This Is Going to Hurt: Weather Anomalies, Supply Chain Pressures and Inflation

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ABSTRACT: As climate change accelerates, the frequency and severity of extreme weather events are expected to worsen and have greater adverse consequences for ecosystems, physical infrastructure, and economic activity across the world. This paper investigates how weather anomalies affect global supply chains and inflation dynamics. Using monthly data for six large and well-diversified economies (China, the Euro area, Japan, Korea, the United Kingdom, and the United States) over the period 1997-2021, we implement a structural vector autoregressive model and document that weather anomalies could disrupt supply chains and subsequently lead to inflationary pressures. Our results—based on the monthly data and robust to alternative estimation methodologies—show that these effects vary across countries, depending on the severity of weather shocks and vulnerability to supply chain disruptions. The impact of weather shocks on supply chains and inflation dynamics is likely to become more pronounced with accelerating climate change that can have heterogeneous effects. These findings have important policy implications. Central bankers should consider the impact of weather anomalies on supply chains and inflation dynamics to prevent entrenching second-round effects and de-anchoring of inflation expectations. More directly, however, governments can invest more for climate change adaptation to strengthen critical infrastructure and thereby minimize supply chain disruptions.

JEL Classification Numbers: E32; F14; F62; F64; G15; G30; Q54

Keywords: Climate change; weather anomalies; temperature; supply chain pressures; inflation; structural VAR

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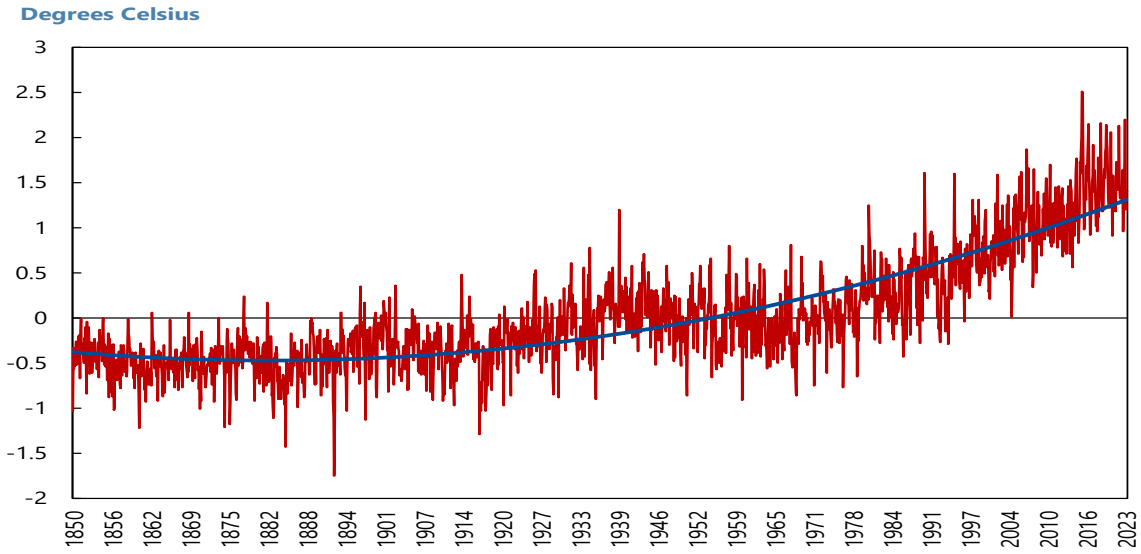
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I. Introduction

The world economy has experienced a multitude of shocks in recent years, disrupting global supply chains, causing a deep recession, and pushing inflation to the highest level since the 1970s. While inflation is on the decline from its post-pandemic peak, long-term vulnerabilities persist. One of the most significant risks to the global economy and financial markets is climate change. The increase in the global land temperature has reached more than 1.1 degrees Celsius (°C) compared with the preindustrial average, before human-induced climate change began to take effect (Figure 1).[1] Projections show that accelerating climate change will raise the mean temperature above the 1.5°C threshold in the near term and by as much as 4°C over the next century absent a global green transition. As climate change accelerates over the coming decades, greater frequency and severity of acute weather events can have far-reaching adverse consequences for physical infrastructure and economic activity (Stern 2007; IPCC 2007, 2014, 2019; 2021). There is convincing evidence that show climate-related natural disasters having significant effects on inflation and growth (Cevik and Jalles, 2023). An important channel of transmission in this context is the complex and interdependent network of supply chains across the world, as shown by disruptions during the COVID-19 pandemic (Bonadio *et al.*, 2021; Binici *et al.*, 2022; Celasun *et al.*, 2022; Santacreu and LaBelle, 2022). With rising temperatures, extreme weather conditions will stress transportation infrastructure and highly-connected global supply chains—interrupting production, causing shortages, and leading to higher prices.[2]

Figure 2. Global Temperature Anomalies



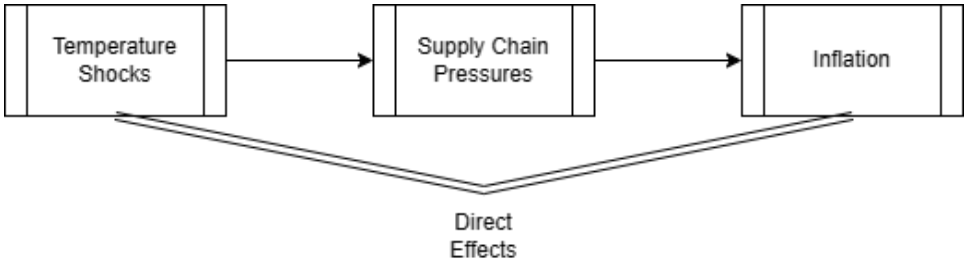
Source: National Oceanic and Atmospheric Administration.

[1] The average global temperature in 2023 was already about 1.5°C warmer than that of the pre-industrial period. However, a temporary increase of 1.5°C is different from the Paris Agreement target of limiting long-term global warming to 1.5°C by 2100.

[2] Supply chain disruptions persisting a month or longer already occur every 3.7 years on average (Lund *et al*., 2020). These disruptions are not just caused by hurricanes and tornadoes, but also by severe drought due to intense heat waves, for example, in the Panama Canal and the Rhine River, which are the only passageway for container vessels between the Atlantic and Pacific oceans and one of the most important inland waterways in Europe, respectively. Carriere-Swallow *et al*. (2023) find that higher shipping costs due to supply chain disruptions have a significant effect on domestic inflation in a sample of 46 countries.

Conceptually, the effects of weather anomalies, as measured by temperature deviations from the seasonal pattern in this paper, can evolve through different direct and indirect transmission mechanisms, with opposing effects simultaneously on demand and supply (Somanathan *et al*., 2021; Cevik and Jalles, 2023; Ciccarelli, Kuik, and Hernández, 2023). First, weather anomalies could increase prices indirectly via supply chain disruptions. Prices increase in industrial production via supply chain disruptions due to delayed delivery of parts and components. The increased costs of delayed delivery would be passed to final goods prices that raise inflation. The increased disruptions in the supply chain generate a cost-push pressure on prices. A large body of literature corroborate that supply chain disruptions increase inflation (Di Giovanni *et al.,* 2022 ; Andriantomanga, Bolhuis, and Hakobyan, 2023 ; Kabaca and Tuzcuoglu, 2023). Second, the sign of direct impact of weather anomalies on inflation is *a priori* difficult to determine due to two opposing effects of weather anomalies on inflation. On the one hand, higher temperature and drier conditions would reduce food supply and lower individual productivity in climate-sensitive sectors of the economy. More varied weather conditions increase volatility in prices due to unpredictable food supply. The combined effect of drought and hotter temperature could further decrease food supply, increasing inflation. However, such an increase in food prices could be partly offset by warmer temperatures in cooler countries, raising food supply. In addition, weather shocks can result in higher energy demand and prices, which could in turn lead to second-round effects on non-energy prices across the economy. On the other hand, warmer temperatures would reduce demand for energy consumption for heating, reducing inflation. Or the demand for energy could rise for cooling during warmer temperatures, increasing inflation. Deroubaix *et al.* (2021) show that the increasing trends in cooling energy are more significant than the decreasing trends in heating as winter becomes warmer. In this complex context, we examine how the weather anomalies affect supply chains and inflation dynamics as illustrated in Figure 2.

Figure 2. Transmission of Temperature Shocks



This paper aims to close an important void in the literature by providing an empirical analysis of how weather anomalies—measured by unseasonal deviation in temperature from the historical average—affect supply chain pressures and inflation dynamics. Using monthly data covering six large economies—China, the Euro area, Japan, Korea, the United Kingdom, and the United States—over the period 1997-2021, we estimate a set of structural vector autoregressive (SVAR) models for each country in the sample and trace the contemporaneous effects of weather shocks on country-specific supply chain pressures and inflation. To the best of our knowledge, this is the first attempt in the literature to investigate the impact of temperature anomalies on supply chain disruptions and alternative measures of inflation using a SVAR model, which offers insights on how climate change could affect global supply networks and inflation dynamics beyond the sample of countries used in the analysis. For robustness, we also implement the panel Local Projection (LP) method to trace the dynamic effects of temperature anomalies on supply chains and inflation dynamics over time.

We find that weather anomalies could disrupt supply chains and subsequently lead to inflationary pressures. Our results—based on monthly data and robust to alternative estimation methodologies—indicate significant heterogeneity across countries in the sample, which we attribute to differences in the severity of weather anomalies and vulnerability to supply chain disruptions. The impact of weather shocks on supply chains and inflation dynamics is likely to become more pronounced with accelerating climate change that tends to have heterogeneous effects across and within countries. Our empirical results do not always show a strong positive link between weather anomalies and supply chain disruptions, due to, in part, the use of aggregated supply-side disruptions. However, this does not imply that we can be complacent about the increasing severity and frequency of weather anomalies, as shown by a plethora of recent shocks including the severe drought has reduced water level considerably in the Panama Canal and disrupted one of the main trade routes connecting Asia and North America.

The empirical analysis presented in this paper has important policy implications. Central bankers should consider the persistent impact of weather anomalies on supply chains and inflation dynamics to prevent entrenching second-round effects and de-anchoring inflation expectations. More directly, however, governments can invest more for climate change adaptation to strengthen critical infrastructure and thereby minimize supply chain disruptions.

The remainder of this study is structured as follows. Section II reviews the related literature. Section III describes the data used in the analysis. Section IV introduces the salient features of our econometric strategy. Section V presents the empirical results. Section VI presents robustness checks. Finally, Section VII offers concluding remarks with policy implications.

II. Literature Review

This paper contributes to a growing branch of the literature focusing on the impact of climate change on economic activity and financial markets.[3] Starting with Nordhaus (1991; 1992) and Cline (1992), aggregate damage functions are widely used to analyze the relationship between climatic conditions and economic developments. Although the identification of macroeconomic effects of annual variation in climatic conditions is a difficult empirical undertaking, Gallup, Sachs, and Mellinger (1999), Nordhaus (2006), and Dell, Jones, and Olken (2012) observe that higher temperatures result in a significant reduction in economic growth in developing countries. Burke, Hsiang, and Miguel (2015) corroborate this finding and determine that higher temperatures would have a greater damage in countries that are concentrated in geographic areas with hotter climates. Using large datasets, Acevedo *et al*. (2018), Burke and Tanutama (2019), Kahn *et al.* (2021), and Akyapi, Bellon, and Massetti (2022) show that the long-term economic impact of weather anomalies, such as persistent changes in the temperature above or below the historical norm, is not homogenous across countries and that economic growth responds nonlinearly to extreme temperature.

It is also well documented that increasing frequency and severity of climate-related natural disasters affect economic development (Loyaza *et al.*, 2012; Noy, 2009; Raddatz, 2009; Skidmore and Toya, 2002), reduce the accumulation of human capital (Cuaresma, 2010) and worsen external balances (Gassebner, Kesk, and The, 2006). More recently, Cevik and Jalles (2020; 2021; 2022) show that climate change vulnerability has significant effects on the cost of government borrowing and the probability of sovereign debt default, especially in developing countries. Similarly, Bansal, Kiku, and Ochoa (2016) and IMF (2020) find that risks associated with climate change—as proxied by temperature increases—

[3] Tol (2018) provides a recent overview of this expanding literature.

have a negative effect on asset valuations, while Bernstein, Gustasson, and Lewis (2019) show that real estate exposed to the risk of sea level rise is priced at a discount relative to otherwise similar unexposed houses. Focusing on the U.S., Painter (2020) finds that counties more likely to be affected by climate change pay more in underwriting fees and initial yields to issue long-term municipal bonds compared to counties unlikely to be affected by climate change.

There is a small but growing literature on the impact of climate change on consumer price inflation. A few studies look at the impact of natural hazards on prices (Parker, 2018; Heinen, Khadan, and Strobl, 2019), while there is almost no research on the effect of extreme weather events including temperature deviations, apart from studies focusing on specific sectors of activity (De Winne and Peersman, 2021) or a single country (Kim, Matthes, and Phan, 2022). Studying how extreme temperatures affect various measures of inflation in 48 advanced and emerging economies during the period 1951–1980, Faccia, Parker, and Stracca (2021) find that higher temperatures play a non-negligible role in driving price developments, especially for emerging market economies. Similarly, Kabundi, Mlachila, and Yao (2022) analyze how climate shocks affect consumer prices and find that the impact depends on the type and intensity of shocks, the level of income, and the type of monetary policy regime. Finally, in a recent study covering 173 countries over the period from 1970 to 2020, Cevik and Jalles (2023) show that climate-related natural disasters have significant effects on consumer price inflation and economic growth.

The literature on supply chain pressures and inflation is limited, but also growing fast after the COVID-19 pandemic. Benigno *et al.* (2022) introduces a new index of global supply chain pressures and find a significant effect on inflation during the pandemic period. With a model-based approach, Di Giovanni *et al.* (2022) shows that supply bottlenecks in international trade contribute to higher inflation. Using data from international container trade, Finck and Tillmann (2022) find that global supply chain disruptions caused by the Tohoku earthquake in 2011, the Suez Canal obstruction in 2021, and the Shanghai backlog in 2022 caused a decline in real economic activity and an increase in consumer prices in the euro area. LaBelle and Santacreu (2022) analyze the effect of supply chain pressures on producer prices in the US and conclude that about one-fifth of the producer price inflation. Likewise, Kabaca and Tuzcuoglu (2023) analyze the contribution of supply-side forces to consumer price inflation in the US and show that global supply chain and oil price shocks are the most principal factors during the COVID-19 pandemic. Using a panel of 29 sub-Saharan African countries, Andriantomanga, Bolhuis, and Hakobyan (2023) find that an increase in global supply chain pressures leads to a significant increase in consumer price inflation.

