Professor Hengguo ZHANG, PhD
E-mail: zszhg@126.com
Shandong University, China

Professor Wenti DU, PhD
E-mail: wdu@aiu.ac.jp
Akita International University, Japan

Lecturer Yuchi XIE, PhD (corresponding author)
E-mail: yuchi.xie@cgu.edu
Shanghai Business School, China

DOES CARBON POLICY UNCERTAINTY AFFECT ECONOMIC GROWTH? EMPIRICAL EVIDENCE FROM ENTERPRISES 'INDUSTRIAL PROFITS IN CHINA

Abstract. *Although the relationship between carbon policy and economic growth has been studied in many papers, few investigate how carbon policy uncertainty affects economic growth and how the market responds to such uncertainty. This paper follows Zhang et al. (2020) to calculate the carbon policy uncertainty and examines the time-varying relationship between carbon policy uncertainty and economic growth by focusing on the industrial profits of three types of enterprises in China. The findings find that there is a hold-up in the response of industrial profits to CCPU. The hold-up from industry to government policies is interpreted as the less confidence of industry toward the uncertainty of Chinese carbon policy.*

Keywords**:** *Carbon Policy Uncertainty Index, Industrial Profits, Learning Process, Bootstrap Causality Test, Time-Varying Relationship*

JEL Classification: D20, E60, E66

1. Introduction

Since the economic reform program started in 1978, China has grown to be the second largest economy in the world. The high growth rate not only helps lift millions of Chinese out of poverty, but also encourages investment and domestic consumption. However, the rapid economic growth comes with a cost of environmental degradation, and the extensive dependence on coal consumption in production makes the country the second largest carbon emitter. The benefits of economic growth could be offset by the environmental threats posed by the emissions from burning fossil fuels. Besides, for countries with a large percentage

DOI: 10.24818/18423264/57.3.23.17

of fossil fuel consumption, the emission reduction policies could slow the economic growth rate down, making these countries reluctant to enforce carbon policies.

A policy is more likely to be adopted if it is perceived to have a high impact or low uncertainty on economic growth. Therefore, a carbon policy that encourages economic growth and carbon emissions makes it more likely to be approved by the government. Accepting such policies provides opportunities for the Chinese economy to shift away from the coal-dependent growth model while maintaining robust economic growth.

The relationship between carbon policy and economic growth has been empirically examined in many papers. Song et al. (2008) explore the relationship between environmental pollution and economic development and find a long-run cointegration relationship between capita emissions and GDP growth in China. Bretschger and Zhang (2017) examine the effect of carbon policy on an economy with a high growth rate and argue that the rigorous international climate agreement cannot be executed due to the cost of welfare reduction. Zhang et al. (2009) studied the Granger causal relationship between Chinese economic growth, energy consumption, and carbon emissions and state that the carbon emissions reduction policy does not impede economic growth. Fisher et al. (2007) analyse the impact of the market reforms on China’s responsiveness to environmental policy and conclude that technological change and efficiency improvement reduce the negative effect of welfare loss.

However, Allcott and Greenstone (2012) find that there is less likely to reduce inefficiencies and increase welfare without consuming more energy. Huebler et al. (2014) also find that it will lead to welfare loss if the Chinese government reaches the target of climate policy given moderate economic growth. Bretschger and Zhang (2017) study China's political cost and find a similar result that there is a welfare reduction if the Chinese government reduces carbon intensity.

Our paper differs from previous studies in the following three aspects. First, we study the relationship between the Chinese Carbon Policy Uncertainty Index (CCPU) and its economic growth from the perspective of industrial profits for three types of enterprises. We focus on the state-owned enterprises (SOEs), the private-owned enterprises (POEs), and the foreign-owned enterprises (FOEs) to examine the diverse relationship between the CCPU and enterprises with different ownerships.

Second, we apply a sub-sample rolling window Granger test as an attempt to study the time-varying relationship between the CCPU and industrial profits. Given the learning process of the market, the effect of carbon policy uncertainty on the market changes over time and is state-dependent. In addition, the government adjusts carbon policy according to the market's responses. Therefore, the relationship between carbon policy uncertainty and industrial profits is time-varying. However, the full-sample causality test fails to illustrate this state-dependent relationship. Thus, the sub-sample rolling window causality test is applied to examine the time-varying relationship between the CCPU and industrial profits.

