Energy Economics 86 (2020) 104627

Contents lists available at ScienceDirect

Energy Economics

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

China's carbon emissions trading and stock returns

Fenghua Wen [a,b,c], Nan Wu [a], Xu Gong [d,*]

[a] School of Business, Central South University, Changsha 410083, China
[b] Supply Chain Management and Logistics Optimization Research Centre, Faculty of Engineering, University of Windsor, Windsor, ON, Canada
[c] Centre for Computational Finance and Economic Agents, University of Essex, Colchester CO4 3SQ, UK
[d] School of Management, China Institute for Studies in Energy Policy, Collaborative Innovation Center for Energy Economics and Energy Policy, Xiamen University, Xiamen 361005, China

ARTICLE INFO

Article history:
Received 15 September 2019
Received in revised form 3 November 2019
Accepted 30 November 2019
Available online 31 December 2019

Keywords:
China's carbon market
Stock returns
Difference-in-differences (DID)
Carbon premium
Carbon risk

ABSTRACT

Taking the Shenzhen pilot as an example, this paper uses a difference-in-differences (DID) method to quantitatively analyze the impact of carbon emissions' environmental regulation on the stock returns of companies. The results show that establishing China's carbon emissions trading market has a positive effect on the excess returns of companies participating in carbon emission allowances trading. Besides, the carbon premium in stock returns has increased after Chinas carbon emissions trading market is established. And we also observe that the carbon premium has a steady upward trend after 2014. In addition, our study proves that the coefficient of carbon risk factor is significantly positive, which can be explained by the fact that companies participating in the carbon market have higher carbon exposures.

1. Introduction

According to the World Bank, there were 17 Emissions Trading Schemes (ETS) in various countries and regions around the world as of August 2015, accounting for 8% of global annual greenhouse gas emissions (World Bank, 2016). Carbon emissions in the trading schemes are characterized by the ability to be capped, priced and traded. These allowances indicate a cost of emissions reduction and can be traded between companies, so they have market value. The companies that have a low cost of reducing emissions would sell their excess allowances, whereas companies with high costs of reducing emissions tend to purchase allowances. Under this condition, the "carbon market" is constructed as an institution where the allowances could be traded effectively (Cong and Lo, 2017). The emergence of this emerging market will have an impact on the costs and benefits of participating companies inevitably.

This paper aims to study the influence of carbon emissions' environmental regulation on the stock return of companies. The existing researches about the correlation of carbon prices and stock returns carry out from the following two aspects. On the one hand, the stock market could reflect the economic situation of a country. In fact, a country with more prosperous economic activity may need the more energy and the more carbon emissions, which further leads to higher carbon allowances price. Thus, the transmission from stock market to carbon prices could be established (e.g., Jiménez-Rodríguez, 2019). On the other hand, a company's profits could be reflected in its stock price. In this paper, we preliminarily analyze the impact of carbon market on the companies' costs and benefits. Some studies focus on estimating the sensitivity of stock returns to carbon prices change (e.g., Fell et al., 2015; Hintermann, 2016). Moreover, many papers focus on the effect of carbon prices on the European electricity industry or companies (e.g., Tian et al., 2015; Veith et al., 2009). Oestreich and Tsiakas (2015) apply the capital asset pricing and Fama-French factor models and use a "dirty" vs. "clean" portfolio approach with data from the German stock market. The abnormal returns (alpha) of the "dirty-minus-clean" portfolios are defined as a carbon premium. A positive carbon premium indicates that companies receiving free carbon emission allowances outperform other firms. The influence of the carbon market on stock returns is analyzed by comparing the spatial and temporal variations of the alpha. Zhang and Gregory-Allen (2018) take the Shenzhen pilot ETS as an example to study the same problem from the perspective of the carbon premium. However, it is still necessary for further discussions on this issue. For instance, no comparison is made for the time period before and after the introduction of the ETS in Shenzhen; The researchers take the Shenzhen pilot ETS as an example, while select companies listed

* Corresponding author.
E-mail address: xugong@xmu.edu.cn (X. Gong).

https://doi.org/10.1016/j.eneco.2019.104627
0140-9883/

on the Shenzhen Stock Exchange and uninvolved in the Shenzhen pilot ETS to form the "clean" portfolio.[1] All the above factors may lead to a bias in the research results. Furthermore, the above study investigates the impact of policy shocks on stock returns by comparing the spatial and temporal variations of the intercept term. This paradigm in general studies is relatively rare. From the perspective of econometrics, we can't control the error term effectively in the regression equation so that the intercept term might contain many immeasurable factors. Therefore, we argue that the method of dividing sample for comparing the variations of the alpha is questionable. However, the researches focused on the intercept term are still attractive because the classical model gives the economic meaning of the abnormal returns to the intercept term. Therefore, in the paper, we also use this method to explore the premium risk in stock returns as a supporting extension.

This paper enriches the previous literature analyzing the effect of Chinas ETS on stock returns by using a comprehensive empirical approach. This paper tries to establish a more formal and standardized DID research process to quantitatively analyze the effect of environmental policy of carbon emissions on the companies' stock returns (e.g., Nunn and Wantchekon, 2011; Moser and Voena, 2012; Tanaka, 2015; Michalopoulos and Papaioannou, 2016; Zhou et al., 2017). In addition, we construct a monthly return on a dynamic portfolio weighted by market value to study whether the stock returns have a carbon premium. It is more suitable for the China's regional environmental policies than the static one. Moreover, we plot the abnormal returns (alpha) of the dirty, clean and dirty-minus-clean portfolios for a rolling window of three years during the entire sample period. Sequentially, we study the trend of the effect of China's carbon emissions trading market on stock returns. The empirical results indicate that establishing China's carbon market has a positive impact on companies' stock returns economically. After the establishment of China's carbon market, the carbon premium increases sustainably and steadily. Furthermore, the coefficient of carbon risk factor is significantly positive, which can be explained by the companies participating in the carbon market having higher carbon exposures.

This paper mainly includes three contributions as follows. First, this paper employs the panel data to quantitatively assess the effect of China's carbon market on the companies' stock returns. To some extent, it complements the previous studies and enriches the research on this issue. Second, due to the particularity of China's regional environmental policies, reasonable factors are controlled by the model according to the theoretical mechanism of cash flow, carbon risk and expected return. Meanwhile, the model considers the industry characteristics, companies' ownership, size and liquidity factors to make the results more accurate. Third, based on the applicability of the model and the realities of policy implementation, this paper constructs a monthly return on a dynamic portfolio weighted by market value to study whether the stock returns have a carbon premium as a supporting extension.

The rest of the paper is structured as follows. The next section is the literature review. Section 3 introduces China's carbon market. Section 4 describes the economic mechanisms and model assumptions. Section 5 presents the data and methodology. Section 6 analyzes the empirical results. Section 7 concludes.

