Department of Land Economy
Environment, Law & Economics

UNIVERSITY OF CAMBRIDGE
Real Estate Research Centre

Working Paper Series No. 2023-02

Title: Political Uncertainty and Carbon Emission Trading: Evidence from China

Authors: Helen Bao and Tony He Tang

Affiliation: [1]University of Cambridge, Department of Land Economy

Contact corresponding author: Helen Bao: hxb20@cam.ac.uk

Political Uncertainty and Carbon Emission Trading: Evidence from China

Helen X. H. Bao & Tony He Tang[1]

Department of Land Economy, University of Cambridge, UK, CB39EP

Abstract

As an alternative carbon pricing tool to carbon taxes, carbon emission trading systems (ETS) combine market incentives with policy targets. Inevitably, ETS markets are linked to domestic and international political environment. Yet, there is a lack of research on the relationship between political uncertainty and activities in carbon emission trading markets. Using data from four carbon ETS markets in China between 2014 and 2019, our logistic regression and AR(1)-GARCH estimations suggest a negative relationship between political uncertainty and carbon emission trading volume, and a risk premium on carbon emission trading daily returns for political uncertainty in China. We also identified significant variations among the responses to political uncertainty in these markets. The locally focused empirical strategy distinguishes our research from existing studies where the analyses are at the national level. The empirical findings from the four largest carbon ETS markets in China are helpful for policymakers in China and beyond to understand how ETS markets work in China, where political uncertainty has always been playing an important role in economic activities.

Keywords: Carbon-emission trading scheme (ETS); Pilot ETS in China; political risk; climate policy; global warming

JEL Classifications: C32; E44; G12; O13; P28

[1] Corresponding author (ht415@cam.ac.uk).

Political Uncertainty and Carbon Emission Trading: Evidence from China

Abstract

As an alternative carbon pricing tool to carbon taxes, carbon emission trading systems (ETS) combine market incentives with policy targets. Inevitably, ETS markets are linked to domestic and international political environment. Yet, there is a lack of research on the relationship between political uncertainty and activities in carbon emission trading markets. Using data from four carbon ETS markets in China between 2014 and 2019, our logistic regression and AR(1)-GARCH estimations suggest a negative relationship between political uncertainty and carbon emission trading volume, and a risk premium on carbon emission trading daily returns for political uncertainty in China. We also identified significant variations among the responses to political uncertainty in these markets. The locally focused empirical strategy distinguishes our research from existing studies where the analyses are at the national level. The empirical findings from the four largest carbon ETS markets in China are helpful for policymakers in China and beyond to understand how ETS markets work in China, where political uncertainty has always been playing an important role in economic activities.

Keywords: Carbon-emission trading scheme (ETS); Pilot ETS in China; political risk; climate policy; global warming

JEL Classifications: C32; E44; G12; O13; P28

1. Introduction

In recent years, carbon emission trading systems (ETS) have been expanding rapidly because of their proven effectiveness in reducing greenhouse gas emissions. For example, The latest report from the World Bank shows that the growth of carbon pricing revenues is entirely driven by carbon ETS since 2017; the carbon pricing revenue of ETS also surpassed that of carbon taxes for the first time in 2019 (World Bank, 2022). As an alternative carbon pricing tool to carbon taxes, ETS combines market incentives with policy targets. Consequently, carbon ETS can response to changes in emission caps effectively and swiftly. For example, the carbon trading prices in the EU carbon ETS markets have been increasing exponentially since 2017; the trend was not disrupted by the COVID-19 pandemic or the modest increase in transaction volume (European Commission, 2021, Figure 2, page 5). This is a good reflection of firms' expectations of tighter emission caps as results of recent climate policies changes following the global climate summit (COP26) in 2021. Consequently, the EU carbon ETS market witnessed the strongest annual growth in terms of both trading turnover and clearing prices in history in 2021 (World Bank, 2022).

Meanwhile, carbon ETS markets are also under the influence of domestic and international political environment. Natural environment, after all, is a public good shared at the global scale. Not surprisingly, major geopolitical events could trigger changes in national or even local decarbonisation policies. For example, in response to US House Speaker Nancy Pelosi's visit to Taiwan on 2 August 2022, China immediately halted the climate talks with the US, which introduced a great level of uncertainty to China's commitments to meet its decarbonisation targets (Mitchell et al., 2022). Therefore, it is important to understand whether and how carbon ETS markets response to political uncertainty.

The need for empirical evidence on this topic is particularly pressing when it comes to China. Firstly, China's carbon emission per capita increased from 2.65 to 7.65 metric tons per capita from 2000 to 2019. Figure 1 shows the distribution of carbon emission in million tons between 2006 and 2019. There is no sign of reduction of CO2 emissions in any part of the country. In 2019, China's CO^2 emission accounted for over 30% of the world total[2]. Therefore, reducing carbon emission is at the centre of environmental reservation and sustainable development policies in China. Although China has set carbon emission targets and pledged to achieve carbon neutrality by 2060, it is challenging to strike the delicate balance between economic growth and environmental sustainability. To date, China's carbon pricing efforts rely heavily on ETS markets, which run through several rounds of pilots since 2011 and eventually launched nationwide in 2017. However, even during the pilot period, the transaction volume in China's carbon emission markets grew rapidly, and stood at 76 Trillion RMB (about 11 Trillion USD) in 2021. As pointed out by the European Commission, the Chinese ETS markets have great potential to reduce carbon emission significantly, and hence will play an important role in the coordinated efforts to reduce carbon emission globally (European Commission, 2021). We need empirical evidence to understand how the carbon ETS market works in China.

On the other hand, there has been limited studies conducted on this topic. Researchers investigated the positive effects of China's carbon ETS markets on improving green firms' performance, reducing carbon emission, and lowering the mitigation costs for national economy (see, for example, Lin and Jia, 2019; Tu et al., 2018; Yang et al., 2021). There is a lack of investigations into the working of the ETS markets in China, and especially the role of political uncertainty in this sector. Our study aims to add empirical evidence to this under-studied area.

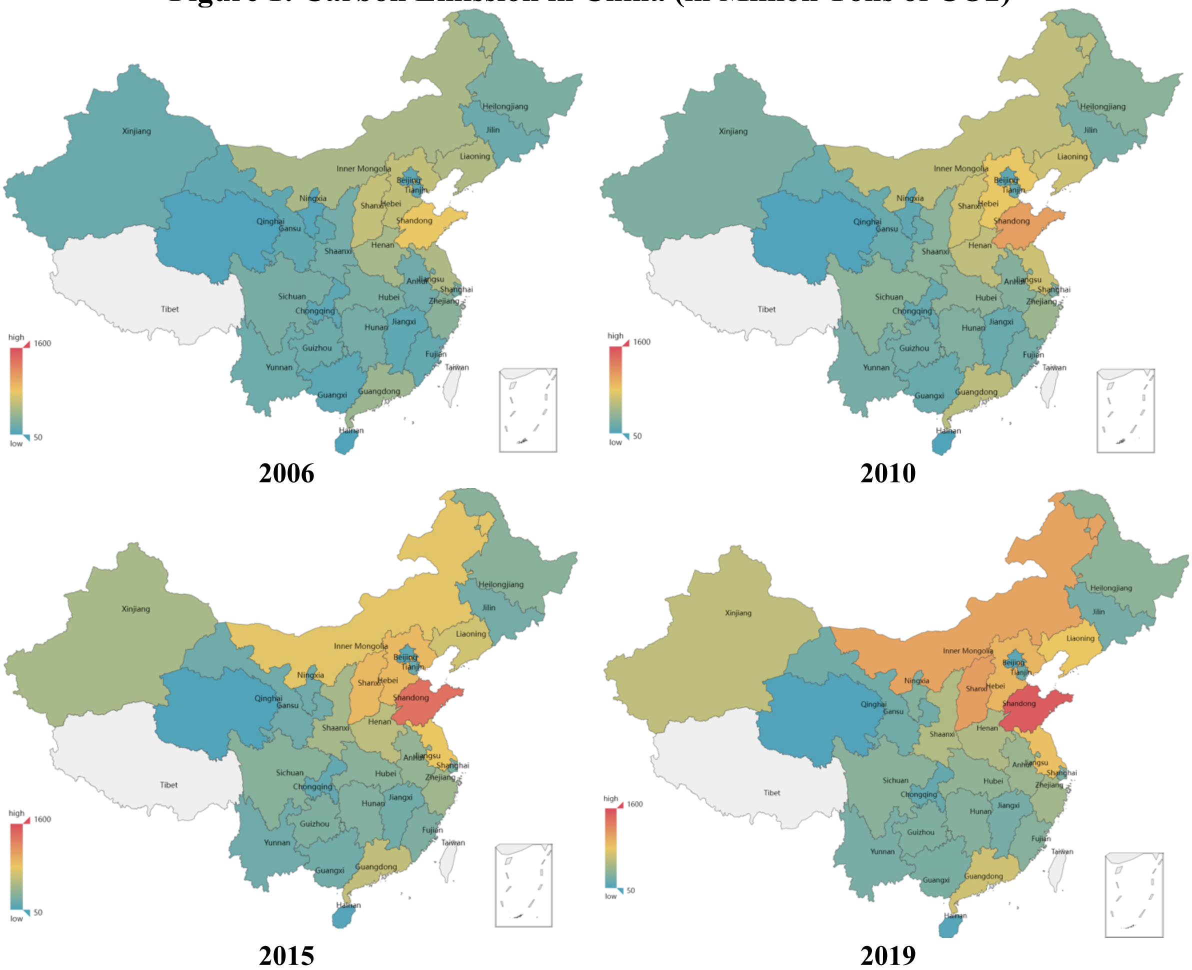
We design the research at the local level by analysing the four largest carbon emission trading markets in China, i.e., Beijing, Shanghai, Hubei, and Guangzhou. We measure political uncertainty locally, by using the turnovers of the governors or mayors in the home province or city of each ETS market. Moreover, we take into account the characteristics of trading activities in China's ETS markets (i.e., low frequency with many trading days without a transaction) by studying both the zero transaction days and daily transaction turnover ratio in each market. Using daily transaction data between 2014 and 2019, our logistic regression and AR(1)-GARCH analyses suggest a negative relationship between political uncertainty and carbon emission trading volume, and a risk premium on carbon emission trading daily returns for political uncertainty in China. We also identify significant variations among the responses to political uncertainty in these markets, which shows the benefits of focusing on local ETS markets instead of the national average.

Our study contributes to the carbon ETS literature in two ways. Firstly, the locally focused empirical strategy distinguishes our investigation from existing studies where the data are usually at the national level. China has nine carbon ETS markets to date. Our approach is necessary to tease out the impacts of political uncertainty on carbon emission trading activities by controlling for the large geographical, economic, and social variations among these regional markets. Secondly, and more importantly, the empirical findings from the four largest carbon ETS markets in China are helpful for policymakers in China and beyond to understand how ETS markets work in China, where political uncertainty has always been playing an important role in economic activities.

[2] The World Bank. https://data.worldbank.org/indicator. Accessed on 6 August 2022.

We organise this paper as follows. The next section gives a systematic and critical review of related literatures, followed by institutional background about the carbon ETS markets in China in Section 3. Section 4 presents the analytical framework and testable hypotheses. The data and econometric models are introduced in Section 5. Discussions of empirical evidence and robustness checks can be found in Sections 6 and 7. Section 8 concludes.

Figure 1: Carbon Emission in China (in Million Tons of CO2)



Data source: China Energy Yearbook 2006 – 2019.

2. Literature Review

2.1 Measurements of political uncertainty

Political uncertainty can be measured based on specific political events or at the aggregate level (Cioffi-Revilla, 1998). Aggregate measurements are appropriate for the analysis of long-run relationship at the national or market level, while event level measurements are useful to gauge the impacts from specific events. Both approaches have seen wide applications in the literature. We identified 28 publications on political uncertainty that are closely related to our study and divided them into two groups based on the type of political uncertainty measurements they adopted. The results are summarised in Table 1.

As shown in panel A in Table 1, political risk indices, such as the political risk index provided by the International Country Risk Guide (Erb et al., 1996) and the descriptive indexes from the World Bank Database of Political Institutions (Beck et al., 2001), are commonly used to gauge the level of political uncertainty at the national or market level. For example, Guo et al. (2021) use the International Country Risk Guide to find that political risk has increasing influence on stock market in China and US after the 2008 crisis. Economic Policy Uncertainty (EPU), developed by Baker et al. (2016), is also a popular choice in this category. For example, Brogaard and Detzel (2015) used EPU as a predictor of stock market returns in the US; Gulen and Ion (2015) analysed the performance of the firm investment by using EPU; and Yu et al. (2021) estimated a provincial EPU to explore the influence of policy uncertainty on firms' carbon emission in China.

Researchers and policymakers are more interested in the impacts of political uncertainty at the event level, because the findings tend to be more informative and relevant. This is evident from the large number of papers included in the panel B of Table 1, where event level measurements are summarised. Among the political events studied in the literature, elections and official turnovers are the most studied type of political shocks. Elections and turnovers not only motivate the government to manipulate fiscal and monetary policy, which lead to political business cycle (Nordhaus, 1975), but also could be followed by significant changes in government policies in other areas. Consequently, the impacts from both national leader elections (Pantzalis et al., 2000), gubernatorial elections (Jens, 2017) and regional elections (Acemoglu et al., 2018) have been investigated extensively in the literature; many studies have been done to investigate the effect of US presidential elections as pollical shocks on as well (see, for example, Belo et al., 2013; Herbst and Slinkman, 1984; Johnson et al., 1999; Li and Born, 2006). Similarly, other important political uncertainty shocks such as global summits (Pastor and Veronesi 2016), referendums (Hill et al., 2019) and coups (Alesina et al., 1996) also received attention.

In China, government officials are appointed rather than publicly elected. Consequently, Chinese political uncertainty studies focus on official turnovers. Local official turnovers (e.g., Cao et al., 2019; Luo et al., 2017; Xu et al., 2016) received much more attention than their national counterparts, because of the greater level of uncertainty involved in these appointments. Of course, political events at the national level, such as the recent anti-corruption campaign, have also drawn attention (Chen and Kung, 2019; Lin et al., 2016). The local impacts of these national events, such as provincial anti-corruption campaigns and city-level anti-corruption shocks are also investigated (Agarwal et al., 2020).

