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# Does climate and economic uncertainties influence inflation? Evidence from a comparative study between US and Euro Area

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## Abstract
This paper examines the impact of uncertainty on inflation components in the Euro area and the United States. Using a Structural Vector Autoregression (SVAR) model, the analysis focuses on the effects of climate risk and economic policy uncertainty on headline, core, food, and energy inflation. The results indicate significant but region-specific influences: in the United States, climate-related uncertainty has emerged as a key driver of price fluctuations, particularly in the post-COVID-19 period, while in the Euro area, economic policy uncertainty remains the predominant inflationary force. These findings highlight the importance of coordinated fiscal and monetary strategies when inflationary pressures stem from diverse sources of uncertainty.

**Keywords** Climate risks · Inflation components · Economic policy uncertainty · Structural VAR

**JEL Classification** E31 · E52 · E61 · Q54

## 1 Introduction

Uncertainty broadly refers to the difficulty in predicting and quantifying future economic and market-related events (Knight, 1921). The uncertainty affects policymaking by increasing information asymmetries and complicating the anticipation of financial shocks. Recently, climate-related and economic policy uncertainties influ-

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ence inflation dynamics by altering supply and demand conditions (as extensively reported in Batten et al., 2020). Despite the extensive literature on the role of uncertainty in economic decision-making (several examples are, Craine, 1979; Bekaert et al., 2013; Oros & Zimmer, 2015), the relationship between climate and economic policy uncertainty with inflation components remains still unclear.

The global price pressures, driven by geopolitical tensions and climate-related disruption, led inflation dynamics to be monitored with caution by macroeconomic actors. In this context, understanding how distinct inflation components (such as core and energy inflation) affect perceptions of economic uncertainty is crucial for both monetary policy and market participants.

The idea that economic and climate uncertainties are starting to influence more and more the decisions of economic actors is becoming interesting: the obligatory reference here is Stern (2008).[1] In particular, economic policy uncertainty can impact inflation through business and consumer expectations, investment hesitancy, and altered monetary policy responses. Higher uncertainty leads firms to delay investment and hiring, potentially dampening demand-driven inflation. Simultaneously, it can generate volatility in financial markets, thus producing effects on capital costs. Conversely, climate-related uncertainty, particularly in energy and food markets, can lead to supply-side inflationary pressures. As discussed in Hasegawa et al. (2021), extreme weather events can reduce agricultural output, leading to higher food prices. In the same vein, Zheng et al. (2023) claimed that energy market disruptions caused by regulatory shifts or geopolitical threats can lead energy prices to rise.

To investigate how inflation reacts to exogenous uncertainty shocks, we focus on a comparative analysis between the United States and the Euro area—two advanced economies with markedly different institutional and policy structures. While the Federal Reserve (FED) operates within a unified fiscal-monetary policy framework, the European Central Bank (ECB) governs a monetary union composed of diverse national fiscal regimes. However, both economies face increasing climate-related risks, yet adopt different climate policy stances: the US approach is more decentralized and market-oriented, while the Euro area is guided by coordinated EU-wide goals and regulatory standards. These contrasts make the two regions an ideal setting to explore how economic and climate-related uncertainty influences inflation components.

Both central banks have emphasized data-driven decision-making, forward guidance, and unconventional tools (such as quantitative easing). However, as showed by Larch (2020), the Euro area's reliance on fiscal rules has required temporary flexibility in response to major shocks. These features underscore the importance of understanding how uncertainty interacts with inflation dynamics in systems with different levels of institutional cohesion and policy autonomy.

Given these considerations, this paper aims to understand the effects of economic and climate policy uncertainty on different inflation components (headline, core, food, and energy) using a standard Structural Vector Autoregression (SVAR) framework to capture dynamic interactions among inflation components and uncertainty measures while addressing simultaneity and endogeneity concerns. Unlike standard

[1] Among the recent studies, Cevik and Jalles (2024) is one of the most interesting.

regressions or simpler time-series models, the SVAR allows us to isolate structural shocks (i.e., unexpected climate occurrences) and trace their impact over time, differentiate between short-term and long-term effects of uncertainty on inflation components, compare policy responses across the US and Eurozone by analyzing impulse response functions and historical decompositions. Additionally, SVARs are widely used in macroeconomic studies analyzing uncertainty shocks (see, among others, Forni & Gambetti, 2014) and provide a rigorous framework for policy-relevant inference.

To the best of our knowledge, this study contributes to the empirical literature in several distinct ways. First, while prior research has predominantly focused on the effects of uncertainty on aggregate inflation—as in Orlowski (2023) for the Euro area, and Caggiano et al. (2020), Ren et al. (2024) for the United States[2]—comparatively few studies have examined how disaggregated inflation components (e.g., food, energy, core) respond to both economic and climate-related uncertainty. Second, in contrast to firm-level studies such as Das et al. (2024), our analysis adopts a macro-sectoral perspective, distinguishing between headline, core, food, and energy inflation to uncover sector-specific inflation dynamics under different uncertainty regimes. This approach provides a more detailed understanding of the transmission mechanisms at play. Third, this paper is the first to incorporate the European Extreme Climate Index (E3CI) into a structural VAR framework to assess its inflationary impact—representing a novel application of a physical climate risk indicator within a macroeconomic setting. By integrating the E3CI for the Euro area and the Climate Policy Uncertainty (CPU) index for the US, we enable a cross-regional analysis using heterogeneous but substitute climate risk proxies, expanding the empirical toolkit for uncertainty-inflation studies. Finally, and perhaps most importantly, by comparing two advanced economies with contrasting institutional and policy frameworks—a centralized fiscal-monetary regime in the US versus a decentralized monetary union in the Euro area—we demonstrate that the transmission of uncertainty to inflation is strongly shaped by institutional architecture. This cross-jurisdictional dimension is largely absent in the existing literature and provides novel insights into how climate and economic uncertainty interact with structural features of economic governance.

Finally, our research sheds light on the growing role of climate-related uncertainty, an increasingly relevant factor for policymakers. Therefore, given all the aforementioned contributions, our paper reverses the lens by asking: *what is the effect of uncertainty (climate and economic) on inflation components?* In a nutshell, our results show that uncertainty does not affect inflation components uniformly in the EU and US, thus providing implications for policymakers.

The remainder of the paper is structured as follows. Section 2 gives a theoretical framework and reviews the empirical literature. Section 3 describes the methodology and the dataset used, while Sect. 4 discusses the results. Section 5 concludes.

[2] With Abbate et al. (2023) focusing more specifically on financial shocks.

## 2 Literature review

### 2.1 Empirical evidences

Understanding the relationship between uncertainty and inflation is crucial for economic policy formulation. This section reviews empirical studies on how economic policy uncertainty (EPU) and climate-related uncertainty influence inflation dynamics for the formulation of economic policies.

Economic policy uncertainty stems from unpredictability events in fiscal, monetary, and regulatory policies. According to traditional macroeconomic theory, uncertainty affects inflation through multiple channels. Bloom (2014) discussed how in presence of sticky prices, uncertainty shocks can lead to financial turbulence since prices do not adapt to new market conditions. This consideration holds in New Keynesian (NK) models where higher uncertainty can alter inflation expectations, leading to lower consumption and investment.

As argued by Baker et al. (2016) when firms face uncertainty about future policy actions, they delay investment and hiring decisions, which can lead to a weakening of the aggregate demand and downward pressure on inflation. However, some studies (see, for instance, Fernández-Villaverde et al., 2015) showed that uncertainty can create inflationary pressures if firms increase markups due to risk aversion and reduced competition.

Climate-related uncertainty primarily affects inflation through supply-side channels. Extreme weather events disrupt agricultural production, leading to higher food prices. Parker (2018) sustained that storms and floods have short-term effects on rising food price inflation. The relevance of extreme weather events on food price inflation is questioned by Malesios et al. (2020), who claimed that a causal relationship cannot be identified. The theory of supply shocks suggests that such uncertainty can create persistent inflationary pressures, particularly in commodity-dependent economies, as showed in Kotz et al. (2024).[3]

Likewise food prices, different components of inflation—namely headline, core and energy—react to uncertainty. In general, Headline inflation captures overall price changes in the economy, thus reflecting both demand- and supply-side shocks. In this context, Kotz et al. (2024) found that rising temperatures significantly and persistently increase both food and headline inflation over a 12-month horizon. By contrast, core inflation excludes volatile food and energy components, being primarily influenced by expectations and monetary conditions, and is less affected (in the immediate) by weather-related shocks.

