



Does economic policy uncertainty matter for carbon emission? Evidence from US sector level data

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Abstract

Economic policy uncertainty (EPU) will affect the external business environment of economic entities, which in turn affects the decision-making of economic entities. Meanwhile, carbon emissions are closely related to the production decisions of micro-economic entities. Thus, studying the relationship between EPU and carbon emissions helps to clarify the impact of institutional factors behind carbon emissions, which is significant for achieving green development. Based on US sector data, we apply a novel parametric test of Granger causality in quantiles to analyze the relationship between EPU and carbon emissions (its growth and uncertainty). We find that there is an outstanding pattern of Granger-causality from the US EPU to the growth of carbon emissions in the tails of the growth distributions of carbon emissions in the industrial sector, residential sector, electric power sector, and transportation sector, except in the commercial sector. That is, carbon emissions are affected by EPU when the growth of carbon emissions is in a higher or lower growth period. Lastly, we find that the US EPU affects carbon emissions uncertainty over the entire conditional distribution for all sectors.

Keywords Economic policy uncertainty · CO₂ emissions · Granger causality in quantiles · US sector

Introduction

Global warming, which is caused by carbon emissions has been recognized as a threat to public health and welfare. The reduction in carbon emissions is, therefore, a necessary task for each country in order to address the severe challenges arising from global warming. Scholars analyze the influencing factors of carbon emissions greatly. However, previous studies

have neglected the macroeconomic institutional factor, which closes the link to carbon emissions. As a reflection of macroeconomic institutional factor, EPU certainly affects the external business environment of economic entities, which in turn affects the decision-making of economic entities. Meanwhile, carbon emissions are closely related to the production decisions of microeconomic entities. Therefore, as the world's second-largest carbon emitter, analyzing the relationship between the US EPU and carbon emissions helps to clarify the impact of institutional factors behind carbon emissions, which is significant for achieving green development.

Currently, the US EPU has markedly increased. Figure 1 shows the dynamics of the EPU and energy-related carbon emissions in the USA. It shows that the US EPU index and its overall carbon emissions maintained a relatively consistent dynamic path. When the US EPU index reaches a peak and then falls, total carbon emissions also experience a local peak and then decline. We speculate that EPU may affect carbon emissions from the following aspects. Firstly, with the EPU increasing, the attention on environmental governance from the government will be transferred and reduced, and the implementation of some environmental protection policies will be affected negatively. For example, the USA withdrawing from the Paris Agreement increases the EPU, which may

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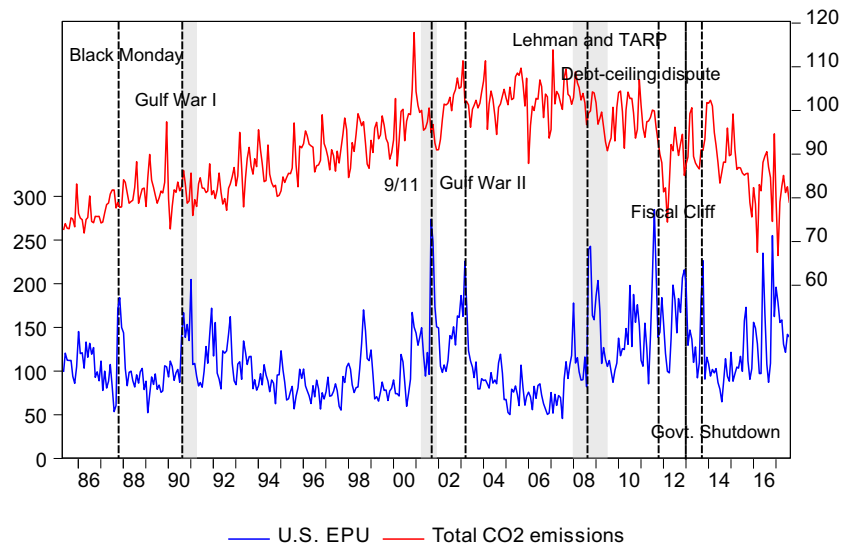
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Fig. 1 Time series of the US EPU and the total US carbon emissions from January 1985 to August 2017.



affect the determination of state governments to reduce carbon emissions negatively. Secondly, the EPU may harm the whole economic situation and the performance of enterprises. On the one hand, the economic demand for energy consumption will be cut down, and then the carbon emission may be decreased. On the other hand, due to the bad economic situation, for enterprises and residents, they may choose to use traditional cheaper energy such as coal and oil that may produce more carbon emissions. Thirdly, facing high EPU, enterprises may anticipate that governmental departments may relax requirements on environmental governance. It may lead enterprises to choose to reduce their efforts for controlling carbon emissions.

Notes: The shaded regions represent NBER recessions in the US economy. EPU constructed by three types of underlying components, namely, news coverage about policy-related economic uncertainty, tax code expiration data, and economic forecaster disagreement data. The data of EPU is sourced from the website of EPU (<http://www.policyuncertainty.com/>). Data on the US CO₂ emission is from the US Energy Information Administration (EIA) (www.eia.gov/).

Our study contributes to the previous literature in the following aspects. First, although a lot of studies have analyzed the influencing factors of carbon emissions (e.g., Stern 2004; Ling et al. 2015; Zhang and Tan 2016; Bekhet and Othman 2017; Abdouli and Hammami 2017), little research has explored whether there is a causal relationship between the EPU and carbon emissions from the empirical or theoretical perspective. As we know, EPU can affect economic activity, enterprise operation, and people’s consumption decisions (Caldara et al. 2016; Baker et al. 2016; Dibiasi et al. 2018). Analyzing the relationship between EPU and carbon emissions helps to clarify the impact of institutional factors behind carbon emissions. In this study, we analyze the relationship between the US EPU and carbon emission across various sectors as carbon emissions are heterogeneous in different sectors. It can provide significant

implications for a country to achieve carbon reduction goals with a more rationality institutional environment.

Second, we establish a carbon emission uncertainty indicator by employing a GARCH (1, 1) model in order to estimate the time-varying carbon emission volatility or uncertainty at the sector level. Unstable factors in the economic cycle and environmental policies commonly lead to uncertain carbon emissions. For example, the USA cut the budget of the US Environmental Protection Agency (EPA) in 2017. The government withdrew from the Paris Agreement in the same year. All these passive measures on carbon emissions reductions may increase the uncertainty of the US carbon emissions and impact the governance attitude to global warming. Thus, we propose the carbon emission uncertainty indicator to reflect the fluctuation on carbon emissions. Based on this, we also reveal the relationship between EPU and carbon emission uncertainty. The results can provide us with deeper information about the impact of institutional factors behind carbon emissions.

Third, this paper is the first to use the parametric test of Granger causality in quantiles, which was recently proposed by Troster (2018), to study whether the US EPU causes the growth and uncertainty of carbon emissions across US sectors. Rather than focusing on specific episodes of carbon emissions, employing this quantile causality testing approach can allow us to examine the impacts of the US EPU on the carbon emissions under different emission periods or market conditions. On the one hand, this approach takes the different locations and scales of the conditional distribution into account, which can provide richer information. On the other hand, the approach can address the problem of structural breaks and sample segmentation. Existing studies have proved that carbon emissions have nonlinear and structural mutation characteristics (Lanne and Liski 2004; Esteve and Tamarit 2012; Liddle and Messinis 2018) and they may have adverse impacts on linear model estimation (Troster 2018). Most studies

choose to segment the sample, but it leads to the loss of the sample's information. This approach allows us to examine the causal relationships at any chosen conditional quantiles without preselecting arbitrary subsamples.

The remainder of the paper is organized as follows: “Literature” provides a brief relevant literature review. “Theoretical framework and analysis” discusses the theoretical framework and hypothesis. “Methodology” introduces the empirical methodologies and research framework. “Preliminary data analysis” presents the data and preliminary analysis. “Empirical results and discussions” discusses the empirical results. “Conclusions” presents the conclusions.