After Bittlingmayer (1998) introduced a framework to estimate the impacts of the transition from Imperial Germany to Weimar Germany, dummy variables are routinely used as political uncertainty indicators to capture the effects of specific political events in regression models. The convention is to use a dummy variable to indicate whether an observation falls in the 'event window' (e.g., when the political event in question was taking place). The coefficient estimate of this dummy variable is used to capture the direction and magnitude of the impacts of the event. This approach is used in most of the papers listed in panel A in Table 1.

The political uncertainty of one single political shock may also be evaluated by continuous polls or surveys. For example, Li and Born (2006) used public opinion polls to calculate the likelihood of a Democratic candidate will win in the 2000 presidential election; He et al. (2009) also used the same approach to study the effects of political uncertainty during the 2000 US national election on the performance of politically sensitive firms. Nevertheless, the costs of polls and surveys are often prohibitively high, and hence the application of this method is not as wide as the dummy variable approach.

2.2 Economic impacts of political uncertainty

Agents tend to hold back investment when facing uncertainty, and this phenomenon has been observed in many aspects of the economy, such as corporate investment, household spending or financial transactions (see, for example, Bernanke, 1983; Pástor and Veronesi, 2013). Consequently, researchers often examine the effects of political uncertainty on economy through the lens of investment. In Table 1 we list the dependent variables in the 28 political uncertainty studies. The focus is overwhelmingly on corporate investment decisions (e.g., capital expenditure and R&D expenses) and performance (e.g., stock returns). Evidence shows that election uncertainty drives the corporate investment cycle globally (Julio and Yook, 2012), influences loan interest rate (Francis et al., 2014) and IPOs outcomes (Çolak et al., 2017), and affects firms' decisions on fixed investment (Gulen and Ion, 2015), cross-border acquisition (Cao et al., 2019), and R&D investment (Atanassov et al., 2015). Political uncertainty is also associated with the cross-country level of investment (Alesina and Perotti, 1996), and could potentially induces aggregate level depression. (Barro, 1991).

Although China does not have a full market economy, official turnovers have a similar impact on economy as elections in western countries. For example, municipal official turnovers influence firms' fixed investment (An et al., 2016) and cash holding (Xu et al., 2016), which subsequently lead to turbulences in financial market (Goodell and Vähämaa, 2013). Some research has also been done to investigate the effects of political uncertainty on carbon emissions. For example, Yu et al. (2021) explored the influence of policy uncertainty on firms' carbon emissions. They used policy uncertainty related words in the provincial daily newspaper to construct a provincial policy uncertainty index. They found that firms raised carbon emission intensity when policy uncertainty increases, and the effect was stronger for manufacturing firms.

Table 1: Summary of key studies on political uncertainty (1990 – 2021)

Articles	Political uncertainty measurements	Dependent variable	Econometric methods	Study area	Sampling period	Effects of political uncertainty
A: Aggregate measurements (indices)						
Alesina and Perotti (1996)	SPI Index	Investment	Linear regression	70 countries	1960-1985	Negative relationship
Liu et al. (2016)	International Country Risk Guide (ICRG)	Oil price volatility	Linear regression	36 oil-exporting countries	1998-2014	Positive relationship
Guo et al. (2021)	International Country Risk Guide (ICRG)	Stock prices	quantile autoregressive distributed lag (QARDL) model	China and US	1993-2019	Negative relationship
Baker et al. (2016)	Economic Policy Uncertainty (EPU)	Depression in macro-economy	Linear regression	12 countries	1985-2012	Leading effects
Yu et al. (2021)	- Provincial EPU	- Firms' carbon emission intensity	- Linear regression	- China	- 2008-2011	Positive relationship
Brogaard and Detzel (2015)	- EPU	- Excess Market Return	- Linear regression	- US	- 1985-2015	Leading effects
Gulen and Ion (2015)	- EPU	- Capital Investment	- Linear regression	- US	- 1987-2013	Negative relationship
B: Event level indicators						
Barro (1991)	Number of Revolution Coups and Political Assassinations	GDP Growth	Linear regression	98 countries	1960-1985	- Negative relationship
Pindyck and Solimano (1993)	Strikes and Riots	Marginal Profitability of Capital	Linear regression	30 countries	1962-1989	- Positive Relationship only for least developed countries
Pantzalis et al. (2000)	National Election Dummies	Stock returns	Event study	33 countries	1974 – 1995	- Positive abnormal return during the two-week period before the election week.
Li and Born (2006)	Closeness in US Election	Stock returns and volatility	GARCH	US	1962-2001	- Positive relationship
He et al. (2009)	Closeness in US Election	Trading cost of politically sensitive stocks	GMM	US	1995-2000	- The unusual delay in election results creates a significant increase in the adverse selection component of the trading cost of politically sensitive stocks
Julio and Yook (2012)	National Election Dummies	Capital Expenditure	Linear regression	48 countries	1980-2005	- Negative relationship

Articles	Political uncertainty measurements	Dependent variable	Econometric methods	Study area	Sampling period	Effects of political uncertainty
Belo et al. (2013)	US Election Dummies	Cash flows and stock returns	Linear regression	US	1955-2009	- Positive effects on firms with high government exposure during the democratic presidencies
Goodell and Vähämaa (2013)	probability of success of the eventual winning presidential candidate	Monthly VIX implied volatility	Linear regression	US	1992-2008	Positive relationship
Francis et al. (2014)	EPU & Firms Political Exposure	Loan Pricing Over LIBOR	Linear regression	US	1990-2010	Positive relationship
Pasquariello and Zafeiridou (2014)	US Election Period Dummies	Trading Volume and Liquidity	Linear regression	US	1928-2012	- Market quality deteriorate before the election and improve afterwards.
Atanassov et al. (2015)	US gubernatorial Election Dummies	R&D	Linear regression	US	1976-2013	Positive relationship
An et al. (2016)	Municipal Officials' Turnover	Corporate Investment	Linear regression	China	2001-2009	Negative Relationship
Lin et al. (2016)	2012 Anti-corruption Campaign in China	Stock Return	Linear regression	China	2012	Positive Relationship
Xu et al. (2016)	Municipal Officials Turnover	Cash held by firms	Linear regression	China	1998-2014	Negative relationship
Çolak et al. (2017)	US gubernatorial Election Dummies	IPO in one State	Linear regression	US	1988-2011	Negative Relationship
Jens (2017)	US gubernatorial Election Dummies	Corporate Investment	Linear regression & IV	US	1984-2008	Negative Relationship
Luo et al. (2017)	Prefectural Officials Turnover	IPOs at the city level	Linear regression	China	1999-2012	Negative relationship
Cao et al. (2019)	Provincial Officials Turnover	Loans of local SOEs	Linear regression	China	2000-2008	Negative relationship
Cao et al. (2019)	National Election Dummies	Firm acquisitions	Linear regression	China	2000 – 2008	Positive effects on outbound cross-border acquisitions Negative effects on inbound acquisitions
Chen and Kung (2019)	2012 Anti-corruption Campaign in China	Discount of Land Price Received by Princeling Firms	Linear regression	China	2004-2016	Negative relationship
Agarwal et al. (2020)	Anti-corruption Campaign in China	Credit Premium for Bureaucrats	Linear regression	China	2003-2005	Negative relationship

2.3 Carbon emission trading

Carbon emission trading scheme (ETS) is one of the most important tools for carbon emission reduction (Meckling et al., 2017; Tvinnereim, 2014). As the global carbon emission trading market develops, the potential of carbon ETS as national greenhouse gas emission control policy has been gaining scholarly attention. Early studies evaluated the costs and returns of different proposals for carbon emission reduction plans (see, for example, Aldy and Stavins, 2012; Olmstead and Stavins, 2006). A growing body of literature has investigated the impacts of carbon ETS on firm performance. For example, Anger and Oberndorfer (2008) shown that the EU-ETS did not put extra burden on firms because their performance and hiring were not affected by firms' involvement in ETS trading. Moreover, low-carbon intensity firms benefited from participating in ETS, because their stock returns were positively related to the return of EU-ETS (Tian et al., 2016).

The picture is less clear in developing countries, where reducing carbon emission is often associated with slowing down economic growth. For example, Lucena et al. (2016) described the conflict between the current mix-energy policy in Brazil and the Copenhagen Accord of 2009. They suggest using a combination of climate policies including carbon tax and energy demand reduction. They also believe that there is not sufficient demand or support for carbon emission trading in Brazil. Therefore, there has not been much research on carbon emission trading using data from developing countries, with probably the only exception for China.

In terms of per capita CO2 emission, China is ahead of many developing countries, and has been catching up with developed countries such as the US and the EU quickly (See Table 1 in Clarke et al., 2016, page 514.). The Chinese government is aware of the challenge. A comprehensive energy intensity reduction plan was announced in the 11th five-year plan (2006 – 2011) to reduce carbon emission. However, the plan was found to be more equity than efficiency oriented, with significant influences from political factors (Ni et al., 2015). The market-based approach, e.g., the carbon emission trading scheme, is a way to address this limitation. Both researchers and policymakers are keen to understand the potential of this new approach. This led to a growing number of studies on the topic. We summarised some representative publications on carbon emission trading schemes in Table 2.

Existing studies found consistent evidence of the positive impacts due to the establishment and development of the Chinese carbon emission trading market. Specifically, carbon emission trading schemes are associated with improved performance in low-carbon industry/projects (Tu et al., 2018; Yang et al., 2021) or ETS-participating firms (Wen et al., 2020a), and higher costs for energy intensive industries and financial sectors (Wen et al., 2020b). Carbon ETS will not only reduce carbon emission steadily over time (Lin and Jia, 2019), but also significantly reduce the mitigation cost for the whole economy (Wang et al., 2015). In summary, despite of some concerns over issues such as carbon leakage (Antoci et al., 2021; Gao et al., 2020; Wu et al., 2022), the overall, long-term effects of China's carbon ETS remains positive and promising since the launch of its pilot scheme in 2011.

Table 2: Summary of studies on carbon trading

Article	Dependent variable	Carbon trading variable	Study area	Econometric methods	Sampling period	Conclusions
Anger and Oberndorfer (2008)	Firm performance and employment	EU-ETS Carbon allowance allocation	Germany	Linear regression	2004-2005	No relationship identified.
Tian et al. (2016)	Stock returns of Carbon Intensive Firms	EUA returns	EU	Linear regression	2005-2012	Negative relationship
Wang et al. (2015)	GDP cost of carbon emission reduction	Carbon ETS pilot scheme	China	Dynamic CGE	2007-2020	Negative relationship
Tu et al. (2018)	Profitability of wind power projects	Carbon ETS policy	China	Event Study	2006-2015	Positive relationship
Lin and Jia (2019)	Commitment to carbon intensity	National carbon ETS	China	Dynamic CGE	2016-2030	Positive relationship
Wen et al. (2020a)	Excess returns of companies participating in carbon ETS	The establishment of China's carbon emissions trading market	China	Linear regression	2009-2018	Positive relationship
Wen et al. (2020b)	Energy Intense Industry and Financial Sector Stock Index	Carbon ETS Price	China	Nonlinear auto-regressive distributed lag (NARDL)model	2013-2019	Positive relationship
Yang et al. (2021)	Green production performance	Carbon ETS	China	Non-parametric data envelop analysis (DEA)	2006-2016	Positive relationship
Chai et al. (2022)	Carbon emission reduction and green growth	Carbon ETS	China	Difference-in-differences	2017-2019	Positive relationship

3. Institutional Background

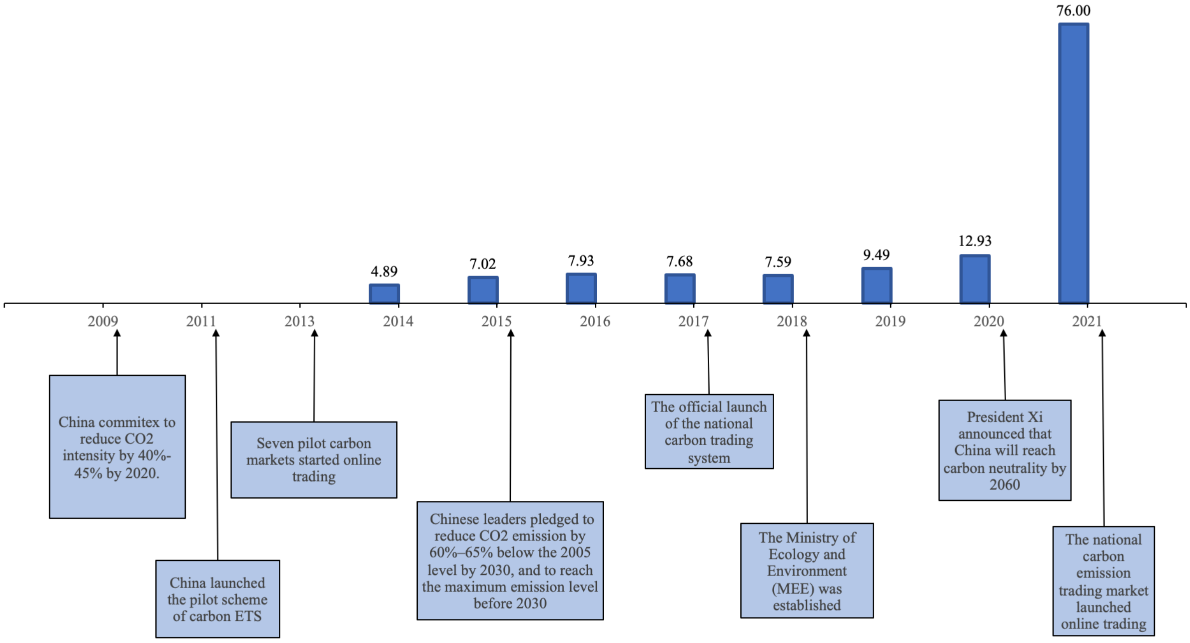
The development of the Chinese carbon emission trading markets has been driven by the carbon emission mitigation commitment and the five-year plans by the central government. The rapid development of the carbon ETS markets in China can be seen from the milestones and trading volume in this market between 2014 and 2021, as given in Figure 1.