Bloom (2014) established that economic uncertainty leads to lower inflation due to weakened demand. In contrast, Baker et al. (2016) showed that EPU can lead to inflationary pressures in periods of policy instability. Climate-related uncertainty has been linked to food price inflation, with Mukherjee and Ouattara (2021) indicating that extreme weather events result in persistent supply shocks. Empirical work on

[3] A parallel strand of literature (starting from Toumi et al. 2025) employs machine learning models to forecast the determinants of climate change, thereby informing early-stage macroeconomic policies.

energy markets also points to the role of climate policies in driving inflation volatility, particularly in economies undergoing energy transitions (see, Shang et al. 2022).

As a matter of fact, global economies respond to inflationary pressures through interest rate adjustments. However, a key distinction lies in the differing economic contexts within which central banks operate. The European Central Bank (ECB) and the Federal Reserve (FED) face uncertainty under distinct macroeconomic conditions. For example, Assenmacher-Wesche and Gerlach (2010) demonstrated that monetary policy is more effective when timing implemented following asset bubble bursts, rather than through preemptive tightening. Additionally, Fornari and Stracca (2012) provided evidence that financial shocks are distinct from other shocks and exert significant effects on macroeconomic indicators such as GDP and investment. Furthermore, Balcilar et al. (2022) revealed that the ECB tends to respond cautiously to uncertainty shocks but tightens policy in the face of financial shocks, whereas the FED adopts a more hawkish stance under uncertainty and acts more moderately during periods of financial stress.

Beyond the differences between the ECB and the FED in their responses to uncertainty shocks, it is also worth highlighting the need for a more integrated approach in defining macro-financial policies. D'Orazio et al. (2024) suggested that environmental degradation, loss of species diversity, and climate change are actual threats to global economic and financial stability, underscoring the need for a multidisciplinary approach with various actors at multiple levels. Interestingly, Aguila and Wullweber (2024) highlighted how high interest rates environment risks holding back the shift towards a more sustainable economy, compromising not only environmental goals but also those related to price stability.

### 2.2 Theoretical framework

While the previous subsection aims to discuss the recent empirical shreds of literature, in this section, we aim to contextualize the theoretical framework of our study. Roughly speaking, our study is placed within the uncertainty-inflation nexus in the framework of macroeconomic uncertainty and price dynamics. Theoretically, economic policy and climate uncertainties influence inflation components through both supply-side and demand-side channels. Therefore, our work is anchored in the New Keynesian (NK) framework, where inflation expectations and price adjustments play a key role in macroeconomic stability. In a very simplistic way, we can sum up the NK Phillips curve as

$$\pi_t = \beta \mathbb{E}_t[\pi_{t+1}] + \kappa m_t + \epsilon_t,$$

where $\pi_t$ is the inflation rate at time $t$, $\mathbb{E}_t[\pi_{t+1}]$ are the expectations about future inflations, $m_t$ represents marginal costs, which are affected by supply shocks such as climate-related risk, $\kappa$ is a parameter related to price stickiness and $\epsilon_t$ is an exogenous inflation shock. While this framework could be originally retrieved in Fischer (1977), part of the current literature is working on that (María-Dolores & Vázquez, 2008).

Supply shocks, particularly from climate risks, are modeled following the cost-push inflation theory (Gordon, 1975). Cost-push inflation occurs when production costs increase, leading to higher price levels. This view contrasts with demand-pull inflation, which arises from excessive demand. In the context of economic policy uncertainty and climate-related uncertainty, cost-push inflation plays a crucial role in explaining sectoral inflation dynamics, particularly in food and energy prices.

Given these foundations, the paper aims to answer the following empirical research questions:

- How do climate-related and economic policy uncertainties affect different components of inflation in the US and the Eurozone?
- Do these uncertainties exert different impacts depending on the institutional framework of the two regions?
- Which component of inflation is most sensitive to uncertainty shocks, and how persistent are these effects?

## 3 Data and methodology

### 3.1 Data

Since we are interested in the effects of different types of uncertainty, we include in our sample Economic Policy Uncertainty (EPU, see Baker et al., 2016), a measure for climate risk (the European Extreme Events Climate Index, E3CI[4] and the Climate Policy Uncertainty, CPU index by Gavriilidis (2021), for Euro area and USA respectively) and a global measure of uncertainty (WUI, Ahir et al., 2022) as an additional external control to mitigate the omitted variable bias.

The E3CI observes, maps, and monitors the intensity and frequency of extreme weather events affecting European territories and communities. Since the available data are at the country level, we aggregate them using a simple average to construct an overall measure of climate risk for the Eurozone. In contrast, in the US case, we employ the CPU. The CPU is a newspaper index that tracks climate risk-related terms in major US newspapers. To the best of our knowledge, we are the first to incorporate the E3CI index into this type of analysis, whereas the CPU index is widely applied in various studies (see, Tarkom & Ujah, 2023; Shahbaz et al., 2024; Huang & Punzi, 2024). To compare climate risk with economic policy uncertainty, we utilize the EPU index, which, like the CPU, is newspaper-based and tracks economic uncertainty. While the EPU index is available for the US, we aggregate individual Euro area country indices to derive a simple average for Euro area countries. We acknowledge the different costruction of CPU and E3CI, however we rely on these different measures given the missing availability of a common measure between US and EU. However, Table 1 summarizes the main differences and highlight how these measures could be used together in this kind of analysis.

Monetary policies aimed at achieving inflation targets may be influenced by various uncertainty measures (Murphy & Hines, 2010; Rozenberg et al., 2013; Dafermos et al., 2018). In this context, we seek to disentangle the effects of these uncertainties

[4] https://www.ifabfoundation.org/e3ci/.

**Table 1** Comparison of climate policy uncertainty (CPU) and European Extreme Risk Index (E3CI)

| | CPU | E3CI | Commonalities |
|---|---|---|---|
| Definition | Measures uncertainty in climate-related policies based on media coverage and text analysis | Captures extreme climate-related risk events in Europe based on multiple hazard indicators | Both relate to climate risks, though CPU focuses on policy uncertainty while E3CI tracks physical risks |
| Methodology | Uses text-based analysis of newspaper articles to quantify policy uncertainty | Aggregates meteorological and climate risk data using statistical modeling | Both are constructed using quantitative methods to track climate-related risks over time |
| Scope | Focuses on policy uncertainty at the country level | Assesses climate risk events across Europe at a regional level | Both can be applied at national or regional scales, allowing for comparative analysis |
| Timeframe | Monthly index since early 2000s | Updated quarterly with historical calibration | Both provide time-series data that enable dynamic analysis of climate-related impacts |
| Application in Research | Used in economic and financial studies to assess policy-related investment risks | Applied in risk management and insurance to quantify extreme event exposure | Both can be integrated to analyze the interplay between policy uncertainty and physical climate risks in economic modeling |

across different categories of inflation: headline, core, energy, and food inflation. Headline inflation refers to the total inflation in an economy, encompassing all goods and services, including volatile items like food and energy. Core inflation, in contrast, represents the underlying trend in price levels, excluding food and energy prices, and is generally less volatile. Energy and food inflation capture the price movements of these specific commodities, which are known for their high volatility.

Our sample spans from January 2000 to July 2024 ($T = 294$ observations). As most of the corresponding studies (see, for instance, Albulescu et al., 2019; Caggiano et al., 2020), we consider inflation components (headline, core, food, energy) of year-on-year percentage changes to capture the entire dynamics within a year. We express the newspaper uncertainty measures in log terms to allow for comparable scale shocks. For the Eurozone, the data were sourced from https://ec.europa.eu/eurostat, while in the US case, we retrieved data from https://fred.stlouisfed.org. Figures 4 and 5 show the datasets used in this study for the Eurozone and the US, respectively.

