Finance Research Letters 53 (2023) 103400

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The dynamic spillover effects of climate policy uncertainty and coal price on carbon price: Evidence from China

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ARTICLE INFO

JEL Classification:
C32
G15
G18
Q54
Q58

Keywords:
Dynamic spillover effect
The time-varying parameters vector autoregression model
Carbon price
Climate policy uncertainty
Coal price

ABSTRACT

This paper applies the time-varying parameters vector autoregression (TVP-VAR) model to investigate the dynamic effects of climate policy uncertainty and coal price on carbon price in China. Based on news from China's mainstream newspapers and websites, a tailor-made climate policy uncertainty index is constructed. The VAR-BEKK-GARCH model is utilized as robustness check. The results indicate that both the climate policy uncertainty and coal price have significant time-varying effects on the carbon price. Additional dynamic connectedness analysis reveals that coal price is the main shock transmitter while climate policy uncertainty and carbon price are mostly net shock receivers.

1. Introduction

A warming climate can accelerate the release of greenhouse gases (Schuur et al., 2015). To tackle climate change and to meet the Paris agreement, a new long-term climate policy called "Dual Carbon Policy" has been proposed in China. The policy aims to peak carbon before 2030 and realize carbon neutrality before 2060. As a tool to reduce carbon dioxide emissions, eight regional carbon markets have been launched in China since 2013 (Shao et al., 2022; Wang and Yan, 2022).

The energy market and policy are two vital factors that affect the carbon market. On the one hand, coal (rather than oil and gas) is a dominant fossil energy in China (Lin and Chen, 2019). Coal-fired power generation is the main source of carbon emissions (Yin et al., 2021; Yu et al., 2014). Many scholars have studied the effects of coal prices on carbon prices (Chang et al., 2019; Cui et al., 2021; Ji et al., 2021; Liu and Jin, 2020; Ma et al., 2020) and the impact of policy on carbon prices (Fischer, 2008; Li et al., 2022; Song et al., 2018; Veugelers, 2012). China's carbon market has a feature of policy-orientation (Chang et al., 2018; Song et al., 2018) . Previous studies have analyzed the relationship between climate policy uncertainty and the stock market or the relationship between climate policy and carbon price (Blyth et al., 2007; Fried et al., 2021; Gavriilidis, 2021; Ye, 2022; Zeng et al., 2022). However, few studies have analyzed the dynamic spillover influence of climate policy uncertainty to carbon price. The influence of climate policy uncertainty on the carbon price remains unclear. Furthermore, many studies have discussed the multivariate linkages among energy market, stock market and carbon market (Ji et al., 2021; Jiang et al., 2018; Li et al., 2021; Lin and Chen, 2019; Wu et al., 2022). There lacks an overall

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https://doi.org/10.1016/j.frl.2022.103400
Received 27 July 2022; Received in revised form 3 October 2022; Accepted 6 October 2022
Available online 8 October 2022
1544-6123/

analysis that investigates the dynamic impacts of the energy (the coal, in particular) market and climate policy uncertainty on the carbon market.

To this end, this paper examines the dynamic spillover effects of climate policy uncertainty and coal price on the Chinese carbon price from a time-varying relationship point of view. In line with Zhou et al. (2020) and Tao et al. (2021), we apply the time-varying parameters vector autoregression (TVP-VAR) approach to analyze the intensity and direction of the dynamic spillover effects. The VAR-BEKK-GARCH model is used as a robustness check. We also apply TVP-VAR based dynamic connectedness approach to further demonstrate these dynamic spillover effects. The main contributions of this study are summarized as follows. First, we construct a daily climate policy uncertainty index in China using Gavriilidis (2021)'s methodology. Second, this paper adds to the existing literature by analyzing the time-varying impacts of the climate policy uncertainty and coal price on the carbon price in China. The empirical results demonstrate that both the climate policy uncertainty and coal price have time-varying effects on carbon price. Coal price is the shock transmitter while climate policy uncertainty and carbon price are net shock receivers in general.

