PROBLEMY EKOROZWOJU/ PROBLEMS OF SUSTAINABLE DEVELOPMENT
SUBMITTED: 28.09.2024, ACCEPTED: 18.11.2024, PUBLISHED ON-LINE: 10.01.2025
2025, 20(1): 190-207
DOI: 10.35784/preko.6635

How Does Economic and Monetary Policy Uncertainty Affect Climate Policy Uncertainty in the United States?

Jak niepewność polityki gospodarczej i monetarnej wpływa na przewidywalność polityki klimatycznej w Stanach Zjednoczonych?

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Abstract
Policy uncertainties can directly affect the outcomes of policies to be implemented. Therefore, it is important to reduce policy uncertainties. Identifying policy uncertainties and related factors is important in this regard. This study examines the impact of economic and monetary policy uncertainty on climate policy uncertainty in the United States. The relationship between the variables is examined asymmetrically using monthly data for 1988-2022. First, the Augmented Dickey-Fuller Unit Root Test and the Fractional Frequency Fourier Augmented Dickey-Fuller Unit Root Test are applied. The Asymmetric Wavelet Transform Coherence Test is also used to determine the direction and frequency of the relationship between the variables. Asymmetric time-varying causality analysis was used for the causality dimension. The significant relationship between *economic policy uncertainty, monetary policy uncertainty* and *climate policy uncertainty* varies at different time periods.

Key words: sustainable development, policy uncertainties, asymmetric tests

Streszczenie
Niepewność polityki może bezpośrednio wpływać na wyniki wdrażanych polityk. Dlatego ważne jest zmniejszenie niepewności polityki. Identyfikacja niepewności polityki i powiązanych czynników jest w tym względzie ważna. W niniejszym badaniu zbadano wpływ niepewności polityki gospodarczej i pieniężnej na niepewność polityki klimatycznej w Stanach Zjednoczonych. Związek między zmiennymi jest badany asymetrycznie przy użyciu miesięcznych danych z lat 1988-2022. Najpierw zastosowano rozszerzony test pierwiastka jednostkowego Dickeya-Fullera i rozszerzony test pierwiastka jednostkowego ułamkowej częstotliwości Fouriera. Asymetryczny test koherencji transformacji falkowej jest również używany do określenia kierunku i częstotliwości związku między

zmiennymi. Asymetryczna analiza przyczynowości zmieniająca się w czasie została użyta do wymiaru przyczynowości. Istotny związek między *niepewnością polityki gospodarczej, niepewnością polityki pieniężnej* i *niepewnością polityki klimatycznej* zmienia się w różnych okresach.

Słowa kluczowe: zrównoważony rozwój, niepewność polityczna, testy asymetryczne

1. Introduction

Climate change, which refers to alterations in contemporary climate patterns attributed to anthropogenic influences, is emerging as a paramount environmental concern in the current discourse. First noticed by the scientific community in the late nineteenth and early twentieth centuries, climate change gradually escalated into a multifaceted challenge threatening physical, ecological, cultural, and socioeconomic frameworks since the early 1980s. Subsequently, its burgeoning magnitude led to widespread recognition and eventually pushed it onto the public agenda (Rahman, 2013). In response, measures such as the implementation of the Paris Agreement on climate change and the pursuit of the goals outlined in the United Nations Sustainable Development Goals (SDGs) have been initiated. These efforts aim to reduce greenhouse gas emissions responsible for climate change, facilitate adaptation strategies to cope with changing climatic conditions, and provide financial support to address climate-related challenges (Xue et al. 2022, Zhang et al. 2023, Chu et al. 2023, Vitenu-Sackey and Acheampong 2022, Iqbal et al. 2023). Although many steps have been taken within the framework of international cooperation to stop climate change, there are many deficiencies in the climate policies of some countries, and accordingly, it is difficult to realize the commitments made by the end of 2030. The main reason for this is the high cost of climate policy uncertainties and climate policy development and implementation (Mao and Huang 2022; Zhang et al. 2023). The United States is one of the countries that contributes most negatively to CO_2 emissions and, according, to climate change (Assamoi and Wang, 2023).

The United States has participated in the Paris Agreement many times in recent years and subsequently terminated the agreement due to uncertainties in climate policies and the high costs of climate policy development and implementation (Mao and Huang 2022). This pattern of behavior demonstrated by the USA disrupts the fight against climate change worldwide. This behavior of the USA, using costs and uncertainties as an excuse, reveals the importance of uncertainties that have been neglected so far in the fight against climate change. In previous studies, academics have analyzed the factors affecting CO_2 emissions, which are the most important contributors to climate change. According to Li et al. (2021), there are many macro- and micro-level factors that increase CO_2 emissions. However, according to Jiang et al. (2019), there is a significant link between CO_2 emissions and macroeconomic variables. Becker et al. (2016) also tried to calculate economic policy uncertainty with economic and non-economic (legislative, regulatory, and government) parameters. In the same study, a different index was developed for the calculation of monetary policy uncertainty with items in the central bank management. In recent years, it has been possible to encounter many studies investigating the relationship between economic policy uncertainty and environmental factors. However, according to Jiang et al. (2019), studies generally focus on the economic effects of economic policy uncertainty rather than its impact on environment. According to a different group of studies in the literature, uncertainty in climate policies moves along with uncertainty indices related to the economy. According to studies such as Hong et al. (2024) and Iqbal et al. (2023), uncertainty in climate policies affects economic variables.

As production systems diversify, carbon footprints and environmental impacts also diversify. Over time, the overshoot day comes earlier. Especially in 2022, the overshoot day was reached on August 1 (Katanalp & Sağlık, 2024). Therefore, environmental issues become more important over time. Leading economies have become pioneers in high-tech sectors over time, rather than only in cost-oriented production (Kumar & Pathak, 2022). Therefore, it becomes more important for leading economies to contribute to sustainable development goals. For this reason, the US economy, one of the world's leading economies, is studied in our study. The study also includes the green economy, which draws attention to the conflicts or solidarities between environmental policies and economic policies (Stanković et al., 2024). For this reason, the fact that our study is based on one of the leading economies and uses variables related to sustainable development goals in the econometric analysis is considered to be important in terms of literary contribution to sustainable development goals.

One of the most important sustainable development goals is poverty reduction. Poverty reduction is directly related to the economy (Piwowarski et al., 2022). One of the sustainable development goals is sustainable economic growth. Income and monetary aggregates directly affect sustainable economic growth (Yilanci et al., 2023). Consistent and logical policies implemented by policymakers in every field can serve sustainable development goals in many areas, especially in the field of gender equality (Lenka, 2023). There are studies showing that policies such as sericulture (Mushtaq et al., 2023), entrepreneurship (Zhu & Wang, 2024), or democracy (Ursavaş & Apaydın, 2024) are also important in determining policies rather than macro policies. Therefore, eliminating policy uncertainties will contribute to achieving sustainable development goals.

When evaluated from these perspectives, it is considered that our study is related to the 1st, 2nd, 8th, 8th, 9th, 12th, 13th and 15th development goals of the United Nations sustainable development goals.
Our study is to analyze when and how economic uncertainty affects environmental policy uncertainty. For this reason, *monetary policy uncertainty index* and *economic policy uncertainty index* are used to represent economic uncertainties. For environmental policy uncertainty, *climate policy uncertainty index* is used. In the reviewed literature, there is no other study investigating the relationship between economic, monetary, and climate policy uncertainty. In this respect, our study is expected to contribute to the literature. In addition, it is thought to contribute to the literature with the asymmetric wavelet transform consistency analysis, which will be used for the first time in the literature. Existing applied economics literature reveals that time series, panel data analysis and ARDL bounds testing approach are generally preferred. Uncertainty variables are heterogeneous, non-stationary, and subject to structural changes and volatility. For these reasons, time information may be lost in the models preferred in the literature, which may hinder the opportunity to identify structural changes and make it difficult to distinguish temporary relationships between variables from permanent relationships. The asymmetric WTC and time-varying asymmetric causality analysis prevents the emergence of such problems and provides a more reliable determination of the relationship between variables. Again, econometric analyses generally analyze a series as a whole and conclude. This result is interpreted for the entire period. Asymmetric WTC and time-varying asymmetric causality tests are not concluded for the entire period, but for the relevant periods separately. This makes it possible to observe the relationship between variables sharply.
The remainder of the study is structured as follows: Literature review is presented in Section-II. The data information and model established are included in Section-III. Section-IV details the methodology to be applied. The empirical results are presented and discussed in Section-V. Section-VI focuses on the conclusion and policy implications.