### 3.2 Methodology

To study the effects of uncertainty measures shocks on inflation, we develop a Structural Vector AutoRegression (SVAR) model.[5] The rationale behind SVARs is mainly to handle endogeneity and simultaneity between variables, which are typical problems in standard regression techniques. In addition, structural identification allows the study of the effect of structural shocks, which is not possible with standard Autoregressive Distributed Lags (ADL)[6] models with external variables. Finally, SVARs are fundamental to understanding the percentage of the impact of shocks between covariates in the past (such as the historical decomposition) to conclude the effect of certain events. Suppose a standard reduced-form VAR representation:

$$\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{y}_{t-i} + \boldsymbol{u}_t \tag{1}$$

where $\boldsymbol{y}_t$ is the $k = 6$ element vector with endogenous variables:

$$\boldsymbol{y} = [y_{Climate}, y_{EPU}, y_{Energy}, y_{Food}, y_{Core}, y_{Headline}]',^{7}$$

[7] $p$ is the order of the model, $\boldsymbol{\Phi}_i$ are the $k \times k$ VAR coefficient matrices, $\boldsymbol{u}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma}_u)$ is the vector of one step ahead prediction errors, and $\boldsymbol{\Sigma}_u$ is the covariance matrix of the reduced-form residuals. We consider the constant and the log of the World Uncertainty Index (WUI) as exogenous variables of the model.

To identify the structural shocks, we assume that there exists a matrix $\boldsymbol{C}$ such that:

$$\mathrm{u}_t = \boldsymbol{C}\boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{\varepsilon}_t$ is the vector of structural shocks and $\boldsymbol{C}$ is a $k \times k$ matrix that maps the structural shocks to the reduced-form residuals.

To achieve identification, we impose a recursive (Cholesky) structure on $\boldsymbol{C}$, which implies that $\boldsymbol{C}$ is lower triangular. This decomposition assumes that the structural shocks affect the endogenous variables in a recursive order, meaning that the order of variables is crucial. To this end, we propose the following scheme:

[5] We decided to use an SVAR approach instead of the Local Projections (LP, Jordà 2005) given the possibility of structural identifying shocks and the need for a system-wide consistency. On the contrary, given their flexibility, LP techniques could be used in future studies for different policy experiments.

[6] Pedantically, part of the literature would say ARDL.

[7] Please note that "Climate" refers to E3CI in the Euro area case and to CPU in the US case.

$$\begin{bmatrix} u_{Climate} \\ u_{EPU} \\ u_{Core} \\ u_{Energy} \\ u_{Food} \\ u_{Headline} \end{bmatrix} = \begin{bmatrix} c_{1,1} & 0 & 0 & 0 & 0 & 0 \\ c_{2,1} & c_{2,2} & 0 & 0 & 0 & 0 \\ c_{3,1} & c_{3,2} & c_{3,3} & 0 & 0 & 0 \\ c_{4,1} & c_{4,2} & c_{4,3} & c_{4,4} & 0 & 0 \\ c_{5,1} & c_{5,2} & c_{5,3} & c_{5,4} & c_{5,5} & 0 \\ c_{6,1} & c_{6,2} & c_{6,3} & c_{6,4} & c_{6,5} & c_{6,6} \end{bmatrix} \begin{bmatrix} \varepsilon_{Climate} \\ \varepsilon_{EPU} \\ \varepsilon_{Core} \\ \varepsilon_{Energy} \\ \varepsilon_{Food} \\ \varepsilon_{Headline} \end{bmatrix}. \quad (3)$$

The structural identification (see Eq. 2) of our SVAR model follows a recursive (Cholesky-type) structure. This approach imposes a contemporaneous causal hierarchy among the variables, allowing us to disentangle structural shocks and trace their dynamic transmission across the system. Although alternative identification strategies exist—such as the Generalized Forecast Error Variance Decomposition (GFEVD) proposed by Koop et al. (1996)—they often rely on weaker assumptions, do not require orthogonalization of shocks, and yield results invariant to variable ordering.[8] While this generality is appealing, it comes at the cost of interpretability, especially when the objective is to identify structural shocks with clear economic meaning.

Therefore, since the order of the variables is crucial, we follow both previous literature and economic intuition to follow the order discussed in Eq. (3). In particular, under the assumption that climate phenomena (such as extreme weather events or regulatory signals) are largely exogenous in the short term and do not respond contemporaneously to economic or inflationary variables, it is reasonable to position the climate variable as the first in the identification scheme. The Economic Policy Uncertainty is fixed as the second variable, reflecting the idea that policy discourse may respond to environmental developments but is unlikely to react instantly to inflation component changes.

Empirical evidence supports these rationale. For instance, Arnell (2022) underscores governments' need to respond immediately to climate shocks, often through emergency fiscal re-allocations and policy interventions that have direct economic consequences. Similarly, Gagliardi et al. (2022) highlight the importance of swift climate mitigation and adaptation measures to cushion the economic and fiscal repercussions of increasingly frequent and severe extreme events. These responses, in turn, can generate significant economic disruptions and political instability, reinforcing the linkage from climate uncertainty to economic policy. To complete, the reason to place the EPU before inflation components aligns with the argument in Caggiano et al. (2020).

The rest of the ordering of inflation components is further supported by the findings of Giri (2022), which shows a significant impact of inflation components on the headline, along with a theoretical null effect of food and energy inflation components on the core. In addition, given the possible debate about the ordering between energy and food inflation, we perform an overidentification test on $c_{5,4} = 0$ to improve the SVAR identification of the model.

As a robustness, we disentangle the effects of uncertainty shocks (climate and economic) using 4 different trivariate SVAR models as follows:

[8] Additionally, other alternative specifications include so-called "spillover analyses" Diebold and Yilmaz (2012).

**Table 2** Log-Likelihood and Information Criteria for EU and US

| | EU | | | | US | | | |
|---|---|---|---|---|---|---|---|---|
| | Loglik | AIC | BIC | HQC | Loglik | AIC | BIC | HQC |
| 1 | 4651.775 | −34.923 | **−34.354** | **−34.694** | 4254.539 | −31.320 | −30.759 | −31.095 |
| 2 | 4713.258 | −35.116 | −34.059 | −34.691 | 4409.924 | −32.208 | **−31.165** | **−31.789** |
| 3 | 4747.057 | −35.099 | −33.555 | −34.478 | 4453.417 | −32.263 | −30.740 | −31.652 |
| 4 | 4769.332 | −34.995 | −32.963 | −34.179 | 4491.832 | **−32.281** | −30.277 | −31.476 |
| 5 | 4795.852 | −34.923 | −32.404 | −33.911 | 4512.039 | −32.164 | −29.678 | −31.166 |
| 6 | 4819.730 | −34.831 | −31.824 | −33.623 | 4543.555 | −32.131 | −29.164 | −30.939 |
| 7 | 4870.268 | −34.941 | −31.447 | −33.537 | 4573.754 | −32.087 | −28.640 | −30.703 |
| 8 | 4921.153 | −35.054 | −31.072 | −33.454 | 4595.616 | −31.982 | −28.053 | −30.404 |
| 9 | 4961.403 | −35.086 | −30.616 | −33.290 | 4619.255 | −31.890 | −27.481 | −30.119 |
| 10 | 4990.766 | −35.036 | −30.079 | −33.044 | 4647.673 | −31.834 | −26.943 | −29.870 |
| 11 | 5024.194 | −35.017 | −29.571 | −32.829 | 4684.660 | −31.841 | −26.469 | −29.684 |
| 12 | 5074.275 | **−35.123** | −29.190 | −32.739 | 4727.106 | −31.889 | −26.036 | −29.539 |

Notes: The bolded values represent the lowest IC.