Literature

As climate change is a common concern across countries in the world, a considerable number of researches analyzing the influencing factors of carbon emissions have been emerging (e.g., Richmond and Kaufmann 2006; Soytas and Sari 2009; Menz and Welsch 2012; Garau et al. 2013; Lee and Min 2015; Katircioğlu and Taşpinar 2017; Mutascu 2018; Balsalobre-Lorente et al. 2018; Jiang et al. 2018; Liu et al. 2019). However, these studies have neglected the macroeconomic institutional factor, which is closely linked to carbon emissions.

According to real the option theory (Abel and Eberly 1993; Gulen and Ion 2015), investment opportunities can be treated as an economic entity's resources when the investment is irreversible. Once the EPU rises, the net income of “waiting” will rise as the value of holding option increases. However, the net income of investment will decrease as the increasing value of holding option leads to the growth of marginal investment cost of economic entities. In addition, social-political theory holds that information disclosure is a response to political or social pressure (Gray et al. 1995). Carbon-related information disclosure transmits a good signal to the external. Connelly et al. (2011) proposed a signal transmission theory, which suggested that by increasing the transparency of carbon disclosure, it could indirectly reduce the pressure on stakeholder environmental issues. Enterprises tend to adopt high-energy and low-cost production methods to reverse the expected downtrend of net income due to EPU. Meanwhile, investors will not lose investment confidence for high energy consumption production as information disclosure is not enough. According to these theories, as a reflection of macroeconomic institutional factor, EPU certainly affects the external business environment of economic entities, which in turn affects the decision-making of economic entities. Meanwhile, carbon emissions are closely related to the production decisions of microeconomic entities.

A large number of studies have argued that EPU has critical impacts on a country's economic growth, stock market, investment, and employment (e.g., Brogaard and Detzel 2015;

Baker et al. 2016). Numerous studies also confirm that EPU could affect international commodity prices such as crude oil, gold, and other commodity prices (Jones and Sackley 2016; Balcilar et al. 2016, 2017). Delios and Henisz (2003) explored the impact of policy uncertainty on Japanese manufacturing firms' investment sequence. They found countries with less policy uncertainty attracted more investment entry. Kalamova et al. (2012) assessed the impact of environment policy uncertainty on innovation and found that policy uncertainty had a negative effect on innovation activity. Handley and Limao (2015) find that policy uncertainty had a large fraction on exporting. Julio and Yook (2016) find that FDI flows from US firms drop greatly when political uncertainty appears. Feng et al. (2017) conclude that a reduction in trade policy uncertainty reduces the firm export activity. Bhattacharya et al. (2017) use nation election to reflect policy uncertainty and examine whether the policy or policy uncertainty affects technological innovation. They find that innovation activities dropped greatly during national election. Charles et al. (2018) establish an uncertainty indicator based on financial, political, and macroeconomic, and then they analyze the impact of uncertainty on economic activity.

To sum up, the existing literature has provided rich references to understand the key impact factors on carbon emission from various aspects, such as FDI (Zhang and Zhou 2016), financial development (Al-Mulali et al. 2015; Abbasi and Riaz 2016), and environmental innovation (Lee and Min 2015), but the critical impact of EPU on carbon emissions has been ignored. A large number of studies find that EPU has a critical impact on a country's economic growth, the stock market, and the investment and innovation activity. In this case, we speculate that the EPU may have an impact on carbon emissions government decision for one country or enterprise. This paper employs a novel parametric test of Granger causality in quantiles to examine whether the US EPU impacts the growth and uncertainty of carbon emissions based on US sector data.

Theoretical framework and hypothesis

EPU affects the carbon emissions through the direct policy adjustment effect and indirect economic demand effect. More specifically, for direction policy adjustment effect, first, negative climate policy may directly harm their determinations to reduce carbon emissions for governments, corporates, and residences. For example, the USA decided to withdraw from the Paris Agreement in 2016, which releases a negative signal that the US government has lost determination to cut emissions. Affected by this event, the uncertainty of economic policies increases, the attention on environmental governance from the government will be transferred and reduced, and the implementation likelihood of some environmental protection policies will be affected negatively. In addition, some

enterprises and residents may doubt the government’s determination to reduce emissions. Therefore, both enterprises and residents will not comply with the requirements of relevant carbon emission reduction policies, which may result in the increase of emissions.

Regarding the indirect economic demand effect of EPU on carbon emissions, briefly, EPU may influence the economic condition and then may induce the changing economic demand for energy consumption. As we know, energy-related carbon emissions account for approximately 98% of the US carbon emissions in 2017 (BP data). Indeed, a large body of literature find that the EPU has impacts on the FDI and firms’ investment (e.g., Delios and Henisz 2003; Asiedu 2006; Kellogg 2014; Rubashkina et al. 2015; Zhao and Sun 2016; Wang and Shen 2016; Julio and Yook 2016; Chen et al. 2018), trade (Handley and Limao 2015; Feng et al. 2017), stock market and economic development (Pastor and Veronesi 2012; Shahzad et al. 2017; Balciyar et al. 2017). For example, Julio and Yook (2016) find that FDI flows from US firms drop greatly when political uncertainty appears. Handley and Limao (2015) find that policy uncertainty had a large fraction on exporting. Charles et al. (2018) establish an uncertainty indicator based on financial, political, and macroeconomic, and they prove the impact of uncertainty on economic activity. Besides, some literature provide evidence that the EPU affects the patent application and innovation (e.g., Kalamova et al. 2012; Rubashkina et al. 2015; Zhao and Sun 2016; Wang and Shen 2016; Chen et al. 2018; Bhattacharya et al. (2017)). Meanwhile, numerous literature document that the FDI, trade openness, financial development, the patent application, and innovation are related to carbon emissions (e.g., Ozturk and Acaravci 2013; Ling et al. 2015; You et al. 2015; Dogan and Turkecul 2016; Shahbaz et al. 2016; Zhang and Zhou 2016; Katircioğlu and Taşpinar 2017; Işik et al. 2017; Çetin and Ecevit 2017). In this way, naturally, we speculate that EPU may affect the carbon emissions by impacting the economic activity including the stock market, investment and trade, and so on.

Moreover, under different carbon emission cycles, the impact of EPU on carbon emissions may be different. In a period of high carbon emissions growth (possibly due to increased energy demand driven by economic growth), the government faces greater pressure to reduce emissions, which may be more vulnerable to the impact of EPU. By contrast, in a period of low carbon emissions growth, excluding the impact of technological progress and energy efficiency (generally considered not to have a significant impact on carbon emissions in the short term), lower carbon emissions may indicate a downturn in the economy. Due to the low growth of the economy, the decline in energy consumption demand leads to a decline in carbon emissions. Facing the pressure of economic growth, the government will introduce more policies to stimulate economic growth, which will more likely increase the EPU. At this time, according to the direct policy adjustment effect, the

government may not pay attention to the implementation of carbon emission reduction policies. Thus, it may make carbon emissions vulnerable to greater EPU shocks. In addition, the blind self-confidence from government and entrepreneur leads to slack policy implementation. In the case of the low growth in carbon emissions, the government and enterprises blindly believe in the effectiveness of emission reduction and may relax the implementation of carbon emission reduction policies. Therefore, during this period, carbon emissions may easily rebound and be more vulnerable to the impact of EPU. Based on the analytic mechanisms commented on above, we propose the following hypothesis.

Hypothesis: there exists causality between EPU and carbon emissions, specifically when the carbon emissions are in a higher or lower growth stage.

Methodology

Here, we present a novel methodology, as proposed by Troster (2018), to examine the heterogeneity of the Granger causality between the US EPU and carbon emissions at the sector level across different conditional quantiles. Suppose EPU is Z_t , and carbon emissions growth or carbon emissions uncertainty at the US sector level is Y_t .