Thirdly, our paper finds that there is a wait in the response of industrial profits to CCPU. The hold-up from industry to government policies delays the enforcement of Chinese carbon policies. We interpret the hold-up phenomenon as the lower confidence of industry toward the uncertainty of Chinese carbon policy. We also find that the delay of the policy response disappears after the effective response from the government.

Therefore, our study contributes to the growing yet limited literature focusing on carbon policies in the following three aspects. First of all, the CCPU is used to investigate the relationship between the CCPU and industrial profits. Second, a sub-sample rolling window Causality test is employed to examine the time-varying relationship between the CCPU and industrial profits. Third, our paper finds that there is the existence of a hold-up response from the industry to CCPU. We interpret this phenomenon as the lack of confidence of industry in government. This hold-up response disappears after the positive response from the government. The rest of the paper is structured as follows. Section 2 demonstrates the theory. Section 3 presents the method. Section 4 describes the data and shows empirical results. Section 5 concludes.

2. Theory

This paper follows the assumption by Pάstor and Veronesi (2013) [1] about the firm profitability and the policy’s impact on the profitability. For the government, the policy considers both economic and non-economic objectives: it maximises industries’ profitability and considers the costs associated with social welfare. These costs are uncertain, and the market is unsure which policy the government will implement. Uncertainty about these costs is the source of policy uncertainty. The market learns about these costs by observing the impact of policy on realised profitability. Meanwhile, the government adjusts its policy by monitoring the market’s reactions to its policy.

2.1 Assumption

According to Pάstor and Veronesi (2013), a policy is more likely to be adopted if its impact on profitability is high.

[1] Pάstor and Veronesi (2013) assume that the market learns about the impact of a new policy by studying realized profitability in a Bayesian fashion. If the government changes policy and the market resets its belief about government policy, there is uncertainty about government policy. However, this uncertainty decreases over time because of the market learning process.

For all $t \in [0, T]$, an industrial profitability dP_t^i follows the process:

$$dP_t^i = (\mu + g_t)dt + \sigma dB_t + \sigma_1 dB_t^i \quad (1)$$

where (μ, σ, σ_1) are constants, B_t follows Brownian motion. B_t^i is the Brownian motion for industry i. g_t represents the effect of Chinese carbon policy on the mean of the industrial's profitability.

There are N new policies, and g^0 is the impact of the old policy 0 at time 0. When the government starts to change its policy at time ε, $0 < \varepsilon < T$, the impact of the policy changes from g^0 to g^n, which is the effect of the n-th new policy. The value of g_t is given as follows:

$g_t = g^0$ for $t > \varepsilon$, if there is no policy change

$g_t = g^n$ for $t > \varepsilon$ if new policy n is imposed, $n = \{1, \ldots, N\}$. (2)

When there is a policy change at time ε, g_t changes from g^0 to g^n, meaning that the effect of the n-th new policy on profitability is g^n.

This paper follows P$\acute{a}$stor and Veronesi (2013)'s assumption that the distributions of g_t are normal:

$$g^0 \sim N(0, \sigma_g^2) \quad (3)$$

$$g^n \sim N(\mu_g^n, \sigma_{g,n}^2) \quad for \quad n = \{1, \ldots\ldots, N\} \quad (4)$$

2.2. *Government utility function*

Based on P$\acute{a}$stor and Veronesi (2013), the government maximises utility on average, but it also randomly deviates from its objective.

At time ε, the government chooses policy n, to maximise the following utility:

$$\max_{n \epsilon \{0,..,N\}} \{E_{\ \varepsilon}[\ C^n P_t^i | policy \ \ n]\} \quad (5)$$

where C^n is the cost of a new policy available to all agents at time ε. If $C^n > 1$, then the government have to take action. Based on P$\acute{a}$stor and Veronesi (2013)'s assumption, C^n follows a lognormal distribution.

$$\log(C^n) \sim N\left(-\frac{1}{2}\mu_c^2, \mu_c^2\right) \quad for \quad n = \{1, \ldots, N\} \quad (6)$$

where u_c^2 is the uncertainty about $\{C^n\}_{n=1}^N$. If $u_c = 0$, the government's policy is completely predicted by the market before ε. However, if $u_c > 0$, there is uncertainty in the policy decision.