**Table 3** Overidentification test for $c_{5,4} = 0$

| | Over-ID statistic | p-value |
|---|---|---|
| Euro area | 1.2122 | 0.2709 |
| US | 0.0640 | 0.8002 |

$$\begin{bmatrix} u_{Climate} \\ u_{EPU} \\ u_{Inflation\ component} \end{bmatrix} = \begin{bmatrix} c_{1,1} & 0 & 0 \\ c_{2,1} & c_{2,2} & 0 \\ c_{3,1} & c_{3,2} & c_{3,3} \end{bmatrix} \begin{bmatrix} \varepsilon_{Climate} \\ \varepsilon_{EPU} \\ \varepsilon_{Inflation\ component} \end{bmatrix}.$$

## 4 Results

We select the optimal lag order $p$ based on the lowest Information Criteria (IC). In the Euro area case, the Bayesian Information Criterion (BIC) and the Hannan-Quinn Criterion (HQC) agree that the optimal lag is $p_{EU} = 2$, while in the US case it is $p_{US} = 2$. All the ICs obtained considering different lags are shown in Table 2.

Consequently, we have developed a Structural VAR model incorporating these lags to ensure comparable evidence of structural shocks. We have considered a forecast horizon of $H = 24$ periods (likely to 2 years) to compute the Impulse Response Functions (IRFs). We use 1000 bootstrap replications to compute 68% confidence bands Forni and Gambetti (2014). In addition, each own shock is normalized to one, thus leading diagonal elements of the $C$ matrix in the Eq. (3) to be one.

As discussed in the identification part of the model, Table 3 reports the overidentification test for the Euro area and the US. As one can easily see, the null hypothesis of $c_{5,4} = 0$ is not rejected, allowing us to both rely on the variable order and to improve the identification of the model.

Figures 1 and 2 report the IRFs from uncertainties to inflation components for US and Euro area.

Looking at the results for food inflation, we expect a pronounced effect of climate uncertainties, as it could generate different supply shocks (pp. 6–7 Backlund et

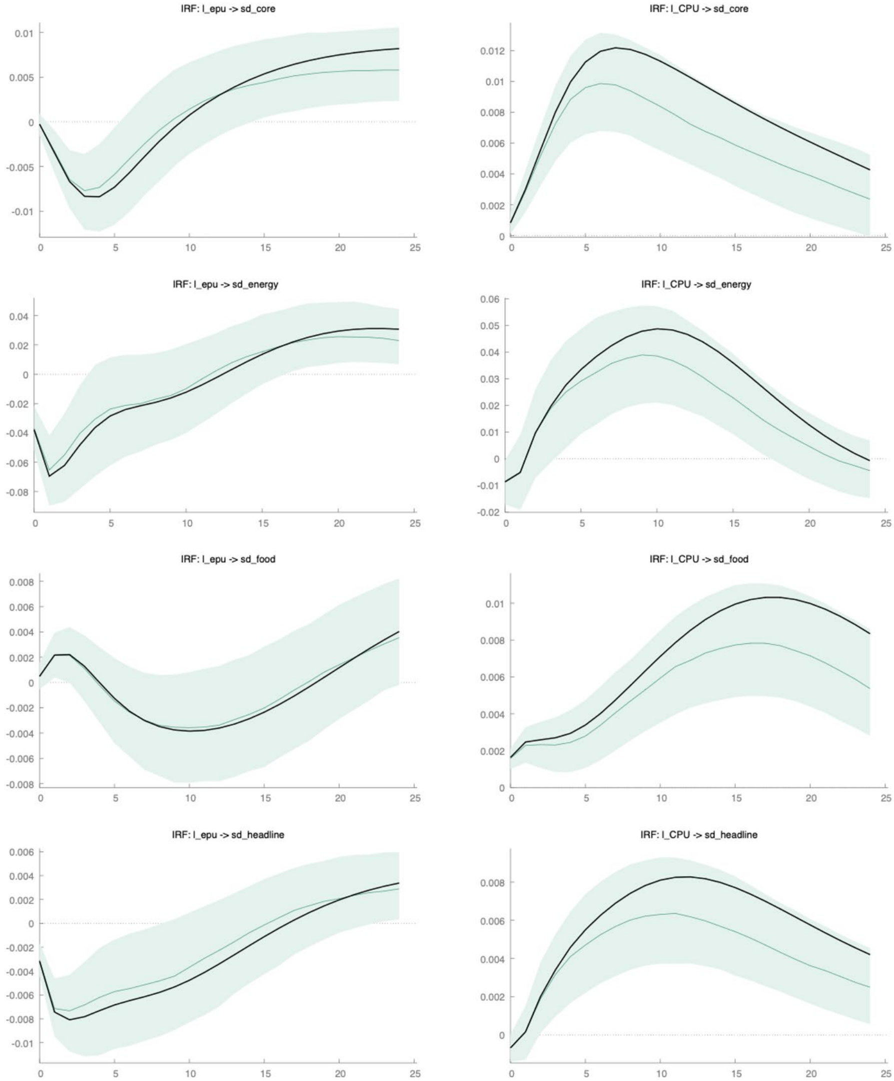


**Fig. 1** US: uncertainty effects on inflation. Notes: The green shadow is the confidence interval of IRFs at 68%. The black line is the IRF while the green line is the median IRF.

al., 2008), confirming the discussion we promoted in Sect. 2.2 when we introduced the cost-push inflation theory. Indeed, this effect is confirmed in the US and—partially—in the Eurozone: a sudden shock in climate uncertainty will increase seasonal food inflation. However, the impact is higher and more persistent in the US, which signals that government food price policies need to consider climate risks. According to Timmer (1989), two different schools of thought have developed in terms of food pricing policy: the neoclassical school, which claims the need to increase trade to mitigate shocks, and the structuralist view, which instead favors national interventions for redistributive policies. However, looking at our results, it seems that the

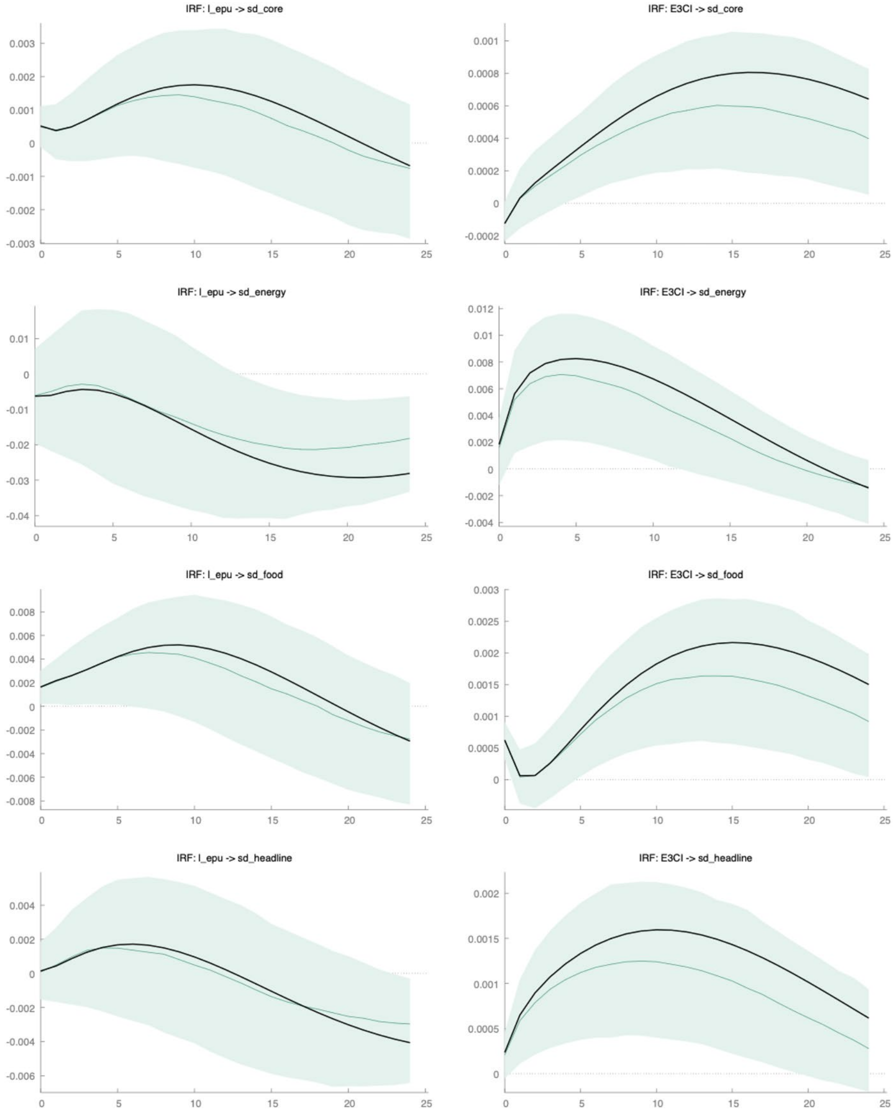


**Fig. 2** Euro area: uncertainty effects on inflation. Notes: The green shadow is the confidence interval of IRFs at 68%. The black line is the IRF while the green line is the median IRF.