2. Literature review

There are no studies in the literature that analyze the impact of economic policy uncertainty and monetary policy uncertainty on climate policy uncertainty or investigate the relationship between these three uncertainty indices. Studies in the literature focus on the effects of economic policy uncertainty on CO_2 emissions, environmental quality and sustainability, environmental degradation, environmental innovations, and renewable energy consumption. For this reason, the literature review is presented in Table-1, including past studies addressing this interaction.

Table 1. Summary of the literature, source: own elaboration

Author(s)	**Region/Country**	**Period**	**Method**	**Variables**	**Impact of EPU on CO_2/EF/ED**
Jiang et al. (2019)	USA	1985-2017	NGCT	EPU, CO_2 emissions, RS, EPS and TS	Mixed results
Anser et al. (2021a)	USA, China, Germany, Russia, Japan, Canada, India, Iran, Saudi Arabia, and South Korea	1990-2015	PMG-ARDL	CO_2 emissions, GDP, EC, TP and WUI	Mixed results
Amin & Dogan (2021)	China	1980-2016	DSNFT	EIN, GDP, RENC, EPU and CO_2 emissions	+ve coefficient
Odugbesan & Aghazadeh (2021)	Japan	1987-2019	FMOLS, DOLS, CCR, and ARDL	CO_2 emission, ERPU, FPU, TPU, MPU, GDP and EC	+ve coefficient
Vitenu Sackey & Acheampong (2022)	18 advanced economies	2005-2018	2SLS, GMM and GLS	EPU, EIN, GDP, TI, CO_2 emissions	Mixed results
Fu et al. (2022)	325 provincial-level cities in China	2001-2017	UPDA	CO_2 emission, EPU, GDP, URBP, NIE and PEI	+ve coefficient
Syed & Bouri (2022)	USA	1985-2019	New bootstrap ARDL	EPU, IPI, RENC, TO and CO_2 emissions	Mixed results
Syed et al. (2022)	BRICS-T countries	1990-2015	PQR	CO_2 emissions, EPU and GPR	Mixed results
Tee et al. (2023)	60 countries	2019	CSRA	EPU and CF	+ve coefficient

Zhang et al. (2023a)	China	1995/Q1-2021/Q4	TVP-VAR model	EPU, CO_2 emissions and RDP	Mixed results
Asgari et al. (2023)	Iran	1979-2018	FAVAR and TVP	EPU, EC and CO_2 emissions	+ve coefficient
Zhang et al. (2023b)	USA	1990-2019	ARDL and SSC	RET, EIN, EPU and GLOB	-ve coefficient
Deng et al. (2024)	30 different Chinese provinces	2004-2017	SEM	EPU, CO_2 emission, REC, TEI, RTR, GPBE	+ve coefficient
Anser et al. (2021b)	Brazil, Mexico, Russia, Colombia, and China	1995-2015	FMOLS and DOLS	EF, EPU, GDP, NRENC, RENC, POP, and GPR	+ve coefficient
Xue et al. (2022)	France	1987-2019	New Augmented ARDL	RENC, CO_2 emissions and EPU	+ve coefficient
Hussain et al. (2022)	BRICS economies	1992-2020	STIRPAT model	EPU, ES, ERT and EF	+ve coefficient
Huang et al. (2023)	19 developed and developing countries	2001-2019	PDA and GLS	EPU, GDP per capita, RENC, FDI and ENS	+ve coefficient
Assamoi & Wang (2023)	China and USA	1995Q1-2020Q4 1985Q1-2020Q4	NARDL and ACT	EPU, EPST and CO_2 emissions	Mixed results
Chu & Le (2022)	G7 countries	1997-2015	DKEM and OLS	EPU, EIN, RENC, ECOMP, and EQ	-ve coefficient
Selmey & Elamer (2023)	Egypt	1990-2018	ARDL	RENC, EG, EPU and ED	+ve coefficient
Chu et al. (2023)	E7 economies	1995-2018	PMG-ARDL	EPU, GPR and ECOMP	Mixed results
Su et al. (2022)	137 countries	2001-2018	STIRPAT model-GMM	EPU, PS, SP and EQ	-ve coefficient
Yang et al. (2022)	China	2010-2018	PDA	EPU and GI	+ve coefficient
Peng et al. (2023)	31 provinces in China	2000-2017	PFEM	GPA, EPU, RDE, GDP per capita, IS, FDI, URB, HC, POP, FE, INF, ER and GS	+ve coefficient
Fakher et al. (2023)	China	2007-2021	The methodology of Liu et al. (2019)	EPU, POP, RDE, FGI and GI	-ve coefficient
Xu & Yang (2023)	269 Chinese cities	2005-2016	BM	GI, EPU, GDP, RDE, POP, FDI, RES, CS, SIS, RIS and PCS	Mixed results
Hong et al. (2024)	Vietnam	2010-2022	MRM	EPU, GF, GI, CPU, interaction between CPU and EPU	+ve coefficient
Shafiullah et al. (2021)	USA	1986-2019	NPEA	RENC, EPU, POP, RDE and OP	-ve coefficient
Lei et al. (2022)	China	1990-2019	ARDL	RENC, EPU, FDI, ECOS and FD	Mixed results
Chu & Le (2022)	G7 countries	1997-2015	DKEM and OLS	EPU, EIN, RENC, ECOMP, and EQ	+ve coefficient

Farouq & Sulong (2024)	11 OPEC members	2000-2020	PDA	Income, OP, FG, EPU and RENC	-ve coefficient

Note: EPU is economic policy uncertainty, RS is residential sector, EPS is electric power sector, TS is transportation sector, GDP is the gross domestic product, EC is energy consumption, TP is total population, WUI is world uncertainty index, EIN is energy intensity, ES is energy structure, TI is technological innovation, URBP is urban population, IPI is industrial production index, RENC is renewable energy consumption, NRENC is non-renewable energy consumption, TO is trade openness, GPR is geopolitical risk, CF is carbon footprint, CI is corporate innovation, RET is renewable energy transition, EI is ecological innovation, GLOB is globalization, REC is regional electricity consumption, TEI is total export-import, RTR is regional tax revenue, GPBE is general public budget expenditures, EF is ecological footprint, POP is population, ERT is environment-related technologies, FDI is foreign direct investment, ENS is environmental sustainability, EPST is environmental policy stringency, EQ is environmental quality, ECOMP is economic complexity, EG is economic growth, ED is environmental degradation, PS is political systems, SP is social progress, ENI is environmental innovation, GI is green innovation, OP is oil prices, FG is financial globalization, FD is financial development, ECOS is economic size, URB is urbanization, GPA is Green patent applications, RDE is R&D expenditure, IS is industry structure, HC is human capital, FE is financial expenditures, INF is infrastructure, ER is environmental regulation, GS is government support, CPU is climate policy uncertainty, GF is green finance, EP is environmental performance and EI is environmental innovation, NIE is number of industrial establishments, PEI proportion of employees in industry, RDP is the full value equivalent of R&D personnel, ERPU is exchange rate policy uncertainty, FPU is fiscal policy uncertainty, TPU is trade policy uncertainty, MPU is monetary policy uncertainty. RES is resource endowment, CS is capital stock, SIS is senior of industrial structure, RIS is rational of industrial structure, PCS is per capita saving.
NGCT is new Granger causality test, PMG is the pooled mean group, ARDL is the autoregressive distributed lag, DSNFT is Dynamic simulations with new frontier tests, 2SLS is two-stage least squares, GMM is the generalized methods of moments, GLS is generalised least squares, UPDA is Unbalanced panel data analysis, PQR is panel quantile regression, CSRA is cross-sectional regression analysis, FAVAR is factor incremental vector autoregressive, TVP is time varying parameter, SSC is stepwise shift causality, SEM is Spatial econometric model, FMOLS denotes fully modified ordinary least square, DOLS is the dynamic ordinary least square, PDA is Panel data analysis, MRM is multivariate regression models, PFEM is panel fixed-effects model, NARDL is nonlinear autoregressive distributed lag, ACT is asymmetric cointegration test, STIRPAT is stochastic ımpacts by regression on population, affluence and technology, OLS is ordinary least square, DSNFT is dynamic simulations with new frontier tests, DKEM is Driscoll and Kraay estimation method, NPEA is nonparametric (nonlinear) econometric approaches, BM is bootstrap method.
The positive (+) sign shows CO_2 emissions/EF/ED/EP/GI/EI and RENC increase and the negative (−) sign shows CO_2 emissions/EF/ED/EP/GI/EI and RENC decrease.

