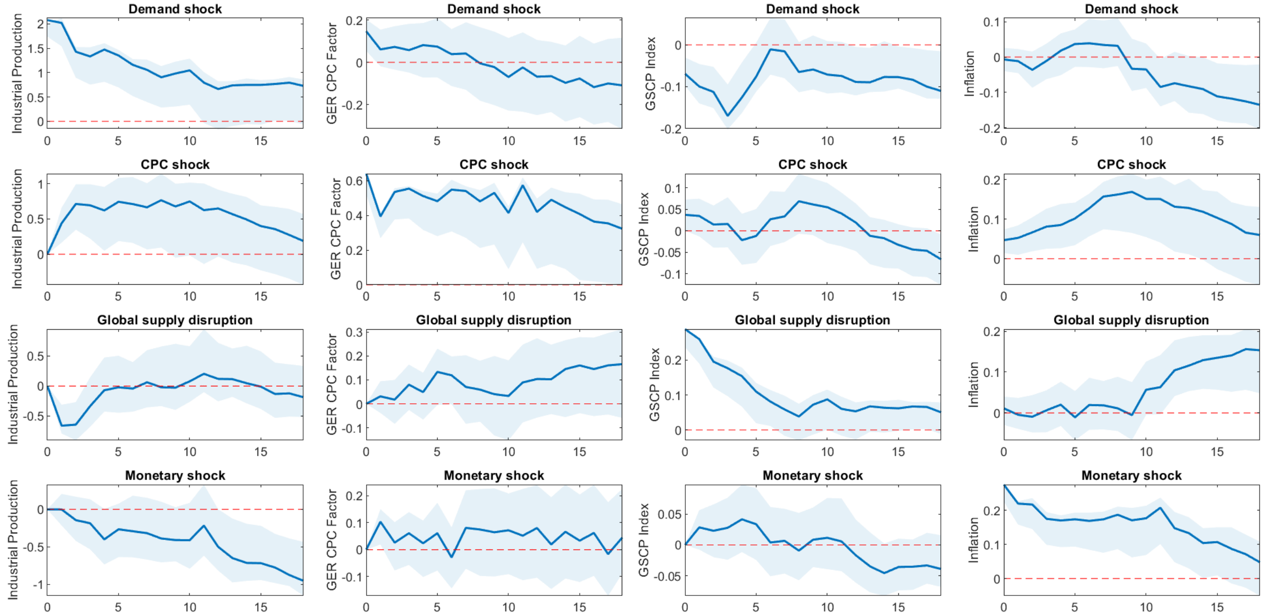
It is interesting to compare the structural impulse response estimates for the selected four economies. As expected, according to economic theory, the response of inflation rates to a CPC shock are positive and qualitatively similar in the short-run (from 1 to 6 months) in all economies. However, CPC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

When we focus on the impact of a global supply disruption shock on inflation rates, we observe a long-run positive and significant effect in Germany, the U.K. and the U.S. Inflation rates in Japan, however, do not respond to a global supply disruption shock.