According to Granger (1969), a series Z_t does not Granger cause another series Y_t if the past Z_t does not help to predict the future Y_t given the past Y_t . Suppose that the explanatory vector $I_t \equiv (I_t^Y, I_t^Z)' \in R^d$, where $Y_t, I_t^Y := (Y_{t-1}, \dots, Y_{t-s})' \in R^s$ and $I_t^Z := (Z_{t-1}, \dots, Z_{t-q})' \in R^q$. The null hypothesis of Granger non-causality from Z_t to Y_t is as follows:

$$H_0^{Z \rightarrow Y} : F_Y(y|I_t^Y, I_t^Z) = F_Y(y|I_t^Y) \text{ for all } Y \in R. \tag{1}$$

where $F_Y(y|I_t^Y, I_t^Z)$ and $F_Y(y|I_t^Y)$ are the conditional distribution functions of Y_t given (I_t^Y, I_t^Z) and I_t^Y , respectively. We test Granger non-causality in the mean, which is only a necessary condition for (1). In this case, Z_t does not Granger cause $F_Y(\cdot|I_t^Y)$ in the mean if

$$E(Y_t|I_t^Y, I_t^Z) = E(Y_t|I_t^Y) \text{ a.s.}, \tag{2}$$

where $F_Y(\cdot|I_t^Y, I_t^Z)$ and $E(Y_t|I_t^Y)$ are the mean of $F_Y(\cdot|I_t^Y, I_t^Z)$ and $F_Y(\cdot|I_t^Y)$, respectively. Granger non-causality in the mean of (2) can be easily extended to higher order moments. However, causality in the mean overlooks the dependence that may appear in the conditional tails of the distribution. Thus, a test Granger non-causality in the conditional quantiles is proposed. Let $Q_\tau^{Y,Z}(\cdot|I_t^Y, I_t^Z)$ be the τ -quantiles of $F_Y(\cdot|I_t^Y, I_t^Z)$, then Eq. (1) can be rewritten as follows:

$$H_0^{Q_C:Z \rightarrow Y} : Q_{\tau}^{Y,Z}(Y_t|I_t^Y, I_t^Z) = Q_{\tau}^Y(Y_t|I_t^Y), \text{ a.s. for all, } \tau \in T, \quad (3)$$

where Γ is a compact set such that $\Gamma \subset [0, 1]$. In addition, the conditional τ -quantiles of Y_t satisfy the following restrictions:

$$\begin{aligned} & \Pr\{Y_t \leq Q_{\tau}^Y(Y_t|I_t^Y)|I_t^Y\} = \tau, \text{ a.s. for all, } \tau \in T, \text{ and} \\ & \Pr\{Y_t \leq Q_{\tau}^{Y,Z}(Y_t|I_t^Y, I_t^Z)|I_t^Y, I_t^Z\} = \tau, \text{ a.s. for all, } \tau \in T \end{aligned} \quad (4)$$

Given an explanatory vector I_t , we have $\Pr\{Y_t \leq Q_{\tau}(Y_t|I_t)|I_t\} = E\{I[Y_t \leq Q_{\tau}(Y_t|I_t)]|I_t\}$, where $I(Y_t \leq y)$ is an indicator function of the event that a is less or equal than y . Thus (4) is equivalent to

$$\begin{aligned} & \left\{ 1 \left[Y_t \leq Q_{\tau}^{Y,Z}(Y_t|I_t^Y, I_t^Z) \right] | I_t^Y, I_t^Z \right\} \\ & = E\{I[Y_t \leq Q_{\tau}^Y(Y_t|I_t^Y)] | I_t^Y, I_t^Z\}, \\ & \text{a.s. for all, } \tau \in T, \end{aligned} \quad (5)$$

where the left-hand side of (5) is equal to the τ -quantile of $F_Y(\cdot|I_t^Y, I_t^Z)$ by definition. Following Troster (2018), we postulate a parametric model in order to estimate the τ th quantile of $F_Y(\cdot|I_t^Y)$, where we assume that $Q_{\tau}(\cdot|I_t)$ is correctly specified by a parametric model $m(\cdot, \theta(\tau))$ belonging to a family of functions $M = \{m(\cdot, \theta(\tau)) \mid \theta(\cdot) : T \rightarrow \Theta \subset R^p, \text{ for } \tau \in T \subset [0, 1]\}$. Let $B \subset M$ be a family of uniformly bounded functions $\tau \mapsto \theta(\tau)$ such that $\theta(\tau) \in \Theta \subset R^p$. Then, under the null hypothesis in (3), the τ -conditional quantile $Q_{\tau}^Y(\cdot|I_t^Y)$ is correctly specified by a parametric model $m(I_t^Y, \theta_0(\tau))$, for some $\theta_0 \in B$, using only the restricted information set $Q_{\tau}^Y(\cdot|I_t^Y)$, and we redefine our testing problem in (3) as

$$\begin{aligned} H_0^{Z \rightarrow Y} : E[I(Y_t \leq m(I_t^Y, \theta_0(\tau))) | I_t^Y, I_t^Z] \\ = \tau, \text{ a.s. for all } \tau \in T, \end{aligned} \quad (6)$$

versus:

$$H_A^{Z \rightarrow Y} : E[I(Y_t \leq m(I_t^Y, \theta_0(\tau))) | I_t^Y, I_t^Z] \neq \tau, \text{ for some } \tau \in T, \quad (7)$$

where $m(I_t^Y, \theta_0(\tau))$ correctly specifies the true conditional quantile $Q_{\tau}^Y(\cdot|I_t^Y)$, for all $\tau \in T$. We rewrite (6) as $H_0^{Z \rightarrow Y} : E\{[I(\mathcal{Y}_t - m(I_t^Y, \theta_0(\tau))) \leq 0] - \tau | I_t^Y, I_t^Z\} = 0$ almost certainly, for all $\tau \in \Gamma$. Then we can characterize the null hypothesis (6) by a sequence of unconditional moment restrictions:

$$H_0^{Z \rightarrow Y} : E\{[I(Y_t - m(I_t^Y, \theta_0(\tau))) \leq 0] - \tau | \exp(i\omega' I_t)\} = 0 \quad (8)$$

Where $\exp(i\omega' I_t) = \exp[i(\omega_1(Y_{t-1}, Z_{t-1})' + \dots + \omega_r(Y_{t-r}, Z_{t-r})')]$ is a weighting function, for all $\omega \in R^d$ with $r \leq d$, and $i = \sqrt{-1}$ is the imaginary root. The remainder of the statistic is a sample analog of $E\{[I(Y_t - m(I_t^Y, \theta_0(\tau))) \leq 0] - \tau | \exp(i\omega' I_t)\}$:

$$v_T(\omega, \tau) = \frac{1}{\sqrt{T}} \sum_{t=1}^T [I(Y_t - m(I_t^Y, \theta_0(\tau))) \leq 0] - \tau \exp(i\omega' I_t) \quad (9)$$

where θ_T is a \sqrt{T} -consistent estimator of $\theta_0(\tau)$, for all $\tau \in T$. Then, we apply the test statistic:

$$S_T = \int_T \int_W |V_T(\omega, \tau)|^2 dF_{\omega}(\omega) dF_{\tau}(\tau) \quad (10)$$

where $F_{\omega}(\cdot)$ is the conditional distribution function of the ad-variate standard normal random vector, $F_{\tau}(\cdot)$ is a uniform discrete distribution over a grid of T in n equi-distributed points, $T_n = \{\tau_j\}_{j=1}^n$, and the vector of weights $\omega \in R^d$ is drawn from a standard normal distribution. The test statistic in (10) can be estimated using its sample counterpart. Let Ψ be the $T \times n$ matrix Ψ with elements $\psi_{i,j} = \Psi_{\tau_j}(Y_i - m(I_i^Y, \theta_T(\tau_j)))$. Then, the test statistic S_T has the form

$$S_T = \frac{1}{Tn} \sum_{j=1}^n |\psi'_{\cdot,j} \mathbf{W} \psi_{\cdot,j}| \quad (11)$$

where \mathbf{W} is the $T \times T$ matrix with elements $w_{t,s} = \exp[-0.5(I_t - I_s)^2]$, and $\psi_{\cdot,j}$ denotes the j th column of Ψ . It rejects the null hypothesis whenever it observes “large” values of S_T .