When the relationship between economic policy uncertainty and environment in the literature is evaluated in general, it is seen that economic policy uncertainty directly affects environmental destruction and environmental quality in a negative way by increasing CO_2 emissions and ecological footprint (Amin and Dogan 2021, Odugbesan and Aghazadeh 2021, Fu et al. 2022, Tee et al. 2023, Asgari et al. 2023, Deng et al. 2024, Anser et al. 2021, Selmey and Elamer 2023, Xue et al. 2022, Hussain et al. 2022, Huang et al. 2023, Su et al. 2022). In addition to this direct impact on environment, economic policy uncertainty affects the environment indirectly by affecting green and environmental innovations and renewable energy consumption. Some studies argue that economic policy uncertainty positively affects environmental quality by increasing green and environmental innovations and renewable energy consumption (Yang et al. 2022, Peng et al. 2023, Hong et al. 2024, Chu and Le 2022), while others argue that economic policy uncertainty negatively affects environmental quality by reducing green and environmental innovations and renewable energy consumption (Fakher et al. 2023, Shafiullah et al. 2021, Farouq and Sulong 2024).

3. Data sources and estimation strategy

3.1. Data sources

Information on the data used in the study and descriptive statistics are given in Table-2 and 3 respectively.

Table 2. Information on variables, source: own elaboration

Variables	Abbreviation	Period	Source
Climate Policy Uncertainty	CPU	Jan 1988–Dec 2022	https://www.policyuncertainty.com/climate_uncertainty.html
Economic Policy Uncertainty	EPU	Jan 1988–Dec 2022	https://www.policyuncertainty.com/
Monetary Policy Uncertainty	MPU	Jan 1988–Dec 2022	https://www.policyuncertainty.com/monetary.html

The descriptive statistics of climate policy uncertainty, economic policy uncertainty, and monetary policy uncertainty reveal that monetary policy uncertainty is the highest uncertainty in the uncertainty indices, followed by economic policy uncertainty and climate policy uncertainty, respectively. A similar situation can be understood by examining the median values. However, when the maximum values are analyzed, the highest uncertainty belongs to economic policy uncertainty, followed by climate policy uncertainty and monetary policy uncertainty.

Table 3. Descriptive statistic, source: own elaboration

Variables	CPU	EPU	MPU
Mean	102.7421	104.0266	116.5297
Median	88.15494	90.52296	103.4638
Maximum	411.2888	503.0123	407.3653
Minimum	28.16193	37.26599	12.6523
Std. Dev	58.83044	53.02222	64.34899
Skewness	1.962238	2.679335	1.651367
Kurtosis	7.388304	15.60572	6.532338
Jargue-Bera	606.5278	3283.344	409.2456
Sum	43151.67	43691.17	48942.49
Sum Sq. Dev	1450167	1177958	1734992

3.2. Estimation strategy

3.2.1. Fractional frequency Fourier augmented Dickey-Fuller unit root test

We apply *fractional frequency Fourier augmented Dickey Fuller unit root test* because it is one of the most up-to-date and advanced unit root tests. The most widely used unit root test in the literature is Dickey-Fuller (1981) unit root test. In this test, the empirical equation with a constant term is shown in equation-1, while the model with a constant term and trend is shown in equation-2. However, the most important update was the Fourier form of the test developed by Enders and Lee (2012). On the other hand, Bozoklu et al. (2020) expressed five frequencies in the Fourier form of this test with decimal values and increased the number of frequencies to 50. In this way, it was possible to perform a more precise analysis. In doing so, *the fractional frequency Fourier augmented Dickey Fuller unit root test* developed by Enders and Lee (2012) in equation-3 and finalized by Bozoklu et al. (2020) and presented in equation-4 are used to analyze the unit root status of the variables.

$$\Delta y_t = \beta_1 + \rho Y_{t-1} + e_t \tag{1}$$

$$\Delta Y_t = \beta_1 + \beta_{2t} + \rho Y_{t-1} + v_t \tag{2}$$

$$\Delta yt = \rho y_{t-1} + c_1 + c_2 t + c_3 \sin\left(\frac{2\pi kt}{T}\right) + c_4 \cos\left(\frac{2\pi kt}{T}\right) + e_t \tag{3}$$

$$\Delta Y_t = \delta_0 + \delta_1 \sin\left(\frac{2\pi kt}{T}\right) + \delta_2 \cos\left(\frac{2\pi kt}{T}\right) + \delta_3 Y_{t-1} + \sum_{i=1}^{P} \alpha i \Delta Yt - i + v_t \tag{4}$$

Here, equation-1 and 3 are the equations in which the constant term effect is included in the calculation. The expression e_t at the end of the equations represents the error term. In these tests, equation-2 and 4 are the equations in which both the constant term and the trend effect are included in the calculation. Similarly, v_t at the end of the equation represents the error term. In equation-3 and 4, sine and cosine functions are added to the equation. With the addition of sine and cosine functions, the unit root test is transformed into a Fourier form.

3.2.2. Wavelet coherence (WTC) test

After analyzing the unit root status of the series, the wavelet coherence (WTC) test was performed to analyze the time-varying causal relationship between the variables. WTC analysis, in contrast to linear time series analysis, analyzes the time series not in its full dimension but in its time-varying dimension. Therefore, it is possible to analyze the relationship between the variables used in the model on a month-by-month basis. The WTC is known in the literature as a very useful method only for bivariate cases. First, to analyze the relationship between the two time series, a bivariate structure called wavelet coherence must be established. The wavelet coherence coefficient equation corrected by Torrence and Webster (1999) can be defined as follows in equation-5:

$$R_n^2(s) = \frac{\left|S\left(s^{-1}\omega_n^{(\mathcal{f},\tau)}(s)\right)\right|^2}{S\left(s^{-1}\left|\omega_n^{\mathcal{f}}\right|^2\right).S(s^{-1}|\omega_n^{\tau}|^2)`} \tag{5}$$

In equation-5, S is represented as a smoothing operator. The range of the square wavelet coherence coefficient is $0 \leq R_n^2(s) \leq 1$. A value close to zero indicates a correlation of low strength, whereas a value close to one indicates a correlation of high strength. Equation-5 (Yilanci and Pata 2022) in equation-6 shows how the Morlet Wavelet (MW) may be represented as time (τ) and frequency ($\mathcal{f}$), respectively:

$$S_\tau(\mathrm{W}) = \left(\mathrm{W}_n(S) * \lambda_1^{-t^2/2S^2}\right);\ S_{\mathcal{f}}(\mathrm{W}) = \left(\mathrm{W}_n(s) * \lambda_2 \Pi((0{,}6s)\right)\lambda_1 + \lambda_2 \tag{6}$$

The rectangle function is represented by Π, and the normalization constants are λ_1 and λ_2. Torrence and Compo (1998) determined the scale averaging factor in equation-4, which has an empirical value of 0.6. The significance of the wavelet coherence estimate was evaluated using Monte Carlo simulations.

3.2.3. Time-varying causality test

Therefore, our analysis uses the time-varying causality test described by Hacker and Hatemi-J (2006). Because WTC analysis, which performs month-by-month analysis, is used in the study, time-varying causality analysis is also used in the causality analysis for the sake of completeness in the econometric analysis. In time-varying causality analysis, WTC analysis is performed on a month-by-month basis. This test uses a lagged vector autoregressive (VAR) model to examine the causal relationship between the series. Hacker and Hatemi-J (2006) used *the Vector Autoregressive Model (VAR) model* shown in equation-7 below to test the causal relationship between the two series:

$$y_t = a + A_1 y_{t-1} + \cdots + A_p y_{p-1} + u_t \tag{7}$$

Equation-8 shows the VAR model corresponding to this equation.

$$\mathrm{Y} = \mathrm{DZ} + \delta \tag{8}$$

The notations Y, D, Z and δ are defined as follows in equation-9 and 10:

$$\begin{gathered} \mathrm{Y} \coloneqq (y_1^+,\, y_2^+,\, y_3^+, \dots,\, y_T^+)\ (\mathrm{nxT})\mathrm{matris}, \\ \mathrm{D} \coloneqq (a,\, A_1,\, A_2,\, A_3, \dots\, A_P)\ \Big(nX\big(1 + n(p+d)\big)\Big) \\ \mathrm{Z} \coloneqq (\, Z_0,\, Z_1,\, Z_2,\, Z_3, \dots\, Z_{T-1})\ \Big(\big(1 + n(p+d)\big)XT\Big)\, matris, \\ \delta \coloneqq (u_1^+,\, u_2^+,\, u_3^+, \dots,\, u_T^+)\ (\mathrm{nxT})\mathrm{matris}, \end{gathered} \tag{9}$$

$$Z_t \coloneqq \begin{bmatrix} 1 \\ Y_1 \\ Y_{t-1} \\ . \\ . \\ . \\ . \\ Y_{t-p+1}^+ \end{bmatrix} \Big(\big(1 + n(p+d)\big)\Big)\ X1\ matrix\ for\ t = 1\ next\ T \tag{10}$$

The main hypothesis indicating that there is *no Granger causality is analyzed with the Wald test statistic value* in equation-11.

$$MWALD = (C\beta)'[C((Z'Z)^{-1} \otimes S_u)C]^{-1}(C\beta) \tag{11}$$

Here, the indicator function with restrictions is denoted by C, and the Kronecker product is represented by ⊗. In this case, β=vec(D) denotes the column accumulation operator and etc. We report the variance-covariance matrix for the unrestricted VAR model, which is computed as $(\delta\ \delta)/(T - q)$, since q indicates the number of lags in the VAR equilibrium.

