Climate and Economic Policy Uncertainty and the Macroeconomy

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Abstract

The paper examines the dynamics between economic and climate policy uncertainty and studies how these uncertainties affect the economy. Using quarterly US data from 1987Q2 to 2022Q2 and a vector autoregressive model, it highlights the importance of considering both types of policy uncertainty in policy-making processes. The findings also indicate that there is a negative relationship between policy uncertainty and investments suggesting that businesses and households become more cautious about their spending when they are uncertain about future economic conditions, governmental policies, or regulatory environments. Unemployment has varying effects depending on whether there is a shock on CPU or EPU, while the stock market is significantly affected only by a positive shock on economic policy uncertainty, implying that investors may be more risk conservative in uncertain environments. When inflation is included in the analysis, suggesting that the effects on prices vary depending on the shocks on the EPU and CPU. There is a negative relationship between EPU and inflation and a favourable relationship between CPU and inflation because of different policies, regulations, and expectations.

JEL Classification: E21, E31, Q54
Keywords: Climate/Economic Policy uncertainty, Investments, Unemployment, Innovation, Government policies.

Contents

1. Introduction

One of the most important and persistent dangers to society in the twenty-first century is climate change. Nevertheless, significant attempts to reduce emissions are still in their early phases despite the seriousness of the situation being acknowledged (Masson-Delmotte et al., 2021). This is because policymakers are finding it difficult to send the right long-term signals that will motivate successful action. In addition, recent occurrences such as the CoVid-19 pandemic, geopolitical crises like the Ukraine War, fuel price increases that result in inflation, and the closure of major banks have increased uncertainty in our lives. This prevailing uncertainty poses challenges for central banks, governments, and policymakers, impeding their ability to make informed decisions and implement effective policies (Bloom et al., 2018).

Both consumers and businesses experience the effects of policy uncertainty, which adds to an environment of pessimism and ambiguity. Understanding the effects of climate and economic policy uncertainty on the broader macroeconomy is crucial. Does a particular type of policy uncertainty consider to be more harmful to an economy? If so, does this imply that appropriate organizations and bodies should take actions focusing on one category over the other?

This study aims to address these critical questions by analyzing aggregate quarterly data from 1987Q2 to 2022Q2 for the United States. The data is collected from a variety of sources such as the U.S. Bureau of Economic Analysis, U.S. Department of the Treasury, Fiscal Service, and U.S. Bureau of Labor Statistics. Employing a vector autoregressive (VAR) model, this study seeks to capture the dynamic relationship between multiple variables over time. Specifically, it investigates the relationship between policy uncertainty (climate and economic) and key macroeconomic indicators such as investments, stock, unemployment, and inflation. Importantly, the study acknowledges the limitations imposed by the availability of data, incorporating them into the analysis.

Our findings indicate that there is a relationship between economic policy uncertainty (EPU) and climate policy uncertainty (CPU). The results show that EPU and itself as well as CPU and itself are positively related however, these relationships die out through time (carryout effect). The existence of an additive effect on EPU after an innovation on CPU adds credence to the idea that climate policy uncertainty increases economic policy uncertainty. This conclusion emphasizes how crucial it is to consider both types of policy uncertainty when formulating policies, as changes in economic and climate policy uncertainty can have an impact on each other.

The findings also show the effects of positive shocks on CPU and EPU on key economic variables after examining the impulse-response functions. Uncertainty surrounding climate policy has an adverse impact on investments, leading businesses to become more cautious and postpone or scale back their investment plans. Unemployment appears to be negatively affected by CPU, possibly opening job chances in the renewable energy industry or other sectors that are in line with sustainable business practices. Economic policy uncertainty has a negative impact on investments, demonstrating that businesses may be less willing to invest in new projects, grow their operations, or make significant capital investments if they are uncertain about future economic conditions, governmental policies, or regulatory environments. Reduced investment activity may result in fewer jobs being created and possible job losses, which will raise unemployment rates. Therefore, there is a positive and long-lasting relationship between EPU and the unemployment rate. Although the relationship between CPU and the stock market is insignificant, the stock market is affected by a positive shock on EPU, and this suggests that investors may become more cautious and risk-averse when there is significant uncertainty around the course or impact of economic policy. Negative sentiment may in turn result in selling pressure and pressure on stock prices to decline. Finally, incorporating inflation into the analysis finds that whereas economic policy uncertainty is linked to lower inflation rates, climate policy uncertainty is linked to higher prices. These connections suggest that pricing dynamics in the economy can be affected by policy uncertainty.

This research contributes significantly to the existing literature as it is the first paper to comprehensively examine the relationship between climate and economic policy uncertainty. It explores the bidirectional causality between climate policy uncertainty and economic policy uncertainty, while also investigating the combined impact of these uncertainties on macroeconomic indicators and the economy in general. By utilizing aggregate data instead of micro-level data related to households or firms, this study expands the body of knowledge by providing a broader understanding of relationships at an aggregate level.

The subsequent sections of this paper provide an overview of the relevant literature in Section 2, followed by a detailed presentation of the data sources and methodology employed in Section 3. Section 4 analyses the key findings of the estimation, leading to further discussion and concluding remarks in Section 5.

2. Literature Review

One could argue that the literature on this issue up to this point is both recent and sparse. With a few exceptions that were published in the previous 6-7 years, the most recent studies have been published during the last 2 years. The number of studies about economic and climate policy uncertainty and whether they have an impact on the economy, however, is still quite modest.

Uncertainty in economic policy refers to the risk posed by future regulatory and governance frameworks that remain unidentified. This tendency raises the possibility that consumers and businesses would put off spending and investments because of a volatile market (Al-Thaqeb et al. 2019). According to Kang et al. (2014), economic policy uncertainty affects firms' investment decisions. Firms become more cautious with investment plans when they are uncertain about the costs of conducting business due to potential changes in regulation, the cost of health care, and taxation. For firms with more firm-level uncertainty and during a recession, the impact of economic policy uncertainty on firm-level investment is more significant. The authors also highlight that economic policy uncertainty (extrinsic uncertainty) combined with firm-level uncertainty (intrinsic uncertainty) works through news-based policy and shocks to federal expenditure policy.

Baker et al. (2016) develop a new index of economic policy uncertainty. Based on much evidence, this index is used as a proxy for changes in economic policy uncertainty. However, in order to examine the utility of their index combined with firm-level data, they find that policy uncertainty is related to higher stock price volatility as well as lower investment and employment in sectors that are affected by EPU, including finance, health care, infrastructure, etc. On the other hand, using macro-level data they find that innovations in policy uncertainty predict declines in investment, output, and employment in the United States. Potential concerns related to newspaper reliability, accuracy, bias, and consistency led Davis (2016) to build on that EPU index and develop a different EPU measure, i.e., a global measure. In particular, this global index is a GDP-weighted average of national EPU indices for 16 countries that account for two-thirds of global output. Major data providers like Bloomberg, FRED, Haver, and Reuters carry his global economic policy uncertainty (GEPU) index in response to requests from banks, hedge funds, companies, and policymakers, giving to the index a market-use validity. According to this market adoption pattern, Davis's index likely contains information that can be helpful to a variety of decision-makers.

Undoubtedly there is climate change, and this much is known. The timing and severity of climate change, as well as the cost of moving to a low-carbon future, are less known. As a result, there is a great deal of policy uncertainty because many programs and policies are still in the development phase. We usually refer to this uncertainty as climate policy uncertainty. Following the methodology of Baker et al., (2016), Gavriilidis (2021) measures climate policy uncertainty by constructing a CPU index based on news from major US newspapers. The CPU index seems to be able to identify significant events related to climate policy. This study additionally investigates how climate policy uncertainty affects CO_2 emissions, suggesting that shocks to this policy uncertainty are linked to decreased emissions across most of the sectors and at the aggregate level.

