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RESEARCH ARTICLE



US domestic sentiment reactions to climate and economic policy uncertainties: a quantile ARDL approach

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ABSTRACT

Over the years, climate and economic policy uncertainties have become critical considerations that shape public attitudes. They have the potential to impact people's perceptions of financial stability, ecosystem integrity, and environmental sustainability. This paper aims to provide evidence on the sensitivity of US business and consumer sentiments to uncertainties arising from climate and economic policies in both short-term and long-term perspectives, and across different sentiment states. Our empirical investigation draws on a quantile ARDL approach, after orthogonalizing original sentiment series with respect to a diverse range of influential factors. The results reveal that climate and economic policy-related uncertainties have a negative impact on business (consumer) sentiment in the short and long run (only in the short run). These effects are particularly more pronounced when pessimistic sentiment begins to take hold. Moreover, we find evidence of locational asymmetry, especially in the long run.

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KEYWORDS

Consumer and business confidence; climate policy uncertainty; economic policy uncertainty; quantile ARDL

1. Introduction

In a world of mounting unpredictability, the effect of uncertainty on human perspectives and decisions cannot be denied. Uncertainty, regardless of its origin, plays a pivotal role in shaping the perceptions and expectations of economic agents (e.g., producers, households, policymakers). Whether arising from financial turbulence, climate issues, policy shifts, or global events, uncertainty has the power to engender doubt, which alters how agents view the future. The level of uncertainty can have a direct impact on people's sentiment, affecting their decisions and behavior, which, in turn, can influence economic activity and market trends. When future circumstances are predictable, uncertainty may foster a sense of cautious optimism. However, in times of ambiguity, people often adopt a more apprehensive and reserved approach (Bachmann et al., 2013; Bloom, 2009). In this respect, policy-related uncertainties continue to be a principal constituent of business and consumer analysis. They typically emerge from government decisions, regulations, or changes in economic, social, and environmental policies. These uncertainties

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can affect a range of dimensions, encompassing business development, consumer behavior, investments, and public sentiment. Kenyon and Naoi (2010) assert that regulatory and policy uncertainty has a notable impact on both public sentiment and macroeconomic outcomes.

While there are many factors that introduce unpredictability and mold the collective sentiment within a country, this paper narrows its focus to assess the potential role of two primary sources of uncertainty: economic and climate policies. Both policies may give rise to uncertainty since they affect the regulations and conditions within which agents operate. Coherent economic and climate policies can provide a more stable business and consumer milieu, while uncertainty can lead to wary sentiments and delayed decisions. More specifically, businesspeople are likely to be cautious about making capital investments, expanding operations, or hiring new employees in the face of rising levels of economic policy uncertainty (EPU, hereafter) due, for example, to sudden changes in government regulations, trade policies, and tax laws (Kirchner, 2020; Martínez-Matute & Urtasun, 2022; Mumtaz & Surico, 2018; Yu et al., 2021). On the contrary, lower levels of EPU may uplift producer confidence, possibly leading to increased investments and job creation. In a parallel way, EPU can also alter consumer sentiment by influencing perceptions of disposable income, spending patterns, and job security. When economic policies are uncertain, households may be less confident in their financial prospects, prompting reduced spending and increased savings. A fall in EPU, however, may uplift consumer optimism, resulting in higher spending and, probably, contributing to economic growth. Correspondingly, climate policy uncertainty (CPU, hereafter) has the potential to affect the sentiment of both producers and households. For instance, as shown by Hu et al. (2023), uncertainty about future climate policies (e.g., new emission standards, new energy efficiency standards, carbon pricing, or renewable energy mandates) can make it difficult for businesses to plan for regulatory compliance. CPU can also affect supply chains and market access, particularly for companies involved in energy-intensive industries or those with global operations. On the household side, CPU can impact sentiment through concerns related, for example, to the cost of living, energy costs, environmental sustainability, and corporate responsibility (Li et al., 2023; Song & Fang, 2024).

Given the paramount consequences of CPU and EPU, whether at the individual, firm, or country level, a great deal of attention has been directed toward examining their respective relationships with several financial markets and fundamental factors. For instance, Xiao and Liu (2023) find that positive changes in CPU and EPU tend to elevate the oil market fear index (OVX). Dong et al. (2023) show that the long-term correlations between conventional and energy stocks on the one hand and conventional and green bonds on the other are affected by CPU, EPU, and geopolitical risks. Liu et al. (2023) demonstrate that increases in CPU have a positive impact on gas prices, whereas increases in global EPU lead to a decrease in carbon and oil prices. Based on firm-level data, Persakis (2023) establishes that CPU has a positive (negative) impact on ESG stock performance (carbon dioxide emission performance and corporate performance). Relying on data from China, Wang and Li (2023) find that climate uncertainty, CPU, and US EPU are important predictors of the volatility of the CSI 300 ESG index. Xiang et al. (2023) demonstrate that life insurance premia in China are negatively and asymmetrically associated with CPU, EPU, and geopolitical risks. Sun et al. (2024) indicate

that higher levels of CPU in China tend to act as a barrier to green innovation, since it leads to a reduction in government green subsidies, imposes constraints on businesses in meeting their environmental and social responsibilities, and raises financial limitations. Wu and Liu (2023) conclude that climate policies have a primary role in affecting the spillover dynamics between green finance markets. The results of Hong et al. (2024) suggest that both domestic and global EPU indices exert substantial effects on developed and emerging stock markets, especially in turmoil times. Chowdhury and Damianov (2024) establish that news-based cryptocurrency uncertainty indices are important predictors of crypto market bubbles.

While the nexus between policy-induced uncertainties and global influences (e.g., financial markets, commodities, green finance) has been a central focus of recent research and discourse, there has been surprisingly meagre attention devoted to exploring how policy uncertainty affects the formation of business and consumer sentiment. Complementing this strand of literature, we investigate whether, and to what extent, CPU and EPU influence the evolution of US sentiment trends in the short and long run and across different regimes of domestic sentiment. More concretely, our research inquiries are:

- (I) Do climate and economic policy uncertainties contribute significant explanatory power for business- and consumer-sentiment trends?
- (II) Does the explanatory power of either type of uncertainty, if any, vary between the short and the long run?
- (III) Does the explanatory power of either type of uncertainty, if any, differ between optimistic, neutral, and pessimistic sentiment states?

There are three chief contributions that our work makes to the existing body of research. First, most relevant papers (e.g., Ajmi et al., 2015; Atukeren et al., 2013; Cai et al., 2022; Cepni et al., 2023; Nartea et al., 2020; Mohammed et al., 2023; Xiao & Liu, 2023) focus solely on exploring the connection between investor sentiment, a merely single segment of the economy, and policy-related uncertainties. In contrast, our analysis expands to include other crucial segments of the US economy beyond investors, namely producers and households. This broader scope allows for a more comprehensive evaluation of how changes in CPU and EPU impact both sides of the economic activity. US domestic sentiment is assessed separately via proxies for business confidence (representing supply-side sentiment) and consumer confidence (representing demand-side sentiment). While likely interrelated, business and consumer sentiment indicators furnish distinct information sets, revealing how diverse agents (i.e., producers and consumers) interpret the current and future trajectory of the economy. Sentiment within the corporate world tends to mirror specific aspects of the business environment, whereas consumer sentiment reflects significant features pertinent to households. To the best of our knowledge, no study has been hitherto undertaken to assess the potential role of policy uncertainty in driving business and consumer sentiment. Our paper aims to fill this void in the existing literature. Second, in an increasingly interconnected world, it is highly likely that sentiment is influenced by global economic, geopolitical, and financial developments. This fact implies that modeling business or household sentiment as a function of solely policy uncertainty will probably produce inaccurate conclusions, because there are other drivers

of sentiment overlooked in the analysis. Therefore, we investigate the potential sensitivity of sentiment to policy uncertainty, after orthogonalizing raw sentiment series with respect to a range of predominant determinants and risk factors. Such an orthogonalization approach reduces the risk of omitted-variable bias in our regression models (Harvey & Liu, 2021). Third, from a methodological perspective, we utilize the dynamic quantile autoregressive distributed lag (QARDL) model of Cho et al. (2015). A chief advantage of this approach is that it serves to distinguish between the probable sensitivities of sentiment to policy uncertainty in the short and long run. At the same time, it considers the potential for locational asymmetry via examining the differential sensitivities of sentiment to policy uncertainty under different sentiment state scenarios (i.e., optimism, neutrality, pessimism). Taken together, the results of this estimation approach offer an all-embracing portrayal of the policy uncertainty-sentiment nexus.

Our main results are summarized as follows. First, CPU exerts a substantial negative impact on business sentiment in the short run (long run) across all sentiment regimes (across pessimistic and normal sentiment regimes). Second, CPU has a negative influence on consumer sentiment in the short and long run, particularly in times of pessimism. Third, business sentiment is negatively correlated with EPU, whether in the short or long run, and regardless of the state of business sentiment. Fourth, consumer sentiment is negatively related to EPU in the short run and across different sentiment regimes. In the long run, nevertheless, EPU appears to have no meaningful impact on consumers' perceptions and expectations.

After this introductory part, the paper proceeds as follows. [Section 2](#) offers a brief review of pertinent literature. [Section 3](#) describes the dataset, while [Section 4](#) outlines the econometric framework. Our findings are discussed in [Section 5](#) and the validity of the results is verified in the penultimate section. We conclude the paper in [Section 7](#).

2. Literature review

2.1. Theoretical background

Policy uncertainty has long been a focal point in the realms of finance and economics, serving as a fundamental concept and a pertinent issue in both academic discussions and real-world decision-making processes. With its pervasive effect on market dynamics, investment behavior, and economic outcomes, policy uncertainty has attracted considerable interest from scholars, policymakers, and professionals alike. Over the years, several theories have emerged to elucidate its complexities and implications. From the perspective of financial markets, policy uncertainty represents a chief source of volatility and risk, influencing investment decisions, asset prices, and market sentiment. In economics, it has profound effects on consumer behavior patterns, business investment decisions, and overall economic activity. In one prominent contribution, Christiano et al. (2010) construct a dynamic stochastic general equilibrium (DSGE) model that integrates financial frictions. In this model, risk shocks produce considerable and enduring decreases in output. Their findings indicate that agency problems within financial contracts, liquidity constraints experienced by banks, and shocks affecting market risk perceptions play crucial roles in driving economic fluctuations. Narita (2011) formulates a model wherein heightened uncertainty interacts with agency problems, resulting in the abandonment of

projects and instigating reduced levels of risk-taking overall. This diminished risk appetite acts as a mechanism for propagating the initial uncertainty shock, as projects with lower risk profiles typically yield lower average returns. Cesa-Bianchi et al. (2020) propose a multi-country framework to analyze the interaction between uncertainty and economic activity, without a priori restricting the direction of causality. They show that in addition to common technology shocks that affect output growth, higher-order moments of technology shocks are also required to explain the cross-country variations of the realized volatility of equity returns. Fernández-Villaverde et al. (2011) contend that fluctuations in interest rate volatility in small open economies, combined with substantial investment adjustment expenses, contribute to prolonged decreases in output. Born and Pfeifer (2014) examine how policy risk contributes to business cycle fluctuations through the utilization of a New Keynesian DSGE model incorporating policy risk alongside uncertainty about technology. Contrary to expectations, their analysis reveals that the influence of policy risk surpasses that of uncertainty related to aggregate total factor productivity (TFP). This indicates a potential overestimation of the significance of policy risk in explaining business cycles. Pástor and Veronesi (2013) develop a general equilibrium framework depicting government policy decisions, where stock prices react to political developments. Their model implies that political uncertainty carries a risk premium, which is more pronounced during periods of economic fragility.