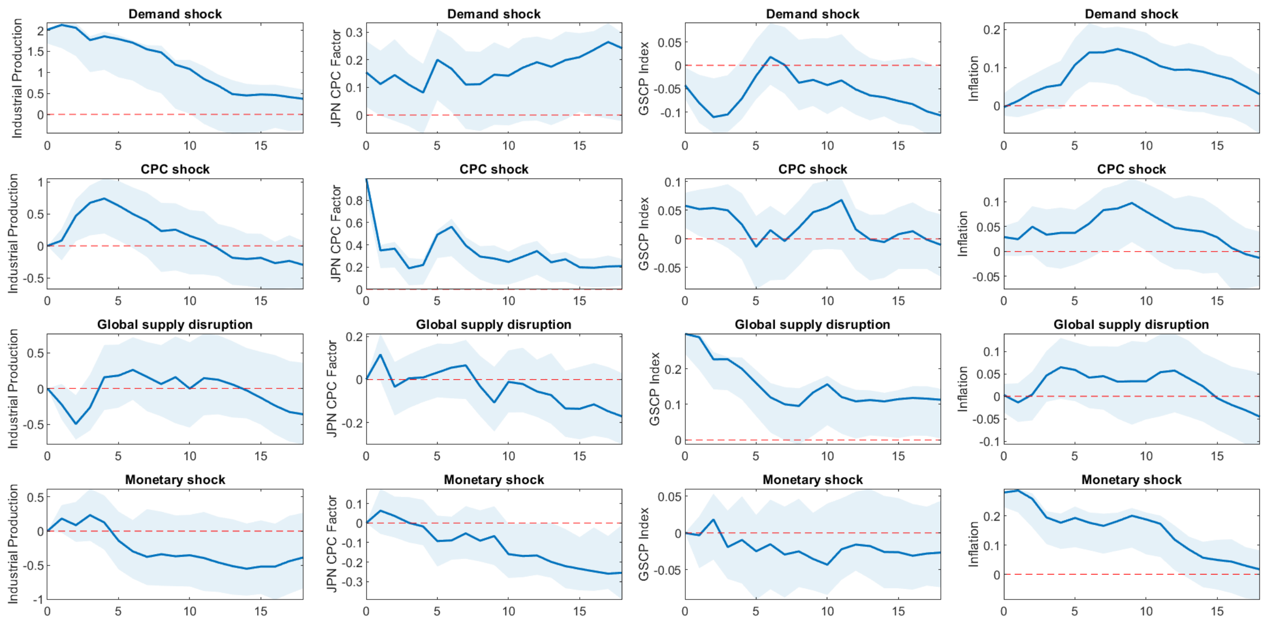
Next, we present the time varying effects of the structural shocks of interest (CPC shock and global supply disruption) on inflation rates. Figure 4 plots the three-dimensional impulse responses of inflation for Germany, Japan, the U.K. and the U.S to a commodity price shock. All economies exhibit positive significant impact responses and hump-shaped medium-run responses except in the case of Japan. In addition, inflation rates in Germany and the U.K. also show a long-run positive impact of a CPC shock on inflation. These results are qualitatively similar to Diaz et al. (2022) 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) find 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.

Figure 5 provides the IRFs of inflation rates with respect to a global supply disruption. Similar to Figure 4, these IRFs are plotted in three-dimensions. Supply chain disruptions have positive and permanent effects on inflation rates in Germany, the U.K. and the U.S., although not in Japan. In the case of Japan, global supply chain disruptions have displayed long-term and negative effects on its inflation rate. Excluding the evidence of the Japanese economy, our main results are in line to 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

Figure 3: Impulse Response Functions of Inflation to a CPC Shock and Global Supply Disruptions