Atsu and Adams (2021) as well as Xue et al. (2022) study climate change, energy consumption, and whether policy uncertainty is a key factor for these concepts. The first study deals with the countries Brazil, Russia, India, China, and South Africa, and investigates the relationship between financial development, energy consumption and EPU, while the second one examines how using sustainable energy affects CO2 emissions in one of the European countries (i.e., France). On the one hand, Atsu and Adams (2021) show that the use of fossil fuels as well as the policy risk influence CO2 emissions. Additionally, they stress the importance of policy and economic policy uncertainties in determining CO2 emissions and, subsequently, the development of measures for climate change adaptation and mitigation. On the other hand, Xue et al.'s (2022) long-run analysis shows that using clean energy does not result in a long-term decrease in emissions. EPU increases emissions, which endangers the sustainability of the environment. Therefore, this study discovers a causality from EPU to emissions and economic growth.

Another important paper that contributes to the literature is that of Fried et al. (2021). The authors use an analytic simple dynamic model to address the channels through which climate policy uncertainty reduces emissions while they use a quantitative general equilibrium model to assess the climate policy risk's effects on the U.S. economy. The difference with the other studies is that in this case, the authors compare the impacts of climate policy uncertainty with the impacts of a future carbon tax from the federal government. Fried et al.'s (2021) findings suggest that the risk associated with climate policy is similar to that of a carbon tax in the sense that it reduces emissions by making the capital stock smaller and cleaner overall. However, climate policy risk is more expensive than a carbon tax because it depends considerably more on lowering the capital stock to reduce emissions. The results additionally emphasize the fact that other studies might ignore the policy uncertainty and that can overestimate the emissions reductions from a carbon tax.

Similar ideas regarding climate policy uncertainty and whether an investment is affected, especially in capital-intensive businesses and more sensitive sectors to climate policies and pollution, are presented in Berestycki et al. (2022) study. However, they study the OECD countries, so they present some differences that arise between the effects among the countries. In addition to giving the indicator at higher frequency of monthly and quarterly levels, the study includes sub-indices that reflect the climate policy uncertainty path related to an improving or a weakening of climate policies for a group of countries. Finally, this study indicates that it is unrealistic to believe that any policy uncertainty can be completely avoided because talks about any new climate policy package, as well as arguments about a potential strengthening of current restrictions, would inevitably create uncertainty as part of regular democratic procedures. So that not all uncertainty in climate policy is bad, policies also need to have some flexibility mechanisms to be able to adapt to new scientific knowledge or shifting macroeconomic conditions.

Other studies that focus on more specific relationships are that of Hoang (2022), Lasisi et al. (2022), Shang et al. (2022), and Hoang (2022). More specifically, Lasisi et al. (2022) by employing the information-efficient analytical technique GARCH-MIDAS, examine the implication of climate policy uncertainty for stock market volatility for both the US and the UK. Its proposed predictability model provides significant evidence that stock market volatility can be predicted using CPU, and that this prediction can be improved when uncertainty resulting from pandemics and epidemics (UPE) is combined with CPU. In other words, US stock market investors are likely to react to climate change uncertainties more so than investors in other economies. The authors also show how profit-maximizing investors can generate higher portfolio returns than those who do not take into account the uncertainty associated with climate change.

On the other hand, Shang et al.'s (2022) aim is to study the impact of CPU on renewable and non-renewable energy consumption in the United States. The study presents important results. For instance, it is established that the demand for non-renewable energy is increased when crude oil prices are high and decreased when climate policy is uncertain. Contrarily, economic growth has a beneficial but insignificant impact on the use of non-renewable energy. Additionally, it is found that rising crude oil prices and economic growth both influence the demand for renewable energy. The former has a negative impact on the demand while the latter has a positive relationship with renewable energy demand. Long-term demand for renewable energy is also positively impacted by climate policy uncertainty.

Finally, Hoang's (2022) contribution to the literature regarding climate policy uncertainty is that the outcomes have policymaking and corporate strategy inferences in response to CPU, for those who have high emissions. Hoang points out that once the major targets of climate legislation, heavy emitters, are faced with more technological uncertainty, they are more likely to limit their R&D spending and adopt a wait-and-see approach until more information is available. Additional analyses on whether management attitudes and leadership abilities deter R&D investment under rising CPU provide a new understanding. Additionally, Hoang's findings demonstrate that the effect is not present in younger, riskier firms but only in more mature ones. Given that technology and resource availability are essential to the long-term process of decarbonization, the implementation of climate policy must take into account the market's existing level of technology. (Fais et al., 2016).

Overall, the available literature examines various channels through EPU and CPU might affect the economy either from the firm or from the household side. Although it may be obvious that economic and climate policy uncertainty are related, this has not yet been explored in the literature. Investigating the relationship between economic and climate policy uncertainty is therefore one of the main aims of this study. In other words, it is examined if there is causality between CPU and EPU. Additionally, this study explores the dynamics between CPU, EPU, and various macroeconomic factors such as investment level, unemployment, stock market, and inflation and indicates whether these relationships are persistent, short-lasting, or even insignificant.

3. Data and Methodology

3.1 Data Description

Concerning the data employed in this paper, they are collected from the U.S. Bureau of Economic Analysis, Economic Policy Uncertainty, U.S. Bureau of Labor Statistics, and Organization for Economic Co-operation and Development. Based on availability, quarterly data for the period 1987Q2-2022Q2 for the United States have been gathered. Table A1 in the Appendix presents details of the variables and their sources, while Table A2 shows more information about the dataset.

The dependent variables used in the analysis are climate policy uncertainty (CPU), economic policy uncertainty (EPU), and the macroeconomic indicators - investments, unemployment, the stock market, and inflation. First, for economic policy uncertainty an index (EPU index) constructed by Baker et al., (2016) is used, and it is based on policy uncertainty newspaper articles. It keeps track of how many articles in newspapers contain the terms “uncertain” or “uncertainty”, “economic” or “economy”, and one or more policy-relevant terms and is associated with the economic risk where the future path of government policy is uncertain. Second, the index used for climate policy uncertainty (CPU index) has been constructed by Gavriilidis (2021) who followed the established methodology of Baker et al. (2016) and their EPU index. That is, the index is based on eight leading US newspapers containing the terms {"uncertainty" or "uncertain"} and {"carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental"} and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy"} (including variants such as "uncertainties", "regulatory", "policies", etc.) and tells what can be done in policy design to reduce costs related with climate change disasters, the transition to a green and low-carbon world and subsidies for environmentally-friendly practices.

Investment, stock market, unemployment, and inflation have been chosen as the macroeconomic variables to be included in the model. These are the primary macroeconomic determinants, and they are frequently used to explain economic trends or to aid authorities, policymakers, or other relevant parties in understanding how a large-scale economy responds to a positive or negative shock to the market (Mügge, 2016). For instance, during times of war, these indicators are studied to gauge the state of the economy and weigh the effects on it, in order to determine the best courses of action and policies to adopt. In particular, net domestic investment measures the change in the amount of investment (which is in billions) that goes toward raising a country’s productive capacity and reflects the net addition of physical capital to the economy. It includes investments in machinery, equipment, and other durable goods as well as structures (such as buildings and infrastructure). Net domestic investment, which is calculated by deducting depreciation from gross domestic investment, serves as a measure of the net accumulation of capital stock, which has an immediate impact on future output and economic expansion.

The total share prices for all U.S. shares are used for the stock market index. This index, which is measured as the growth rate change in total share prices, was compiled because it captures the overall value and movement of the underlying stocks. They also provide insights into the condition and trends of the stock market, as well as optimism and sentiment among investors. Furthermore, the percentage of the labor force that is without work and actively looking for work is captured by the unemployment rate. It measures the state of the labor market and the level of unemployment in a country's economy. It is a crucial statistic for decision-makers, economists, and analysts to assess labor market dynamics, gauge how well economic policies are working, and keep track of an economy's general health.