4. Empirical results

The unit root test of Augmented Dickey-Fuller (ADF) is a popular technique for time series data analysis. It is not without restrictions, though. Because the lag duration and model specification affect the test outcome, it is based on a predefined autoregressive model structure. The statistical power of the test may be weakened, especially when the sample size is small or the deviation from stationarity is not statistically significant. In addition to the ADF unit root test, we also use the Fractional Frequency Fourier ADF unit root test, which investigates the frequency and time dimensions of the same test in more detail and is more recent in the literature. The first step in performing asymmetric WTC and time-varying asymmetric causality tests is figuring out whether or not the variables are stationary. Therefore, *Augmented Dickey-Fuller unit root test* and *Fractional Frequency Fourier Augmented Dickey-Fuller unit root test* are applied to analyze the stationary properties of the variables. The results of the unit root tests are reported in Table 4 and 5. The results of ADF test are analyzed. In the model with a constant term, climate policy uncertainty is stationary at the first degree difference level, while economic policy uncertainty and monetary policy uncertainty are stationary at the level. In the model with constant term and trend effect, all variables are stationary at the level. Based on *Fractional Frequency Fourier Augmented Dickey Fuller unit root analysis*, it is concluded that all of the variables do not contain unit root in the constant model and in the trend and constant model; therefore, all the variables are stationary at the level at the %1 significance level.

After determining that the variables are stationary, the causal relationship between the variables is analyzed using asymmetric WTC and time-varying asymmetric causality tests. When interpreting the graphs obtained by asymmetric WTC analysis; the color indicator represents the significance level. Blue represents non-significance, while red represents a high level of significance. Frequency represents the frequency level at which the relationship between variables is valid. The black lines in the graph show the areas in which a significant relationship was detected. Finally, the arrows in Figure(s) show the direction of the causal relationship. While the upward and rightward directions of the prevailing opinion in the arrows are interpreted as a positive relationship between the variables in the relevant period, the downward and leftward directions indicate a negative relationship between the variables.

Table 4. Augmented Dickey Fuller unit root analysis, source: own elaboration

Variable	ADF Stat	%1 CV	%5-CV	%10-CV
Constant Model				
CPU	-0.72321	-3.44563	-2.86817	-2.57037
DCPU	-14.1254***	-3.44563	-2.86817	-2.57037
EPU	-6.64247***	-3.44541	-2.86807	-2.57032
MPU	-10.0989***	-3.44541	-2.86807	-2.57032
Trend and Constant Model				
CPU	-5.88121***	-3.9797	-3.42038	-3.13287
EPU	-6.69953***	-3.97965	-3.42036	-3.13286
MPU	-10.1728***	-3.97965	-3.42036	-3.13286

Table 5. Fractional frequency Fourier Augmented Dickey Fuller Unit Root Analysis, source: own elaboration

Variable	Freq.	MinKKT	F	Lag	FFFADF Stat	%1 CV	%5-CV	%10-CV
Constant Model								
CPU	0.1	479718.3	26.60697	1	-8.40534***	-4.42136	-3.85494	-3.56574
EPU	3.7	369005.7	10.67007	1	-8.10358***	-3.64671	-2.9968	-2.66891
MPU	0.1	967160.9	10.19823	1	-8.62137***	-4.42136	-3.85494	-3.56574
Trend and Constant Model								
CPU	0.1	458116.3	23.79385	1	-9.21072***	-4.79821	-4.23169	-3.93726
EPU	3.7	367272.9	10.85699	1	-8.21007***	-4.30508	-3.66658	-3.34356
MPU	0.8	935131.9	9.626641	1	-9.40998***	-4.84929	-4.28089	-3.99018

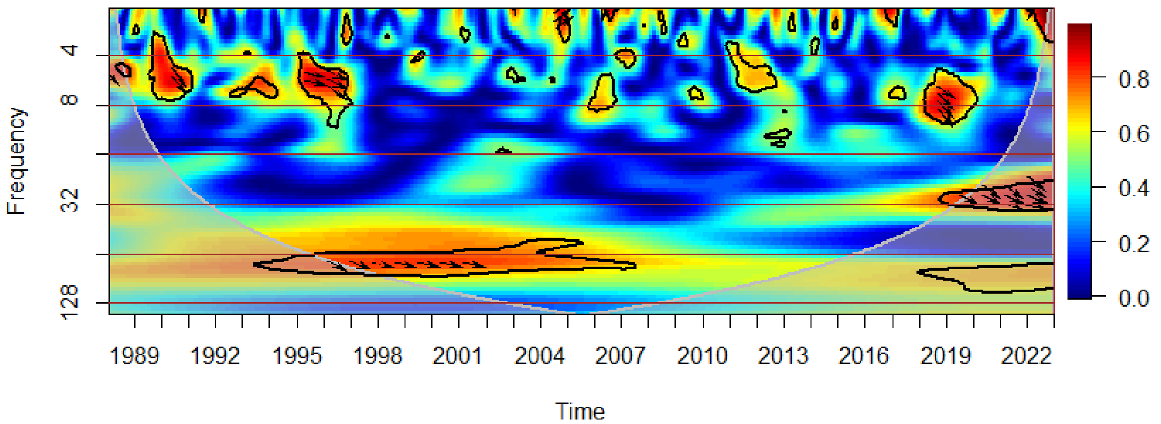

Figure 1. WTC Analysis for the CPU and MPU, source: own elaboration

The relationship between climate policy uncertainty and monetary policy uncertainty is significant and positive at a high frequency between 1995 and 2007 (Figure 1). A similar situation exists at a low frequency at the beginning of the analysis period. There is no significant relationship between the variables for the period of 2008-2019. However, it is also valid at medium and high frequencies between 2019 and 2022.

In Figure 2, when the relationship between the positive shocks of climate policy uncertainty and monetary policy uncertainty is analyzed, it is observed that there is a significant and positive relationship with medium and high frequency between 2012 and 2022 at the end of the analysis period. In Figure 3, the relationship between positive shocks of climate policy uncertainty and negative shocks of monetary policy uncertainty is analyzed. There is a negative relationship at medium frequency for the period of 1991-2000 at the beginning of the analysis period. This relationship is positive at medium frequency over the period of 2014-2019. For the period of 2018-2021, there is a low frequency negative relationship.

In Figure 4, the relationship between the negative shock of climate policy uncertainty and the positive shock of monetary policy uncertainty is analyzed by WTC analysis, and no significant relationship is found. In the relationship between the negative shocks of climate policy uncertainty and monetary policy uncertainty, a significant relationship is generally observed at low frequency in Figure 5. Over the period of 2001-2008, there is a negative