III. Data Overview

The vector of endogenous variables includes three variables: weather anomalies, supply chain pressures and consumer price inflation. We assemble a dataset of monthly observations covering six countries (China, the Euro area, Japan, Korea, the United Kingdom, and the United States) over the period 1997–2021. The sample selection is determined by the availability of country-specific data on supply chain pressures. Inflation is computed as the year-on-year percentage change in the Consumer Price Index (CPI) as follows:

$$\pi_{i,t} = \left(\frac{CPI_{i,t}}{CPI_{i,t-12}} - 1\right) * 100 \qquad (1)$$

where $\pi_{i,t}$ denotes inflation in country *i* at time *t* based on headline CPI or core CPI, drawn from the World Bank's global database of inflation (Ha, Kose, and Ohnsorge, 2023). The year-on-year percentage change eliminates seasonality. For the euro area, inflation data are taken from Eurostat[4].

We measure country-specific supply chain disruptions with the Supply Chain Pressures Index (SCPI) constructed by the Federal Reserve Bank of New York (Benigno *et al.*, 2022). The SCPI is a novel measure of supply chain pressures based on monthly information from 27 indicators including international transportation costs, port congestions, shortage of containers and drivers, and supply chain-related components of the Purchasing Managers' Index surveys for manufacturing firms. The SCPI is measured in standard deviations from the sample average and normalized to have an average value of zero over the full time series. Accordingly, a reading above zero implies an increase in supply chain disruptions relative to the average.

Weather anomalies are measured as a deviation of monthly mean temperature from the historical average, which are obtained from the World Bank's Climate Change Knowledge Portal. We follow the literature and calculate monthly deviations in temperature as $T_{i,t} = T_{i,t} - \overline{T}_{i,(t)}$ in country *i* at time *t*. In other words, weather anomalies are derived from the difference between the temperature observation at time *t* and the historical average for that month during the reference period of 1901-1996. Given that the SCPI begins in 1997, we choose the reference year for weather anomalies from 1996 backward. For the Euro area, we aggregate 19 countries to calculate a GDP-weighted average series of temperature deviations to account for the differences in country size.

Descriptive statistics, presented in Table 1, show significant variation across countries and over time. First, we observe that the deviation of monthly mean temperature from its historical average ranges from 0.86°C in the United Kingdom to 1.26°C in Japan, with an upward trend across all countries. Second, supply chain pressures as measured by the SCPI vary from -0.02 in Japan to -0.01 in the Euro Area. Third, headline inflation moves from an average of 0.12 percent in Japan to 2.52 percent in Korea, while core inflation stands at -0.09 percent in Japan and 2.07 percent in the United States.

For the appropriate implementation of the SVAR model, it is necessary to analyze the time-series properties of the data. The stationarity of all variables is checked by applying the augmented Dickey-Fuller (1981) test and the Zivot and Andrews test (1992), which accounts for structural breaks. These results, presented in Appendix Table A1, indicate that temperature and supply chain pressures are stationary, while inflation series show mixed results, particularly for the Zivot and Andrews test (1992). Sims, Stock and Watson (1990) and Ramey (2016) show that a log level specification provides consistent estimates. Elliott (1998) argues that imposing the unit root and cointegration relationship would produce a large size distortion in theory. Therefore, we follow Ramey (2016) and add constant and time trends in the SVAR specifications to address the non-stationary variables. This is the safest approach in the SVAR specifications in case of the non-stationary variables.

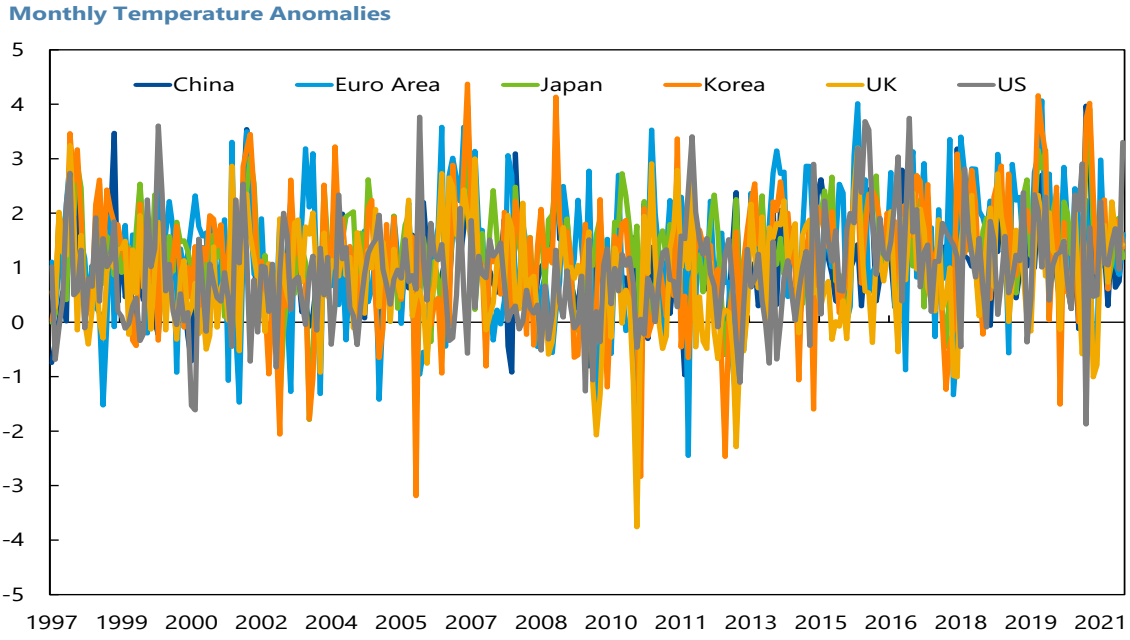
[4] For robustness, to mitigate outliers and handle the possible negative values of inflation, we resorted to an inverse hyperbolic sine transformation, i.e., $\ln\left(\pi_{i,t} + \sqrt{\pi_{i,t}^2 + 1}\right)$, and obtained similar results (results are available upon request).

Table 1. Summary Statistics

China	Obs	Mean	SD	Min	Median	Max
Temperature	292	0.96	0.850	-1.758333	.8689062	3.974688
SCPI	292	-0.02	0.969	-1.793194	-.1585425	4.358228
Headline CPI	292	1.91	2.094	-2.200009	1.738521	8.804665
Core CPI	192	1.23	0.819	-1.697495	1.436658	2.4241
Euro Area	Obs	Mean	SD	Min	Median	Max
Temperature	292	1.24	1.181	-2.457838	1.259421	4.069844
SCPI	292	-0.01	0.997	-3.28	-.01	3.5
Headline CPI	292	1.65	0.969	-.6415135	1.78945	4.964337
Core CPI	241	1.48	0.550	.3712164	1.365485	2.678672
Japan	Obs	Mean	SD	Min	Median	Max
Temperature	292	1.27	0.889	-1.794687	1.30901	3.918333
SCPI	292	-0.02	0.966	-2.755975	-.0644083	3.626369
Headline CPI	292	0.12	1.005	-2.515091	-.0499002	3.699789
Core CPI	292	-0.09	0.825	-1.603206	-.1990052	2.574665
Korea	Obs	Mean	SD	Min	Median	Max
Temperature	292	1.18	1.158	-3.194062	1.256771	4.37875
SCPI	292	-0.02	0.980	-7.159352	-.0140127	3.104874
Headline CPI	292	2.52	1.681	-.4260584	2.335785	9.547748
Core CPI	292	2.13	1.156	-.6969713	2.112118	6.121933
UK	Obs	Mean	SD	Min	Median	Max
Temperature	292	0.86	0.981	-3.765937	.8557813	3.251042
SCPI	292	-0.01	0.991	-4.118337	-.1256114	3.315986
Headline CPI	292	1.97	0.875	.1998002	1.888574	4.844607
Core CPI	292	1.62	0.609	-.129199	1.67875	3.811252
US	Obs	Mean	SD	Min	Median	Max
Temperature	292	0.92	0.945	-1.878437	.88125	3.773437
SCPI	292	-0.02	0.976	-1.899615	-.2075876	4.085564
Headline CPI	292	2.21	1.323	-2.097161	2.073482	7.036403
Core CPI	292	2.07	0.596	.6586169	2.083333	5.490549

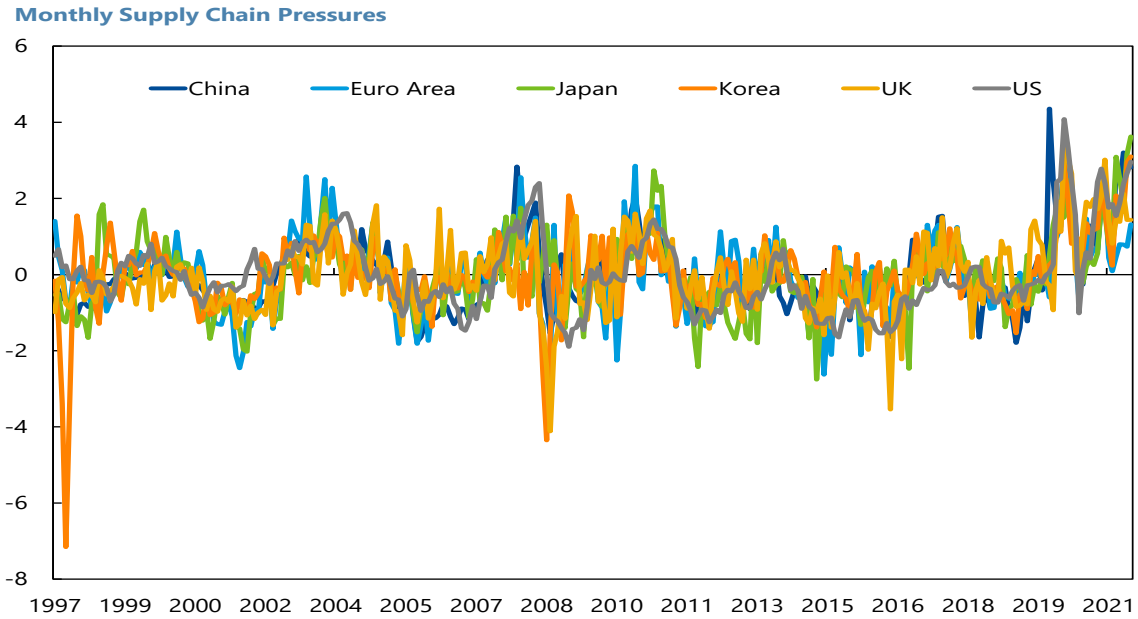
Source: Authors' calculations.

Figure 3. Country-Specific Weather Anomalies



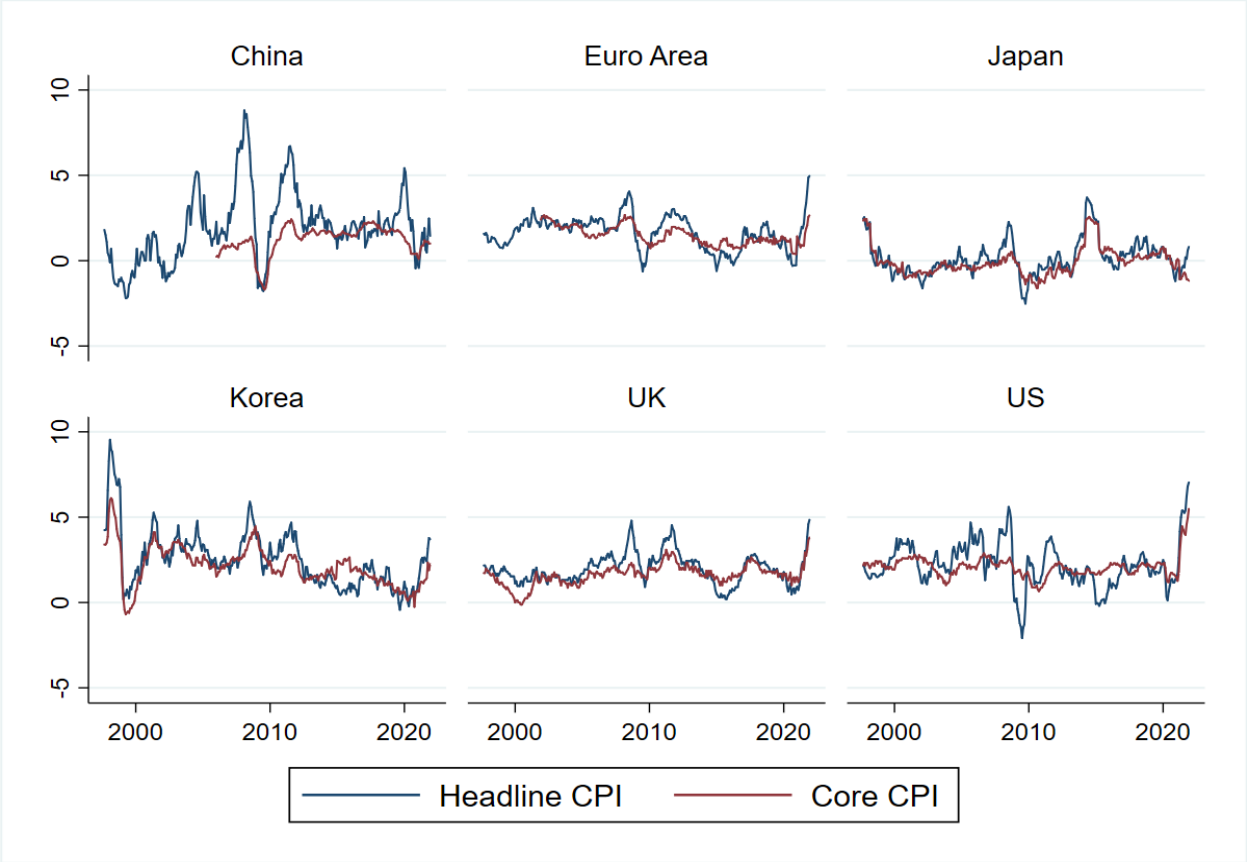
Note: Weather anomalies are measured by monthly deviations in temperature from the historical average. EA is Euro Area counties whose temperature deviation is calculated based on the weighted average, with GDP as a weight.
Source: World Bank Climate Change Knowledge Portal; authors' calculations.

