



International Journal of Global Environmental Issues

ISSN online: 1741-5136 - ISSN print: 1466-6650

<https://www.inderscience.com/ijgenvi>

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DOI: [10.1504/IJGENVI.2024.10066777](https://doi.org/10.1504/IJGENVI.2024.10066777)

Article History:

Received:	01 March 2023
Last revised:	02 March 2023
Accepted:	27 February 2024
Published online:	26 September 2024

The effect of global economic and geopolitical uncertainty on global food commodity prices

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Abstract: The paper aims to assess the impact of global uncertainty, on global food commodity prices. The global uncertainty variables include global economic policy uncertainty index, global climate policy uncertainty, and global geopolitical risk indexes. Markov switching dynamic regression (MSDR) model is employed using monthly data during the period from January 1997 to September 2022. Results of MSDR show that there are two distinct states during the sample period, the state of low volatility period (state 1) and the state of high volatility (state 2). In state 1, all explanatory variables have a significant impact on the global food commodity price index. However, in state 2, only the economic policy uncertainty has a significant impact on food commodity prices, implying that uncertainty in global economic policy is the principal driver of global food commodity prices in the two states.

Keywords: global economic policy uncertainty; GEPU; climate policy uncertainty; food commodity.

Reference to this paper should be made as follows: Onour, I.A. (2024) 'The effect of global economic and geopolitical uncertainty on global food commodity prices', *Int. J. Global Environmental Issues*, Vol. 23, No. 1, pp.47–58.

Biographical notes: Ibrahim A. Onour is a Professor of Economics at the School of Management Studies, University of Khartoum. He graduated with a PhD in Econometrics from the University of Manitoba – Canada, and obtained his Master's in Economics at Lakehead University, Canada, and BSC honours in Statistics from the University of Khartoum-Sudan. He taught in a number of Universities in Canada, Middle East, and Africa. He published extensively in leading international journals in the areas of development economics, financial econometrics, macroeconomics, international finance, capital markets, environmental economics, and energy economics.

1 Introduction

Since the Russian invasion of Ukraine earlier this year, significant global attention has been directed toward bolstering energy security, as crude oil and gas prices displayed a steep upward move in a relatively short period. Due to the war-related energy crisis, the

agriculture commodity supply chain has also been interrupted, further spurring inflationary pressures in many developing countries. Global food commodity prices were already on the rise due to supply chain restrictions brought on by COVID-19, but the Russian war crisis has exacerbated the trend. As a result, agricultural commodity basket prices have significantly risen during the war, as wheat and corn prices have risen by 37% and 21%, respectively in the first two-month period after the war breakout. Russia and Ukraine are both major producers and exporters of agricultural commodities, as together both account for 50% of global sunflower oil exports and 25% of global wheat exports. With Russia's blockade of the black sea and fighting around the Sea of Azov, the major Ukraine grain export seaport, already creating a shortage of wheat in global markets. As a result, it is highly expected that the ongoing war between Russia-Ukraine will exacerbate global economic uncertainty as it will influence global energy and food markets, which already felt its impact on the major economies of Europe and North and South America. Disruption in global wheat export can influence directly as importing countries draw down their stocks due to the decline of export from the major producer, Ukraine, and also will influence indirectly the level of stocks because of the resulting volatility in global wheat prices.

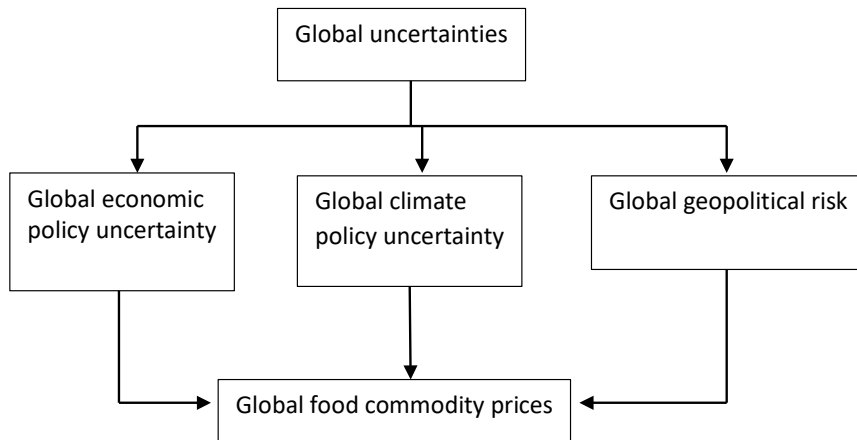
The impact of global political shocks on global economic uncertainty transmits via its effect on the global energy markets, and climate policy impact. The impact of global economic uncertainty on wheat production can take different venues, besides its effect on energy prices, also through exchange rate policies, and through its impact on other food commodity markets.