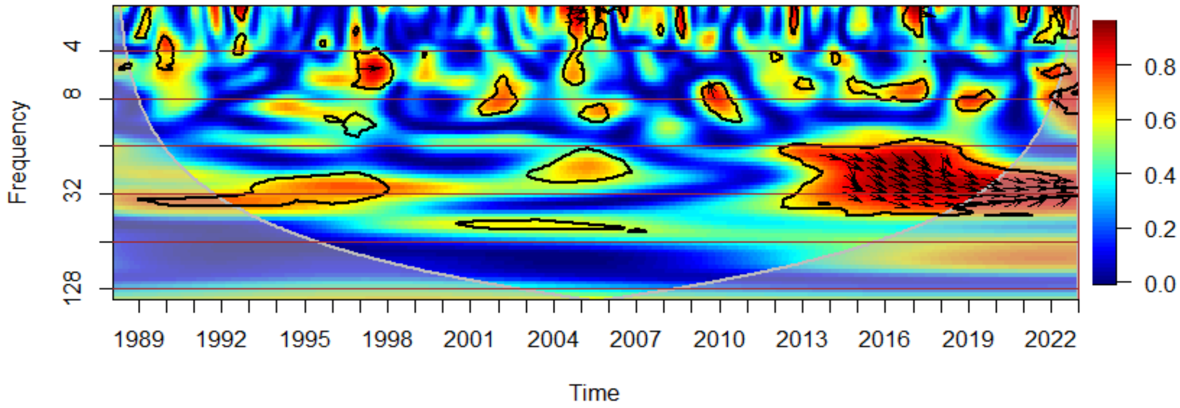

Figure 2. WTC Analysis for CPU (+) and MPU (+), source: own elaboration

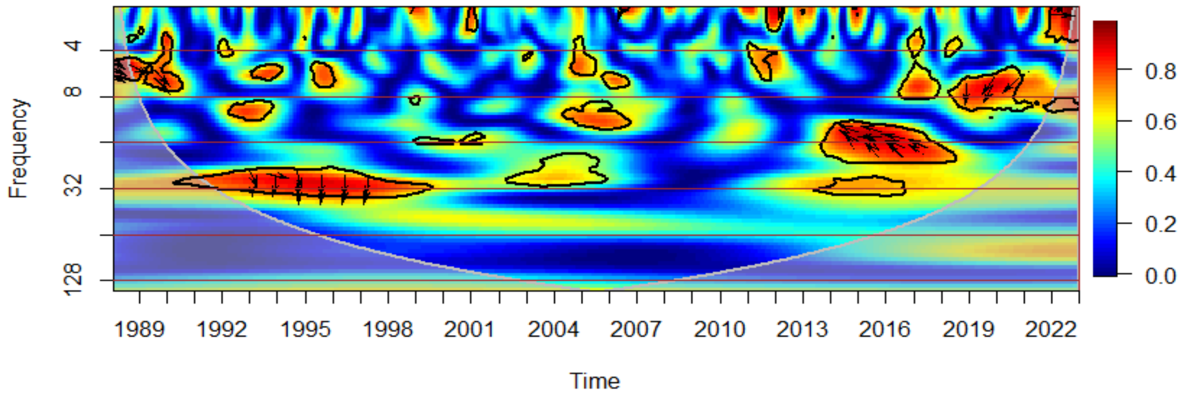

Figure 3. WTC Analysis for CPU (+) and MPU (-), source: own elaboration

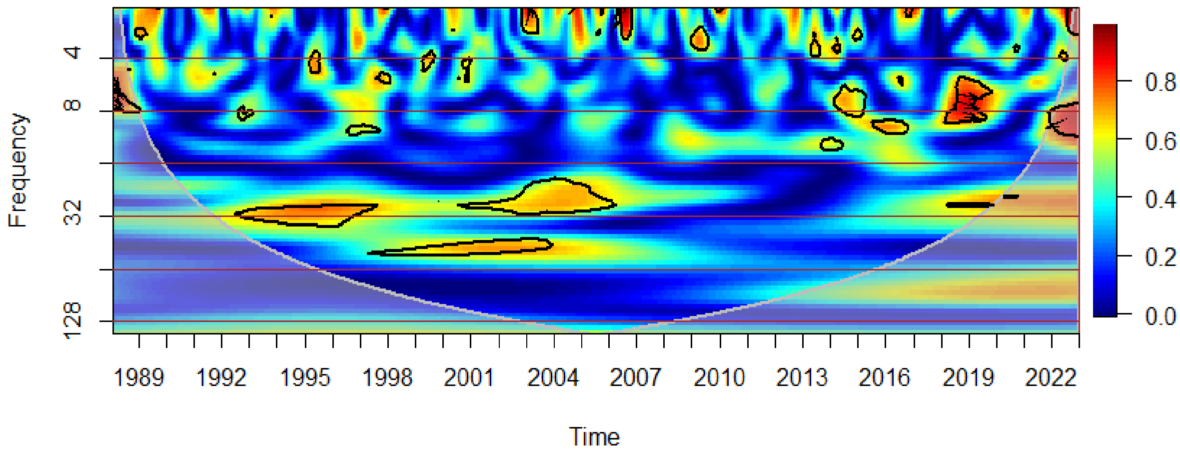

Figure 4. WTC Analysis for CPU (-) and MPU (+), source: own elaboration

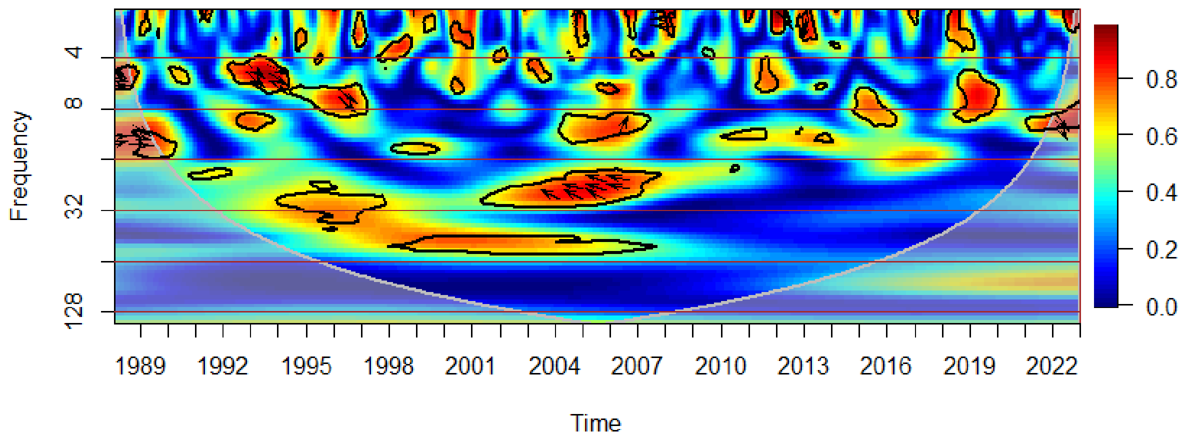

Figure 5. WTC Analysis for CPU (-) and MPU (-), source: own elaboration

relationship at medium frequency. Likewise, at the end of the analysis period, a negative relationship was found at a low frequency.
In the graphs of the time-varying asymmetric causality tests, the limit of 1 is accepted as the causality limit. Values above the limit of 1 indicate causality between that period. Values below the limit of 1 indicate the period in which there is no causality. When applying time-varying asymmetric causality tests, possible lags are normalized by distributing them over the period.

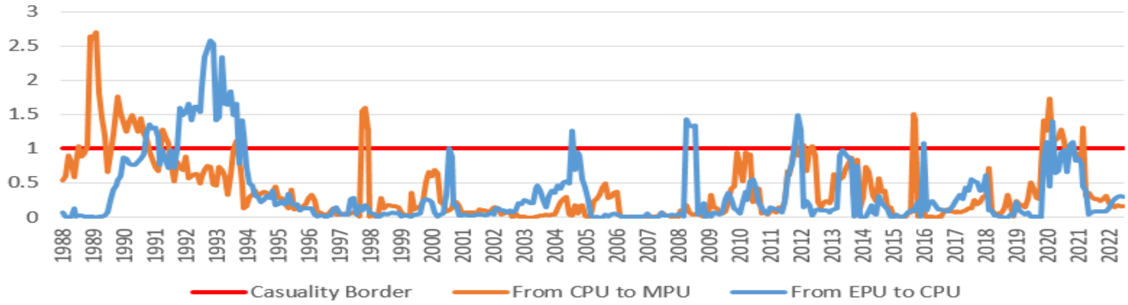

Figure 6. Time-varying causality analysis for CPU and MPU, source: own elaboration

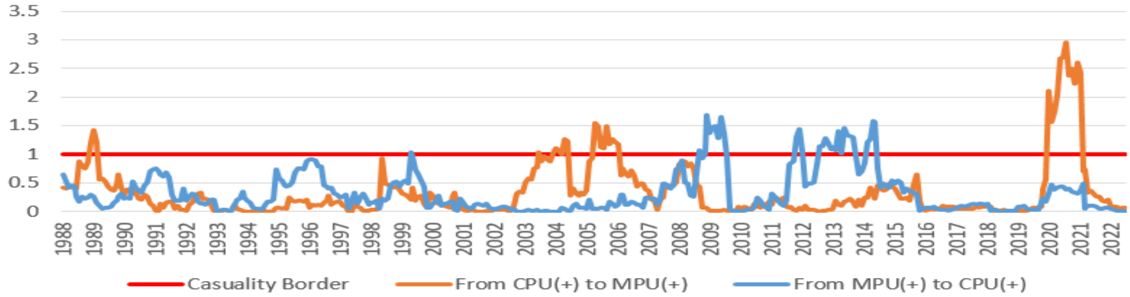

Figure 7. Time-varying causality analysis for CPU (+) and MPU (+), source: own elaboration

According to the results of the time-varying causality analysis in Figure 6, while the causality relationship was from climate policy uncertainty to monetary policy uncertainty at the beginning of the analysis period, the situation reversed in 1992 for 2 years. Although causality between the variables is frequently observed throughout the analysis period, there is no dominant direction of causality. In Figure 7, according to the results of the time-varying causality analysis, the causality relation intensified, especially in the second half of the analysis period. While the direction of causality was from monetary policy uncertainty to climate policy uncertainty for the period of 2008-2014, the direction of causality was from climate policy uncertainty to monetary policy uncertainty at the end of the analysis period.

