Journal of Economic Behavior and Organization 212 (2023) 610–628

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

The relationship between climate risk, climate policy uncertainty, and CO2 emissions: Empirical evidence from the US

Khaled Guesmi[a], Panagiota Makrychoriti[b,*], Spyros Spyrou[c,1]

[a] Paris School of Business, France
[b] Birkbeck, University of London, UK
[c] Athens University of Economics & Business, Greece

ARTICLE INFO

Article history:
Received 10 February 2023
Revised 15 May 2023
Accepted 12 June 2023

JEL:
E0
e2
q2
q4
q5

Keywords:
Climate
Uncertainty shocks
FAVAR
Natural disasters
CO2 emissions

ABSTRACT

This paper examines the relationship between climate risk and climate policy uncertainty, and CO2 emissions in the US over the 2000–2022 period using a structural Factor- Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis based on monthly observations. We employ a very recent measure to proxy for uncertainty regarding climate policy based on the Climate Policy Uncertainty Index (CPU) of Gavriilidis (2021), while Climate Risk is proxied by financial cost of natural disasters and number of deaths. We use different variables for CO2 emissions, based on total and sectoral emission (commercial, electric power, residential sector, transportation, and industrial sector). The results indicate that a significant percentage of the variance of CO2 emissions in the US, is explained by Natural Disasters Cost, which also seem to account for a significant percentage of the US Total Renewable Energy Consumption variance. Shocks to disaster costs seem to decrease all type of emissions significantly and also increase renewable energy use significantly. Natural disasters increase political disagreement among U.S. politicians, as well as, the climate policy uncertainty, highlighting the need for efficient policymaking and regulations. In further results, we find that an increase in Partisan Conflict decreases emissions and explains a significant amount of renewable energy variance.

1. Introduction

Climate risk may be a transmission channel for policy action in the sense that it affects public and political opinion; the stronger the impact of climate changes the higher the public pressure for policymakers to adopt appropriate policies to address climate change. If that holds, it is important to address climate change through policies that reduce uncertainty and mitigate climate risk. This paper examines the relationship between climate risk, climate policy uncertainty, and CO2 emissions in the US over the 2000–2022 period using a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis. We employ a very recent measure to proxy for uncertainty regarding climate

* Corresponding author.
E-mail address: p.makrychoriti@bbk.ac.uk (P. Makrychoriti).
[1] S. Spyrou acknowledges support from the Behavioral Finance Laboratory, Athens University of Economics & Business.

https://doi.org/10.1016/j.jebo.2023.06.015
0167-2681/

policy based on the Climate Policy Uncertainty Index (CPU) of Gavriilidis (2021), while Climate Risk is proxied by financial cost of natural disasters and number of deaths. We use different variables for CO2 emissions based on total and sectoral emission (commercial, electric power, residential sector, transportation, and industrial sector). The paper contributes to the relevant literature in several ways.

Firstly, to proxy for Climate Risk we use different variables. More specifically, we study the impact of climate risk using two variables, namely the financial cost of natural disasters and the number of deaths caused by each such disaster, collected from the National Oceanic and Atmospheric Administration (NOAA). More specifically, NOAA reports the financial cost and number of deaths over the span of each of the 249 costly natural disasters identified including wildfires, hurricanes, flooding, earthquakes, droughts, tornadoes, freezes, and winter storms. Total costs are in billions of 2019 dollars and the data are collected either from national programs but also from agencies such as FEMA, USDA, and Army Corps.

Secondly, to capture uncertainty regarding climate policy we examine Climate Policy Uncertainty in the US using the Climate Policy Uncertainty (CPU) Index of Gavriilidis (2021). Recently, Gavriilidis (2021) shows that there is uncertainty surrounding the implementation of policies to address climate change and introduces a new metric (CPU) that is based on information from important US newspapers. Gavriilidis finds a significant and negative impact of climate policy uncertainty (CPU) on CO2 emissions, and argues that, on the one hand, policy uncertainty regarding climate regulation may lead to delayed investments and/or reduced investments in new technologies and related research, but on the other hand, it may also encourage firms to reduce their ecological footprint. Atsu and Adams (2021) find, for the BRICS countries, that fossil fuel consumption along with policy uncertainty are contributors to CO2 emissions, while financial development, the quality of bureaucracy, and renewable energy, tend to mitigate emissions. They argue that economic policies that support innovation and investment in energy efficient technologies tend to reduce emissions.

Thirdly, we investigate the effect that natural disasters might have on the political alignment in the US Congress and on the adoption and formulation of efficient regulations and policies that can force firms to adopt more sustainable practices. Baccini and Leemann (2021) find that the experience of natural disasters can positively affect political behavior and support the adoption of environmentally friendly policies that deal with global warming. Thus, the final part of our analysis investigates how political disagreement among US politicians, elections, and debates over various policies, might impact firms' adoption of sustainable practices and consequently CO2 emissions. To proxy for the political uncertainty, we use the Partisan Conflict Index of Azzimonti (2014, 2018; Federal Reserve Bank of Philadelphia).

Fourthly, to study energy emissions, we not only use Total CO2 emissions in the US, but also sectoral CO2 emissions from the commercial sector, the electric power sector, the residential sector the transportation sector, and the industrial sector. In addition, to capture US macroeconomic conditions and financial market behavior for the period 2000 and 2022, we employ a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis using a balanced panel of 117 monthly variables that, except CO2 emissions, include series like Brent crude oil and Natural gas, energy consumption and renewable energy consumption, among others.

Our paper is motivated by the observation that one of the most significant and difficult challenges that governments, policymakers, and societies are facing during the recent period, is how to achieve economic growth that is environmentally sustainable. The environmental pollution from human economic activity affects climate change[2] and has a significant impact on the global population and the long-term prosperity of future generations. For instance, approximately 99% of the global population, especially people in low- and middle-income countries, is breathing air that includes elevated levels of pollutants and exceeds the limits of the World Health Organization (WHO).[3] At the same time, climate change has significant costs, not only in human lives and livelihoods, but also causes a significant economic cost to societies (see, among others, Smith and Matthews, 2015).[4]

The results of many studies indicate that economic growth is related to the level of CO2 emissions (Soytas et al., 2007; Zhang and Cheng, 2009; Sharma, 2011; Acheampong, 2018; Ajmi et al., 2015; among others).[5] Guan et al. (2008) point out that China's CO2 emissions have increased significantly since the 1980s and estimate that they will have a similar increase by 2030, driven mainly by the consumption of households, capital investment, and growth in exports. They argue that efficiency improvements alone may not be able to stabilize emissions. Also note that, emissions tend to increase after prolonged periods of uncertainty and volatility. According to the International Energy Agency (IEA), after the Covid-19 pandemic, global GDP increased by approximately 6%; at the same time, the CO2 emissions from industrial processes and energy combustion increased by 6% in 2021 (the highest annual increase ever). A similar pattern is also observed in 2010, when following the Global Financial Crisis, global emissions increased by 6.1% and global GDP increased by 5.1%.[6]

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[2] As Rovinaru et al (2023) point out, human activity such as burning of fossil fuels, agriculture, the change of land use, and deforestation, among others, are also responsible for the growing release of greenhouse gases, that increase the greenhouse effect and affect the climate.

[3] See WHO at: https://www.who.int/health-topics/air-pollution#tab=tab_1

[4] For example, the National Centers for Environmental Information estimate that, in the US, 341 weather and climate disasters for the period between 1980 to 2022, had a total cost in excess of $2.475 trillion. NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2023). https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73

[5] For instance, Soytas et al (2007) find that emissions are not long-run Granger-caused by income in the US, while energy use is long-run Granger-caused by income, while Sharma (2011) examines 69 countries and finds that, on a country level, GDP per capita, the consumption of energy, trade openness, and urbanization, are important determinants of CO2 emissions and all have a positive impact on emissions, except urbanization that has a negative effect. When a panel of all countries is examined, only the first two are significant.

[6] International Energy Agency at: https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2.

On the other hand, more recent empirical studies find a reduction in emissions. For instance, the International Energy Agency (IEA) reports that, globally, carbon dioxide emissions related to energy increased by less than 1% in 2022, an increase much smaller than anticipated, despite significant events such as the price shocks in energy, rising consumer prices, and disruptions in trade flows.[7] Also, Feng et al. (2015) analyze the factors driving US emissions and find that while before 2007 emissions were driven by economic growth, since then, the recession along with the fuel mix led to a decrease in emissions.[8] Wu et al. (2021), examine 18 countries and find that for many developed economies there is a reduction in emissions recently. Their analysis shows that the transition to renewable energy and energy intensity and fossil intensity are main factors that drive this reduction in emissions. Moreover, the forecasting results indicated that changes in the renewable energy share and fossil CO2 intensity will be the two primary factors for the decline in CO2 emissions in the next thirty years, while the contribution from the industrial structure, economic growth, and fossil energy intensity are rather limited. These findings highlight the importance of improved energy efficiency and the use of renewable energy in reducing CO2 emissions.

Our empirical results indicate that a significant percentage of the variance of CO2 emissions in the US is explained by Natural Disasters Cost, which also seems to drive US Total Renewable Energy Consumption variance. Furthermore, the cost of natural disasters also affects Partisan conflict importantly. Impulse Response Functions (IRFs) indicate that shocks to disaster costs seem to decrease all types of emissions significantly and also increase renewable energy use significantly. Natural disasters increase the political disagreement among US politicians, as well as, climate policy uncertainty, highlighting the need for efficient policymaking and regulations that can fight global warming (Baccini and Leemann, 2021). In further results, we find that an increase in Partisan Conflict decreases emissions, increases Renewable Energy consumption and explains a significant amount of renewable energy variance.

Overall, the findings presented above seem to support the argument (see Gavriilidis, 2021) that elevated climate policy uncertainty and climate risk might discourage energy consumption and at the same time climate policy uncertainty shocks encourage renewable energy consumption and more sustainable practices adoption, thus leading to decreased CO2 emissions. Moreover, natural disasters affect the political disagreement among US politicians, but also impact the adoption and formulation of efficient climate regulations and policies that can force firms adopt more sustainable and environmentally friendly practices. The rest of the paper is organized as follows. Section 2 presents the data and the methodology, Section 3 the results, while Section 4 discusses the conclusions.

2. Data and testing methodology

To study the effect of climate risk and various types of uncertainty, we employ a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis (Bernanke et al., 2005; Boivin et al., 2009) in a large dataset of monthly time series. More specifically, our FAVAR model includes a balanced panel of 117 monthly variables, following the standard dataset originally introduced by Stock and Watson (2002) and later used by Bernanke et al. (2005), Boivin et al. (2009) and other studies (Lutz, 2015; Galariotis et al., 2018 and others) .[9] The standard setting captures macroeconomic conditions and financial market behavior and is further enhanced with additional series like Brent crude oil and Natural gas, and series of interest such as US imports and exports,[10] energy consumption and renewable energy consumption and CO2 emissions.[11] This approach copes with the common problem of omitted variables, since it utilizes standard VAR methods combined with factor analysis and allows the inclusion of a large set of informational economic variables (see, among others, Boivin et al., 2008; Lutz, 2015; Belke and Osowski, 2019; Krokida et al., 2020). Appendix I presents a list of the variables employed in the FAVAR model.