2.2. Empirical evidence

Given the far-reaching implications of uncertainty-generating policies, whether at the level of individuals, enterprises, or entire countries, considerable focus has been devoted to understanding their linkages with diverse financial markets and macroeconomic fundamentals. This heightened attention is driven by the desire to unravel the nuanced interplay and consequences that these uncertainties can exert on many facets of the economic and financial landscape, offering insights into how such policies resonate across different scales of operation. For the sake of consistency, we divide empirical research into two distinct streams: (i) studies investigating the relationship between a sole policy uncertainty type and other factors; and (ii) studies exploring the association between a set of policy uncertainty types and other factors.

The first line of literature restricts the scope of analysis to assessing the nature of the connection between a single category of policy uncertainty and a wide array of factors. For instance, utilizing US firm-level datasets, Persakis (2023) demonstrates that CPU has a positive influence on ESG stock performance. However, it exerts a negative impact on both carbon dioxide emission performance and corporate performance. Sun et al. (2024) find that elevated levels of CPU in China are associated with a decline in government green subsidies, constraints on businesses in fulfilling their environmental and social responsibilities, and an increase in financial limitations, thereby serving as an impediment to green innovation. Using information from Chinese A-share listed companies, Zhou et al. (2023) observe that corporate innovation efficiency diminishes as firms perceive greater EPU. However, this adverse effect is mitigated for companies with greater board independence and lower board ownership. Lv and Li (2023) show that CPU has substantial out-of-sample predictive ability for the sectoral price volatility of utilities, energy, consumer discretionary, materials, healthcare, and industrials. Similarly,

Raza et al. (2024) conclude that CPU is a primary component in forecasting the volatility of clean, green, and sustainable financial markets. The results also indicate that elevated volatility in the corresponding benchmark indices is correlated with an increase in CPU. Azimli (2023) establishes that higher engagement levels of corporate social responsibility allay the negative influence of CPU on the valuation of US firms. Based on multi-scale time-varying Granger causality tests, Hong et al. (2024) document that developed and emerging stock markets are negatively correlated with global (domestic) EPU in the short (long) run. Zhang et al. (2024) find that the stability of cryptocurrency returns increases during periods of higher EPU, implying that cryptocurrencies may be regarded as a safe-haven asset amidst heightened EPU. Chen and Chen (2022) demonstrate considerable feedback causal relationships between the cyclical components of S&P 500 index, EPU, and Twitter's happiness sentiment in most quantiles. Xu (2023) finds, based on panel data from 21 countries, that EPU is positively linked to increased household saving rates. This linkage becomes more conspicuous when levels of institutional quality and financial development are low. Azad and Serletis (2022) find that macroeconomic fundamentals and financial markets of emerging economies are adversely affected by US monetary policy uncertainty (MPU, hereafter) shocks. Employing datasets from the US and 32 economies, Lastauskas and Nguyen (2024) show that the US MPU plays an essential role in influencing global business and financial cycles. Beckmann and Czudaj (2023) demonstrate a significant negative impact of MPU on production growth and stock market returns in industrialized economies, which is propagated by media coverage. The results of Fasani et al. (2023) suggest that a positive shock to MPU triggers a drop in output and inflation, a decline in stock prices, reduced entry of new companies, and increased exit of companies. Cho and Im (2023) show that the marginal impacts of MPU are different across Korean firms, due to the peculiar firm characteristics. Besides, a rise in MPU induces a decrease in debt ratios in the short run. Guenich et al. (2022), utilizing monthly data across 22 OECD economies, document that EPU, interest rate fluctuations, and oil price uncertainty exert notably asymmetric impacts on investor sentiment, both in the short term and over longer periods.

The second line of research broadens the investigative scope by incorporating different types of policy uncertainties and exploring their unique interactions with other factors. For example, Montes and Nogueira (2022) find that heightened levels of both political uncertainty and EPU in Brazil lead to a decline in domestic business confidence. Xiang et al. (2023) show that geopolitical risks, CPU, and EPU are asymmetrically and negatively correlated with life insurance premia in China. Dong et al. (2023) demonstrate that CPU, EPU, and geopolitical risks impact the long-term correlations between conventional and green bonds on the one hand and conventional and energy stocks on the other. Xiao and Liu (2023) find that the oil market fear index (OVX) is positively correlated with CPU and EPU. Liu et al. (2023) document that rises in CPU (EPU) contribute positively (negatively) to gas (carbon and oil) prices. Li et al. (2023) show that EPU has a negative (positive) effect on renewable (non-renewable) energy consumption. The results also suggest a positive causal link between CPU and non-renewable energy consumption, barring during turmoil periods. According to J. Wang and Li (2023), the Chinese CSI 300 ESG index's volatility can be reliably predicted by CPU, EPU, US EPU, and climatic uncertainty. Likewise, Zhang et al. (2024) document that China's energy market volatility is positively linked to global and Chinese EPU, CPU, and the

geopolitical risk act index. Li et al. (2022) finds that trade policy uncertainty and MPU exhibit a remarkable positive effect on China's carbon emissions trading, while exchange rate policy uncertainty has a negative influence. He and Zhang (2022) evaluate the predictive capability of six uncertainty indicators, namely CPU, EPU, MPU, VIX, geopolitical risk, and equity market volatility, for oil industry returns. Their findings indicate that CPU demonstrates superior predictive power when compared to other uncertainty proxies. Xue and Wang (2023) demonstrate that the volatility of bond returns in emerging markets is positively correlated with US EPU, MPU, and fiscal policy uncertainty, especially in the upper quantiles of volatility. Zeng et al. (2022) show that EPU and CPU of China provide valuable information for predicting the volatility of the Wind carbon neutral concept index. Guo et al. (2023) find that the composite EPU reinforces the long-term equity-green bonds nexus but weakens equity-conventional bond nexus. Moreover, MPU, fiscal policy uncertainty, trade policy uncertainty, and exchange rate policy uncertainty exhibit diverse effects on long-term correlations in terms of significance, magnitude, and sign. Wang and Li (2023) report evidence of a positive (negative) connection between the price volatility of Bitcoin and fiscal (monetary) policy uncertainty, which confirms the viability of bitcoins as a hedge instrument against monetary uncertainty.

Two primary conclusions can be extracted from the above research survey. First, an immense portion of pertinent studies (e.g., Idnani et al., 2023; Mohammed et al., 2023; Montes & Nogueira, 2022; Sui et al., 2022; Wang et al., 2020; Xiao & Liu, 2023; Zhang, 2019; Zhou et al., 2023) chiefly concentrate on investigating the relationship between investor sentiment and policy-related uncertainties, addressing only a segment of the economy. Our analysis distinguishes itself by broadening its scope to encompass vital stakeholders in the US economy, namely producers and households, thus providing a thorough assessment of how changes in CPU and EPU affect both aspects of economic activity. To our best knowledge, no prior research has assessed the potential influence of policy uncertainty on business and consumer sentiment, making our study a novel contribution to the existing literature. Second, in terms of methodology, the vast majority of studies (e.g., Ahmed, 2020; Chen & Chen, 2022; Guenich et al., 2022; Kirchner, 2020; Lutz, 2015; Nartea et al., 2020; Ugurlu-Yildirim et al., 2021; Wu & Liu, 2023; Zhang, 2019) explore the linkage between policy uncertainty and public sentiment in isolation of other potentially influential variables. It is probable that modeling sentiment purely as a function of policy uncertainty leads to faulty inferences, as certain relevant factors are not taken into consideration in the analysis. To address this critical issue, our paper examines the potential sensitivity of sentiment to policy uncertainty only after orthogonalizing raw sentiment time series with respect to a range of principal influencers and risk factors. This orthogonalization approach alleviates the risk of omitted-variable bias in our QARDL models, enhancing the robustness of our investigation.

3. Data description

This paper focuses on the US, due to its prominent position in the global economic landscape and its leading involvement in climate research, technological advancements, and scientific expertise related to climate change. To this end, we collect data with monthly frequency over the period from January 2000 to August 2023, which gives 284

observations. Data limitations on some variables dictate the starting date of the sample and the monthly timeframe. In what follows, we provide a brief account of the variables used in the empirical investigation.

3.1. Policy uncertainty and sentiment proxies

US domestic sentiment is captured by both business confidence index (BCI, hereafter) and consumer confidence index (CCI, hereafter) sourced from the OECD Main Economic Indicators database. The OECD releases month-end standardized BCI and CCI metrics, based on a rich range of datasets compiled from business and household opinion surveys. The BCI aims to evaluate the attitudes and expectations of US businesses with reference to the future economic environment. The index is typically generated through surveys conducted among a diverse group of enterprises, spanning various sectors and industries to ensure its representativeness. It considers such crucial factors as expectations for sales, investment, employment, and overall business conditions, thus offering insights into potential upcoming economic trends. The BCI is scaled with a threshold value of 100, where a score above 100 signifies that businesspeople are upbeat about future economic prospects, anticipating growth and expansion. On the contrary, a score lower than 100 suggests a more downbeat outlook, indicating concerns about economic conditions in the upcoming period (OECD, 2023a). Likewise, the CCI is constructed to reveal the prospects of household consumption and saving, based on survey participants' expectations regarding their own financial situation, their ability to save, unemployment trends, and aggregate economic circumstances. The index is scaled with a cut-off point of 100, where a score greater than 100 typically means that consumers are more optimistic about economic conditions. It suggests that they have a positive outlook on the economy, and thus they are likely to increase spending. Conversely, a score below 100 indicates a more pessimistic consumer sentiment, often resulting in reduced spending and a more wary approach to economic activities (OECD, 2023b). Both forward-looking sentiment proxies have been widely deployed in the literature (e.g., Ahmed, 2020; Atukeren et al., 2013; Cepni et al., 2023; Moran et al., 2019).