Considerable portion of existing literature on this area associate economic policy uncertainty on global agricultural food price changes via trade restrictions, climate change, energy markets, and speculations in financial markets, as indicated by Anser et al. (2021). More specifically, Boczar and Błażejczyk-Majka (2022) estimate the impact of global uncertainty on agriculture food prices by assessing technical efficiency of European Union's wheat producers and showing that the EU producers' competitive position strongly dependent on sustainability of direct payments (subsidy) of EU governments to wheat producers. Bobojonov et al. (2020) investigated the causes of wheat price spikes in Central Asia countries to verify limited effect of trade restrictions on price spikes. Sağlam Çeliköz et al. (2022) showed that economic globalisation increase environmental consciousness, and thereby reduce ecological impact of food security. Moschini and Henessey (2001) assess the impact of uncertainty, risk aversion attitude, and risk management tools on wheat producers by showing that volatility in wheat prices is linked to the use of wheat for non-food uses such as biofuels, in particular when energy prices rise at higher levels in developing countries and Similarly, Du et al. (2011) showed that integration of agricultural commodity markets with energy and financial markets created a complex association between oil and wheat markets and has increased speculative effects on future agriculture commodity markets. Chang and Su (2010) indicated that volatility in crude oil futures contracts had an influence on the future prices of soybeans and corn and showed evidence of volatility transmission from crude oil to corn and soybeans. Onour and Sergi (2011) studied volatility of global food prices, and showed that volatility of global agricultural food prices characterised with the intermediate and short memory behaviour, implying that the volatility of food agricultural prices is mean reverting. Gohin and Chantret (2010) assessed the long-run association between energy markets and agriculture markets and showed that that the association between these markets increased following the biofuels market creation in 2004. A

similar finding was revealed by Abbott et al. (2008) and Baffes (2007) who have shown that the rise in international wheat and corn prices during times of food crisis can be attributed to biofuels markets, and speculative factors. However, some researchers, Zhang et al. (2010) indicate there is no direct long-run price association between fuel and agricultural commodity prices but only limited, if any, direct short-run relationships. Gilbert and Morgan (2010) indicated that there is no direct association between oil and agricultural markets but associated high volatility of agricultural prices with monetary and financial developments. Onour (2010) showed evidence of linear and nonlinear association between agricultural commodity markets and oil prices.

In light of all these complexities between global food commodity prices and global uncertainties, the initial purpose of this paper is to assess more formally the impact of global uncertainty on global food commodity prices by breaking down global uncertainties into global economic policy uncertainty (GEPU), global environmental policy uncertainty (GEU), and global geopolitical risk (GPR).^{1,2,3,4} The contribution of this paper is to fill the gap of associating global food commodity prices with major indicators reflecting global uncertainty, as indicated in the schematic illustration below (Figure 1).

Figure 1 Global uncertainty transmission effects



Source: Author's own elaboration

The remaining parts of the paper structured as follows. Section 2, present material and research methods; Section 3 includes data analysis and validation; Section 4 discusses estimation results. Section 5 concludes the research finding.

2 Material and methods

Markov-switching models (MSMs) are increasingly becoming important in economic and business analysis that requires capturing the impact of random shocks that creates structural change and transition from one state to another. Attractive feature of these models, is that, they display transition probabilities that estimate the time duration of the process in each separate state.

For illustrative purpose in the following we assume the transition of stochastic process constitutes only two states, that is the series x_t , where $t = 1, 2, \dots, T$, is displayed by two states:

$$\text{state 1: } x_t = \mu_1 + s_t$$

$$\text{state 2: } x_t = \mu_2 + s_t$$

where μ_1 and μ_2 are constant terms in state 1 and state 2, respectively. s_t is a white noise error term with variance σ^2 . The two states model shifts between the intercept term, and if the time of transition between the two states is known, the above model can be indicated as

$$x_t = s_t \mu_1 + (1 - s_t) \mu_2$$

where s_t is indicator variable that takes the value of 1 if the process in state 1 and 0 otherwise.