In COP15 in Copenhagen, China committed to reduce CO2 intensity by 40%-45% by 2020. This is the first carbon emission pledge by the Chinese government, and marked the start of a series of proactive initiatives to reducing carbon emissions. In 2011, just two years after the Copenhagen pledge, China launched the pilot scheme of carbon ETS in seven provinces and cities, i.e., Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen as part of the twentieth five-year plan. These pilot carbon markets gradually started online trading since 2013, and effectively promoted the greenhouse gas emission reduction in the pilot regions.

Before the COP21 in 2015, China promised to reduce its carbon intensity by 60%–65% below the 2005 levels by 2030 and reach peak emissions before 2030. In December 2016, Fujian Province launched the eighth pilot carbon trading market in China. A year later, the National Development and Reform Commission announced the plan to establish a national carbon emission trading market, which is considered as the official launch of the national carbon trading system. In 2020, the Ministry of Ecology and Environment issued the guidelines and procedures for the administration of carbon emission trading and implemented the national carbon emission trading quotas for 2019-2020. This officially launched the first compliance cycle of the national carbon market in China (i.e., an analogue to the five-year national plan). Given the rapid development and notable performance in the carbon emission trading market, Chairman Xi Jinping announced in the fall of 2020 that China is confident to reach carbon neutrality by 2060.

On July 16, 2021, the national carbon emission trading market started online trading. The power generation industry was the first industry participated in the national carbon market, covering 2162 key emission units and 4 billion tons of annual carbon dioxide emission. In comparison, EU-ETS covered 1.9 billion tons of carbon dioxide in 2019. As of November 2020, the pilot carbon market has covered nearly 3000 key emission units in more than 20 industries such as power, steel and cement. The market boosts a cumulative quota trading volume of about 430 million tons of carbon dioxide equivalent and a cumulative turnover of nearly 10 billion RMB (about 1.5 billion USD). China's carbon market has become the largest market covering greenhouse gas emissions in the world. The next step is to include seven high energy-intensive industries (e.g., petrochemical, chemical, building materials, steel, non-ferrous metals, papermills and civil aviation) in the carbon emission trading market. Once these industries enter the market, the carbon emission capacity covered by China's carbon trading market will reach 7 billion tons.

Figure 2: Milestones and carbon emission trading volume in Trillion RMB in China (2014 – 2021)



Data source: www.xinhua.net and China Stock Market & Accounting Research Database.

In China the National Development and Reform Commission was responsible for monitoring and regulating carbon ETS until 2018, when the Ministry of Ecology and Environment (MEE) was established. Since then, the MEE and its local representative offices oversee the operations of China's national carbon ETS. MEE local offices are responsible for the supervision and management of carbon emission quota allocation at the provincial and municipal level.

The MEE, with the headquarter located in Beijing, is in charge of setting up the rules for transactions, overseeing the performance of local offices, maintaining emissions records, and coordinating with other departments of the State. Within this broad framework, there are also two national agencies of administration under MEE. The first one is the National Carbon Emissions Rights Registration Agency, located in Wuhan, the capital of Hubei province, keeps records of ETS holdings, modifications and payments of emission allowances using the national carbon emission rights registration system. It also provides settlement services. The second agency is the National Carbon Emissions Trading Agency, located in Shanghai, overseeing the centralized exchange of quotas among participants. Both agencies provide regular updates to the MEE.

Although the total carbon emissions quota and reduction plans are determined centrally by the MEE, the allocation of the quota and implementations of the plans are carried out by its local offices. Hence, local governments can influence the carbon emission trading market in multiple ways. Except for the general administration by the MEE, normal administration including monitoring, reporting and verification (MRV) is conducted by local branches of MEE. The measure and regulation of MRV changes over time and varies among different provinces. For example, Beijing has the most comprehensive MRV rules among all MEE local offices. It has certification requirements that are not common in other provinces, such as random audits of emission records by third-party emissions verification organizations. To date, there are over 400 emission verification organisations registered in the national ETS. Firms use these organisations to verify their carbon emission records for pilot ETS trading based on local rules.

Firms and verifiers incur a fine if they report emissions incorrectly or fail to submit records to local MEE offices in time. Besides these financial penalties, restricted access to financing or other forms of government subsidies are also used to deter non-compliance. There are also penalties on registered emissions verification organizations for collusions, such as commission cancellation, credit record impairment, and even prohibition to enter the market for three years. However, there have not been clear rules about how the annual review of local government officials for failures to comply with ETS rules.

Collusion, corruption, and manipulation are not unheard of in the carbon emission treading market. For example, in 2011 the computer-aided thievery of carbon allowance in the Czech Republic caused significant disruptions in the EU-ETS market (Gronewold and Fialka, 2011). Even in well-developed and closely-regulated places such as the US, there was also a fraudulent case in the RECLAIM system (Stavins, 2019). Not surprisingly, the MEE in China is concerned about falsified data and collusions between firms and local governments. The MEE had dispatched auditing teams to 22 provinces and 47 cities since October 2021. To date, there are several intermediate firms that were identified and penalised by the MEE for falsifying carbon emission data. Although MEE also scrutinises local governments for loose regulation, poor management and outsourcing regulation responsibilities to private firms, the approach remains light-touched, and there has not been report of any significant misconduct in local offices. This relatively hands-off approach might necessary to encourage the rapid development of the carbon emission trading market across the country. Nevertheless, this approach also gives local governments a good control over this emerging market. Hence, the turnovers of local government leaders inevitably introduce significant political uncertainty to the carbon emission trading market in China.

4. Analytical Framework and Testable Hypotheses

Given the institutional background outlined above, it is important to understand how political uncertainty affects the working of carbon ETS in China. The general relationship between political uncertainty and carbon emission trading can be captured by the following equation.

$$Y = f(P, \boldsymbol{X}) + \varepsilon \,, \tag{1}$$

where Y is the activity of interests in the carbon emission trading market, P is the measurement of political uncertainty, $\boldsymbol{X}$ is a matrix of control variables, and ε is the error term.

We define P as local government official turnovers, because it is one of the most significant sources of political uncertainty in China's carbon emission trading market. In China both the initial allocations and the subsequent exchanges of carbon emission allowances are at the local level. Local governments also play a crucial role in the daily operations of carbon emission trading markets. First, the appointment of the head of local MEE offices are essentially determined by their corresponding provincial or city superiors. This is because Chinese bureaucrats of local ministries are nominally led by the central ministry but are effectively controlled by local governments. Therefore, turnovers of provincial or municipal leaders often followed by adjustments of local political structure, such as turnovers of the head in important local offices and ministries.

Second, local MEE offices are given the power to allocate emission allowances. This gives local governments the control over the carbon emission trading market from the start. It also imposes significant influence on activities in the market indirectly through carbon emission monitoring, reporting and verification. Most importantly, the most carbon intensive industries are dominated by state owned enterprises (SOEs). For example, all major electricity generators in China are SOEs, and they are among the largest carbon emitters in China. In other words, all major players in China's carbon emission trading market are SOEs. Because the appointment and promotion of senior executives of these local SOEs are controlled by local governments, we expect that local government official turnovers will be closed watched by these SOEs. Consequently, the activities in the carbon emission trading market will be affected by these turnovers too.

We use both the trading volume and returns as the dependent variable Y in Equation (1). The dates of turnovers of important government officials will be used to define P. Yang et al. (2021) has shown that the benefit of carbon ETS appeared even before the launch of the pilot scheme, which means the information has been capitalised as soon as local governments started to prepare for the scheme. Similarly, some of the turnovers might be well expected and the market could respond before the official announcement dates. We follow the practice in event studies by using an event window surrounding the turnover dates. Specifically, P is a dummy variable that equals one for transactions recorded within a certain days before or after the official turnover dates, and zero otherwise. $\boldsymbol{X}$ will include other important determinants of carbon emission trading volume and returns.

Evidence shows that firms tend to reduce transactions or activities when facing political uncertainty (An et al., 2016; Çolak et al., 2017). This 'wait and see' strategy is rational because the allocation and regulation of carbon emission allowances might be changed after the turnover. Moreover, there are some evidence that firms in certain industries (such as manufacturing companies) increased fossil fuel application and carbon emission intensity when facing policy uncertainty at the provincial level (Yu et al., 2021). This may lead to the under-supply of carbon emission allowances in the marketplace, and hence a reduction of transaction volume. In summary, we expect that $\partial Y/\partial P < 0$ when Y is the carbon emission trading volume. Hypothesis 1 is set up as follows.

Hypothesis 1: Transaction volume of carbon ETS declines in response to local political leader turnovers.

A positive relationship between stock returns and the level of political uncertainty is often reported in the literature (see, for example, Belo et al., 2013; Lin et al., 2016). This is because investors demand a higher rate of returns to compensate the increased risk from political shocks. The nature of carbon emission trading is different from the investment in the stock market. Firms participate in the carbon emission trading market with the objective of meeting carbon emission requirements instead of maximizing investment returns. Therefore, the 'risk premium' commonly observed in the stock market might not apply in the carbon emissions trading market. Nevertheless, the findings in Yu et al. (2021) suggest that prices and returns of carbon emission allowances are likely to increase when the level of political uncertainty is high, because some firms' response is to increase carbon emission intensity. Moreover, if firms hold back their supply of carbon emission allowance when facing political uncertainty (e.g., Hypothesis 1 is true), the unmet demand might push up the price and subsequently the daily returns. Consequently, we expect that the returns in the carbon emission trading market will increase during the turnover event period, or $\partial Y/\partial P > 0$ when Y is the carbon emission trading returns. This gives us the second testable hypothesis as follows.

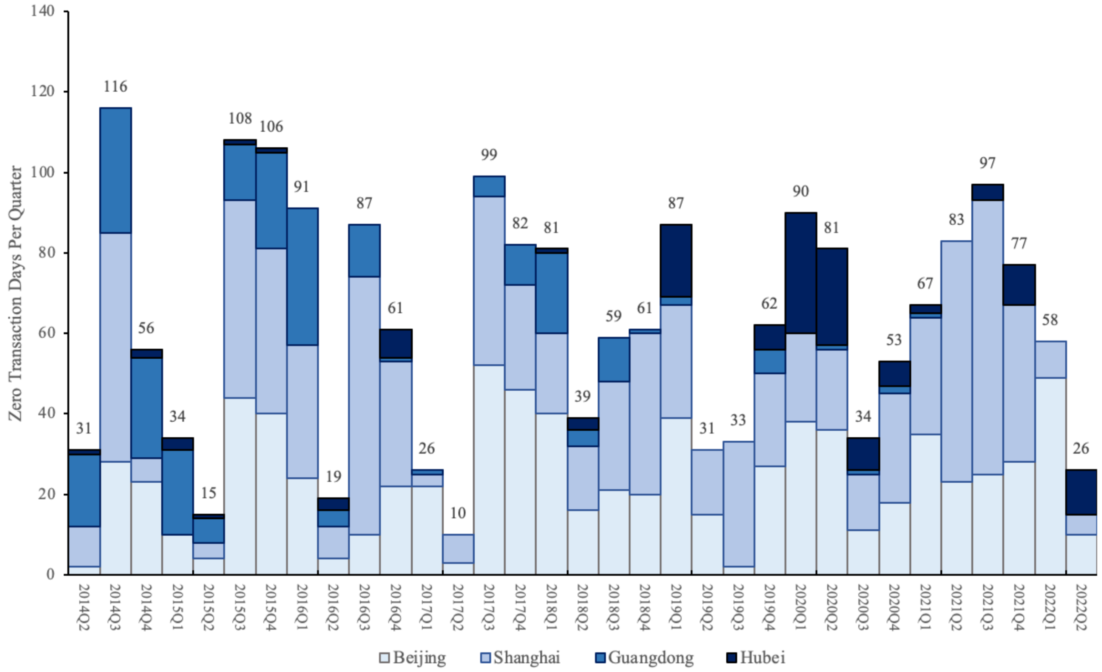
Hypothesis 2: Daily returns of carbon ETS increase in response to local political leader turnovers.

5. Data and Methods

We collected daily carbon ETS transaction data from the China Stock Market & Accounting Research Database (CSMAR) from 2 April 2014 to 9 April 2022. Among the seven changes[3], we chose Beijing, Shanghai, Hubei and Guangdong because they have longer transaction periods to cover a sufficient number of political events. The transactions in these carbon emission trading markets are not as active as those in stock markets. We recorded 1157,1022, 1822 and 1688 trading days with at least one transaction in Beijing, Shanghai, Hubei and Guangdong market, respectively.

In Figure 2 we give the quarterly number of zero transaction days for each market. The total number of trading days without a transaction is marked on top of each bar, which is broken down by the four markets within each bar. Each quarter in our sampling period had zero transaction days, ranging from 10 to 116 days. The largest number of zero transaction days (i.e., 68) was recorded in the Shanghai Exchange in the third quarter of 2021. Overall, the Beijing and Shanghai Exchanges had much more zero transaction days than the other two exchanges. Specifically, the total number of zero transaction days during the whole sampling period is 787, 875, 142, and 256 for the Beijing, Shanghai, Hubei and Guangdong market, respectively. Given the significant proportion of zero transaction days in these carbon emission trading markets, we will further examine the patterns of these days during politically uncertain periods.

Figure 3: Quarterly Zero Transaction Days (2014 Q2 – 2022 Q2)



5.1 Measurements of political uncertainty

Our measurement of political uncertainty is based on the turnovers of governors in Hubei and Guangdong provinces as well as the mayors in Beijing and Shanghai[4], because the policies regulating carbon emissions are primarily determined at the provincial level. A total of 16

[3] Besides the seven markets from the pilot stage, there are also two new exchanges opened in recent years, i.e., the Sichuan Unified Environment Exchange on 6 December 2016 and the Haixia Environment and Energy Exchange (Fujian Province) on 22 December 2016. Given the very short history of these exchanges, we did not consider them in the analysis.

[4] Beijing and Shanghai are direct-administered municipalities of the People's Republic of China. They are at the highest level of classification for cities, and hence have the same status as provinces.

turnovers are identified and included in the analysis, as can be seen in Table 3. We define the 30 calendar days before and after the official turnover date as the event window. If a transaction fell in this event window, the political uncertainty indicator will be assigned a value of one, and zero otherwise. The coefficient estimate of the political uncertainty indicator is used to identify the impact of political uncertainty on carbon emission trading. According to Table 4, there are 153， 177， 221 and 160 transaction days (or about 4%, 10%, 13% and 11% of all transaction days) within the turnover windows in the Beijing, Shanghai, Hubei and Guangdong carbon ETS exchange, respectively. The sensitivity of our findings to the choice of the [-30, 30] event window is discussed in the Robustness Checks session.