2.3. *Learning about policy impacts*

According to P$\acute{a}$stor and Veronesi (2013), a policy's impact is unknown to all agents before the enforcement of the policy. At time 0, the effect of the policy is given by Equations (3) and (4). Before times ε, markets learn about g^0 by examining realised profitability. P$\acute{a}$stor and Veronesi (2013) assume a Bayesian learning process of agents: the distribution of g^0 at time $t \leq \varepsilon$ is given as follows:

$$g_t \sim N(\hat{g}_t, \hat{\sigma}_t^2) \quad (7)$$

where the mean and variance are given by

$$d\hat{g}_t = \hat{\sigma}_t^2 \ \ \sigma^{-1} d\hat{B}_t \tag{8}$$

$$\hat{\sigma}_t^2 \ \ = \frac{1}{\frac{1}{\sigma_g^2}+\frac{1}{\sigma^2}t} \tag{9}$$

where $d\hat{B}_t$ represents the shocks to the average profitability across all industries.

If the average profitability is higher than expected after the policy’s enforcement, agents revise their expectations about g^0 according to Equation (8). However, the uncertainty about g^0 reduces due to the learning process described in Equation (9). Before ε, there is no learning procedure, and agents’ beliefs about $\{g^n\}_{n=0}^N$ are determined by the previous distribution in Equation (4). If the government does not change the policy at time ε, markets learn about g^0, and this process continues to hold after time ε. If the government changes the policy at time ε, markets start to learn about g^n, which is the effect of new policy n on markets. Therefore, the new policy resets agents' expectations about g_t from $N(\hat{g}_t, \hat{\sigma}_t^2)$ to $N(\mu_g^n, \sigma_{g,n}^2)$.

A change in the government policy resets the market’s belief about the government policy, and the market starts to learn about the government’s new policy. Therefore, a government affects industries by changing their expectation about the new policy, while the uncertainty related to the new policy declines due to the learning process of the market. The market's response to government policies’ uncertainty signals the government to adjust its policies and achieve long-term goals.

3. Methodology

3.1. Bootstrap Causality Test with bivariate VAR model

This paper employs the bootstrap causality test proposed by Balcilar et al. (2010) to examine the causality between the CCPU and Industrial profits. This test employs the bivariate VAR(p) model, which studies the dynamic relationship between government and industries over time. We first test the null hypothesis that the CCPU does not Granger cause industrial profits. If the null hypothesis is rejected, industrial profits are Granger caused by the CCPU.

$$\begin{bmatrix} X(t) \\ Y(t) \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \beta_{11}(l) & \beta_{12}(l) \\ \beta_{21}(l) & \beta_{22}(l) \end{bmatrix} \begin{bmatrix} X(t) \\ Y(t) \end{bmatrix} + \begin{bmatrix} \theta_{1t} \\ \theta_{2t} \end{bmatrix} \ \ \text{t=1,.., T} \tag{10}$$

where $\theta_t = (\theta_{1t}, \theta_{2t})^T$ follows white noise process. $X(t)$ and $Y(t)$ are the first differences between the CCPU and industrial profits, respectively. l is the lag operator. Based on Equation (10), if the null hypothesis $\beta_{21}(l) = 0$ is rejected, there is a significant causal relationship from the CCPU to industrial profits. Similarly, if $\beta_{12}(l) = 0$ is rejected, industrial profits Granger cause the CCPU can be inferred.

3.2. *Sub-sample Rolling-window Causality Test*

We first use the $Sup - F$, $Mean - F$, and $Exp - F$ tests to examine the stability of parameters. The L_c test is used to investigates the stability of cointegration parameters. The entire sample is split into a series of s sub-samples, and we employ an RB-based modified LR causality test to examine the single causality for each sub-sample. The linkage changes between the CCPU and industrial profits are given by the bootstrap p-values of the LR tests. The impact of the CCPU on industrial profits is calculated from the formula of $N_b^{-1}\sum_{l-1}^{\theta}\hat{\beta}_{21,l}^{*}$. The impact of industrial profits on the CCPU is calculated from the formula of $N_b^{-1}\sum_{l-1}^{\theta}\hat{\beta}_{12,l}^{*}$. N_b^{-1} refers to the number of bootstrap repetitions. The $\hat{\beta}_{21,l}^{*}$ and $\hat{\beta}_{12,l}^{*}$ are the fifth and the ninety-fifth quantiles of the bootstrap estimates.