In spite of its difficulty to determine accurately, the transition probabilities can be estimated at any point of time in MSM models. As a result, in a process of two states the transition probabilities can be indicated as $p_{s_t s_{t+1}}$. For instance, p_{21} denotes the probability of switching from state 2 in the current period to state 1 in the next immediate period. Similarly, p_{22} indicate the probability of staying in state 2, given that in the last most recent period the process in state 2. Probability values closer to 1 imply persistence of the same state for longer period of time.

Adjustment of MSDM process from one state to another, can be reflected in the following specifications:

$$y_t = \mu_{s_t} + z_t \beta_{s_t} + s_s$$

where y_t is the dependent variable, μ_{s_t} is the state dependent constant (intercept) term, z_t is a vector of exogenous variables with state dependent coefficients β_{s_t} and s_s is independent and identically distributed error term.

3 Results

The sample of the data constitutes monthly data on the GEPU index, the global climate policy uncertainty, the geopolitical risk index, and the global food commodity price index, during the period from January 1997 to September 2022 (309 observations).

To check if the data display structural change we used Hansen instability test, which shows (Table 1) evidence of instability of the coefficients of the three explanatory variables, as well as the variances of the coefficients.

Given results in Table 1 demonstrate evidence of structural break in the data, then to specify the date of structural change we employed graphical illustration, as in Figures A1–A5, which monitor the time path of the three explanatory variables during the sample period. The figures indicate there is a distinct two states of low volatility and high volatility periods for the three explanatory variables, before and after January 2016.⁵ The descriptive summary statistic results in Table 2 as well as Figures 2 and 3 also show evidence of low volatility period (state 1) and higher volatility (state 2). Similarly in Table 2, the mean of all variables is significantly higher in state 2, compared to state 1.

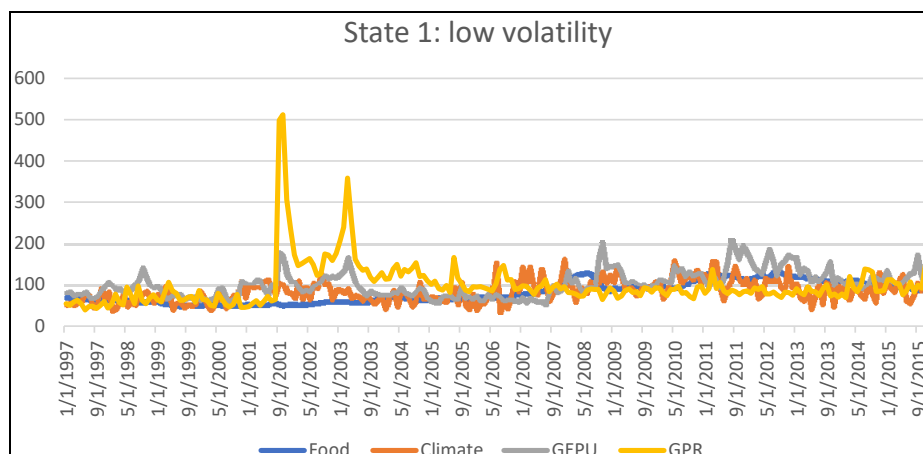
Also volatility of the variables, as represented by the standard error and the standard deviation statistics, show there is significant change in all variables in state 2, compared to state 1. The skewness statistic is positive in both states for all variables, implying that for all these variables there is higher likelihood that the uncertainties on all these variables are likely to continue increasing in the coming years. The maximum statistic values in the two states in Table 2 and Figures 2 and 3 also display similar results for all variables.⁶ Taking into account the evidences of the two states, Table 3 report Markov switching dynamic regression results in each state.

Table 1 Hansen parameters instability test

<i>Coefficients</i>	<i>Test stat</i>	<i>Critical values*</i>	<i>Decision</i>
X1	7.75	0.748	Unstable
X2	7.82	0.748	Unstable
X3	8.54	0.748	Unstable
C	8.70	0.748	Unstable
Variance	1.51	0.748	Unstable
Joint	16.3	0.748	Unstable

Notes: *1% significance level. X1 = global climate policy uncertainty; X2 = GEPU; X3 = global geopolitical risk. **The data source for all these variables is indicated in footnotes 1, 2, 3 and 4.