Consider a $N \times 1$ vector of variables X_t, and assume that the relevant conditions are affected by a $K \times 1$ vector of factors (F_t) that are not observed. Subsequently, suppose that there is an observed factor R_t such that:

$$C_t = \left[\frac{F_t}{R_t}\right] \tag{1}$$

With the employment of Principal Components Analysis, we can estimate the following observation equation:

$$X_t = \Lambda^f F_t + \Lambda^r R_t + e_t \tag{2}$$

In (2) Λ^f, is the $N \times K$ matrix of factor loadings, Λ^r is the $N \times 1$ vector of factor loadings, and e_t is the $N \times 1$ vector of (zero mean) error terms. The next step is to estimate the standard VAR with the C_t as:

$$C_t = \Phi(L)C_{t-1} + u_t \tag{3}$$

In the above, $\Phi(L)$ is the lag polynomials of finite order matrix.

[7] IEA: CO2 Emissions in 2022, see https://www.iea.org/reports/co2-emissions-in-2022.

[8] See also, Saidi and Omri (2020), among others.

[9] Some series are excluded due to limited data availability and replaced where possible.

[10] US Imports and Exports were disaggregated into monthly frequency using cubic spline interpolation (see, among others Abbate, et al., 2016; Lescaroux and Mignon, 2009).

[11] The series of CO2 emissions and energy consumption are seasonally adjusted using the Census X-13 (Gavriilidis, 2021).

The variables that enter the model are transformed for stationarity. In addition, they are standardized, since there may be issues with different scales in the time series with the factor extraction. We adopt a Cholesky ordering and divide the variables in X_t to fast moving variables that are presumed to react to uncertainty shocks contemporaneously and slow-moving variables that do not (see Bernanke et al., 2005), and list policy related uncertainty (climate policy, political uncertainty/partisan conflict[12]) and/or risks (natural disasters/climate risk) first in the ordering of the various models to recover orthogonal shocks (see Baker et al., 2016; Bloom, 2009; Caggiano et al., 2014; Born et al., 2019; Makrychoriti and Spyrou, 2022; among others).

Although previous studies suggest criteria when it comes to the number of the factors employed (see Bai and Ng, 2002), here, we examine various specifications to exploit how sensitive our results are to different numbers of factors, with our baseline model employing 3 lags and 3 factors according to recent studies using as empirical setting the FAVAR model (see Krokida et al., 2020; Laine, 2020; Galariotis et al., 2018; Makrychoriti and Spyrou, 2022). On the optimal factor selection in factor models there exist indeed several methods for the determination; nevertheless, as Bernanke et al. (2005) mention, none of those methods can address the question of the optimal number of factors included in VAR model. Note that our results remain robust to employing different combinations of factors (3 and 4 factors) and lags (2 and 3 lags). Our analysis covers the period January 2000 to June 2022, and our FAVAR model includes a total of 117 informational variables, presented in Appendix I.

As proxies for emissions, we use 6 different variables to examine the impact on different types and origins of emissions. More specifically, we use the Total US Energy CO2 Emissions (Total CO2), Commercial sector US Energy CO2 Emissions (Com CO2), Electric power sector US Energy CO2 Emissions (Elect CO2), Residential sector US Energy CO2 Emissions (Resid CO2), Transportation sector US Energy CO2 Emissions (Transport CO2) and Industrial sector US Energy CO2 Emissions (Indust CO2) obtained from EIA (Energy Information Administration). All series are seasonally adjusted using the Census X-13 (Gavriilidis, 2021).

We first study the impact of climate risk, using two variables, namely the financial cost of natural disasters and the number of deaths caused by each such disaster (see Fig. 1), collected from the National Oceanic and Atmospheric Administration (NOAA) .[13] More specifically, NOAA reports the financial cost and number of deaths over the span of each of the 249 costly natural disasters identified, including wildfires, hurricanes, flooding, earthquakes, droughts, tornadoes, freezes, and winter storms. Total costs are in billions of 2019 dollars and data collected are from national programs but also from agencies such as FEMA, USDA, and Army Corps, and are based on insurance, such as flood insurance, property claims and crop insurance (see also, Smith and Katz, 2013).

In order to construct the climate risk proxy, we use the CPI-adjusted financial cost series, and consider the starting date of a natural disaster occurrence as the event date. Since multiple disasters might take place in the same month, as monthly value we sum the costs of all events that took place in the same month. Our proxy has 152 non-zero cost values monthly observations (from $T = 270$) (Ludvigson et al., 2020). We follow the same concept for our second proxy for climate risk, the number of deaths.[14]

In order to investigate the impact of climate policy related uncertainty on CO2 emissions, we employ the Climate Policy Uncertainty (CPU) Index of Gavriilidis (2021).[15] This index is constructed according to the methodology of Baker at al. (2016) for measuring Economic Policy Uncertainty and employs textual analysis in articles from 8 leading US newspapers; among others, terms used in the analysis are “carbon dioxide”, “climate risk”, “CO2”, “emissions”, etc. We also examine variables such as the US Energy Consumption that includes the residential, commercial, industrial and transportation sectors (Energy) and the US Total Renewable Energy Consumption (RenEnergy). Fig. 2 presents the evolution of CPU and Total CO2 emissions overtime (2000–2022); it can be seen that, total CO2 emissions overtime seem to follow a downward trend with a significant downward adjustment since the 2007–2009 financial crisis. CPU has its highest spikes from 2016 onwards, indicating intense climate policy uncertainty.

Note that several recent papers utilize the CPU index to examine the impact of climate policy uncertainty on tourism demand (Apergis et al., 2022), oil and gas prices (Guo et al., 2022), crude oil futures volatility (Niu et al., 2022) and oil industry stock returns (He and Zhang, 2022). Shang et al. (2022) use the CPU index and demonstrate a positive effect on renewable energy demand in the long run, while Li et al. (2023) show that the relationship between renewable energy and climate policy uncertainty depends on the political ideology of the Administration on environmental issues. Ren et al. (2023) investigate the causality between climate policy uncertainty and traditional energy and green markets and find that CPU behaves as a risk receiver rather than a risk sender. Zhou et al. (2023) reveal that CPU positively affects oil prices and renewable energy consumption, while Liang et al. (2022) show a negative impact of CPU on renewable energy volatility. Bouri et al. (2022) show that during turbulent periods the effect of CPU on green energy stocks is positive and homogenous. Sarker et al. (2023) provide evidence that climate policy uncertainty positively affects the returns of clean energy prices in the US, while Dutta et al. (2023) show a positive CPU effect on green energy assets but negative on their volatility.

[12] Azzimonti (2018) points out that an increase in political uncertainty can potentially cause higher economic policy uncertainty.

[13] Data can be downloaded from ncdc.noaa.gov/billions/events; see also Smith and Katz (2013), Smith and Matthews (2015).

[14] Cost of Natural Disasters and Deaths from Natural Disasters are transformed into natural logarithms before entering the model (Toya and Skidmore, 2007).

[15] Source: for details see https://www.policyuncertainty.com/climate_uncertainty.html.

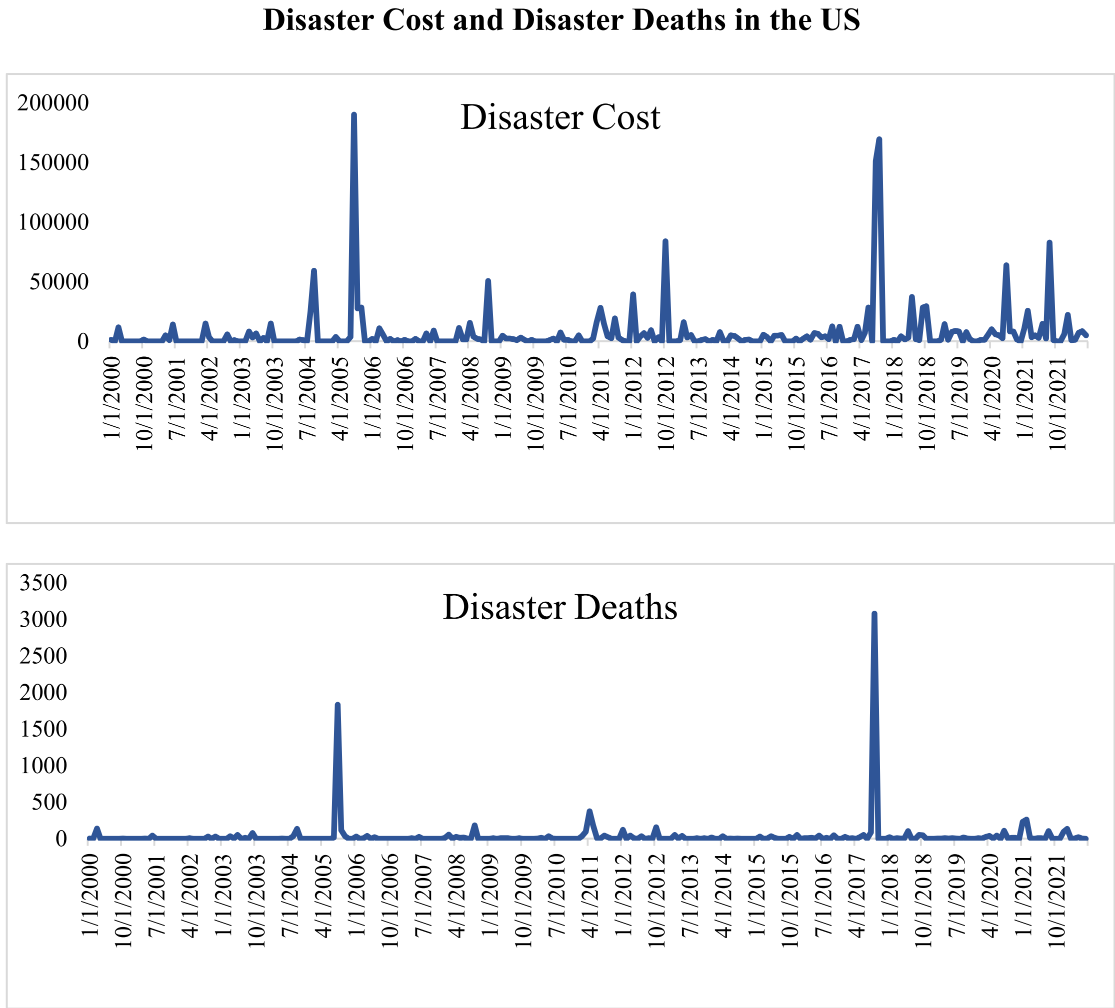

Fig. 1. Disaster Cost and Disaster Deaths in the US
The figure plots the Disaster Cost and Disaster Deaths series. The sample covers the period 2000:01 to 2022:6. National Oceanic and Atmospheric Administration (NOAA). Data can be downloaded from ncdc.noaa.gov/billions/events; see also Smith and Katz (2013), Smith and Matthews (2015).