2. Literature review

The paper reviews the previous literature on ETS from three main aspects. The first focuses on the carbon allowances price. The current research is mainly to analyze the fluctuations and influencing factors of carbon prices and to predict the spot price or future carbon price (see, e.g., Aatola et al., 2013; Chevallier et al., 2011; Chevallier, 2011a; Chevallier, 2011b; Wen et al., 2016; Zhang et al., 2018; Zhu et al., 2015). Zhao et al. (2018) use a mixed frequency data regression model to predict the weekly carbon price of the EU-ETS' (the European Union's emissions trading schemes). The results indicate that, compared with traditional models, the combination-MIDAS model provides improved forecasting performance and supports the economic and energy factors with different sampling frequencies to forecast the weekly carbon price. Chang et al. (2018) show that the liquidity of China's carbon market has an important effect on carbon price movement and pricing efficiency. Zhu and Chevallier (2017) construct a carbon price forecasting model to predict the price of carbon futures contracts more accurately than traditional ARIMA time series models. Overall, these studies reflect the maturity of the emerging financial market (ETS) from the perspective of price information. From the above literature, we can conclude that, comparing with the EU-ETS, the China's carbon price is not sufficient to reflect the effective information of market transactions so far.

The second focuses on the evaluation of China's ETS design and operation. The existing studies discuss the background and the inevitability of establishing China's carbon market. Therefore, it is very important to perform a relevant assessment of China's ETS. Such researches are primarily conducted from the following two perspectives. On the one hand, some researches focus on the top-level design of China's carbon market, using simulation methods to assess the macroeconomic impact of China's carbon market (see. e.g., Ma et al., 2015; Tang et al., 2015). Duan et al. (2018) develop a stochastic 3E (energy-economy-environment) integrated model to evaluate China's energy and climate targets in 2030. Taking Shanghai, China as an example, Wu et al. (2016) use a static CGE model to evaluate the economic effect of ETS policy, and conclude that carbon cap-and-trade can reduce the negative influence on economic output and employment. Because the carbon allowances price and trade volume are mainly determined by the cap allocation scheme, the policymakers should design the mechanism carefully. On the other hand, to assess the effectiveness of carbon emissions trading markets, some studies investigate the driving factors of carbon emissions and the impact of a country or region's carbon market on carbon emissions in neighboring countries or regions. Tan et al. (2018) confirm that the competitiveness and demand channels often result in the transfer of energy-intensive production to other regions. Energy channels lead to increased carbon intensity in other regions which results in a positive leakage. However, the simulation method on the macro level depends on the setting of model parameters and the sampling method, so there is a probability of model-driven inevitably.

The third is to analyze the effect of the carbon market at the microeconomic level and the links between different markets (see, e.g., Anger and Oberndorfer, 2008; Gong and Lin, 2018; Hu et al., 2018; Koch and Mama, 2019; Lin and Jia, 2019; Tian et al., 2015; Wen et al., 2018a; Xiao et al., 2018). Anger and Oberndorfer (2008) analyze the impact of European Union Allowance (EUA) on the performance and employment of German companies and observe no evidence that the distribution of emission rights affects employment and income. Tian et al. (2015) study the impact of carbon price on the stock returns and volatility of electricity companies in the EU-ETS.

In general, the literature on carbon emissions trading is scarce relatively in China's market. According to China's energy market development report, China's oil, coal, electricity and other industries are in the process of market-oriented reform facing the uncertain choice of energy policy. How will China's ETS affect the profitability of micro-enterprises? It's been five or six years since the pilot carbon emissions trading market was launched in China, it is necessary to do empirical study on t the functioning of the various Chinese ETS and the unified China's ETS.

[1] China had not established a unified carbon emissions trading market by the end of the sample period. A company listed on the Shenzhen exchange did not participate in the Shenzhen carbon emissions trading pilot, but it cannot be excluded from being affected by the rest of the carbon emissions trading pilots. Thus, the results will inevitably be disturbed.

3. China's carbon emissions trading market

Under the joint efforts of the international community, the Chinese government has taken several vigorous actions to cope with the problem of global climate change. Following the European Union's emissions trading schemes (EU-ETS), the seven pilot projects for carbon emissions trading in June 2013–June 2014 established the largest carbon market of the world (Tan et al., 2018). These facts mean that the operation of China's carbon emissions trading market plays an important part in the construction of the global unified carbon market and the reduction of greenhouse gas emissions (Zhang and Wang, 2011).

Due to the externality and long-term impact of carbon emissions, the necessary policy regulations are vital for the reduction of energy consumption and emissions. In the past decade, Chinese executive-directed policy tools were ineffective and costly, which prompts us to seek a more flexible and effective policy tool to address the problem of climate change (Zhang, 2016). The introduction of market-oriented policy tools of emissions reduction in China is an innovative attempt. As a market-oriented emissions reduction policy tool, the carbon emissions trading system enables companies, industries and regions to reduce emission through carbon price. Therefore, the carbon emissions trading system helps to ensure a decrease of the entire society's emissions reduction costs and an improvement of emissions reduction efficiency. According to pilot projects, many studies have shown that the design, establishment and operation of China's carbon market are faced with many challenges and result in low market liquidity and inefficiency (see, e.g., Duan et al., 2018; Tan et al., 2018; Wu et al., 2016). Once China's carbon emissions trading market collapses, it will pose large financial risks to the global carbon finance system.

The carbon emissions trading markets in developed countries are becoming mature and gradually form a system. In fact, few developing countries (except for China and Kazakhstan) establish their own carbon markets. As a result, the academic community lacks the evaluation and understanding of the performance of these countries' carbon markets. A lot of developing economies (such as Brazil, Chile, Mexico, Thailand and Vietnam) have showed intention to construct their own carbon emissions trading markets (International Carbon Action Partnership, 2016). Accordingly, China's experience can make significant contributions to these developing countries and regions in the academic debates, as it is the only developing country that has constructed its own ETS (a carbon market in Kazakhstan has been temporarily suspended). Our research may help to develop economies identify and further overcome the potential weaknesses of carbon markets from a financial perspective.

The EU-ETS is implemented in three stages, with each stage having its own policies and laws. As a result, there is more than one policy shock. However, the situation in China is different. At present, the allowances in China's carbon market are almost free throughout the sample period, so there is only one policy shock. Due to the nature of program design, the program could be considered as a quasi-natural experiment. The Shenzhen ETS is one of the first carbon trading schemes approved by the central government in China and has the most complete carbon emissions records. In general, the Shenzhen pilot is the most representative among all pilots from the perspective of heterogeneity including the legal basis, modes of quota allocation and the trading conditions (Xiong et al., 2017).

4. Economic mechanisms and hypothesis

Our empirical analysis mainly relies on the following two economic mechanisms.

(1) The cash flow effect: In this part, we start to discuss whether and how a cap-and-trade system with free allocations will generate additional profits for companies involved in carbon emissions trading from the perspective of costs and benefits. We employ the theory of Goulder and Mathai (2010) to illustrate that a cap-and-trade system raises the production marginal cost which further leads to a change of cash flow. First, we will explain the economic impact of the rising marginal costs of the affected companies. Second, we will identify how changes in marginal costs lead to an increase or decrease in company profits.