Figure 2 State 1: low volatility (see online version for colours)



Source: Author's own elaboration

4 Discussion

Estimation results of Markov switching dynamic regression (MSDR) in Table 3 indicate more formally the association between the dependent variable, which is global food commodity price index and the explanatory variables. Results of MSDR in the table corroborate with the plots of Figures 2 and 3, confirm that there are two distinct states

during the sample period, the state of low volatility and the state of high volatility, before and after 2016. As indicated in the table, the explanatory variables: global climate uncertainty, GEPU, and global geopolitical risk, have all significant impact on the global food commodity price index in state 1 period. However, in state 2 only the economic policy uncertainty has significant impact on food commodity price. It worth mentioning that the geopolitical risk indicator have a negative impact on food commodity price index in state 1, and a positive association in state 2, though insignificant. However, the economic policy uncertainty has a significant positive impact on global food commodity prices in the two states, while the effect of climate policy uncertainty has a significant positive impact in state 1, but insignificant in state 2. As indicated in Figure A6, higher global geopolitical risk, associated with the period of state 1, in which we had major global shocks such as Gulf war, Bosnian war, Iraq and Afghanistan invasions.

Table 2 Descriptive statistics*

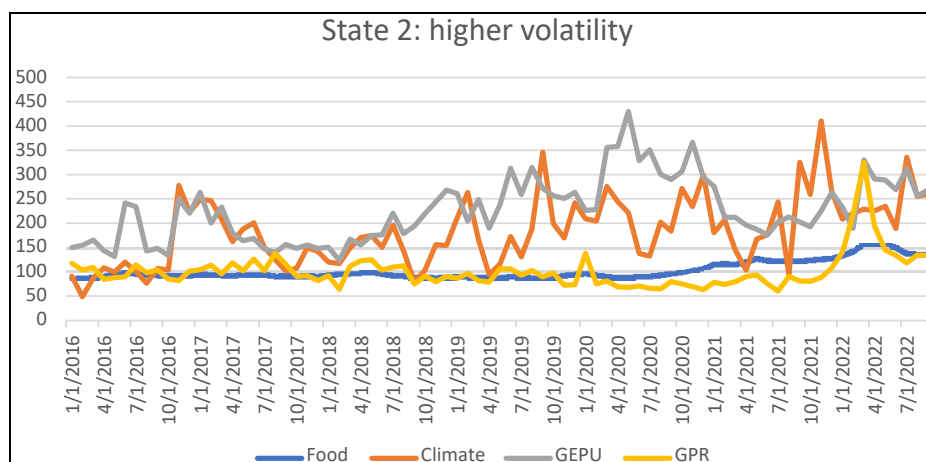
<i>State 1</i>	<i>Food</i>	<i>Climate</i>	<i>GEPU</i>	<i>GPR</i>
Mean	79.48	82.75	101.10	99.47
Standard error	1.80	1.90	2.26	3.73
Median standard	67.85	78.90	98.15	87.05
Deviation sample	27.13	28.75	34.14	56.32
Variance	735.98	826.48	1,165.58	3,171.49
Kurtosis	-1.24	-0.12	0.32	25.21
Skewness	0.43	0.55	0.83	4.25
Range	87.86	135.10	165.49	473.48
Minimum	44.50	28.16	48.88	39.05
Maximum	132.36	163.26	214.36	512.53
<i>State 2</i>	<i>Food</i>	<i>Climate</i>	<i>GEPU</i>	<i>GPR</i>
Mean	100.90	183.72	227.40	101.57
Standard error	2.25	7.85	7.32	4.09
Median	91.52	176.76	221.03	92.60
Standard deviation	20.28	70.67	65.85	36.82
Sample variance	411.39	4,994.61	4,336.67	1,356.01
Kurtosis	1.09	0.32	-0.04	17.44
Skewness	1.48	0.59	0.59	3.44
Range	75.93	362.16	306.41	264.61
Minimum	83.11	49.13	123.86	60.68
Maximum	159.04	411.29	430.26	325.29

Note: *the data source for all these variables is indicated in footnotes 1, 2, 3 and 4.