Finally, in the US, an effective measure of inflation is the Consumer Price Index for All Urban Consumers (CPI-U). It offers details on changes in the average costs urban consumers paid through time for a basket of goods and services. Because it captures changes in the cost of living for ordinary households, the CPI-U is regarded as an essential economic indicator. It includes a broad range of products and services that urban consumers frequently buy, such as food, housing, transportation, healthcare, education, and leisure. The index's goal is to quantify inflation in a way that is reflective of the entire economy while also capturing price changes over time.

Moving on to the study’s methodology, a statistical test is known as the Dickey-Fuller unit root test is used to determine whether a time series is stationary or has a unit root, which suggests non-stationarity (Dickey and Fuller, 1979). Because it provides for stable statistical features, such as constant mean and variance throughout time, stationarity is a key presumption in time series analysis. All the time series mentioned above are stationary, according to the findings of the Dickey-Fuller unit root test, which are shown in Table A3 in the Appendix (see also Figures A1 and A2 in the Appendix). In a nutshell, they don't show significant fluctuations that cause trends or seasonality. Although they can vary from period to period, stationarity indicates that the mean and variance of these time series are constant across time. Due to their more predictable patterns and statistical characteristics, stationary time series is simpler to model and analyze than non-stationary ones.

3.2 Estimating the effects of policy uncertainty

As it was mentioned above, one of the study's goals is to investigate how climate and economic policy uncertainty affect the macroeconomy. Thus, a Vector Auto-Regressive (VAR) model is also employed to investigate such a relationship (i.e., the relationship between CPU, EPU and investment, stock market, unemployment, and inflation). The VAR representation is

$$\Delta y_t = \alpha + \sum_{j=1}^{k} \beta_{1j} \Delta y_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \boldsymbol{\Sigma}) \tag{2}$$

where y_t is a vector of endogenous variables (i.e., CPU, EPU, investments, unemployment, stock market and inflation), Δ is the first difference, j is the appropriate lag length (2 lags in our case) and ε_t denotes the vector of serially and mutually uncorrelated structural innovations, with variance-covariance matrix $\boldsymbol{\Sigma}$. β_{1j} is the specific coefficients related with lag j of the vector of endogenous dependent variables.

Since estimates of β_{1j}, might be inaccurate when the time-series dimension is small, the sample size is important in this (Weale and Wieladek, 2016). The data range for the estimation is constrained: the climate policy uncertainty index for the U.S. is only available starting in April 1987 until August 2022. Subsequently, in what has come to be known as Minnesota prior, Bayesian methods are used, as presented by Litterman (1986), to deal with this issue. The disadvantage of this prior is that it presupposes knowledge of the variance-covariance matrix, which makes it too rigid and leads to the dominance of information from the data. Hence, to avoid this problem, as in Uhlig (2005) and Weale and Wieladek (2016), models can be estimated using a non-informative Normal-inverse Wishart prior.

Albeit being more flexible than Minnesota prior, the normal-Wishart prior has some limitations. In particular, assuming an unknown variance-covariance matrix comes at the cost of imposing a Kronecker structure on the prior distribution. This structure results in an assumption that the variance of the residual term depends on the variance of the VAR coefficients for each equation, and this might be problematic (see Dieppe et al., 2016). An Independent Normal-Wishart (INW) prior with unknown $\mathbf{\Sigma}$ and an arbitrary variance-covariance matrix is used, Ω_0 in order to prevent this.

Hence, the prior distribution is specified such that, $\beta \sim N(\beta_0, \Omega_0)$. While β_0 and Ω_0 may have any structure, β_0 is frequently specified as the Minnesota β_0 vectors, with one in the first lag of each endogenous variable and zero for additional lags and cross-variable lag coefficients (Dieppe et al., 2016). Similarly, Ω_0 also takes the form of the Minnesota covariance matrix. The Gibbs sampler can be used to generate random draws from the unconditional posterior distributions of the relevant parameters given these conditional distributions. The use of Bayesian estimation also has the benefit of allowing zero constraints (block exogeneity). In particular, it allows us to withhold the direct prospective effect of variable *i* on variable *j* by applying a zero-prior mean and a very small prior variance on the respective locations on the prior structure. As a result, there is an assurance that the posterior values will be nearly zero. Still, this paper does not employ this kind of analysis.

4. Results

4.1. How policy uncertainty interacts and affects the macroeconomy

Figures 1, 2, 3, and 4 depict the impulse-response functions of the Bayesian Vector Autoregression model in response to a positive shock on climate policy uncertainty (Figures 1 and 3) and economic policy uncertainty (Figures 2 and 4). Each figure shows the response of each system variable i.e., investment, EPU index, stock market, CPU index, inflation, and unemployment. Figures 1 and 2 show the responses without considering inflation, while Figures 3 and 4 present the responses of all the system variables.

Starting with Figure 1, investments appear to be negatively affected by a positive shock on the CPU. The initial response of investment is not significant however, after five quarters until the end of the horizon investment significantly decreases, while it approaches zero in the long run. The presence of climate policy uncertainty introduces additional risks and costs for businesses, potentially impacting their investment decisions. Uncertainty about future regulations, such as carbon pricing, emissions standards, or renewable energy incentives, can create a challenging environment for firms, making them more cautious and delaying or reducing investment plans (Berestycki et al., 2022).

A positive shock on the CPU index has a negative impact on unemployment, suggesting that unemployment decreases during periods of climate policy uncertainty. This may be because climate policy uncertainty can create opportunities for job creation in the renewable energy sector or other industries aligned with sustainable practices (green job creation). This can result in a decrease in unemployment as new job opportunities emerge. However, the overall impact on employment may depend on the specific policies implemented and their effectiveness in promoting green job growth (Böhringer and Rutherford, 2008). Another possible explanation is that climate policy uncertainty can affect different sectors of the economy differently, leading to variations in employment outcomes. For example, sectors heavily reliant on fossil fuels may experience more significant employment effects compared to sectors focused on renewable energy or energy efficiency. Understanding the sectoral impacts of climate policy uncertainty is crucial for developing targeted policies to mitigate potential adverse effects on employment (Hanson, 2023).

On the other hand, climate policy risk appears not to have any significant impact on the stock market. Economic policy uncertainty has a significant follow-up to innovation on climate policy uncertainty. It is evident that EPU rises following a positive CPU shock however, this increase is only significant from the 3rd until the 10th quarter. This suggests that uncertainty in climate policy influences uncertainty in economic policy. It can be explained by the fact that EPU evaluates changes in government policies on broader economic concerns, such as those that arise during recessions, wars, pandemics, etc., while CPU measures the changes in government policies on environmental issues (Shang et al., 2022). Since the effects of climate uncertainty will raise the need for implementing other policies regarding, for example, reduced investment, higher climate uncertainty can therefore lead to higher economic uncertainty overall. As the figure suggests, a positive relationship between the CPU index and itself holds, with the expected gradual dying out of the shock, indicating that the model is well-behaved. This relationship results from the so-called carryout effect, that is, the contribution of the previous year to the index in the current year (Tödter, 2011). In general, after a favorable shock on climate policy uncertainty, economic policy uncertainty rises. Economic policy uncertainty can be influenced by uncertainty in climate policy, and the implications of climate uncertainty may increase economic uncertainty. A well-behaved model is shown by the carryout effect and the gradual deterioration of the link between the current and past values of the CPU.

Figure 2 illustrates how each system variable reacts to a positive shock on economic policy uncertainty (i.e., an increase in the EPU index). Investments and EPU have an adverse relationship, implying that the higher the economic uncertainty is, the fewer people and businesses spend. This effect is significant for seven quarters. Investment and spending become less attractive when economic policy is uncertain, affecting both businesses and average households. Corporations become more conservative with their investment plans as a result of possible regulatory changes and decreased business profitability (Kang et al., 2014; Al-Thaqeb et al. 2019), whereas households postpone investment due to decreased personal income. This is in line with Giglio et al. (2016) who support that this effect is higher during recessions the impact of EPU on the whole economy is higher since new opportunities and incentives related with the market as well as price signals are less appealing for the average household.