Regarding our two main independent variables, we adopt the EPU index, introduced by Baker et al. (2016), and the CPU index, developed by Gavrilidis (2021), as indicators for economic and climate policy-induced uncertainties, respectively. The EPU index is designed to quantify and track the level of uncertainty pertaining to economic policy choices in the US. This is achieved via an analysis of newspaper articles, tax code provisions, and other pertinent resources to gauge the prevalence of terms connected to uncertainty, economics, and policymaking. In a similar fashion, the CPU index is built by analyzing how often climate policy-related articles appear in eight major US newspapers, based on text mining techniques. It focuses on identifying and recording significant events that exclusively pertain to climate policy.

Figure 1 depicts the behavior of BCI and CCI levels over the sample period. We notice remarkable declines in BCI and CCI levels during turbulent periods (e.g., the 2001 terrorist attacks, the 2008–2009 global financial crisis, the 2010–2012 European sovereign debt crisis, and more recently, the emergence and spread of COVID-19 pandemic worldwide). Such downturns suggest that investors and households alike are profoundly concerned about the prospects of the US economy.

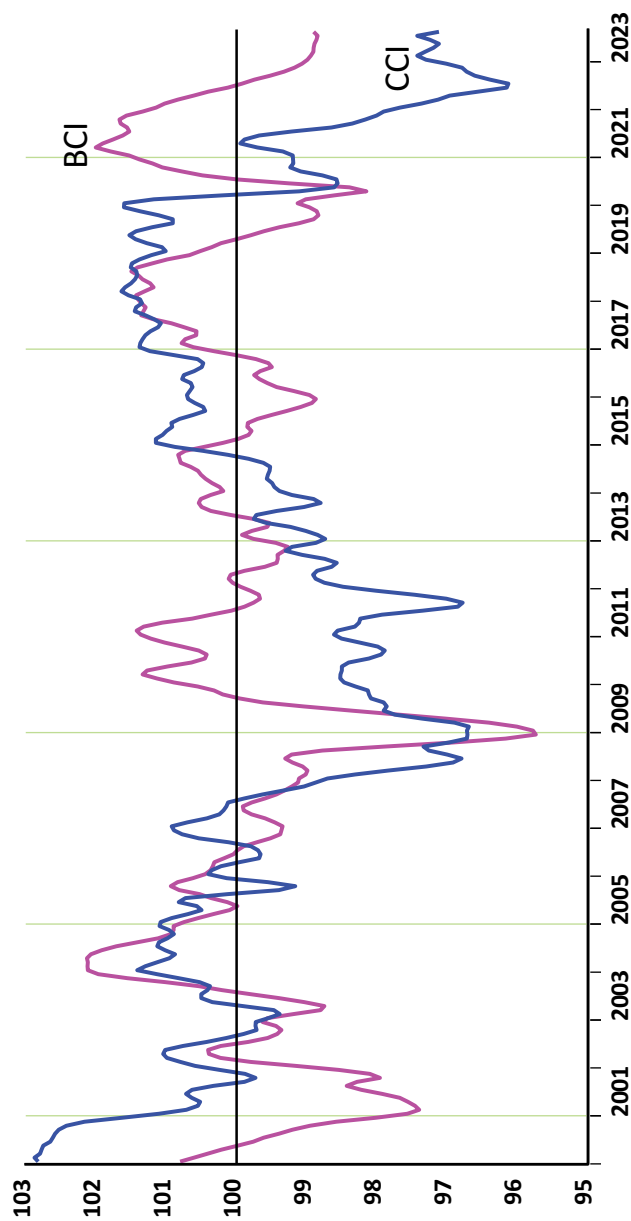


Figure 1. Time trends of BCI and CCI over the study period.

BCI (CCI) hit its lowest level throughout the global financial crisis (the pandemic crisis). [Figure 2](#) illustrates the time trends of EPU and CPU. The EPU exhibits a pro-cyclical behavior, which means that it moves in the same direction as the broader economic cycle. During periods of global economic downturns and crises, it tends to spike, expressing heightened uncertainty about the future economic outlook and rising risk aversion among businesses, investors, and policymakers. The CPU, on the other hand, displays a clear increasing trend, especially in recent years (2016–2023). This suggests that concerns and uncertainties related to climate policy have been on the rise over time, underlining a growing stress on climate policy and environmental issues.

3.2. Orthogonalizing variables

Since public sentiment is by no means immune to economic cycle dynamics, political scene, and global events, it is essential that we cleanse BCI and CCI series of the confounding effects that these forces may have, using an orthogonalization procedure in a similar spirit to Harvey and Liu (2021), Goodell and Vähämaa (2013), and Gulen and Mayhew (2000). In our analysis, such developments are represented by ten germane variables, of which three are dummies corresponding to momentous events in the sample period. The selection of those factors is governed by data availability constraints and past research evidence confirming their close link with market sentiment. The quantitative variables are industrial production index (IPI), term spread (TS), inflation (INF), unemployment rate (UR), US geopolitical risk index (GPR), VIX, and global energy prices index (ENG). A concise overview of those candidate factors is given in [Table 1](#). The dummy variables stand for the global financial crisis, European sovereign debt crisis, and the outbreak of COVID-19 pandemic. These dichotomous variables are assigned a value of one during September 2008–August 20 October 2009, 10–July 2012, and February 2020–August 2023, respectively, and zero otherwise.

The data series of CPU, EPU, and GPR indices are extracted from the economic policy uncertainty website (<https://www.policyuncertainty.com/>), whereas the remaining series are from Federal Reserve Economic Data (FRED) database of St. Louis Fed. As a prelude to the empirical work, all the time series are seasonally adjusted, where applicable to economic activity proxies, and are made stationary using a first difference or a logarithmic first difference transformation.

4. Econometric methods

The empirical investigation is comprised of two chief steps. First, to provide a clearer and more accurate assessment of how CPU and EPU affect both BCI and CCI, we commence our analysis by removing the potential effects of ten germane variables from sentiment proxies. Subsequently, a quantile ARDL approach is employed to investigate how important climate and economic policy uncertainties are in explaining developments in domestic sentiment. A concise rendition of both steps is given below.

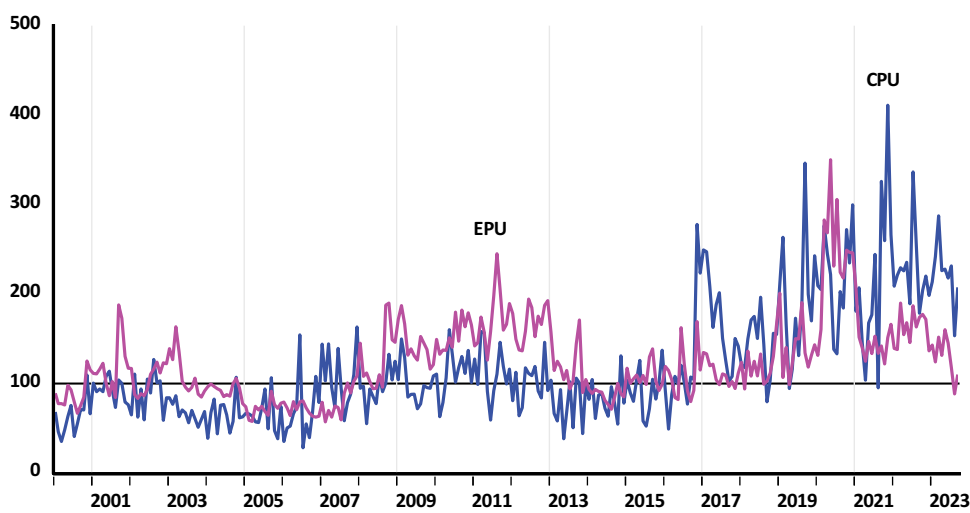


Figure 2. Time evolution of CPU end EPU over the study period.

Table 1. Definition of orthogonalizing variables.

Variable	Description
Industrial production index (IPI)	Published by the Federal Reserve, the IPI is a critical economic indicator serving primarily to assess the overall health and performance of the industrial sector in the US economy.
Term spread (TS)	TS is the difference between the yield on 10-year treasury bonds and the yield on 3-month treasury bills. TS provides valuable insights into market expectations and can serve as an important early warning signal for economic conditions.
Inflation (INF)	The monthly percentage change in the Consumer Price Index (CPI) is utilized to calculate inflation. INF is a vital indicator of the health and stability of the US economy.
Unemployment rate (UR)	Changes in the UR can signal shifts in the US broader economy. A rising (declining) UR often suggests economic distress and job losses (economic growth and increased job opportunities).
US geopolitical risk index (GPR)	We use the news-based GPR, developed by Caldara and Iacoviello (2022), as a measure for adverse geopolitical events and related threats in the US. The GPR is generated by tallying and analyzing the number of articles that shed light on ominous geopolitical events and associated risks in the world's ten most globally recognized newspapers.
VIX	Derived from the prices of S&P 500 index options, the VIX, also known as the fear gauge, is a financial metric that measures the market's expectation of near-term volatility.
Global energy prices index (ENG)	Global price trends in energy commodities (crude oil, natural gas, coal, and propene) are tracked by ENG.

4.1. Orthogonalization procedure

In empirical analysis involving a response variable and one or two regressors, the use of the orthogonalization regression procedure is crucial. Modeling the response variable solely as a function of a single explanatory variable increases the likelihood of reaching erroneous conclusions. This oversimplified approach disregards other pertinent factors that could hugely impact the response variable, possibly introducing bias and yielding misleading results (Eleswarapu & Reinganum, 2004). The orthogonalization procedure addresses this issue by eliminating any confounding effects on the response variable

stemming from influential factors not explicitly considered in the analysis. Its purpose is to mitigate the risk of omitted variable bias, a common concern in regression modeling (Goodell & Vähämaa, 2013; Harvey & Liu, 2021). Gujarati (2003) points out that omitted variable bias emerges when relevant variables that should be included in the analysis are left out, resulting in biased and unreliable estimates of variable relationships. In the context of our study, the orthogonalization procedure ensures the effective disentanglement of the influence of important factors (i.e., industrial production, term spread, inflation, unemployment rate, VIX, US geopolitical risks, energy prices, the global financial crisis, European sovereign debt crisis, the outbreak of COVID-19 pandemic) from the sentiment series. In other words, it isolates the confounding effects that these variables may have on sentiment proxies, yielding more accurate estimates when subsequently running the QARDL models. Essentially, orthogonalization enhances the robustness and validity of the QARDL estimation results by tackling potential sources of bias and confirming that the estimated relationships are more reflective of the true underlying dynamics.