We use the subsampling procedure of Troster (2018) to calculate the critical values for S_T in Eq. (11). Given our series $\{X_t = (Y_t, Z_t)\}$ of sample size T , we generate $B = T - b + 1$ subsamples of size b (taken without replacement from the original data) of the form $\{X_b, \dots, X_{T-b+1}\}$. Then, the test statistic S_T is calculated for each subsample and we obtain the p values by averaging the subsample test statistics over the B subsamples. Following Troster (2018), we choose a subsample of size $b = [kT^{2/5}]$, where $[\cdot]$ is the integer part of a number, and k is a constant parameter. To apply the S_T test, we specify three different QAR models $m(\cdot)$, for all $\tau \in \Gamma \subset [0, 1]$, under the null hypothesis of non-Granger causality in Eq. (9) as follows:

$$\begin{aligned} QAR(1) : m^1(I_t^Y, \theta(\tau)) &= \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \sigma_t \Phi_u^{-1}(\tau) \\ QAR(2) : m^2(I_t^Y, \theta(\tau)) &= \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \sigma_t \Phi_u^{-1}(\tau) \\ QAR(3) : m^3(I_t^Y, \theta(\tau)) &= \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \sigma_t \Phi_u^{-1}(\tau) \end{aligned} \quad (12)$$

where the parameters $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \mu_4(\tau), \sigma_t)'$ are estimated by the maximum likelihood in an equally spaced grid of quantiles, and $\Phi_u^{-1}(\cdot)$ is the inverse of a standard normal distribution function. To verify the signature of the causal relationship between the variables, we estimate the quantile autoregressive models in Eq. (12) including lagged variables of another variable. For simplicity, we present the results using only a QAR (3) model with the lagged values of the other variable as follows:

$$Q_{\tau}^{Y,Z}(Y_t|I_t^Y, I_t^Z) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \beta(\tau)Z_{t-1} + \sigma_t\Phi_u^{-1}(\tau) \quad (13)$$

Preliminary data analysis

This paper uses monthly data on the energy-related carbon dioxide (CO₂) emissions over the total USA and at the sector levels covering the period from January 1985 to August 2017. Given the fact that the carbon emissions are heterogeneous in different sectors, we select five US sectors as samples in this paper, namely the industrial sector, the residential sector, the transportation sector, the electric power sector, and the commercial sector. We mainly investigate whether there are significant differences in the relationship between the US EPU and carbon emission across these sectors. The series of carbon emissions exhibiting seasonality have been seasonally adjusted using the Census X-13 method. The carbon emission data can be obtained from the US Energy Information Administration (EIA) in the US Department of Energy¹. We calculate the carbon emissions growth by $\ln(E_{i,t}/E_{i,t-1})$, where $E_{i,t}$ is the carbon emissions for sector i at time t . We obtain the EPU index as the measure of the EPU, which is sourced from Baker et al. (2016)². We use the EPU index after a logarithmic transformation in our empirical model.

Figure 2 plots the dynamics of the carbon emissions in the various sectors. As shown in Fig. 2, most of the sectors generally have an inverted U-shaped trajectory, except for the transportation sector. Further observations show that the carbon emissions from the transportation sector have N-type changes and are currently still rising. The EIA data show that the carbon emissions of the transportation sector increased by 1.9% in 2016, exceeding the electric power sector for the first time. In addition, the data shows that the carbon emissions curve of each sector is not smooth, and the phenomena of substantial growth and the sharp decline alternately appear. This finding suggests that there is significant uncertainty regarding the carbon emissions trend in all sectors in the United States. In addition, we find that during the economic recession, the carbon emissions of various sectors declined. This finding verifies the basic understanding of environmental economics, that is, there is a significant relationship between carbon emissions and economic growth.

The summary statistics of the variables have been reported in Table 1. Table 1 shows that four out of five sectors have a positive carbon emissions change rate on average with the exception of the industrial sector. With respect to the standard deviation, we find that the residential sector possesses the largest values among the five sectors, thereby indicating that the largest carbon

emissions uncertainty is in this sector. The Skewness and kurtosis values indicate that the distributions of carbon emissions growth for all sectors are negatively skewed (except for the industrial sector) and leptokurtic. The Jarque–Bera statistic rejects the null hypothesis that the carbon emissions growth is normally distributed for all cases. By applying the ARCH test of Engle (1982), we reject the null hypothesis of no ARCH effects for the carbon emissions growth in all sectors and thus find that the use of a GARCH-based approach is appropriate for modeling the stylized facts such as the fat-tails, volatility clustering, and persistence in carbon emissions growth. Thus, in the next section, we estimate the conditional volatility of emission growth by a GARCH (1, 1) model, and select this as the proxy of carbon emission uncertainty for US sectors.

Table 2 reports the unit root tests for the carbon emissions growth of US sectors and the EPU series using two tests: the augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips–Perron (PP) test (Phillips and Perron, 1988). The null hypothesis is the non-stationarity for all series. The tests yield large negative values in all cases for the growth of carbon emission and EPU, such that the growth and EPU series reject the null hypothesis at the 1% significance level. Thus, we conclude that all series of carbon emission growth for five sectors and the EPU are stationary processes. However, a major shortcoming with the standard unit root tests is that they do not allow for the possibility of structural breaks. Therefore, we follow Lee and Strazicich (2003) by allowing two breaks at an unknown location on both the trend and the intercept. Table 2 reports the results of the Lee and Strazicich (2003) unit root test and the estimated break date. The results confirm that these series are stationary, and there are two breaks for the carbon emissions growth and the EPU variables, respectively. This finding of breakpoints in the growth of carbon emissions and EPU indicates that the linear model based on the conditional mean estimation may not be suitable for depicting the relationship between them.

In this paper, the GARCH (1, 1) model is used to measure the conditional volatility of carbon emissions growth for the US sectors. We set the conditional volatility as a proxy variable for the carbon emissions uncertainty. This variable is used to reflect the phenomenon that the carbon emissions for one country or one sector are uncertain in the future. The GARCH (1, 1) model is often used to estimate the volatility of equity returns, energy returns and economic output (Badinger 2010; Choudhry et al. 2016; Diaz et al. 2016). A plot of the carbon emission volatility (uncertainty) is shown in Fig. 3. As shown in Fig. 3, overall, there are sharp fluctuations in the carbon emissions for each sector. More specifically, it is found that around the US recession, carbon emissions widely fluctuated across sectors, especially in the industrial sector. For example, we find that around the years of 1991, 2001, and 2008, especially before and after the USA entered the recession, there was large volatility in the carbon emissions for the industrial

¹ www.eia.gov/.