Furthermore, a positive shock to the EPU index has a positive and significant effect on unemployment. The unemployment rate appears to be rising by about 0.10 percentage points, and this increase appears to be long-lasting (i.e., having both a short- and long-term effect). According to Bloom (2014), shifts in uncertainty frequently cause a slowdown in employment and investment since businesses are typically hesitant to make crucial or expensive decisions under unpredictably changing regulatory environments. Additionally, Caggiano et al. (2014), who employ a non-linear VAR approach, report that the same shock is predicted to result in an increase in unemployment of 0.36 percentage points four quarters after the shock and 0.41 points two years after the shock when it affects the economy during a recession. This implies that when the economy is already in a recession, uncertainty shocks may have a severe impact on unemployment, thus when analysing the reasons for the increase in unemployment during recessions, shocks related with uncertainty may require greater caution than shocks related with monetary policy (Caggiano et al., 2017).

While the stock market does not have any important response after a positive shock on the CPU index (i.e., in Figure 1), it does have a change after a positive shock on the EPU index. In other words, there is a negative relationship between the stock market and economic policy uncertainty however, it is only significant for two quarters. In line with Christou et al., (2017), the impact of EPU on the stock market is not entirely obvious because it depends on each country, the size, and the strength of an economy. Stock prices are lower when there is a lot of uncertainty, as demonstrated by Veronesi (2013) using the options market to examine how investors factor uncertainty into their pricing. Consequently, the increased risk in the cross-section of yields may be driven by economic policy risk. Therefore, this finding indicates that the EPU index has some ability to foresee market shocks and affect stock returns as well as volatility.

Economic and climate policy uncertainty responds similarly after an innovation on the EPU index. On the one hand, there is a positive relationship between the EPU index and itself, with the increase appearing to eventually decrease. The carryout effect, or the fact that the index value from one year contributes to the index value of the current year, is responsible for this positive relationship. As it was mentioned before, this effect is also presented in the case of the CPU. Therefore, both economic and climate uncertainty's past values contribute to their current values. On the other hand, after an increase in EPU, the Climate Policy Uncertainty (CPU) declines. This shows that while economic uncertainty increases, climate uncertainty decreases and approaches zero in the long run. This result implies that governments and policymakers focus on tackling more urgent economic issues like inflation, unemployment, and interest rates during times of economic uncertainty. As a result, during these periods, climate change efforts (strategies) may be deemphasized or postponed. It is important to note that when making decisions, economic considerations and concerns take precedence over environmental issues. This may happen during economic downturns or crises when policymakers may place a greater emphasis on preserving economic stability and addressing economic challenges.

The inclusion of inflation in the analysis allows us to examine the relationship between prices and climate and economic policy uncertainty. Figures 3 and 4 demonstrate the responses of the system variables to shocks in CPU and EPU indexes, respectively, with the addition of inflation. These figures show that the overall patterns of the responses are similar to those of the previous figures (Figures 1 and 2), indicating the persistence of the relationships between policy uncertainty and the other variables. On the one hand, inflation has a positive relationship with the CPU. This finding suggests that climate policy uncertainty is associated with higher prices. This could be attributed to factors such as potential changes in energy prices, resource allocation, or supply chain disruptions resulting from climate-related policies. The positive relationship between inflation and CPU indicates that climate policy uncertainty can influence price dynamics in the economy (Vavra, 2014). On the other hand, the negative relationship between inflation and EPU suggests that economic policy uncertainty is associated with lower inflation levels. Economic policy uncertainty may lead to cautious spending and investment behavior, resulting in reduced demand and downward pressure on prices. It is important to note that the relationship between policy uncertainty and inflation is complex and can be influenced by various factors. The specific dynamics may vary depending on the characteristics of the economy, the policy environment, and other contextual factors (Bloom, 2014).

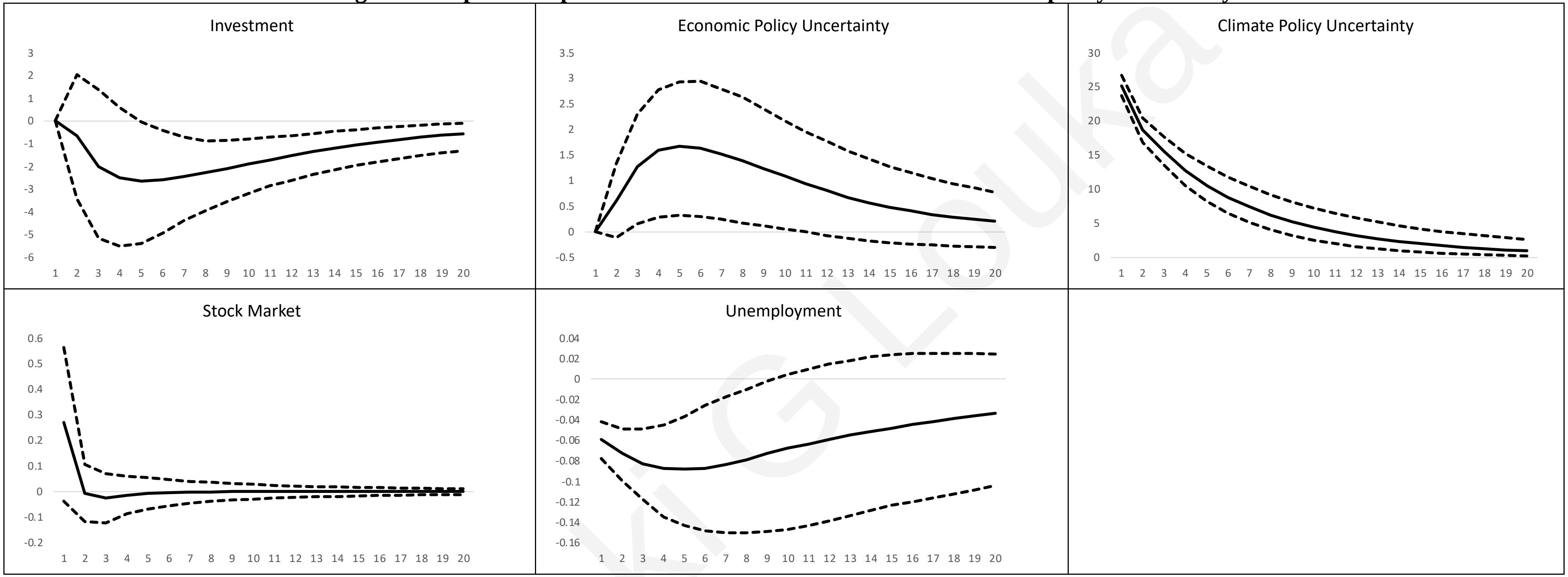
Overall, the analysis provides valuable insights into the interplay between economic policy uncertainty (EPU) and climate policy uncertainty (CPU) and their effects on various economic variables[1]. The findings indicate that there is a positive relationship between EPU and itself, suggesting that past economic policy uncertainty influences current levels. However, the relationship is not driven by autocorrelation. A long-run relationship (cointegration) between EPU and CPU further supports the notion of a sustained connection between economic and climate policy uncertainty. This finding highlights the importance of considering both types of policy uncertainty in policy-making processes, as changes in climate policy uncertainty can impact economic policy uncertainty and vice versa.

Analyzing the impulse-response functions, the results demonstrate the effects of positive shocks on CPU and EPU on various economic variables. Climate policy uncertainty has a negative impact on investments, suggesting that businesses become more cautious and delay or reduce investment plans in the face of uncertainty. Also, climate policy uncertainty appears to have a negative impact on unemployment, potentially creating job opportunities in the renewable energy sector or other industries aligned with sustainable practices. Economic

[1] More information on the estimations is given in tables A4–A9 in the Appendix. A deeper comprehension of the impacts is made possible by subsequent estimations and covariance matrices.