US national government should promote the neoclassical view as the extreme event could increase food inflation. US policymakers should consider food price volatility when designing inflation-targeting policies, potentially incorporating climate risk into macroeconomic forecasting models. In the case of the Eurozone, the situation is quite different, as the shock seems to have a marginal effect on food prices.

The effect of EPU on energy inflation seems to have a negative impact in the US case, while it is not significant for the Eurozone. Accordingly, high uncertainty discourages long-term investment in energy infrastructure, particularly with those with low-carbon intensity. Moreover, this result is explained by looking at the results of Feng and Zheng (2022), according to which the EPU favors renewable energy innovation in countries with high institutional quality. These results align with those of Ezcurra and Rios (2019) and Rios and Gianmoena (2020), as institutional quality could effectively deal with the external shock. In this sense, the evidence favors developing renewable energy programs in the United States, while the Euro area necessitates greater engagement: institutional structure may try to buffer the effects of policy uncertainty on energy inflation.

In terms of core and headline inflation, the results are pretty interesting. The effect of an EPU shock on core inflation in the eurozone is zero, while that of the E3CI tends to increase core inflation after $H = 2$ horizons. This result can be explained by the historical decomposition of shocks represented in Fig. 3 because, while the economic policy shock was significant and reached a maximum impact during the Covid-19, climate shocks started to have a crucial role after the outbreak of the war in Ukraine.

This result is in line with what is described in Chen et al. (2021) and Boneva et al. (2022), which also attribute the growing role of climate in monetary policy decisions by studying the asset purchase programs of the European Central Bank that are promoting the purchase of green bonds under the asset purchase program (APP, De Santis et al., 2018). Moreover, this outcome is also confirmed in the headline case. Therefore, it is crucial to adopt policies to contain extreme weather phenomena by promoting cooperation among Eurozone states to reduce the impact of these events on the real Euro area economy.

In the case of the United States, EPU and CPU shocks have different results on the core and headline inflation components. A sudden EPU shock harms the headline and core components, but it seems to be reabsorbed relatively quickly. This result depends on the periods when EPU increased in the United States. Looking at the original time series in Fig. 5, EPU increased during the 2008 crisis and the pandemic, while it appears to be stable between 2010 and 2014 and decreased after the Covid-19 pandemic. In fact, from 2009 to 2017, the stable trend of EPU was mainly due to the stability of the government led by the Obama administration. This trend remained constant even for the Biden government, which had some difficulties in the latter part of its term.

Moreover, looking at the historical decomposition in Fig. 3, it is quite evident how the role of EPU has been mainly constant with positive or negative effects around elections. Therefore, the role of uncertainties in inflation spikes could be mitigated if national governments are stable. Moreover, given the “newspaper index” structure of the EPU, it is evident how media attention on economic policies increases during local election periods. The initial decrease in inflation rates is mainly due to coordination between fiscal and monetary policies, which is lacking in the case of the EU. For example, raising taxes, which reduces an individual’s ability to spend, can help reduce inflation.

In the CPU case, the shape of the IRFs is similar to that of the Euro area but seems to have a larger amplitude. This larger effect is also confirmed in Fig. 3, where the historical decomposition shows a larger role of CPU (in almost all components of inflation) than in the Euro area case. According to Kayani et al. (2024) in the US

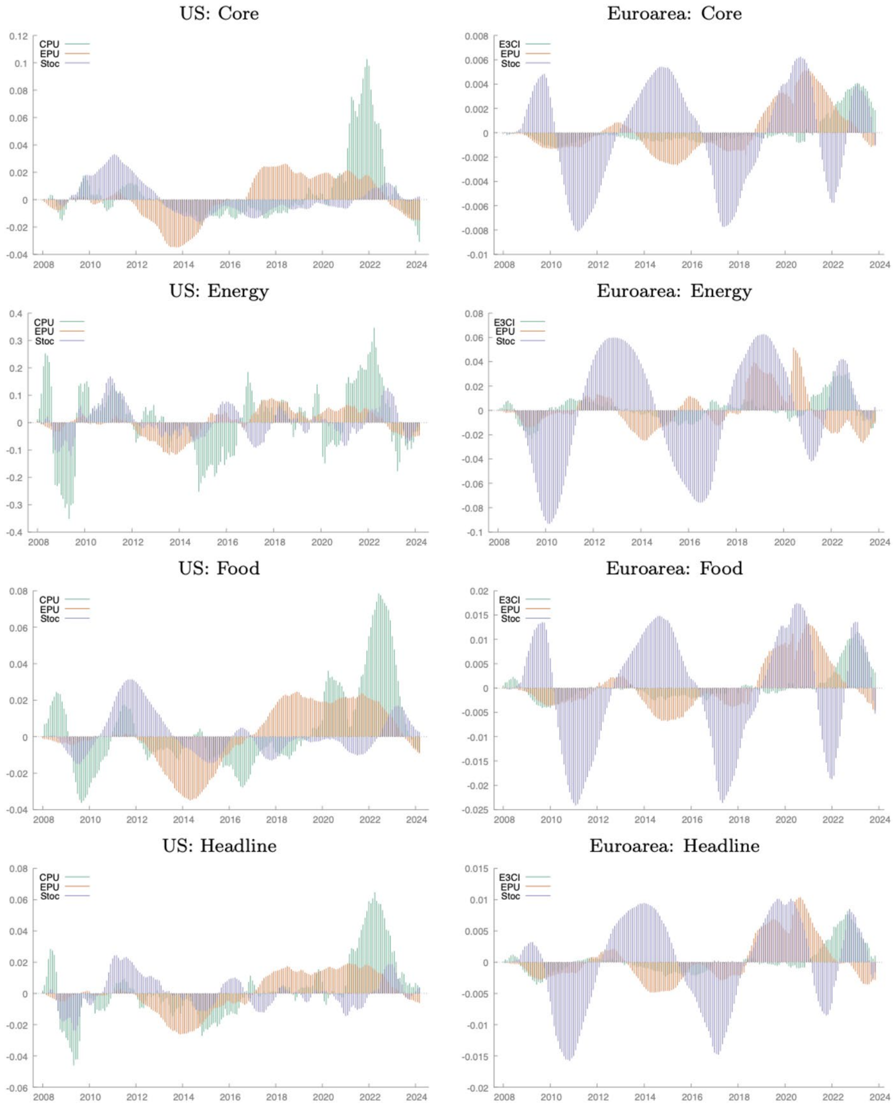


**Fig. 3** Historical decomposition. Notes: In each period the length of the bar represents the decomposition of the variable.

case, a CPU shock has a long-term impact on consumer services, financial sectors, industries, telecommunications, and utilities, all of which have a direct effect on the real economy. We also align with Parker (2018) and Mukherjee and Ouattara (2021), which discuss an important effect of climate risks on inflation rates. The impact of climate uncertainty on the United States and the effect of economic policy uncertainty in the Euro area are then confirmed by the results of the simple trivariate VAR shown in Fig. 6.