Fig. 1 shows the impact of the allocation of free carbon emissions allowances on company profits in specific industries from the perspective of the basic economic principles—demand and supply. When there is no policy shock, the initial market equilibrium price and output at the industry level are denoted as P_0 and X_0, respectively. These are decided by the intersection (at point b) of the initial supply and demand curves S_0 and D. A cap-and-trade mechanism encouraging companies to release emissions with a free allocation of carbon allowances, leads the supply curve shift up from S_0 to S_1.

In general, a company can use two ways to accomplish the production without exceeding a certain amount of carbon emissions. For one way, the cap-and-trade system obliged the company to purchase additional allowances, or release the number of surplus allowances that the company can sell. Note that, the incremental marginal cost to a company is equal to the market value of the allowances needed to produce per unit of product, which is either the explicit cost (actual) of the allowances purchased in the carbon emissions trading market or the implicit cost (opportunity) of not being able to sell in the trading market due to the use of allowances. The other way is a company can accomplish emissions reductions by switching to less carbon-intensive fuels, installing end-of-pipe equipment, or reducing its level of output. In Fig. 1, we assume that the higher marginal cost due to the actual or opportunity cost of the carbon allowances required per unit of output, denoted by r. We also assume the higher marginal cost associated with a less carbon-intensive technology, denoted by c. The regulation thus yields the new supply curve S_1. In the new equilibrium, output is X_1 and the consumer price P_c exceeds the original marginal supply cost by $c + r$.

In this case the green rectangle A ($P_c$aef) which is equal to $r\,^*X_1$ represents rents producers, the red area B (P_0bdP_s) represents the gross loss of producer surplus (the loss before considering the rents). In the figure, the difference of area A minus area B is positive, which suggests that the free allocation of carbon allowances provides the company with higher profits in the presence of carbon regulation.

Finally, we discuss the existence of uncertainties from the newly established Emissions Trading Scheme (ETS) and model assumptions. The data on carbon emissions information is not public at the end of sample period, such as the number of carbon allowances allocated to each company and each company's carbon intensity. There are other unknowns as well: The location of f is uncertain, that is, the degree to which the opportunity cost of the allowances is incorporated into prices and the degree to which companies invest in alternative less carbon-intensive technologies are certain. The location of point f raises the following questions: Does the ETS trigger innovation in terms of processes or management at the company-level, thus increasing excess returns due to Porter effect. Dong et al. (2019) find that the China's ETS policy regulations don't bring short-term Porter effect, however, Wu et al. (2018) consider that China's ETS can realize the environmental dividend and reduce some the economic dividend in the short term. In addition, the analysis in Fig. 1 is targeted at companies in a specific industry level, so there are differences in supply elasticity, emissions reduction costs, energy conversion rate and other aspects in different industries, which will lead to changes in producer surplus. Moreover, the significance of the cash flow effect mainly depends on the amounts of free certificates and on how much a company is able to pass-through emissions costs to output prices. In some industries the pass-through rates are large. For instance, Fabra and Reguant (2014) find that there

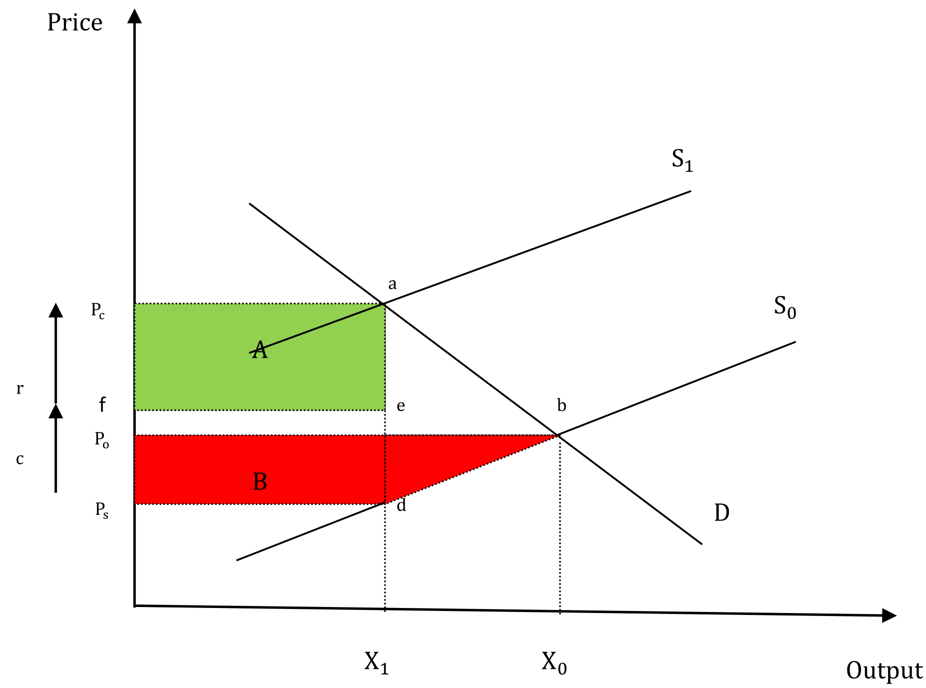

Fig. 1. Free carbon emissions allowances, rents and company profits.

is above 80% pass-through rate in the Spanish electricity market indicating that 1 EUR increasing in emission costs which transfer to the electricity market would increase more than 80 cents in electricity prices, on average. Based on the above considerations, we believe that it is necessary to control the industry factors in the model. At present, many studies are devoted to research the impact of government policy uncertainty on stock prices, and identify the effect of uncertainty on companies' profitability (Pastor and Veronesi, 2012). Because of the opacity of policy, we need to control certain characteristics at the company level. For example, due to the particularity of China's national conditions, the degree of carbon costs transmission may vary between state-owned companies and private companies (as many prices are set by the government rather than the market).

Overall, this analysis induces our hypothesis 1:

Hypothesis 1. *Other things being equal, companies which receive free carbon allowances will generate a positive producer surplus (A minus B is positive) on average, and thus will experience higher cash flow. In other words, we assume that the carbon trading market (Shenzhen pilot) will have a positive impact on the excess return of companies involved in carbon emission allowances trading.*

(2) The "carbon risk" effect: Next, we try to discuss whether and how a cap-and-trade system with free allocations will generate additional profits for companies involved in carbon emissions trading from the perspective of expected return. The stock returns of companies on financial markets reflect the discounted value of expected future profits (Jensen, 1986). According to this effect, the companies involved in the carbon emissions trading market have higher carbon exposures for the uncertainty of carbon price in the future, which in turn results in future cash flows uncertainty. The carbon price represents the present value of the social costs of emitting one tonne of CO_2. Liu et al. (2015) show that, from the perspective of politics and economy or from the perspective of survival and development, reducing greenhouse gas emissions is an irreversible policy, and the social cost of environmental pollution cannot be accurately estimated at present. We can almost expect the cap is getting tighter and tighter. Besides, the cost changes in the companies will affect production assessment and decisions (such as the position of f and quantity of output), thus bringing more fluctuations to the company's future cash flow. Studies have shown that companies involved in carbon emissions trading market will be exposed to carbon risk as they may face a higher carbon price in the future due to the catastrophic climate change. The carbon risk is non-diversifiable and will generate risk premium determined by societal risk aversion (Weitzman, 2009; Litterman, 2013; Pindyck, 2013). Moreover, as discussed above, in the early stages of Emissions Trading Scheme (ETS), the lack of policy transparency or institutional changes, such as initial free allowances of carbon emissions and then use them for auctions, will also affect future cash flow.