Figure 4. Country-Specific Supply Chain Pressures



Note: Supply chain pressures are measured in standard deviations from the sample average. Source: Benigno *et al.* (2022).

Figure 5. Headline and Core CPI



Note: The year-on-year percentage changes on a monthly basis.
Source: World Bank; Authors' calculations.

IV. Econometric Strategy

The empirical objective of this paper is to estimate the impact of weather anomalies—as measured by temperature deviations—on supply chain disruptions and alternative measures of inflation, using monthly data covering six large economies (China, the Euro area, Japan, Korea, the United Kingdom, and the United States) over the period 1997–2021. To gain better insights into the dynamic relationship between climate change, supply chain disruptions and alternative measures of inflation, we implement a three-variable SVAR model and resort to the Cholesky decomposition to orthogonalize the reduced-form residuals that impose causal chains in this framework.

We are interested in how temperature shocks affect supply chains and inflation dynamics, which are also partly determined by supply chain disruptions. In our SVAR framework, we assume that temperature anomalies are strictly exogenous, and that no variable could influence the weather variable. One may argue that temperature anomalies are indeed an outcome of human activity, but the anthropogenic impact on weather anomalies is a slow-moving process over centuries (Ciccarelli, Kuik, and Hernández, 2023). Given that our focus is the short-run effect of temperature shocks on supply chain pressures and inflation, it is less likely that supply chain pressures and inflation affect weather anomalies.

Our identification of temperature shocks is based on the idea that weather anomalies cause supply chain disruptions that lead to changes in transportation costs and cross-border shipment quantities. Accordingly, in this paper, we use the identification assumption that weather anomalies cause supply chain disruptions that in turn reduce the supply of goods and services and lead to higher inflation. We estimate the AB model SVAR specification for each country separately as follows (Lütkepohl, 2005)[5]:

$$AX_t = \sum_{j=1}^{p} \Pi_j X_{t-j} + B\varepsilon_t \qquad (2)$$

in which X_t is a *3 x 1* vector of endogenous variables including weather anomalies (as measured by temperature deviations), the country-specific SCPI and headline or core inflation at time *t*. ε_t is an independent and identically distributed random vector with variance equal to the identity matrix of dimension of 3. Under these restrictions, we specify the SVAR model with the 3x3 matrix as below:

$$A = \begin{bmatrix} 1 & a_1 & a_2 \\ 0 & 1 & a_3 \\ 0 & 0 & 1 \end{bmatrix} \qquad (3)$$

Π_j is a 3x3 matrix such that

$$\Pi_j = \begin{bmatrix} \pi_{y,j}^{y} & \pi_{s,j}^{y} & \pi_{\tau,j}^{y} \\ 0 & \pi_{s,j}^{s} & \pi_{\tau,j}^{s} \\ 0 & 0 & \pi_{\tau,j}^{\tau} \end{bmatrix} \qquad (4)$$

Given that the A matrix is upper triangular, its inverse is also upper triangular and corresponds to

$$A^{-1} = \begin{bmatrix} 1 & -a_1 & a_1 a_3 - a_2 \\ 0 & 1 & -a_3 \\ 0 & 0 & 1 \end{bmatrix} \qquad (5)$$

Hence, the reduced form of our model is as follows:

$$X_t = \sum_{j=1}^{p} A^{-1} \Pi_j X_{t-j} + A^{-1} B\varepsilon_t \qquad (6)$$

$$\Phi_j = A^{-1}\Pi_j = \begin{bmatrix} \pi_{y,j}^{y} & \pi_{s,j}^{y} - a_1\pi_{s,j}^{y} & \pi_{\tau,j}^{y} - a_1\left(\pi_{s,j}^{y} - a_3\pi_{\tau,j}^{\tau}\right) - a_2\pi_{\tau,j}^{\tau} \\ 0 & \pi_{s,j}^{s} & \pi_{\tau,j}^{s} - a_3\pi_{\tau,j}^{\tau} \\ 0 & 0 & \pi_{\tau,j}^{\tau} \end{bmatrix} \qquad (7)$$

This implies that Φ_j is also upper triangular, and we can therefore directly impose those restrictions onto the reduced form coefficients. The B matrix is a diagonal matrix. For the optimal lag length of the SVAR model for each country, we resort to the SIC criteria that indicates 1 to 2 lags depending on the country[6].

[5] We omit constant and time trends for simplicity in the SVAR specifications. As discussed in data overview section, including constant and time trends in the SVAR specifications is the common approach in case of the non-stationarity of the variables (Ramey, 2016).

[6] We are aware that monetary policy and global oil prices affect inflation. However, the SVAR approach we use in this paper cannot isolate inflation only to depend on the monetary policy and global oil prices. In other words, including the exogenous shocks will make weather anomalies and supply chain disruptions to depend on the contemporaneous values of the exogenous variables, which contradicts our intuitions. We instead consider them in a panel local projection, which is a flexible approach to account for the exogenous variables only in inflation.

V. Empirical Results

In this section, we provide a visual presentation of the impulse response of supply chain pressures and inflation to temperature shocks over the 24-month horizon, together with corresponding 90 percent confidence intervals.[7] In Figure 7, we begin with the impact of weather shocks on supply chain pressures in six economies that we analyze. These results indicate that a larger temperature deviation with respect to the historical average tends to exert upward pressure on supply chain pressures. The estimated coefficients are economically intuitive, but not statistically significant for all countries in the sample. Quantitatively, we find that a 1°C increase in temperature with respect to historical average increases supply chain pressures by roughly 0.3 and 0.6 standard deviation after 2 years in the Euro Area, Korea and the United States. On the other hand, the impact of weather shocks on supply chain pressures appears to show negative relationship in China, Japan, and the United Kingdom. Altogether, these findings confirm that weather shocks could cause greater supply chain disruptions as climate change accelerates, showing different country-specific dynamics to temperature shocks.

It is also important to highlight the components forming the supply chain pressures. As described in the previous section, the SCPI is constructed based on shipping rates, air freight prices, and the sub-components of the PMI, such as delivery time, backlogs, and purchased stocks. These components tend to be affected more by, for instance, oil price fluctuations and port congestion that have a direct influence on supply chain pressures. Thus, the share of weather shocks explaining supply chain pressures might be smaller than what we would have expected. In addition, our results may have been contaminated by various external shocks, such as the 1997 Asian financial crisis, 2008 global financial crisis, and the unprecedented COVID-19 pandemic, which we exclude as a robustness check in the next section.

In Figures 8 and 9, we present the impact of supply chain pressures on headline and core inflation, respectively, in each economy. There is a clear upward pressure on headline inflation across all countries, except Korea. Quantitatively, a one-standard deviation shock of supply chain pressures on inflation is associated with large and persistent increases in headline inflation in China, the United Kingdom and the United States, amounting to about 2 percent, 2.1 percent, and 3.8 percent, respectively, over the 24-month period. The magnitude of this supply-chain effect on headline inflation is significantly smaller in the Euro Area and Japan, and supply chain pressures do not appear to have an adverse effect in the case of Korea. However, we should note that inflation in Korea may have been affected to a significant extent by the Asian financial crisis (1997-1999) that disrupted supply chains. After excluding the Asian financial crisis and the COVID-19 pandemic, we find that greater supply chain pressures lead to higher inflation in Korea[8]. We also observe that the impact of supply chain disruptions on core inflation follows a similar pattern (except for Japan), with considerably lower estimated coefficients (except for the United States).

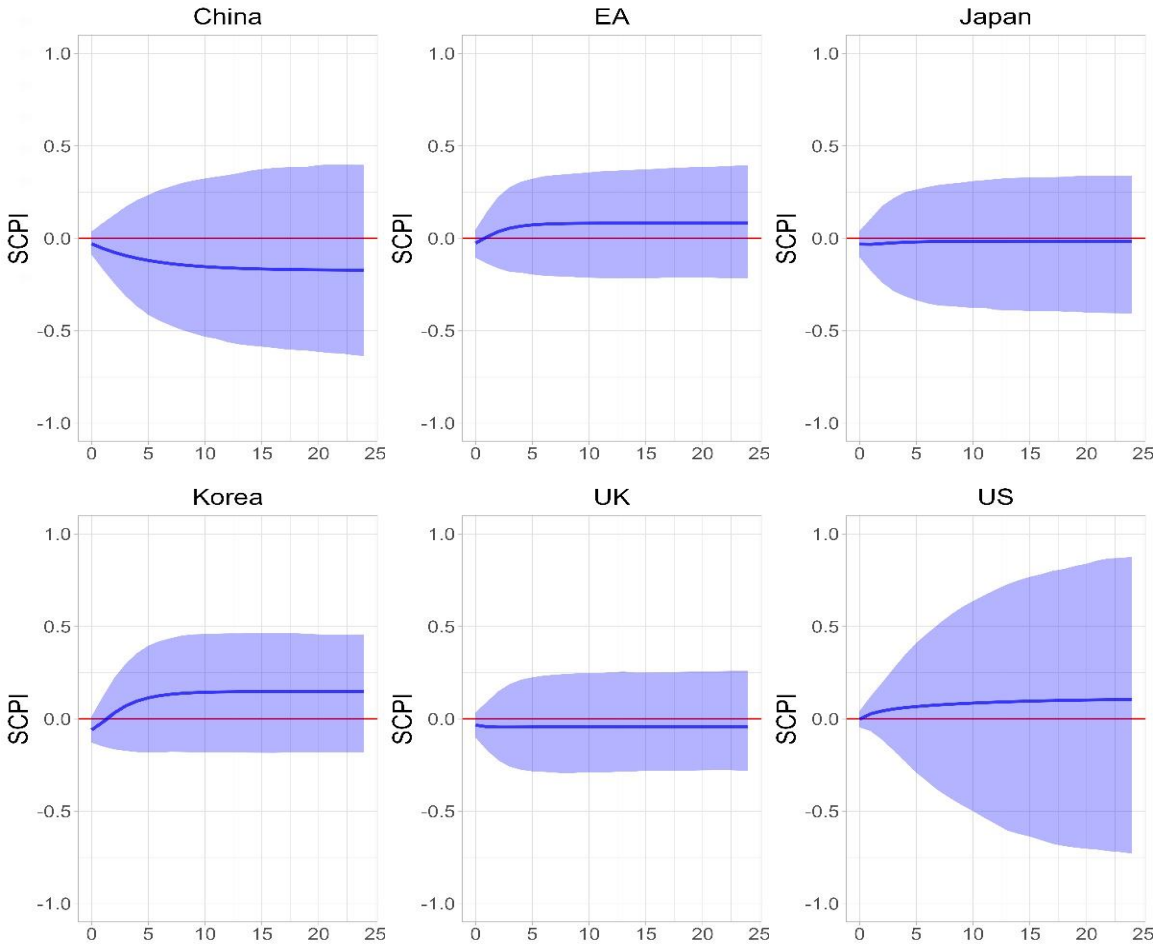
Finally, in Figures 10 and 11, we present the direct impact of weather shocks on headline and core inflation, respectively, for each economy separately. These statistically insignificant results for some countries yield an ambiguous picture of the relationship between temperature shocks and inflation dynamics. This should not be surprising since our sample consists of six large and well-diversified economies where inflation dynamics are shaped by more powerful domestic and global factors. It is also important to note that higher temperatures may have a positive effect on agricultural output and depress energy demand, which in turn lowers inflation pressures. As Lucidi *et al*. (2022) argue, warmer winters decrease energy

[7] We estimate 1,000 bootstrapped error bands for the impulse response coefficients.

[8] Results not shown here to save space. However, as we will see in the robustness checks, the results are qualitatively similar when the Asian financial crisis period is removed.

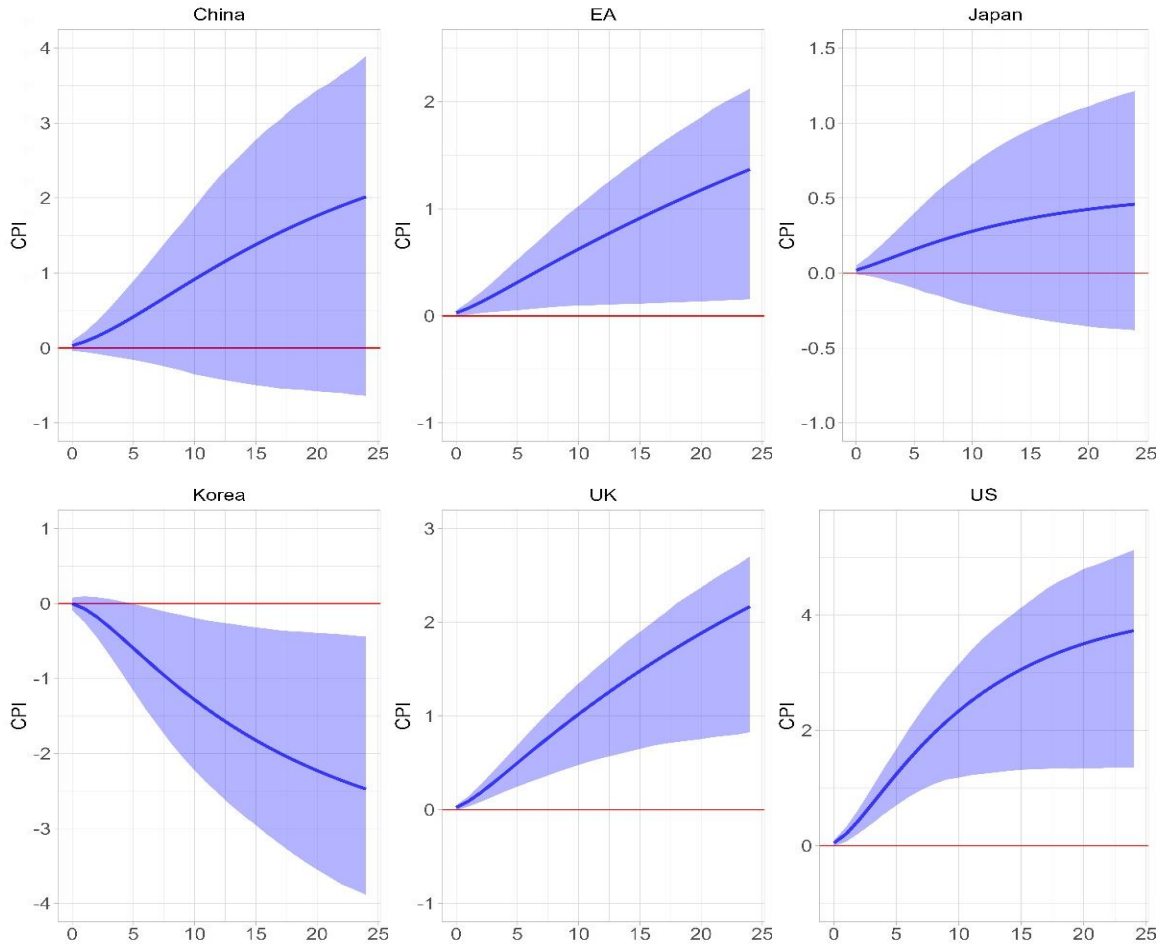
demand more than warmer summers raise it. Therefore, a decline in inflation could result from reduced energy demand. Nevertheless, with accelerating climate change, there is also an increase in the volatility of weather patterns, which we find to be associated with supply chain disruptions and consequently higher inflation.