² <http://www.policyuncertainty.com/>

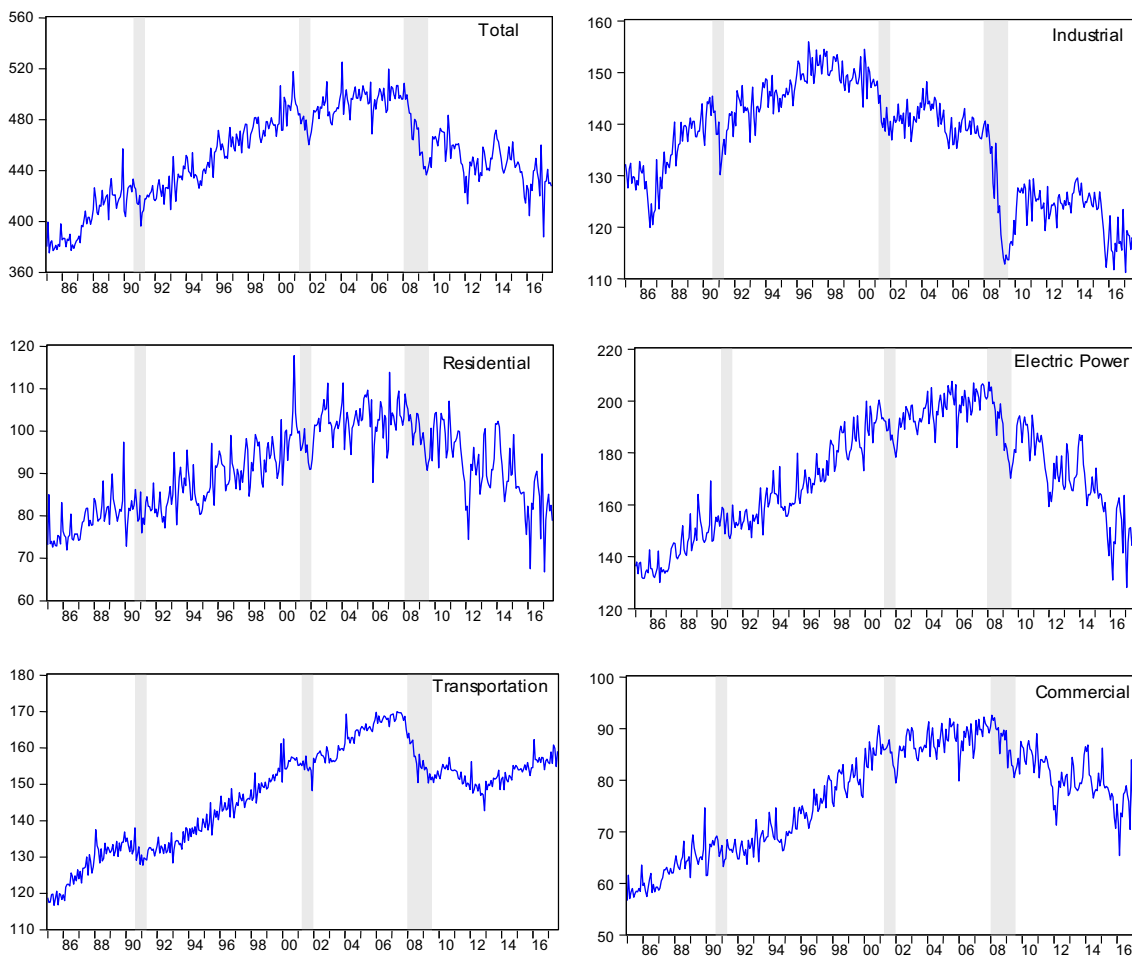


Fig. 2 CO₂ emissions for US sectors: 1985:01–2017:08. The series exhibiting seasonality have been seasonally adjusted using the Census X-13 method. The shaded regions represent NBER recessions

sector. This finding is similar to the existing literature that confirms the strong link between carbon emissions and economic growth (Tzeremes 2017). In addition, the data show that there is a large fluctuation in US carbon emissions after December 12, 2015 (see the dotted lines). This fluctuation

corresponds to the event when nearly 200 countries attending the United Nations Framework Convention on climate change reached the Paris Agreement at the Paris Climate Change Conference in December 2015. Meanwhile, the formal enactment of the agreement was announced in December 2016,

Table 1 Descriptive statistics and unit root tests

	Total	Industrial	Residential	Transportation	Electric	Commercial	EPU
Mean	0.030	− 0.031	0.019	0.075	0.014	0.061	4.641
Median	0.069	− 0.011	0.221	0.014	− 0.021	0.007	4.615
Maximum	10.613	8.183	23.847	7.597	14.648	17.557	5.502
Minimum	− 11.319	− 7.588	− 20.077	− 6.802	− 14.799	− 19.436	4.047
Std. Dev.	2.548	2.419	5.714	1.988	3.777	3.816	0.280
Skewness	− 0.245	0.121	− 0.022	− 0.044	− 0.041	− 0.148	0.306
Kurtosis	5.618	3.587	5.120	4.560	4.864	6.254	2.562
Jarque–Bera	115.629***	6.561***	73.240***	39.759***	56.708***	173.889***	9.242***
ARCH test	56.599***	4.876**	39.295***	13.964	38.130***	53.305***	
Observations	391	391	391	391	391	391	391

***Indicate significance at the 1% level

Table 2 Unit root test

	Total	Industrial	Residential	Transportation	Electric	Commercial	EPU
Panel 1: Conventional unit root test							
ADF(C)	− 22.362***	− 22.282***	− 21.396***	− 25.115***	− 20.737***	− 22.062***	− 3.645***
ADF(C+T)	− 22.437***	− 22.357***	− 11.682***	− 25.260***	− 20.834***	− 22.147***	− 3.689***
PP(C)	− 42.442***	− 41.218***	− 49.430***	− 46.132***	− 36.584***	− 41.015***	− 5.563***
PP(C+T)	− 53.046***	− 61.667***	− 74.672***	− 48.349***	− 52.262***	− 61.471***	− 5.625***
Panel 2: Lee and Strazicich (2003) LM two breaks unit root test							
Statistic	− 22.261***	− 9.774***	− 20.839***	− 3.990**	− 18.765***	− 20.472***	− 5.520***
Break 1	2013M10	2002M12	2002M02	2012M02	1989M05	1995M01	2000M04
Break 2	2014M01	2003M04	2004M07	2012M12	2014M05	2003M05	2008M08

For ADF and PP test, C denotes constant, T denotes trend; for Lee and Strazicich (2003) LM two breaks unit root test (crash model), the test critical value of 1% level is 4.178, for 5% level is − 3.619 and for 10% level is − 3.316

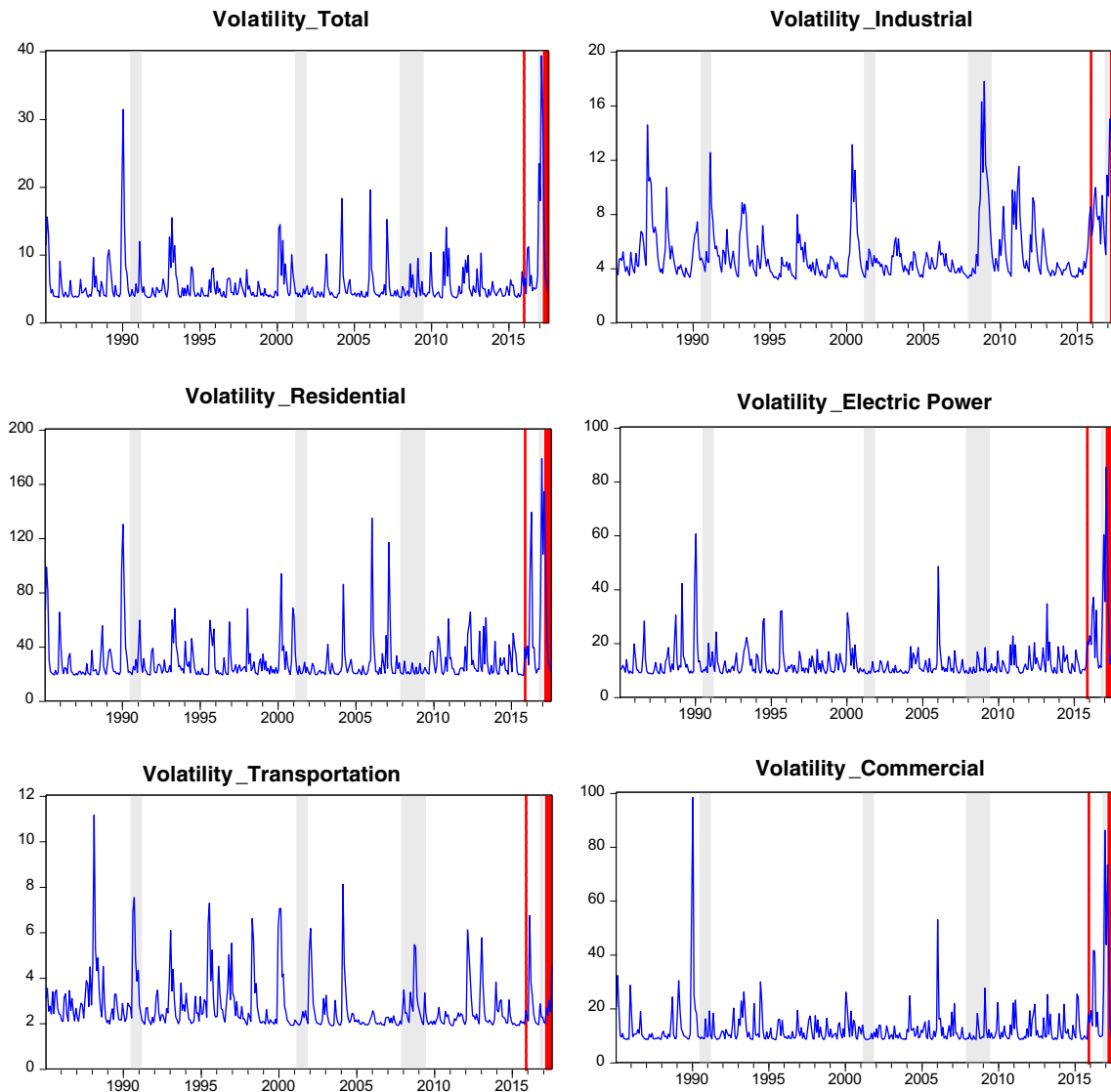


Fig. 3 Carbon emission uncertainty (volatility) for the US sectors. The shaded regions represent NBER recessions. Red shaded regions denote the period of June 2017 in which the USA withdrew from the Paris Agreement