Finally, given these results and the past evidence shown in Sect. 2, we conduct a very simple T-test on the historical decomposition series to understand whether the impact is the same in the US and the Eurozone. To do so, we test the hypothesis that the average decomposition for climate in the US equals the average decomposition for economic policy uncertainty in the Eurozone. The results are reported in Table 4 and show that the impact of climate uncertainty is significantly higher than that of economic policy uncertainty in the US than in the Euro area for each of the inflation components considered. Therefore, we can conclude that climate uncertainty is becoming a crucial element that policymakers should consider in their policy decisions.

## 5 Conclusions

The present study deals with the analysis of different kinds of uncertainties—economic policy and climate—related risk and their impacts on the dynamics of inflation in the Euro area and the United States. We contribute to the ongoing debate on how uncertainty influences inflation dynamics in structurally different economies. Our results highlight the importance of climate risk as a rising inflationary driver, necessitating innovative monetary and fiscal strategies.

First, we emphasize that climate risk and economic uncertainty have distinct impacts on the components of inflation, particularly food, energy, core, and headline inflation. In particular, the effects of climate uncertainty on food inflation are more pronounced in the United States than in the euro area. This consequence suggests that climate risk should be taken into account when formulating food pricing policies in the United States, where extreme weather events are likely to exert significant pressure on food prices. The Eurozone, on the other hand, shows a marginal impact of similar shocks on food prices. At the same time, it appears to be affected in structural terms (core inflation), suggesting concrete problems in managing external shocks, especially given the different fiscal policies of Eurozone countries.

The study also finds that EPU plays a crucial role in influencing energy inflation, particularly in the US, where robust institutions and policies promoting renewable energy innovation seem to buffer the economy from some negative impacts. This outcome contrasts with the Eurozone, where the institutional response to energy inflation due to EPU remains less clear. The divergent outcomes between these two economic areas suggest that institutional quality and the ability to foster innovation are crucial for mitigating the adverse effects of policy uncertainty on energy markets.

Further, the results indicate that EPU shocks have different effects on core and headline inflation across the Eurozone and the US. In the Eurozone, core inflation

**Table 4** Test on HD differences

| Core | Energy | Food | Headline |
|---|---|---|---|
| 2.1E-12*** | 2.0E-15*** | 3.8E-07*** | 3.2E-07*** |

Notes: The null hypothesis ($H_0$) is that the Historical Decomposition (HD) of CPU in US in equal to the HD of EPU in the Euro area. The alternative hypothesis ($H_1$) is that the CPU's HD of the US is higher of the EPU's HD in the Euro area. *** is a p-value lower than 1%.

seems to remain unaffected by EPU shocks, while climate risks begin to influence core inflation only after a lag. The historical decomposition of shocks reveals that while economic policy shocks were significant during the Covid-19 pandemic, the influence of climate shocks has grown in prominence, particularly after the onset of the war in Ukraine. This result highlights the increasingly important role that climate considerations are playing in monetary policy decisions, especially in terms of asset purchase programs by central banks such as the European Central Bank (ECB), which has shifted towards the acquisition of green bonds.

The US case presents a different narrative, where EPU shocks initially exert a negative influence on both core and headline inflation, but the effects are quickly reabsorbed. This evidence reflects the relative stability in governance during specific periods, such as the Obama and Biden administrations. The "newspaper index" structure of the EPU, which tracks media attention on economic policies, shows that inflation rates in the US can be heavily influenced by electoral cycles.

From a monetary policy perspective, central banks should not only incorporate climate uncertainty indicators (such as E3CI or CPU indices) into inflation forecasting models, but also adjust their reaction functions conditionally—for instance, by adopting non-linear inflation targeting frameworks that differentiate between uncertainty-driven and demand-driven inflation. This distinction would prevent over-tightening in response to climate shocks that temporarily raise food or energy prices.

Moreover, in light of the evidence that uncertainty shocks—especially from climate risk—can persist and impact specific inflation components, monetary authorities should consider explicitly referencing climate risks in their forward guidance to enhance credibility and shape expectations more effectively. This applies particularly to the Federal Reserve, where climate risk was shown to significantly affect food inflation.

On the fiscal side, policymakers should implement contingency-based stabilization mechanisms: automatic food or energy price subsidies linked to extreme weather indexes, which can reduce volatility in headline inflation and stabilize market price. Additionally, dedicated investment buffers for green infrastructure can simultaneously mitigate supply-side inflation and support long-term price stability.

In the US context, where EPU negatively affects energy prices, streamlined permitting and fiscal incentives for clean energy projects can help counteract investment hesitation due to policy uncertainty.

For the Eurozone, the results suggest that cross-country climate resilience funds should be integrated into the EU fiscal framework to account for asymmetric inflationary effects of climate risk across member states. Furthermore, the European Central Bank could improve transmission effectiveness by greening its collateral frameworks, offering preferential treatment to securities from climate-resilient sectors in its refinancing operations.

Although our analysis focuses on the US and the Euro area, the identified mechanisms (the transmission of climate-related and economic policy uncertainty to inflation components) could plausibly extend to other advanced economies with comparable institutional features. Countries such as Canada, the UK, or Japan share important structural commonalities: inflation-targeting central banks, open economies with significant exposure to global energy and food markets, and high media responsiveness that underpins the construction of uncertainty indices. These similarities suggest that comparable dynamics may emerge in the presence of uncertainty shocks. However, this extension is less likely in economies with weaker institutional frameworks, limited central bank independence, or low media penetration—such as some Eastern European or Latin American countries—where uncertainty may transmit through different, often less transparent, channels. Thus, while generalization could be possible within a certain institutional and economic context, caution is warranted when extrapolating to structurally dissimilar settings.

Importantly, by disaggregating inflation into its key components and applying a structural framework across two institutional regimes, this paper identifies that headline inflation responses can mask critical heterogeneity across food, energy, and core categories. Prior studies focusing on aggregate inflation often overlook these divergent channels, especially when climate and policy uncertainty affect components differently in economies with distinct fiscal-monetary architectures. This structural insight—e.g., the resilience of Eurozone food inflation versus the vulnerability of US food inflation to climate shocks—is especially relevant for policymakers designing targeted inflation stabilization measures.

However, as we already discussed in Table 1, we have compared two different measures of climate risk; future studies could seek to develop a Climate Policy Uncertainty (CPU) index for the euro area along the lines of Gavriilidis (2021) and subsequent studies such as Di Tommaso et al. (2024). In addition, the literature could directly study the influence of uncertainties in the context of the interaction between fiscal and monetary policies by including several variables, such as the ratio of government spending to GDP and the primary account balance, which are commonly used proxies in the fiscal policy literature, and interbank rates, which basically represent monetary policy.

## Appendix

See Figs. 4, 5, 6.