Figure 7. Weather Shocks and Supply Chain Pressures



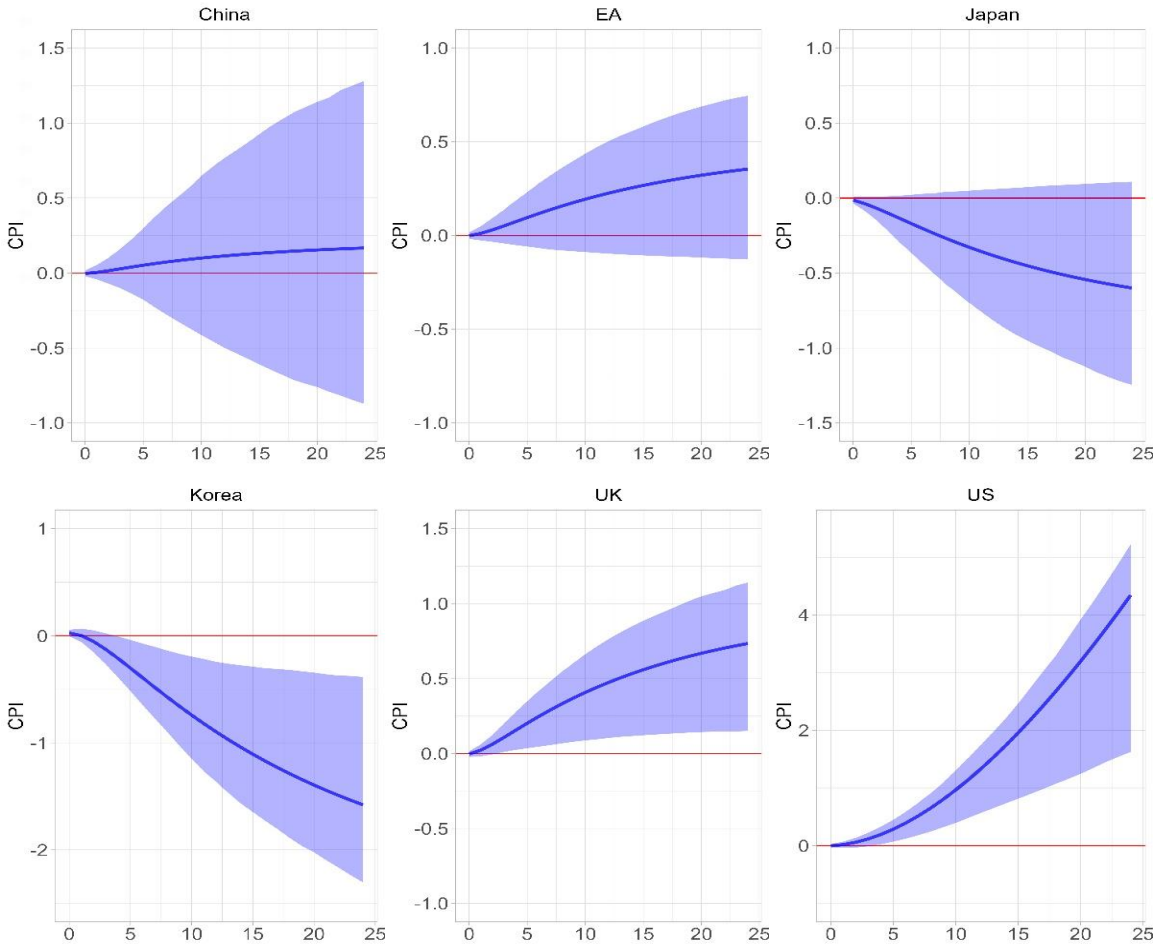
Note: The figure presents the cumulative response of supply chain pressures to temperature shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates of the Euro Area and China began from December 2001 and January 2006, respectively, to December 2021.

Figure 8. Supply Chain Pressures and Inflation: Headline CPI



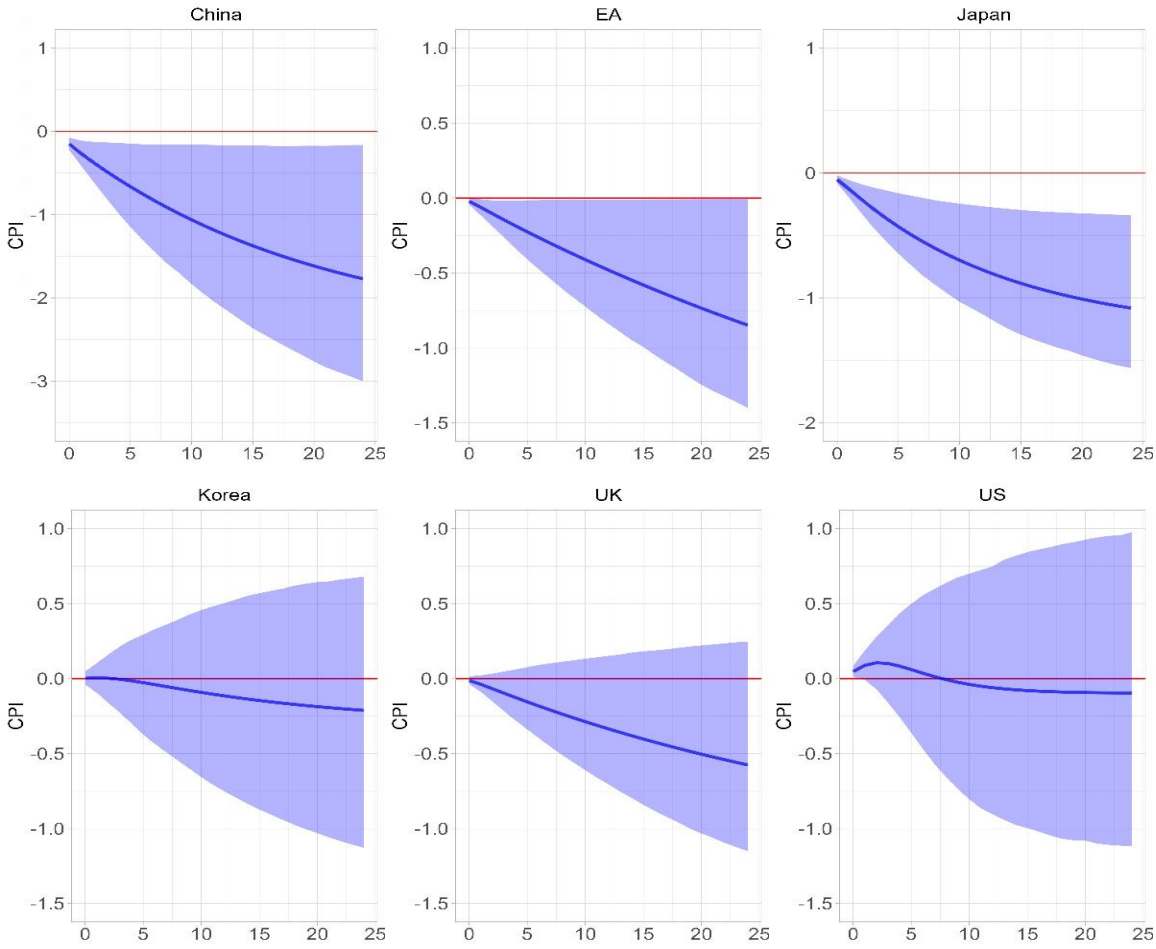
Note: The figure presents the cumulative response of headline inflation to supply chain pressures in dark blue line and 90 percent confidence intervals in light blue.

Figure 9. Supply Chain Pressures and Inflation: Core CPI



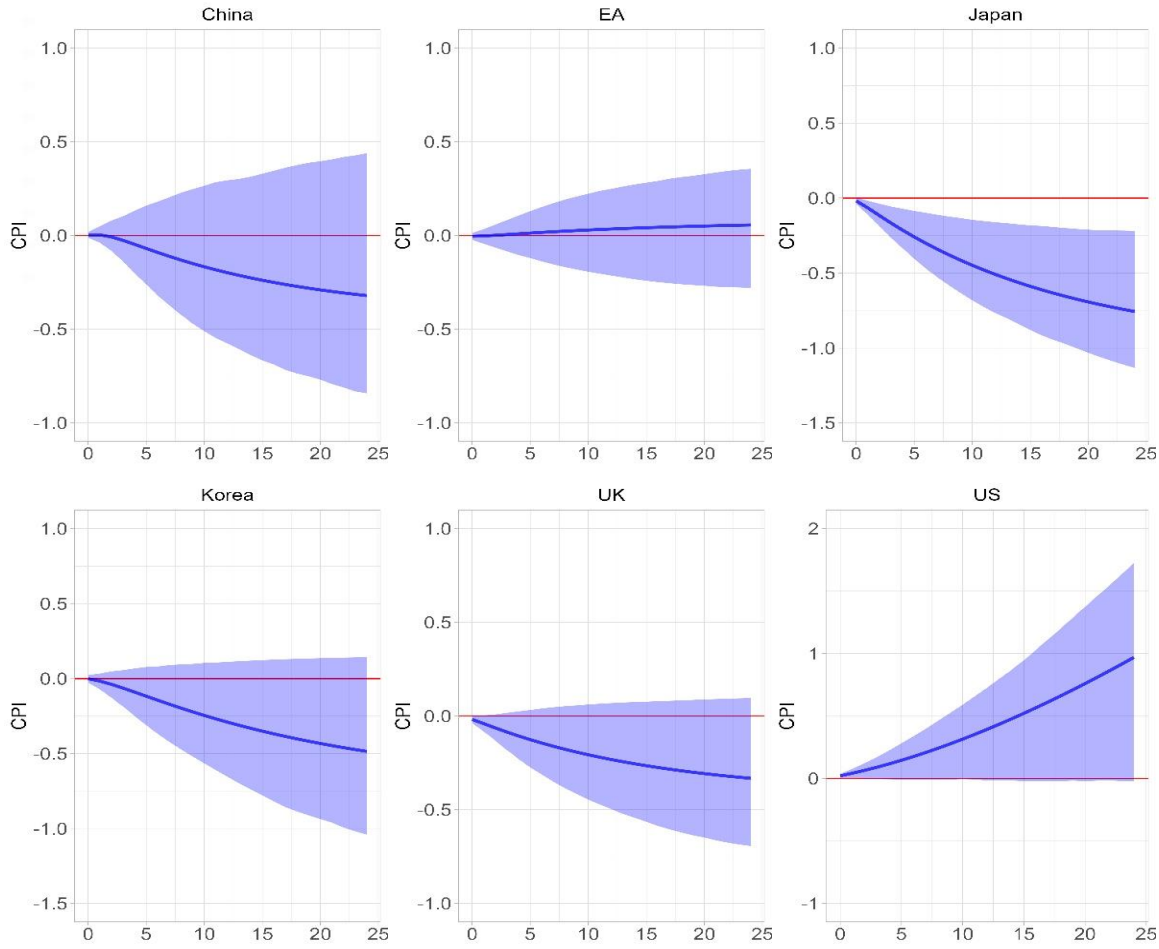
Note: The figure presents the cumulative response of core inflation to supply chain pressures in dark blue line and 90 percent confidence intervals in light blue. Estimates of the Euro Area and China began from December 2001 and January 2006, respectively, to December 2021.

Figure 10. Weather Shocks and Inflation: Headline CPI



Note: The figure presents the cumulative response of headline inflation to weather shocks in dark blue line and 90 percent confidence intervals in light blue.

Figure 11. Weather Shocks and Inflation: Core CPI



Note: The figure presents the cumulative response of core inflation to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates of the Euro Area and China began from December 2001 and January 2006, respectively, to December 2021.

VI. Robustness Checks

To check the robustness of our baseline results, we estimate the model (i) for a panel of six countries in our sample, (ii) for the periods excluding the COVID-19 pandemic and pre- and post-global financial crisis, (iii) using the cyclical component of inflation.

First, we implement the panel Local Projection (LP) method developed by Jordà (2005) to capture the dynamic effects of temperature anomalies on supply chains and inflation over time in a panel setting. The panel LP approach is a flexible alternative to SVAR as it does not constrain the shape of IRFs. We follow our previous causal chains for the panel LP estimations. In this framework, we control the exogenous shocks in inflation due to the flexibility of the panel LP method, contrary to the SVAR estimations. Thus, we consider a change in domestic interest rate to account for the monetary policy and the year-on-year global oil price changes as exogenous variables for inflation, taken from the BIS and IMF, respectively. We include four lags of each of inflation, temperature shocks, supply chain pressures, a change in interest rate, and the year-on-year global oil price changes to estimate the temperature and the supply chain shocks on inflation[9]. Only the country fixed effect is included in the panel LP method because the time-fixed effect would remove the time-varying global oil prices that are constant across the countries[10].

Figure 12 displays that supply chain pressures exert upward pressure on headline inflation, which is consistent with our previous results and our intuitions. We see a sharp rise in headline inflation induced by supply chain pressures, and it declines rapidly after one year. This indicates that supply-side shocks are not persistent in five large countries and the Euro Area. In contrast, temperature shocks rather reduce inflation, which aligns with our previous results. In addition, we have dropped the COVID-19 pandemic period (2020-2021), and the results are qualitatively the same[11].