after which US carbon emissions also greatly fluctuated. This finding suggests that global climate policy may impact the carbon emissions in the USA. Moreover, it is found that the economic policies of the US government may also affect the volatility of carbon emissions. For example, in late March 2017, US President Trump signed a presidential executive order aimed at boosting energy independence and economic growth, which reduced the budgets related to climate policy and scientific research programs. For example, the executive order stipulates a cut to the EPA budget of more than 31%, calls for the direct cancellation of the executive orders of the previous president (the Obama administration) related to climate change, and calls for an immediate review of the relevant provisions of the Clean Power Plan. Afterwards, the USA withdrew from the Paris Agreement in June 2017. As can be seen in Fig. 3, the US carbon emissions volatility has risen sharply since these events.

In summary, influenced by economic factors or policy factors, there is an obvious increase in the volatility or uncertainty of carbon emissions in the US sectors. Together with Fig. 1, these findings show that US carbon emissions significantly fluctuated during a period when the US EPU index was at a high level. This phenomenon implies that there may exist a causal relationship between the two variables, which increases our interest. This issue is also the main motivation of this paper.

Empirical results and discussions

Linear Granger causality test

Though our objective is to analyze the quantiles causality between the US EPU and the carbon emissions in each sector, for the sake of completeness and comparability, we also conducted a standard linear Granger causality test (Granger 1969) based on the VAR model. Table 3 presents the results for the linear Granger causality test. For most sectors, the null hypothesis of non-causality from the US EPU to carbon emission growth cannot be rejected at the 10% significance level. In particular, at the 10% significance level, with the exception of the industrial and commercial sectors, there is no evidence of Granger causality from the US EPU to carbon emissions growth for other sectors such as the residential, transportation, and electric power sectors. For the carbon emissions uncertainty, we find that only the carbon emission uncertainty of the industrial sector is affected by the US EPU, and for other sectors, the null hypothesis of non-causality cannot be rejected. These results that are estimated in our paper may have resulted from the misspecification of the test model. It is well known that the linear Granger causality test could overlook the important nonlinear causal relationship (Balcilar et al. 2017). Therefore, the insufficient or weak evidence for the causal relationship can be attributed to the low

Table 3 Linear Granger causality test (EPU and carbon emissions)

Null hypothesis	Lag	Chi-sq	<i>p</i> value	Causality or not
Panel 1: from EPU to carbon emission growth				
<i>EPU</i> → <i>Total</i>	8	16.033**	0.042	Yes
<i>EPU</i> → <i>Industrial</i>	5	14.716**	0.012	Yes
<i>EPU</i> → <i>Residential</i>	8	11.920	0.155	No
<i>EPU</i> → <i>Transportation</i>	5	4.538	0.475	No
<i>EPU</i> → <i>Electric</i>	5	7.594	0.180	No
<i>EPU</i> → <i>Commercial</i>	8	15.656**	0.048	Yes
Panel 2: from EPU to carbon emission uncertainty				
<i>EPU</i> → <i>Total</i>	5	13.232**	0.021	Yes
<i>EPU</i> → <i>Industrial</i>	4	15.060***	0.005	Yes
<i>EPU</i> → <i>Residential</i>	5	8.472	0.132	No
<i>EPU</i> → <i>Transportation</i>	5	4.821	0.438	No
<i>EPU</i> → <i>Electric</i>	4	2.440	0.656	No
<i>EPU</i> → <i>Commercial</i>	4	4.909	0.297	No

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively; the symbol → represents the null hypothesis of Granger non-causality. The lag parameters are selected based on the Akaike information criterion (AIC). Yes in the last column indicates that the null hypothesis was rejected at least at the 10% significance level

power of the linear Granger causality test if the time series that are analyzed are nonlinear or non-normal.

BDS test for the nonlinear feature

To motivate the use of the causality test in quantiles, this section investigates the possibility of nonlinearity in the relationship between the US EPU and the growth and uncertainty of carbon emission in five sectors. To this end, following Balcilar et al. (2017), we apply the BDS test (Broock et al. 1996) to the residuals of carbon emissions growth or the uncertainty equation of the VAR involving (relative) the US EPU, respectively. The BDS test is one of the most popular tests for nonlinearity. The BDS test determines if increments of a data series are independent and identically distributed (i.i.d.). The test is asymptotically distributed as standard normal under the null hypothesis of i.i.d. increments.

The results of the BDS test are reported in Table 4. As shown in panel 1 of Table 4, for the carbon emissions growth and uncertainty series, the null hypothesis of i.i.d. residuals is strongly rejected at the 1% significance level across various dimensions (*m*). From panel 2 of Table 4, we also see that residuals of the carbon emission growth and the uncertainty equation of the VAR of (relative) the US EPU also pass the BDS test at the 1% significance level. This finding indicates that the relationship between the US EPU and carbon emissions growth and uncertainty for these five sectors are nonlinear and implies that the Granger causality tests based on a linear

Table 4 BDS test

m	2	3	4	5	6
Panel 1: BDS test for each variable					
<i>EPU</i>	0.107	0.177	0.217	0.236	0.243
<i>Total</i>	0.032	0.054	0.060	0.057	0.051
<i>Industrial</i>	0.025	0.048	0.061	0.064	0.063
<i>Residential</i>	0.034	0.055	0.060	0.057	0.049
<i>Transportation</i>	0.051	0.079	0.095	0.096	0.092
<i>Electric</i>	0.025	0.039	0.043	0.041	0.037
<i>Commercial</i>	0.026	0.041	0.044	0.042	0.037
<i>Total_volatility</i>	0.062	0.105	0.118	0.113	0.101
<i>Industrial_volatility</i>	0.116	0.190	0.230	0.246	0.246
<i>Residential_volatility</i>	0.058	0.093	0.104	0.095	0.083
<i>Transportation_volatility</i>	0.073	0.119	0.140	0.144	0.138
<i>Electric_volatility</i>	0.040	0.061	0.069	0.062	0.053
<i>Commercial_volatility</i>	0.034	0.059	0.066	0.065	0.055
Panel 2: BDS test for the residuals of carbon emission equation of the VAR model with EPU					
<i>Total-VAR(8)</i>	0.013	0.022	0.023	0.020	0.018
<i>Industrial-VAR(5)</i>	0.009	0.022	0.031	0.034	0.034
<i>Residential-VAR(8)</i>	0.015	0.025	0.030	0.026	0.023
<i>Transportation-VAR(5)</i>	0.018	0.029	0.038	0.038	0.035
<i>Electric-VAR(5)</i>	0.019	0.028	0.032	0.030	0.028
<i>Commercial-VAR(8)</i>	0.011	0.017	0.017	0.015	0.015
<i>Total_volatility-VAR(5)</i>	0.048	0.087	0.103	0.100	0.091
<i>Industrial_volatility-VAR(4)</i>	0.037	0.072	0.089	0.095	0.096
<i>Residential_volatility-VAR(5)</i>	0.035	0.062	0.074	0.071	0.059
<i>Transportation_volatility-VAR(5)</i>	0.034	0.062	0.072	0.076	0.071
<i>Electric_volatility-VAR(4)</i>	0.035	0.054	0.055	0.054	0.049
<i>Commercial_volatility-VAR(4)</i>	0.028	0.052	0.059	0.055	0.049

framework are likely to suffer from misspecification problem. In other words, the results of the linear test for Granger non-causality cannot be deemed to be robust and reliable.