The final part of our analysis investigates how political disagreement among US politicians, elections, and debates over various policies, might impact firms' adoption of sustainable practices and consequently CO2 emissions.[16] Recent literature shows that the political environment in a country affects the energy provision and consumption (Moss, 2014), energy prices (van Beers and Strand, 2013), and the energy and growth relationship (Squalli, 2007). More specifically, studies show that a stable political system is an important factor to lower CO2 emissions and to slow down environmental degradation (Su et al., 2021), and that democracy influences climate policy and emission reduction process (Policardo, 2016; Fredriksson and Neumayer, 2013). In addition, political polarization might be beneficial for the environment since political parties might be forced to adopt more extreme policies in order to slow down environmental degradation; for instance, Aller et al. (2021) find that increased political polarization causes a decline in CO2 emissions through a direct and indirect impact on the environment. The direct impact is through differences among political parties and the environmental policies and regulations promoted.

Garmann (2014) empirically test whether government ideology influences the CO2 levels and find that center and left-wing governments tend to contribute more to the emission reduction process than right-wing governments do. Managi (2006) shows that doubling efforts to slow down environmental degradation reduces CO2 emissions more than twice. Those links show that disagreement among political parties can lead to larger gaps in expenditures claimed for sustainable practices and technologies on pollution abatement, and eventually lower CO2 levels (Aller et al., 2021). On the other hand, the direct impact of political polarization on CO2 levels, is through the effect of policies and regulations on the

[16] We proxy for US political uncertainty with the Partisan Conflict Index of Azzimonti (2014, 2018; Federal Reserve Bank of Philadelphia).

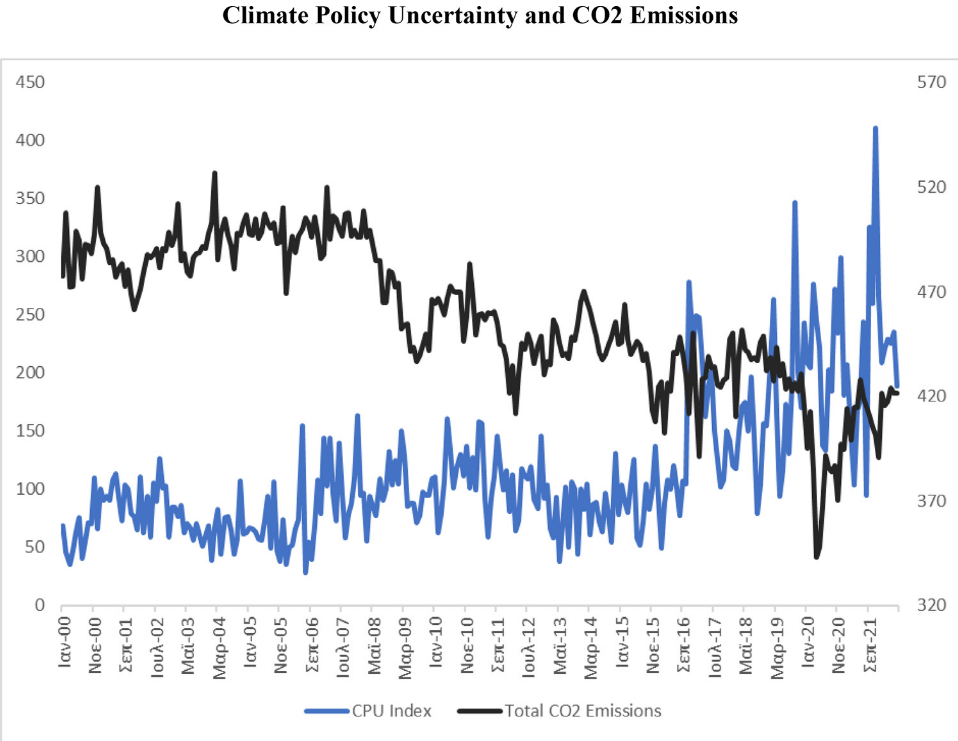

Fig. 2. Climate Policy Uncertainty and CO2 Emissions
The figure plots the Climate Policy Uncertainty Index and CO2 Emissions in the US for the period 2000–2022. We obtain the Total US Energy CO2 Emissions (Total CO2) from the Energy Information Administration, US, and the Climate Policy Uncertainty (CPU) Index of Gavriilidis (2021) from: https://www.policyuncertainty.com/climate_uncertainty.html.

economies and the environment. A polarized political system causes increased levels of policy uncertainty (Azzimonti and Talbert, 2014), with economies slowing down investments (Azzimotti, 2018), which decreases growth and subsequently CO2 levels.

3. Results

This section presents the results of the FAVAR models, in the form of Forecast Error Variance Decompositions (FEVDs) and Impulse Response Functions (IRFs). In Table 1 we present Variance Decomposition (VD) results and model R^2, where we examine the contribution of the shock to the Variance of the Common Component for selected variables, i.e., the% of the variance of the selected variables that is explained by Climate Risk as proxied by the Natural Disasters Cost adjusted to CPI (Shock: monetary Cost of Natural Disasters, CD). We examine various specifications with regards to lags and factors and present here the results from 3 models as follows: in Model 1 we use 3 Factors and 3 Lags, in Model 2 we use 4 Factors and 3 Lags and in Model 3 we use 3 Factors and 2 Lags.

The selected variables of interest are Industrial Production (IP), Personal Consumption (Consumption), the returns of the S&P500 Equity Index (S&P500); Imports; Exports; the Baker and Wurgler (2006) Sentiment (BW Sentiment), the Michigan Consumer Sentiment Index (MCSI), the Total US Energy CO2 Emissions (Total CO2), Commercial sector US Energy CO2 Emissions (Com CO2), Electric power sector US Energy CO2 Emissions (Elect CO2), Residential sector US Energy CO2 Emissions (Resid CO2), Transportation sector US Energy CO2 Emissions (Transport CO2), Industrial sector US Energy CO2 Emissions (Indust CO2). We also examine US Energy Consumption that includes residential, commercial, industrial and transportation sectors (Energy), US Total Renewable Energy Consumption (RenEnergy), the Climate Policy Uncertainty Index of Gavriilidis (2021) (CPU) and the Partisan Conflict Index of Azzimonti (2014, 2018) (Partisan) .[17]

From Table 1 (columns 2 and 3) we can see that in Model 1 (3 Factors and 3 Lags) approximately 14% (0.141) of the variance in Total CO2 emissions is explained by Natural Disasters Cost (R^2 = 0.718), while 20% (0.20) of Industrial CO2 emissions is explained by Natural Disasters Cost (R^2 = 0.780). For Commercial, Electricity, Residential, and Transport emissions the % of the variance explained is below 10% (0.081, 0.084, 0.073, 0.052, respectively). Note that the % of the variance of US Total

[17] The Climate Policy Uncertainty Index and Partisan Conflict Index enter the model in levels (Gavriilidis (2021; Azzimonti, 2014). Nevertheless, when transformed into natural logarithms, results remain qualitatively the same.

Table 1
Contribution of Climate risk shock (proxied by the Cost of Natural Disasters) to the variance of selected variables.

	Model 1: 3 Factors - 3 Lags (Shock: Cost of Natural Disasters)		Model 2: 4 Factors - 3 Lags (Shock: Cost of Natural Disasters)		Model 3: 3 Factors - 2 Lags (Shock: Cost of Natural Disasters)	
	VD	R^2	VD	R^2	VD	R^2
IP	0.017	0.854	0.023	0.877	0.019	0.851
Consumption	0.015	0.715	0.021	0.766	0.016	0.713
S&P500	0.005	0.138	0.003	0.256	0.007	0.138
Imports	0.005	0.381	0.006	0.650	0.005	0.380
Exports	0.004	0.329	0.006	0.626	0.004	0.328
BW Sentiment	0.000	0.043	0.001	0.043	0.000	0.043
MCSI	0.002	0.083	0.002	0.093	0.002	0.082
Total CO2	0.141	0.718	0.240	0.887	0.178	0.719
Com CO2	0.081	0.641	0.241	0.863	0.098	0.640
Elect CO2	0.084	0.659	0.250	0.887	0.102	0.658
Resid CO2	0.073	0.583	0.223	0.775	0.088	0.581
Transport CO2	0.052	0.518	0.055	0.573	0.071	0.522
Indust CO2	0.200	0.780	0.256	0.864	0.255	0.783
Energy	0.017	0.335	0.017	0.348	0.023	0.338
RenEnergy	0.142	0.777	0.329	0.875	0.175	0.777
CPU	0.028	0.331	0.085	0.450	0.035	0.330
Partisan	0.057	0.438	0.091	0.443	0.076	0.438

The Table presents results from FAVAR models with various specifications with regards to lags and factors. More specifically it presents the contribution of the shock to Variance of the Common Component for the selected variables, i.e., the% of the variance of the variables that is explained by Climate Risk proxied by the Natural Disasters Cost adjusted to CPI (CD) (Models 1 to 3). The selected Variables are IP: Industrial Production; Consumption: Personal Consumption; S&P500: The returns of the S&P500 Equity Index; Imports; Exports; BW Sentiment: Baker and Wurgler Sentiment; MCSI: Michigan Consumer Sentiment Index; Total CO2: US Total Energy CO2 Emissions; Com CO2: Commercial sector US Energy CO2 Emissions; Elect CO2: Electric power sector US Energy CO2 Emissions; Resid CO2: Residential sector US Energy CO2 Emissions; Transport CO2: Transportation sector US Energy CO2 Emissions; Indust CO2: Industrial sector US Energy CO2 Emissions; Energy: US Energy Consumption (including residential, commercial, industrial and transportation sectors); RenEnergy: US Total Renewable Energy Consumption; CPU: Climate Policy Uncertainty Index; Partisan: Partisan Conflict Index.

Renewable Energy Consumption (RenEnergy) explained is approximately 14% (0.142, $R^2 = 0.777$). In columns 4 and 5 we present the results from Model 2 where we now use 4 Factors and 3 Lags, and the findings indicate that the % of emission variance explained is higher. For instance, approximately 24% of the variance in Total CO2 emissions is explained by Natural Disasters Cost ($R^2 = 0.887$), while 25.6% of Industrial CO2 is explained by Natural Disasters Cost ($R^2 = 0.864$). For Commercial, Electricity, Residential, and Transport emissions the % of the variance explained is also significantly higher (0.241, 0.250, 0.223, 0.055, respectively).

Note that interestingly the % of the variance of US Total Renewable Energy (RenEnergy) explained, is now approximately 33% (0.329, $R^2 = 0.875$). Note that by including one more factor in our model the variance decomposition is affected, and the proportions explained are higher, as is the explanatory power for many variables. This is especially true for Renewable Energy and can perhaps be attributed to the fact that RenEnergy is associated with the fourth factor added (Stock and Watson, 2005). Nevertheless, results remain qualitatively the same since the portion of RenEnergy explained appears important in both cases.