Second, we estimate the countries without the COVID-19 pandemic periods (2020-2021) using the SVAR for each country (Figures 13, 14, and 15). Given the unprecedented impact of the COVID-19 pandemic, it may have affected inflation that may not be explained by weather anomalies and supply chain pressures. The results suggest that weather shocks do not generally affect supply chain pressures. In contrast, we see that supply chain pressures raise inflation in most countries, and the negative relationship between supply chain pressures and inflation in Korea are due to the Asian financial crisis, as explained in the baseline results. When it comes to weather shocks and inflation, we see that the estimation outcomes are also similar to the baseline estimates. Accordingly, the COVID-19 pandemic did not considerably alter the baseline estimates.

Third, since inflation and supply chain pressures in respective countries are affected by the COVID-19 pandemic and shocks specific to each country, we attempt to account for it. For instance, the Asian financial crisis considerably affected inflation and supply chain pressures in Asian countries. The European debt crisis from 2009 to mid-2010s also impacted inflation and supply chain pressures in the Euro Area. The 2008-2009 global financial crisis affected all the countries considered in this study. We, therefore, re-estimate each country with the SVAR and divide the time into two periods. First, we run from January 2000 to December 2007 to circumvent the Asian and global financial crisis. Second, we run from January 2010 to December 2019 to avoid the 2008 global financial crisis shock and the COVID-19 pandemic.

We see that the estimation outcomes in different periods show contrasting results (Figures 16-21). First, we find that weather anomalies could raise supply chain pressures before 2008, particularly in the US, whereas they have no impact on it after (excluding the COVID-19 pandemic period). This implies that supply chain pressures in recent periods have been driven more significantly by factors, such as energy prices and delays in delivery of parts and components. Second, the effects of supply chain pressures on inflation are statistically more significant after 2008 in four countries (China, Korea, the UK, and the US) than before (China and Japan). Our intuition is the growing demand for manufactured goods

[9] Results do not change when additional lags are used. For the temperature shocks on supply chain pressures, no exogenous variables are included.

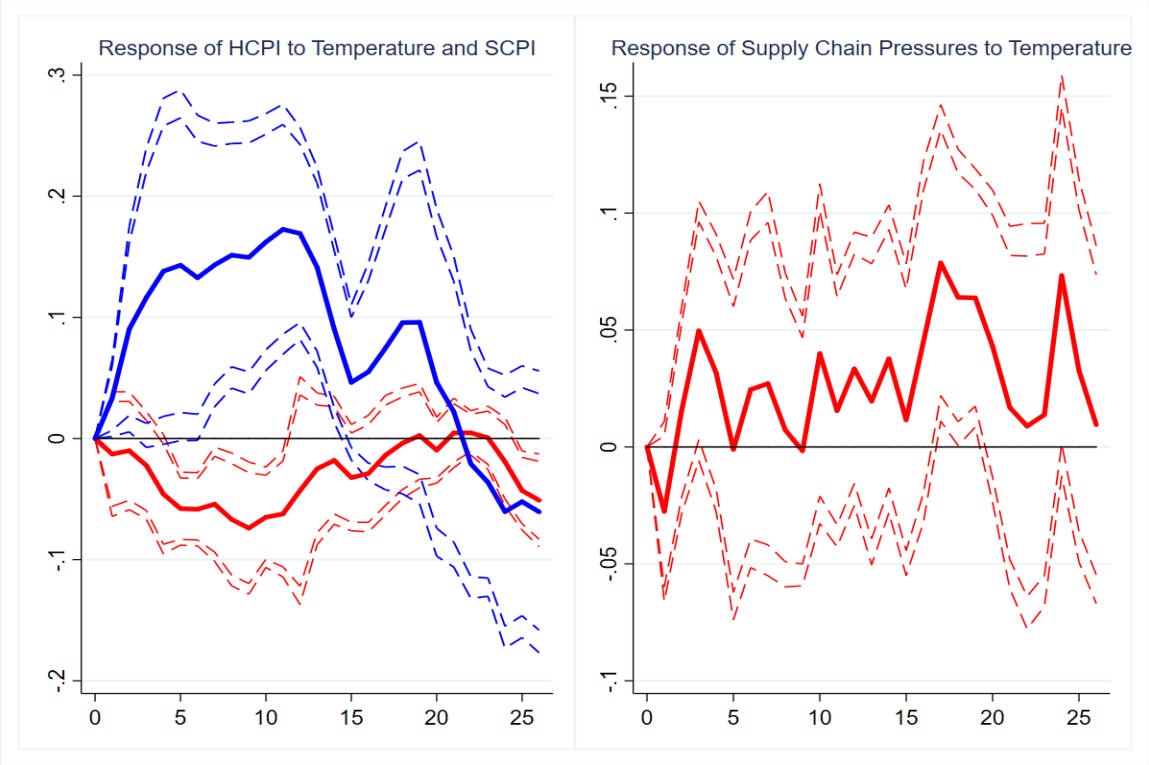
[10] Olea and Plagborg-Moller (2021) argue that the lag augmentation corrects standard errors for serial correlation.

[11] Results not shown here to save space.

combined with the rising global value chain participation of the countries considered. Third, weather anomalies could raise inflation before 2008, particularly in the US, but it has no impact on inflation generally, or it reduces it after 2008.

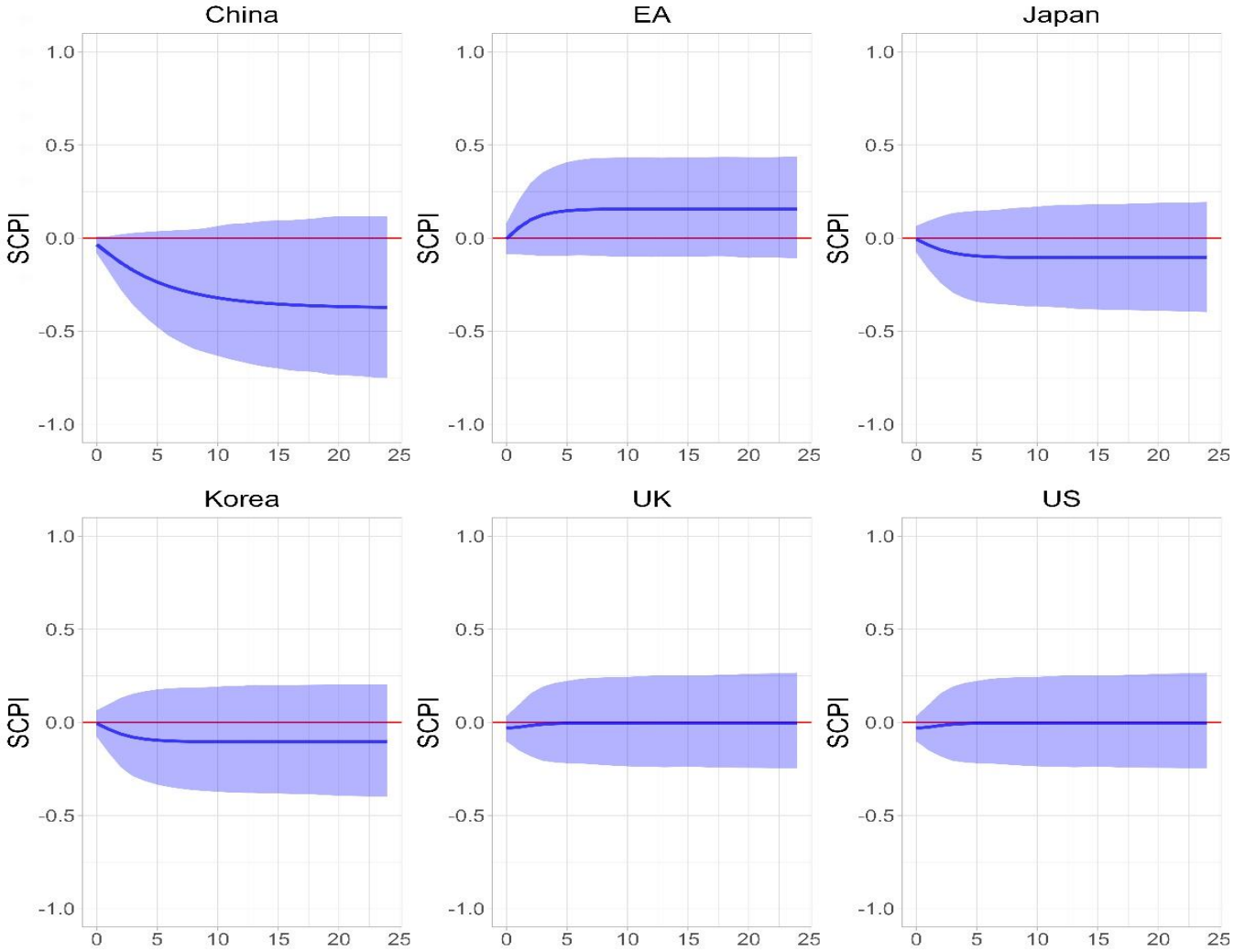
Fourth, we decompose inflation into cyclical and trend components by applying the Hodrick-Prescott filter. Our baseline results could pick up trend inflation, which has declined over time. Although the falling trend inflation would be more significant in Japan, we use the cyclical component of inflation for all countries by eliminating the trend component for robustness. Our results are broadly similar to the baseline results. One difference is that weather shocks could increase the cyclical component of inflation in the US for about three months. Again, the negative relationship between supply chain pressures and the cyclical component of inflation in Korea is driven by the Asian financial crisis in 1998.

Figure 12. Weather Shocks on Supply Chain Pressures and Headline Inflation: Panel Setting



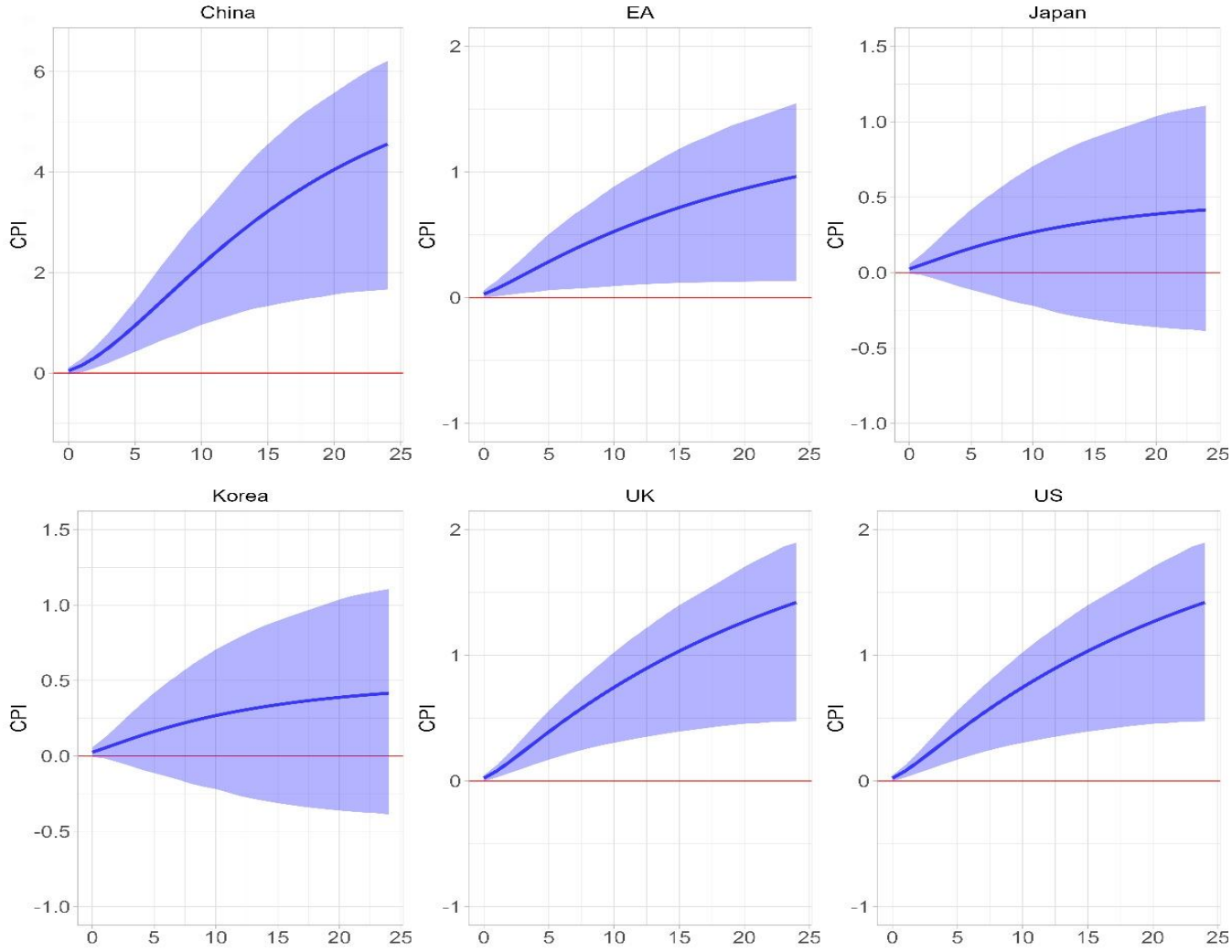
Note: Blue and red lines indicate an impulse of supply chain shocks and temperature, respectively. Dotted lines represent the 90% and 95% confidence intervals, with country fixed effect, according to the LP method. A change in domestic interest rate and the year-on-year global oil prices are considered as exogenous variables in inflation.