2. Methodology and data

2.1. Methodology

In this study, the dynamic impacts of climate policy uncertainty and coal price on China's carbon price is examined by the time-varying parameters vector autoregression (TVP-VAR) model. The TVP-VAR model, first developed by Primiceri (2005) and extended by Nakajima (2011) to allow for stochastic volatility, has been widely applied for capturing the time-varying relationships between the variables. The state space representation of the TVP-VAR model can be expressed as:

$$y_t = x_t\beta_t + \varepsilon_t \tag{1}$$

$$\beta_t = \beta_{t-1} + \mu_t \tag{2}$$

where y_t denotes the matrix of variables, $x_t = I_3 \otimes (y_{t-1}, \ldots, y_{t-k})^T$,$k$ is the lagged order of the variables, $\varepsilon_t \sim N(0,\Sigma)$, $\mu_t \sim N(0, \Omega)$. Note that the Markov chain Monte Carlo (MCMC) algorithm is utilized for estimation with 10,000 sampling (Nakajima, 2011).

2.2. Data

The data ranges from January 2, 2019, to May 5, 2022. The daily market closing prices of steam coal dominant futures in China (*Coal*) are used to measure coal price (Lin and Chen, 2019; Ma et al., 2020), and are collected from Auto-Trader software. Hubei pilot is chosen to represent the China's regional carbon market for its leading position in China's carbon markets (Chen et al., 2021; Wen et al., 2020a). The data of carbon emission rights in Hubei (*Carbon*) are collected from the CSMAR database and China Hubei Emission Exchange.

2.3. The construction of climate policy uncertainty (CPU) for China

Gavriilidis (2021) develops a news-based climate policy uncertainty based on the criteria of Baker et al. (2016) (see also Huang and Luk (2020) and Engle et al. (2020)). We follow Gavriilidis (2021) and construct a similar index for China as follows. First, a set of keywords (see Table A.1 of the Appendix A) is first determined based on the three aspects of China climate policy uncertainty (namely, climate, policy and uncertainty). Second, we search for news in twenty-one popular newspapers and websites[1] (see Table A.2 of the Appendix A) containing at least one keyword in each aspect of Chinese climate policy uncertainty. Third, the daily ratio of the quantity of relevant news to the total quantity of news in each of these newspapers are computed (Gavriilidis, 2021), resulting in twenty-one time series, which were standardized, and then daily average is computed from these time series. Finally, we normalized the daily average series so that its mean is 100.

3. Empirical results

3.1. Estimation results of TVP-VAR model

Table 1 shows the parameter estimation results of the TVP-VAR model. The posterior mean is within the 95% confidence interval for each parameter. Meanwhile, the parameters all converge to the posterior distribution as all Geweke convergence diagnostic values are lower than the critical value (i.e., 1.96) at 5% level. Moreover, inefficiency factor for each parameter is low, indicating that there are enough irrelevant samples obtained for the model estimation. Further discussion on auto correlation, sample path and posterior distribution of each estimated parameter can be found in Appendix B.

Fig.1 shows the dynamic impulse responses of *Carbon* to *CPU* shocks and *Coal* shocks (with 95% confidence band). The 1^{st}, 5^{th} and 10^{th} lag periods ahead are chosen for impulse response analysis. All the dynamic impulse responses are statistically significant.

[1] https://www.hurun.net/zh-CN/Info/Detail?num=65537CD76E20; http://www.gov.cn/xinwen/2021-10/20/content_5643834.htm.

Table 1
TVP-VAR model estimation.