The negative association between global food commodity prices and geopolitical risk in state 1, implies that since political turmoil in the period of state 1, was almost in major food commodity importing countries (mostly in the oil rich Middle East countries), then the excess surplus in food commodities caused by demand downturn pushed global food prices downward. However, after 2016, state 2 period, since no major global political risk events, the impact of geopolitical risk on global food commodity prices is insignificant. The transition probability $P_{22} = 0.99$, implies that duration of state 2, the high volatility period which started from 2016, is expected to continue till the year 2024 (eight years

period), and $P12 = 0.02$ implies that the likelihood of reverting from state 2 to state 1 in the coming few years is of very minimal probability

Figure 3 State 2: high volatility (see online version for colours)



Source: Author's own elaboration

Table 3 Markov-switching dynamic regression

Global food index	Coef.	Std. error	p-value
State 1			
Climate	0.078*	0.026	0.003
GEPU	0.094*	0.020	0.000
GPR	-0.033*	0.010	0.002
Constant	47.98*	1.824	0.000
State 2			
Climate	0.010	0.032	0.75
GEPU	0.170*	0.040	0.000
GPR	0.028	0.049	0.56
Constant	78.08*	4.955	0.000
Sigma 1	8.88	0.58	
Sigma 2	15.64	0.92	
Transition probabilities			
P11	0.98		
P12	0.02		
P21	0.01		
P22	0.99		
D(2, 2)	99 months		
Log-likelihood	1,220		
AIC	7.98		

Note: *significant at 1% sig.level.

Source: Author's own elaboration

5 Conclusions

The paper investigates the impact of a number of variables that reflect global uncertainty on global food commodity price index using Markov switching dynamic regression. The variables pertaining to global uncertainty include GEPU index, global climate policy uncertainty, and global geopolitical risk indexes. The findings of the paper indicate evidence of two distinct states during the sample period (January 1997 to September 2022), the state of low volatility of the three explanatory variables before 2016, and the state of high volatility, after 2016. Estimation results also indicate all explanatory variables, have significant impact on the global food commodity price index in the state 1 period (low volatility period). However, in state 2 (high volatility) only the economic policy uncertainty has significant impact on food commodity price, implying that uncertainty in global economic policy is the principal driver of global food commodity prices in both periods. However, the other two variables related with global political risk and global environmental issues affect global food prices only in periods of low volatility. The negative association between global food commodity prices and geopolitical risk in state 1, implies that as political turmoil in the period of state 1, was almost in major food commodity importing countries (mostly in the oil rich Middle East countries), then the excess surplus with major producers of food commodities caused drop in demand for food commodities and decrease in global food commodity prices. However, after 2016, state 2 period, as there are no major events of global political risks, the impact of geopolitical risk on global food commodity prices turned out to be insignificant. The transition probability $P_{22} = 0.99$, implies that duration of state 2, the high volatility period which started from 2016 and onward, is expected to continue till the year 2024 (eight years period).

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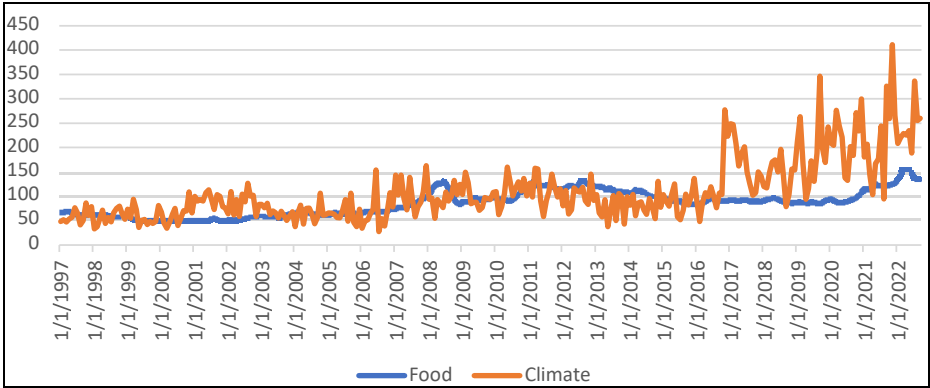
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Notes