Against this backdrop, the BCI and CCI series are orthogonalized with respect to our array of candidate variables through estimating the following orthogonalization regression model:

$$S_{i,t} = \alpha_i + \sum_{j=1}^p \zeta_{i,j} S_{i,t-j} + \sum_{k=1}^{10} \delta_{i,k} Orth_{i,k,t-1} + \epsilon_{i,t}^{\perp} \quad (1)$$

where $S_{i,t}$ denotes the sentiment proxy i (i.e., BCI and CCI) in month t , α is a constant term, and $Orth_k$ is a 10-dimensional vector of orthogonalizing regressors. To address the potential for autocorrelation, we prewhiten the BCI and CCI series by incorporating the autoregressive terms into Eq (1). The Akaike Information Criterion (AIC) is used to pinpoint each regression's optimal number of autoregressive lags. Since the data extracted from the survey assessments are compiled and processed in the weeks leading up to the publication date of BCI and CCI, all quantitative independent variables are adjusted for a one-period lag. This procedure also alleviates concerns of possible endogeneity. In OLS regression analysis, endogeneity arises when independent variables are correlated with the error term due to simultaneity, omitted variables, or measurement errors. To mitigate these concerns, we follow the approach of lagging the independent variables by one period, as supported by numerous studies (e.g., Ahmed, 2021; Chau et al., 2014; Goodell & Vähämaa, 2013; Gulen & Mayhew, 2000; Harvey & Liu, 2021). Such a robust approach establishes a clear causal direction, reduces simultaneity bias, controls for autocorrelation, mitigates measurement errors, and addresses omitted variable bias, resulting in more reliable and unbiased coefficient estimates. Empirically, we lag our set of explanatory variables to ensure they are determined before the dependent variables (i.e., BCI and CCI), reducing reverse causality risk. This technique assumes that past values of the independent variables influence current sentiment proxies, not vice versa, thus minimizing simultaneity bias. Lagging also captures serial correlation effects, improves estimation accuracy, and diminishes measurement error impact. Additionally, it mitigates omitted variable bias by accounting for unobserved variables that may influence

both the independent and dependent variables. Overall, this approach ensures that the independent variables are not contemporaneously associated with the error term in the current period, thereby effectively addressing endogeneity concerns. By construction, the regression residuals of Eq (1) correspond to the portion of S_i that is typically unrelated to the vector of explanatory variables, such that $COV(Orth_{i,k}, \varepsilon_i) = 0$. This ensures that the explanatory variables are not causing or contributing to ε_i and that any variation in S_i is not due to the independent variables being considered.

4.2. Quantile ARDL model

Having obtained the $\varepsilon_{i,t}^\perp$ series, we move on to the second step, which involves evaluating simultaneously the long-run relationship between the US domestic sentiments, proxied by $\varepsilon_{BCI,t}^\perp$ and $\varepsilon_{CCI,t}^\perp$, and policy uncertainties, proxied by CPU and EPU, as well as the corresponding short-run dynamics across various quantiles ($0 < \tau < 1$) of the respective conditional distributions of $\varepsilon_{BCI,t}^\perp$ and $\varepsilon_{CCI,t}^\perp$. To this end, we apply the dynamic QARDL modeling approach. To begin, each sentiment proxy i is modeled as a function of climate and economic policy uncertainties, as shown in the following equation:

$$\varepsilon_{i,t}^\perp = f(CPU_t, EPU_t) = C_i + \omega_i CPU_{i,t} + \vartheta_i EPU_{i,t} + Z_{i,t} \quad (2)$$

where $Z_{i,t}$ is the residual term with a zero mean and constant variance. In the above specification, all variables are in logarithmic form. Following Pesaran et al. (2001), we can rewrite Eq (2) as an OLS-based ARDL (p, q_1, q_2) as follows:

$$\varepsilon_{i,t}^\perp = C_i + \sum_{j=1}^p \varphi_{ij} \varepsilon_{i,t-j}^\perp + \sum_{j=0}^{q_1} \omega_{ij} CPU_{i,t-j} + \sum_{j=0}^{q_2} \vartheta_{ij} EPU_{i,t-j} + Z_{i,t} \quad (3)$$

Once a proper lag structure is identified, Eq. (3) can be estimated to verify the presence of a long-run relationship among the variables in levels, regardless of whether those variables are $I(0)$, $I(1)$ processes, or have complex cointegrated relationships. Unlike the ARDL model, which is restricted to exploring long- and short-run relationships in the conditional mean, the QARDL accounts for locational asymmetry, in the sense that the CPU and EPU parameter coefficients could be associated with the location of $\varepsilon_{BCI,t}^\perp$ and $\varepsilon_{CCI,t}^\perp$ within their respective conditional Cho et al. (2015) extend the ARDL approach into a quantile regression context, which can be expressed in the following basic form:

$$Q\varepsilon_{i,t}^\perp = C_i(\tau) + \sum_{j=1}^p \varphi_{ij}(\tau) \varepsilon_{i,t-j}^\perp + \sum_{j=0}^{q_1} \omega_{ij}(\tau) CPU_{i,t-j} + \sum_{j=0}^{q_2} \vartheta_{ij}(\tau) EPU_{i,t-j} + Z_{i,t}(\tau) \quad (4)$$

where $Z_{i,t}(\tau)$ is the stochastic term defined as $\varepsilon_{i,t}^\perp - Q_{\varepsilon_{i,t}^\perp}(\tau | \mathcal{F}_{t-1})$ with $Q_{\varepsilon_{i,t}^\perp}(\tau | \mathcal{F}_{t-1})$ denoting the τ^{th} quantile of $\varepsilon_{i,t}^\perp$ conditional on $\mathcal{F}_{t-1} = \{CPU_{i,t}, EPU_{i,t}, \varepsilon_{i,t-1}^\perp, CPU_{i,t-1}, EPU_{i,t-1}, \dots\}$. Considering the possibility of $Z_{i,t}$ being autocorrelated, Eq. (4) can be generalized to the following form:

$$\begin{aligned}
Q\Delta_{i,t}^{\perp} = & C_i(\tau) + \rho_i(\tau)\epsilon_{i,t-1}^{\perp} + \psi_i(\tau)CPU_{i,t-1} + \xi_i(\tau)EPU_{i,t-1} + \sum_{j=1}^p \varphi_{i,j}(\tau)\Delta_{i,t-j}^{\perp} \\
& + \sum_{j=0}^{q_1-1} \omega_{i,j}(\tau)\Delta CPU_{i,t-j} + \sum_{j=0}^{q_2-1} \vartheta_{i,j}(\tau)\Delta EPU_{i,t-j} + V_{i,t}(\tau)
\end{aligned} \quad (5)$$

To control for the potential contemporaneous correlation between $V_{i,t}$ and our main explanatory variables, $V_{i,t}$ is projected on ΔCPU_i and ΔEPU_i using the specification:

$$V_{i,t} = \emptyset_{1,i} \Delta CPU_{i,t} + \emptyset_{2,i} \Delta EPU_{i,t} + U_{i,t} \quad (6)$$

By substituting this projection, the QARDL parameters can be expressed in the following error correction model form (QARDL-ECM):

$$\begin{aligned}
Q\Delta\epsilon_{i,t}^{\perp}(\tau|\cdot) = & C_i(\tau) + \rho_i(\tau)\left(\epsilon_{i,t-1}^{\perp} - \beta_{1,i}(\tau)CPU_{i,t-1} - \beta_{2,i}(\tau)EPU_{i,t-1}\right) \\
& + \sum_{j=1}^{p-1} \varphi_{i,j}(\tau) \Delta \epsilon_{i,t-j}^{\perp} + \sum_{j=0}^{q_1-1} \omega_{i,j}(\tau) \Delta CPU_{i,t-j} + \sum_{j=0}^{q_2-1} \vartheta_{i,j}(\tau) \Delta EPU_{i,t-j} \\
& + U_{i,t}(\tau)
\end{aligned} \quad (7)$$

where $Q\Delta\epsilon_{i,t}^{\perp}(\tau|\cdot)$ denotes the τ^{th} conditional quantile of $\Delta\epsilon_{i,t}^{\perp}$, C_i is the intercept term at the τ^{th} quantile, and $\rho_i(\tau)$ indicates the speed of quantile-specific adjustment to the long-run equilibrium. The ECM coefficient must carry a negative sign with statistical significance. In Eq. (7), the long-run cointegration parameters are given as $\beta_{1,i} = -\psi_i/\rho_i$ and $\beta_{2,i} = -\xi_i/\rho_i$. In light of the delta method, we define the cumulative short-term effects of past observations of the sentiment proxy i on its current observation as $\varphi_i = \sum_{j=1}^{p-1} \varphi_{i,j}$. Likewise, the cumulative short-term effects of both past and current

observations of CPU and EPU on the sentiment proxy i are calculated as $\omega_i = \sum_{j=0}^{q_1-1} \omega_{i,j}$

and $\vartheta_i = \sum_{j=0}^{q_1-1} \vartheta_{i,j}$, respectively. The AIC criterion is employed to determine the appropriate lag lengths of p , q_1 , q_2 .

The estimation of the QARDL-ECM models is carried out for a range of seven quantiles, $\tau \in \{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95\}$. Besides, we examine whether CPU and EPU exert asymmetric effects on each sentiment proxy in the short and long run, using the standard Wald test.

5. Findings

5.1. Data filtration results

As indicated in Subsection 4.1, the residual series, $\epsilon_{i,t}^{\perp}$, of Eq (1) represent the portion of the sentiment series that is uncorrelated with the vector of our explanatory variables (i.e., industrial production, term spread, inflation, unemployment rate, VIX, US geopolitical risks, energy prices, the global financial crisis, European sovereign debt crisis, the outbreak of COVID-19 pandemic). This ensures that these explanatory variables do not

affect or contribute to the residuals. Consequently, any variations observed in the sentiment series are independent of the ten explanatory variables under consideration. Such process makes the subsequent QARDL estimates more realistic, because they are based on sentiment data that is not influenced by the variables being examined.