The results of Model 3 are similar to the findings from Model 1, i.e., it seems that the addition of a factor in the model increases the explanatory power. From all Models 1, 2 and 3, we can also see that Natural disasters affect Partisan conflict importantly, explaining 5.7%, 9.1% and 7.6% of the total variance, in Model 1, 2 and 3, respectively. Although there seems to be some sensitivity to the number of factors employed; overall, the results remain qualitatively the same.

In Fig. 3 we present Impulse Response Functions (IRFs) from the FAVAR Model 1, with 3 lags and 3 factors, for selected variables to a shock in Climate Risk proxied by the Cost of Natural Disasters. The IRFs seem to indicate that shocks to disaster costs seem to decrease all type of emissions significantly and also increase renewable energy use significantly. Interestingly, natural disasters increase the political disagreement in Congress as well as the climate policy uncertainty, highlighting the need for efficient policymaking and regulations that are able to fight global warming (Baccini and Leemann, 2021). The IRFs from Model 2 and 3 (not reported here but are available upon request) are consistent with the findings reported above, in the sense that the results are similar to Model 1 but with a stronger response.

To examine the sensitivity of our results to the proxy of Climate Risk we next re-examine the models presented above, replacing the monetary Natural Disasters Cost with the cost in human lives from natural disasters using the Number of Deaths from Natural Disasters as our proxy. In Table 2 we present Variance Decomposition (VD) results and model R^2, where we examine the contribution of the shock to the Variance of the Common Component for selected variables, i.e., the % of the variance of the selected variables that is explained by Climate Risk proxied by the Number of Deaths from Natural Disasters (Shock: Number of Deaths from Natural Disasters, DD). The Table is organized in the same manner as Table 1. As we can see the results are qualitatively similar: in Model 1 (3 Factors and 3 Lags) approximately 12% of the variance in Total CO2 emissions is explained by Natural Disasters Deaths ($R^2 = 0.715$), while about 16.8% of Industrial CO2 is explained by

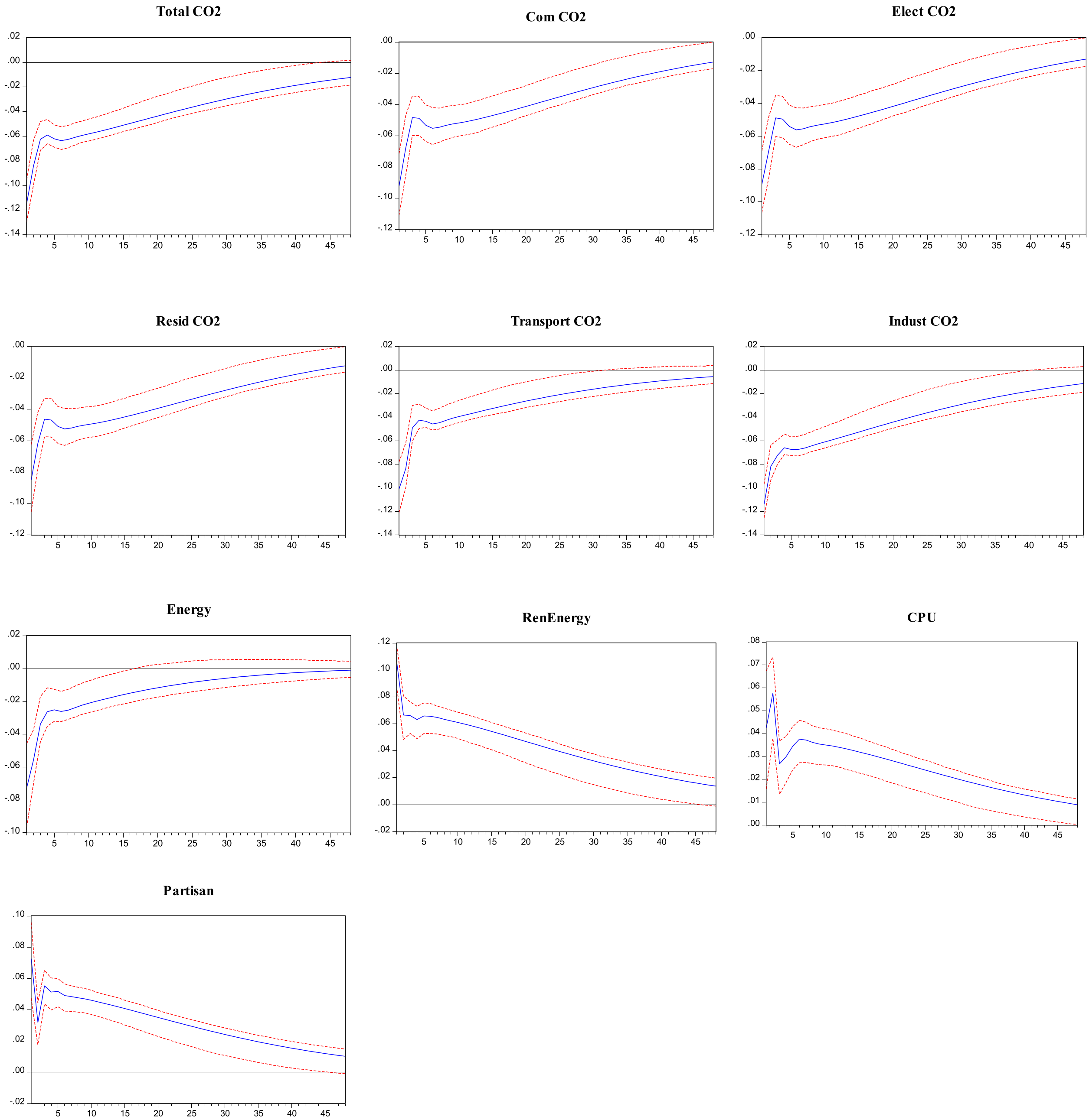

Fig. 3. The effect of Climate Risk proxied by the Cost of Natural Disasters
The Figure presents Impulse Response Functions (IRFs) from a FAVAR model (Model 1: 3 lags - 3 factors) for selected variables to a shock in Climate Risk proxied by the Cost of Natural Disasters (adjusted to CPI).

Natural Disasters Deaths ($R^2 = 0.776$). For Commercial, Electricity, Residential, and Transport emissions the % of the variance explained is below 10%. Note that the % of the variance of US Total Renewable Energy Consumption (RenEnergy) explained, is approximately 12% ($R^2 = 0.775$). The results, again, seem to be sensitive to the number of factors employed; nevertheless, they remain qualitatively the same.

In Model 2 (4 Factors and 3 Lags), the findings indicate that the % of CO2 emissions' variance explained is higher. For instance, approximately 20% of the variance in Total CO2 emissions is explained by Natural Disasters Deaths ($R^2 = 0.887$), while 20% of Industrial CO2 is explained by Natural Disasters Deaths ($R^2 = 0.863$). For Commercial, Electricity, Residential, and Transport emissions the % of the variance explained is also significantly higher (0.185, 0.183, 0.167, 0.058, respectively). Note that interestingly the % of the variance of US Total Renewable Energy Consumption (RenEnergy) explained is now

Table 2
Contribution of Climate risk shock (proxied by the Number of Deaths from Natural Disasters) to the variance of selected variables.

	Model 1: 3 Factors - 3 Lags (Shock: Number of Deaths)		Model 2: 4 Factors - 3 Lags (Shock: Number of Deaths)		Model 3: 3 Factors - 2 Lags (Shock: Number of Deaths)	
	VD	R^2	VD	R^2	VD	R^2
IP	0.018	0.854	0.024	0.877	0.017	0.851
Consumption	0.015	0.715	0.022	0.766	0.014	0.712
S&P500	0.008	0.138	0.004	0.256	0.010	0.137
Imports	0.003	0.376	0.003	0.649	0.004	0.376
Exports	0.003	0.327	0.004	0.627	0.003	0.326
BW Sentiment	0.005	0.049	0.005	0.049	0.005	0.049
MCSI	0.003	0.085	0.003	0.095	0.002	0.085
Total CO2	0.124	0.715	0.198	0.887	0.153	0.717
Com CO2	0.065	0.640	0.185	0.864	0.079	0.639
Elect CO2	0.065	0.658	0.183	0.888	0.079	0.657
Resid CO2	0.057	0.581	0.167	0.775	0.069	0.581
Transport CO2	0.056	0.521	0.058	0.576	0.071	0.524
Indust CO2	0.168	0.776	0.206	0.863	0.212	0.780
Energy	0.022	0.341	0.020	0.353	0.025	0.342
RenEnergy	0.117	0.775	0.259	0.874	0.145	0.775
CPU	0.020	0.334	0.060	0.452	0.025	0.334
Partisan	0.057	0.437	0.087	0.442	0.074	0.438

The Table presents results from FAVAR models with various specifications with regards to lags and factors. More specifically it presents the contribution of the shock to Variance of the Common Component for the selected variables, i.e., the% of the variance of the variables that is explained by Climate Risk proxied by the Number of Deaths from Natural Disasters (DD) (Models 1 to 3). The selected Variables are IP: Industrial Production; Consumption: Personal Consumption; S&P500: The returns of the S&P500 Equity Index; Imports; Exports; BW Sentiment: Baker and Wurgler Sentiment; MCSI: Michigan Consumer Sentiment Index; Total CO2: US Total Energy CO2 Emissions; Com CO2: Commercial sector US Energy CO2 Emissions; Elect CO2: Electric power sector US Energy CO2 Emissions; Resid CO2: Residential sector US Energy CO2 Emissions; Transport CO2: Transportation sector US Energy CO2 Emissions; Indust CO2: Industrial sector US Energy CO2 Emissions; Energy: US Energy Consumption (including residential, commercial, industrial and transportation sectors); RenEnergy: US Total Renewable Energy Consumption; CPU: Climate Policy Uncertainty Index; Partisan: Partisan Conflict Index.

approximately 25.9% ($R^2 = 0.874$). Fig. 4 presents IRFs from the FAVAR Model 1, and a visual inspection indicates that the results are similar to Fig. 3, with the exception of a small spike in IRF at the beginning. We can also see that, as in Table 1, by including one more factor in our model the proportions explained are higher, as is the explanatory power, for many variables. Again, the effect of the fourth factor on Renewable Energy is more pronounced, and it may be attributed to the fact that RenEnergy is associated with the fourth factor added. As in Table 1, however, the main result, i.e., that climate risk affects emissions, still holds.

Next, we replace the above Climate risk proxies with the Climate Policy Uncertainty (CPU) Index of Gavriilidis (2021), to investigate the effect of climate related regulations and policies' uncertainty on CO2 emissions. Table 3 presents the results, and we can see that the results are similar as above, and stronger. In Model 1 (3 Factors and 3 Lags) approximately 26% of the variance in Total CO2 emissions is explained by CPU ($R^2 = 0.759$), while about 31.8% of Industrial CO2 is explained by CPU ($R^2 = 0.812$). For Commercial, Electricity, Residential, and Transport emissions the % of the variance explained is much higher now: 0.20, 0.209, 0.174, and 0.069, respectively. As above the results, seem to be sensitive to the number of factors employed, i.e., when more factors are employed the % of the variance explained is much higher for all variables (except transportation emissions); nevertheless, they appear to be qualitatively the same. Overall, our results suggest that climate policy uncertainty, as captured by uncertainty related to climate regulations and policies has a significant effect on CO2 emissions.