Table 3: Local government official turnovers

Carbon Emission Market	Official turnover date	Name of the official	Position before the turnover	Position after the turnover
(1)	(2)	(3)	(4)	(5)
Beijing	31 October 2016	Qi Cai	Deputy Minister of Central National Security Commission	Deputy Mayor of Beijing
	10 January 2017	Qi Cai	Deputy Mayor of Beijing	Mayor of Beijing
	27 May 2017	Jining Chen	Minister of Environmental Protection	Deputy Mayor of Beijing
	30 January 2018	Jining Chen	Deputy Mayor of Beijing	Mayor of Beijing
Shanghai	20 January 2017	Yong Ying	Deputy Party Chief of Shanghai	Mayor of Shanghai
	13 February 2020	Yong Ying	Mayor of Shanghai	Party Chief of Hubei Province
	23 March 2020	Zheng Gong	Governor of Shandong	Deputy Mayor of Shanghai
	21 July 2020	Zheng Gong	Deputy Mayor of Shanghai	Mayor of Shanghai
Guangdong	30 December 2016	Xingrui Ma	Mayor of Shenzhen	Deputy Governor of Guangdong
	23 January 2017	Xingrui Ma	Deputy Governor of Guangdong	Governor of Guangdong
	15 December 2021	Weizhong Wang	Deputy Party Chief of Guangdong	Deputy Governor of Guangdong
	22 January 2022	Weizhong Wang	Deputy Governor of Guangdong	Governor of Guangdong
Hubei	15 September 2016	Xiaodong Wang	Deputy Party Chief of Hubei	Deputy Governor of Hubei
	20 January 2017	Xiaodong Wang	Deputy Governor of Hubei	Governor of Hubei
	07 May 2021	Zhonglin Wang	Party Chief of Jinan	Deputy Governor of Hubei
	30 May 2021	Zhonglin Wang	Deputy Governor of Hubei	Governor of Hubei

5.2 Carbon emission trading activity measurements

We consider both daily returns and trading volume as the outcome indicators. We collect daily closing price of carbon emission transactions in RMB per ton, and use the natural log transformation of the price series to calculate daily returns. The descriptive statistics of daily returns are given in Table 4. Carbon market returns vary significantly among the four markets. The Beijing exchange has the highest average daily returns (i.e., 0.24%) with the largest standard deviation (i.e., 6.70%). The variations of daily returns are also large in the Shanghai exchange, as can be seen from the wide range of daily returns (between -40% and 142%). Overall, the returns on carbon emission trading is positive but small, with substantial variations among trading days.

We use two measurements for daily trading volume. Given the large number of zero transaction days, we create a dummy variable that equals one when no transaction was recorded on the day, and zero otherwise. Following the practice in studies using stock market data, we use daily turnover ratio as the second measurement of trading volume. The daily turnover ratio is calculated by dividing the daily trading volume (in tons) by the total amount of carbon trading allowance granted in the host province/city (in million tons). Official data of carbon trading allowance distributed in each year is not available at the provincial level. The most recent and reliable figures that we could find is the estimations in Tian and Li (2021).

The descriptive statistics of zero transaction days, daily trading volume, and daily turnover ratio are given in Table 4. Guangdong and Hubei markets are much more active than the Beijing and Shanghai exchanges, because they have fewer zero transaction days, and their daily transaction volume is large both in the absolute term and relative to the total supply of carbon emission allowances granted in their province/city. We anticipate that returns and trading activities in these two 'liquid' markets would be more responsive to political shocks.

5.3 Control variables

Carbon emission trading is closely related to activities in the general economy. This is evident from the correlation between the stock market and the carbon emission trade (Wen et al., 2020a; Wen et al., 2020b). Following this line of literature, we include the Shanghai Stock Exchange Composite Index (base date: 19 December 1990) as a control for general economic factors. The Shanghai Stock Exchange Composite Index includes all stocks that are traded in the Shanghai Stock Exchange. The total market capitalization of these stocks is over US$7 trillion, which makes the exchange the third largest stock exchange in the world[5]. It is a good indicator of the economy and activities in the financial market in China.

Carbon emission trading is also affected by the performance of the low-carbon industries in China (Wen et al., 2020a). We add the China Low-carbon Index (base date: 31 December 2006) to control for industry-specific movements in the market. The China Low-carbon Index was launched by the Beijing Environmental Exchange and the Shanghai Stock Exchange in 2006. It includes 43 Chinese firms listed both in China and overseas with a total market capitalisation of over 417 billion RMB[6]. Therefore, it is a representative sample of major players in China's low carbon industry.

Finally, the cost of thermal coal, which is still the primary inputs of electricity firms in China, will affect carbon emission trading too. We include the closing price of thermal coal futures from the Zhengzhou Commodity Exchange in our analysis. The Zhengzhou Commodity Exchange, regulated by China Securities Regulatory Commission, was established in 1990. Thermal coal is included in both its 23 futures products and 6 options products that covers important sectors of the national economy such as agriculture, energy, chemicals, textile, construction materials and metallurgical industries[7]. The closing price of thermal coal futures from this exchange is a reliable measurement of thermal coal prices in China.

The descriptive statistics of these control variables are given in Table 4. In our empirical models we divide the Shanghai Stock Exchange Composite Index and the China Low-carbon Index by 1,000 in order to show significant figures.

Table 4: Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
Political Uncertainty (=1 if in the 30 days event window)				

[5] http://english.sse.com.cn/markets/indices/overview/. Accessed on 30 June 2022.

[6] https://www.csindex.com.cn/uploads/indices/detail/files/zh_CN/773_H11113_Index_Methodology_cn.pdf?t=1621824318#/indices/family/detail?indexCode=H11113. Accessed on 30 June 2022.

[7] http://english.czce.com.cn/enportal/AboutZCE/Overview/Overview/H69010101index_1.htm. Accessed on 30 June 2022.

• Beijing	0.0400	0.1960	0	1
• Shanghai	0.0959	0.2945	0	1
• Hubei	0.1271	0.3332	0	1
• Guangdong	0.1063	0.3083	0	1
Daily returns				
• Beijing	0.24%	6.70%	-38%	60%
• Shanghai	0.17%	5.98%	-40%	142%
• Hubei	0.09%	3.28%	-33%	44%
• Guangdong	0.11%	4.34%	-36%	41%
Zero transaction day (=1 if no transaction)				
• Beijing	0.4003	0.0049	0	1
• Shanghai	0.4451	0.0045	0	1
• Hubei	0.0722	0.0026	0	1
• Guangdong	0.1302	0.0034	0	1
Daily trading volume (tons)				
• Beijing	10,796	22,346	0	186,057
• Shanghai	28,473	76,174	0	546,049
• Hubei	41,650	77,975	0	1,200,000
• Guangdong	59,561	155,112	0	2,400,000
Daily turnover ratio (daily trading volume over total annual carbon permits volume in million tons)				
• Beijing	10.58	25.90	0	235.96
• Shanghai	20.80	72.16	0	1,318.00
• Hubei	74.01	189.83	0	3,376.00
• Guangdong	63.81	125.67	0	1,967.86
Control variables				
Low-Carbon Index	5,796	2,104	3,389	12,428
Shanghai Stock Exchange Index	3,138	473	2,003	5,166
Price of Thermal Coal (RMB Yuan Per Ton)	598	202	303	2,302

5.4 Econometric models

We use logistic regression to estimate the effect of local official turnovers on daily carbon emission trading volume when *zero transaction day* is used as the dependent variable, because the dependent variable is a dummy variable. The model is given in the Equation (2) below.

$$Zero\ Transaction\ Day_{i,t} = \alpha_0 + \alpha_1^i Political\ Uncertainty_{i,t} + \mathbf{Controls_t}\boldsymbol{\beta^i} + \epsilon_{i,t} \quad , \quad (2)$$

where $Zero\ Transaction\ Day_{i,t}$ equals one if there were no transactions recorded on day *t* in market *i*, *i* = Beijing, Shanghai, Hubei, or Guangdong. $Political\ Uncertainty_{i,t}$ equals one if day *t* falls within a [-30, 30] event window in market *i*. $\mathbf{Controls_t}$ includes the three control variables in Table 4, i.e., Shanghai Stock Exchange Index (divided by 1000), the Low-Carbon Index (divided by 1000), and the futures prices of thermal coal. $\boldsymbol{\beta^i}$ is a vector of parameters to be estimated. If α_1^i is positive, Hypothesis 1 is true. However, the zero transaction day is not a comprehensive measurement of the activeness of trading, because higher trading volume could happen in other trading days within the event window. Therefore, $\alpha_1^i > 0$ is a necessary condition for hypothesis to be true, not a sufficient condition.

Next, we estimate AR(1)-GARCH models by using the time series of daily returns and turnover ratio as the dependent variables. Ideally, VAR-GARCH models should be used given the large variations in both trading volume and prices and the potential correlation among the four carbon emission exchanges. However, the extended periods when no transactions were recorded in each exchange and the relatively short sampling period render the VAR-GARCH impractical (i.e., the models do not converge). Our solution is to estimate an AR(1)-GARCH model for each market separately, while including time series of turnover ratio or returns from the other three exchange as controls, as described in the following equations.

$$DV_{i,t} = \gamma_0 + \gamma_1^i DV_{i,t-1} + \gamma_2^i Political\ Uncertainty_{i,t} + \mathbf{Controls_t}\boldsymbol{\delta^i} + \epsilon_{i,t}, \tag{3}$$

where $E_t[\epsilon_{i,t}^2] = \sigma_{i,t}^2 = \theta_0^i + \theta_1^i \epsilon_{i,t-1}^2 + \theta_1^i \sigma_{i,t-1}^2$. $DV_{i,t}$ is daily turnover ratio or returns in exchange *i* on day *t*, *i* = Beijing, Shanghai, Hubei, or Guangdong. γ_1^i captures the AR(1) effect in exchange *i*. γ_2^i is the impacts from political uncertainty measured by local official turnovers. $\mathbf{Controls_t}$ is a set of control variables that includes Shanghai Stock Exchange Index (divided by 1000), the Low-Carbon Index (divided by 1000), the futures prices of thermal coal, and the corresponding $DV_{i,t}$ series in the other three exchanges. $\boldsymbol{\delta^i}$ is a vector of parameters to be estimated. If Hypothesis 1 is true, we expect γ_2^i to be negative when daily turnover ratio is the $DV_{i,t}$ in Equation (3). If Hypothesis 2 is true, we expect γ_2^i to be positive when daily returns is the $DV_{i,t}$ in Equation (3).

6. Empirical Findings

The logistic regression results are reported in Table 5. The dependent variable in these models is the dummy variable *Zero Transaction Day*. We give results for the whole event window as well as the before- and after-event window. This approach allows the identification of possible 'leak-out' or 'anticipation' effect before the official announcement of official turnovers.

The dynamics in the four exchanges are interesting and complex. The Beijing exchange, being the smallest of the four in terms of daily trading volume, saw little changes in zero transaction days during the period of 30 days before or after the event dates. The Hubei exchange, which has the largest daily turnover ratio among the four exchanges, had significantly more trading days without a transaction in both the before- and the after-event windows. Firms in Hubei province are sensitive to provincial leader turnovers, and held back their transactions of carbon emission allowances all together on those days.

The responses to political uncertainty in the Shanghai and Guangdong exchanges, on the other hand, were different in two ways. Firstly, both markets witnessed a significant lower proportion of zero transaction days during the event window. In other words, these markets are more active during official turnover periods as measured by zero transaction days. Secondly, the Shanghai exchange responded more in the after-event window, while the reactions in Guangdong market were mainly from the pre-event period. All else being equal, this indicates that firms in Guangdong province responded to official turnovers much faster than their counterparts in Shanghai.

As pointed out in section 5.4, having a positive coefficient estimate of the political uncertainty dummy is a necessary condition for hypothesis 1 to be true. In this part analysis, we found solid evidence to support hypothesis 1 in Hubei exchange only. We will proceed to the analysis of daily returns and turnover ratio by using AR(1)-GARCH models to further verify the hypotheses.

Table 5: Zero transaction day analysis (logistic regression)

Variables	Beijing	Shanghai	Hubei	Guangdong
[-30, 0] Window				
Political Uncertainty	0.092	-0.285	1.781***	-2.058**
	(0.37)	(-1.27)	(7.13)	(-2.03)
Shanghai Stock Exchange Index	-0.0004***	-0.001***	-0.002***	0.0004**
	(-3.83)	(-5.50)	(-9.05)	(2.13)
Low-Carbon Index	0.0002***	0.0001***	0.001***	-0.0005***
	(5.82)	(3.40)	(6.25)	(-4.60)
Thermal Coal Price	-0.001***	0.001**	-0.003***	-0.004***
	(-3.68)	(2.18)	(-3.13)	(-6.00)
[0, 30] Window				
Political Uncertainty	0.051	-0.396*	1.446***	-0.427
	(0.20)	(-1.87)	(5.57)	(-0.80)
Shanghai Stock Exchange Index	-0.0004***	-0.0007***	-0.002***	0.0004*
	(-3.79)	(-5.53)	(-8.98)	(1.93)
Low-Carbon Index	0.0002***	0.0001***	0.0005***	-0.0005***
	(5.74)	(3.48)	(6.17)	(-4.52)
Thermal Coal Price	-0.001***	0.0008**	-0.003***	-0.004***
	(-3.63)	(2.10)	(-3.22)	(-6.27)
[-30, 30] Window				
Political Uncertainty	0.053	-0.33**	1.425***	-0.855*
	(0.28)	(-2.00)	(6.34)	(-1.81)
Shanghai Stock Exchange Index	-0.0004***	-0.001***	-0.002***	0.0004**
	(-3.77)	(-5.43)	(-9.10)	(2.10)
Low-Carbon Index	0.0002***	0.0001***	0.001***	-0.0005***
	(5.65)	(3.36)	(6.31)	(-4.57)
Thermal Coal Price	-0.001***	0.001**	-0.003***	-0.004***
	(-3.60)	(2.18)	(-3.19)	(-5.93)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

In Table 6 we report the impacts of political uncertainty on both daily carbon trading turnover and returns. The AR(1) coefficients are positive and significant in the turnover ratio models (i.e., models 1 though 4). This captures the growth of transaction activities over time in all four exchanges. The AR(1) coefficient estimates are mostly negative and significant in the returns models (i.e., models 5 through 8). This could be interpreted as a mean-reversion process where prices are stable in the long run. Both sets of AR(1) estimates are consistent with the development of carbon emission trading scheme in China during the sampling period.