Figure 13. Weather Shocks and Supply Chain Pressures, Without COVID-19 Pandemic



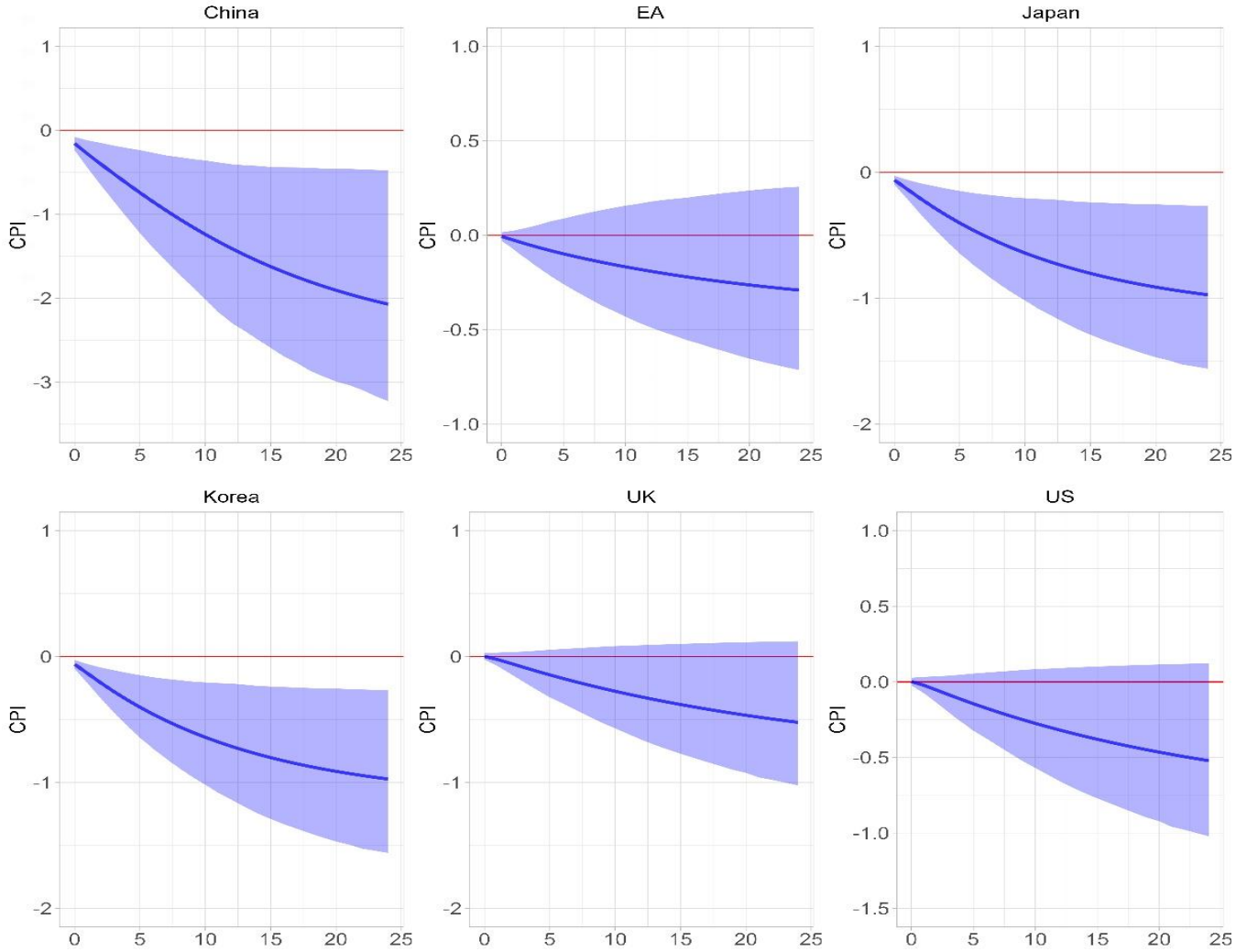
Note: The figure presents the cumulative response of supply chain pressures to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates of the Euro Area and China began from December 2001 and January 2006, respectively, to December 2019. The COVID-19 pandemic period (2020-2021) is dropped.

Figure 14. Supply Chain Pressures and Inflation, Without COVID-19 Pandemic



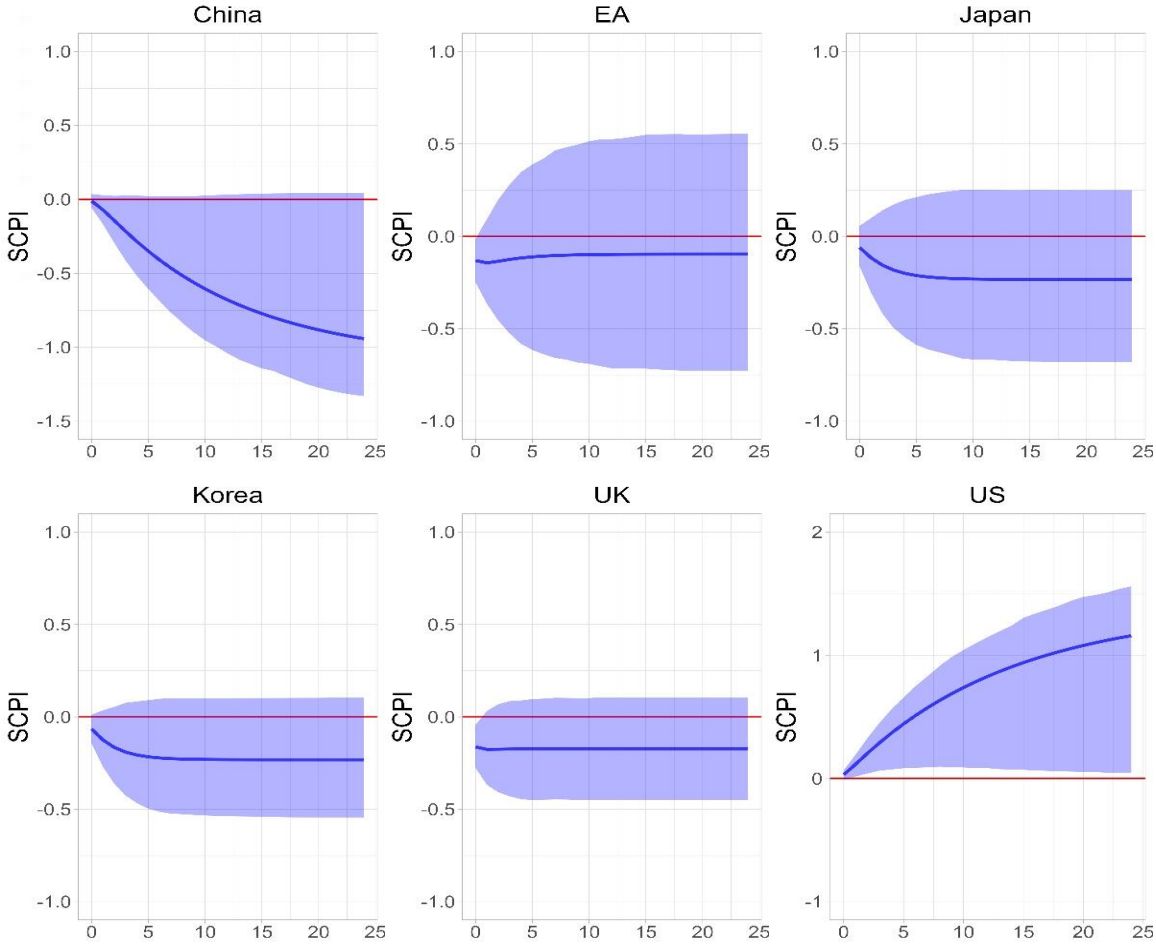
Note: The figure presents the cumulative response of headline inflation to supply chain pressures in dark blue line and 90 percent confidence intervals in light blue. Estimates of the Euro Area and China began from December 2001 and January 2006, respectively, to December 2019. The COVID-19 pandemic period (2020-2021) is dropped.

Figure 15. Weather Shocks and Inflation, Without COVID-19 Pandemic



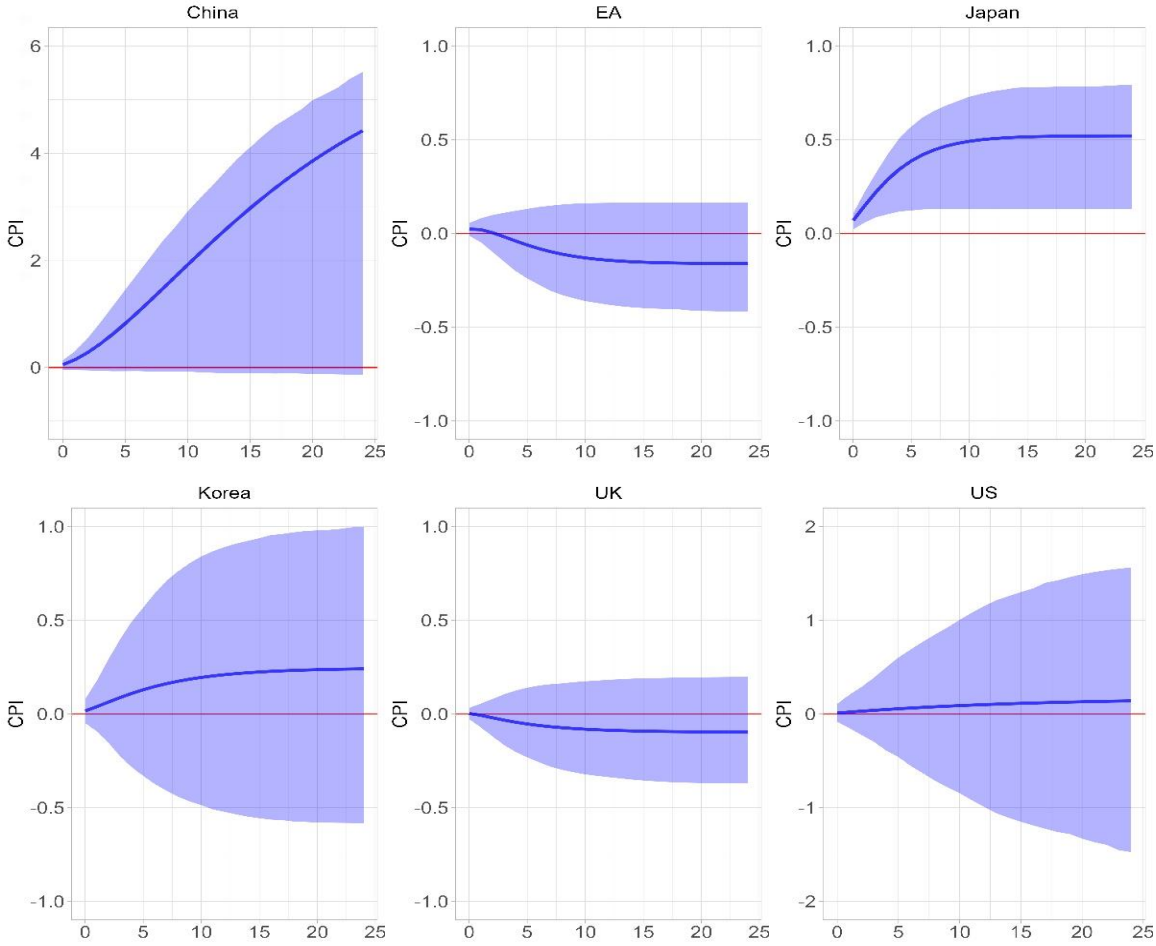
Note: The figure presents the cumulative response of headline inflation to weather anomalies in dark blue line and 90 percent confidence intervals in light blue. Estimates of the Euro Area and China began from December 2001 and January 2006, respectively, to December 2019. The COVID-19 pandemic period (2020-2021) is dropped.

Figure 16. Weather Shocks and Supply Chain Pressures: January 2000-December 2007



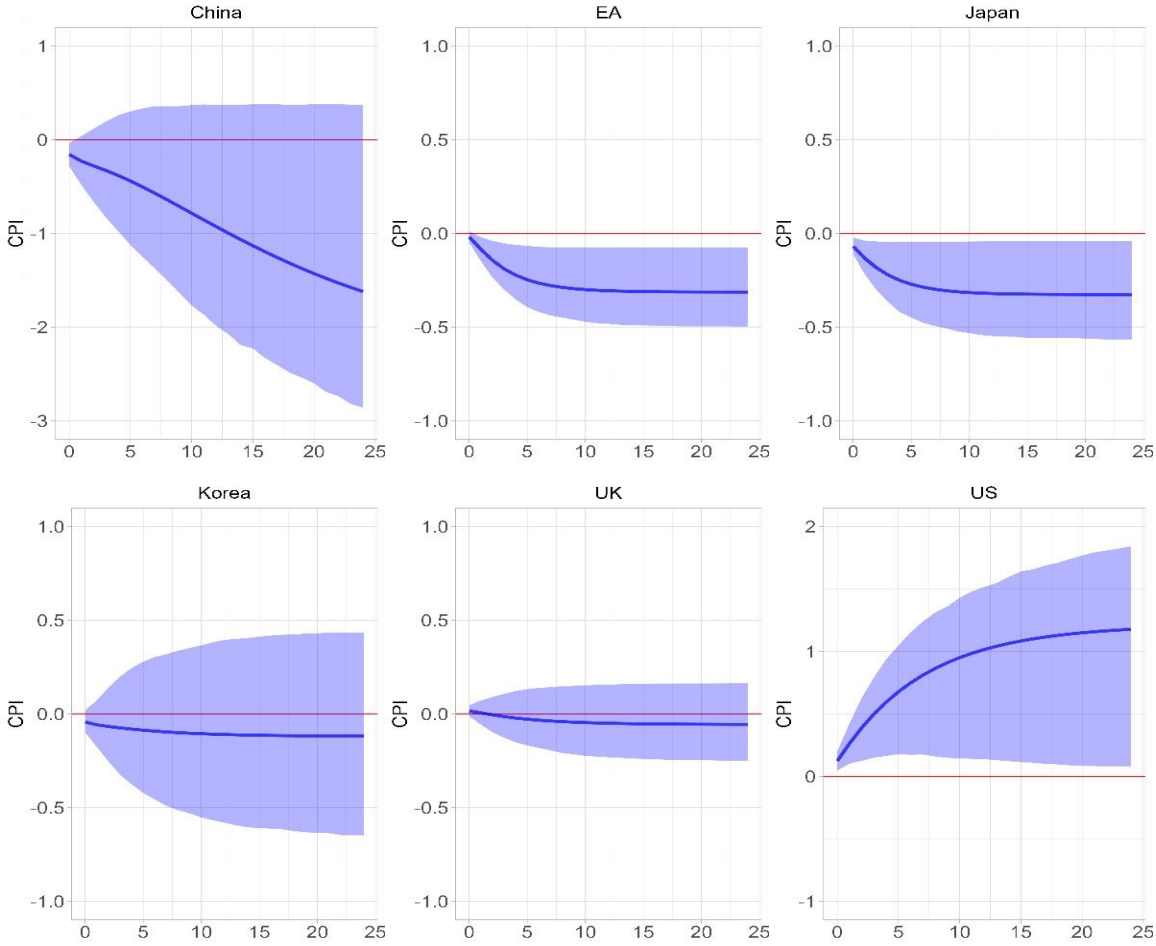
Note: The figure presents the cumulative response of supply chain pressures to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates began from January 2000 to December 2007.