Parameter	Mean	Standard Deviation	95% Confidence Interval	Geweke	Inef.
$\Sigma_{\beta 1}$	0.0023	0.0003	[0.0018, 0.0029]	0.039	29.74
$\Sigma_{\beta 2}$	0.0023	0.0003	[0.0019, 0.0029]	0.206	35.64
$\Sigma_{\alpha 1}$	0.0050	0.0011	[0.0033, 0.0077]	0.971	106.80
$\Sigma_{\alpha 2}$	0.0035	0.0005	[0.0026, 0.0045]	0.762	49.35
Σ_{h1}	0.1839	0.0295	[0.1308, 0.2518]	0.003	73.48
Σ_{h2}	0.2875	0.0408	[0.2138, 0.3744]	0.419	63.17

Fig.1(a) illustrates dynamic impulse response of *Carbon* to *CPU* shocks. The reaction of *CPU* follows a positive and negative alternating trend. This seems to be driven by some important carbon-related policies or low-carbon events. For example, there are three intersection points of *x*-aixs at the 5^{th} period horizon. The first intersection point is the opening ceremony of the China International Low-carbon Technology Online Expo (June 18, 2020). The second intersection point is July 23, 2021; a Guideline on Promoting the High-quality Development of the Country's Central Region in the New Era was issued the night before. The third intersection point is on February 10, 2022; the Opinions on Improving Institutional Mechanisms and Policy Measures for Green and Low-Carbon Energy Transition was issued to optimize the policy framework of carbon neutral and carbon peak and to propose related safeguard measures in energy sector. For another example, the impulse response reaches its height at the end of December 2019 at the 1^{st} and 5^{th} period horizon. A policy called interim provisions on the accounting treatment regarding carbon trading has been issued before and has been carried out since January 1, 2020, which is a crucial policy that ensures effective supervision of corporate carbon emissions in China. The examples above indicate that the reaction of carbon price becomes volatile whenever climate-related news is released (Zhou and Li, 2019) as they may bring about climate policy uncertainty and add to the investment risk, leading to the fluctuation of carbon price (Blyth et al., 2007).

Fig. 1(b) depicts the dynamic impulse response of *Carbon* to *Coal* shocks. *Carbon* mainly exhibits a negative reaction towards the *Coal* shocks at the 1^{st}, 5^{th} and 10^{th} period horizons. This negative impact of the *Coal* shocks to the *Carbon* is consistent with Ma et al. (2020). The impulse response curve suggests that *Coal* exerts a constraining influence on *Carbon* especially during the winter. The energy supply becomes tight because of the increasing demand for heat in winter. One reason is that the increasing coal price results in the reduction of coal consumption and the increasing substitution demand for substitution power generation such as wind power generation and hydroelectric generation. Thus, the reduction of carbon emissions lowers the demand for carbon trading. This is in line