A very interesting finding in Table 3 is the effect of CPU on US Total Renewable Energy Consumption (RenEnergy). In Model 1 (3 Factors and 3 Lags) approximately 28% of the variance in RenEnergy is explained by CPU ($R^2 = 0.803$), in Model 2 (4 Factors and 3 Lags) approximately 45% of the variance in RenEnergy is explained by CPU ($R^2 = 0.876$), in Model 3 (3 Factors and 2 Lags) approximately 31% of the variance in RenEnergy is explained by CPU ($R^2 = 0.805$). This finding indicates a strong impact of Climate Policy Uncertainty on US Total Renewable Energy Consumption and a visual inspection of the IRFs[18] indicate that this strong relationship is positive, i.e., an increase in CPU increases Renewable Energy consumption. Moreover, the IRFs in Fig. 5 seem to indicate that shocks to CPU seem to decrease all types of emissions significantly.

In Table 4 we present the Contribution of Partisan Conflict (Partisan) to the variance of the selected variables. We can see, that in Model 1, Partisan Conflict has a significant contribution of 9% (0.09) to Total CO2 emissions, with a moderate effect to other types of emissions, apart from Industrial emissions (0.15), where the effect is quite strong. However, when more factors are employed (Model 2), Partisan Conflict seems to explain an even more significant amount in emissions variance: about 16% for total emissions, about 16% for electricity emissions, about 19% for residential and industrial emissions. The examination of IRFs (Fig. 6) implies that the effect is negative, i.e., an increase in Partisan Conflict decreases industrial

[18] Figure 5 presents the IRFs from Model 1.

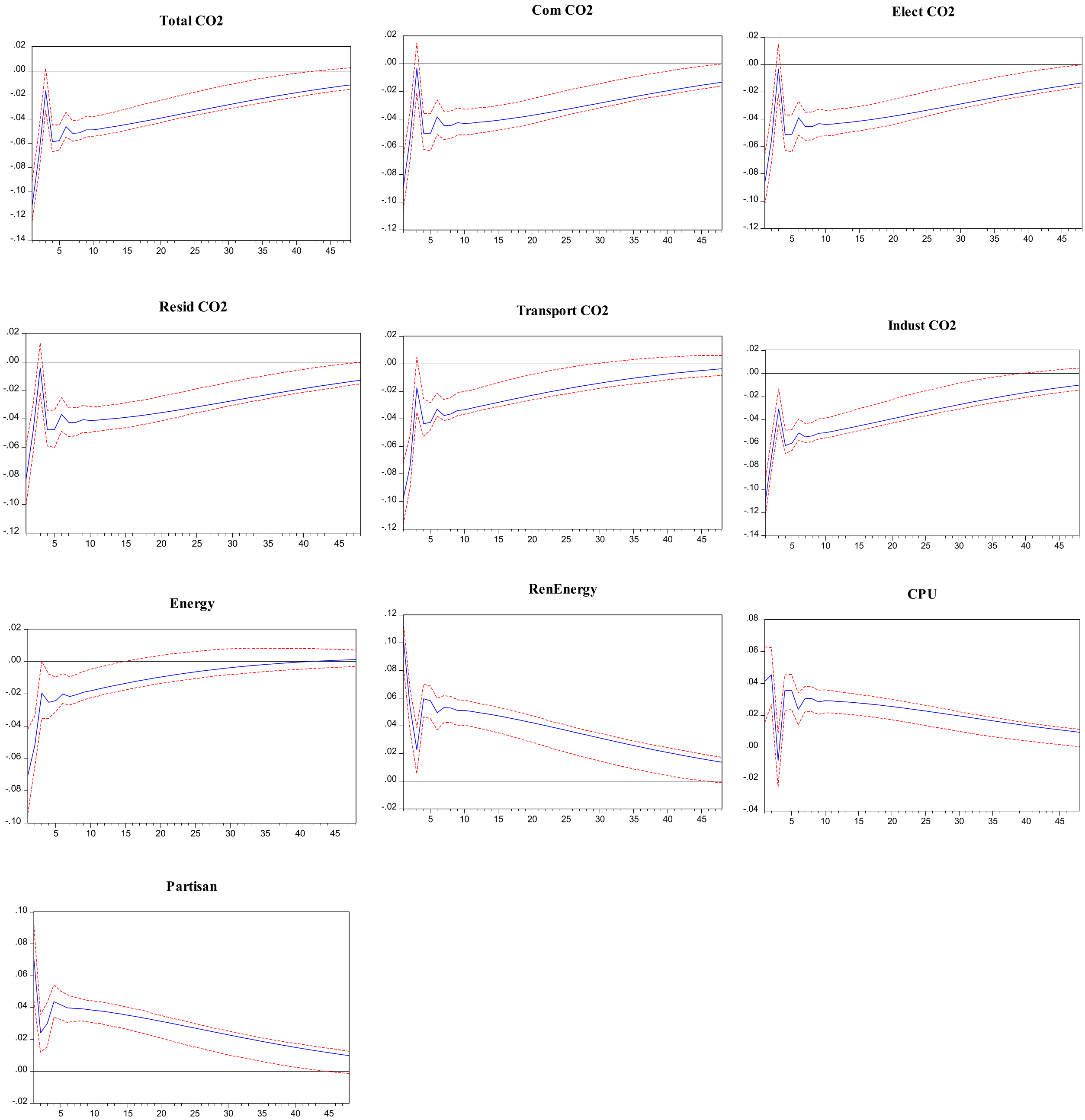

Fig. 4. The effect of Climate Risk proxied by the Number of Deaths from Natural Disasters
The Figure presents Impulse Response Functions (IRFs) from a FAVAR model (Model 1: 3 lags - 3 factors) for selected variables to a shock in Climate Risk proxied by the Number of deaths from Natural Disasters.

and transport emissions, while it also decreases the rest of the emissions, as well. An interesting finding is that Partisan Conflict explains a significant amount of renewable energy consumption: 15.5% in Model 1, 34.6% in Model 2, 19.4% in Model 3. Furthermore, the examination of IRFs (Fig. 6) implies that Partisan Conflict increases importantly Renewable Energy consumption, while it also increases the uncertainty in climate related policies and regulations (CPU).

Note here that Farrell (2016) states that polarization is an effective strategy for creating controversy and delaying environmental policy progress. Subsequently, that increases climate policy uncertainty, something that is supported from our findings, with higher levels of partisan conflict causing to higher levels of CPU. Moreover, other studies like Li et al. (2023) show that the causality between renewable energy and climate policy uncertainty depends on the political ideology of the Administration on environmental issues. The fact that the impact is not very strong, could be due to the fact that although the

Table 3
Contribution of Climate Policy Uncertainty (CPU) shock to the variance of selected variables.

	Model 1: 3 Factors - 3 Lags (Shock: CPU)		Model 2: 4 Factors - 3 Lags (Shock: CPU)		Model 3: 3 Factors - 2 Lags (Shock: CPU)	
	VD	R^2	VD	R^2	VD	R^2
IP	0.017	0.857	0.025	0.877	0.016	0.854
Consumption	0.015	0.717	0.023	0.769	0.015	0.714
S&P500	0.004	0.193	0.004	0.266	0.003	0.192
Imports	0.004	0.401	0.004	0.653	0.003	0.402
Exports	0.003	0.343	0.003	0.637	0.003	0.344
BW Sentiment	0.001	0.043	0.001	0.043	0.001	0.043
MCSI	0.002	0.090	0.002	0.095	0.002	0.090
Total CO2	0.264	0.759	0.331	0.888	0.298	0.763
Com CO2	0.200	0.717	0.374	0.871	0.216	0.718
Elect CO2	0.209	0.744	0.388	0.898	0.224	0.744
Resid CO2	0.174	0.628	0.327	0.776	0.190	0.628
Transport CO2	0.069	0.519	0.061	0.577	0.087	0.524
Indust CO2	0.318	0.812	0.343	0.868	0.362	0.818
Energy	0.012	0.336	0.012	0.356	0.016	0.339
RenEnergy	0.281	0.803	0.451	0.876	0.315	0.805

The Table presents results from FAVAR models with various specifications with regards to lags and factors. More specifically it presents the contribution of the shock to Variance of the Common Component for the selected variables, i.e., the% of the variance of the variables that is explained by Climate Policy Uncertainty (CPU) (Models 1 to 3). The selected Variables are IP: Industrial Production; Consumption: Personal Consumption; S&P500: The returns of the S&P500 Equity Index; Imports; Exports; BW Sentiment: Baker and Wurgler Sentiment; MCSI: Michigan Consumer Sentiment Index; Total CO2: US Total Energy CO2 Emissions; Com CO2: Commercial sector US Energy CO2 Emissions; Elect CO2: Electric power sector US Energy CO2 Emissions; Resid CO2: Residential sector US Energy CO2 Emissions; Transport CO2: Transportation sector US Energy CO2 Emissions; Indust CO2: Industrial sector US Energy CO2 Emissions; Energy: US Energy Consumption (including residential, commercial, industrial and transportation sectors); RenEnergy: US Total Renewable Energy Consumption.

Table 4
Contribution of Partisan Conflict (Partisan) shock to the variance of selected variables.