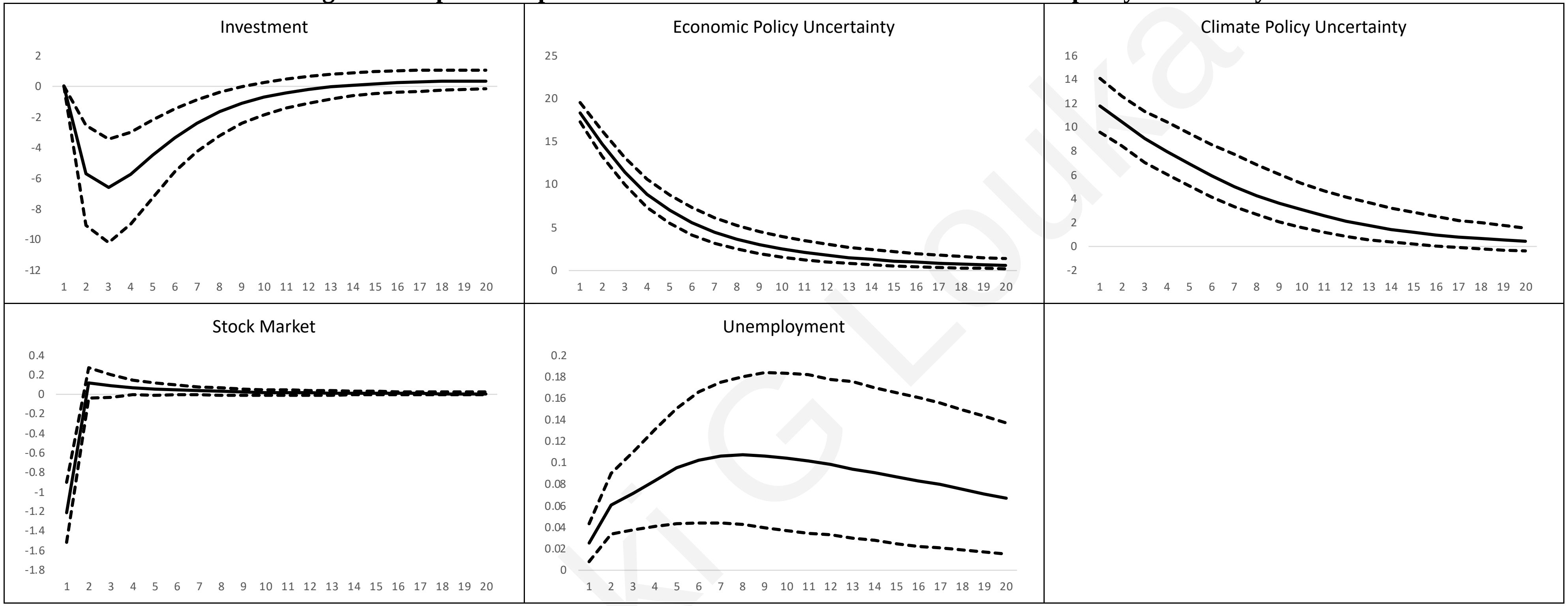
policy uncertainty affects investments and spending negatively, indicating that higher economic uncertainty leads to decreased investment and consumption. Moreover, economic policy uncertainty has a positive and lasting effect on unemployment, suggesting that uncertainty can result in a slowdown in employment. The stock market response to policy uncertainty varies, with economic policy uncertainty showing a negative relationship with stock market performance. Incorporating inflation into the analysis reveals that climate policy uncertainty is associated with higher prices, while economic policy uncertainty is associated with lower inflation levels. These relationships indicate that policy uncertainty can influence price dynamics in the economy.

Figure 1: Impulse Response Functions after an innovation on climate policy uncertainty



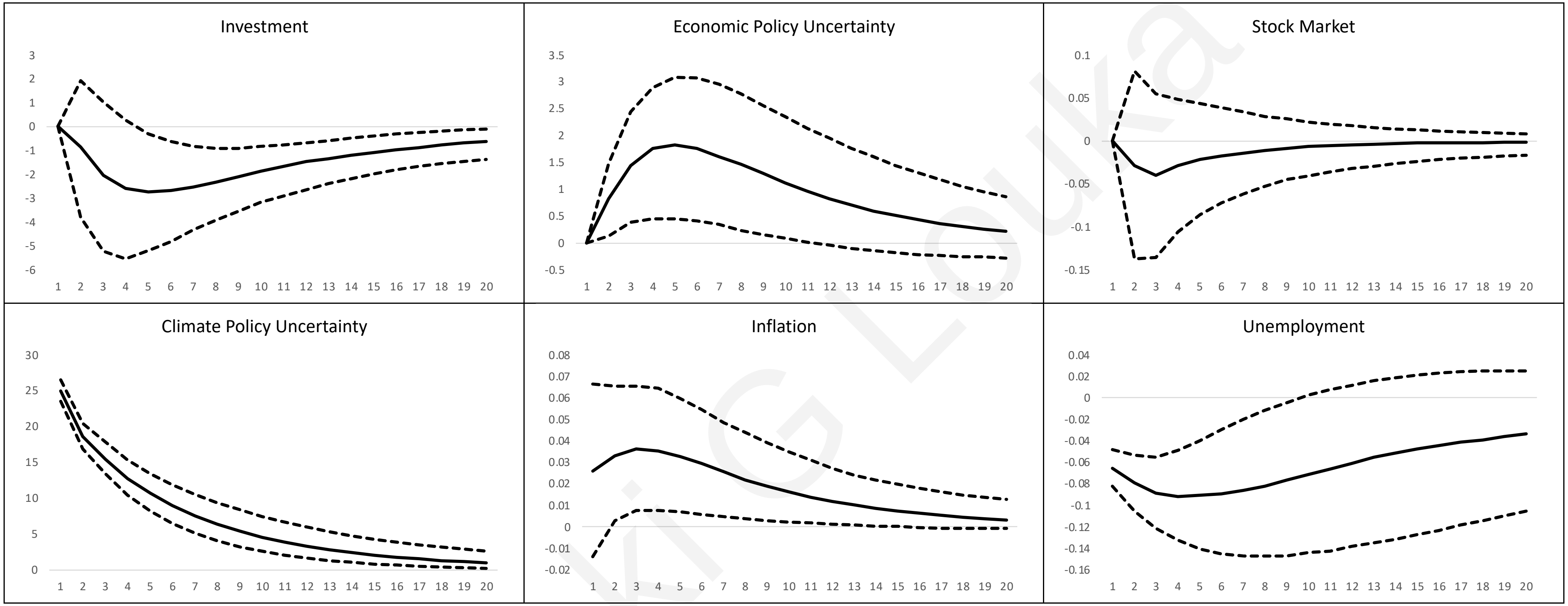
This figure shows the impulse-response functions of a BVAR model after a positive shock on climate policy uncertainty. The responses of investment, EPU, CPU, stock market, and unemployment are observed. Dashed lines denote the 95% confidence intervals. Structural identification by Cholesky ordering is also used. The estimated VAR model satisfies the stability condition since the roots of its characteristic polynomial lie inside the unit circle. The lag length for all the variables is 2.