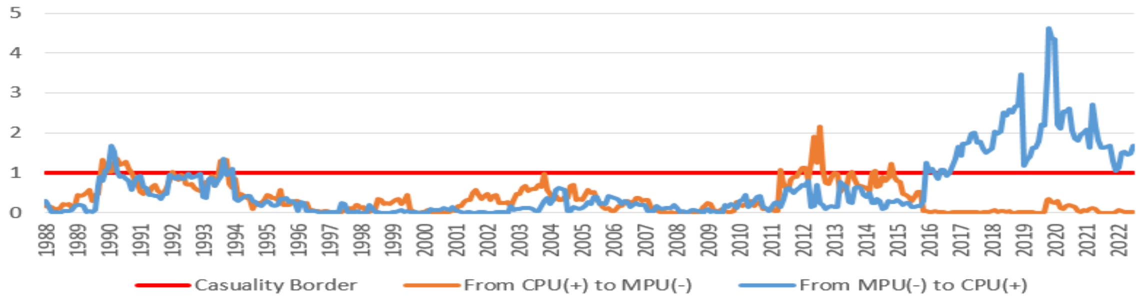

Figure 8. Time-varying causality analysis for CPU (+) and MPU (-), source: own elaboration

According to the results of the time-varying causality analysis, the causality relation intensifies toward the end of the analysis period in Figure 8. While the direction of causality between 2011 and 2015 is from the positive shock of climate policy uncertainty to the negative direction of monetary policy uncertainty, the direction of causality in 2017 until the end of the analysis period is from the negative shock of monetary policy uncertainty to the positive shock of climate policy uncertainty.

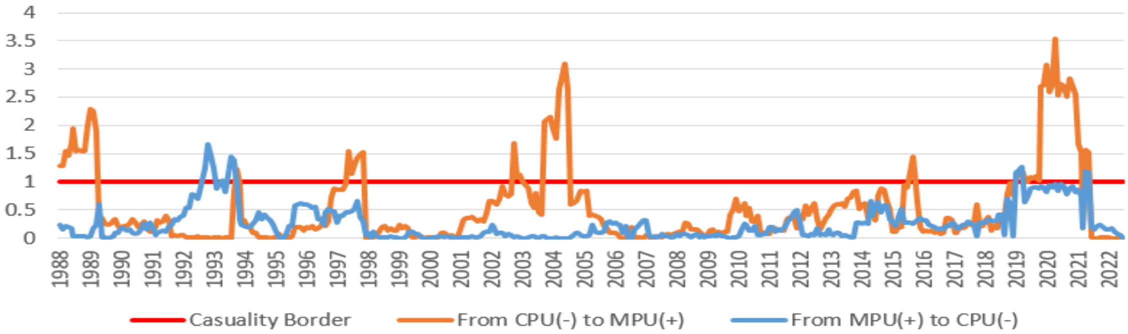

Figure 9. Time-varying causality analysis for CPU (-) and MPU (+), source: own elaboration

In Figure 9, the results of the time-varying causality analysis are analyzed. The dominant direction of the causality relationship is from the negative shock of climate policy uncertainty to the positive shock of monetary policy uncertainty. There is a relationship between the negative shock of climate policy uncertainty and the positive shock of monetary policy uncertainty for the period of 1988-1989, 1997-1998, 2002-2004, 2015-2016 and 2020-2021.

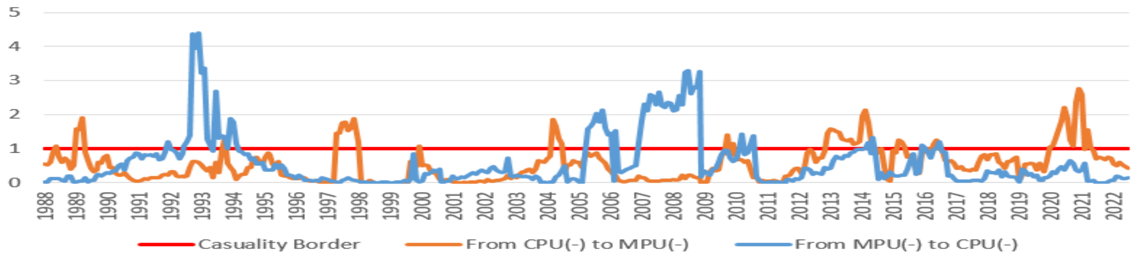

Figure 10. Time-varying causality analysis for CPU (-) and MPU (-), source: own elaboration

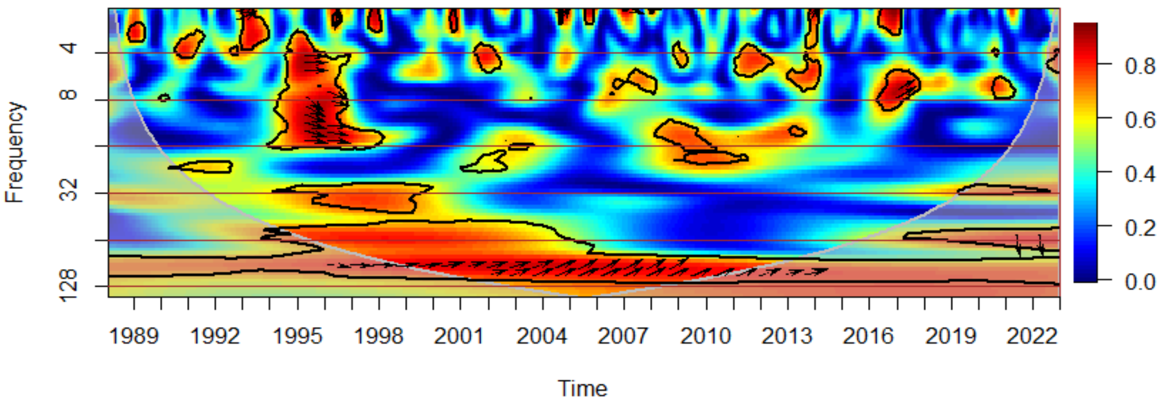

Figure 11. WTC analysis for the CPU and EPU, source: own elaboration

In Figure 10, according to the results of the time-varying causality analysis, the direction of the causality relationship is from the negative shock of monetary policy uncertainty to the negative shock of climate policy uncertainty variable at the beginning and middle of the analysis period, while the direction of the dominant causality is from the negative shock of climate policy uncertainty to the negative shock of monetary policy uncertainty toward the end of the analysis period. The results of the asymmetric ect analysis for climate policy uncertainty and economic policy uncertainty are as follows. The relationship between climate policy uncertainty and economic policy uncertainty is more intense than that between climate policy uncertainty and monetary policy uncertainty in Figure 11. Especially in all years from the beginning to the end of the analysis period, there is a positive and significant relationship at high frequency. Especially between 1994 and 1998, the significant and positive relationship observed at high frequency is also observed at low and medium frequencies.

In Figure 12, the relationship between positive shocks of climate policy uncertainty and economic policy uncertainty is weaker than the relationship between climate policy uncertainty and economic policy uncertainty in the WTC analysis and in the time-varying causality analysis. Throughout the analysis period, significant relationship in the WTC analysis is generally low-frequency and positively correlated.