The table shows the BDS Statistic. Italic *p* values denote rejection of the null hypothesis at the 5% significance level. The lag parameters for the VAR model are selected based on the Akaike information criterion (AIC). *m* stands for the embedded dimension

Nonlinear Granger causality tests

Given the strong evidence of nonlinearity that was obtained from the BDS tests, we further investigate whether there is a nonlinear Granger causality running from the US EPU to the total and the sectors’ carbon emissions. To this end, we use the D&P nonlinear Granger causality test (Diks and Panchenko 2006). The results for the D&P nonlinear Granger causality test are presented in Table 5. We perform the tests for the

embedding dimension $m = 1.5$ and select the lags 1–6. As seen, the null hypothesis of no nonlinear Granger causality running from US EPU to the carbon emissions growth in the sample period cannot be rejected at the 10% significance level, with the industrial sector being an exception. With respect to carbon emissions uncertainty, it is found that there is no evidence in favor of the nonlinear Granger causality from EPU to the total and all five sectors’ carbon emissions uncertainty at the 5% significance level. For both linear and nonlinear Granger causality test, results are fairly similar. There is no causality for most sectors. That is slightly counterintuitive, for the intimate connection between EPU and carbon emissions, as we have discussed above. At this point, we need to think twice about the models that have been used here. These two models, linear and nonlinear Granger causality tests, both merely rely on conditional-mean-based estimations and thus fail to capture the entire conditional distribution of the growth and uncertainty of carbon emissions. Therefore, in order to obtain the full picture, we next turn to the causality-in-quantiles tests, which consider all quantiles of the distribution. This test can provide more detailed information on the relationship between the US EPU and its carbon emissions behavior.

Granger causality test in quantiles

In this section, we analyze the importance of US EPU in predicting the growth and uncertainty of carbon emissions by employing a causality test in quantiles proposed by Troster (2018). The model considers all quantiles of the distribution of carbon emissions growth and uncertainty, which can provide richer information on the relationship between EPU and carbon emissions.

Table 6 reports the *p* values for the test of the quantile causality which runs from the US EPU to the carbon emissions growth for the five US sectors. Based on the total carbon emissions data, the test results of quantile causality running from US EPU to carbon emission growth are insignificant at the median (quantiles at 0.5), but there is an outstanding pattern of Granger-causality from the US EPU to the total carbon emissions growth in the tails of the distribution of the emissions growth. Furthermore, the data show that the effects are more likely to be concentrated on the lower quantiles of the carbon emission growth distribution. Meanwhile, at high quantiles, we only find evidence of causality in the 0.7 and 0.9 quantiles. This finding reveals that the effects of EPU on carbon emissions growth are more likely to be concentrated on the lower quantiles of the carbon emission growth distribution, which corresponds to an extreme period of big drops. This finding is consistent with our intuition in “Theoretical framework and hypothesis.”

As for the industrial sector, the *p* values of the quantile-causality test provide supporting evidence of causality from

Table 5 Nonlinear Granger causality tests of Diks and Panchenko (2006)

Null hypothesis	$l_X=l_Y$					
	1	2	3	4	5	6
Panel 1: carbon emission growth						
<i>EPU</i> → <i>Total</i>	0.469 (0.319)	0.901 (0.183)	0.617 (0.268)	0.897 (0.185)	0.935 (0.174)	0.494 (0.311)
<i>EPU</i> → <i>Industrial</i>	1.478 (0.069)	1.111 (0.133)	1.196 (0.116)	1.856** (0.032)	1.962** (0.025)	2.076** (0.019)
<i>EPU</i> → <i>Residential</i>	− 0.385 (0.649)	0.923 (0.118)	0.016 (0.493)	0.730 (0.232)	0.370 (0.355)	− 0.055 (0.522)
<i>EPU</i> → <i>Transportation</i>	− 0.756 (0.775)	0.117 (0.453)	0.114 (0.454)	− 0.295 (0.616)	0.718 (0.236)	0.598 (0.275)
<i>EPU</i> → <i>Electric</i>	− 0.398 (0.654)	− 0.087 (0.535)	− 0.467 (0.679)	0.627 (0.265)	0.646 (0.2580)	− 0.155 (0.561)
<i>EPU</i> → <i>Commercial</i>	− 0.085 (0.534)	0.103 (0.458)	− 0.042 (0.516)	0.692 (0.244)	0.637 (0.261)	0.494 (0.310)
Panel 2: carbon emission uncertainty						
<i>EPU</i> → <i>Total</i>	0.098 (0.461)	0.512 (0.303)	0.814 (0.207)	1.134 (0.128)	1.028 (0.151)	0.929 (0.176)
<i>EPU</i> → <i>Industrial</i>	0.231 (0.408)	1.570 (0.058)	1.421 (0.077)	1.286 (0.099)	1.209 (0.113)	1.434 (0.075)
<i>EPU</i> → <i>Residential</i>	0.329 (0.370)	0.455 (0.324)	0.590 (0.277)	0.461 (0.322)	0.694 (0.243)	0.864 (0.193)
<i>EPU</i> → <i>Transportation</i>	1.074 (0.141)	0.702 (0.241)	1.404 (0.080)	1.432 (0.075)	1.526 (0.063)	1.601 (0.054)
<i>EPU</i> → <i>Electric</i>	− 0.423 (0.663)	− 1.177 (0.881)	− 0.986 (0.838)	− 0.605 (0.727)	− 0.626 (0.734)	− 0.696 (0.756)
<i>EPU</i> → <i>Commercial</i>	− 0.698 (0.757)	− 1.015 (0.844)	− 0.850 (0.802)	− 0.633 (0.736)	− 0.852 (0.802)	− 0.787 (0.784)

The *p* value in the parentheses; *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively; $l_X=l_Y$ denotes the lag length. *EPU* → *Total* denotes the null hypothesis of no nonlinear Granger causality from EPU to total carbon emission

EPU to carbon emissions growth in all three types of quantiles (lower, median and higher quantiles). More specifically, we find that the causality is significant both in the lower and median quantiles, such as 0.1, 0.2, 0.3, 0.4, and 0.5 quantiles at the 5% significance level. However, for higher quantiles, we just find evidence of causality in the 0.6 and 0.9 quantiles.

This finding suggests that despite EPU affecting the carbon emissions growth for the industrial sector both in lower and higher quantiles to some extent, the effects are more likely to be significant when carbon emissions growth is at a lower level than at a higher level. In terms of the residential sector and the electric power sector, we find similar conclusions with

Table 6 Quantile causality test results (subsampling *p* values) from EPU to carbon emissions growth

	Lag	[0.1,0.9]	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Total	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.062	0.276	0.193	0.122	<i>0.003</i>	0.095	<i>0.003</i>
	2	<i>0.024</i>	<i>0.003</i>	<i>0.006</i>	0.077	<i>0.039</i>	0.196	0.142	<i>0.003</i>	0.125	0.196
	3	<i>0.027</i>	<i>0.018</i>	<i>0.030</i>	0.059	0.136	0.122	0.098	<i>0.003</i>	0.142	0.513
Industrial	1	<i>0.033</i>	0.353	0.412	0.053	<i>0.033</i>	0.430	0.344	0.350	0.068	<i>0.003</i>
	2	<i>0.003</i>	<i>0.024</i>	0.181	<i>0.009</i>	0.098	<i>0.003</i>	<i>0.015</i>	0.148	0.226	<i>0.024</i>
	3	<i>0.003</i>	<i>0.027</i>	0.190	<i>0.021</i>	<i>0.033</i>	<i>0.003</i>	0.113	0.110	0.166	<i>0.039</i>
Residential	1	<i>0.003</i>	<i>0.006</i>	<i>0.003</i>	<i>0.003</i>	<i>0.021</i>	<i>0.003</i>	<i>0.027</i>	<i>0.036</i>	0.122	0.249
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.006</i>	<i>0.003</i>	0.068	0.098	0.365
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.024</i>	0.128	0.214
Transportation	1	<i>0.012</i>	0.104	<i>0.003</i>	<i>0.003</i>	0.341	0.763	0.056	0.071	0.160	0.261
	2	0.056	<i>0.021</i>	0.148	0.107	0.475	0.053	0.107	<i>0.042</i>	0.178	0.804
	3	<i>0.036</i>	<i>0.018</i>	0.089	0.092	0.409	0.125	0.125	<i>0.045</i>	0.154	0.703
Electric	1	<i>0.003</i>	<i>0.006</i>	<i>0.003</i>	<i>0.030</i>	0.065	0.107	<i>0.039</i>	<i>0.012</i>	<i>0.003</i>	0.258
	2	<i>0.003</i>	<i>0.036</i>	<i>0.003</i>	0.306	0.074	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.163	0.104
	3	<i>0.006</i>	<i>0.033</i>	<i>0.003</i>	0.190	0.059	<i>0.030</i>	<i>0.003</i>	<i>0.003</i>	0.098	0.107
Commercial	1	0.053	0.065	0.047	0.101	0.193	0.561	0.214	0.063	0.095	0.145
	2	0.142	0.169	0.181	0.318	0.211	0.389	0.122	0.184	0.412	0.184
	3	0.151	0.380	0.267	0.252	0.098	0.469	0.104	0.472	0.148	0.261