Figure 2: Impulse Response Functions after an innovation on economic policy uncertainty



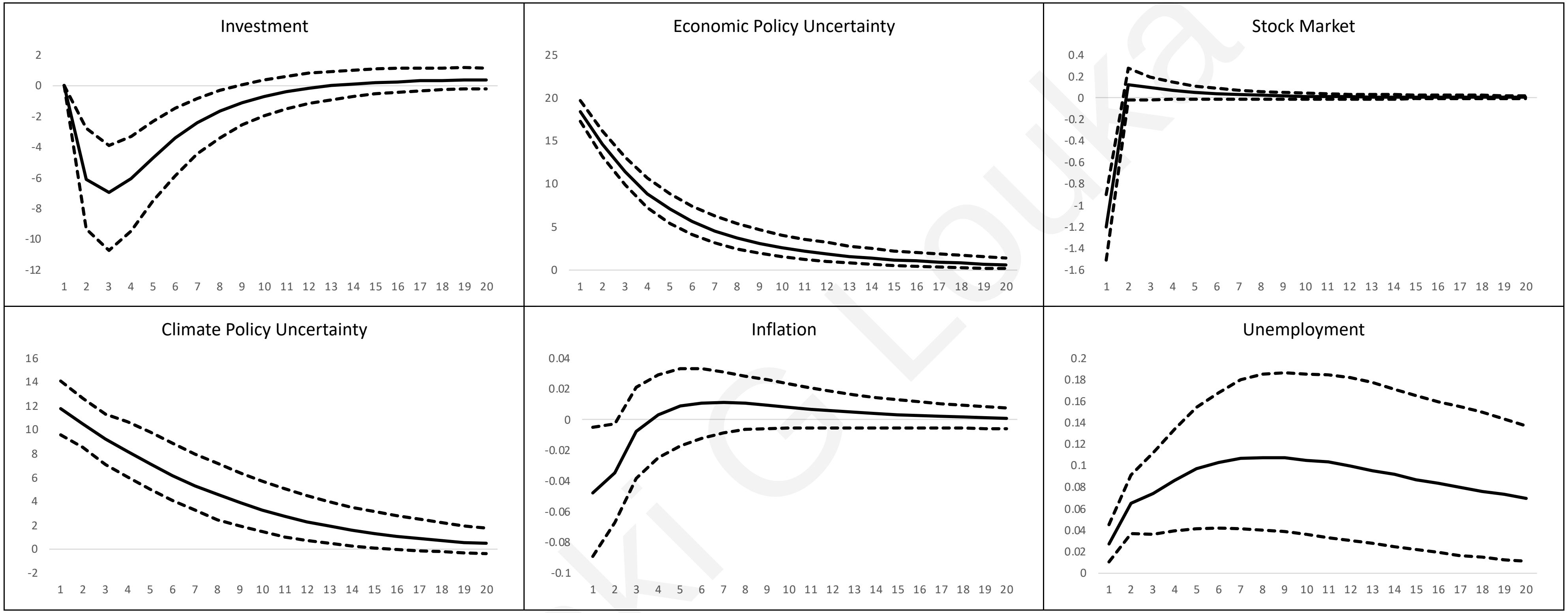
This figure shows the impulse-response functions of a BVAR model after a positive shock on economic policy uncertainty. The responses of investment, EPU, CPU, stock market, and unemployment are observed. Dashed lines denote the 95% confidence intervals. Structural identification by Cholesky ordering is also used. The estimated VAR model satisfies the stability condition since the roots of its characteristic polynomial lie inside the unit circle. The lag length for all the variables is 2.

Figure 3: Impulse Response Functions after an innovation on climate policy uncertainty (additional model)



This figure shows the impulse-response functions of a BVAR model after a positive shock on climate policy uncertainty. The responses of investment, EPU, stock market, CPU, inflation, and unemployment are observed. Dashed lines denote the 95% confidence intervals. Structural identification by Cholesky ordering is also used. The estimated VAR model satisfies the stability condition since the roots of its characteristic polynomial lie inside the unit circle. The lag length for all the variables is 2.

Figure 4: Impulse Response Functions after an innovation on economic policy uncertainty (additional model)



This figure shows the impulse-response functions of a BVAR model after a positive shock on economic policy uncertainty. The responses of investment, EPU, stock market, CPU, inflation, and unemployment are observed. Dashed lines denote the 95% confidence intervals. Structural identification by Cholesky ordering is also used. Also, no root of the characteristic polynomial lies outside the unit circle. Thus, the estimated VAR model satisfies the stability condition. The lag length for all the variables is 2.

5. Conclusions

Climate change is one of the most important ongoing dangers to society in the twenty-first century. Even so, significant attempts to reduce emissions are still in their early phases, and legislators are finding it difficult to send the right long-term signals to motivate successful action. In addition, recent occurrences like the Covid-19 pandemic, geopolitical issues like the Ukraine crisis, fuel price increases that result in inflation, and the collapse of significant banks have increased uncertainty in our life. The current level of uncertainty makes it difficult for governments, central banks, and policymakers to make well-informed choices and put effective measures into place. The risks brought on by more policy uncertainty, whether it is due to the economy or the climate, have consequently taken the forefront in policy deliberations.

However, when should an economy pay attention and proceed with targeted actions regarding the policies it will follow? Also depending on which criteria, a state will choose to focus on changes and improvements that concern specific types of policies (e.g., climate-related risks, more general risks). The main goal of the study, therefore, is to answer these questions and examine how economic policy uncertainty interacts with climate policy uncertainty and how these in turn affect a country's macroeconomic indicators using US data from 1987Q2 to 2022Q2 in line with a vector autoregressive model.

The paper shows that there is a positive correlation between CPU and EPU. In other words, higher climate policy risk leads to higher economic policy risk, underling the necessity for the proper bodies to exercise greater caution and implement a variety of policies that address a wide range of risks (such as climate change, geopolitical threats, etc.). Examining the effect of EPU on CPU, however, shows that CPU is declining despite the apparent positive relationship. This means that higher economic uncertainty outweighs the significance of climate uncertainty and encourages policymakers to focus more on the risks of the economy (e.g., high inflation, unemployment, etc.) than on specific climate change-related concerns.

The findings demonstrate that both types of policy uncertainty have a detrimental effect on investment levels, indicating that policy uncertainty raises the perceived risk associated with investments. As a result, people may be concerned about the possibility of sudden policy changes that could harm their investments, such as changes in tax rates, regulations, or trade policies. This elevated risk perception may cause investors to hesitate to make investments or to seek larger returns in order to make up for the increased risk. On the other hand, unemployment and inflation react differently after a positive shock on climate or economic policy uncertainty. While there is a negative correlation between unemployment and CPU, there is a positive correlation between EPU and unemployment. Greater CPU could, on the one hand, open up employment chances in the green or sustainable industries, but greater EPU raises the unemployment rate because it can have a detrimental effect on investment levels and productivity growth. Reduced investment may make it more difficult for businesses to develop, adopt new technology, and become more productive, all of which could prevent the creation of new jobs.

The EPU index is the only factor that affects the stock market; however, this association is only short-lived because it only lasts for two quarters. Considering the effects of inflation, CPU has a positive impact on pricing whereas EPU has a negative impact. These connections suggest that pricing dynamics in the economy can be affected differently depending on the type of policy uncertainty we are considering. As policy uncertainty can affect consumers' and firms' expectations and confidence, these changes in turn can affect price dynamics.

The identification of relationships such as the above is of high importance for the US economy and the economies in general, since understanding the reactions of the macroeconomy to shocks on policy uncertainties allows us to identify the impact of these events on economic performance. These relationships can also help policymakers, governments, central banks, and other organizations to consider some policy approaches that can help mitigate these uncertainties and their impacts. For example, they can create stable and transparent policy frameworks that will give businesses and households long-term direction. This can include clear regulations, by offering guidance on a range of matters, including consumer protection, trade legislation, and environmental standards, predictable tax procedures, and ongoing encouragement of sustainable economic expansion. Such frameworks can promote investment, consumption, and economic growth and lessen uncertainty by providing predictability and lowering policy volatility. They can also create plans for managing and adapting to climate risks. They can include climate resilience in the planning and decision-making processes for policies by evaluating and addressing the possible effects of climate change on the infrastructure, economy, and vulnerable sectors. Future research could successfully investigate such relationships by utilizing cross-national or global data as well as enricher methods.