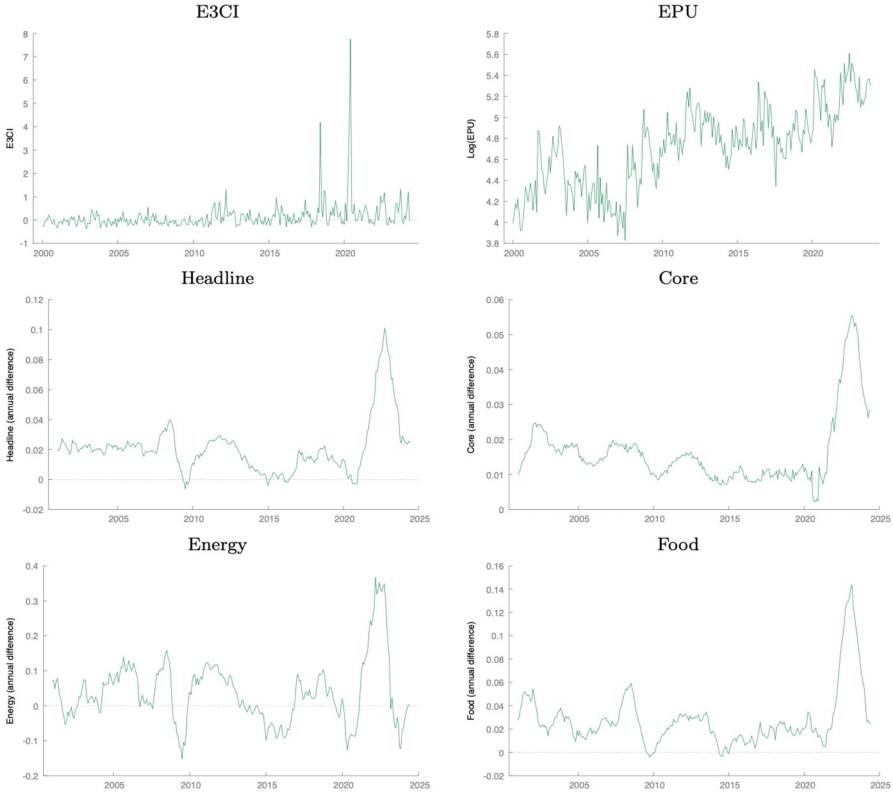


**Fig. 4** Euro area timeseries used

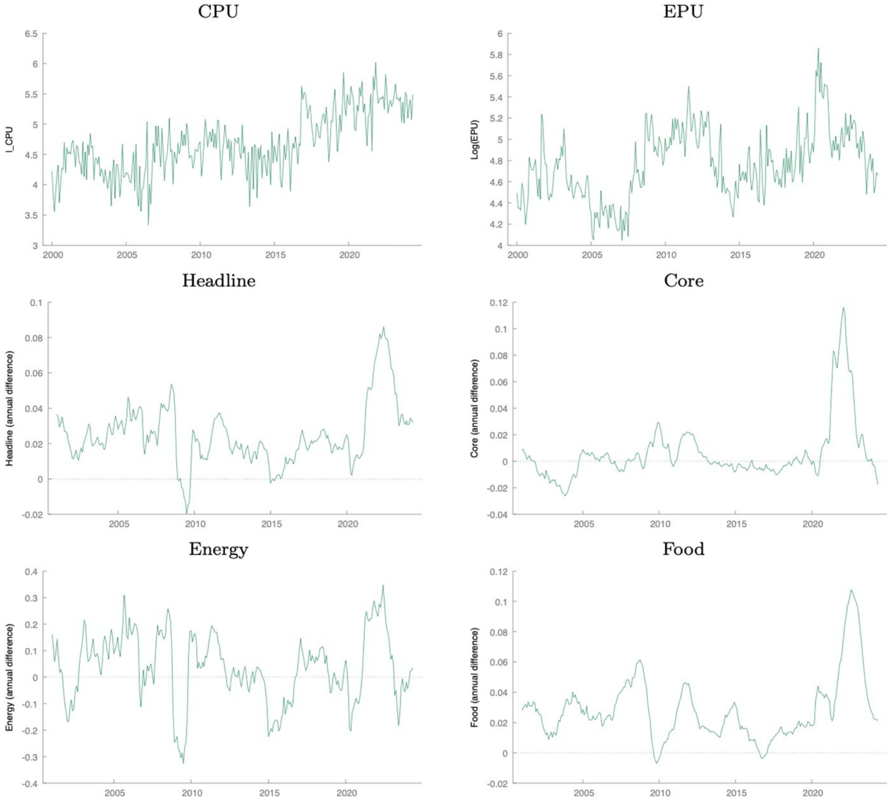


**Fig. 5** US timeseries used

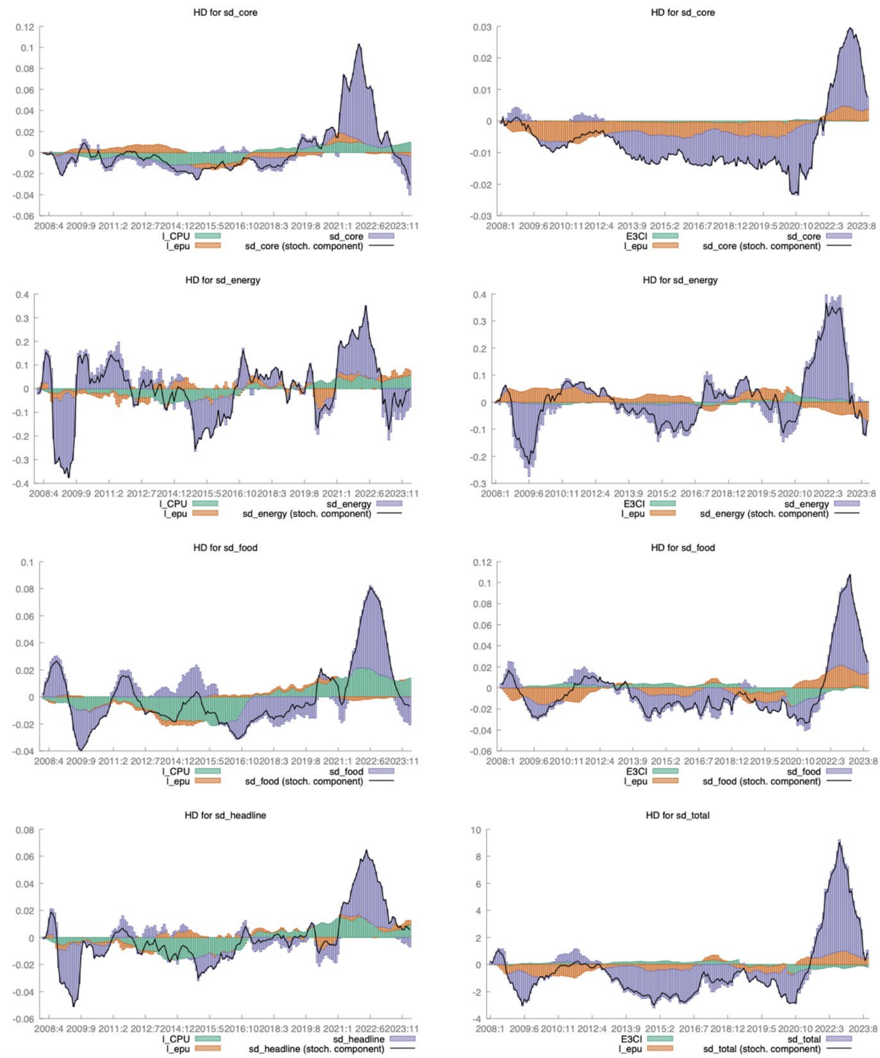


**Fig. 6** Historical decomposition from trivariate SVAR

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## References

Abbate, A., Eickmeier, S., & Prieto, E. (2023). Financial shocks and inflation dynamics. *Macroeconomic Dynamics, 27*(2), 350–378.

Aguila, N., & Wullweber, J. (2024). Greener and cheaper: Green monetary policy in the era of inflation and high interest rates. *Eurasian Economic Review, 14*(1), 39–60.

Ahir, H., Bloom, N., & Furceri, D. (2022). *The world uncertainty index*. Technical report, National bureau of economic research.

Albulescu, C. T., Tiwari, A. K., Miller, S. M., & Gupta, R. (2019). Time-frequency relationship between us inflation and inflation uncertainty: Evidence from historical data. *Scottish Journal of Political Economy, 66*(5), 673–702.

Arnell, N. W. (2022). The implications of climate change for emergency planning. *International Journal of Disaster Risk Reduction, 83*, Article 103425.

Assenmacher-Wesche, K., & Gerlach, S. (2010). Monetary policy and financial imbalances: Facts and fiction. *Economic Policy, 25*(63), 437–482.

Backlund, P., Janetos, A. C., & Schimel, D. S. (2008). The effects of climate change on agriculture, land resources, water resources and biodiversity in the united states. *US Climate Change Science Program*, 4.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Vol. 131 november 2016 issue 4. *The Quarterly Journal of Economics, 1593*, 1636.

Balcilar, M., Ozdemir, Z. A., Ozdemir, H., Aygun, G., & Wohar, M. E. (2022). The macroeconomic impact of economic uncertainty and financial shocks under low and high financial stress. *The North American Journal of Economics and Finance, 63*, Article 101801.