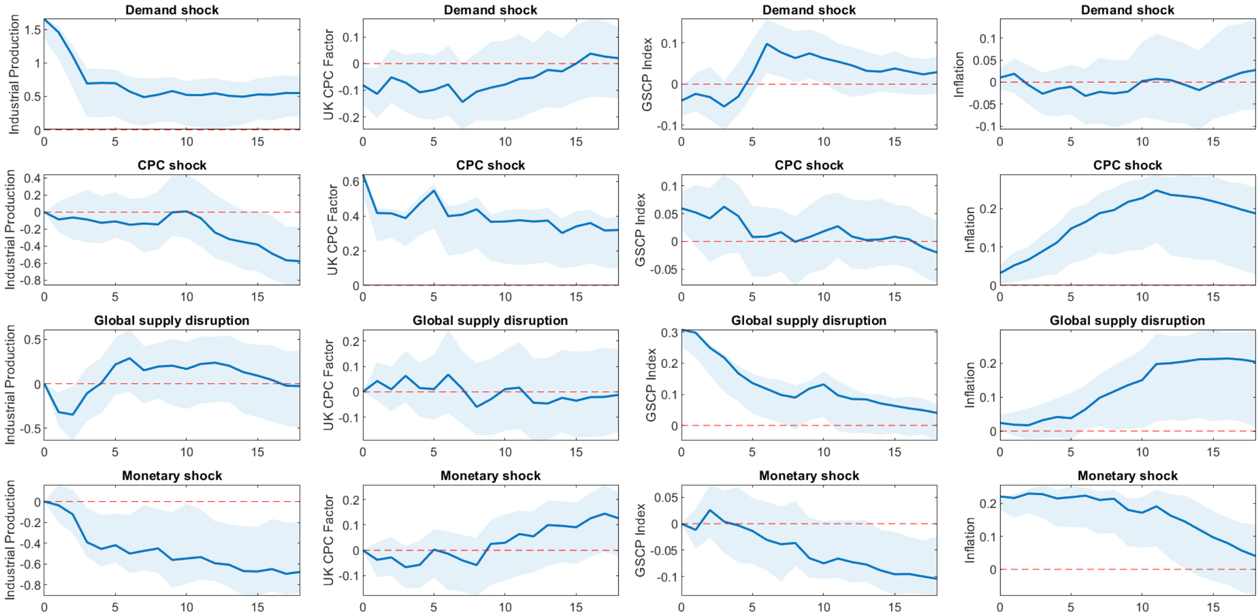


(a) Germany

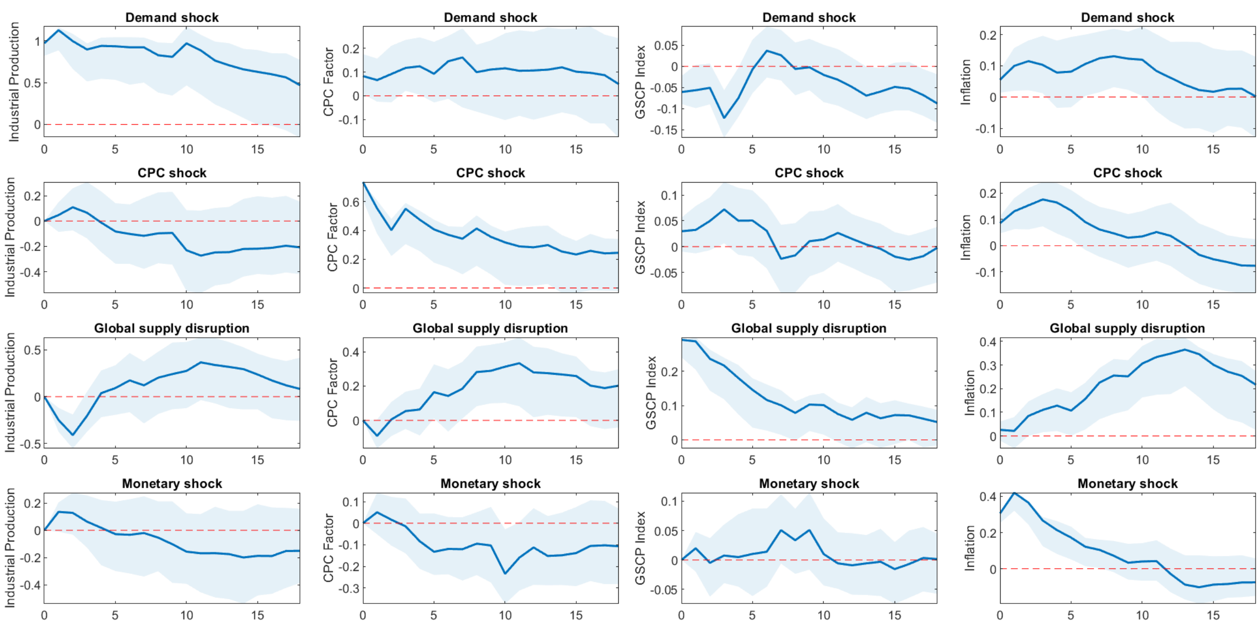


(b) Japan

Tillman, 2022).



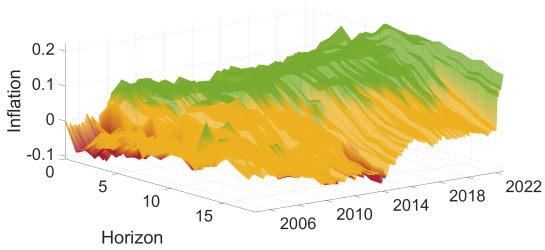
(c) U.K.



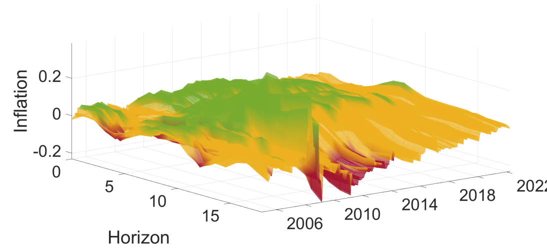
(d) U.S.

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.

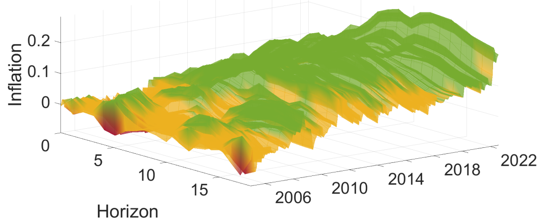
Figure 4: Impulse Response Functions of Inflation to a CPC Shock