Italic *p* values denote rejection of the null hypothesis at the 5% significance level

that of the industrial sector. That is, regardless of whether the carbon emissions growth is in lower, median or higher quantile, we can always find that the US EPU impacts the carbon emissions growth. However, this finding proves that for higher quantiles such as in 0.8 and 0.9 quantiles, the null hypothesis of non-causality from US EPU to the carbon emission growth cannot be rejected at the 5% significance level. This finding fits our observation of the data. As shown in Fig. 1, lower carbon emissions growth is generally accompanied by an economic recession and high uncertain economic policy. Therefore, under the lower carbon emissions growth (lower quantiles), carbon emissions are more vulnerable to the impact of economic policy uncertainty. Unfortunately, we have not found any study on the relationship between EPU and carbon emission. Some researchers provide evidence that higher policy uncertainty leads to higher macroeconomic volatility, which has been theoretically proven by Pastor and Veronesi (2012, 2013). In this way, the reduction of energy consumption demand due to the decrease in corporate production and resident living activities will result in a reduction of carbon emissions. In addition, the increase in the unemployment rate caused by EPU will also affect residents' carbon emissions. For example, when affected by unemployment, some residents will choose to reduce travel by car, thus leading to the carbon emissions reduction. In addition, the uncertainty of economic policy gives entrepreneurs pause. Entrepreneurs doubt that the carbon reduction policies will change at any time, which cause them not to implement the current policies. Meanwhile, with the increase of EPU, the

attention on environmental governance from the government will be reduced, and the implementation of some environmental protection policies will be affected negatively.

Regarding causality from the US EPU to the transportation-related carbon emissions growth, our results reveal that the EPU Granger causes the growth of carbon emission in the lower quantiles such as the 0.1, 0.2, and 0.3 quantiles for the transportation sector. However, for the mediate and upper quantiles, we find limited evidence of existence of causality, with the 0.7 quantiles being an exception. For the commercial sector, the null hypothesis of no causality from EPU to carbon emission growth cannot be rejected over the entire conditional distribution. This finding indicates that the US EPU has no impact on the carbon emission growth for the commercial sector. For the different results across five sectors, it may be because different sectors have varied energy dependence and policy response.

Next, we examine whether the US EPU impacts the carbon emissions uncertainty. Table 7 displays the results of the causality in a quantile test. As seen from Table 7, it is proven that the US EPU affects the carbon emissions uncertainty over the entire conditional distribution, i.e., at various phases of the carbon emission volatility (uncertainty). This finding is in line with previous literature suggesting that shocks in policy uncertainty foreshadow decreased investment, output, and employment in the USA. In this way, EPU affects the production and consumer consumption decision-making that is associated with carbon emission, which in turn naturally leads to uncertainty in the carbon emissions from production and consumption activities.

Table 7 Quantile causality test results (subsampling *p* values) from EPU to carbon emissions uncertainty

	Lag	[0.1,0.9]	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Total	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.188	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.060	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.042</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
Industrial	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
Residential	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.063</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.131
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.018</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.119
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.196</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.116
Transportation	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
Electric	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.024</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.042</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.009</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
Commercial	1	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.226	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	2	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.158	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>
	3	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	0.188	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>	<i>0.003</i>

Italic *p* values denote rejection of the null hypothesis at the 5% significance level

Conclusions

In recent years, although the growth of global carbon emissions is declining, it still faces challenges and uncertainties in the future with respect to environment management. In June 2017, the USA, which is the second-largest carbon emissions country in the world, announced that it had withdrawn from the Paris Agreement. This action increased the uncertainty of future US carbon emissions. Therefore, in this context, understanding the dynamics and behavior of US carbon emissions is a matter of utmost significance. The motivation of this paper is derived from the research interest to determine if EPU has a relationship with carbon emissions growth and uncertainty. To serve this purpose, based on US sectoral data, a standard linear Granger causality test is implemented, but no evidence is found for most sectors regarding causality running from US EPU to carbon emissions growth and uncertainty. Following the nonlinearity BDS tests, we find that the relationship between EPU and carbon emissions growth and uncertainty has nonlinear characteristics. In this case, we further investigate whether there is a nonlinear Granger causality running from the US EPU to carbon emissions growth and uncertainty, and the results indicate that no evidence has been found for most sectors. Since the linear and nonlinear Granger causality test merely relies on conditional-mean-based estimations, the results may not be reliable. To overcome this problem, we employ a novel parametric test of Granger causality in quantiles as proposed by Troster (2018). This approach takes the different locations and scales of the conditional distribution into account, which can provide richer information than the traditional mean causality on causality between the US EPU and carbon emission.

The main findings of the current study can be summarized as follows. First, our main results suggest that EPU is relevant for understanding the behavior of total and sectoral carbon emissions. In particular, we provide evidence that for total carbon emission, there is no causality running from the US EPU to carbon emission growth in the median quantiles (quantiles at 0.5), but there is an outstanding pattern of Granger-causality from US EPU to total carbon emissions growth in the tails of the emissions growth distribution. More specifically, it shows that the effects of EPU on carbon emissions growth are more likely to be concentrated on the lower quantiles distribution of the carbon emission growth. We find that EPU tends to affect carbon emissions growth when the latter is in an extreme state of great decreases or lower growth. Furthermore, for various sectors such as the industrial sector, residential sector, electric power sector, and transportation sector, we find results that are similar to the total emissions data. However, the US EPU has no impact on the carbon emission growth for the commercial sector. For the different results across five sectors, it may be because different sectors have varied energy dependence and responses to policy. Finally, it is proven that the US EPU affects

the carbon emissions uncertainty over the entire conditional distribution, i.e., at various phases of the carbon emission volatility for all sectors. The reason behind our finding is perhaps that EPU impacts macroeconomic operations and household consumption decisions, which in turn affects the carbon emissions of the whole society. In addition, the uncertainty of the policy will lead to doubts in entrepreneurs, who suspect that the carbon emissions reductions policy will change at any time. Therefore, entrepreneurs will not do their best to implement the current emissions reduction targets.

These results are important for policymakers and traders in the carbon market. To be more explicit, it is important for traders in the carbon market to understand that attention should be given to EPU during lower emission periods, considering that it affects the carbon emission behavior in most sectors. This relationship, in turn, will affect the trader's demand for carbon emissions trading rights, which will lead to fluctuations in the carbon market. Therefore, accounting for the variations in the political environment could aid with the more accurate timing of carbon trades. Furthermore, policymakers should become more aware that their decisions and actions have tangible ramifications for carbon emissions behavior. Maintaining stable economic policies, especially climate policies, could promote its realization of carbon reductions targets.

Lastly, fellow researchers ought to realize that our work is one of the first attempts to link economic policy uncertainty to the carbon emissions. More study is required in this field in order to explore all aspects of this nexus. Future research is required to address the following questions. First, the impacts of different economic policies on the economic situation vary, and enterprises and residents may react differently to different policies. Therefore, future work can study the heterogeneous effects of different policies such as money policies, fiscal policies and tax policies on carbon emissions policies. Second, we can use causality tests in the frequency domain in order to investigate the impacts of concentrated business condition in the short or long term. Understanding the effect of the time horizon on the impact of EPU on carbon emissions is useful for environmental management.

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