Batten, S., Sowerbutts, R., & Tanaka, M. (2020). Climate change: Macroeconomic impact and implications for monetary policy. *Ecological, Societal, and Technological Risks and the Financial Sector, 8*, 13–38.

Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics, 60*(7), 771–788.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives, 28*(2), 153–176.

Boneva, L., Ferrucci, G., & Mongelli, F. P. (2022). Climate change and central banks: What role for monetary policy? *Climate Policy, 22*(6), 770–787.

Caggiano, G., Castelnuovo, E., & Figueres, J. M. (2020). Economic policy uncertainty spillovers in booms and busts. *Oxford Bulletin of Economics and Statistics, 82*(1), 125–155.

Cevik, S., & Jalles, J. (2024). Eye of the storm: The impact of climate shocks on inflation and growth. *Review of Economics, 75*(2), 109–138.

Chen, C., Pan, D., Huang, Z., & Bleischwitz, R. (2021). Engaging central banks in climate change? the mix of monetary and climate policy. *Energy Economics, 103*, Article 105531.

Craine, R. (1979). Optimal monetary policy with uncertainty. *Journal of Economic Dynamics and Control, 1*(1), 59–83.

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2018). Climate change, financial stability and monetary policy. *Ecological Economics, 152*, 219–234.

Das, B. C., Hasan, F., & Sutradhar, S. R. (2024). The impact of economic policy uncertainty and inflation risk on corporate cash holdings. *Review of Quantitative Finance and Accounting, 62*(3), 865–887.

De Santis, R. A., Roos, M., Hettler, K., & Tamburrini, F. (2018). Purchases of green bonds under the Eurosystem's asset purchase programme. *Economic Bulletin Boxes, 7*, 8.
Di Tommaso, C., Foglia, M., & Pacelli, V. (2024). The impact of climate policy uncertainty on the Italian financial market. *Finance Research Letters, 69*, Article 106094.
Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*(1), 57–66.
D'Orazio, P., Schäfer, D., & Stephan, A. (2024). Macro-financial policy at the crossroad: Addressing climate change, biodiversity loss, and environmental degradation-introduction to the special issue. *Eurasian Economic Review, 14*(1), 1–11.
Ezcurra, R., & Rios, V. (2019). Quality of government and regional resilience in the European union. Evidence from the great recession. *Papers in Regional Science, 98*(3), 1267–1291.
Feng, G.-F., & Zheng, M. (2022). Economic policy uncertainty and renewable energy innovation: International evidence. *Innovation and Green Development, 1*(2), Article 100010.
Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., & Rubio-Ramírez, J. (2015). Fiscal volatility shocks and economic activity. *American Economic Review, 105*(11), 3352–3384.
Fischer, S. (1977). Long-term contracts, rational expectations, and the optimal money supply rule. *Journal of Political Economy, 85*(1), 191–205.
Fornari, F., & Stracca, L. (2012). What does a financial shock do? first international evidence. *Economic Policy, 27*(71), 407–445.
Forni, M., & Gambetti, L. (2014). Sufficient information in structural vars. *Journal of Monetary Economics, 66*, 124–136.
Gagliardi, N., Arévalo, P., & Pamies-Sumner, S. (2022). The fiscal impact of extreme weather and climate events: Evidence for eu countries. *Publications Office of the European Union*.
Gavriilidis, K. (2021). Measuring climate policy uncertainty. *Available at SSRN 3847388*.
Giri, F. (2022). The relationship between headline, core, and energy inflation: A wavelet investigation. *Economics Letters, 210*, Article 110214.
Gordon, R. J. (1975). Alternative responses of policy to external supply shocks. *Brookings Papers on Economic Activity, 1975*(1), 183–206.
Hasegawa, T., Sakurai, G., Fujimori, S., Takahashi, K., Hijioka, Y., & Masui, T. (2021). Extreme climate events increase risk of global food insecurity and adaptation needs. *Nature Food, 2*(8), 587–595.
Huang, B., & Punzi, M. T. (2024). Macroeconomic impact of environmental policy uncertainty and monetary policy implications. *Journal of Climate Finance, 7*, Article 100040.
Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review, 95*(1), 161–182.
Kayani, U., Sheikh, U. A., Khalfaoui, R., Roubaud, D., & Hammoudeh, S. (2024). Impact of climate policy uncertainty (CPU) and global energy uncertainty (EU) news on us sectors: The moderating role of CPU on the EU and us sectoral stock nexus. *Journal of Environmental Management, 366*, Article 121654.
Knight, F. H. (1921). *Risk, uncertainty and profit*. Hart, Schaffner and Marx.
Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74*(1), 119–147.
Kotz, M., Kuik, F., Lis, E., & Nickel, C. (2024). Global warming and heat extremes to enhance inflationary pressures. *Communications Earth & Environment, 5*(1), 116.
Larch, M. (2020). Fiscal policy in the COVID-19 crisis: Temporary deviations from EU fiscal rules. *VoxEU*.
Malesios, C., Jones, N., & Jones, A. (2020). A change-point analysis of food price shocks. *Climate Risk Management, 27*, Article 100208.
María-Dolores, R., & Vázquez, J. (2008). The new Keynesian monetary model: Does it show the comovement between GDP and inflation in the us? *Journal of Economic Dynamics and Control, 32*(5), 1466–1488.
Mukherjee, K., & Ouattara, B. (2021). Climate and monetary policy: Do temperature shocks lead to inflationary pressures? *Climatic Change, 167*(3), 32.
Murphy, R., & Hines, C. (2010). *Green quantitative easing: Paying for the economy we need.* Norfolk: Finance for the Future.
Orlowski, L. T. (2023). How susceptible is the European financial stability to economic policy uncertainty? *Journal of Policy Modeling, 45*(4), 864–875.
Oros, C., & Zimmer, B. (2015). Uncertainty and fiscal policy in a monetary union: Why does monetary policy transmission matter? *Economic Modelling, 50*, 85–93.

Parker, M. (2018). The impact of disasters on inflation. *Economics of Disasters and Climate Change, 2*(1), 21–48.

Ren, Y.-S., Klein, T., Jiang, Y., Ma, C.-Q., & Yang, X.-G. (2024). Dynamic spillovers among global oil shocks, economic policy uncertainty, and inflation expectation uncertainty under extreme shocks. *Journal of International Financial Markets, Institutions and Money, 91*, Article 101951.

Rios, V., & Gianmoena, L. (2020). The link between quality of government and regional resilience in Europe. *Journal of Policy Modeling, 42*(5), 1064–1084.

Rozenberg, J., Hallegatte, S., Perrissin-Fabert, B., & Hourcade, J.-C. (2013). Funding low-carbon investments in the absence of a carbon tax. *Climate Policy, 13*(1), 134–141.

Shahbaz, M., Sheikh, U. A., Tabash, M. I., & Jiao, Z. (2024). Shock transmission between climate policy uncertainty, financial stress indicators, oil price uncertainty and industrial metal volatility: Identifying moderators, hedgers and shock transmitters. *Energy Economics, 136*, Article 107732.

Shang, Y., Han, D., Gozgor, G., Mahalik, M. K., & Sahoo, B. K. (2022). The impact of climate policy uncertainty on renewable and non-renewable energy demand in the United States. *Renewable Energy, 197*, 654–667.

Stern, N. (2008). The economics of climate change. *American Economic Review, 98*(2), 1–37.

Tarkom, A., & Ujah, N. U. (2023). Inflation, interest rate, and firm efficiency: The impact of policy uncertainty. *Journal of International Money and Finance, 131*, Article 102799.

Timmer, C. P. (1989). Food price policy: The rationale for government intervention. *Food Policy, 14*(1), 17–27.

Toumi, S., Aljadani, A., Toumi, H., Ammouri, B., & Dhiabi, M. (2025). Ai for climate change: Unveiling pathways to sustainable development through greenhouse gas emission predictions. *Eurasian Economic Review, 2*, 1–41.

Zheng, T., Gong, L., & Ye, S. (2023). Global energy market connectedness and inflation at risk. *Energy Economics, 126*, Article 106975.