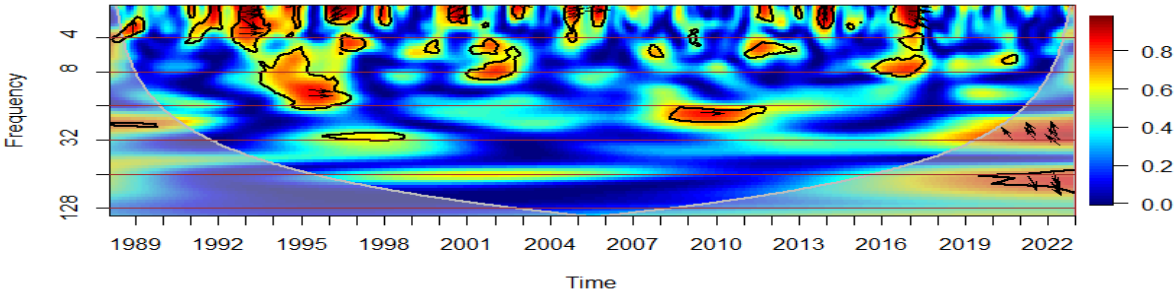

Figure 12. WTC analysis for CPU (+) and EPU (+), source: own elaboration

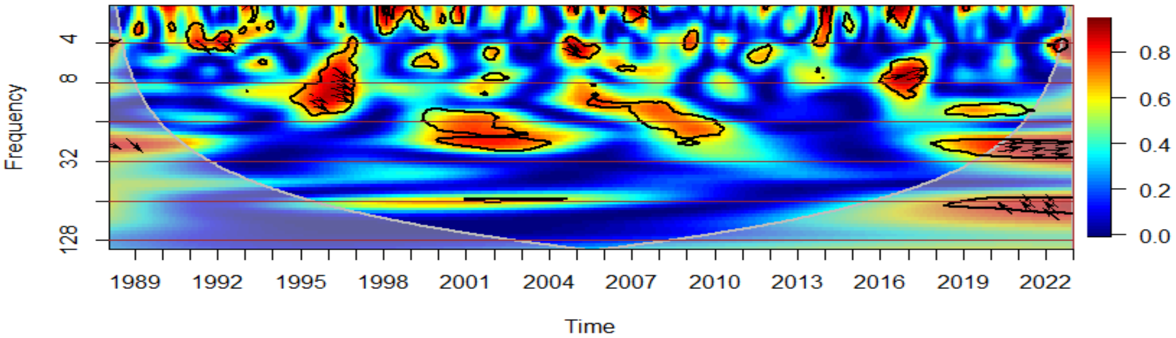

Figure 13. WTC Analysis for CPU (+) and EPU (-), source: own elaboration

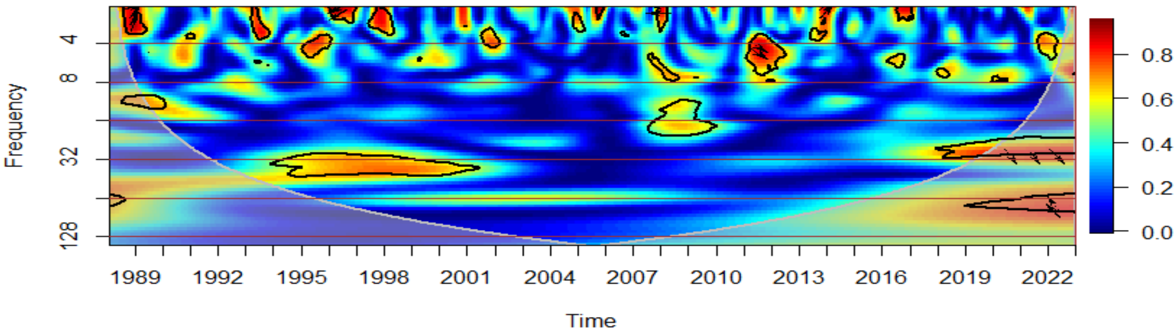

Figure 14. WTC Analysis for CPU (-) and EPU (+), source: own elaboration

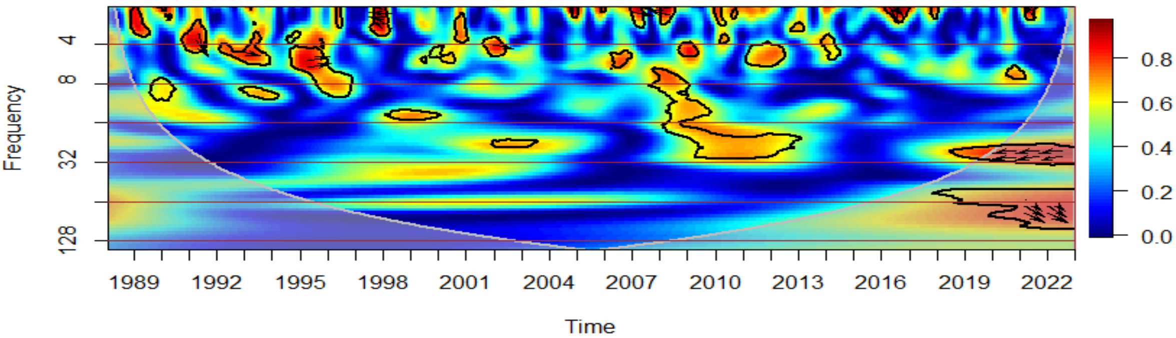

Figure 15. WTC Analysis for CPU (-) and EPU (-), source: own elaboration

In the relationship between the positive shock of climate policy uncertainty and the negative shock of economic policy uncertainty, there is a positive and significant relationship at medium and low frequencies over the period of 1994-1997 and at medium and high frequencies between 2018 and 2022, as shown in Figure-13. In Figure-14, according to the WTC analysis, there is a negative relationship between the negative shock of climate policy uncertainty and the positive shock of economic policy uncertainty at medium frequency and a positive relationship at high frequency between 2019 and 2022.

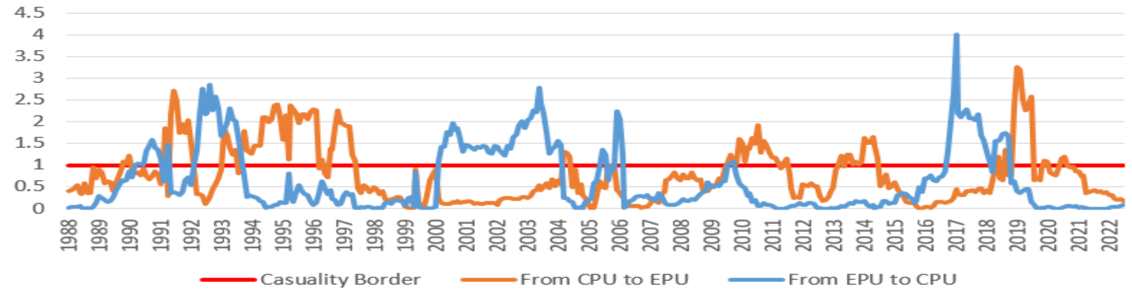

Figure 16. Time-varying causality analysis for the CPU and EPU, source: own elaboration

Finally, in Figure 15, when the relationship between the negative shocks of climate policy uncertainty and economic policy uncertainty is analyzed, according to the results of the WTC analysis, there is a medium- and high-frequency negative relationship between 2018 and 2022 in the last period of the analysis. The results of the time-varying causality analysis for climate policy uncertainty and economic policy uncertainty reveal that similar to the intense relationship between the WTC analysis, it is also observed in the time-varying causality analysis results. At the beginning and end of the analysis period (Figure 16), the direction of the causality relationship is from climate policy uncertainty to economic policy uncertainty, whereas in the middle of the analysis period, the direction of the causality relationship is mostly from economic policy uncertainty to climate policy uncertainty. In Figure 17, when the results of the time-varying causality analysis are analyzed, the direction of causality for the period of 1993-1996 and 2018-2019 is from the positive shock of climate policy uncertainty to the positive shock of economic policy uncertainty. Over the period of 2003-2004, there is a causal relationship between the positive shock of economic policy uncertainty and the positive shock of climate policy uncertainty. According to the results of the time-varying causality analysis in Figure-18, there is a causality relationship from the negative shock of economic policy uncertainty to the positive shock of climate policy uncertainty for the period of 1989-1993, 2005-2006 and 2017-2018. In 1996-1997, 2003-2004, 2007-2009, 2019, and 2020, there is a causal relationship between the positive shock of climate policy uncertainty and the negative shock of economic policy uncertainty.

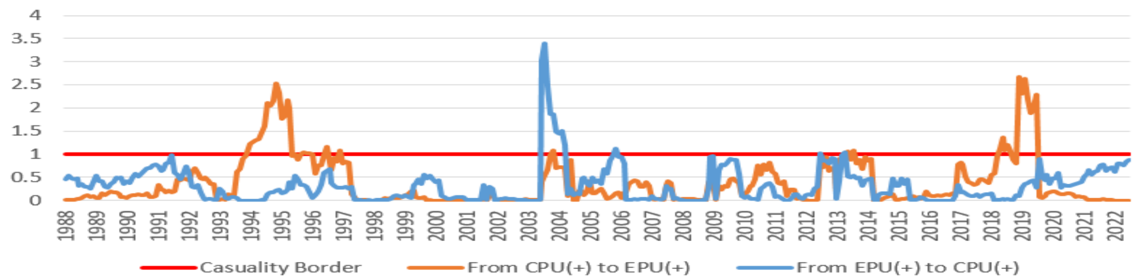

Figure 17. Time-varying causality analysis for CPU (+) and EPU (+), source: own elaboration

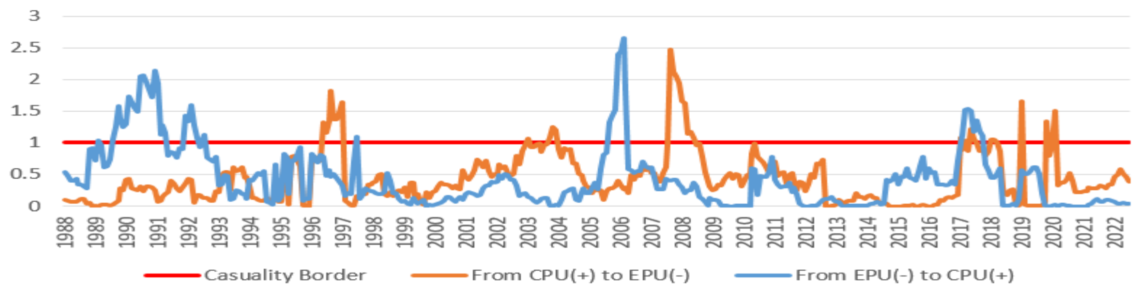

Figure 18. Time-varying causality analysis for CPU (+) and EPU (-), source: own elaboration

According to the results of the time-varying causality analysis in Figure 19, it is possible to discuss a bidirectional causality relationship for the period of 1992-1993. While there is a causality relationship between the positive shock of economic policy uncertainty and the negative shock of climate policy uncertainty over the period of 2003-2004 and 2013-2014, there is a causality relationship between the negative shock of climate policy uncertainty and the positive shock of economic policy uncertainty during 2011-2013 and 2016.