Estimation results of the orthogonalization regressions are shown in Table 2. The autoregressive coefficients are positive and statistically different from zero, regardless of the dependent variable. This means that past sentiment tends to carry forward and influence current sentiment positively. For both BCI and CCI, we notice that industrial production, inflation, and energy commodity prices seem to be important common predictors. BCI (CCI) is negatively associated with geopolitical risks and VIX (term spread and unemployment rate) at conventional significance levels. This result implies that as those factors experience increases, domestic confidence becomes weak. The coefficients pertaining to the global financial crisis and the COVID-19 pandemic are negative in sign and statistically distinguishable from zero, irrespective of the sentiment proxy used. When looking at business sentiment, the European-crisis dummy variable shows a negative coefficient, although its statistical significance is only marginal. This suggests that the European crisis may have a somewhat depressive effect on BCI.

5.2. Univariate stochastic properties

We utilize the white-noise residual series, $\varepsilon_{i,t}^\perp$, generated by each orthogonalization regression model, in our subsequent analysis. Panel A of Table 3 lists basic statistics for our main independent variables and the orthogonalized series of BCI and CCI. It is evident that the respective distributions of the filtered BCI and CCI series display

Table 2. Coefficient estimates of the orthogonalization regressions.

Variables	CCI	BCI
α	0.230 (1.175)	0.074** (2.371)
$S_{i,t-1}$	0.325** (2.288)	0.437*** (3.138)
$S_{i,t-2}$	0.308*** (6.035)	0.252* (1.763)
$S_{i,t-3}$	0.165* (1.845)	—
IPI_{t-1}	0.289** (2.142)	0.155* (1.869)
TS_{t-1}	0.026 (1.035)	0.164* (1.808)
INF_{t-1}	−0.309* (−1.782)	−0.214** (−2.076)
UR_{t-1}	−0.187 (−1.125)	−0.197** (−2.402)
GPR_{t-1}	−0.149** (−2.374)	−0.119 (−0.839)
ENG_{t-1}	−0.158* (−1.905)	−0.401** (−2.134)
VIX_{t-1}	−0.465** (−2.418)	−0.176 (−1.382)
DUM_1	−0.567*** (−4.256)	−0.161** (−2.397)
DUM_2	−0.283* (−1.934)	0.128 (0.539)
DUM_3	−0.579*** (−5.120)	−0.394*** (−4.709)

This table shows the coefficient estimates of Eq (1). BCI and CCI are business and consumer confidence proxy indices, respectively. S_i denotes the sentiment proxy i . IPI, TS, INF, UR, GPR, and ENG are the industrial production index, term spread, inflation rate, unemployment rate, geopolitical risk index, and global energy prices index, respectively. DUM_1 , DUM_2 , and DUM_3 are dummy variables representing the global financial crisis, European sovereign debt crisis, and the COVID-19 pandemic, respectively. The AIC criterion is utilized to select the appropriate number of autoregressive lags. The Newey and West (1987) HAC t -statistics are given in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3. Univariate characteristics of the key variables.

Panel A: Summary statistics							
Variables	Mean	Standard deviation		Skewness	Kurtosis	JB test	
Panel A: Summary statistics							
$\varepsilon_{BCI}^{\perp}$	1.54E-14	0.100		-0.061	3.941	10.552***	
$\varepsilon_{CCI}^{\perp}$	-3.58E-18	0.115		-0.416	3.437	10.251***	
CPU	4.655	0.502		0.215	2.649	3.643	
EPU	4.770	0.336		0.245	2.844	3.124	
Panel B: BDS test results							
m	2	3	4	5	6	7	8
$\varepsilon_{BCI}^{\perp}$	10.708***	14.581***	17.920***	20.248***	22.405***	23.839***	21.541***
$\varepsilon_{CCI}^{\perp}$	14.250***	16.068***	19.037***	22.026***	25.337***	29.147***	42.300***
CPU	9.680***	9.874***	9.314***	8.687***	8.154***	7.748***	7.632***
EPU	15.435***	16.407***	16.129***	16.493***	17.342***	14.721***	12.618***
Panel C: Quantile unit root test results							
	$\tau_{0.05}$	$\tau_{0.10}$	$\tau_{0.25}$	$\tau_{0.50}$	$\tau_{0.75}$	$\tau_{0.90}$	$\tau_{0.95}$
$\varepsilon_{BCI}^{\perp}$	0.349	-2.299	-4.020***	-5.963***	-7.062***	-7.983***	-7.450***
$\varepsilon_{CCI}^{\perp}$	-6.475***	-4.221***	-5.981***	-5.977***	-6.797***	-6.717***	-6.695***
CPU	-3.472**	-2.941	-4.866***	-5.263***	-5.898***	-4.586***	-4.213***
EPU	-5.999***	-3.418**	-7.307***	-6.885***	-6.010***	-4.891***	-3.768**

Panel A presents estimates of the first four moments of the variables under study, along with normality test results. $\varepsilon_{BCI,t}^{\perp}$ and $\varepsilon_{CCI,t}^{\perp}$ are the filtered time series of business and consumer confidence indices, respectively. CPU and EPU are the climate and economic policy uncertainty indices, respectively. Panel B lists the results of Brock et al.'s (1996) (BDS) test for nonlinearity and independence. The null hypothesis of the BDS test is that the data series is independently and identically distributed (*i.i.d.*). m stands for the embedding dimension. Different values of m are used to check for dependencies across various time scales. Panel C reports the results of Koenker and Xiao's (2004) quantile unit root test. The test operates under the null hypothesis of a unit root (i.e., $H_0: \hat{\alpha}(\tau) = 1$). In each regression run, we allow for a maximum of five lags. ***, **, and * indicate rejection of the corresponding null hypothesis at the 0.01, 0.05, and 0.10 significance levels, respectively.

negative skewness and a trifle of leptokurtosis, whereas those of CPU and EPU are positively skewed and almost mesokurtic relative to the Gaussian distribution. As suggested by the Jarque-Bera test statistics, CPU and EPU series are normally distributed, while those of BCI and CCI are not. According to this finding, the traditional OLS estimator is unlikely to adequately capture crucial information on the distribution's tails for either BCI or CCI. This conclusion substantiates the adoption of the QARDL technique as a superior option to the OLS.

To motivate the use of the QARDL-ECM models, we first investigate the presence of nonlinear dependence in the four time series data through the BDS test developed by Brock et al. (1996). As indicated by Lee et al. (2022), the BDS test is a powerful diagnostic tool that helps to identify nonlinearity and dependence in the data, providing a robust foundation for applying the QARDL-ECM models. The test statistics, shown in Panel B of Table 3, are highly significant, rejecting the null hypothesis of identically and independently distributed residuals (*i.i.d.*) for all series. This evidence justifies the need for a modeling approach, such as the QARDL-ECM, that can effectively account for these complexities and offer more nuanced insights into the behavior of the time series under consideration.

To explore the unit root behavior of each series across various parts of the underlying distribution, we perform the quantile unit root test proposed by Koenker and Xiao (2004). This test is an extension of the Augmented Dickey-Fuller unit root test. The test statistics are reported in Panel B of Table 3. Apart from the 0.05th and 0.10th

quantiles for ε_{BCI}^\perp and the 0.10th quantile for CPU, the null hypothesis of a unit root (i.e., $H_0: \hat{\alpha}(\tau) = 1$) is rejected at the 0.05 significance level or better over the representative segments of conditional distributions of the four variables. The evidence that none of the variables is an $I(2)$ process at any quantile lends support to the application of QARDL approach.

5.3. QARDL estimation results

Based on the AIC criterion, the suitable lag orders of p , q_1 , q_2 are (1, 2, 2) and (1, 2, 1) for BCI and CCI models, respectively. We categorize the quantiles of BCI and CCI distributions into three groups. These groups are defined by specific τ values, with the lower group including τ values of 0.05, 0.10, and 0.25, representing the pessimistic sentiment state; the median group with a τ value of 0.50, indicating neutral sentiment; and the upper group consisting of τ values of 0.75, 0.90, and 0.95, denoting the optimistic sentiment state. In Table 4, Panels A and B report the short- and long-run parameter estimates, respectively, for the QARDL specifications. The results are also graphically shown in Figures 3 and 4, for BCI and CCI models, respectively. In each plot, the solid pink line denotes the parameter estimates (i.e., the horizontal axis) across different quantiles (i.e., the vertical axis), while the dashed blue lines are the lower and upper 95% confidence limits.

A perusal of Panel A reveals noteworthy remarks. First, past variations in sentiment proxies, φ_{BCI} , and φ_{CCI} , have a statistically significant positive impact on their respective current variations only when businesses and households are upbeat about the future economic prospects. During downbeat and neutral sentiment states, however, the observed persistence is not strong enough to draw statistically meaningful conclusions. Generally, the momentum effect of BCI (CCI) tends to fall (increase) as we shift from the median to the right-hand side of the distribution. Second, the coefficient estimates ω_{BCI} , and ϑ_{BCI} , are statistically different from zero across almost all quantiles, demonstrating the cumulative short-term effects of past and current observations of CPU and EPU, respectively, on business sentiment. The corresponding signs are negative in most quantiles, suggesting that higher levels of either policy uncertainty tend to depress business owners' expectations for the near economic future. In terms of absolute magnitude, the cumulative impact of EPU on business sentiment is much greater (less) than that of CPU during periods of reduced (heightened) business confidence. We also observe that EPU has a stronger negative effect on business sentiment during optimistic times vis-à-vis pessimistic times, which might seem counterintuitive. A plausible explanation for this finding is that upbeat sentiment may lead to more significant investments and commitments. In this context, EPU can be perceived as a greater risk. Businesses may be more exposed to the potential negative consequences of uncertain policies, and this amplified risk perception can trigger a more negative sentiment response. Additionally, optimistic businesses may experience cognitive dissonance when faced with adverse policy developments (Antoniou et al., 2013). This discomfort can induce a stronger negative sentiment reaction as they attempt to reconcile their optimism with the reality of policy uncertainty. Third, the estimated coefficients ω_{CCI} , are negative across all quantiles. However, statistical significance is observed only in periods of downbeat

Table 4. Estimation results of QARDL models.