- 1 Global Commodity Food Price Index includes cereal, vegetable oils, meat, seafood, sugar, bananas, and oranges price indices. The data on global food price index gathered from Index Mundi website: commodity prices – price charts, data, and news – IndexMundi.
- 2 The GEPU index is a GDP-weighted average of national economic policy uncertainty (EPU) data collected from daily national news papers in 21 countries that constitutes over 70% of global output. Each national EPU index reveals three components pertaining to the economy (E), policy (P) and uncertainty (U).
- 3 Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the UK, and the USA.
- 4 For a detailed explanation of a country-based EPU indices, see *Measuring Economic Policy Uncertainty and Paper and Figures and Audit Coding Guide*.
- 5 During 2016, the Heidelberg Institute for International Conflict Research indicated that there were 226 politically driven armed conflicts world-wide (of which 38 as highly violent: 18 full-scale wars, 20 limited wars).
- 6 The spikes in the global geopolitical risk index in 2001–2003 are mainly due to the Gulf War impact.

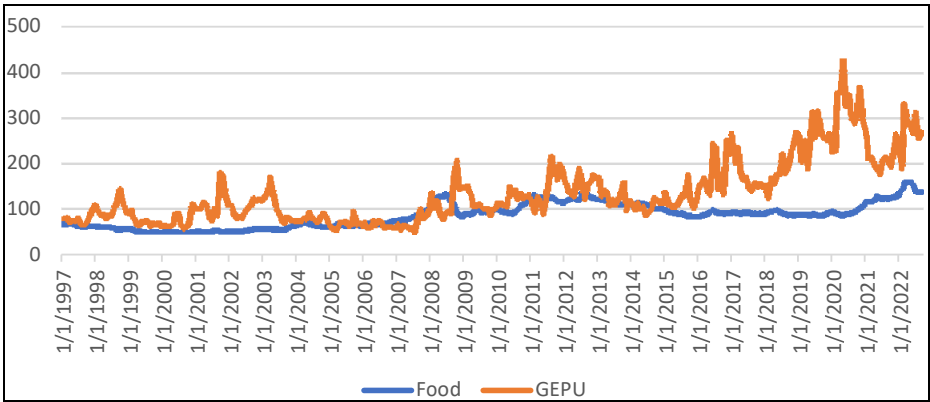
Appendix

Figure A1 Global food price index vs. global climate policy uncertainty (see online version for colours)



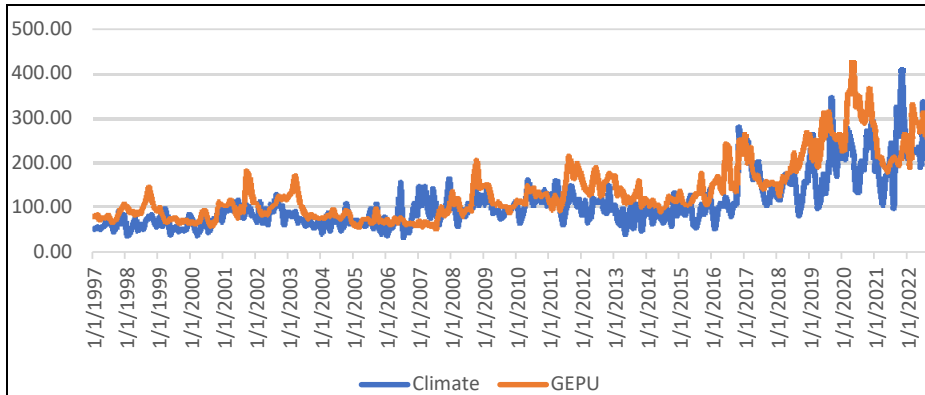
Source: Author's own elaboration

Figure A2 Global food price index vs. global economic policy uncertainty (see online version for colours)



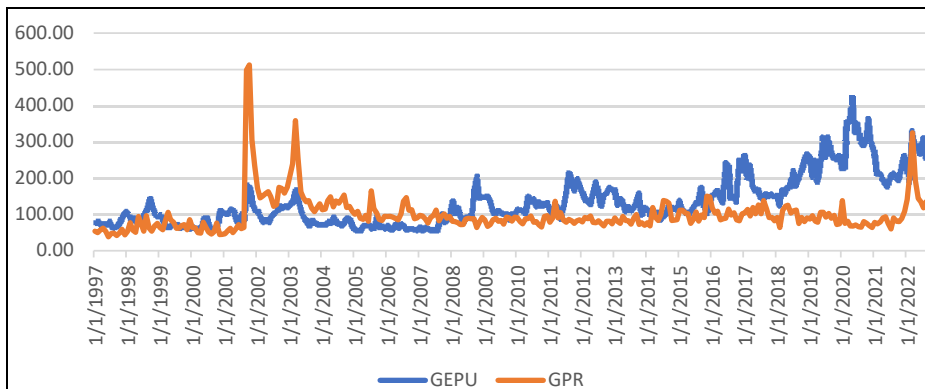
Source: Author's own elaboration

Figure A3 Global climate policy uncertainty vs. global economic policy uncertainty (see online version for colours)