Overall, this discussion induces our hypothesis 2:

Hypothesis 2. *Other things being equal, the companies participating in the carbon market have higher carbon exposures than other companies. This is a further reason why the carbon trading market (Shenzhen pilot) will have a positive impact on the excess return of companies participating in the carbon market. In other words, the stock returns have a carbon premium.*

5. Data and methodology

5.1. Data

Shenzhen Pilot ETS commenced operations in June 2013. By 2018, there are 297 listed companies in Shenzhen. According to the list of regulated companies issued by the Shenzhen Carbon Emissions Exchange, a total of 52 listed companies are identified for participating in carbon emissions trading and fulfilling their obligations (see Table A1 in

Table 1
Balancing test by the participation status.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$SIZE_t$	9.89e−9***	9.88e−9***	8.14e−9***	8.10e−9***	7.52e−9***	7.61e−9***	7.61e−9***	7.50e−9***	7.50e−9***	3.18e−9***	2.98e−9***	2.82e−9***	3.13e−9
	(23.74)	(23.78)	(19.02)	(18.97)	(17.76)	(17.86)	(17.85)	(17.62)	(17.64)	(7.81)	(7.15)	(7.12)	(1.08)
$OWNERSHIP_t$	.	−0.027*	−0.036**	−0.036**	−0.041***	−0.041***	−0.041***	−0.040**	−0.040**	−0.114***	−0.114***	−0.121***	−0.136
		(−1.68)	(−2.25)	(−2.26)	(−2.60)	(−2.62)	(−2.61)	(−2.53)	(−2.54)	(−7.75)	(−7.75)	(−8.64)	(−0.95)
$R_{m,t}$			0.404***	0.496***	0.487***	0.461***	0.461***	0.408***	0.430***	0.023	−0.014	0.004	−0.259
			(14.77)	(15.98)	(15.58)	(14.52)	(14.50)	(12.52)	(12.69)	(0.70)	(−0.38)	(0.12)	(−1.29)
SMB_t				−0.460***	0.723***	0.527***	0.526***	0.542***	0.468***	0.153	0.142	−0.096	−1.077
				(−6.22)	(6.33)	(4.08)	(4.07)	(4.21)	(3.53)	(1.26)	(1.17)	(−0.83)	(−1.13)
HML_t					2.558***	2.578***	2.575***	2.671***	2.796***	1.069***	1.109***	−0.003	−2.111
					(13.49)	(13.59)	(13.04)	(13.53)	(13.67)	(5.58)	(5.76)	(−0.02)	(−1.10)
RMW_t						−0.677***	−0.675***	−0.888***	−0.903***	−0.913***	−1.099***	−0.039	−1.079
						(−3.26)	(−3.19)	(−4.17)	(−4.24)	(−4.68)	(−5.16)	(−0.19)	(−1.03)
CMA_t							0.014	−0.600**	−0.630**	−0.802***	−0.897***	−0.011	0.948
							(0.05)	(−2.05)	(−2.15)	(−2.99)	(−3.30)	(−0.04)	(0.93)
$ILLIQ_t$								−0.406***	−0.403***	−0.532***	−0.514***	−0.026	−0.514
								(−7.18)	(−7.14)	(−10.27)	(−9.77)	(−0.51)	(−1.14)
DMC_t									0.125**	0.003	−0.005	0.021	−0.241
									(2.34)	(0.06)	(−0.09)	(0.45)	(−0.81)
Trend										0.005***	−0.011	0.012*	−0.067
										(42.29)	(−1.48)	(1,73)	(−0.17)
Trend^2											1.82e−4**	−9.34e−5*	3.58e−6
											(2.18)	(−1.82)	(0.16)
Year*Trend												0.001***	0.002
												(33.47)	(0.45)
Company fixed effects	N	N	N	N	N	N	N	N	N	N	N	N	Y
Year fixed effects	N	N	N	N	N	N	N	N	N	N	N	N	Y

Notes: This table shows the coefficient of the interaction term of participation status and a post policy-change dummy (equal to 1 if the year corresponds to June 2013 or later) from a separate regression performed using the respective variable as the independent variable based on Model (1). T-statistics are in parentheses. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Table 2
Estimation results of Model (1).

	(1)	(2)	(3)
Treat*T	0. 009	0.009	0.012
	(1.56)	(1.55)	(1.43)
$SIZE_t$	1.18e-9	1.00e-9	3.56e-10
	(3.67)	(2.07)	(0.72)
$OWNERSHIP_t$	0.001	0.001	−0.001
	(0.15)	(0.15)	(−0.04)
$R_{m,t}$	2.488	2.434	2.208
	(2.60)	(2.44)	(1.58)
SMB_t	6.510	6.189	4.838
	(1.66)	(1.51)	(0.85)
HML_t	12.722	12.070	9.474
	(1.65)	(1.50)	(0.85)
RMW_t	3.964	3.425	0. 790
	(0.84)	(0.70)	(0.11)
CMA_t	−3.533	−3.104	−1.217
	(−1.00)	(−0.84)	(−0.24)
$ILLIQ_t$	2.893	2.768	2.142
	(1.45)	(1.33)	(0.74)
DMC_t	1.405	1.327	0. 933
	(1.19)	(1.08)	(0.54)
Trend	0.533	0.547	1.876
	(0.41)	(0.41)	(0.360)
Trend^2	−0.000	−0.000	−0.001
	(−0.42)	(−0.42)	(0.359)
Year*Trend	0.065	0.065	N
	(0.52)	(0.50)	
Observations	9494	9424	4299
R^2	0.264	0.266	0.282
Company fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y

Note: T-statistics are in parentheses.

Appendix A). Among them, 30 listed companies have been involved in carbon emissions trading and fulfilled their obligations.[2]

The sample period is from August 2009 to June 2018. 52 listed companies involved in carbon emissions trading are selected as the treatment group. Monthly stock returns are computed as $r_{j,\ t+1} = \mathrm{Ln}(P_{j,\ t+1}) - \mathrm{Ln}(P_{j,\ t})$, where $P_{j,\ t}$ denote the monthly closing price of stock j at time t obtained from the Cathay database. According to the industry characteristics of 52 companies, 125 of the 245 companies that do not participate in carbon emissions trading are matched as a control group.