Quantiles	$\tau_{0.05}$	$\tau_{0.10}$	$\tau_{0.25}$	$\tau_{0.50}$	$\tau_{0.75}$	$\tau_{0.90}$	$\tau_{0.95}$	Asymmetry test
Panel A: Short-term analysis								
Coefficients								
φ_{BCI}	0.025 (0.745)	0.023 (0.643)	0.061 (1.044)	0.110 (1.290)	0.169** (2.405)	0.128** (2.127)	0.116** (2.461)	0.589
ω_{BCI}	-0.044*** (-3.979)	-0.051*** (-4.177)	-0.012 (-0.078)	-0.108*** (-5.412)	-0.138*** (-8.947)	-0.163*** (-13.256)	-0.174*** (-19.974)	0.022
ϑ_{BCI}	-0.326*** (-14.055)	-0.294*** (-11.393)	-0.231*** (-7.830)	-0.134*** (-3.354)	-0.045* (-1.694)	0.016 (0.666)	0.045** (2.444)	0.000
φ_{CCI}	0.060 (1.169)	0.096 (1.456)	0.104 (1.087)	0.191* (1.730)	0.211** (2.166)	0.236*** (3.412)	0.263*** (5.095)	0.049
ω_{CCI}	-0.275*** (-4.680)	-0.199*** (-2.634)	-0.268** (-2.356)	-0.221 (-1.597)	-0.146 (-1.057)	-0.159 (-1.604)	-0.161** (-2.184)	0.582
ϑ_{CCI}	-0.096*** (-6.467)	-0.094*** (-4.020)	-0.098*** (-3.961)	-0.095*** (-3.177)	-0.094*** (-4.732)	-0.096*** (-5.002)	-0.096*** (-2.352)	0.570
Panel B: Long-term analysis								
Coefficients								
ζ_{BCI}	0.955 (0.481)	0.640* (1.767)	0.691 (1.054)	0.739* (1.898)	0.852 (1.213)	1.101** (2.425)	1.231 (0.853)	—
ρ_{BCI}	-0.808*** (-6.726)	-0.767*** (-5.045)	-0.624*** (-2.977)	-0.501** (-2.546)	-0.469*** (-3.753)	-0.333*** (-2.712)	-0.305*** (-2.808)	0.002
$\beta_{1,BCI}$	-0.167*** (-4.363)	-0.263*** (-6.004)	-0.339*** (-6.513)	-0.289*** (-4.106)	-0.074 (-0.651)	-0.036 (-0.261)	0.032 (0.172)	0.003
$\beta_{2,BCI}$	-0.139*** (-10.903)	-0.163*** (-11.189)	-0.171*** (-9.868)	-0.140*** (-5.949)	-0.089** (-2.349)	-0.139*** (-3.006)	-0.349*** (-5.463)	0.000
ζ_{CCI}	0.493 (1.345)	0.488 (1.124)	0.387** (2.077)	0.409** (2.443)	0.549* (1.765)	0.576* (1.939)	0.671 (1.443)	—
ρ_{CCI}	-0.269*** (-9.109)	-0.254*** (-6.475)	-0.205*** (-3.645)	-0.201*** (-3.053)	-0.175*** (-3.128)	-0.109** (-2.424)	-0.107*** (-3.342)	0.000
$\beta_{1,CCI}$	-0.631*** (-3.151)	-0.436 (-1.375)	-0.396*** (-3.316)	-0.249* (-1.785)	-0.156 (-0.712)	-0.083* (-1.710)	-0.023 (-0.221)	0.094
$\beta_{2,CCI}$	-0.517 (-1.004)	-0.747 (-1.621)	-0.121 (-0.408)	-0.036 (-0.119)	-0.210 (-0.518)	-0.365 (-0.877)	-0.557* (-1.717)	0.386

Panels A and B report parameter estimates of the QARDL models in the short and long run, respectively, across a range of quantiles. The subscripts, BCI and CCI, denote the dependent variables. According to the AIC criterion, the appropriate lag structures are (1, 2, 2) and (1, 2, 1) for BCI and CCI models, respectively. φ_i captures the cumulative short-term impacts of past observations of the sentiment proxy i on its current observation. ω_i and ϑ_i measures the cumulative short-term effects of both past and current observations of CPU and EPU, respectively, on the sentiment proxy i . ζ_i denotes a quantile-specific intercept. ρ_i is the error correction term. $\beta_{1,i}$ and $\beta_{2,i}$ capture the long-term effects of CPU and EPU, respectively, on the sentiment proxy i . Asymmetry test is the Wald χ^2 test for the joint equality of quantile slope estimates of a regressor. The test has the null hypothesis that the slopes of a given independent variable are jointly equal across different quantiles of the conditional distribution of the response variable (e.g., $H_0: \omega^{\tau=0.05} = \omega^{\tau=0.10} = \dots = \omega^{\tau=0.90} = \omega^{\tau=0.95}$). Values in the last column represent the critical probabilities associated with the results of the Wald test. The t -statistics are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

consumer sentiment and at the 95th percentile of CCI distribution. This finding implies that the combined influence of past and present CPU levels tends to diminish how households perceive their future financial situations, especially when pessimism prevails. Fourth, without exception, the coefficient estimates ϑ_{CCI} , demonstrate negative signs and statistical significance at the 0.05 level or better, though the respective magnitudes are small. This result suggests that households regard economic policies as a crucial factor with potential economic repercussions for sustainability and environmental responsibility.

Long-term estimation results are given in Panel B of Table 4. Some salient remarks stand out. First, the quantile-specific error correction term's coefficients ρ_{BCI} and ρ_{CCI} , are negatively signed and statistically significant across all quantiles, thus confirming the

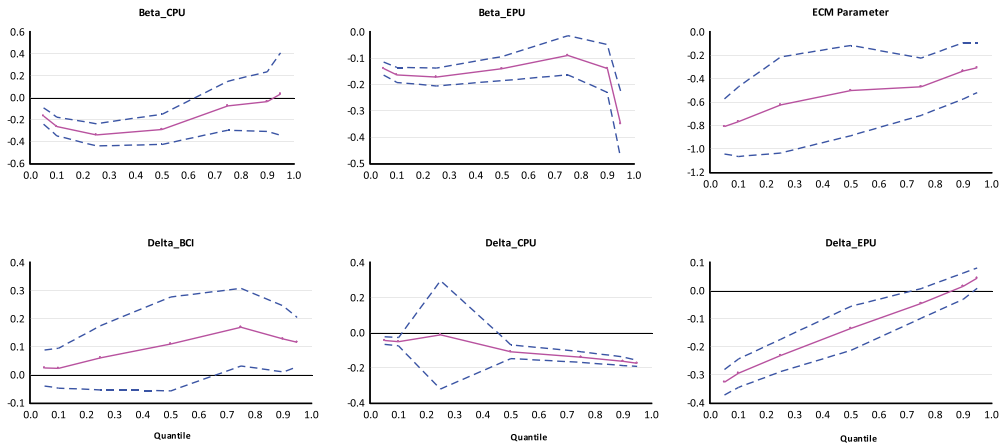


Figure 3. Quantile-specific long-term (β) and cumulative short-term (Δ) parameter estimates (solid pink lines) with a 95% confidence interval (dashed blue lower and upper lines), where the dependent variable is BCI.

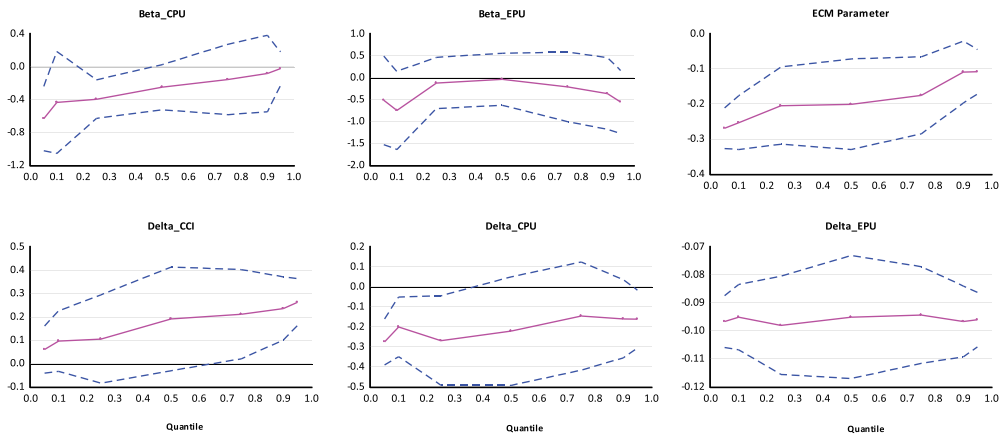


Figure 4. Quantile-specific long-term (β) and cumulative short-term (Δ) parameter estimates (solid pink lines) with a 95% confidence interval (dashed blue lower and upper lines), where the dependent variable is CCI.

existence of cointegration relationships between the variables under scrutiny. In terms of absolute magnitude, quantile-specific ρ_{BCI} values are larger than those of ρ_{CCI} , implying faster convergence to equilibrium in the case of business sentiment compared to that of consumer sentiment. Second, the coefficient estimates $\beta_{1,BCI}$ carry a negative sign in almost all quantiles but demonstrate statistical significance only over the left-hand side of the BCI distribution. This connotes that the long-term impact of lagged CPU on business sentiment is more meaningful in pessimistic and normal times. In contrast, we observe that the corresponding coefficients of EPU, $\beta_{2,BCI}$, are negative and statistically distinguishable from zero at the 0.05 level or better, irrespective of the state of business sentiment. The long-term effect of CPU on business sentiment is larger (smaller), in

absolute size, than that of EPU in periods of reduced (elevated) market confidence. For instance, a one-percentage point increase in CPU (EPU) is forecast to drag down the next-month business sentiment by nearly 0.167% (0.139%) when mainstream confidence in the economy is extremely low (i.e., $\tau = 0.05$), *ceteris paribus*. Third, the coefficient estimates $\beta_{1,CCI}$ have a negative sign across all quantiles, with statistical significance detected at 0.05th, 0.25th, 0.50th, and 0.90th quantiles. In terms of absolute size, the coefficients exhibit a monotonic decrease as we transition from the left to the right tail of the CCI distribution. This suggests that the long-term impact of lagged CPU tends to taper off as consumer sentiment shifts from a pessimistic state to an optimistic one. For instance, an increase of one-percentage point in CPU is expected to induce a 0.631% (0.083%) fall in the next-month consumer confidence at 0.05th (0.90th) quantile, with other variables held constant. Fourth, we notice that $\beta_{2,CCI}$ estimates are negative in sign but lack statistical significance across different consumer sentiment states. This means that, in the long run, EPU has no meaningful bearing on households' perceptions and anticipations.

Finally, the last Column in Table 4 reports the p -values of the Wald test. The null hypothesis of parameter constancy across various quantiles is strongly rejected for the error correction term, ρ_i . Past changes in BCI (CCI) influence symmetrically (asymmetrically) their own contemporaneous changes in the short run. Whether in the short or long term, CPU appears to have an asymmetric (a symmetric) impact on BCI (CCI) across different parts of the empirical distribution. Comparably, the impact of EPU on BCI varies significantly among optimistic, neutral, and pessimistic business sentiment states, while these effects on CCI remain consistent across consumer sentiment states, in both short-term and long-term contexts.