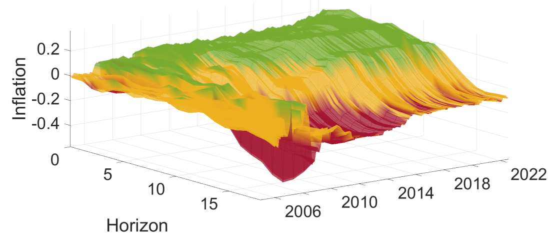
(a) Germany



(b) Japan



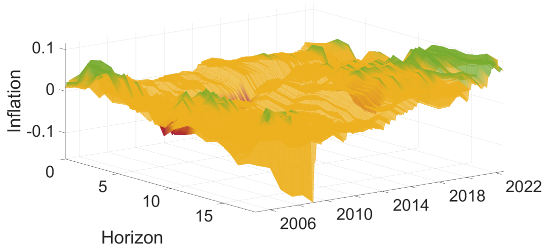
(c) U.K.



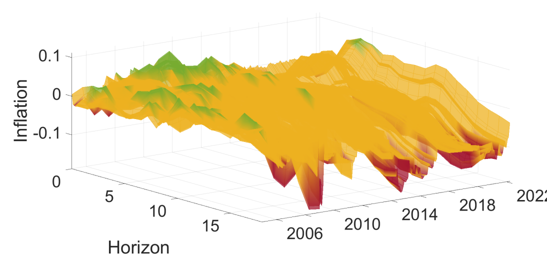
(d) U.S.

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.

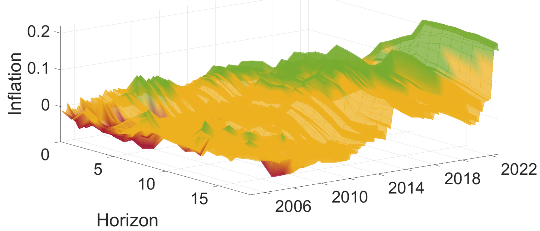
Figure 5: Impulse Response Functions of Inflation to a Global Supply Disruption



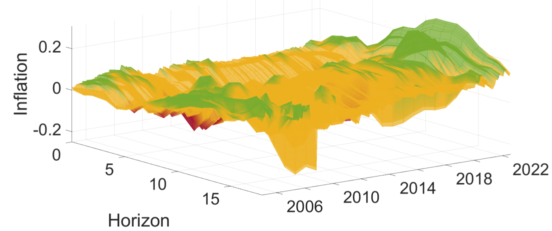
(a) Germany



(b) Japan



(c) U.K.



(d) U.S.

Notes: The 3-D figure above shows the recursively estimated impulse response functions of inflation to a global supply 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.

4. Conclusions

This paper examines the differential impacts of both commodity price shocks and global supply chain disruptions on the inflation rates of Germany, Japan, the U.K., and the U.S. by means of estimating different SVAR models using monthly data for the period 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 to recursively select the combination of commodity prices that best explain each country's inflation over time. In order to account for global supply chain disruptions, we use the GSCP index proposed by Benigno et al. (2022). The inclusion of these two variables in the SVAR model together with industrial production and inflation rates allows us to identify shocks to domestic demand, commodity prices, global supply disruptions and inflation.

The main results of the paper can be summarized as follows. First, and regarding each of our country level CPC factors, the temporal evolution of this variable shows the different relevance of each of the commodities in each of the country's inflation rates. For example, we observe that inflation rates in Germany and the U.S. are very sensitive to energy prices. In contrast, for the case of Japan and the U.K., the weight of energy prices on inflation rates in these countries remained relatively high during the GFC, but not in the rest of the period of analysis. Regarding energy policy implications, these results suggest that, since their inflation rates are more vulnerable to energy price shocks, countries such as Germany and the U.S., will have more incentives to shift away from fossil fuels to renewable energy in a situation of high energy prices. In contrast, for the U.K., we observe an increasing weight of agricultural prices on inflation rates. Inflation rates in Japan, on the other hand, have responded mainly to raw materials and metals in the period after the GFC. Second, average impulse response functions calculated from the model suggest that the CPC factor has only a transitory effect of CPC factors on inflation rates in Germany, Japan and the U.S., but a more permanent effect on the U.K. inflation rate.

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.

We believe our results are useful for all agents concerned with inflation rates. For example, they allow to understand to which extent inflation rates can be explained by supply or demand factors. Since monetary policies to control inflation rates mainly work through demand channels, identifying when inflation rates are mainly supply-driven invites the use of other measures in order to contain inflation. As explained above, and regarding the energy transition policies, they could help us to understand the vulnerability of each domestic economy to energy price shocks and the incentives of each country to invest in renewable energy sources.

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