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Appendix

Table A1: Variable details

Variable	Units	Source
Climate Policy Uncertainty	Index, Not Seasonally Adjusted	Economic Policy Uncertainty
Unemployment Rate	Percent of the labor force, Seasonally Adjusted	U.S. Bureau of Labor Statistics
Economic Policy Uncertainty	Index, Not Seasonally Adjusted	Economic Policy Uncertainty
Total Share Prices for all Shares for the US	Change, Growth rate previous period, Not Seasonally Adjusted	Organization for Economic Co-operation and Development
Consumer Price Index for All Urban Consumers: All Items in U.S. City Average	Percent Change, Quarterly, Seasonally Adjusted	U.S. Bureau of Labor Statistics
Net Domestic Investment	Change, Billions of Dollars, Seasonally Adjusted Annual Rate	U.S. Bureau of Economic Analysis

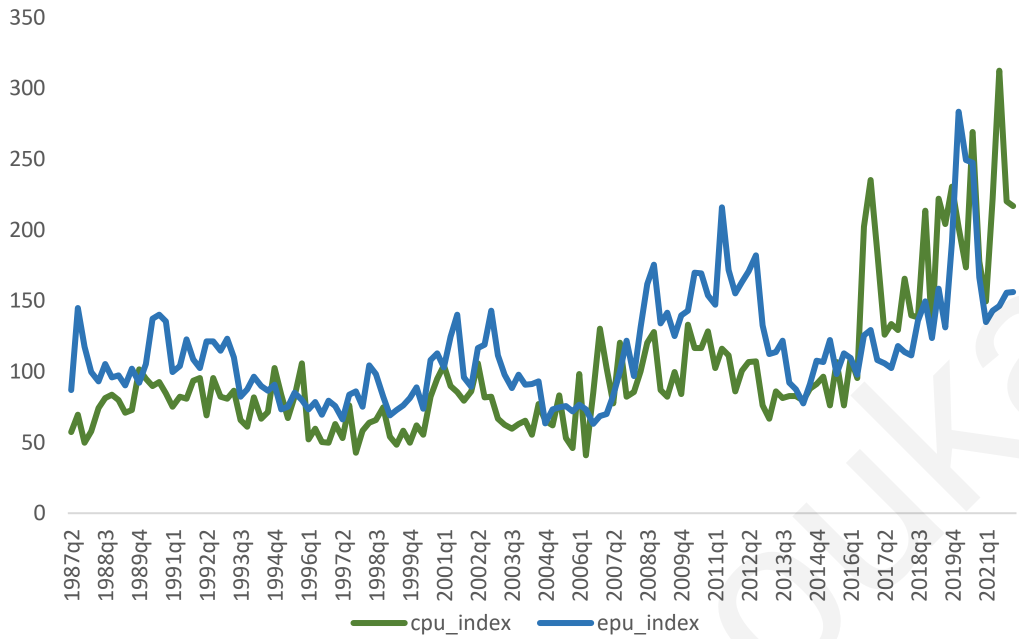
This table presents the variables employed in the paper, the units, and the sources they have been collected from.

Table A2: Descriptive Statistics

	N	Mean	Std. dev.	Min	Max
Unemployment	141	5.84	1.65	3.60	12.97
Stock Market	141	-0.06	3.52	-10.55	13.09
Inflation	141	0.68	0.55	-2.30	2.30
Investment	141	5.68	95.04	-601.62	547.64
CPU Index	141	99.07	48.90	40.87	312.43
EPU index	141	113.66	37.44	63.12	283.45

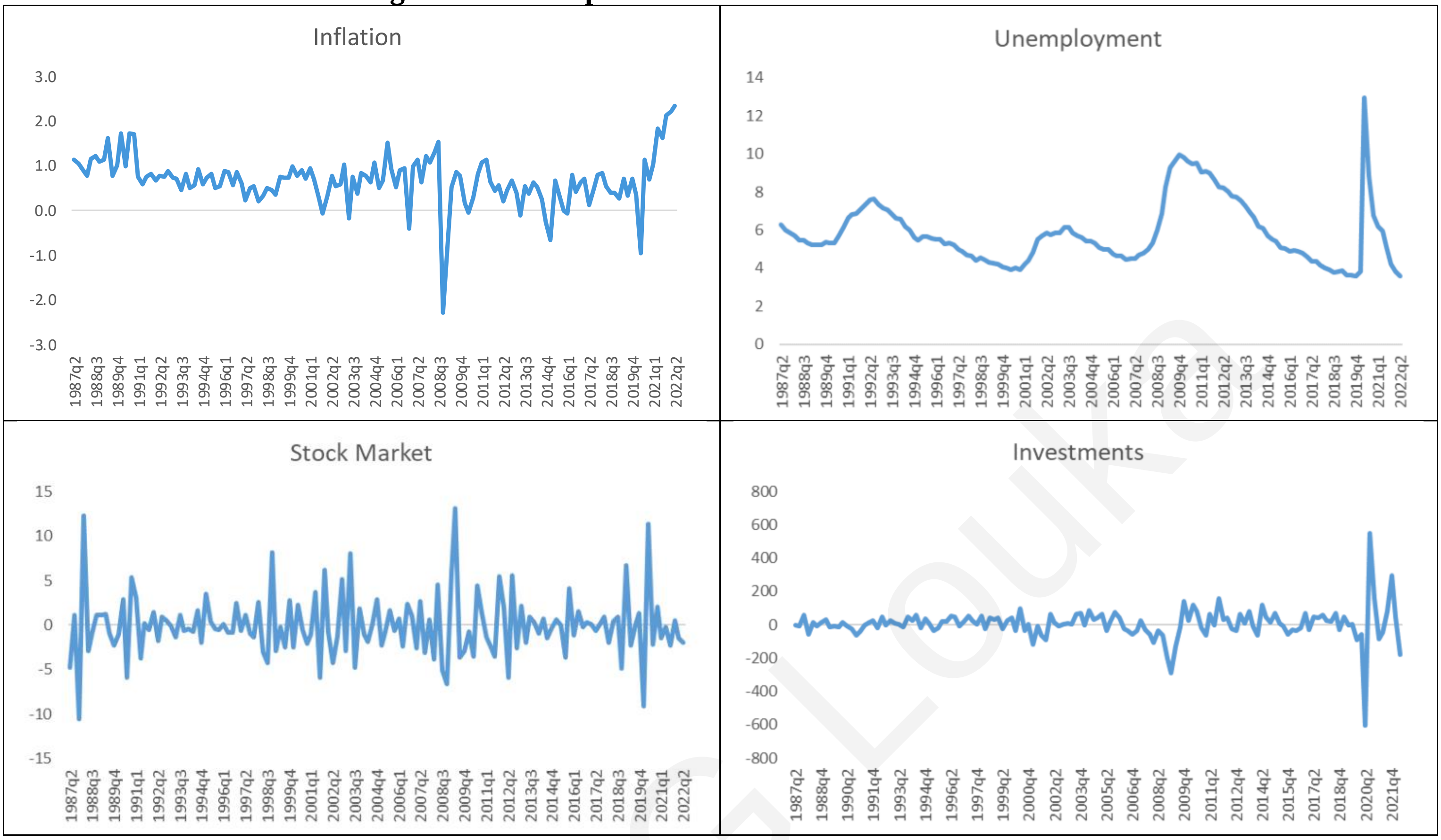
This table presents the summary statistics for the dataset.

Figure A1: Economic and Climate Policy Uncertainty Indices



The figure shows the time plots for economic and climate policy uncertainty indices and captures how they change over time. Both are stationary time series that have constant mean and variance over time. This is also supported by the Dickey-Fuller unit root test as reported in Table A3.

Figure A2: Time plots for the macroeconomic variables



The figure captures how the changes in prices (i.e., inflation), unemployment, the changes in stock prices (i.e., stock market), and the changes in investments vary over time. All are stationary time series meaning that they have constant mean and variance over time. This is also supported by the Dickey-Fuller unit root tests which are reported in Table A3. However, some structural breaks are observed that are taken into account for the analysis.