4. Data and Empirical results

The CCPU, constructed by Zhang et al. (2021) from the open Internet domains, is used in this study. The calculation of the CCPU index is given by:

$$Index_t = \frac{N_{t,ccpu}}{N_{news}} * 100 \tag{11}$$

$$Index_t^N = Index_t * 100/Index_{ave} \tag{12}$$

where $Index_t$ and $Index_t^N$ refer to the CCPU index and the standardised CCPU index for t months, respectively. $N_{t,ccpu}$ is the number of Chinese carbon policy uncertainty news in t months, whereas N_{news} is the total number of news. $Index_{ave}$ indicates the average of the monthly CCPU index.

The industrial profits dataset is obtained from the National Bureau of Statistics. The CCPU and industrial profits are monthly from February 2012 to February 2020. The results of the unit root tests, which are given in Table 1, cannot reject the null hypothesis of non-stationarity for all series except for the foreign-owned enterprises. Since the null hypotheses are rejected when the series is in their first differences, the CCPU and industrial profits are stationary in their first differences.

Table 1. Unit Root Tests

Series (Level)	ADF	PP	KPSS
CCPU	-2.09(1)	-2.92(2)**	0.64(4)**
IPS	-0.22(4)	-4.29(2)***	0.30(4)***
IPP	-0.89(5)	-4.31(4)***	0.14(4)***
IPF	-3.16(3)**	-4.35(4)***	0.29(4)***
Series (First Differences)	ADF	PP	KPSS
CCPU	-10.37(1)***	-16.30(5)***	0.10(2)***
IPS	-3.44(3)*	-6.71(4)***	0.06(4)***
IPP	-3.51(4)*	-8.35(3)***	0.10(5)***
IPF	-3.29(5)**	-8.32(4)***	0.08(6)***

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The numbers in parentheses are the lag order, which is based on the t-statistic proposed by Perron (1989). CCPU indicated the Chinese carbon policy uncertainty. IPS represents the industrial profits of state-owned enterprises in China. IPP represents the industrial profits of private-owned enterprises in China. IPF represents the industrial profits of foreign-owned enterprises in China.

We then test the bidirectional relationship between the CCPU and industrial profits for the full sample. The Bivariate VAR models with the CCPU and industrial profits in their first differences are tested according to Equation (10), which is shown in Table 2. The null hypothesis that the CCPU does not Granger cause industrial profits of the state-owned enterprise is rejected. However, the null hypothesis that the state-owned enterprise's industrial profits do not Granger cause the CCPU cannot be rejected. As a result, there are no full-sample causal links between the CCPU and industrial profits.

Table 2. Full-Sample Granger Causality Tests

H_0: CCPU does not Granger cause IPS		H_0: IPS does not Granger cause the CCPU	
LR Statistics	*p*-values	LR Statistics	*p*-values
10.20**	0.01	1.26	0.68
H_0: CCPU does not Granger cause IPP		H_0: IPP does not Granger cause the CCPU	
LR Statistics	*p*-values	LR Statistics	*p*-values
9.51**	0.02	2.50	0.42
H_0: CCPU does not Granger cause IPF		H_0: IPF does not Granger cause the CCPU	
LR Statistics	*p*-values	LR Statistics	*p*-values
9.26**	0.01	1.75	0.59

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Moreover, the government can change carbon policies according to its policy objectives so that the parameters estimated in the above VAR models could vary over time. Table 3 shows the results of the long-term stability test of parameters, which is given by $the\ \ Sup-F,\ Mean-F,\ Exp-F$, and L_c tests. According to the results in Table 3, there is no causal relationship between the CCPU and industrial profits in the long term.