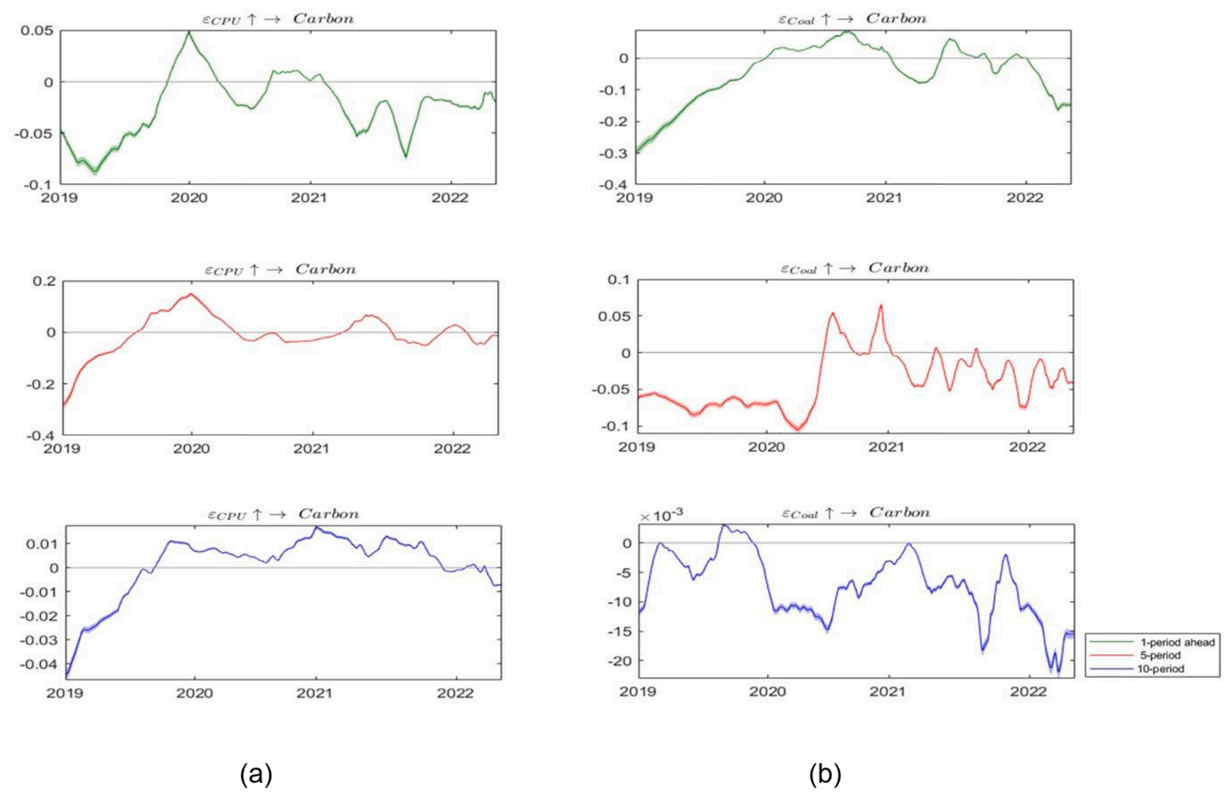

Fig. 1. The impulse responses of *Carbon* to *CPU* shocks and *Coal* shocks at different lag periods.

with results of Li et al. (2021) as well as Lardic and Mignon (2008). Therefore, the carbon price is lowered.

3.2. Robustness check

The VAR-BEKK-GARCH model is used in the literature to analyze the spillover effects among markets (Chen et al., 2022; Wen et al., 2020b; Yu et al., 2020). Based on AIC, the VAR (8)-BEKK-GARCH (1,1) model is selected and served as a robustness check. The distribution is assumed to follow the generalized elliptical distribution. This model imposes further restrictions on the conditional variance-covariance matrix (i.e., H_t)of the VAR-GARCH model as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{3}$$

Matrix A captures ARCH effects, the elements of matrix $A(A_{ij})$ shows the degree of innovation from variable i to variable j. Matrix B captures GARCH effects, the elements of matrix $B(B_{ij})$ shows the persistence in conditional volatility between variables i and j. It is easily seen that the off-diagonal elements of the matrix $A(B)$ depict how the past squared error (conditional variance) of one variable affects the conditional variance of another variable. The estimation results of the mean equation of VAR-BEKK-GARCH are reported in Appendix C. The estimated conditional variance equations are showed in Table 2.

As shown in Table 2, the diagonal elements of matrix A and matrix B are statistically significant at the 1% significant level except for B_{22}. This indicates that significant ARCH effects exist in *CPU, Coal* and *Carbon* while significant GARCH effects exist in *Coal* and *Carbon*. The ARCH effect is strongest in *Carbon* while the GARCH effect is strongest in *Coal.*

The off-diagonal elements of matrix A are statistically significant at the 1% level, indicating that there are significant bidirectional shock spillovers among three variables. The coefficient of A_{32} is the largest, revealing that *Carbon* is the most sensitive to the shocks from *CPU*. Besides, B_{12} and B_{13} are statistically significant at the 1% level, indicating that *CPU* and *Carbon* have volatility spillover effects to *Coal*, respectively. B_{21} and B_{31} are statistically significant at the 1% level, indicating that there are volatility spillover effects from *Coal* to *CPU* and *Carbon*, respectively.

Fig. 2 shows that the conditional correlations between pairs of the three variables are time-varying. The correlations fall within [-0.5 + 0.5]. Some clustering effects are observed, especially for the correlation between *Coal* and *Carbon*, and that between *CPU* and *Carbon*.