	Model 1: 3 Factors - 3 Lags (Shock: Partisan)		Model 2: 4 Factors - 3 Lags (Shock: Partisan)		Model 3: 3 Factors - 2 Lags (Shock: Partisan)	
	VD	R^2	VD	R^2	VD	R^2
IP	0.007	0.855	0.007	0.879	0.008	0.851
Consumption	0.006	0.715	0.006	0.768	0.007	0.712
S&P500	0.002	0.145	0.001	0.258	0.003	0.144
Imports	0.003	0.391	0.004	0.654	0.003	0.390
Exports	0.002	0.327	0.003	0.627	0.002	0.326
BW Sentiment	0.000	0.043	0.000	0.043	0.000	0.043
MCSI	0.001	0.083	0.001	0.093	0.001	0.082
Total CO2	0.090	0.715	0.158	0.890	0.131	0.717
Com CO2	0.041	0.642	0.135	0.873	0.060	0.642
Elect CO2	0.051	0.657	0.166	0.889	0.073	0.656
Resid CO2	0.061	0.590	0.194	0.777	0.080	0.589
Transport CO2	0.022	0.549	0.025	0.613	0.038	0.553
Indust CO2	0.150	0.776	0.188	0.864	0.213	0.780
Energy	0.006	0.371	0.005	0.389	0.011	0.374
RenEnergy	0.155	0.804	0.346	0.894	0.194	0.804
CPU	0.021	0.331	0.069	0.448	0.030	0.330

The Table presents results from FAVAR models with various specifications with regards to lags and factors. More specifically it presents the contribution of the shock to Variance of the Common Component for the selected variables, i.e., the% of the variance of the variables that is explained by Partisan Conflict (Partisan) (Models 1 to 3). The selected Variables are IP: Industrial Production; Consumption: Personal Consumption; S&P500: The returns of the S&P500 Equity Index; Imports; Exports; BW Sentiment: Baker and Wurgler Sentiment; MCSI: Michigan Consumer Sentiment Index; Total CO2: US Total Energy CO2 Emissions; Com CO2: Commercial sector US Energy CO2 Emissions; Elect CO2: Electric power sector US Energy CO2 Emissions; Resid CO2: Residential sector US Energy CO2 Emissions; Transport CO2: Transportation sector US Energy CO2 Emissions; Indust CO2: Industrial sector US Energy CO2 Emissions; Energy: US Energy Consumption (including residential, commercial, industrial and transportation sectors); RenEnergy: US Total Renewable Energy Consumption; CPU: Climate Policy Uncertainty Index.

index is considered as US specific, it includes global climate events (not only US) that are covered in US newspapers, and some of those issues are beyond the power of just the US politics but are considered politically on a global level; for that reason although the sign is the expected one, the magnitude appears less strong. Overall, our results show a positive effect of partisan conflict on CO2 emissions with a stronger effect on industrial CO2 emissions. This may be because the industrial sector is more directly influenced by policy decisions and regulations, making it more susceptible to the effects of political

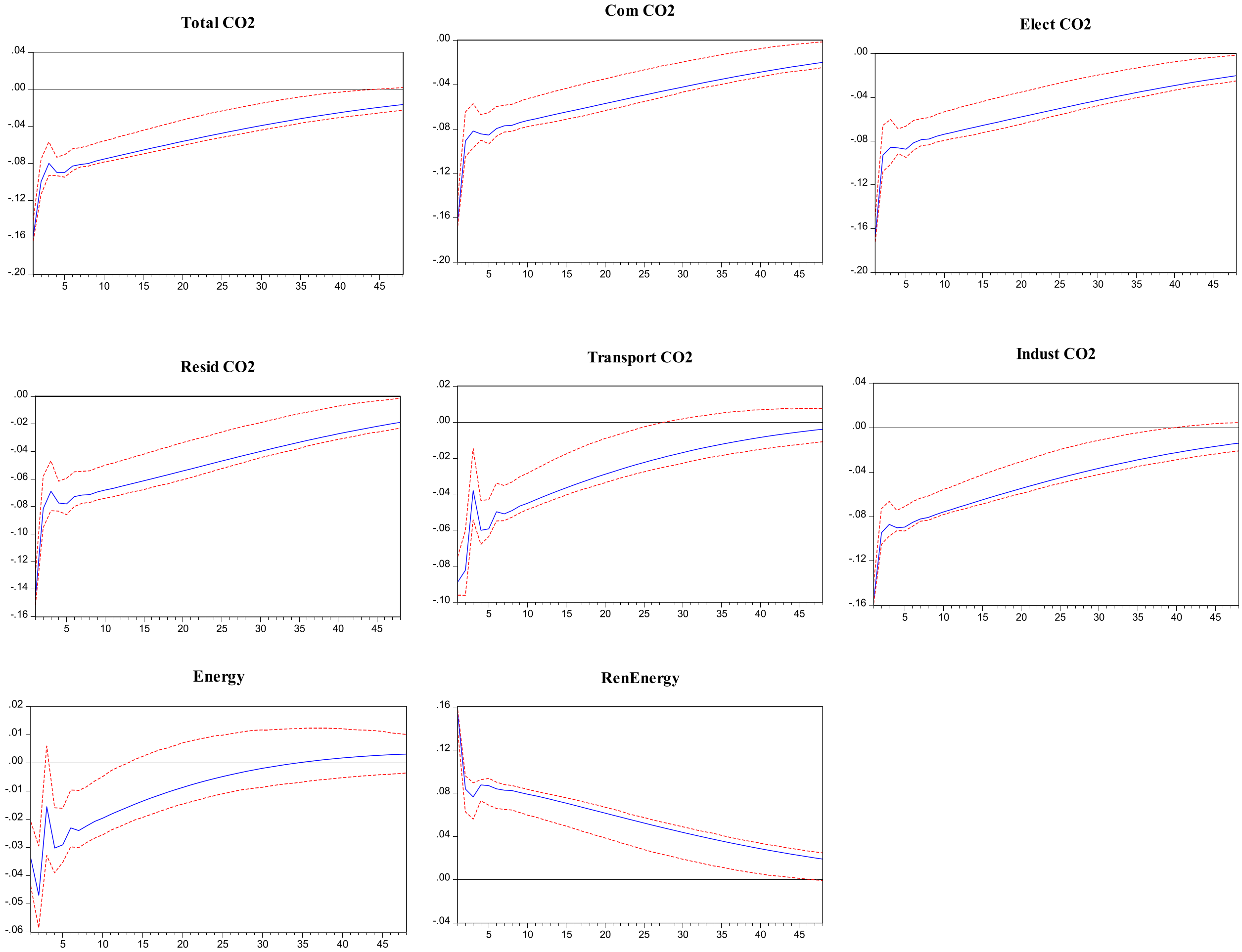

Fig. 5. The effect of Climate Policy Uncertainty on selected variables
The Figure presents Impulse Response Functions (IRFs) from a FAVAR model (Model 1: 3 lags - 3 factors) for selected variables to a shock in Climate Policy Uncertainty.

conflict and uncertainty. In addition, the industrial sector is a major contributor to greenhouse gas emissions in the US and globally (IPCC, 2014), highlighting the need for effective policies and regulations to address emissions from this sector.

Thus, political governance appears to be an important determinant in climate policy, especially since political polarization in environmental issues has become extremely intense over time (Daniels et al., 2012). Partisan polarization is a significant obstacle in climate policy actions, with Democrats being in favor of climate policy adoption, while Republicans appear opposed to climate legislation (Coley and Hess 2012; Trachtman 2020; McCright and Dunlap, 2011). Left-wing parties appear to be more engaged with environmental issues, supporting and promoting actions to prevent climate change (Biressieloglu and Karaibrahimoglu, 2012). Recent literature shows that left and central-oriented parties are more in favor of strengthened climate policies and regulations (Chang and Berdiev, 2011), support and promote renewable energy consumption (Biresselioglu and Karaibrahimoglu, 2012) and renewable energy investments (Abban and Hasan, 2021; Cadoret, and Padovano, 2016).

Finally, in Table 5 we present the Contribution of Renewable Energy consumption (RenEnergy) to the variance of the selected variables. We can see, that in Model 1, Renewable Energy consumption contributes significantly to the variance of emissions. For Model 1, the contribution in Total CO2 emission variance is 31.6% ($R^2 = 0.757$), for Industrial emissions 39.1% ($R^2 = 0.853$), for Electricity emissions 35.2% ($R^2 = 0.770$), for Residential emissions 26.3%, for Commercial emissions 25.5%, while for Transportation emissions only 2.5%. The contribution is also significant in Model 3, and less significant in Model 2; nevertheless, results appear to be qualitatively the same. As expected, the examination of IRFs (Fig. 7) implies that Renewable Energy consumption decreases importantly CO2 emissions.[19]

[19] We also examine the Contribution of Energy Consumption (Energy) to the variance of the selected variables, (results not reported here but are available upon request) and we find that the effect is somehow weaker compared to the results presented above, but still important; the highest contribution

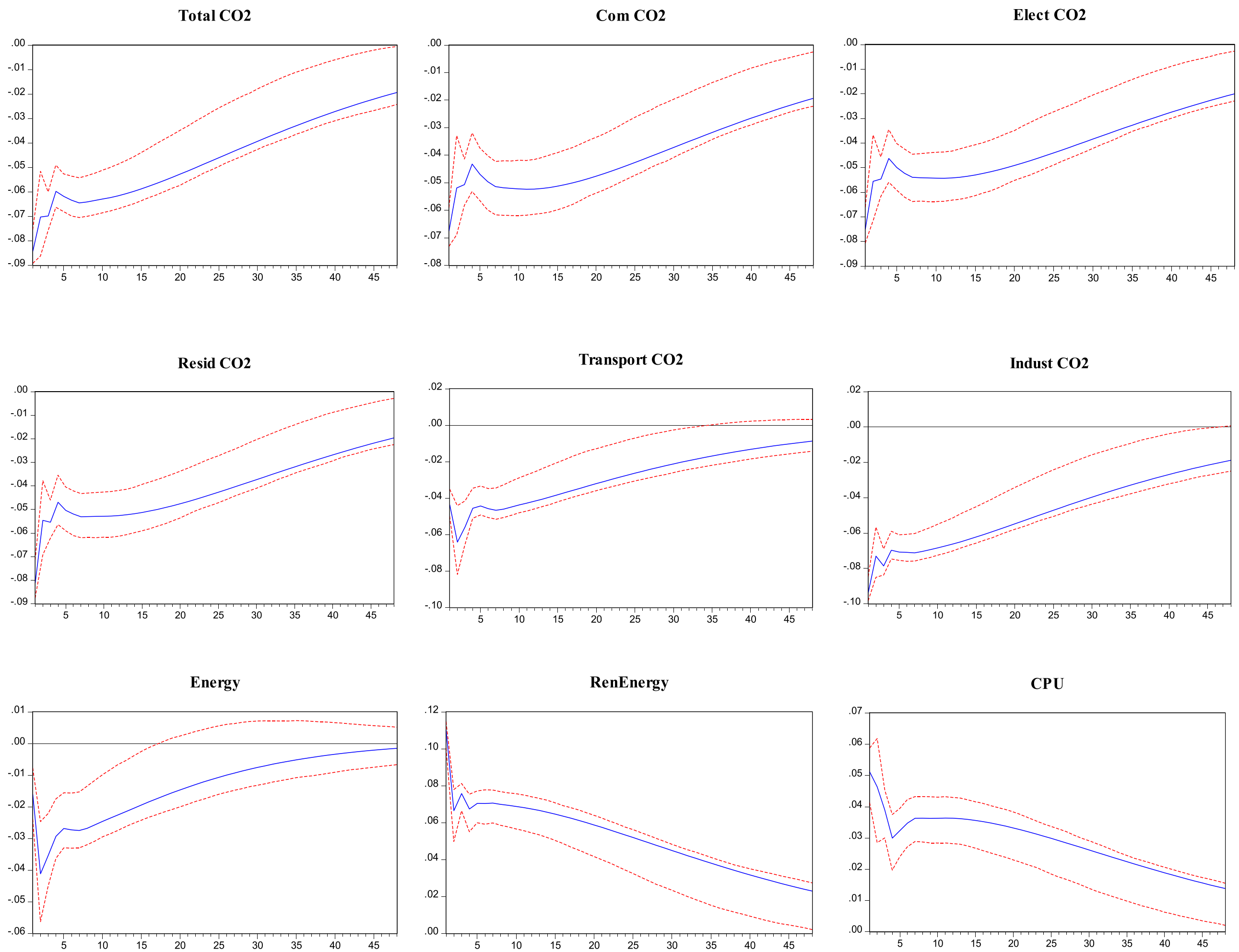

Fig. 6. The effect of Partisan Conflict on selected variables
The Figure presents Impulse Response Functions (IRFs) from a FAVAR model (Model 1: 3 lags - 3 factors) for selected variables to a shock in Partisan Conflict.