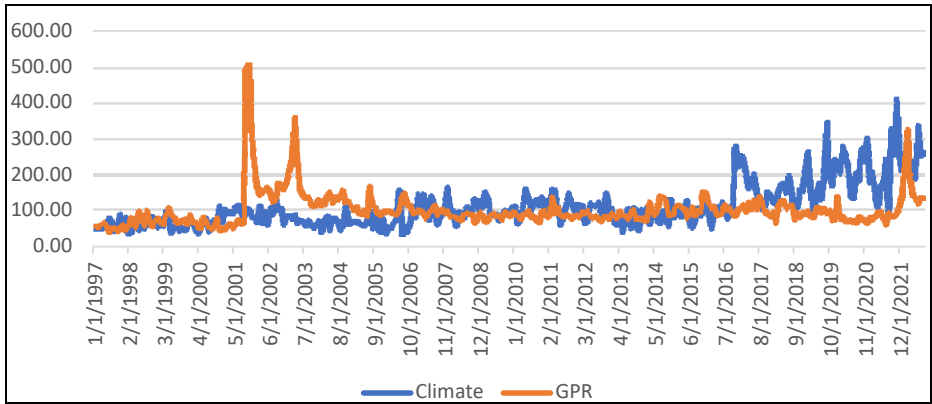
Source: Author's own elaboration

Figure A4 Global economic policy uncertainty vs. global geopolitical risk (see online version for colours)



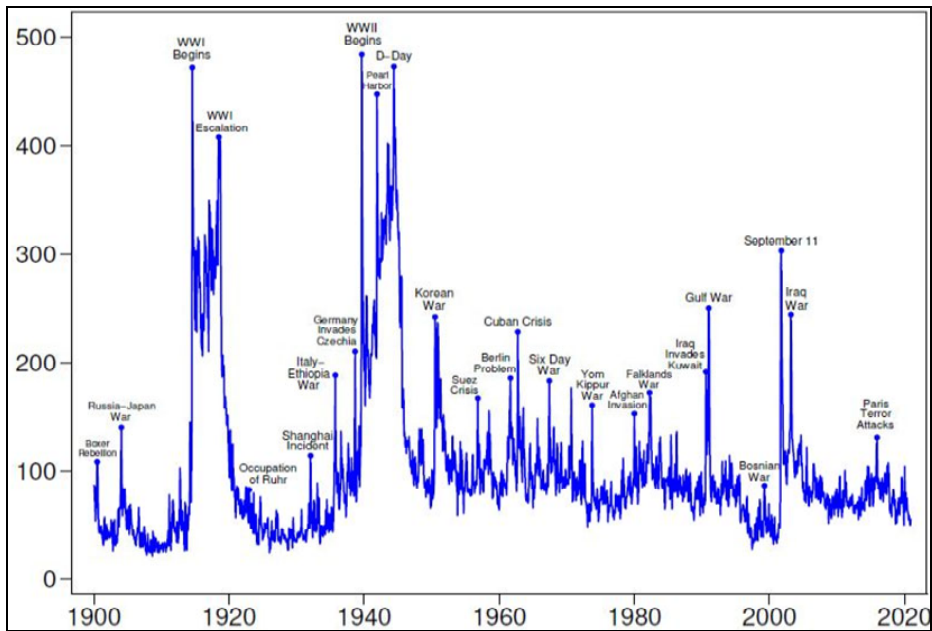
Source: Author's own elaboration

Figure A5 Global climate policy uncertainty vs. global geopolitical risk (see online version for colours)



Source: Author's own elaboration

Figure A6 Historical geopolitical risk index (see online version for colours)



Notes: Historical Geopolitical Risk Index from January 1900 through December 2020.
Index is normalised to 100 throughout the 1900–2019 period.

Source: Caldara and Matteo (2021)