Table 3. Long-run Parameter Stability Tests

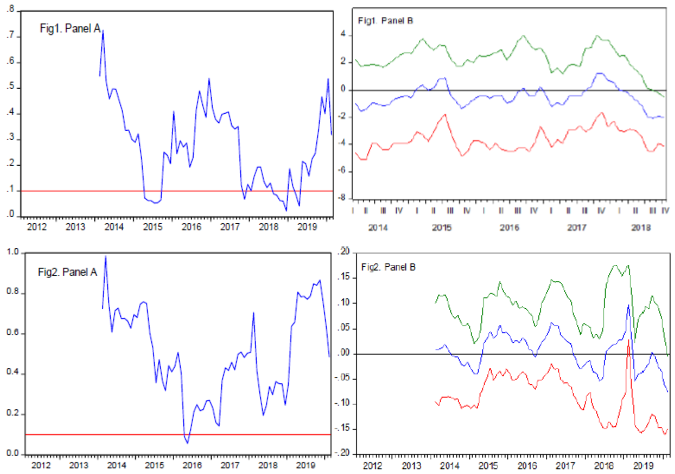
	Sup-*F*	Mean-*F*	Exp-*F*	L_c
IPS	12.83**	4.68**	3.76**	0.95**
P-value	0.02	0.04	0.02	0.01
	Sup-*F*	Mean-*F*	Exp-*F*	L_c

	Sup-*F*	Mean-*F*	Exp-*F*	L_c
IPP	12.60**	8.80***	4.87**	2.22**
P-value	0.03	0.00	0.01	0.01
	Sup-F	Mean-F	Exp-F	*Lc*
IPF	13.13**	7.77**	4.52**	1.73**
P-value	0.02	0.01	0.01	0.01

Note: ***, ** indicate statistical significance at 1% and 5% level.

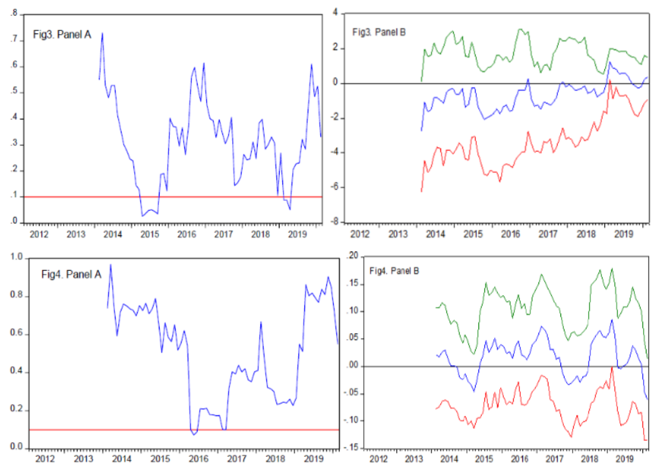
Given the absence of a stable causal relationship between the CCPU and industrial profits in the long term, we perform a rolling-window causality test with sub-sample data using the RB-based modified-LR causality tests. The VAR models in Equation (10) used the basic models to implement the test. We first estimate the bootstrap p-values of LR-statistics from VAR models in Equation (10) using the rolling sub-sample data that include 97 months of observations from February 2012 to February 2020. The results for the rolling bootstrap p-values of the LR statistics are shown in Panel A of Figures 1-6, and the bootstrap estimates of the sum of the rolling-window coefficients are shown in Panel B of Figures 1-6.

Panel A of Figure 1 shows the results of the rolling bootstrap p-values of the LR statistics. The null hypothesis that the CCPU does not Granger cause industrial profits of the state-owned enterprises is rejected at the 10% significance level, and p-values higher than 10% (the area above the black line) are ignored. Panel B of this figure shows the sum of the rolling-window coefficients of the response of the CCPU to the industrial profits of state-owned enterprises. In general, Figure 1 suggests that the CCPU negatively Granger caused industrial profits of the state-owned enterprises in 2015, but positively Granger caused industrial profits of the state-owned enterprises in 2018. In Figure 2, Panel A shows the bootstrap p-value of the rolling test that the state-owned enterprises' industrial profits do not Granger cause the CCPU. Panel B shows the sum of the rolling window coefficients of the impact of the state-owned enterprises' industrial profits on the CCPU for China. Overall, Figure 2 demonstrates that the state-owned enterprises' industrial profits positively Granger caused the CCPU in 2016.