5.2. DID approach

The primary purpose of this paper is to evaluate the influence of establishing China's carbon emissions trading market on stock returns. In an ideal research setting, the status of participation in carbon emissions trading will be randomly assigned across companies, creating variations uncorrelated with baseline characteristics. In the absence of a randomized controlled trial, we employ a difference-in-differences (DID) approach on the basis of the participation in carbon emissions trading status (Chen et al., 2013; Ebenstein et al., 2017):

$$y_{it} = \alpha + \beta^{*}\mathrm{Treat}_{it} * T_t + \gamma \mathrm{Treat}_{it} + \delta T_t + \mathrm{Control}_{it} + \mathrm{Trend} + k_t + u_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the abnormal return of the stock of company i in year t. Treat_{it} is an indicator variable that has the value of one if company i participated in the carbon emissions trading in June 2013. T_t is an indicator variable that is one for years corresponding to June 2013 or later. The company fixed effects u_i control for the permanent heterogeneity across companies, whereas the year fixed effects k_t control for year-specific shocks that are common to both participating and nonparticipating companies. $\mathrm{Control}_{it}$ variables include the monthly excess return $R_{m,t}$ of the market portfolio, the "small-minus-big" size factor SMB_t, the "high-minus-low" value factor HML_t (Fama and French, 2004, 2006), the "robust-minus-weak" profitability factor $RMW_{t,}$ the "conservative-minus-aggressive" investment factor CMA_t (Fama and French, 2015), the liquidity factor $ILLIQ_t$ (Amihud, 2002), the "dirty-minus-clean" (DMC) risk factor (Oestreich and Tsiakas, 2015), the market value factor $SIZE_t$, the ownership factor $OWNERSHIP_t$ of the company as of the respective year, and the trend factor controlling for the company-specific linear trend. All standard errors are clustered at the company level, allowing for an arbitrary correlation among companies over time.

The parameter of interest is β, the influence of the construction of China's carbon market on stock returns, capturing the changes in stock returns before and after the regulations between the companies that participated and no participated by June 2013.

6. Empirical results

6.1. Validity of the identification assumptions

The key identification assumption needed the Model (1) to provide for a causal inference is that the nonparticipating companies provide valid and counterfactual changes in stock returns for the participating companies. Two potential hypotheses may violate this assumption: (1) there is no a systematic difference in pre-existing trends in stock returns, and/or (2) the participation status is not orthogonal to factors explaining the changes of stock returns in the posttreatment period.

To analyze the pre-existing trend, we present the evolution of stock returns over time for participating and nonparticipating companies in Fig. 1. The figure provides visual support that the stock returns' trends are similar in the preintervention period.

[2] From June to July every year, Shenzhen Carbon Emissions Exchange publishes the list of carbon trading control companies that have fulfilled their obligations on time from the second half of the previous year to the first half of this year. We have identified a total of 52 listed companies that have successively fulfilled their obligations. As the list of companies changes every year, we adopt the multi-period DID estimation. Among them, 30 companies have not changed during the sample period (they have been fulfilled their obligations on time).

Table 3
Primary results for propensity score matching.

Psmatch2: treatment assignment	Psmatch2: common support		Total
	Off support	On support	
Untreated	70	6401	6471
Treated	0	3023	3023
Total	70	9424	9494

Another concern is that the influence of establishing China's carbon market may be confounded by other concurrent changes in regulations or factors affecting stock returns. For example, there might be policy preferences when the government allocates the emission allocations through administrative measure, such as giving more compensations to state-owned companies. In other words, the impact of such environmental regulation on company stock returns may not be random. To solve this issue, we study whether the participation status has any association with observable characteristics change. The idealized assumption state is that the treatment status and unobservable characteristics show no comovement. That is, we should choose the treatment group randomly. The insignificant correlation between the treatment status and observable characteristics indicates that there should not be significant correlations between the treatment status and unobservable variables either, even though this is not a formal test of exclusion restrictions (Altonji et al., 2005; Moser and Voena, 2012).

We use the respective variables as the independent variables based on Model (1) to perform two-way fixed effects regressions, while the dependent variable is defined as the interaction term of participation status and a post policy-change dummy (equal to 1 if the year corresponds to June 2013 or later).

Table 1 reports the potential differences of characteristic variables between participating and nonparticipating companies in trends before and after the policy change. The results in Table 1 indicate that a systematic difference in trend patterns may confound the policy effects. Column 14 of Table 1 shows that after controlling the respective variables, the regression results are insignificant, indicating that the control variables have not been related to the policy shock so far. Although it cannot be asserted that the policy shock must be random, at least the hypothesis of the policy shock being random cannot be rejected.

In short, these results provide supporting evidence that participation in China's carbon emissions trading market is not related to trends in observable determinants of stock returns. It indicates that the current research method is unlikely to be biased by changes in unobservable variables.

6.2. Primary DID results for stock returns

We report the DID results of the impact of establishing China's carbon market on stock returns in Table 2. Table 2 provides the result from Model (1) with company and year fixed effects. The results in Table 2 show positive coefficients throughout the Treat*T variable indicating the carbon trading market (Shenzhen pilot) might have a positive impact on the excess return of companies participating in carbon emission allowances trading. Although the coefficient is not statistically significant, with t-statistics around 1.56 it is much closed to the 10% significance level. The sample selection bias could be one explanation for the lack of significance. Thus, we do the sample matching to avoid this problem.

6.3. Main PSM+DID results on stock returns

As we all known, it is difficult to select a subset from the control group that is the same as or similar to the treatment group because there are many unobservable or unquantifiable factors that measure the individual characteristics of a company. Therefore, we choose a combination of propensity score matching and DID for a further robustness test.

We match 52 companies involved in carbon emissions trading with 125 nonparticipating companies. Table 3 and Fig. 2 present the