Figure 17. Supply Chain Pressures and Headline Inflation: January 2000-December 2007



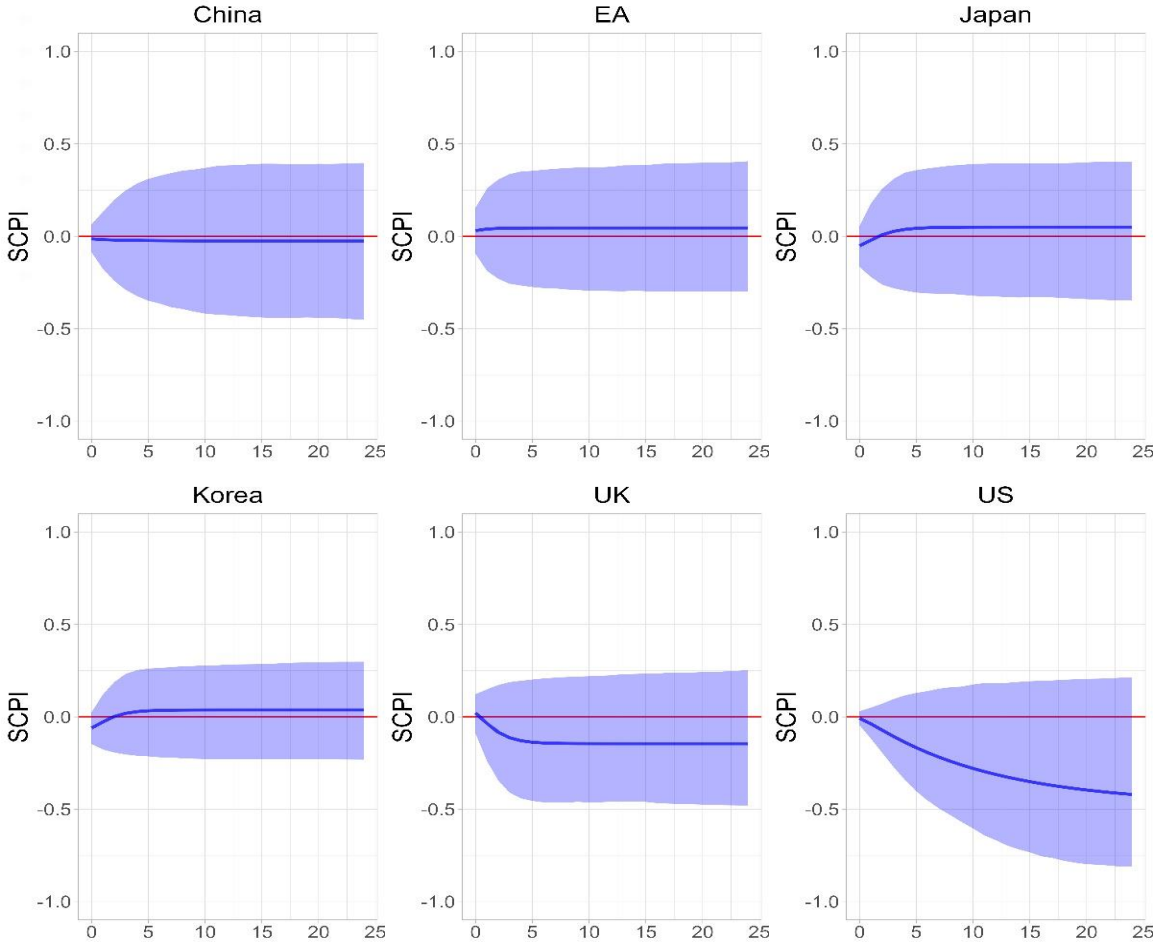
Note: The figure presents the cumulative response of headline inflation to supply chain pressures in dark blue line and 90 percent confidence intervals in light blue. Estimates began from January 2000 to December 2007.

Figure 18. Weather Shocks and Headline Inflation: January 2000-December 2007



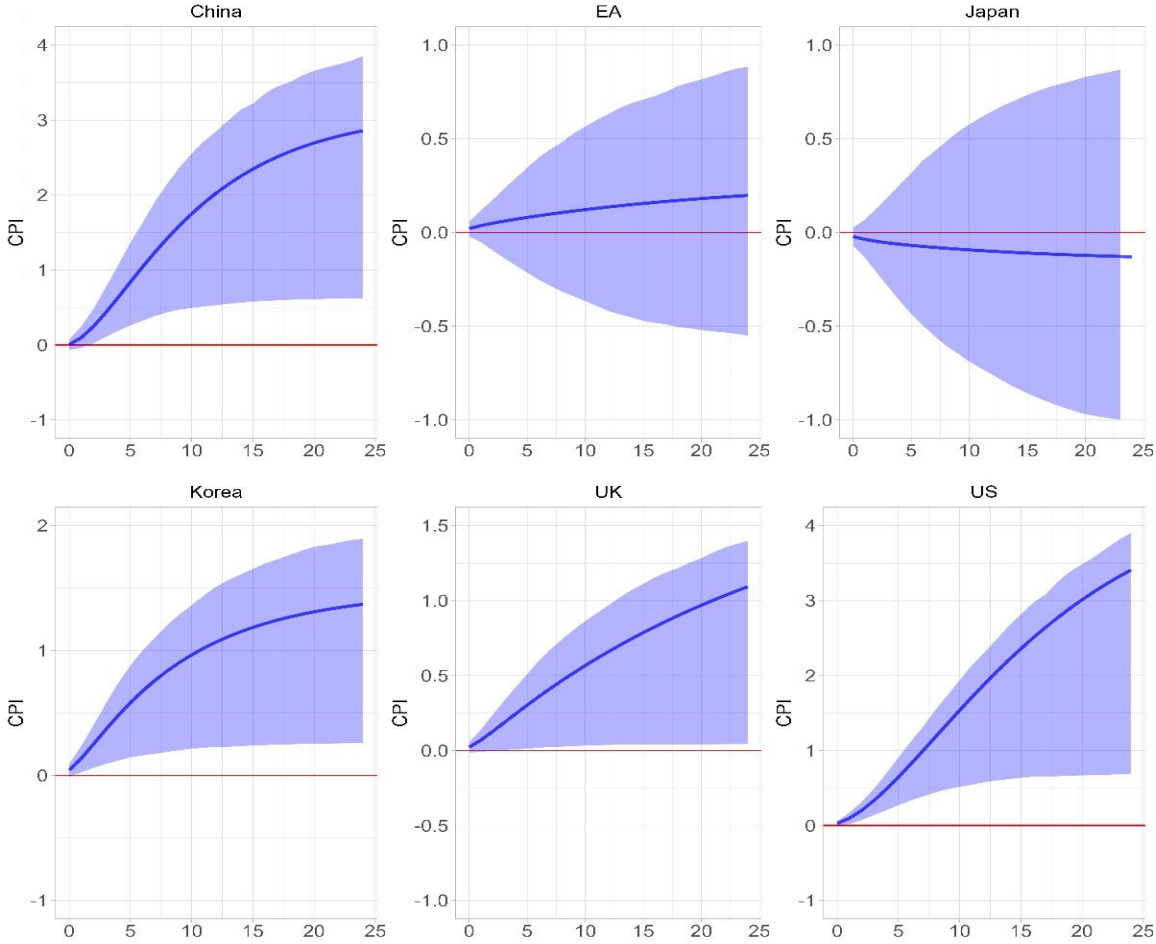
Note: The figure presents the cumulative response of headline inflation to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates began from January 2000 to December 2007.

Figure 19. Weather Shocks and Supply Chain Pressures: January 2010-December 2019



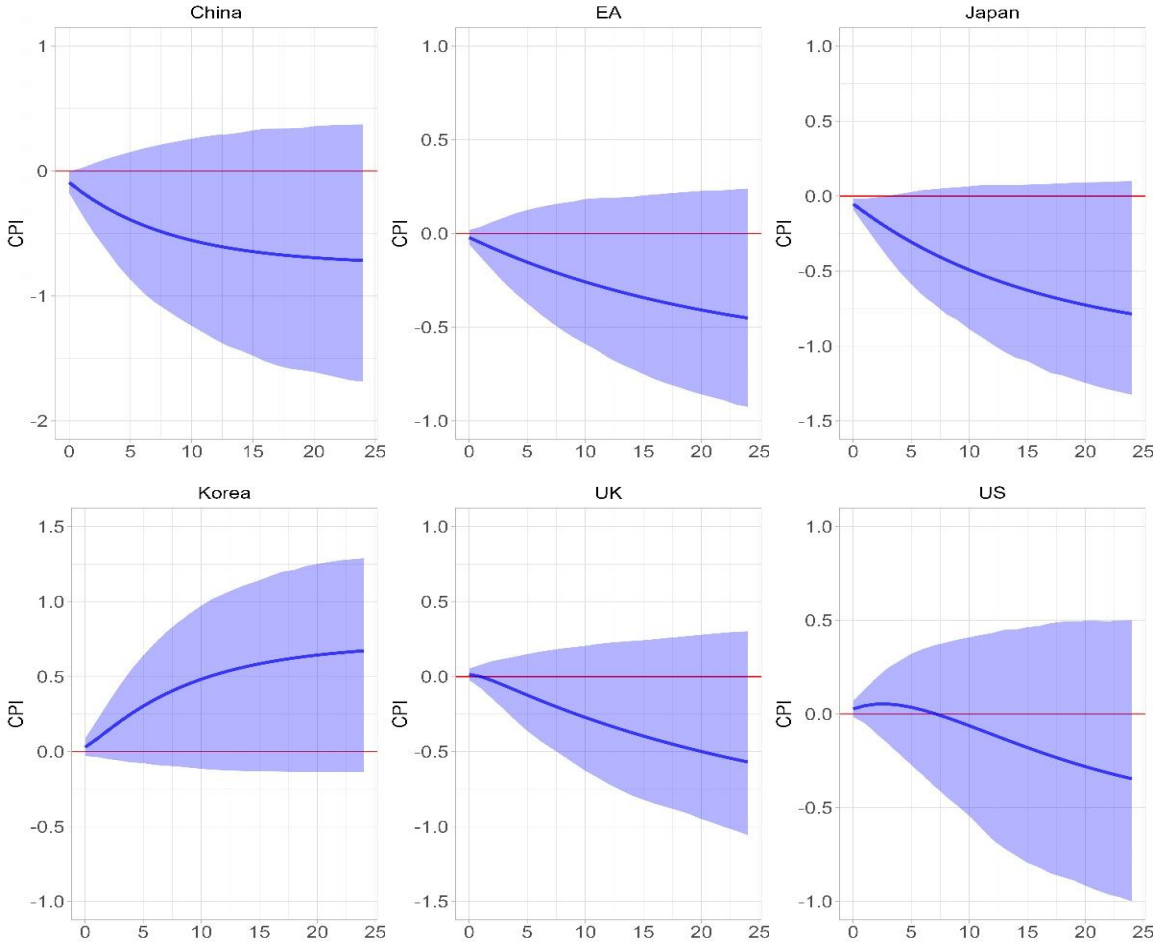
Note: The figure presents the cumulative response of supply chain pressures to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates began from January 2010 to December 2019.

Figure 20. Supply Chain Pressures and Headline Inflation: January 2010-December 2019



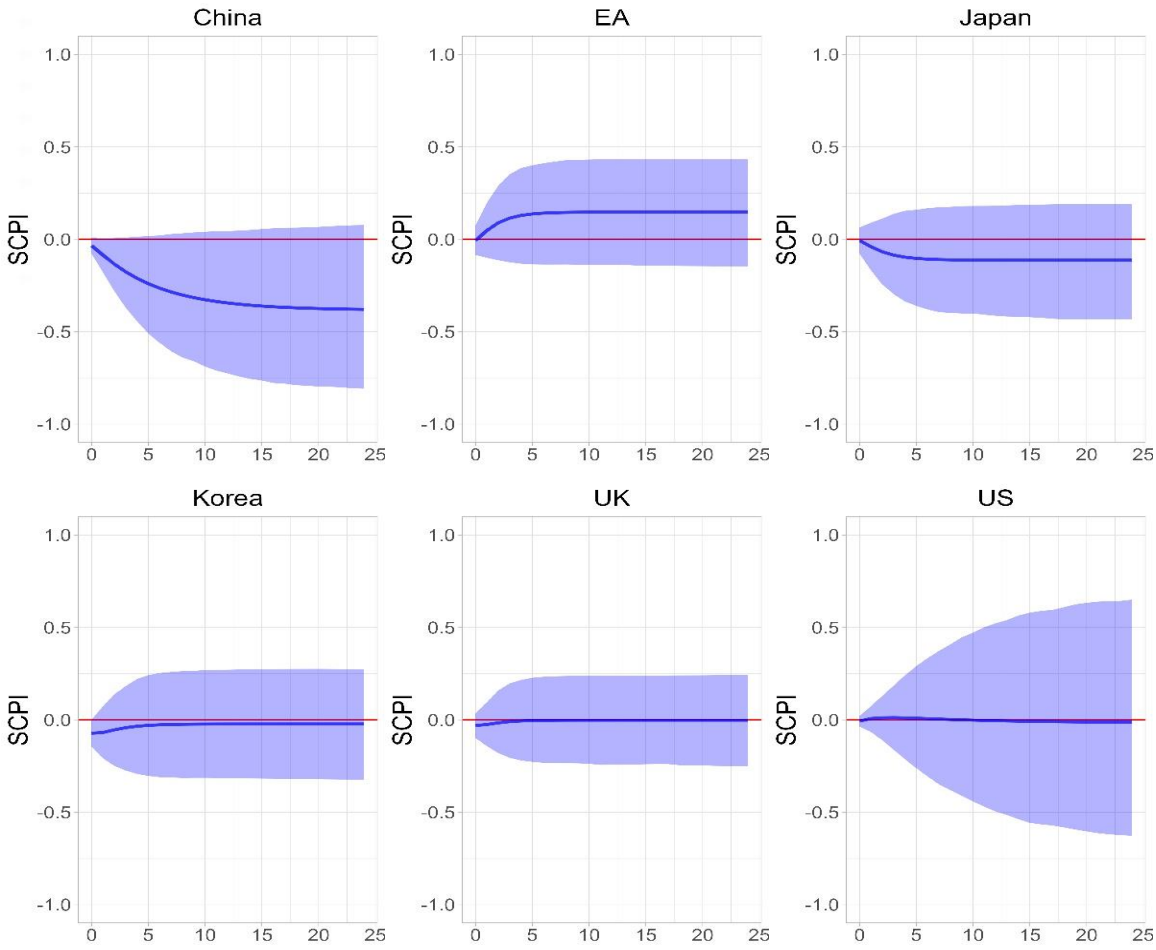
Note: The figure presents the cumulative response of headline inflation to supply chain pressures in dark blue line and 90 percent confidence intervals in light blue. Estimates began from January 2010 to December 2019.