Table 5
Contribution of Renewable Energy Consumption (RenEnergy) shock to the variance of selected variables.

	Model 1: 3 Factors - 3 Lags (Shock: RenEnergy)		Model 2: 4 Factors - 3 Lags (Shock: RenEnergy)		Model 3: 3 Factors - 2 Lags (Shock: RenEnergy)	
	VD	R^2	VD	R^2	VD	R^2
IP	0.003	0.862	0.003	0.877	0.000	0.859
Consumption	0.003	0.728	0.003	0.771	0.000	0.726
S&P500	0.000	0.289	0.000	0.297	0.000	0.288
Imports	0.002	0.501	0.000	0.652	0.000	0.501
Exports	0.002	0.413	0.000	0.649	0.000	0.413
BW Sentiment	0.000	0.046	0.000	0.049	0.000	0.046
MCSI	0.001	0.094	0.000	0.095	0.000	0.094
Total CO2	0.316	0.757	0.125	0.885	0.363	0.758
Com CO2	0.255	0.702	0.122	0.869	0.291	0.701
Elect CO2	0.352	0.770	0.203	0.888	0.387	0.769
Resid CO2	0.263	0.653	0.147	0.770	0.294	0.652
Transport CO2	0.025	0.501	0.010	0.654	0.023	0.506
Indust CO2	0.391	0.853	0.270	0.874	0.443	0.856

The Table presents results from FAVAR models with various specifications with regards to lags and factors. More specifically it presents the contribution of the shock to Variance of the Common Component for the selected variables, i.e., the% of the variance of the variables that is explained by US Total Renewable Energy Consumption (RenEnergy) (Models 1 to 3). The selected Variables are IP: Industrial Production; Consumption: Personal Consumption; S&P500: The returns of the S&P500 Equity Index; Imports; Exports; BW Sentiment: Baker and Wurgler Sentiment; MCSI: Michigan Consumer Sentiment Index; Total CO2: US Total Energy CO2 Emissions; Com CO2: Commercial sector US Energy CO2 Emissions; Elect CO2: Electric power sector US Energy CO2 Emissions; Resid CO2: Residential sector US Energy CO2 Emissions; Transport CO2: Transportation sector US Energy CO2 Emissions; Indust CO2: Industrial sector US Energy CO2 Emissions.

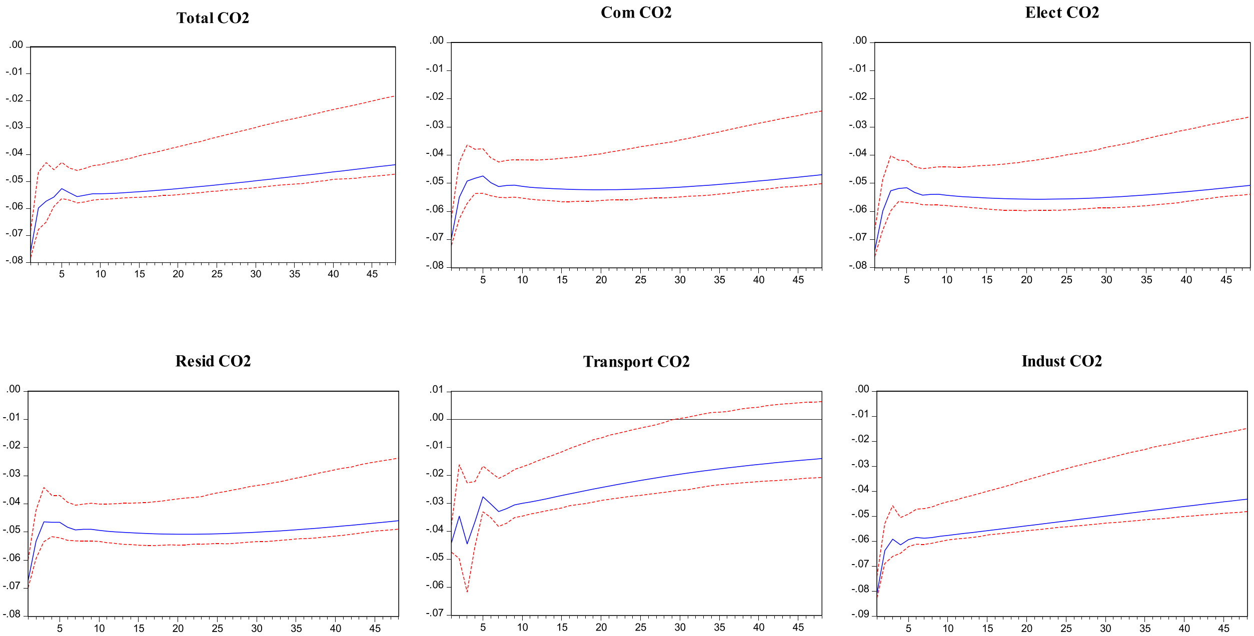

Fig. 7. The effect of Renewable Energy Consumption on selected variables
The Figure presents Impulse Response Functions (IRFs) from a FAVAR model (Model 1: 3 lags - 3 factors) for selected variables to a shock in Renewable Energy Consumption.

in Model 1 is to the variance of industrial emissions (14.1%), while the highest contribution in Model 2 is also for Industrial emissions (18.7%). Total CO2 emissions' variance is explained by 9.3% in Model 1 and 14.3% in Model 2. As expected, the IRFs indicate that the higher the Energy Consumption, the higher the CO2 emissions. We adopt a Cholesky ordering and divide the variables in X_t to fast moving and slow-moving variables and list energy consumption first in the ordering assuming that it affects contemporaneously real output (Squalli, 2007; Ebohon, 1996; Chien and Hu, 2008). Nevertheless, results remain qualitatively the same for alternative orderings.

Overall, the findings presented above seem to support the argument (see Gavriilidis, 2021) that Climate Policy Uncertainty and Climate Risk may be a transmission channel; elevated climate policy uncertainty and climate risk (proxied in this paper with Natural Disasters Cost, CPU, etc.) might discourage energy consumption and at the same time climate policy uncertainty shocks encourage renewable energy consumption and more sustainable practices adoption, thus leading to decreased CO2 emissions. Moreover, natural disasters affect the political disagreement among US politicians, but also impact the adoption and formulation of efficient climate regulations and policies that can force firms adopt more sustainable and environmentally friendly practices.

4. Conclusion

One of the most significant and difficult challenges that governments, policy makers, and societies are facing during the recent period is how to achieve economic growth that is environmentally sustainable. This paper examines the relationship between climate risk and climate policy uncertainty and CO2 emissions in the US. Recent empirical results seem to indicate that there is a significant and negative effect of climate policy uncertainty on CO2 emissions. Gavriilidis (2021) points out that, on the one hand, policy uncertainty regarding climate regulation may lead to delayed investments and/or reduced investments in new technologies and related research, but on the other hand, it may also encourage firms to reduce their ecological footprint.

Motivated by this observation, we examine the relationship between climate risk, climate policy uncertainty, and CO2 emissions in the US. To proxy for Climate Risk and Climate Policy Uncertainty in the US, we use the financial cost natural disasters, the number of deaths caused by each such disaster, and the Climate Policy Uncertainty Index of Gavriilidis (2021), and examine the effects on Total emissions and emissions from the commercial sector, the electric power sector, the residential sector, the transportation sector and the industrial sector. The empirical analysis covers the period between 2000 and 2022, and we employ a structural Factor-Augmented Vector AutoRegression (FAVAR) model with a two-step principal component analysis using a balanced panel of 117 monthly variables to capture US economic conditions. Moreover, we investigate the effect that natural disasters might have on the political alignment in the US Congress and on the adoption and formulation of efficient regulations and policies.

Our results indicate that a significant percentage of the variance of CO2 emissions in the US is explained by Natural Disasters, which also seem to account for a significant percentage of the US Total Renewable Energy Consumption variance. Furthermore, Natural Disasters also affect Partisan conflict importantly; that is, Natural Disasters tend to increase the disagreement among political parties, Congress and the President, as well as, the climate policy uncertainty, highlighting the need to strengthen policies against global warming. When we replace the Climate risk proxies with the Climate Policy Uncertainty (CPU) Index of Gavriilidis (2021) the results are similar as above, and stronger; also approximately 28% to 45% of the variance in Total Renewable Energy Consumption is explained by CPU and this strong relationship is positive, i.e., an increase in CPU increases Renewable Energy consumption. Moreover, shocks to CPU seem to decrease all type of emissions significantly.

Overall, the findings presented above seem to support the argument that climate policy uncertainty and climate risk may be related to CO2 emissions; elevated climate policy uncertainty and climate risk might discourage energy consumption and at the same time climate policy uncertainty shocks encourage the consumption of renewable energy and the adoption of more sustainable practices, thus leading to decreased CO2 emissions. Moreover, natural disasters affect the political disagreement among US politicians, but also impact the adoption and formulation of efficient climate regulations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix I

Notes to Appendix I. Our dataset is a monthly balanced panel including 117 time series of global variables, various macroeconomic aggregates, and financial variables. We use the dataset from Lutz (2015) (following Boivin et al., 2009; Stock and Watson, 2005) updated with additional variables of interest from January 2000 to June 2022. Some series are excluded due to limited data availability and replaced where possible. Our dataset includes additional variables featuring in the categories Trade, Oil and Gas, CO2 Emissions and Energy Consumption. The format adopted is from Stock and Watson (2002) and transformations according to Bernanke et al. (2005), Boivin et al. (2009). More specifically, 1 stands for – no transformation; 2 for – first difference; 4 for – logarithm; 5 for– first logarithmic differences. EIKON is Thomson Reuters EIKON Database, FRED is FRED Economic Database of the Federal Reserve Bank of St. Louis, Shiller is Robert Shiller's website, BW is Baker and Wurgler (2006) and Baker and Wurgler (2007) and EIA is US Energy Information Administration.