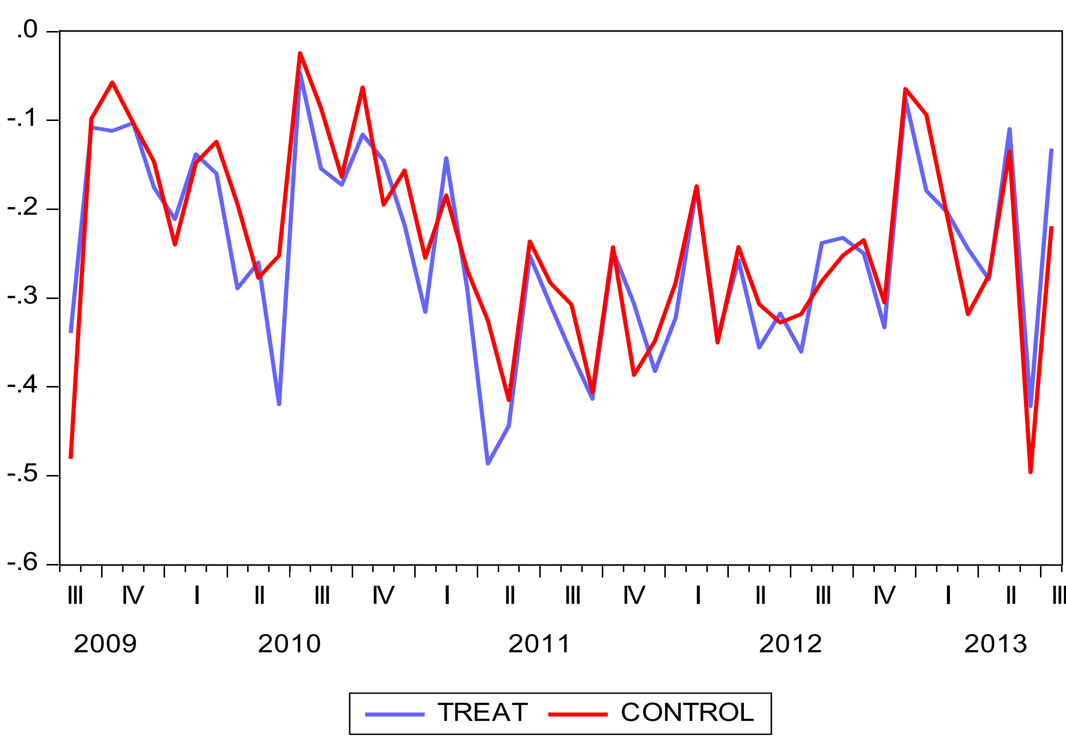

Fig. 2. Excess stock returns before June 2013. Notes: this figure plots the trend of excess stock returns causes for the participating (blue line) and nonparticipating (red line) companies before the intervention. We construct the market value-weighted dynamic portfolio's monthly returns for the treatment group and the control group.

Table 4
Balancing test of propensity score matching.

Variable	Unmatched	Mean		% reduct		*t*-Test		V(T)/
	Matched	Treated	Control	%bias	[bias]	t	*p* > [t]	V(C)
$SIZE_t$	U	1.5e+7	7.7e+6	49.1		18.53	0.000	1.39*
	M	1.5e+7	1.4e+7	8.6	82.4	2.16	0.031	0.94
$OWNERSHIP_t$	U	1.837	1.774	11.7		4.12	0.000	0.93
	M	1.837	1.945	−20.3	−73.3	−5.70	0.000	1.02
$R_{m,t}$	U	−0.167	−0.213	44.1		15.57	0.000	0.96
	M	−0.167	−0.171	3.7	91.6	1.03	0.333	1.02
SMB_t	U	0.019	0.015	8.2		3.27	0.001	1.82*
	M	0.019	0.017	4.0	51.7	0.97	0.333	1.03
HML_t	U	0.002	−0.002	12.7		4.98	0.000	1.69*
	M	0.002	0.002	−2.1	83.3	−0.52	0.604	1.00
RMW_t	U	−0.007	−0.003	−15.8		−6.10	0.000	1.58*
	M	−0.007	−0.007	1.5	90.3	0.38	0.704	1.03
CMA_t	U	0.002	0.001	9.0		3.42	0.001	1.43*
	M	0.002	0.001	6.3	30.3	1.59	0.111	1.02
$ILLIQ_t$	U	0.060	0.072	−23.7		−8.29	0.000	0.90*
	M	0.060	0.059	2.5	89.4	0.73	0.466	1.12
DMC_t	U	−0.010	−0.003	−9.7		−3.54	0.000	1.18*
	M	−0.010	−0.011	1.5	84.9	0.37	0.708	0.91
Trend	U	662.52	637.45	132.0		39.23	0.000	0.25*
	M	662.52	661.45	5.7	95.7	2.55	0.011	1.01
Trend^2	U	4.4e+5	4.1e+5	131.4		39.26	0.000	0.23*
	M	4.4e+5	4.4e+5	5.8	95.6	2.55	0.011	1.01
T*Trend	U	662.52	261.84	174.7		47.86	0.000	1.59*
	M	662.52	661.45	0.5	99.7	2.55	0.011	1.01
Company fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y

Note: asterisk denotes statistical significance at the 10% (*) levels.

propensity score matching results. Table 4 reports the results for propensity score matching the balance test (see Fig. 3).

The results of propensity score matching show that 70 samples fail to match in the control group indicating that only a small amount of the samples do not match successfully. By comparing the changes of normalized deviations of each variable before and after matching, it can be seen intuitively that the normalized deviations of most variables are greatly reduced after matching, and the normalized deviations of more than half of the variables are less than 10%. After matching, the results of t-test for almost all variables do not reject the original hypothesis that there is no systematic difference between the treatment group and the control group. These findings can be explained that the method of propensity score matching is applicable, and the sample selection bias is corrected to some extent after matching.

Column 3 in Table 2 reports the results of the combination of propensity score matching and DID. The regression coefficients are very similar to Column 2, indicating that a small number of sample selection biases of the control and treatment groups do not result in the lack of significance.

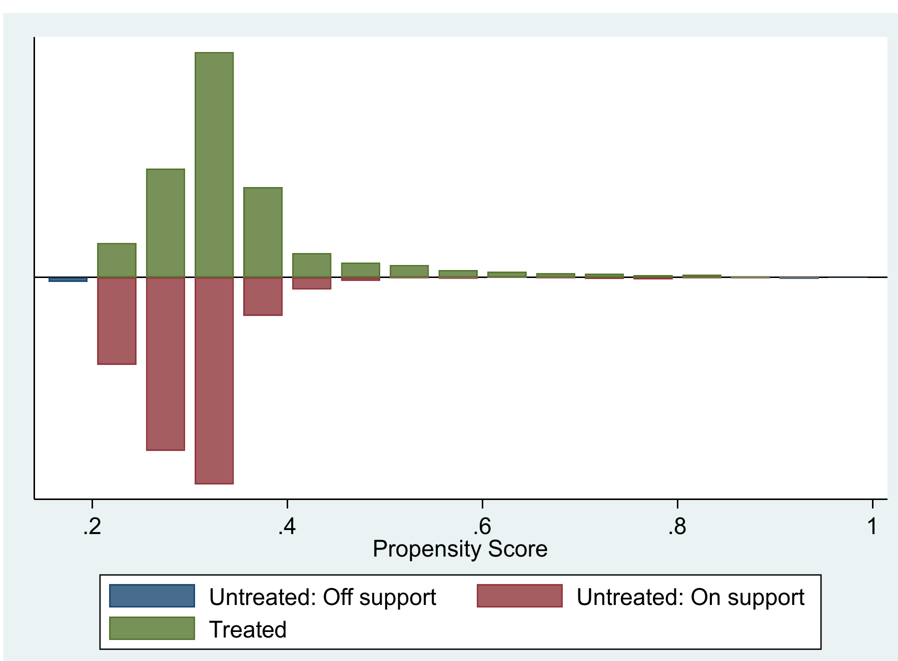

Fig. 3. Range of common values for propensity scores.