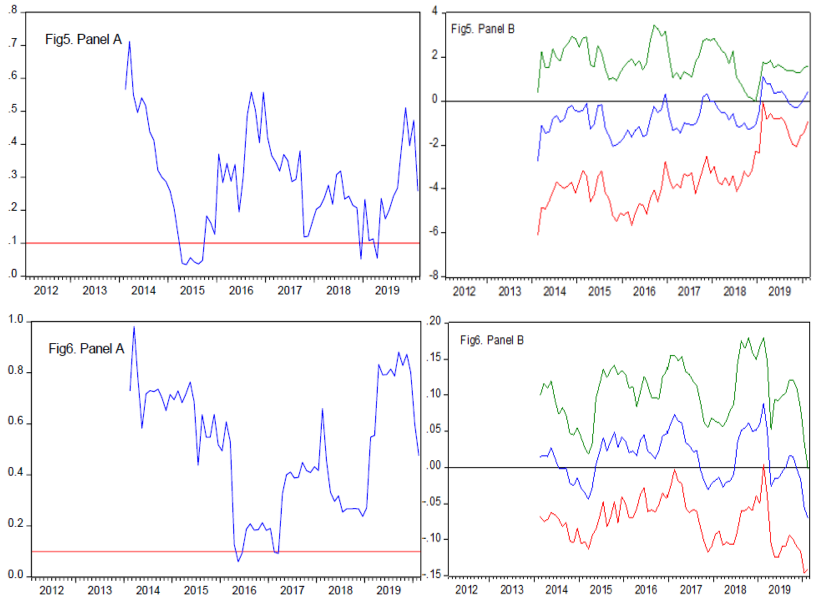
Figures 1-2. Rolling Bootstrap P-Values of LR Statistics

Next, in Figure 3, Panel A illustrates the bootstrap p-value of the rolling test that the CCPU does not Granger cause the private-owned enterprises’ industrial profits. Panel B shows the sum of the rolling window coefficients of the impact of the CCPU on the private-owned enterprises’ industrial profits. This figure shows that the CCPU positively Granger caused industrial profits of the private-owned enterprises in 2016. Panel A of Figure 4 presents the bootstrap p-value of the rolling test that the private-owned enterprises’ industrial profits do not Granger cause the CCPU. Panel B of the figure shows the sum of the rolling window coefficients of the impact of the private-owned enterprises’ industrial profits on the CCPU. This figure indicates that the industrial profits of the private-owned enterprises positively Granger caused the CCPU in 2016.



Figures 3-4. Rolling Bootstrap P-Values of LR Statistics

After that, in Figure 5, Panel A exhibits the bootstrap p-value of the rolling test statistic that the CCPU does not Granger cause industrial profits of the foreign-owned enterprises. Panel B shows the sum of the rolling window coefficients of the impact of the CCPU on the foreign-owned enterprises' industrial profits. This figure shows that the CCPU negatively Granger caused industrial profits for the foreign-owned enterprises in 2015 while positively Granger caused industrial profits for the foreign-owned enterprises in 2019. While in Figure 6, Panel A tests the null hypothesis that the industrial profits of the foreign-owned enterprises industrial profits do not Granger cause the CCPU. Panel B shows the sum of the rolling window coefficients of the impact of the foreign-owned enterprises' industrial profits on the CCPU. Thus, Figure 6 illustrates that the foreign-owned enterprises' industrial profits positively Granger caused CCPU in 2016.



Figures 5-6. Rolling Bootstrap P-Values of LR Statistics

According to the empirical results, the relationship between the CCPU and industrial profits varies over time. In addition, the pattern of the relationship changes for enterprises with different ownerships. Specifically, the industrial profits' responses to the CCPU were significantly negative in 2015 for all types of enterprises. However, in 2016, though, the CCPU significantly positively caused industrial profits of the private-owned enterprises. However, the impact of CCPU on industrial profits was not significant in 2017. Results also show that industrial profits for the state-owned and foreign-owned enterprises responded significantly negatively to the CCPU in 2018. Then, the responses of industrial profits of all types of enterprises to the CCPU turned significantly positive in 2019. In terms of the reaction of the CCPU to industrial profits, the results suggest that industrial profits from all types of enterprises positively caused the CCPU in 2016.

These findings are closely related to the Chinese carbon policies. China’s green transition has accelerated during the 13th Five-year Plan (2016-2020), and the Chinese government is committed to establishing a modern, clean, decarbonised, safe, and efficient energy system. However, the energy-intensive industry dominates the Chinese economy, and the transition to non-fossil energy consumption adds uncertainty to the energy-intensive industry, such as the iron and steel industry.