Number	Mnemonic	Description	Trans.	Source
Real Output and Income				
1	USIPPRDTD	US Gross Value of Production - Industrial Production – Products Total (2009 Dollars, SA)	5	EIKON
2	USIPMPROG	Industrial Production – Final Products & Nonindustrial supplies	5	EIKON
3	USIPMCOGG	Industrial Production – Consumer Goods (2007 = 100, SA)	5	EIKON
4	USIPMDUCG	Industrial Production – Durable Cons. Goods (2007 = 100, SA)	5	EIKON
5	USIPMNOCG	Industrial Production – Nondurable Cons. Goods (2007 = 100, SA)	5	EIKON
6	USIPMBUQG	Industrial Production – Business Equipment (2007 = 100, SA)	5	EIKON
7	USIPINTDD	US Gross Value of Production - Industrial Production – Intermediate Products (2009 Dollars, SA)	5	EIKON
8	USIPMNEMG	Industrial Production – Materials Nonenergy (2007 = 100, SA)	5	EIKON
9	USIPMDUMG	Industrial Production – Nonenergy Durable Goods Materials (2007 = 100, SA)	5	EIKON
10	USIPMNDMG	Industrial Production – Nonenergy Nondurable Goods Materials (2007 = 100, SA)	5	EIKON
11	USIPMAN.G	Industrial Production – Manufacturing (2007 = 100, SA)	5	EIKON
12	USIPNALGG	Industrial Production – Nondurables, Apparel & Leather Goods (2007 = 100, SA)	5	EIKON
13	USIPMIN.G	Industrial Production – Mining (2007 = 100, SA)	5	EIKON
14	USIPUTL.G	Industrial Production – Electric and Gas Utilities (2007 = 100, SA)	5	EIKON
15	USIPTOT.G	Industrial Production – Total Index (2007 = 100, SA)	5	EIKON
16	USMBS076Q	Rate of Capacity Utilization – Manufacturing (% of Capacity, SA)	1	EIKON
17	USCNFBUSQ	ISM Purchasing Managers Index (SA)	1	EIKON
18	USPMCHBB	Chicago Purchasing Manager Business Barometer Index (SA)	1	EIKON
19	USNAPMPR	ISM Manufacturers Survey – Production Index (SA)	1	EIKON
20	USPERINCD	Personal Income (2009 Chained Prices, SA)	5	EIKON
21	USPERXTRD	Personal Income Less Transfer Payments (2009 Chained Prices, SA)	5	EIKON
Employment				
22	USEMPTOTO	Total Civilian Employment (Thousands, SA)	5	EIKON
23	USUN%TOTQ	Unemployment Rate (16–65 Years,%, SA)	1	EIKON
24	USUNWKMDO	Median Duration of Unemployment in Weeks (Median, SA)	1	EIKON
25	USUNWK5.O	Unemployed for Less Than 5 Weeks (Thousands, SA)	1	EIKON
26	USUNWK14O	Unemployed for 5 to 14 Weeks (Thousands, SA)	1	EIKON
27	USUNPLNGE	Unemployed for 15 Weeks or More (Thousands, SA)	1	EIKON
28	USUNWK26O	Unemployed for 15 to 26 Weeks (Thousands, SA)	1	EIKON
29	USCOINARB	Employees On Nonagricultural Payrolls (Thousands, SA)	5	EIKON
30	USEMIP..O	Employed – Total Private (Thousands, SA)	5	EIKON
31	USEMPG..O	Employed – Goods-Producing (Thousands, SA)	5	EIKON
32	USEW23..O	Employed Production Workers – Construction (Thousands, SA)	5	EIKON
33	USEMPMANO	Employed – Manufacturing (Thousands, SA)	5	EIKON
34	USEMIMD.O	Employed – Durable Goods (Thousands, SA)	5	EIKON
35	USEMPP..O	Employed – Private Service Producing (Thousands, SA)	5	EIKON
36	USEMIT..O	Employed – Trade, Transportation, & Utilities (Thousands, SA)	5	EIKON
37	USEMIR..O	Employed – Retail Trade (Thousands, SA)	5	EIKON
38	USEM42..O	Employed – Wholesale Trade (Thousands, SA)	5	EIKON
39	USEMPS..O	Employed – Service Providing (Thousands, SA)	5	EIKON
40	USEMIG..O	Employed – Government (Thousands, SA)	5	EIKON
41	USHKIM..O	Avg Weekly Hours – Manufacturing (SA)	1	EIKON
42	USHXPMANO	Avg Weekly Overtime Hours – Manufacturing (SA)	1	EIKON
43	USNAPMEM	ISM Manufacturers Survey – Employment Index (SA)	1	EIKON
Consumption				
44	USN4BXR3E	Personal Consumption Expenditure (2009 = 100, SA)	5	EIKON
45	USN4DCPHE	Personal Consumption Expenditure – Durable Goods (2009 = 100, SA)	5	EIKON
46	USN0SVK4E	Personal Consumption Expenditure – Nondurable Goods (2009 = 100, SA)	5	EIKON
47	USNY1H9FE	Personal Consumption Expenditure – Services (2009 = 100, SA)	5	EIKON
Housing Starts and Sales				
48	USHOUSE.O	New Private Housing Units Started (Total, Thousands, SA)	4	EIKON
49	USHBRN..O	Housing Started – Northeast (Thousands, SA)	4	EIKON
50	USHBRM..O	Housing Started – Midwest (Thousands, SA)	4	EIKON
51	USHBRS..O	Housing Started – South (Thousands, SA)	4	EIKON
52	USHBRW..O	Housing Started – West (Thousands, SA)	4	EIKON
53	USHOUSATE	New Private Housing Units – Authorized Permits (Thousands, SA)	4	EIKON
54	USIP321HG	Manufactured Home (Mobile Home) (2007 = 100, SA)	4	EIKON
Real Inventories, Orders				
55	USNAPMNO	ISM Manufacturers Survey – New Orders Index (SA)	1	EIKON
Exchange Rates				
56	SWXRUSD.	Swiss Francs to USD	5	EIKON
57	JPXRUSD.	Japanese Yen to USD	5	EIKON
58	UKXRUSD.	US Dollar to UK Pound	5	EIKON

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Number	Mnemonic	Description	Trans.	Source
59	CNXRUSD.	Canadian Dollar to USD	5	EIKON
Stock Prices				
60	S&PCOMP(DY)	S&P500 Composite Dividend Yield	1	EIKON
61	S&PCOMP(PI)	S&P500 Composite Price Index	5	EIKON
62	S&PCOMP(PE)	S&P500 Composite P/E Ratio	1	EIKON
63	NYSEALL	New York Stock Exchange Composite Index	5	EIKON
64	DJINDUS	Dow Jones Industirals	5	EIKON
65	NASCOMP	NASDAQ Composite	5	EIKON
66	NASA100	NASDAQ 100	5	EIKON
Interest Rates				
67	FEDFUNDS	Effective Federal Funds Rate	1	FRED
68	TB3MS	3-Month Treasury Bill: Secondary Market Rate	1	FRED
69	TB6MS	6-Month Treasury Bill: Secondary Market Rate	1	FRED
70	GS1	1-Year Treasury Constant Maturity Rate	1	FRED
71	GS5	5-Year Treasury Constant Maturity Rate	1	FRED
72	GS10	10-Year Treasury Constant Maturity Rate	1	FRED
73	AAA	Moody's Seasoned Aaa Corporate Bond Yield	1	FRED
74	BAA	Moody's Seasoned Baa Corporate Bond Yield	1	FRED
75	TB3MS – FEDFUNDS	3 Month Treasury Rate minus the Fed Funds Rate	1	FRED
76	TB6MS – FEDFUNDS	6 Month Treasury Rate minus the Fed Funds Rate	1	FRED
77	GS1 – FEDFUNDS	1 Year Treasury Rate minus the Fed Funds Rate	1	FRED
78	GS5 – FEDFUNDS	5 Year Treasury Rate minus the Fed Funds Rate	1	FRED
79	GS10 – FEDFUNDS	10 Year Treasury Rate minus the Fed Funds Rate	1	FRED
80	AAA – FEDFUNDS	AAA Corp Bond Yield minus the Fed Funds Rate	1	FRED
81	BAA – FEDFUNDS	BAA Corp Bond Yield minus the Fed Funds Rate	1	FRED
Money and Credit Aggregates				
82	M1SL	M1 Money Stock	5	FRED
83	M2SL	M2 Money Stock	5	FRED
84	MABMM301USM189S	M3 for the United States	5	FRED
85	BOGMBASE	Monetary Base; Total	5	FRED
86	BUSLOANS	Commercial and Industrial Loans, All Commercial Banks	5	FRED
87	TOTALSL	Total Consumer Credit Owned and Securitized, Outstanding	5	FRED
Price Indices				
88	WPSFD49207	Producer Price Index by Commodity: Final Demand: Finished Goods (1982 = 100)	5	FRED
89	WPSFD4111	Producer Price Index by Commodity: Final Demand: Finished Consumer Foods (1982 = 100)	5	FRED
90	WPSID611	Producer Price Index by Commodity: Intermediate Demand by Commodity Type: Materials and Components for Manufacturing (1982 = 100)	5	FRED
91	PCEPI	Personal Consumption Expenditures: Chain-type Price Index	5	FRED
92	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	5	FRED
93	CPIAPPSL	Consumer Price Index for All Urban Consumers: Apparel	5	FRED
94	CPITRNSL	Consumer Price Index for All Urban Consumers: Transportation	5	FRED
95	CPIMEDSL	Consumer Price Index for All Urban Consumers: Medical Care	5	FRED
96	CUSR0000SAC	Consumer Price Index for All Urban Consumers: Commodities	5	FRED
97	CUSR0000SAD	Consumer Price Index for All Urban Consumers: Durables	5	FRED
98	CUSR0000SAS	Consumer Price Index for All Urban Consumers: Services	5	FRED
Trade				
99	IMPGS	Imports of Goods and Services (Billions of Dollars)	5	FRED
100	EXPGS	Exports of Goods and Services (Billions of Dollars)	5	FRED
Oil and Gas				
101	POILBREUSDM	Global price of Brent Crude, U.S. Dollars per Barrel	5	FRED
102	PNGASEUUSDM	Global price of Natural gas, EU, U.S. Dollars per Million Metric British Thermal Unit	5	FRED
Investor Sentiment				
103	BW Sentiment	Baker and Wurgler (2006), Baker and Wurgler (2007) Sentiment Index	2	BW
104	MCSI	University of Michigan: Consumer Sentiment	2	FRED
105	AdvSent	Advisors Sentiment	2	EIKON
Other Stock Market Variables				
106	PE10	Shiller's 10-Year P/E Ratio	1	Shiller
107	CBOEVIX	CBOE SPX Volatility VIX (New) - Price Index	1	EIKON

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Number	Mnemonic	Description	Trans.	Source
Average Hourly Earnings				
108	CES2000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	5	FRED
109	CES3000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	5	FRED
CO2 Emissions				
110	Total CO2	US Total Energy CO2 Emissions	4	EIA
111	Commercial CO2	Commercial sector US Energy CO2 Emissions	4	EIA
112	Electric power CO2	Electric power sector US Energy CO2 Emissions	4	EIA
113	Residential CO2	Residential sector US Energy CO2 Emissions	4	EIA
114	Transportation CO2	Transportation sector US Energy CO2 Emissions	4	EIA
115	Industrial CO2	Industrial sector US Energy CO2 Emissions	4	EIA
Energy Consumption				
116	Energy Consumption	US Energy Consumption (including residential, commercial, industrial and transportation sectors)	4	EIA
117	Renewable Energy Consumption	US Total Renewable Energy Consumption	4	EIA

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