Second, the coefficient estimates of activities/performance in other three exchanges capture the dynamics among these four markets. Specifically, smaller exchanges are more affected by larger ones. For example, Guangdong exchange, the largest market in our sample, is independent of the influence from other smaller exchanges in terms of turnover ratio.

The relationship between the three control variables and carbon emission trading turnover ratio and returns is complex. For example, the daily turnover ratio in the Guangdong and Beijing markets is significantly affected by all three control variables, but the daily returns in the Shanghai and Guangdong markets are not associated with the movements in any of the control variables. The opposite pattern is observed in the Hubei market. The direction of the influences from these control variables is not consistent across markets either. For example, while thermal coal prices is positively related to daily turnover ratio and negatively related to daily returns in the Beijing, Shanghai, and Guangdong markets, the opposite is true in the Hubei exchange. We attribute these variations among the effect of control variables to the natural, social and economic conditions in the four provinces/cities. We conclude that the inclusion of these control variable is necessary to remove the confounding effect, because the varied coefficient estimates shows a great level of heterogeneity among the four exchanges.

Finally, both the ARCH(1) and the GARCH(1) components are statistically significant, as shown in the last four rows in Table 6. Overall, there are strong evidence to support our choice of empirical estimation methods. We now turn our attention to the political uncertainty variable to test the hypotheses.

In the turnover ratio models (i.e., models 1 to 4), the coefficient estimate of *Political Uncertainty* is negative in all exchanges. The response is the strongest in the Hubei exchange, which is an average drop of 16.369 points during the event window. In other words, the daily turnover ratio is about 22% below the average level (i.e., 74.01 points in Table 3) in the Hubei exchange 30 days before and after provincial governor turnovers. The smallest drop is observed in the Shanghai market, i.e., 1.714 points per day on average and statistically insignificant from zero. The daily turnover ratio in the Beijing exchange shrunk by 3.523 points during the event window. However, given the average turnover ratio in the Beijing exchange is only 10.58 points, relatively speaking this is a substantial decrease of trading activities in this small market. Therefore, we find general support to Hypothesis 1: carbon emission trading volume declines during the event period.

Finally, in Panel C in Table 6, we also give the coefficient estimates of *Political Uncertainty* for three different event windows, i.e., the [-30, 0], [0, 30], and [-30, 30] windows to identify when responses to political uncertainty took place. Combining the results from the AR(1)-GARCH models and the logistic regression models, we can draw two conclusions about the response of trading volume to political uncertainty among these four markets. Firstly, larger markets have stronger responses. For example, although the number of zero transaction days in the Guangdong exchange reduced when facing political uncertainty, the daily turnover ratio dropped significantly at the same time. This means there are more, small transactions during the event windows. We take it as a sign of the cautiousness about potential changes in carbon emission trading rules introduced by the new provincial governor. This pattern is even stronger in the Hubei exchange, where both the likelihood of having transactions during a trading day and the daily turnover ratio dropped during the event window. This is in stark contrast with the trading activities in the two smaller exchanges, i.e., the Beijing and Shanghai exchanges, where the effect size is much smaller and sometimes even statistically insignificant.

Secondly, larger markets also responded more promptly. Specifically, trading activities, measured by both the probability of having no transactions and the daily turnover ratio, changed significantly in the Hubei and Guangdong markets during the pre-event window already. On the contrary, all significant changes in trading activities were observed in the post-event period in the Beijing and Shanghai exchanges. We conclude that trading activities are more sensitive and responsive to political uncertainty in larger carbon emission markets.

Results from the returns models (i.e., models 4 through 8) shows small positive effect on returns from political uncertainty. Hubei market is the only exchange that recorded a statistically significant risk premium for political uncertainty. We find weak evidence to support hypothesis 2: carbon emission trading returns are positively affected by local governor/mayor turnovers.

Table 6: Impacts of political uncertainty on carbon emission trading turnover ratio and returns – AR(1)-GARCH estimations

Variable	Turnover ratio				Returns			
	Beijing	Shanghai	Hubei	Guangdong	Beijing	Shanghai	Hubei	Guangdong
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Conditional Mean Equation [-30, 30] window								
Political Uncertainty	-3.523***	-1.714	-16.369***	-13.819*	0.101	0.291	0.529***	0.443
	(-4.69)	(-1.39)	(-5.64)	(-1.76)	(0.17)	(0.56)	(3.06)	(1.44)
AR(1)	0.548***	0.156***	0.594***	0.552***	-0.034	-0.021	-0.326***	-0.193***
	(32.00)	(7.55)	(36.11)	(22.03)	(-1.03)	(-0.67)	(-11.82)	(-6.88)
Beijing		0.499***	-0.007	-0.116		-0.026	-0.021***	0.007
		(12.13)	(-0.14)	(-1.24)		(-1.23)	(-3.12)	(0.75)
Shanghai	0.013***		-0.044***	-0.036	-0.067***		-0.003	0.02*
	(3.34)		(-2.69)	(-1.25)	(-2.98)		(-0.39)	(1.90)
Hubei	-0.0004	-0.001		0.017	-0.006	0.004		-0.018
	(-0.38)	(-0.19)		(1.23)	（-0.20）	(0.11)		(-1.20)
Guangdong	-0.001	0.016***	-0.004		0.084**	0.069**	-0.027**	
	(-0.99)	(7.45)	(-0.63)		(2.44)	(1.99)	(-2.03)	
Shanghai Stock Exchange Index	1.106**	2.256	-1.532	10.022**	-0.527	-0.034	1.12***	-0.074
	(2.53)	(1.28)	(-0.65)	(2.15)	（-1.30）	(-0.09)	(7.48)	(-0.61)
Low-Carbon Index	-0.542**	-4.919***	-0.002	9.726***	0.254*	-0.034	-0.791***	0.053
	(-2.38)	(-10.25)	(-0.00)	(4.06)	(1.70)	(-0.26)	(-15.30)	(0.95)
Thermal Coal Price	0.023***	0.016***	-0.032***	0.129***	-2.801**	0.1	2.904***	-0.17
	(11.47)	(3.50)	(-3.69)	(6.96)	(-2.12)	(0.09)	(6.41)	(-0.35)
Panel B: Conditional Variance Equation [-30, 30] window								
ARCH(1)	1.232***	1.503***	1.34***	1.337***	0.287***	0.028**	1.106***	0.519***
	(9.88)	(7.46)	(9.41)	(11.76)	(6.79)	(2.13)	(15.41)	(11.14)
GARCH(1)	0.327***	0.27***	0.059***	0.218***	0.512***	0.931***	0.099***	0.562***
	(11.33)	(7.18)	(3.00)	(6.21)	(3.93)	(13.25)	(3.97)	(25.77)
Panel C: Coefficient Estimates of Political Uncertainty in Different Event Windows								
[-30, 30] window	-3.523***	-1.714	-16.369***	-13.819*	0.101	0.291	0.529***	0.443
	(-4.69)	(-1.39)	(-5.64)	(-1.76)	(0.17)	(0.56)	(3.06)	(1.44)
[-30, 0] window	-1.017	-0.185	-13.634***	-22.655**	0.717	0.689	0.624***	0.659*
	(-0.92)	(-0.07)	（-3.72）	（-2.18）	（0.93）	（0.96）	（3.10）	(1.78)
[0, 30] window	-4.241***	-3.474	-16.226***	4.457	-0.674	0.283	0.485**	0.389
	(-3.87)	(-1.49)	（-4.57）	(0.50）	（-0.86）	（0.43）	（2.11）	(0.93)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1. Only the coefficient estimate of Political Uncertainty is reported in Panel C. Full sets of regression outputs of the pre- and post-event window models can be found in Tables A1 and A2 in the Appendix.*

7. Robustness Checks

In this section we perform two robustness checks to verify the sensitivity of our results to a different measurement of political uncertainty and an alternative event window definition.

7.1 Alternative measurements of political uncertainty

In China, there have been multiple waves of anti-corruption campaigns in recent years, which often led to government official turnovers and a great level of political uncertainty during the investigations. Some researchers constructed anti-corruption indices as measurements of political uncertainty in their studies (see, for example, Cai and Wu, 2019; Yu et al., 2021). We follow the approach in Liu et al. (2017) to construct a political uncertainty index by using the search volume data at Baidu.com. We used Baidu instead of newspapers because search engines are the main source of information nowadays (Francis et al., 2021).

We use the keyword 'anti-corruption' to obtain search volume data during the sampling period. The daily time series of this anti-corruption index is included in the models as an additional independent variable. The anti-corruption index measures political uncertainty at the national level. It is essentially the response of internet users to any anti-corruption movements in any part of the country. Therefore, it does not capture the changes of political uncertainty at the local level, and hence should not replace our local level political uncertainty measurement. Instead, the anti-corruption index should be treated as a national level political uncertainty measurement

We re-estimate the models in Tables 5 and 6 by adding the anti-corruption index (*Anti-Corruption* hereafter), and the results are reported in Table 7. For brevity, we report the coefficient estimate of only two independent variables, i.e., *Political Uncertainty* (in Panel A) and *Anti-Corruption* (in Panel B). The full sets of regression outputs of models included in Table 7 can be found in the Appendix.

As show in Table 7, the effects of *Anti-Corruption* are negative for Zero Transaction Day except for the Guangdong market, and for Turnover Ratio except for the Shanghai exchange. None of the coefficient estimate of Anti-Corruption in the daily returns models is statistically distinguishable from zero. The patterns are less clear than those in the main findings in Tables 5 and 6. However, and more importantly, the addition of this national level political uncertainty indicator does not change our main conclusions. The coefficient estimates of *Political Uncertainty* indicator are very similar to those reported in Tables 5 and 6. This shows that our locally-focused political uncertainty measurement is better than a national one, and our main findings are robust to the addition of a national level political uncertainty indicator.

Table 7: Robustness check - alternative political uncertainty measurement

	Beijing	Shanghai	Hubei	Guangdong
Panel A: Coefficient estimates of Political Uncertainty				
Zero Transaction Day				
[-30, 0]	0.099	-0.361	1.389***	-1.973*
	(0.41)	(-1.60)	(5.27)	(-1.94)
[0, 30]	0.001	-0.504**	0.804***	-0.358
	(0.00)	(-2.35)	(2.90)	(-0.67)
[-30, 30]	0.027	-0.425**	0.874***	-0.769
	(0.14)	(-2.53)	(3.68)	(-1.62)
Turnover Ratio				
[-30, 0]	-1.112	0.706	-13.199***	-25.633**
	(-1.01)	(0.26)	(-3.62)	(-2.42)
[0, 30]	-4.42***	-2.307	-15.69***	2.428
	(-4.10)	(-0.88)	(-4.39)	(0.26)
[-30, 30]	-3.703***	-1.578	-15.989***	-17.283**
	(-5.06)	(-0.70)	(-5.48)	(-2.12)
Returns				
[-30, 0]	0.715	0.68	0.608***	0.676*
	(0.92)	(0.95)	(3.00)	(1.83)
[0, 30]	-0.686	0.268	0.462**	0.402
	(-0.88)	(0.40)	(1.99)	(0.96)
[-30, 30]	0.095	0.279	0.513***	0.458
	(0.16)	(0.53)	(2.94)	(1.49)
Panel B: Coefficient estimates of Anti-Corruption				
Zero Transaction Day				
[-30, 0]	-0.00003***	-0.0002***	-0.002***	0.0003***
	(-3.76)	(-2.88)	(-6.71)	(4.12)
[0, 30]	-0.0003***	-0.0002***	-0.002***	0.0003***
	(-3.75)	(-3.06)	(-6.64)	(4.20)
[-30, 30]	-0.0003***	-0.0002***	-0.002***	0.0003***
	(-3.75)	(-3.11)	(-6.50)	(4.13)
Turnover Ratio				
[-30, 0]	-0.0001	0.002**	0.001	-0.002**
	(-0.75)	(2.26)	(1.15)	(-2.06)
[0, 30]	-0.0001	0.001**	0.001	-0.002*
	(-1.11)	(1.97)	(0.95)	(-1.74)
[-30, 30]	-0.0002	0.001**	0.001	-0.003**
	(-1.56)	(1.96)	(0.79)	(-2.22)
Returns				
[-30, 0]	-0.034	-0.023	-0.039	-0.088
	(-0.29)	(-0.17)	(-0.89)	(-1.46)
[0, 30]	-0.039	-0.027	-0.044	-0.086
	(-0.34)	(-0.19)	(-0.98)	(-1.42)
[-30, 30]	-0.035	-0.024	-0.037	-0.087
	(-0.29)	(-0.17)	(-0.83)	(-1.45)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1. This table gives the coefficient estimate of two independent variables only, i.e., Political Uncertainty (in Panel A) and Anti-Corruption (in Panel B). Other control variables in Tables 5 and 6 are also included in these models, but not reported in this table for brevity. The full sets of regression outputs of models included in this table can be found in Tables A3 to A6 in the Appendix.*

7.2 Sensitivity to the definition of the event window

To check how much our main findings are sensitive to the choice of the event window, we re-estimate the models in Tables 5 and 6 by using a [-60, 60] window. The results are given in Table 8. For brevity we report the coefficient estimates of the political uncertainty variable only. The full set of estimations of each model can be found in the Appendix. The results are largely in line with the main findings.