The negative responses of industrial profits of all types of enterprises to the CCPU in 2015 signalled the adjustment of carbon policies from government. Then, the reaction of the CCPU to industrial profits turned significantly positive in 2016, which could be the result of active responses of the government to the market’s negative reaction in 2015. Our paper interprets the negative responses of industrial profits to the CCPU in 2015 as the wait for industrial responses, which delays the enforcement of Chinese carbon policies. The hold-up of industrial responses could be the lower confidence of industry toward the uncertainty of government carbon policy. The delay in policy response disappears after the active responses from the government, which reduces the negative effect of the uncertainty of carbon policies on industry.

The findings show that adjustments of the government's carbon policies based on the market reactions not only help to reset the market's expectation toward future policies but also build up the market confidence toward the government's future carbon policies. Therefore, interactions and communications between the government and the market are strongly recommended for policymakers and market participants in order to fulfil the sustainable development goal of the Chinese government.

5. Conclusions

This paper applies a sub-sample rolling window causality test to investigate the time-varying relationship between the CCPU and Chinese economic growth from the perspective of industrial profits of enterprises in three types of ownerships (the state-owned, the private-owned, and the foreign-owned). We find that, as expected, the relationship between the CCPU and industrial profits changes over time, and enterprises of different ownerships do not react to the CCPU in the same pattern.

Our findings are closely related to the Chinese carbon policies. Although the Chinese government is determined to build a decarbonised economy with a clean, secure, and efficient modern energy system, the transition to non-fossil energy consumption adds uncertainty to its energy-intensive industries.

This study of the time-varying relationship between the CCPU and industrial profitability helps the market to learn the government's policy and allows the government to adjust its policy to the market. The findings suggest that effective and transparent interactions between the government and enterprises are strongly recommended for policymakers and managers in order to establish a sustainable and decarbonised and development.

REFERENCES

[1] **Apergis, N., Payne, J.E. (2012), *Renewable and non-renewable energy consumption-growth nexus: Evidence from a panel Error Correction Model.*** *Energy Economics*, 34(3), 733-738;

[2] **Beckerman, W. (1992), *Economic growth and the environment: Whose growth? Whose environment?*** *World Development*, 20(4), 481-496;

[3] **Su, C.W., Zhang, H.G., Chang, H., Nian, R. (2016), *Is exchange rate stability beneficial for stabilizing consumer prices in China?*** *The Journal of International Trade and Economic development,* 25(6), 857-879;

[4] **Fisher-Vanden, K., Ho, M.S. (2007), *How do market reforms affect China's responsiveness to environmental policy?*** *Journal of Development Economics*, 82, 200-233;

[5] **Bretschger, L., Ramer, R., Schwark, F. (2011), *Growth effects of carbon policies: Applying a fully dynamic CGE model with heterogeneous capital.*** *Resource and Energy Economics*, 33, 963-980;

[6] **Bretschger, L., Zhang, L. (2017), *Carbon policy in a high-growth economy: The case of China.*** *Resource and Energy Economics*, 47, 1-19;

[7] **Pástor, L., Veronesi, P. (2013), *Political Uncertainty and risk premia.*** *Journal of Financial Economics*,110(3), 520-545;

[8] **Payne, J.E. (2010), *Survey of the international evidence on the causal relationship between energy consumption and growth.*** *Journal of Economic Studies*, 37(1), 53-95;

[9] **Stern, D.I., Common, M.S., Barbier, E.B. (1996), *Economic growth and environmental degradation: the environmental Kuznets curve and sustainable development.*** *World Development*, 24(7),1151-1160;

[10] **Stern, D.I., Enflo, K. (2013), *Causality between energy and output in the long-run.*** *Energy Economics*, 39, 135-146;

[11] **Zhang, X.P., Cheng, X.M. (2009), *Energy consumption, carbon emissions, and economic growth in China.*** *Ecological Economics*, 68, 2706-2712;

[12] **Zhang, H.G., Cao, T., Li, H., Xu, T. (2021), *Dynamic measurement of news-driven information friction in China's carbon market: Theory and evidence.*** *Energy Economics*, 95, 104994.