5.4. Results of quantile Granger causality analysis

As a complement to the QARDL analysis, we also conduct Granger causality in quantiles analysis (GCQ) as proposed by Troster (2018).¹ This method allows to explore the directional predictive relationships between variables across different quantiles of the distribution, offering a deeper understanding of how public sentiments respond to policy uncertainties under varying conditions. Unlike traditional Granger causality tests, which assume linear relationships and focus on mean effects, GCQ captures the heterogeneous effects across different parts of the distribution, such as periods of extreme pessimism or optimism (Lee et al., 2022). Such a robust approach helps identify whether the influence of policy uncertainties on sentiments is more pronounced in certain quantiles, thus providing a more nuanced view of the relationships. Additionally, it enhances the robustness of our findings by addressing potential nonlinearities and outliers, which are often present in financial and economic data. This thorough examination ensures that the insights gained are comprehensive and reliable, contributing to a better understanding of the dynamics between policy uncertainties and public sentiments.

P -values associated with the estimation results of GCQ are listed in Table 5. The results are quite consistent with those obtained from the QARDL models. We find strong

¹Technical details of the Granger causality in quantiles analysis are not shown here. Interested readers can refer to Troster (2018) for more information.

Table 5. Estimation results of quantile Granger causality.

Quantiles	$\tau_{0.05}$	$\tau_{0.10}$	$\tau_{0.25}$	$\tau_{0.50}$	$\tau_{0.75}$	$\tau_{0.90}$	$\tau_{0.95}$
$\Delta \varepsilon_{BCI}^{\perp} \nrightarrow \Delta CPU$	0.000	0.005	0.031	0.006	0.000	0.000	0.000
$\Delta \varepsilon_{BCI}^{\perp} \nrightarrow \Delta CPU$	0.329	0.186	0.246	0.431	0.214	0.109	0.154
$\Delta CPU \nrightarrow \Delta \varepsilon_{CCI}^{\perp}$	0.002	0.000	0.000	0.152	0.213	0.014	0.029
$\Delta \varepsilon_{CCI}^{\perp} \nrightarrow \Delta CPU$	0.652	0.259	0.371	0.205	0.498	0.328	0.543
$\Delta EPU \nrightarrow \Delta \varepsilon_{BCI}^{\perp}$	0.000	0.001	0.007	0.000	0.002	0.000	0.004
$\Delta \varepsilon_{BCI}^{\perp} \nrightarrow \Delta EPU$	0.632	0.809	0.488	0.742	0.403	0.263	0.682
$\Delta EPU \nrightarrow \Delta \varepsilon_{CCI}^{\perp}$	0.000	0.000	0.000	0.002	0.001	0.015	0.004
$\Delta \varepsilon_{CCI}^{\perp} \nrightarrow \Delta EPU$	0.146	0.119	0.209	0.308	0.281	0.137	0.165

This table presents the results from the Granger causality-in-quantiles analysis. The symbol $0 = \Rightarrow 0$ stands for “does not Granger cause”. Figures in the table represent the p -values of the quantile Granger causality test statistics. Figures in bold denote rejection of the null hypothesis of no Granger causality-in-quantile at the 0.05 level of significance or better.

evidence of unidirectional causality running from policy uncertainty indicators (CPU and EPU) to business and consumer confidence indices across almost all quantiles. Such a robust lead-lag linkage suggests that when there is uncertainty in climate or economic policies, it likely impinges on confidence among businesses and consumers, potentially affecting economic decisions and overall economic stability. Policymakers should be aware of the pervasive impact of policy uncertainties on economic sentiment, highlighting the importance of clear and consistent policy communication to maintain confidence levels in the market.

Generally, our evidence is in line with the results of several relevant works. For example, Zhang (2019) reports evidence of linear and non-linear Granger causality relationships running from the US EPU to the index of consumer sentiment. The results of Guenich et al. (2022) suggest that EPU has asymmetric negative effects on the OECD investor sentiment in the short and long term. Nartea et al. (2020) show that EPU premium is stronger during periods when investor sentiment is low, and it is less significant during periods of high investor sentiment. Wu and Zhao (2022) demonstrate that China’s EPU reduces households’ inclination to consume, with this impact being particularly remarkable among households that are well-educated, older, and more affluent. Mohammed et al. (2023) show that EPU (investor sentiment) is a chief shock transmitter (receiver) at times of extreme market conditions. Taking Australia as a case study, Kirchner (2020) finds that positive changes in the official cash rate target and short-term interest rates (the 90-day bank accepted bill rates) negatively influence consumer (business) confidence. Lewis et al. (2019) demonstrate that a surprise rise in the federal funds target rate causes an immediate decrease in the Michigan Index of Consumer sentiment. Based on panel data from 21 countries, Xu (2023) shows that an increase in EPU is positively associated with higher household saving rates, and this link is more pronounced when institutional quality and financial development is weak.

In practice, CPU and EPU can impact business and consumer sentiments through various channels at individual, corporate, national, and international levels. At the individual level, uncertainty surrounding climate and economic policies may influence people’s confidence in their personal financial situation and future prospects, thereby affecting their spending and saving patterns (Xu, 2023). Changes in employment levels

resulting from policy uncertainty can directly impinge on job security, income stability, and overall well-being (Li et al., 2023). On the corporate front, uncertainty regarding policy direction can trigger hesitancy among business owners to invest in new projects, hire more employees, or expand operations, ultimately impacting growth and profitability (Hu et al., 2023; Wen et al., 2022). Volatility in financial markets due to policy uncertainty can affect businesses' access to capital, cost of borrowing, and ability to finance operations and investments. At the national level, policy uncertainty can give rise to swings in overall economic activity and employment rates, affecting the nation's economic performance and outlook (Kirchner, 2020; Mumtaz & Surico, 2018). Changes in regulatory frameworks and compliance requirements can impact the ease of doing business, competitiveness, and attractiveness of the country as an investment destination (Kenyon & Naoi, 2010). Internationally, policy uncertainty may disrupt trade agreements and supply chain dynamics, which may impinge on global trade volumes and patterns (Ruhl, 2011). CPU can remarkably impact perceptions of a country's commitment to environmental sustainability, thereby influencing foreign investment and trade relationships (Gu & Hale, 2023).

6. Further analysis

The main methodology adopted in this paper is the QARDL approach. To reinforce the robustness of our evidence, we re-examine the association between policy uncertainty and domestic sentiment employing wavelet coherence phase analysis (WCPA). As pointed out by Gençay et al. (2002) and Walker (2008), WCPA provides insights into the temporal relationship and synchronization patterns between two time series across different frequencies and time scales. Specifically, it quantifies the phase lag or lead between corresponding frequencies in the time series, casting light on whether one series leads or lags behind the other and the degree of synchronization between them. The use of WCPA is likely to yield a deeper understanding of the policy uncertainty-sentiment nexus. While QARDL captures short and long-term links across different quantiles, its focus is primarily on the time-domain dynamics. WCPA furnishes a broader perspective via integrating both time and frequency domains, thereby enabling exploration of interactions over different temporal scales. Our further analysis offers insights into the complex interplay between policy uncertainties and domestic sentiment reactions that may not be fully captured by examining the time-domain dynamics alone. Below, we offer a concise account of WCPA, followed by a summary of the results.

6.1. An overview of WCPA

We employ continuous wavelet transformations (CWT) with the Morlet mother-wavelet function (Morlet et al., 1982) to investigate the lead-lag relationships between policy uncertainty metrics (i.e., CPU and EPU) and sentiment proxies (BCI and CCI). As indicated in Torrence and Compo (1998) and Aguiar-Conraria and Soares (2014), let $W_x(u, s)$ and $W_y(u, s)$ denote the CWT of $x(t)$ and $y(t)$ time series, respectively, where u and s are the time and scale parameters, respectively. The wavelet squared coherence,

$R_{xy}^2(u, s)$, can be expressed as the smoothed cross-wavelet power spectrum of both series, standardized by the product of their respective smoothed wavelet power spectra. Thus, $R_{xy}^2(u, s)$ is given as:

$$R_{xy}^2(u, s) = \frac{|\mathbb{N}(s^{-1} W_{xy}(u, s))|^2}{\mathbb{N}[s^{-1} |W_x(u, s)|^2] \mathbb{N}[s^{-1} |W_y(u, s)|^2]} \quad (8)$$

where \mathbb{N} is a smoothing parameter in scale and time. Percival and Walden (2000) underscore that $R_{xy}^2(u, s)$, ranging from zero to unity, serves as a direct indicator of the contemporaneous associations between $x(t)$ and $y(t)$ at each time point and frequency. A value of $R_{xy}^2(u, s)$ nearing zero implies a negligible linear link, whereas a value nearing one suggests a strong linear link within a particular time-frequency range.

Since the wavelet coherence tool is quadratic, it cannot capture the potential lead-lag interactions between $x(t)$ and $y(t)$ at different frequencies, nor can it determine the direction of association between them. This is where the WCPA becomes relevant, supplementing the function of the wavelet coherence tool. The complexity of the Morlet wavelet function means that CWT of $x(t)$ can be broken down into both a real component, denoted as $\Re\{W_x\}$, and an imaginary component, denoted as $\Im\{W_x\}$. Torrence and Webster (1999) and Grinsted et al. (2004) point out that the phase difference, which illustrates the phase relationship between $x(t)$ and $y(t)$, can be expressed as:

$$\phi_{xy}(u, s) = \tan^{-1} \left(\frac{\Im[\mathbb{N}(s^{-1} W_{xy}(u, s))]}{\Re[\mathbb{N}(s^{-1} W_{xy}(u, s))]} \right), \phi_{xy} \in (-\pi, \pi) \quad (9)$$

where \Re and \Im are the real and imaginary components, respectively, of the smoothed cross-wavelet transform. At a given time-frequency, synchronization of $x(t)$ with $y(t)$ is demonstrated by a zero-degree phase difference. $\phi_{xy}(u, s)$ is shown on the wavelet coherence plots as black rightward, upward, leftward, and downward arrow symbols inside statistically significant regions. Explicitly, a \rightarrow sign signifies that $x(t)$ and $y(t)$ are in phase (i.e., contemporaneously positively related), a \leftarrow sign means that $x(t)$ and $y(t)$ are out of phase (i.e., contemporaneously negatively related), a \nearrow sign means that $x(t)$ positively leads $y(t)$, a \searrow sign signifies that $x(t)$ negatively leads $y(t)$, a \swarrow sign means that $y(t)$ positively leads $x(t)$, and a \nwarrow sign signifies that $y(t)$ negatively leads $x(t)$.