6.4. Main DID results of further robustness test

The lists of 52 listed companies that have successively fulfilled their obligations change every year. Although we adopt the multi-period DID estimation, the reasons behind these changes are still not clear. For example, for what reasons does a company choose to join or withdraw? Is there an implicit reward or punishment mechanism that affects the costs and benefits of the company? This will also lead to sample selection bias to some extent. For the robustness of the empirical results, we select 30 companies as the treatment group that have been involved in carbon emissions trading and fulfilled their obligations. Based on the industry characteristics of these 30 companies, 96 of 245 companies that have not participated in carbon emissions trading are matched as the control group, and the experiment is repeated. The results of balancing test are reported in Table 5.

Similar to the results in Table 1, Column 13 of Table 5 shows that after controlling the respective variables the regression results are insignificant, indicating that there is no a systematic difference in trend patterns between the participating and nonparticipating companies.

We report the DID results of the impact of establishing China's carbon emissions trading market on stock returns in Column 4 of Table 2. Compared to Column 2 and Column 3, there is no significant difference in DID regression results. The regression coefficients are positive, and the t-values are very close to the significance level of 10% generally. So far, we can conclude cautiously that the results in Table 2 indicate that sample selection may not be the reason for the lack of significance of regression results.

Our primary finding from the above analysis is that the free allocation of carbon emissions allowances at the early stage of the Shenzhen pilot ETS may not generate a significant impact on stock returns statistically. In conclusion, our empirical results might not statistically support hypothesis (H1) - the carbon trading market (Shenzhen pilot) will have a positive impact on the excess return of companies participating in carbon emission allowances trading.

Table 6
Descriptive statistics of the daily spot trading volume and turnover in the Shenzhen pilot ETS.

Variable	Obs	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
Turnover	1416	487,061.6	3,656,372	0	1.00e +08	24.613	639.730
Volume	1416	17,473.94	156,046.7	0	4.00e +06	21.850	514.776

6.5. Discussion of the theoretical mechanism

In this section, we will further analyze and discuss the above conclusions from the perspective of carbon emissions trading market.

Table 6 presents the descriptive statistics of the daily spot trading volume and turnover in the Shenzhen pilot ETS during the sample period. Fig. 4 plots the daily spot trading volume and turnover in the Shenzhen pilot ETS during the sample period. Table 6 shows that both trading volume and turnover show intense volatility and extremely high peaks. Fig. 4 shows that, except for a few large transactions, the daily trading volume and turnover are small. We can speculate that the unusual market trend seems to be driven by private negotiations between institutional buyers and sellers. Liu et al. (2015) believe that China's carbon emissions trading is mainly driven by the executive order of the government. The initial carbon emissions trading in Beijing and Shanghai is conducted under the coordination of the local governments, with the buyer and seller negotiating to form a transaction price.

In China's carbon emissions trading market, the liquidity of the market and the enthusiasm of companies are both low (Zhao et al., 2016). This phenomenon is due to the following reasons: First, from the perspective of investor awareness, there is a poor understanding of the operation of carbon trading systems. Although some companies have knowledge and skills about carbon trading rules and carbon asset management, they are weak in market awareness. They merely regard participation in emissions trading as a responsibility or participate for compliance purposes and lack investment awareness (Jiang et al., 2016). Second, from the perspective of market regulation, many

Table 5
Balancing test by the participation status.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$SIZE_t$	1.80e−8***	1.80e−8***	1.63e−8***	1.63e−8***	1.56e−8***	1.58e−8***	1.58e−8***	1.56e−8***	1.56e−8***	9.28e−9***	9.98e−9***	9.61e−9
	(28.77)	(28.73)	(24.71)	(24.75)	(23.59)	(23.83)	(23.83)	(23.61)	(23.62)	(14.31)	(14.83)	(1.08)
$OWNERSHIP_t$	.	−0.066**	−0.069***	−0.068**	−0.070***	−0.071***	−0.071***	−0.069***	−0.069***	−0.109***	−0.108***	−0.112
		(−2.43)	(−2.56)	(−2.53)	(−2.63)	(−2.65)	(−2.66)	(−2.60)	(−2.60)	(−4.32)	(−4.31)	(−0.95)
$R_{m,t}$			0.247***	0.341***	0.341***	0.305***	0.303***	0.260***	0.280***	−0.104***	−0.027	0.113
			(7.35)	(8.95)	(9.02)	(7.79)	(7.74)	(6.47)	(6.74)	(−2.57)	(−0.61)	(0.54)
SMB_t				−0.464***	0.566***	0.299*	0.302*	0.316**	0.247	−0.011	0.010	0.376
				(−5.20)	(4.07)	(1.90)	(1.92)	(2.01)	(1.53)	(−0.08)	(0.07)	(0.35)
HML_t					2.231***	2.254***	2.294***	2.371***	2.490***	0.974***	0.888***	0.440
					(9.62)	(9.72)	(9.49)	(9.81)	(9.96)	(4.12)	(3.74)	(0.19)
RMW_t						−0.911***	−0.941***	−1.113***	−1.123***	−1.283***	−0.876***	0.473
						(−3.60)	(−3.65)	(−4.28)	(−4.32)	(−5.33)	(−3.33)	(0.36)
CMA_t							−0.200	−0.719**	−0.746**	−1.032***	−0.821**	0.270
							(−0.59)	(−2.02)	(−2.10)	(−3.13)	(−2.46)	(0.18)
$ILLIQ_t$								−0.338***	−0.336***	−0.439***	−0.475***	0.208
								(−4.96)	(−4.93)	(−6.95)	(−7.45)	(0.41)
DMC_t									0.121*	−0.014	0.001	0.104
									(1.87)	(−0.23)	(0.01)	(0.27)
Trend										0.005***	0.041***	0.056
										(31.38)	(4.35)	(1.03)
Trend^2											−1.10e-4**	−3.21e-6
											(−3.82)	(−0.99)
Company fixed effects	N	N	N	N	N	N	N	N	N	N	N	Y
Year fixed effects	N	N	N	N	N	N	N	N	N	N	N	Y

Notes: This table shows the coefficient of the interaction term of participation status and a post policy-change dummy (equal to 1 if the year corresponds to June 2013 or later) from a separate regression performed using the respective variable as the independent variable based on Model (1). T-statistics are in parentheses. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