In Figure 20, the results of the time-varying causality analysis show an intense causality relationship. At the beginning, middle, and end of the analysis period, the causality relationship is observed from the negative shock of climate policy uncertainty to the negative shock of economic policy uncertainty. However, over the period of

1992-1994, 2005-2006 and 2009-2010, there is a causal relationship between the negative shock of economic policy uncertainty and the negative shock of climate policy uncertainty.

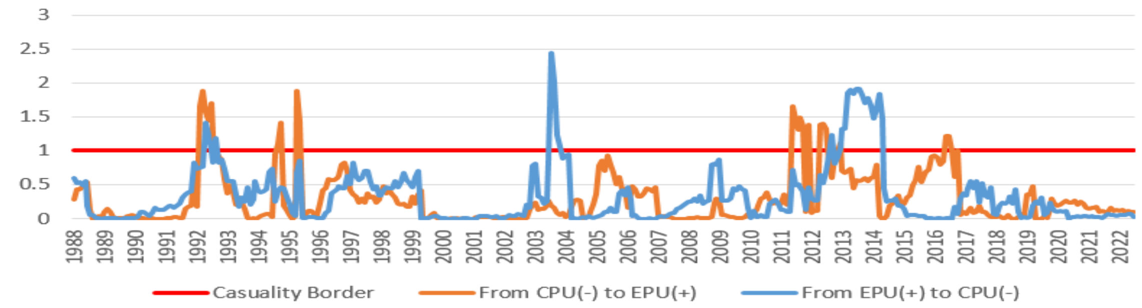

Figure 19. Time-varying causality analysis for CPU (-) and EPU (+), source: own elaboration

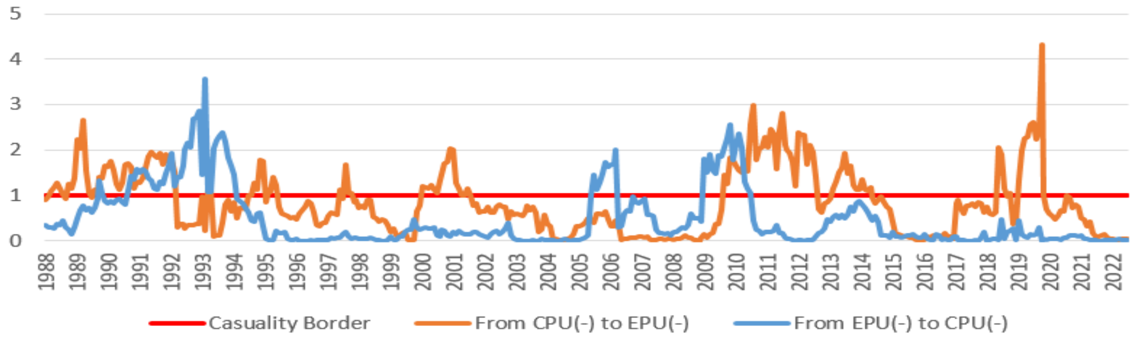

Figure 20. Time-varying causality analysis for CPU (-) and EPU (-), source: own elaboration

5. Conclusion and policy implications

The empirical link between economic, monetary, and climate policy uncertainty is of great importance in many ways. First, climate change is a major and urgent global problem for humanity that needs to be addressed and measures taken. A sustainable economic system may only be possible with low-carbon green economic systems. This issue is a problem for all world economies, and many countries have made serious commitments to transition to a green economy. Transition to a sustainable and low-carbon economy may only be possible by increasing the sensitization of policymakers, investors, businesses, the financial sector, and other stakeholders. The biggest obstacle in this regard is the problem of economic and monetary policy uncertainty. The identification of the impact of economic and monetary policy uncertainty on climate policy uncertainty may increase the interest of decision makers from all sides on the issue.

In doing so, we used the US monthly data for the period 1988–2022 to examine how economic and monetary policy uncertainties affect climate policy uncertainty. For empirical purposes, we performed a fractional frequency Fourier-augmented Dickey Fuller unit root test to determine the unit root properties of the variables. To determine the causal relationship between economic policy uncertainty, monetary policy uncertainty, and climate policy uncertainty, we applied asymmetric wavelet transform coherence and asymmetric time-varying causality tests. The relationship between climate policy uncertainty, monetary policy uncertainty, and economic policy uncertainty is analyzed separately and asymmetrically using time-varying causality and asymmetric wavelet transform coherence frameworks. The common feature of tests applied in the analysis is that they do not give a single result for the entire period but multiple results that vary over time. Therefore, the study could not reach a single result, but the dominant results were identified. Therefore, the relationship between climate policy uncertainty and monetary policy uncertainty is analyzed via the asymmetric wavelet transform coherence test. At different frequencies and time periods, the results demonstrate a favorable association.

According to the results of the time-varying asymmetric causality test, which examines the relationship between policy uncertainties, a time-varying, sometimes unidirectional, and sometimes bidirectional causality relationship has been detected in the United States of America. Therefore, in today's world, where climate change is on the agenda worldwide, when any policy is to be implemented, it is necessary to direct the policy to be implemented by considering the environmental, economic, and financial effects of these policies. In addition, when environmental or economic policies are to be implemented, it is important that all policies are not evaluated unilaterally but are implemented in a coordinated manner by other stakeholders in the economy, environment, and society. In this regard, economic managers, central banks, and environmental institutions and organizations should work together.

In this study, asymmetric wavelet transform coherence is used to examine the relationship between climate policy uncertainty and economic policy uncertainty. The results show that there is a high frequency and positive relationship between the variables. Time-varying causality analysis reveals that there is a bidirectional causal relationship between climate policy uncertainty and policy uncertainty in different historical periods. Along with the direction of causality, positive and negative multiplicities are found to periodically affect each other as reciprocity. Uncertainty about climate policy can lead to uncertainty about U.S. economic policy, which can negatively affect investment, economic growth, market stability, and corporate strategy at the micro level. This unpredictability can lead to policy gridlock, increase market volatility, and dampen investors' appetite for investment. Moreover, uncertainty can affect the cost of capital, increasing the cost of capital for companies trying to attract investors or borrow. Since increased uncertainty can also increase the perception of risk, financing alternatives for projects with inherent risks may be limited, again increasing the cost of capital. Economic policy uncertainty can make it difficult for companies to adapt to new regulations, leading to additional costs, barriers to new regulations, and uncertain legal outcomes. In the US, climate policy uncertainty clearly contributes to economic policy uncertainty. All these reasons make it clear that governments should focus on harmonizing climate and economic policies to minimize conflicting objectives and guarantee a stable economic environment.

The study offers important messages to all interested parties, especially policymakers. Encouraging and sustaining investment and economic growth can only be achieved by ensuring clear and decisive climate policies and uniform regulatory frameworks. Stakeholder engagement can increase policy coherence and reduce uncertainty. Funding research, education, and training can lead to a better understanding of climate and economic drivers. Academic work in this area would be particularly beneficial to this process. Businesses can manage the uncertainties surrounding climate policies by creating risk management tools such as insurance policies and green bonds. Information on climate policy should be transparent to support mitigation and decision-making processes. Policy frameworks must be flexible and include mechanisms for continuous assessment responsive to changing environmental conditions. It is not enough for these policies to be country-based. International cooperation and joint regulations are also needed to maintain a stable global investment climate. Sustainable economic growth and development for all countries of the world will only be possible if these issues are considered. This study clearly demonstrates the responsibility of all the relevant parties.

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