Table 8: Coefficient Estimates of Political Uncertainty with Alternative Event Windows

	Beijing	Shanghai	Hubei	Guangdong
Zero Transaction Day				
[-60, 0]	0.146	-0.203	1.661***	-1.546***
	(0.82)	(-1.26)	(7.54)	(-2.58)
[0, 60]	0.601***	-0.738***	1.383***	-0.135
	(3.40)	(-4.40)	(6.32)	(-0.37)
[-60, 60]	0.476***	-0.54***	0.992***	-0.618*
	(3.29)	(-4.23)	(4.83)	(-1.91)
Turnover Ratio				
[-60, 0]	-2.657***	-2.187	7.436**	-28.868***
	(-2.96)	(-1.18)	(2.20)	(-3.94)
[0, 60]	-4.76***	-0.261	-17.044***	-13.685**
	(-5.96)	(-0.10)	(-6.39)	(-2.03)
[-60, 60]	-4.261***	-1.714	-1.507	-28.742***
	(-7.00)	(-0.93)	（-0.58）	(-4.89)
Returns				
[-60, 0]	0.104	0.873*	0.406**	0.549*
	（0.19）	（1.67）	（2.25）	（1.84）
[0, 60]	-0.025	-0.083	0.854***	0.397
	（-0.05）	（-0.17）	（4.80）	（1.23）
[-60, 60]	-0.07	0.471	0.488*	0.364
	(-0.16)	(1.18)	（1.86）	（1.52）

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1. This table gives the coefficient estimate of Political Uncertainty only. Other control variables in Tables 5 and 6 are also included in these models, but not reported in this table for brevity. The full sets of regression outputs of models included in this table can be found in Tables A7 to A10 in the Appendix.*

8. Conclusions

The objective of this research is to identify the impacts of political uncertainty on the trading activities in carbon ETS markets. We develop an analytical framework and two testable hypotheses based on a comprehensive review of studies on pollical uncertainty and carbon emission trading. China is chosen as the study area given the size of its carbon emission footprint, as well as the potential contribution of its newly established ETS markets in solving the climate crisis.

Our empirical strategy is innovative in the sense that both carbon emission trading activities and political uncertainty measurements are at the local level. Specifically, we choose the four largest carbon ETS markets in China, namely, Beijing, Shanghai, Hubei, and Guangdong markets, to collect daily transaction data. Correspondingly, political uncertainty is measured by recording the turnovers of governors/mayors in the home province/city of these markets. In addition to daily turnover ratio and returns, we also investigate the impact of political uncertainty on the probability of having no transactions on a trading day, which is common in China's carbon ETS markets. We use logistic regression and AR(1)-GARCH models to reliably separate the net effect of political uncertainty. The robustness of the findings are also verified with a different political uncertainty measurement and an alternative definition of event window.

Overall, we find evidence to support both hypotheses. Specifically, trading volume (measured by the probability of having no transactions on a trading day and daily turnover ratio) contracts when facing political uncertainty, while daily returns increases at the same time. This indicates that firms are cautious when there are changes of local leadership; they trade less and demand a risk primum to compensate for the political uncertainty in carbon emission trading in China. We also find that firms in larger carbon ETS markets (i.e., Hubei and Guangdong) are much more responsive to political uncertain; they tend to act before the official turnover dates, and the effect size is also larger. These findings are helpful for the Chinese government to manage and develop the newly established national ETS markets. Reducing political uncertainty would certainly be beneficial to stabilize the markets. If this is not practical, larger markets could be helpful to allow firms to hedge the risks effectively.

Our analysis is constrained by data availability in many ways, such as the large number of non-transaction days as well as the short sampling period. These are inevitable because the ETS markets in China is still at an early stage. However, for the very same reason, it is important to obtain empirical evidence from this young and fast-growing markets, so that policymakers could make informed decisions about next steps. The initial investigations of the relationship between political uncertainty and carbon emission trading activities in this research should be verified and refined when more reliable data are made available in future.

References

1) Acemoglu, D., Hassan, T.A., Tahoun, A., 2018. The power of the street: Evidence from Egypt's Arab Spring. The Review of Financial Studies 31, 1-42.
2) Agarwal, S., Qian, W., Seru, A., Zhang, J., 2020. Disguised corruption: Evidence from consumer credit in China. Journal of Financial Economics.
3) Aldy, J.E., Stavins, R.N., 2012. The promise and problems of pricing carbon: Theory and experience. The Journal of Environment & Development 21, 152-180.
4) Alesina, A., Özler, S., Roubini, N., Swagel, P., 1996. Political instability and economic growth. Journal of Economic growth 1, 189-211.
5) Alesina, A., Perotti, R., 1996. Income distribution, political instability, and investment. European economic review 40, 1203-1228.
6) An, H., Chen, Y., Luo, D., Zhang, T., 2016. Political uncertainty and corporate investment: Evidence from China. Journal of Corporate Finance 36, 174-189.
7) Anger, N., Oberndorfer, U., 2008. Firm performance and employment in the EU emissions trading scheme: An empirical assessment for Germany. Energy policy 36, 12-22.
8) Antoci, A., Borghesi, S., Iannucci, G., Sodini, M., 2021. Should I stay or should I go? Carbon leakage and ETS in an evolutionary model. Energy Economics 103.
9) Atanassov, J., Julio, B., Leng, T., 2015. The bright side of political uncertainty: The case of R&D. Available at SSRN 2693605.
10) Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. The quarterly journal of economics 131, 1593-1636.
11) Barro, R.J., 1991. Economic growth in a cross section of countries. The quarterly journal of economics 106, 407-443.
12) Beck, T., Demirgüç-Kunt, A., Levine, R., 2001. Law, politics, and finance. Available at SSRN 269118.
13) Belo, F., Gala, V.D., Li, J., 2013. Government spending, political cycles, and the cross section of stock returns. Journal of Financial Economics 107, 305-324.
14) Bernanke, B.S., 1983. Irreversibility, uncertainty, and cyclical investment. The quarterly journal of economics 98, 85-106.
15) Bittlingmayer, G., 1998. Output, stock volatility, and political uncertainty in a natural experiment: Germany, 1880–1940. The Journal of Finance 53, 2243-2257.
16) Brogaard, J., Detzel, A., 2015. The asset-pricing implications of government economic policy uncertainty. Management Science 61, 3-18.
17) Cai, Y., Wu, Y., 2019. Time-varied causality between US partisan conflict shock and crude oil return. Energy Economics 84, 104512.
18) Cao, C., Dong, Y., Hou, W., Liu, Y., Qian, X., 2019. Provincial official turnover and bank loans. Pacific-Basin Finance Journal 57, 101202.
19) Chai, S.L., Sun, R.X., Zhang, K., Ding, Y.T., Wei, W., 2022. Is Emissions Trading Scheme (ETS) an Effective Market-Incentivized Environmental Regulation Policy? Evidence from China's Eight ETS Pilots. International Journal of Environmental Research and Public Health 19.
20) Chen, T., Kung, J.K.-s., 2019. Busting the "Princelings": The campaign against corruption in China's primary land market. The Quarterly Journal of Economics 134, 185-226.
21) Cioffi-Revilla, C., 1998. Politics and uncertainty: theory, models and applications. Cambridge university press.
22) Clarke, L., McFarland, J., Octaviano, C., van Ruijven, B., Beach, R., Daenzer, K., Herreras Martínez, S., Lucena, A.F.P., Kitous, A., Labriet, M., Loboguerrero Rodriguez, A.M., Mundra, A., van der Zwaan, B., 2016. Long-term abatement potential and current policy trajectories in Latin American countries. Energy Economics 56, 513-525.

23) Çolak, G., Durnev, A., Qian, Y., 2017. Political uncertainty and IPO activity: Evidence from US gubernatorial elections. Journal of Financial and Quantitative Analysis 52, 2523-2564.
24) Erb, C.B., Harvey, C.R., Viskanta, T.E., 1996. Political risk, economic risk, and financial risk. Financial Analysts Journal 52, 29-46.
25) European Commission, 2021. Report from the Commission to the European Parliament and the Council on the Functioning of the European Carbon Market in 2020 pursuant to Articles 10(5) and 21(2) of Directive 2003/87/EC (as amended by Directive 2009/29/EC and Directive (EU) 2018/410). European Commission, Brussels.
26) Francis, B.B., Hasan, I., Zhu, Y., 2014. Political uncertainty and bank loan contracting. Journal of Empirical Finance 29, 281-286.
27) Francis, B.B., Hasan, I., Zhu, Y., 2021. The impact of political uncertainty on institutional ownership. Journal of Financial Stability 57, 100921.
28) Gao, Y.N., Li, M., Xue, J.J., Liu, Y., 2020. Evaluation of effectiveness of China's carbon emissions trading scheme in carbon mitigation. Energy Economics 90.
29) Goodell, J.W., Vähämaa, S., 2013. US presidential elections and implied volatility: The role of political uncertainty. Journal of Banking & Finance 37, 1108-1117.
30) Gronewold, N., Fialka, J.J., 2011. European Commission Halts Transfers of Carbon Emissions Allowances Until Thefts Are Sorted Out, The New York Times.
31) Gulen, H., Ion, M., 2015. Policy uncertainty and corporate investment. The Review of Financial Studies 29, 523-564.
32) Guo, Y., Li, J., Li, Y., You, W., 2021. The roles of political risk and crude oil in stock market based on quantile cointegration approach: A comparative study in China and US. Energy Economics 97, 105198.
33) He, Y., Lin, H., Wu, C., Dufrene, U.B., 2009. The 2000 presidential election and the information cost of sensitive versus non-sensitive S&P 500 stocks. Journal of financial markets 12, 54-86.
34) Herbst, A.F., Slinkman, C.W., 1984. Political-economic cycles in the US stock market. Financial Analysts Journal 40, 38-44.
35) Hill, P., Korczak, A., Korczak, P., 2019. Political uncertainty exposure of individual companies: The case of the Brexit referendum. Journal of Banking & Finance 100, 58-76.
36) Jens, C.E., 2017. Political uncertainty and investment: Causal evidence from US gubernatorial elections. Journal of Financial Economics 124, 563-579.
37) Johnson, R.R., Chittenden, W.T., Jensen, G.R., 1999. Presidential politics, stocks, bonds, bills, and inflation. The journal of portfolio management 26, 27-31.
38) Julio, B., Yook, Y., 2012. Political uncertainty and corporate investment cycles. The Journal of Finance 67, 45-83.
39) Li, J., Born, J.A., 2006. Presidential election uncertainty and common stock returns in the United States. Journal of Financial Research 29, 609-622.
40) Lin, B., Jia, Z., 2019. What will China's carbon emission trading market affect with only electricity sector involvement? A CGE based study. Energy Economics 78, 301-311.
41) Lin, C., Morck, R., Yeung, B., Zhao, X., 2016. Anti-corruption reforms and shareholder valuations: Event study evidence from China. National Bureau of Economic Research.
42) Liu, C., Sun, X., Chen, J., Li, J., 2016. Statistical properties of country risk ratings under oil price volatility: Evidence from selected oil-exporting countries. Energy policy 92, 234-245.
43) Liu, L.X., Shu, H., Wei, K.J., 2017. The impacts of political uncertainty on asset prices: Evidence from the Bo scandal in China. Journal of financial economics 125, 286-310.

44) Lucena, A.F., Clarke, L., Schaeffer, R., Szklo, A., Rochedo, P.R., Nogueira, L.P., Daenzer, K., Gurgel, A., Kitous, A., Kober, T., 2016. Climate policy scenarios in Brazil: A multi-model comparison for energy. Energy Economics 56, 564-574.
45) Luo, D., Chen, K., Wu, L., 2017. Political uncertainty and firm risk in China. Review of Development Finance 7, 85-94.
46) Meckling, J., Sterner, T., Wagner, G., 2017. Policy sequencing toward decarbonization. Nature Energy 2, 918-922.
47) Mitchell, T., Telling, O., Sevastopulo, D., 2022. China suspends links with US military and climate talks over Taiwan, Financial Times, p. 5 August 2022.
48) Ni, J., Wei, C., Du, L., 2015. Revealing the political decision toward Chinese carbon abatement: Based on equity and efficiency criteria. Energy Economics 51, 609-621.
49) Nordhaus, W.D., 1975. The political business cycle. The review of economic studies 42, 169-190.
50) Olmstead, S.M., Stavins, R.N., 2006. An international policy architecture for the post-Kyoto era. American Economic Review 96, 35-38.
51) Pantzalis, C., Stangeland, D.A., Turtle, H.J., 2000. Political elections and the resolution of uncertainty: the international evidence. Journal of banking & finance 24, 1575-1604.
52) Pasquariello, P., Zafeiridou, C., 2014. Political uncertainty and financial market quality. Ross School of Business Paper.
53) Pástor, Ľ., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financial Economics 110, 520-545.
54) Pindyck, R.S., Solimano, A., 1993. Economic instability and aggregate investment. NBER macroeconomics annual 8, 259-303.
55) Stavins, R.N., 2019. The future of US carbon-pricing policy: Normative assessment and positive prognosis, in: John F. Kennedy School of Government (Ed.), Discussion Paper 19-95, Harvard University.
56) Tian, Y., Akimov, A., Roca, E., Wong, V., 2016. Does the carbon market help or hurt the stock price of electricity companies? Further evidence from the European context. Journal of Cleaner Production 112, 1619-1626.
57) Tian, Y., Li, Z.-j., 2021. Provincial distribution of China’s carbon emission rights and assessment of its emission reduction potential under the Paris Agreement. Journal of Natural Resources (in Chinese) 2021, 921-933.
58) Tu, Q., Betz, R., Mo, J., Fan, Y., Liu, Y., 2018. Can carbon pricing support onshore wind power development in China? An assessment based on a large sample project dataset. Journal of cleaner production 198, 24-36.
59) Tvinnereim, E., 2014. The bears are right: Why cap-and-trade yields greater emission reductions than expected, and what that means for climate policy. Climatic Change 127, 447-461.
60) Wang, P., Dai, H.-c., Ren, S.-y., Zhao, D.-q., Masui, T., 2015. Achieving Copenhagen target through carbon emission trading: Economic impacts assessment in Guangdong Province of China. Energy 79, 212-227.
61) Wen, F., Wu, N., Gong, X., 2020a. China's carbon emissions trading and stock returns. Energy Economics 86, 104627.
62) Wen, F., Zhao, L., He, S., Yang, G., 2020b. Asymmetric relationship between carbon emission trading market and stock market: evidences from China. Energy Economics 91, 104850.
63) World Bank, 2022. State and Trends of Carbon Pricing 2022. World Bank, Washington, DC.
64) Wu, L.B., Zhou, Y., Qian, H.Q., 2022. Global actions under the Paris agreement: Tracing the carbon leakage flow and pursuing countermeasures. Energy Economics 106.