3.3. Additional analysis-TVP-VAR based dynamic connectedness

The above analysis is limited in the sense that only the impact of one variable on another variable can be shown and information about its relative importance is not available. To address these limitations, we examine dynamic connectedness in terms of forecast error variance using the TVP-VAR model (Antonakakis et al., 2020, 2019). Several measures of total connectedness are available. Total directional connectedness (TDC) measures how a shock in one variable spill over to other variables. Two similar measures are available. The first one is total directional connectedness to others (TDC-TO), which captures the directional connectedness that a

Table 2
VAR (8)-BEKK-GARCH results.

Matrix element	Estimated coefficient	T-statistic	*P*-Value
C_{11}	0.3458	1.2123	0.2254
C_{21}	-8.4010***	-8.8458	0.0000
C_{22}	3.9600*	1.8739	0.0609
C_{31}	0.1621	1.1032	0.2699
C_{32}	-0.2244	-1.3607	0.1736
C_{33}	-0.0000	-0.0000	0.9999
A_{11}	0.3461***	18.1503	0.0000
A_{12}	-0.1553***	-6.8192	0.0000
A_{13}	0.0075***	4.2942	0.0000
A_{21}	0.0724***	3.0776	0.0021
A_{22}	0.3478***	6.9848	0.0000
A_{23}	0.0151***	4.5835	0.0000
A_{31}	-0.9358***	-3.0554	0.0022
A_{32}	4.5275***	4.7445	0.0000
A_{33}	0.8854***	17.8133	0.0000
B_{11}	0.9599***	238.3492	0.0000
B_{12}	0.0530***	3.7128	0.0002
B_{13}	-0.0013**	-2.3828	0.0172
B_{21}	0.0602**	2.1908	0.0285
B_{22}	-0.1006	-0.9730	0.3305
B_{23}	-0.0069	-0.7945	0.4269
B_{31}	0.2846**	2.5311	0.0114
B_{32}	-0.5803	-1.4553	0.1456
B_{33}	0.7210***	35.6542	0.0000

Note: ***, ** and * respectively indicate the 1%, 5% and 10% significance levels. 1,2, 3 in the subscript of the matrix denote *Coal, CPU* and *Carbon*, respectively.

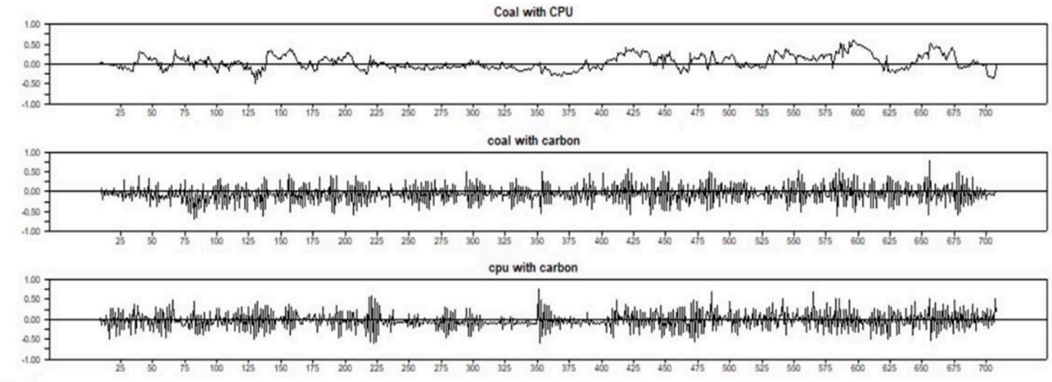

Fig. 2. Conditional correlations.

variable *i* transmits its shock to all other variables *j*, while the other is called total directional connectedness from others (TDC-FROM), which measures the directional connectiveness that the variable *i* receives from variables *j*. Net total directional connectedness (TDC—NET), defined as the difference between TDC-TO and TDC-FROM, measures the net influence of variable *i* on all the other variables. The final measure is called total connectedness index (TCI), which is just the overall measure of how all variables are connected with each other.