Table A3: Dickey-Fuller test for unit root

	H0: Random walk without drift, d=0		
	Dickey-Fuller critical values		
	1%	***5%***	***10%***
	-3.497	*-2.887*	-2.577
	Test statistic		**p-value for Z(t)**
EPU Index	-3.496**		0.0081
CPU Index	-3.565***		0.0065
Inflation	-7.130***		0.0000
Unemployment	-3.253**		0.0171
Stock Market	-19.558***		0.0000
Investments	-11.967***		0.0000

The table shows the t-statistics and the p-values of the Dickey-Fuller unit root test for all the variables (EPU and CPU indices, change in prices - inflation, unemployment, change in stock prices – stock market, and changes in investments) used in the study. All the variables seem to be stationary. ***, ** denote significance for the statistical levels 1% and 5% respectively.

Table A4: Posterior coefficient estimates for the first BVAR model (EPU)

Endogenous Variable: EPU Index					
	Coefficient	**Median**	**St.dev**	**Low. bound**	**Upp. bound**
Investment (-1)	0.026	0.006	0.010	-0.014	0.025
Investment (-2)	0.602	-0.003	0.005	-0.012	0.007
EPU Index (-1)	0.038	0.646	0.056	0.540	0.758
EPU Index (-2)	-2.180	0.038	0.040	-0.037	0.115
CPU Index (-1)	8.946	0.050	0.028	0.000	0.106
CPU Index (-2)	-0.057	0.015	0.017	-0.019	0.048
Stock Market (-1)	0.071	-0.529	0.300	-1.105	0.045
Stock Market (-2)	0.160	-0.108	0.161	-0.416	0.217
Unemployment (-1)	-1.295	0.641	0.884	-1.021	2.479
Unemployment (-2)	-7.309	0.180	0.569	-0.952	1.220
Constant	9.293	24.450	6.237	11.924	36.261

Sum of squared residuals: 57717.91

R-squared: 0.705

Adj. R-squared: 0.679

Sample size: 139

Number of lags included: 2

The table presents the coefficient posterior estimates for the endogenous variable CPU index, after examining the dynamics between investment, EPU, CPU, stock market, and unemployment. (-1) and (-2) show the first and second lag effects respectively.

Table A5: Posterior coefficient estimates for the first BVAR model (CPU)

Endogenous Variable: CPU Index

	Coefficient	Median	St. dev	Low. bound	Upp. bound
Investment (-1)	-0.067	0.003	0.013	-0.024	0.029
Investment (-2)	0.144	-0.004	0.007	-0.018	0.009
EPU Index (-1)	0.542	0.084	0.056	-0.019	0.201
EPU Index (-2)	-1.077	0.012	0.032	-0.050	0.076
CPU Index (-1)	-22.925	0.648	0.052	0.549	0.750
CPU Index (-2)	-0.069	0.084	0.039	0.015	0.165
Stock Market (-1)	-0.138	-0.467	0.380	-1.197	0.281
Stock Market (-2)	0.305	0.219	0.226	-0.203	0.693
Unemployment (-1)	0.435	-1.170	1.189	-3.563	1.104
Unemployment (-2)	21.745	0.016	0.754	-1.504	1.437
Constant	22.306	23.387	8.687	6.277	40.153

Sum of squared residuals: 109800.60

R-squared: 0.668

Adj. R-squared: 0.639

Sample size: 139

Number of lags included: 2

The table shows the coefficient posterior estimates for the endogenous variable CPU index, after examining the dynamics between investment, EPU, CPU, stock market, and unemployment. (-1) and (-2) show the first and second lag effects respectively.

Table A6: Innovations Covariance Matrix (Sigma) for the first model

	Investment	EPU Index	CPU Index	Stock Market	Unemployment
Investment	5728.219	-563.970	421.566	-34.496	-41.971
EPU Index	-563.970	422.195	197.611	-13.112	7.807
CPU Index	421.566	197.611	809.072	-11.403	-3.350
Stock Market	-34.496	-13.112	-11.403	10.603	0.663
Unemployment	-41.971	7.807	-3.350	0.663	0.661

This table reports the residual covariance matrix (posterior estimates) after estimating the BVAR model using the variables investment, EPU index, CPU index, stock market, and unemployment.

Table A7: Posterior coefficient estimates for the second BVAR model (EPU)

Endogenous Variable: EPU Index					
	Coefficient	**Median**	**St. dev**	**Low. bound**	**Upp. bound**
Investment (-1)	0.022	0.005	0.010	-0.014	0.024
Investment (-2)	0.583	-0.003	0.005	-0.013	0.007
EPU Index (-1)	-2.093	0.650	0.056	0.537	0.756
EPU Index (-2)	0.038	0.031	0.039	-0.046	0.109
Stock Market (-1)	-0.326	-0.511	0.285	-1.095	0.018
Stock Market (-2)	7.601	-0.129	0.162	-0.445	0.195
CPU Index (-1)	-0.059	0.052	0.029	-0.005	0.108
CPU Index (-2)	0.079	0.015	0.017	-0.015	0.050
Unemployment (-1)	-1.352	0.848	1.670	-2.685	4.003
Unemployment (-2)	0.163	-0.333	0.992	-2.324	1.653
Inflation (-1)	1.630	0.693	0.927	-0.995	2.524
Inflation (-2)	-5.792	0.151	0.555	-0.921	1.224
Constant	8.101	23.700	6.718	11.321	37.625

Sum of squared residuals:

R squared:

Adj. R squared:

Sample size: 139

Number of lags included: 2

The table shows the coefficient posterior estimates for the endogenous variable EPU index, after examining the dynamics between investment, EPU, stock market, CPU, inflation, and unemployment. (-1) and (-2) show the first and second lag effects respectively.

Table A8: Posterior coefficient estimates for the second BVAR model (CPU)

Endogenous Variable: CPU Index					
	Coefficient	**Median**	**St. dev**	**Low. bound**	**Upp. bound**
Investment (-1)	-0.073	0.004	0.014	-0.023	0.031
Investment (-2)	0.120	-0.004	-0.007	-0.017	0.009
EPU Index (-1)	-0.788	0.085	0.058	-0.027	0.201
EPU Index (-2)	0.552	0.015	0.031	-0.046	0.074
Stock Market (-1)	-5.039	-0.457	0.404	-1.274	0.311
Stock Market (-2)	-24.975	0.211	0.218	-0.237	0.637
CPU Index (-1)	-0.079	0.645	0.054	0.536	0.740
CPU Index (-2)	-0.140	0.088	0.042	0.003	0.164
Unemployment (-1)	0.632	-0.498	2.353	-5.331	4.102
Unemployment (-2)	0.311	0.258	1.249	-2.176	2.870
Inflation (-1)	7.394	-1.264	1.196	-3.718	1.057
Inflation (-2)	24.246	-0.041	0.773	-1.577	1.460
Constant	19.427	24.084	8.578	7.153	41.697

Sum of squared residuals: 109145.94

R squared: 0.670

Adj. R squared: 0.633

Sample size: 139

Number of lags included: 2

This table presents the coefficient posterior estimates for the endogenous variable CPU index, after examining the dynamics between investment, EPU, stock market, CPU, inflation, and unemployment. (-1) and (-2) show the first and second lag effects respectively.

Table A9: Innovations Covariance Matrix (Sigma) for the second model

	Investment	**EPU Index**	**Stock Market**	**CPU Index**	**Inflation**	**Unemployment**
Investment	5468.840	-529.700	-43.702	435.884	4.727	-40.843
EPU Index	-529.700	419.486	-12.222	197.523	-1.388	7.649
Stock Market	-43.702	-12.222	9.883	-10.201	-0.157	0.657
CPU Index	435.884	197.523	-10.201	817.628	1.067	-3.339
Inflation	4.727	-1.388	-0.157	1.067	0.164	-0.103
Unemployment	-40.843	7.649	0.657	-3.339	-0.103	0.659

This table reports the residual covariance matrix (posterior estimates) after estimating the BVAR model using the variables investment, EPU index, stock market, CPU index, inflation, and unemployment.