6.2. WPCA results

In Figure (5), Panels A through D depict the output of WCPA. For the sake of clarity, each plot is shown across three dimensions: frequency (on the ordinate axis), time (on the abscissa axis), and the covariability structure of the two series under study. The frequency component is converted into time units and divided into five time-scale levels. The shortest level (2–4 months) represents the highest frequency band, while the longest level (32–64 months) denotes the lowest frequency band. Although the common practice in pertinent literature is to partition frequency levels into three investment timeframes (short-, medium-, and long-term horizons), we simplify this classification to short- and long-term timeframes. This adjustment is intended to

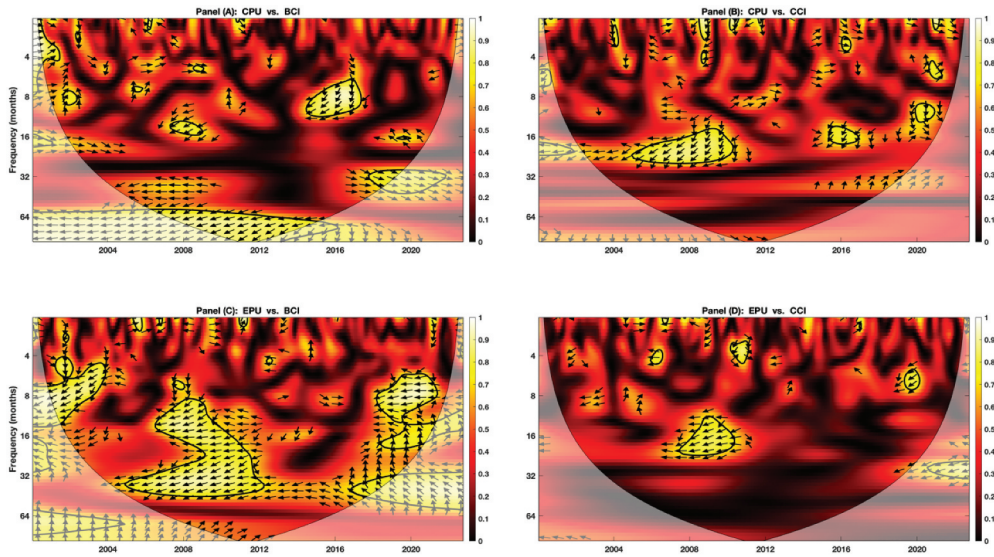


Figure 5. Cross-wavelet coherence between policy uncertainty and sentiment. Upper (lower) plots depict CPU (EPU) versus BCI and CCI. The frequency bands and sample period in months are depicted on the vertical and horizontal axes, respectively. On the right-hand side of each plot, a color gradient code represents localized covariability, with black indicating very low covariability and white indicating very high covariability. The thin black line specifies the cone of influence (COI) region. Areas with pale colors within the COI are excluded from the analysis due to potential edge artifacts. Outside the COI, statistically significant regions at the 0.05 level are delineated by thick black contours.

ensure comparability with QARDL, which generates estimation results for short- and long-time perspectives. Hence, we split the frequency bands into two primary time-frames: the 2–4, 4–8, and 8–16 month cycles correspond to the short-term horizon, while the 16–32 and 32–64 month cycles pertain to the long-term horizon. This division allows for a clear distinction between short-term fluctuations (e.g., seasonal, or quarterly variations) and long-term trends (e.g., multi-year cycles or structural changes). The color-coded depiction of the covariability structure reflects areas with varying degrees of coherence phase strength. To wit, white regions denote high strength, while black regions denote negligible strength. Shades of red, orange, and yellow represent intermediate levels of strength. The thick black contours delineate areas within the time-frequency domain where $R_{xy}^2(u, s)$ is statistically significant at our predefined significance level, $\alpha = 0.05$. On the other hand, the thin black line identifies the cone of influence (COI), a threshold below which regions of the wavelet spectrum may be affected by edge effects that could potentially distort the findings (Grinsted et al., 2004; Hudgins et al., 1993). In interpreting the outcomes, we disregard any areas of the wavelet spectrum falling within the COI.

In Panel A, there are statistically significant regions at high frequency bands (i.e., short-term horizons) exhibiting a high degree of covariation between CPU and BCI. These regions appear to be dispersed across almost the sample period. The arrowheads indicate a left-down direction, suggesting that CPU negatively leads BCI, particularly in the periods 2008–2010 and 2014–2018. At low frequency bands (i.e., long-term

horizons), we see a large area featuring a substantial level of covariation extended over the period 2006–2014. The corresponding arrows take a left-down direction, implying that CPU negatively leads BCI in the long run as well. In Panel B, we observe several regions showing predominantly high levels of covariation between CPU and CCI. These areas are primarily clustered at low frequency bands, with only a few appearing at high frequency bands. However, it is important to note that this pattern is not uniform throughout the entire sample period, because it is mainly concentrated in the time periods of 2004–2010 and 2016–2020. In most areas, the direction of the arrowheads indicates that CPU negatively leads CCI. Accordingly, we conclude that CPU negatively influences BCI and CCI across high and low frequencies and throughout almost the entire sample period. These findings lend strong support to the QARDL results.

In panel C, we can notice large statistically significant areas, spanning both high and low frequency bands. Within these areas, strong covariations between EPU and BCI are evident. The arrows inside the areas stretching over the period 2000–2012 mostly take a left-down direction, indicating that EPU negatively leads BCI throughout this period. Nonetheless, a nuanced shift is detected in the subsequent period of 2016–2022. Two distinct regions emerge: in the first region, the corresponding arrows in the high-frequency band of 8–16 months exhibit a leftward direction, suggesting a negative link between EPU and BCI with negligible time lag. In the second region located in the low-frequency band of 16–32 months, the arrows show an upward direction, implying that EPU leads BCI. These findings underscore the dynamic nature of the relationship between EPU and BCI across different time periods and frequency bands. In panel D, we see a sparse distribution of statistically significant areas across both high and low frequency bands. Despite their scarcity, these areas demonstrate a notable degree of covariation between EPU and CCI. Specifically, the arrows within the regions spanning the periods 2006–2010 and 2019–2020 predominantly exhibit a left-down direction, signifying EPU's negative influence on CCI during these intervals. Additionally, the prevalence of statistically insignificant black- and red-colored regions at both short- and long-term scales suggests a lack of association between EPU and CCI for much of the sample period. Therefore, we deduce that EPU exerts a negative impact on BCI and CCI across the short- and long-term horizons and over nearly the entire span of the sample period. These results largely support the findings derived from the QARDL analysis.

7. Conclusion

Uncertainty surrounding economic and climate policies has a profound impact on people's attitudes and perspectives. Economic policy uncertainty can give rise to worries about the economy's overall health, employment security, and financial stability. Similarly, uncertainties regarding climate policy may cause concerns over the sustainability of the environment and its long-term effects. People may experience heightened consternation about the future state of the planet and the stability of their communities. The combination of these uncertainties can influence sentiment, potentially resulting in shifts in business attitudes and consumer behavior. This paper explores whether CPU and EPU affect US business- and consumer-confidence trends in the short and long run and across optimistic, neutral, and pessimistic sentiment states. Our empirical analysis begins with cleansing sentiment series of the confounding effects of influential factors

that encompass industrial production, term spread, inflation, unemployment rate, VIX, US geopolitical risks, and global energy prices. Subsequently, we utilize the quantile ARDL model to assess how public sentiments respond to climate and economic policy uncertainties not only over different time horizons, but also across optimistic, neutral, and pessimistic regimes.

Our key findings are summarized as follows. First, CPU seems to have a considerable negative impact on business sentiment in the short run (long run) across all sentiment states (in pessimistic and normal periods). Second, CPU exerts a negative influence on consumer sentiment in the short and long run, especially during periods of a pessimistic outlook. Third, business sentiment is negatively related to EPU, whether in the short or long run, and irrespective of the state of business sentiment. Fourth, consumer sentiment is negatively associated with EPU only in the short run and across different sentiment states. However, in the long run, EPU does not have a meaningful impact on consumers' perceptions and expectations.

Overall, some vital policy implications can be drawn from our findings. For purposes of clarity and relevance, we explicitly link each policy implication to specific results as follows. First, the finding that CPU has a considerable negative impact on both BCI and CCI, especially during pessimistic periods, underscores the significance of policymakers providing clear and consistent frameworks for climate policies. This suggests that uncertain climate policy environments can significantly affect sentiment levels, highlighting the need for stability and clarity in policy implementation. Second, the observation that BCI is negatively related to EPU across all sentiment states and timeframes indicates the importance of developing risk mitigation strategies and contingency plans to address the disruptive effects of EPU. This result implies that businesses should be prepared to adapt to changing economic policy landscapes to reduce the impact on sentiment and overall business operations. Third, the finding that EPU exerts a negative influence on CCI in the short run, particularly during pessimistic periods, underscores the need for continuous assessments of economic policy impacts on sentiment. Policymakers should regularly evaluate the economic and social impact of policies on both businesses and households to make necessary adjustments and ensure alignment with public welfare. Equally important, businesses may need to assess and disclose climate-related risks, as is becoming increasingly critical in the business landscape. This can lead to more transparency and accountability regarding environmental concerns. Furthermore, CPU can incentivize businesses to innovate and adapt to potential regulatory changes. It may also lead to the development of cleaner technologies and practices to prepare for a more sustainable future.

Lastly, our analysis has some limitations that could possibly pave the way for intriguing avenues of future investigation. First, while we utilize business and consumer indices as proxies for US domestic sentiment, future research could explore additional sentiment indicators or alternative measures (e.g., ISM Manufacturing and Non-Manufacturing Indexes, the Conference Board survey of consumer confidence, the University of Michigan Consumer Sentiment Index) to capture a more inclusive understanding of public sentiment. Second, the analysis primarily relies on aggregate data for economic and climate policy uncertainties, as represented by the EPU index and CPU index. Future research could delve deeper into disaggregated data to better capture nuanced variations in policy

uncertainties at sectoral levels, which may yield valuable insights into their differential impacts on sentiment trends. Third, our empirical analysis does not examine the specific channels through which CPU and EPU impact US domestic sentiment. Although our study establishes the negative influence of these uncertainties on business and consumer sentiments, we do not empirically investigate the underlying mechanisms and pathways driving these effects. Future research can delve deeper by carrying out additional inquiries to explore potential mediating variables and causal pathways.

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