Fig.3 shows that TCI exhibits a cyclical pattern; in particular, the first cycle reached its highest (i.e., 88.86%) at the beginning of 2019 and fell down to approximately 13% at the beginning of 2020. Another cycle started in late 2020 and ended in late 2021 where a new cycle began. This confirms that the relationships among *Coal, CPU* and *Carbon* are time-varying.

Table 3 shows the summary result of the dynamic connectedness analysis. In Table 3, the value of total connectedness is 46.91% among *CPU, Coal* and *Carbon. Coal* (24.25%) is the net shock transmitter while *CPU* (-8.74%) and *Carbon* (-15.51%) are the net shock receivers. Regarding *Carbon*, the largest pairwise connectedness is from itself (78.8%), followed by *Coal* to *Carbon* (15.57%), and then from *CPU* to *Carbon* (5.55%).

4. Conclusions and policy implications

In this paper, a daily tailor-made climate policy uncertainty index is constructed for China. Additionally, the dynamic spillover effects of the climate policy uncertainty and coal price on the carbon price are investigated in terms of TVP-VAR model. VAR (8)-BEKK-GARCH model is used as robustness check and TVP-VAR based dynamic connectedness is utilized as additional analysis. By analyzing the data from January 2, 2019, to May 5, 2022, we have the following main findings. Firstly, both *Coal* and *CPU* have time-varying effects on *Carbon*. There exist significant time-varying spillover effects among *CPU, Coal* and *Carbon. Coal* plays a leading role as shock transmitter while *CPU* and *Carbon* are mainly shock receivers. Secondly, *CPU* shocks generally show a positive and negative alternating impact on *Carbon* driven by some important carbon-related policies or low-carbon events. Thirdly, *Coal* shocks mainly exert a negative impact on *Carbon*. Based on the above results, we propose some policy implications. Firstly, our evidence suggests that government ought to pay attention not only to the climate policy uncertainty but also the energy price fluctuations for their significant time-varying characteristic impact. Secondly, climate policy makers should manage the market expectation, aiming to lower the uncertainty of climate policy and minimize its adverse impact on the carbon price. To reduce the risk contagion from the coal price, more risk management instruments need to be developed and more market participants should be involved.

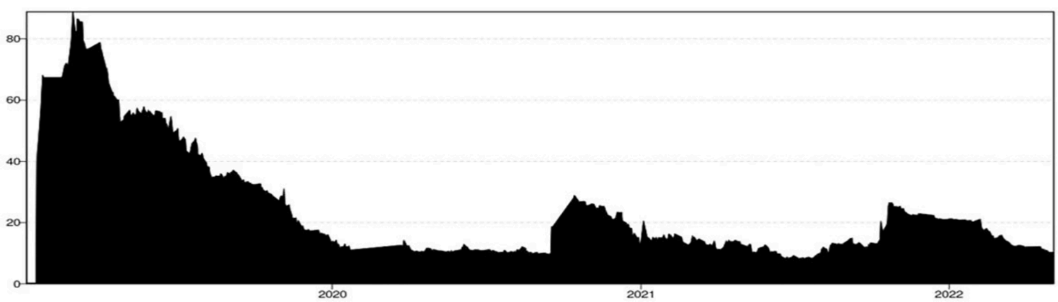

Fig. 3. Dynamic total connectedness (TCI).

Table 3
Average dynamic connectedness.

	Coal	*CPU*	*Carbon*	*TDC-FROM*
Coal	92.88	4.39	2.74	7.12
CPU	15.80	81.32	2.87	18.68
Carbon	15.57	5.55	78.88	21.12
TDC-TO	31.37	9.93	5.61	46.91
TDC—NET	24.25	-8.74	-15.51	23.46/15.64

Note: *TDC—NET* denotes the difference of spillovers between "*TDC-TO*" and "*TDC-FROM*".

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Wan-Lin Yan: Conceptualization, Data curation, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Adrian (Wai Kong) Cheung:** Methodology, Supervision, Visualization, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

None.

Data Availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.103400.

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