65) Xu, N., Chen, Q., Xu, Y., Chan, K.C., 2016. Political uncertainty and cash holdings: Evidence from China. Journal of Corporate Finance 40, 276-295.
66) Yang, L., Li, Y., Liu, H., 2021. Did carbon trade improve green production performance? Evidence from China. Energy Economics 96, 105185.
67) Yu, J., Shi, X., Guo, D., Yang, L., 2021. Economic policy uncertainty (EPU) and firm carbon emissions: evidence using a China provincial EPU index. Energy Economics 94, 105071.

Appendix

Table A1: Impacts of political uncertainty on carbon emission trading turnover ratio and returns – AR(1)-GARCH estimations: [-30, 0] window

Variable	Turnover Ratio				Returns			
	Beijing	Shanghai	Hubei	Guangdong	Beijing	Shanghai	Hubei	Guangdong
Conditional Mean Equation								
Political Uncertainty	-1.017	-0.185	-13.634***	-22.655**	0.717	0.689	0.624***	0.659*
	(-0.92)	(-0.07)	(-3.72)	(-2.18)	(0.93)	(0.96)	(3.10)	(1.78)
AR(1)	0.568***	0.156***	0.604***	0.555***	-0.033	-0.021	-0.328***	-0.194***
	(29.99)	(7.48)	(36.63)	(22.49)	(-1.01)	(-0.66)	(-11.91)	(-6.89)
Beijing		0.506***	0.004	-0.108		-0.026	-0.021***	0.006
		(11.29)	(0.10)	(-1.15)		(-1.23)	(-3.11)	(0.70)
Shanghai	0.013***		-0.042**	-0.034	-0.068***		-0.002	0.019*
	(2.98)		(-2.52)	(-1.18)	(-3.00)		(-0.18)	(1.90)
Hubei	0.001	0.0003		0.018	-0.005	-0.042		-0.017
	(0.46)	(0.06)		(1.28)	(-0.17)	(-0.11)		(-1.11)
Guangdong	-0.002	0.015***	-0.003		0.084**	0.068**	-0.027**	
	(-1.20)	(5.62)	(-0.53)		(2.46)	(1.98)	(-2.02)	
Shanghai Stock Exchange Index	0.019	2.618	-2.445	8.821**	-0.563	-0.029	1.12***	-0.061
	(0.03)	(1.35)	(-1.02)	(1.96)	(-1.42)	(-0.23)	(7.49)	(-0.50)
Low-Carbon Index	0.009	-4.716***	0.481	10.439***	0.272*	-0.029	-0.794***	0.046
	(0.03)	(-8.81)	(0.55)	(4.52)	(1.89)	(-0.23)	(-15.40)	(0.80)
Thermal Coal Price	0.017***	0.014***	-0.036***	0.125***	-2.928**	0.065	2.886***	-0.134
	(6.87)	(2.71)	(-3.96)	(6.97)	(-2.28)	(0.06)	(6,37)	(-0.28)
Conditional Variance Equation								
ARCH(1)	1.059***	1.374***	1.296***	1.356***	0.288***	0.028**	1.102***	0.518***
	(11.04)	(7.99)	(9.77)	(12.32)	(6.83)	(2.12)	(15.41)	(11.13)
GARCH(1)	0.348***	0.295***	0.06***	0.211***	0.512***	0.931***	0.104***	0.563***
	(12.59)	(8.11)	(3.00)	(6.64)	(3.97)	(13.27)	(4.10)	(25.85)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A2: Impacts of political uncertainty on carbon emission trading turnover ratio and returns – AR(1)-GARCH estimations: [0, 30] window

Variable	Turnover Ratio				Returns			
	Beijing	Shanghai	Hubei	Guangdong	Beijing	Shanghai	Hubei	Guangdong
Conditional Mean Equation								
Political Uncertainty	-4.241***	-3.474	-16.226***	4.457	-0.674	0.283	0.485**	0.389
	(-3.87)	(-1.49)	(-4.57)	(0.50)	(-0.86)	(0.43)	(2.11)	(0.93)
AR(1)	0.56***	0.156***	0.601***	0.555***	-0.034	-0.021	-0.325***	-0.193***
	(29.93)	(7.52)	(37.24)	(23.02)	(-1.01)	(-0.66)	(-11.81)	(-6.85)
Beijing		0.499***	0.002	-0.107		-0.026	-0.021***	0.007
		(11.95)	(0.04)	(-1.14)		(-1.22)	(-3.02)	(0.78)
Shanghai	0.012***		-0.044***	-0.032	-0.066***		-0.004	0.019*
	(3.13)		(-2.72)	(-1.13)	(-2.92)		(-0.46)	(1.89)
Hubei	0.0003	-0.0005		0.02	-0.006	0.004		-0.02
	(0.23)	(-0.12)		(1.44)	(-0.22)	(0.12)		(-1.35)
Guangdong	-0.001	0.016***	-0.005		0.085**	0.069***	-0.027**	
	(-0.87)	(7.26)	(-0.75)		(2.47)	(1.99)	(-2.03)	
Shanghai Stock Exchange Index	0.523	2.102	-2.2442	6.938	-0.442	-0.022	1.141***	-0.081
	(1.05)	(1.17)	(-0.96)	(1.51)	(-1.10)	(-0.06)	(7.72)	(-0.67)
Low-Carbon Index	-0.261	-4.777***	0.265	11.482***	0.214	-0.038	-0.797***	0.059
	(-1.00)	(-10.14)	(0.31)	(4.83)	(1.46)	(-0.30)	(-15.44)	(1.06)
Thermal Coal Price	0.019***	0.015***	-0.034***	0.119***	2.488*	0.127	2.929***	-0.182
	(8.71)	(3.22)	(-3.85)	(6.68)	(-1.90)	(0.11)	(6.50)	(-0.37)
Conditional Variance Equation								
ARCH(1)	1.128***	1.476***	1.332***	1.389***	0.293***	0.028**	1.112***	0.519***
	(11.62)	(8.13)	(9.66)	(12.30)	(6.74)	(2.13)	(15.29)	(11.14)
GARCH(1)	0.344***	0.275***	0.057***	0.199***	0.497***	0.931***	0.095***	0.562***
	(13.24)	(7.84)	(2.98)	(6.39)	(3.85)	(13.24)	(3.81)	(25.68)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A3: Zero transaction day analysis with Anti-Corruption as an additional political uncertainty measurement

	Beijing	Shanghai	Hubei	Guangdong
[-30, 0] Window				
Political Uncertainty	0.099	-0.361	1.389***	-1.973*
	(0.41)	(-1.60)	(5.27)	(-1.94)
Anti-corruption	-0.00003***	-0.0002***	-0.002***	0.0003***
	(-3.76)	(-2.88)	(-6.71)	(4.12)
Shanghai Stock Exchange Index	-0.0004***	-0.001***	-0.003***	0.0003
	(-3.43)	(-5.28)	(-7.56)	(1.63)
Low-Carbon Index	0.0002***	0.0001***	0.0005***	-0.0004***
	(5.26)	(3.01)	(5.30)	(-4.00)
Thermal Coal Price	-0.002***	0.001*	-0.004***	-0.003***
	(-4.13)	(1.77)	(-3.78)	(-5.36)
[0, 30] Window				
Political Uncertainty	0.001	-0.504**	0.804***	-0.358
	(0.00)	(-2.35)	(2.90)	(-0.67)
Anti-corruption	-0.0003***	-0.0002***	-0.002***	0.0003***
	(-3.75)	(-3.06)	(-6.64)	(4.20)
Shanghai Stock Exchange Index	-0.0003***	-0.001***	-0.002***	0.0003
	(-3.35)	(-5.20)	(-7.51)	(1.45)
Low-Carbon Index	0.0002***	0.0001***	0.0005***	-0.0004***
	(5.12)	(3.09)	(5.21)	(-3.91)
Thermal Coal Price	-0.002***	0.001	-0.004***	-0.004***
	(-4.04)	(1.63)	(-3.89)	(-5.61)
[-30, 30] Window				
Political Uncertainty	0.001	-0.504**	0.804***	-0.358
	(0.00)	(-2.35)	(2.90)	(-0.67)
Anti-corruption	-0.0003***	-0.0002***	-0.002***	0.0003***
	(-3.75)	(-3.06)	(-6.64)	(4.20)
Shanghai Stock Exchange Index	-0.0003***	-0.001***	-0.002***	0.0003
	(-3.35)	(-5.20)	(-7.51)	(1.45)
Low-Carbon Index	0.0002***	0.0001***	0.0005***	-0.0004***
	(5.12)	(3.09)	(5.21)	(-3.91)
Thermal Coal Price	-0.002***	0.001	-0.004***	-0.004***
	(-4.04)	(1.63)	(-3.89)	(-5.61)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A4: AR(1)-GARCH models with Anti-Corruption as an additional political uncertainty measurement [-30, 30] window

Variable	Turnover Ratio				Returns			
	Beijing	Shanghai	Hubei	Guangdong	Beijing	Shanghai	Hubei	Guangdong
Conditional Mean Equation								
Political Uncertainty	-3.703***	-1.578	-15.989***	-17.283**	0.095	0.279	0.513***	0.458
	(-5.06)	(-0.70)	(-5.48)	(-2.12)	(0.16)	(0.53)	(2.94)	(1.49)
Anti-corruption	-0.0002	0.001**	0.001	-0.003**	-0.035	-0.024	-0.037	-0.087
	(-1.56)	(1.96)	(0.79)	(-2.22)	(-0.29)	(-0.17)	(-0.83)	(-1.45)
AR(1)	0.546***	0.154***	0.594***	0.541***	-0.034	-0.021	-0.326***	-0.194***
	(32.90)	(7.28)	(36.46)	(20.25)	(-1.03)	(-0.67)	(-11.81)	(-6.92)
Beijing		0.493***	-0.005	-0.124		-0.026	-0.021***	0.006
		(11.09)	(-0.11)	(-1.31)		(-1.23)	(-3.11)	(0.71)
Shanghai	0.013***		-0.044***	-0.042	-0.067***		-0.003	0.019*
	(3.18)		(-2.69)	(-1.42)	(-2.98)		(-0.38)	(1.90)
Hubei	-0.0005	-0.0003		0.017	-0.006	0.003		-0.018
	(-0.56)	(-0.07)		(1.17)	(-0.21)	(0.11)		(-1.21)
Guangdong	-0.001	0.016***	-0.004		0.084**	0.069**	-0.027**	
	(-1.45)	(5.40)	(-0.68)		(2.44)	(1.99)	(-2.04)	
Shanghai Stock Exchange Index	1.209***	2.271	-1.659	11.3**	-0.522	-0.029	1.138***	-0.046
	(2.82)	(1.17)	(-0.71)	(2.52)	(-1.29)	(-0.08)	(7.50)	(-0.38)
Low-Carbon Index	-0.582***	-4.735***	0.08	8.492***	0.251*	-0.036	-0.797***	0.044
	(-2.59)	(-8.73)	(0.09)	(3.58)	(1.68)	(-0.28)	(-15.25)	(0.78)
Thermal Coal Price	0.023***	0.016***	-0.032***	0.124***	-2.838**	0.082	2.898***	-0.174
	(11.92)	(3.23)	(-3.67)	(6.77)	(-2.14)	(0.07)	(6.39)	(-0.36)
Conditional Variance Equation								
ARCH(1)	1.261***	1.415***	1.348***	1.311***	0.288***	0.028**	1.106***	0.526***
	(9.68)	(7.08)	(9.52)	(12.08)	(6.78)	(2.13)	(15.42)	(11.05)
GARCH(1)	0.318***	0.282***	0.059***	0.239***	0.511***	0.931***	0.096***	0.559***
	(10.46)	(6.91)	(3.01)	(6.45)	(3.90)	(13.25)	(3.88)	(25.24)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A5: AR(1)-GARCH models with Anti-Corruption as an additional political uncertainty measurement [-30, 0] window

Variable	Turnover Ratio				Returns			
	Beijing	**Shanghai**	**Hubei**	**Guangdong**	**Beijing**	**Shanghai**	**Hubei**	**Guangdong**
Conditional Mean Equation								
Political Uncertainty	-1.112	0.706	-13.199***	-25.633**	0.715	0.68	0.608***	0.676*
	(-1.01)	(0.26)	(-3.62)	(-2.42)	(0.92)	(0.95)	(3.00)	(1.83)
Anti-corruption	-0.0001	0.002**	0.001	-0.002**	-0.034	-0.023	-0.039	-0.088
	(-0.75)	(2.26)	(1.15)	(-2.06)	(-0.29)	(-0.17)	(-0.89)	(-1.46)
AR(1)	0.567***	0.154***	0.605***	0.547***	-0.033	-0.021	-0.328***	-0.195***
	(30.03)	(7.25)	(37.08)	(20.78)	(-1.01)	(-0.67)	(-11.90)	(-6.94)
Beijing		0.496***	0.006	-0.114		-0.026	-0.021***	0.006
		(10.37)	(0.13)	(-1.20)		(-1.23)	(-3.11)	(0.66)
Shanghai	0.012***		-0.042**	-0.037	-0.068***		-0.002	0.019*
	(2.94)		(-2.52)	(-1.28)	(-3.00)		(-0.17)	(1.91)
Hubei	0.001	0.001		0.018	-0.005	0.003		-0.017
	(0.42)	(0.15)		(1.24)	(-0.18)	(0.11)		(-1.12)
Guangdong	-0.002	0.015***	-0.004		0.084**	0.068**	-0.027**	
	(-1.26)	(3.31)	(-0.58)		(2.46)	(1.98)	(-2.03)	
Shanghai Stock Exchange Index	0.094	2.526	-2.629	9.793**	-0.559	-0.038	1.139***	-0.033
	(0.15)	(1.14)	(-1.10)	(2.18)	(-1.41)	(-0.10)	(7.52)	(-0.27)
Low-Carbon Index	-0.017	-4.523***	0.592	9.198***	0.269*	-0.031	-0.799***	0.036
	(-0.06)	(-7.79)	(0.68)	(3.93)	(1.86)	(-0.24)	(-15.36)	(0.64)
Thermal Coal Price	0.018***	0.014***	-0.035***	0.12***	-2.968**	0.048	2.88***	-0.136
	(6.98)	(2.67)	(-3.92)	(6.70)	(-2.30)	(0.04)	(6.35)	(-0.28)
Conditional Variance Equation								
ARCH(1)	1.069***	1.326***	1.307***	1.319***	0.288***	0.028**	1.102***	0.524***
	(10.95)	(7.53)	(9.85)	(12.49)	(6.82)	(2.12)	(15.42)	(11.04)
GARCH(1)	0.345***	0.3***	0.059***	0.234***	0.512***	0.931***	0.1***	0.559***
	(12.43)	(7.59)	(3.00)	(6.98)	(3.95)	(13.27)	(3.99)	(25.34)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A6: AR(1)-GARCH models with Anti-Corruption as an additional political uncertainty measurement [0, 30] window