Figure 21. Weather Shocks and Headline Inflation: January 2010-December 2019



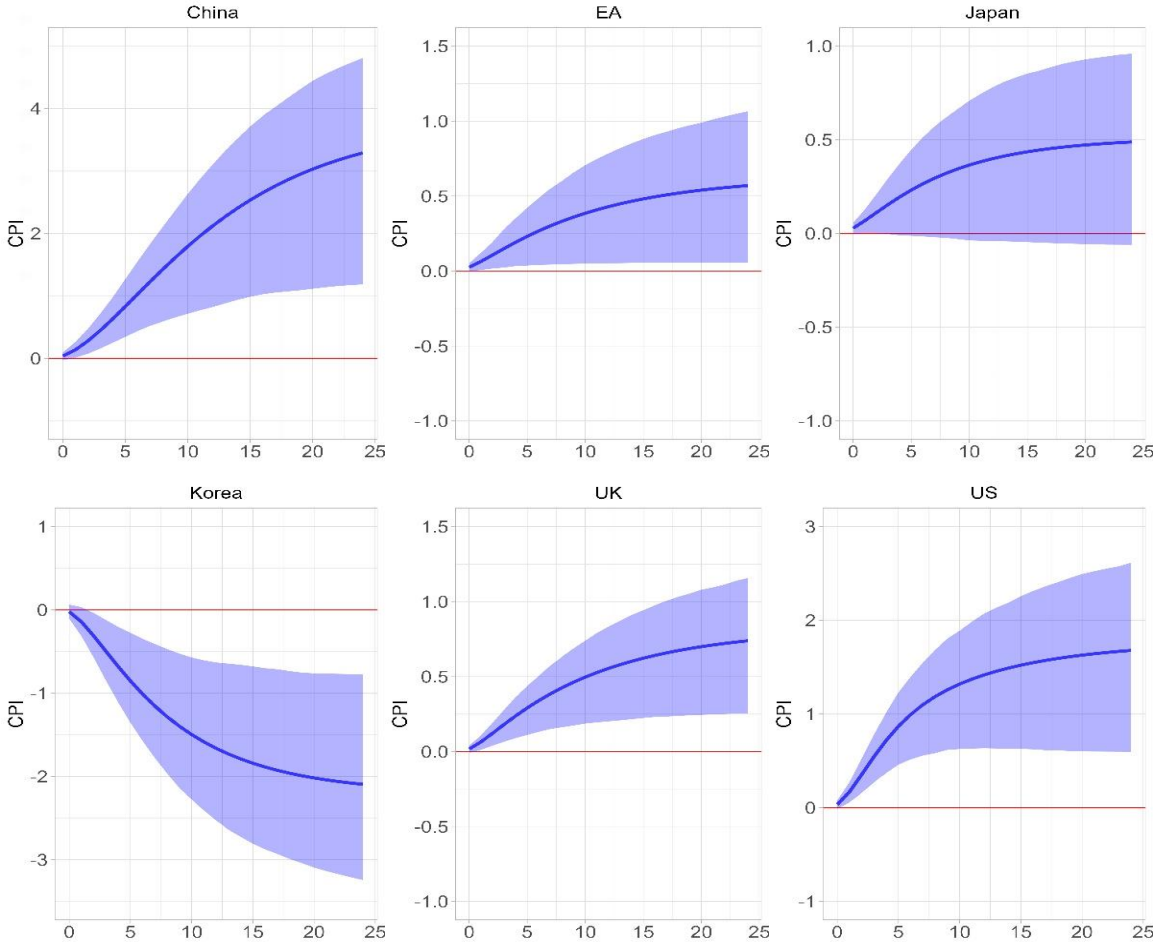
Note: The figure presents the cumulative response of headline inflation to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates began from January 2010 to December 2019.

Figure 22. Weather Shocks and Supply Chain Pressures: Cyclical Part of Headline Inflation



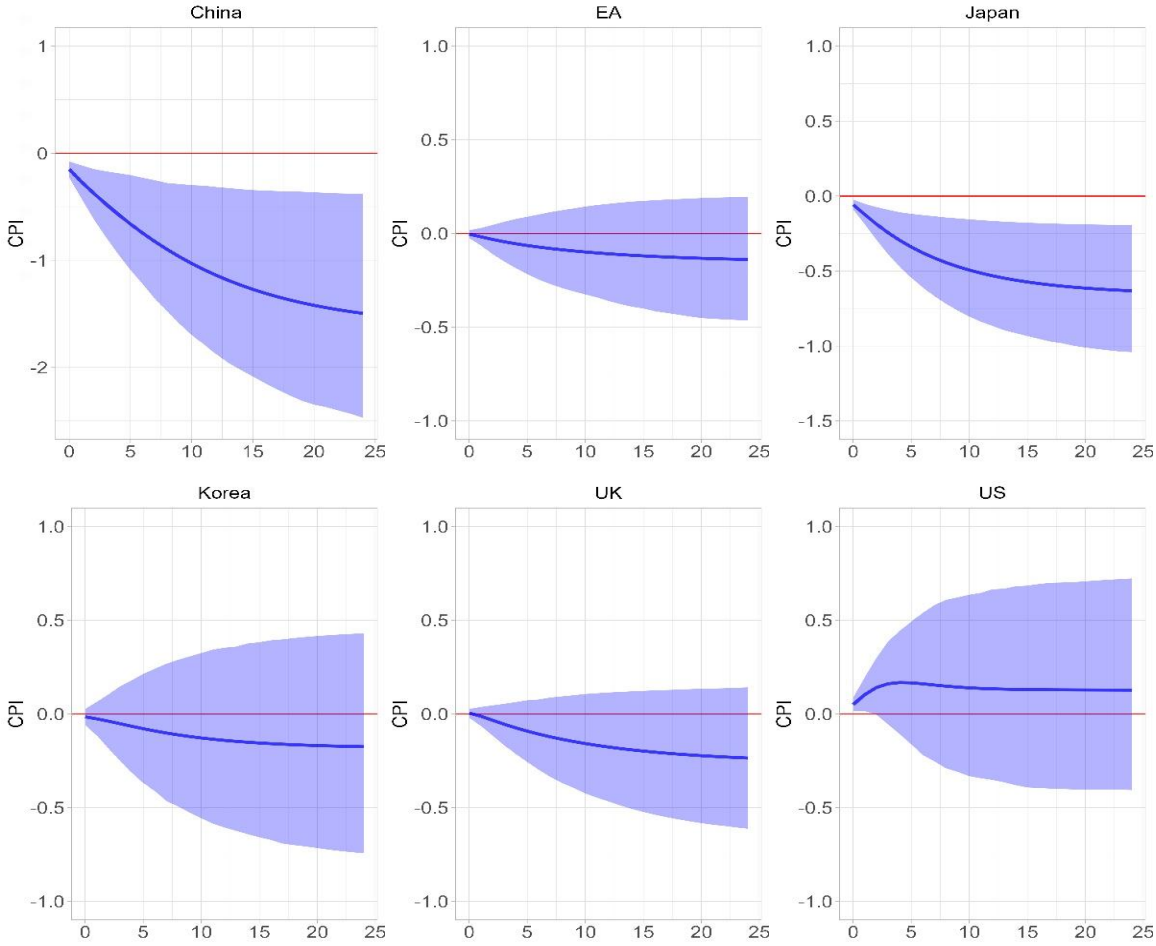
Note: The figure presents the cumulative response of supply chain pressures to weather shocks in dark blue line and 90 percent confidence intervals in light blue. Estimates began from September 1997 to December 2019.

Figure 23. Supply Chain Pressures and Cyclical Part of Headline Inflation



Note: The figure presents the cumulative response of supply chain pressures to cyclical component of headline inflation in dark blue line and 90 percent confidence intervals in light blue. Estimates began from September 1997 to December 2019.

Figure 24. Weather Anomalies and Cyclical Component of Headline inflation



Note: The figure presents the cumulative response of cyclical component of headline inflation to weather anomalies in dark blue line and 90 percent confidence intervals in light blue. Estimates began from September 1997 to December 2019.

VII. Conclusion

The world economy has experienced a series of unprecedented shocks over the past three years, disrupting supply chains, causing a deep recession, and pushing inflation to the highest level since the 1970s. While inflation is on a downward trajectory with economic activity on the mend, vulnerabilities persist. One of the most significant risks to the global economy and financial markets is climate change. As human-induced climate change accelerates over the coming decades, greater frequency and severity of extreme weather conditions can have far-reaching adverse consequences for physical infrastructure and economic activity. There is convincing evidence that climate-related natural disasters have significant effects on inflation and economic growth. An important channel of this relationship is the impact of weather anomalies—caused by climate change—on global supply chains in the production and distribution of goods and services. Disruptions during the COVID-19 pandemic and the ensuing sharp increase in global inflation have highlighted the

importance of risks to the complex and interdependent network of supply chains across the world. With rising global temperatures, extreme weather events stress transportation infrastructure and highly-connected global supply chains, interrupting production, causing shortages, and leading to higher prices.

Demand-side factors certainly play a significant role in driving inflation, but this paper aims to close an important gap in the literature by investigating the impact of weather anomalies on global supply chains and inflation dynamics. Using monthly data covering six large and well-diversified economies—China, the Euro area, Japan, Korea, the United Kingdom, and the United States—over the period 1997-2021, we implement a SVAR model and trace the contemporaneous effects of weather anomalies on supply chains and inflation dynamics. To the best of our knowledge, this is the first attempt in the literature to investigate the impact of weather shocks on supply chain pressures and alternative measures of inflation using a SVAR model, which offers insights on how climate change could affect global supply networks and inflation dynamics beyond the sample of countries used in the analysis.

We find that weather anomalies could disrupt supply chains and subsequently lead to inflationary pressures. Our results show significant heterogeneity across countries in the sample, which we attribute to differences in the severity and frequency of weather anomalies and vulnerability to supply chain disruptions. The impact of weather shocks on supply chains and inflation dynamics is likely to become more pronounced with accelerating climate change. Although our empirical results do not always show a strong positive link between weather shocks and supply chain disruptions, partly due to the use of aggregated supply-side disruptions, this does not mean that we can be complacent about the increasing severity and frequency of weather anomalies, as shown by a plethora of recent shocks including the severe drought has reduced water level considerably in the Panama Canal and disrupted one of the main trade routes connecting Asia and North America. Our results have important policy implications. Central bankers should consider the persistent impact of weather anomalies on supply chains and inflation dynamics to prevent entrenching second-round effects and de-anchoring inflation expectations. More directly, however, governments can invest more for climate change adaptation to strengthen critical infrastructure and thereby minimize supply chain disruptions.

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Appendix Table A1. Unit Root Test Without Structural Break

	China		EA		Japan		Korea		UK		US	
	C	T	C	T	C	T	C	T	C	T	C	T
Temperature	-8.9***	-9.0***	-7.7***	-8.1***	-8.5***	-8.9***	-8.2***	-8.3***	-7.9***	-7.7***	-6.8***	-7.2***
SCPI	-3.2***	-3.4**	-5.8***	-5.9***	-4.4***	-4.6***	-6.5***	-6.7***	-5.4***	-5.8***	-3.9***	-3.9***
Headline CPI	-3.0***	-3.0	-2.6***	-2.4	-3.8***	-4.2***	-3.4***	-3.9***	-2.3***	-2.3	-3.0***	-2.9
Core CPI	-2.7***	-2.7	-2.3***	-1.6	-3.3***	-3.5**	-3.2***	-3.6**	-1.0	-2.1	-1.0	-0.86

Note: Augmented Dickey-Fuller unit root test is employed. C and T indicate constant and trend, respectively. T-statistic is reported. ***, **, and * denote 1%, 5% and 10% significance levels, respectively. 2 lags are used.

Appendix Table A2. Unit Root Test with Structural Break

	China	**EA**	**Japan**	**Korea**	**UK**	**US**
			Intercept and Trend			
Temperature	-13.319***	-14.518***	-13.638***	-13.747***	-12.805***	-14.55***
SCPI	-4.817*	-9.303***	-6.212***	-8.187***	-10.464***	-5.153**
Headline CPI	-4.010	-3.271	-5.061*	-4.380	-3.015	-4.108
Core CPI	-4.892	-2.077	-4.858*	-3.727	-2.330	-2.305
			Intercept			
Temperature	-13.293***	-14.544***	-13.644***	-13.640***	-12.809***	-14.424***
SCPI	-3.904	-9.038***	-5.697***	-7.013***	-9.692***	-4.215
Headline CPI	-3.478	-3.080	-4.601*	-4.386	-3.237	-4.199
Core CPI	-3.828	-1.883	-4.176	-3.727	-2.812	-1.557
			Trend			
Temperature	-13.091***	-14.231***	-13.501***	-13.552***	-12.472***	-13.813***
SCPI	-4.422**	-9.034***	-5.935***	-7.818***	-10.148***	-5.041***
Headline CPI	-3.506*	-2.567	-4.355*	-4.142*	-2.361	-3.597
Core CPI	-2.872	-1.931	-3.688	-3.681	-2.116	-2.284

Note: Zivot-Andrews unit root test (1992) with structural break is employed. T-statistic is reported. ***, **, and * denote 1%, 5% and 10% significance levels, respectively. The element of the process in a break is both intercept and trend, intercept only, and trend only. Lags are determined based on the BIC.