Variable	Turnover Ratio				Returns			
	Beijing	**Shanghai**	**Hubei**	**Guangdong**	**Beijing**	**Shanghai**	**Hubei**	**Guangdong**
Conditional Mean Equation								
Political Uncertainty	-4.42***	-2.307	-15.69***	2.428	-0.686	0.268	0.462**	0.402
	(-4.10)	(-0.88)	(-4.39)	(0.26)	(-0.88)	(0.40)	(1.99)	(0.96)
Anti-corruption	-0.0001	0.001**	0.001	-0.002*	-0.039	-0.027	-0.044	-0.086
	(-1.11)	(1.97)	(0.95)	(-1.74)	(-0.34)	(-0.19)	(-0.98)	(-1.42)
AR(1)	0.557***	0.154***	0.601***	0.549***	-0.034	-0.021	-0.324***	-0.193***
	(30.12)	(7.28)	(37.55)	(21.54)	(-1.01)	(-0.66)	(-11.81)	(-6.89)
Beijing		0.493***	0.003	-0.11		-0.026	-0.021***	0.006
		(11.03)	(0.07)	(-1.16)		(-1.22)	(-3.02)	(0.74)
Shanghai	0.012***		-0.044***	-0.035	-0.066***		-0.004	0.019*
	(3.12)		(-2.71)	(-1.21)	(-2.92)		(-0.44)	(1.89)
Hubei	0.0001	-0.0002		0.021	-0.007	0.004		-0.021
	(0.12)	(-0.04)		(1.39)	(-0.23)	(0.11)		(-1.37)
Guangdong	-0.001	0.016***	-0.005		0.085**	0.069**	-0.027**	
	(-0.95)	(5.39)	(-0.78)		(2.47)	(1.99)	(-2.04)	
Shanghai Stock Exchange Index	0.645	2.147	-2.406	7.972*	-0.436	-0.017	1.161***	-0.055
	(1.30)	(1.09)	(-1.03)	(1.73)	(-1.09)	(-0.04)	(7.74)	(-0.45)
Low-Carbon Index	-0.312	-4.655***	0.364	10.295***	0.209	-0.041	-0.804***	0.051
	(-1.22)	(-9.17)	(0.43)	(4.26)	(1.42)	(-0.32)	(-15.41)	(0.91)
Thermal Coal Price	0.02***	0.015***	-0.034***	0.115***	-2.533*	0.105	2.922***	-0.187
	(9.08)	(3.20)	(-3.82)	(6.43)	(-1.93)	(0.09)	(6.47)	(-0.38)
Conditional Variance Equation								
ARCH(1)	1.146***	1.408***	1.339***	1.35***	0.293***	0.028**	1.112***	0.526***
	(11.52)	(7.78)	(9.76)	(12.32)	(6.72)	(2.13)	(15.31)	(11.05)
GARCH(1)	0.342***	0.284***	0.057***	0.22***	0.496***	0.931***	0.092***	0.559***
	(13.56)	(7.52)	(2.99)	(6.53)	(3.83)	(13.25)	(3.72)	(25.16)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A7: Zero Transaction Day analysis with the [-60, 60] event windows

	Beijing	Shanghai	Hubei	Guangdong
[-60, 0] Window				
Political Uncertainty	0.146	-0.203	1.661***	-1.546***
	(0.82)	(-1.26)	(7.54)	(-2.58)
Shanghai Stock Exchange Index	-0.0005***	-0.001***	-0.002***	0.0004**
	(-3.90)	(-5.45)	(-9.16)	(2.32)
Low-Carbon Index	0.0002***	0.0001***	0.001***	-0.001***
	(5.85)	(3.34)	(6.32)	(-4.72)
Thermal Coal Price	-0.001***	0.001**	-0.002***	-0.004***
	(-3.74)	(2.21)	(-2.90)	(-5.63)
[0, 60] Window				
Political Uncertainty	0.601***	-0.738***	1.383***	-0.135
	(3.40)	(-4.40)	(6.32)	(-0.37)
Shanghai Stock Exchange Index	-0.001***	-0.001***	-0.002***	0.0003*
	(-4.51)	(-5.35)	(-8.85)	(1.90)
Low-Carbon Index	0.0003***	0.0001***	0.001***	-0.0005***
	(6.57)	(3.35)	(6.22)	(-4.51)
Thermal Coal Price	-0.002***	0.001**	-0.003***	-0.004***
	(-4.36)	(2.09)	(-3.45)	(-6.25)
[-60, 60] Window				
Political Uncertainty	0.476***	-0.539***	0.992***	-0.618*
	(3.29)	(-4.23)	(4.83)	(-1.91)
Shanghai Stock Exchange Index	-0.001***	-0.001***	-0.002***	0.0004**
	(-4.63)	(-5.03)	(-8.81)	(2.21)
Low-Carbon Index	0.0003***	0.0001***	0.0005***	-0.0005***
	(6.59)	(2.95)	(6.04)	(-4.63)
Thermal Coal Price	-0.002***	0.001**	-0.003***	-0.004***
	(-4.45)	(2.34)	(-3.09)	(-5.54)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A8: AR(1)-GARCH models with the [-60,60] event window

Variable	Turnover Ratio				Returns			
	Beijing	Shanghai	Hubei	Guangdong	Beijing	Shanghai	Hubei	Guangdong
Conditional Mean Equation								
Political Uncertainty	-4.261***	-1.714	-1.507	-28.742***	-0.07	0.471	0.488*	0.364
	(-7.00)	(-0.93)	(-0.58)	(-4.89)	(-0.16)	(1.18)	(1.86)	(1.52)
AR(1)	0.549***	0.157***	0.612***	0.536***	-0.034	-0.022	-0.231***	-0.193***
	(33.82)	(7.54)	(38.34)	(20.65)	(-1.03)	(-0.68)	(-6.99)	(-6.85)
Beijing		0.499***	0.014	-0.157*		-0.026	-0.007	0.008
		(11.71)	(0.31)	(-1.69)		(-1.24)	(-0.49)	(0.88)
Shanghai	0.011***		-0.042**	-0.045	-0.067***		-0.0003	0.019*
	(2.85)		(-2.55)	(-1.53)	(-2.97)		(-0.02)	(1.89)
Hubei	-0.0001	-0.001		0.009	-0.006	0.004		-0.018
	(-0.09)	(-0.16)		(0.72)	(-0.21)	(0.11)		(-1.21)
Guangdong	-0.0004	0.016***	-0.005		0.084**	0.068**	-0.007	
	(-0.89)	(7.27)	(-0.90)		(2.44)	(1.98)	(-0.29)	
Shanghai Stock Exchange Index	1.766***	2.344	-2.962	15.716***	-0.487	-0.078	0.452*	-0.075
	(3.73)	(1.29)	(-1.24)	(3.54)	(-1.16)	(-0.20)	(1.82)	(-0.61)
Low-Carbon Index	-0.909***	-4.858***	0.736	7.083***	0.236	-0.019	-0.207**	0.059
	(-3.58)	(-9.86)	(0.85)	(3.24)	(1.51)	(-0.16)	(-2.23)	(1.04)
Thermal Coal Price	0.025***	0.015***	-0.039***	0.15***	-2.664**	0.053	0.791	-0.201
	(12.05)	(3.23)	(-4.22)	(7.70)	(-1.96)	(0.05)	(1.00)	(-0.60)
Conditional Variance Equation								
ARCH(1)	1.212***	1.461***	1.314***	1.305***	0.289***	0.027**	0.018***	0.518***
	(13.44)	(7.53)	(9.71)	(12.05)	(6.78)	(2.11)	(4.52)	(11.15)
GARCH(1)	0.331***	0.279***	0.058***	0.233***	0.508***	0.932***	-1.043***	0.562***
	(15.64)	(7.64)	(2.95)	(6.50)	(3.89)	(13.29)	(-347.28)	(25.70)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A9: AR(1)-GARCH models with the [-60,0] event window

Variable	Turnover Ratio				Returns			
	Beijing	**Shanghai**	**Hubei**	**Guangdong**	**Beijing**	**Shanghai**	**Hubei**	**Guangdong**
Conditional Mean Equation								
Political Uncertainty	-2.657***	-2.187	7.436**	-28.868***	0.104	0.873*	0.406**	0.549*
	(-2.96)	(-1.18)	(2.20)	(-3.94)	(0.19)	(1.67)	(2.25)	(1.84)
AR(1)	0.554***	0.157***	0.608***	0.547***	-0.034	-0.022	-0.329***	-0.193***
	(28.72)	(7.54)	(37.20)	(21.85)	(-1.03)	(-0.68)	(-11.91)	(-6.88)
Beijing		0.501***	0.034	-0.126		-0.026	-0.021***	0.008
		(11.70)	(0.75)	(-1.35)		(-1.25)	(-3.06)	(0.88)
Shanghai	0.013***		-0.039**	-0.039	-0.067***		-0.002	0.019*
	(3.09)		(-2.32)	(-1.36)	(-2.98)		(-0.20)	(1.89)
Hubei	-0.00002	-0.001		0.014	-0.006	0.004		-0.017
	(-0.01)	(-0.14)		(1.06)	(-0.20)	(0.12)		(-1.13)
Guangdong	-0.001	0.016***	-0.007		0.084**	0.068**	-0.028**	
	(-0.67)	(6.86)	(-1.33)		(2.45)	(1.96)	(-2.08)	
Shanghai Stock Exchange Index	0.878	2.497	-3.767	12.34***	-0.528	-0.082	1.118***	-0.058
	(1.59)	(1.36)	(-1.56)	(2.67)	(-1.31)	(-0.21)	(7.50)	(-0.47)
Low-Carbon Index	-0.437	-4.882***	0.915	8.686***	0.254*	-0.013	-0.792***	0.052
	(-1.54)	(-9.79)	(1.02)	(3.62)	(1.72)	(-0.10)	(-15.43)	(0.91)
Thermal Coal Price	0.021***	0.016***	-0.039***	0.136***	-2.797**	-0.004	2.906***	-0.307
	(8.52)	(3.24)	(-4.11)	(7.32)	(-2.15)	(-0.00)	(6.41)	(-0.62)
Conditional Variance Equation								
ARCH(1)	1.137***	1.447***	1.233***	1.343***	0.288***	0.027**	1.104***	0.519***
	(10.82)	(7.95)	(10.44)	(12.34)	(6.82)	(2.11)	(15.38)	(11.15)
GARCH(1)	0.346***	0.281***	0.064***	0.216***	0.511***	0.932***	0.102***	0.562***
	(13.47)	(7.87)	(3.21)	(6.73)	(3.94)	(13.30)	(4.02)	(25.65)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*

Table A10: AR(1)-GARCH models with the [0 , 60] event window

Variable	Turnover Ratio				Returns			
	Beijing	**Shanghai**	**Hubei**	**Guangdong**	**Beijing**	**Shanghai**	**Hubei**	**Guangdong**
Conditional Mean Equation								
Political Uncertainty	-4.759***	-0.261	-17.044***	-13.685**	-0.025	-0.083	0.854***	0.397
	(-5.96)	(-0.10)	(-6.39)	(-2.03)	(-0.05)	(-0.17)	(4.80)	(1.23)
AR(1)	0.551***	0.156***	0.589***	0.551***	-0.034	-0.021	-0.323***	-0.193***
	(33.66)	(7.48)	(35.85)	(22.35)	(-1.03)	(-0.65)	(-11.91)	(-6.86)
Beijing		0.505***	-0.006	-0.118		-0.026	-0.021***	0.007
		(11.24)	(-0.13)	(-1.26)		(-1.22)	(-2.91)	(0.79)
Shanghai	0.011***		-0.044***	-0.036	-0.067***		-0.005	0.019*
	(2.91)		(-2.81)	(-1.27)	(-2.97)		(-0.55)	(1.89)
Hubei	-0.0002	0.0002		0.017	-0.006	0.004		-0.084
	(-0.19)	(0.06)		(1.22)	(-0.21)	(0.12)		(-0.69)
Guangdong	-0.0005	0.016***	-0.004		0.084**	0.069***	-0.03**	
	(-0.90)	(5.68)	(-0.59)		(2.45)	(1.99)	(-2.27)	
Shanghai Stock Exchange Index	1.177***	2.572	-1.879	9.59**	-0.505	-0.014	1.141***	0.061
	(2.74)	(1.30)	(-0.87)	(2.17)	(-1.24)	(-0.04)	(7.80)	(1.07)
Low-Carbon Index	-0.589***	-4.711***	-0.087	10.152***	0.244	-0.039	-0.783***	0.061
	(-2.59)	(-9.21)	(-0.11)	(4.61)	(1.62)	(-0.30)	(-15.48)	(1.07)
Thermal Coal Price	0.023***	0.014***	-0.029***	0.128***	-2.722**	0.108	2.859***	-0.19
	(11.88)	(2.81)	(-3.40)	(7.01)	(-2.05)	(0.09)	(6.42)	(-0.39)
Conditional Variance Equation								
ARCH(1)	1.195***	1.378***	1.399***	1.362***	0.288***	0.028**	1.13***	0.519***
	(13.13)	(7.63)	(8.90)	(12.06)	(6.81)	(2.14)	(15.64)	(11.14)
GARCH(1)	0.336***	0.295***	0.057***	0.211***	0.509***	0.93***	0.081***	0.563***
	(15.19)	(7.91)	(3.00)	(6.24)	(3.92)	(13.23)	(3.58)	(25.75)

*Note: t statistics in parentheses. *** p-value < 0.01, ** p-value < 0.05, and * p-value < 0.1.*