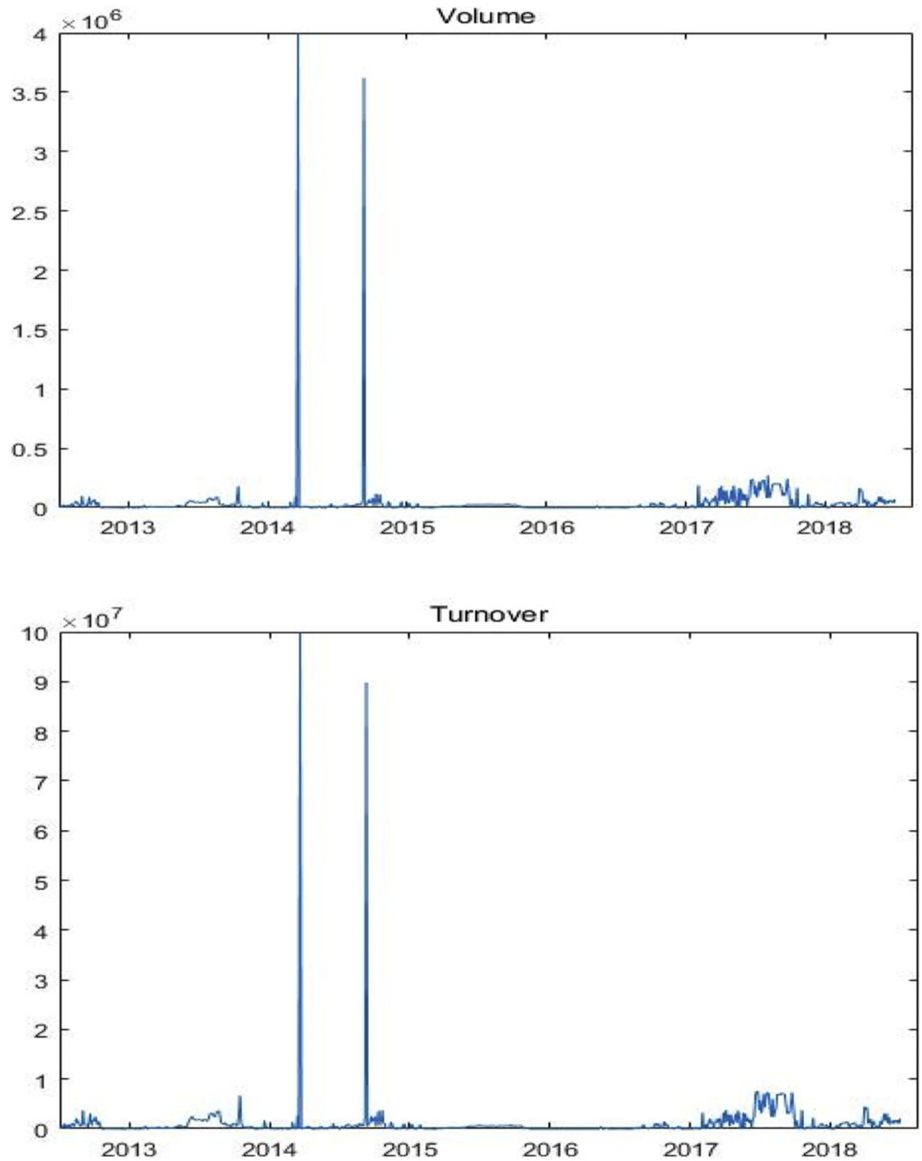

Fig. 4. Plots of the daily spot trading volume and turnover in the Shenzhen pilot ETS during the sample period.

companies tend to consider that the government is not strict in enforcing compliance, which in some ways makes China's carbon trading lack momentum (Munnings et al., 2016). China Carbon Market Research Report (2014) covers companies participating in the Shanghai ETS. It shows that only 6% of companies are actively involved in carbon emissions trading, while the rest are passively involved. In addition, from the perspective of market maturity, the imperfect development of China's pilot secondary market for carbon emissions trading has also hampered the positivity for companies to take part in trading and investment. Furthermore, from the perspective of market supply and demand, Anger and Oberndorfer (2008) point out that the price of emissions rights (EUAs) is affected by licensing. More stringently they are allocated, the higher the price of EUAs will be. Thus, further the stocks of related industries and enterprises will be affected. We can infer from this observation that there is excessive compensation in China's carbon emissions trading market (Wen et al., 2018b). Finally, from the perspective of uncertainty, the uncertainty of carbon emissions trading system information makes it more difficult for market participants to predict the future trend of carbon prices and manage participants' portfolios. Due to imperfections in China's carbon emissions data, market regulation, laws and regulations, and uncertainty about future climate and environmental impacts, participants in carbon emissions trading are often conservative. Companies with excess allowances are reluctant to sell, while companies producing large amounts of carbon emissions are keen to buy, resulting in supply and demand not being met (Wen et al., 2014).

In general, it may be that the low maturity of the current carbon market distorts the price formation mechanism, which further results in the deviation between the empirical results and the theoretical hypothesis. However, it is precisely because of this non-market price formation mechanism and the particularity of small samples that we can cautiously infer that our empirical results are economically significant. Moreover, the empirical results also indicate that the emission trading pilot policy doesn't bring the short-term Porter effect at the microeconomic level.

6.6. The carbon premium in stock returns

The results in Table 2 show positive coefficients throughout for the Treat*T variable, indicating the possible existence of a carbon premium. Oestreich and Tsiakas (2015) apply the capital asset pricing model and Fama-French factor models, and use a “dirty” vs. “clean” portfolio

Table 7
Results of the first portfolio classification approach.

	CAPM-α	FF3-α	FF5-α	ILLIQ-α	DMC-α
2009.8–2013.5	−0.176***	−0.252***	−0.221***	−0.217***	−0.148***
	(−5.74)	(−7.66)	(−6.77)	(−6.11)	(−9.68)
2013.6–2018.6 (2013.6–2016.11)	−0.131***	−0.205***	−0.181***	−0.191***	−0.135***
	(−5.97)	(−6.69)	(−6.34)	(−5.80)	(−6.80)
	CAPM+SZA-α	FF3+SZA-α	FF5+SZA-α	ILLIQ+SZA-α	DMC+SZA-α
2013.6–2018.6 (2013.6–2016.11)	−0.130***	−0.207***	−0.181***	−0.191***	−0.134***
	(−5.82)	(−6.58)	(−6.16)	(−5.65)	(−6.89)
β_{SZA}	0.060	−0.039	0.011	0.011	0.030
	(0.73)	(−0.40)	(0.12)	(0.12)	(0.59)
β_{DMC}					1.180***
					(8.65)

Notes: the "dirty" portfolio contains 52 companies that are involved in carbon emissions trading and receive the free carbon allowance over the sample period. The "clean" portfolio contains 245 companies that do not receive any carbon allowance and do not participate in the Shenzhen pilot ETS. The return of dirty-minus-clean portfolio is that of the "dirty" portfolio less that of the "clean" portfolio. All portfolios are market value-weighted. CAPM-α is the alpha of a CAPM regression. FF3-α is the alpha of the Fama-French three-factor model regression. FF5-α is the alpha of the Fama-French five-factor model regression. ILLIQ-α is the alpha of the regression model with a liquidity factor based on the Fama-French five-factor model. DMC-α is the alpha of the regression model with a risk factor. SZA is the spot price of carbon emissions in the Shenzhen Pilot Emissions Trading Scheme. T-statistics are in parentheses. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

approach with data from the German stock market. The abnormal return (alpha) of the "dirty-minus-clean" portfolios is defined as a carbon premium. They compare the spatial and temporal variations of alpha to analyze the effect of the carbon market on stock returns. Our empirical results provide a framework for studying whether carbon emission allowances could bring higher expected returns for companies involved in carbon emissions trading.

We do not have data on carbon emissions information, so we refer to the method of Zhang and Gregory-Allen (2018). First, according to the list of regulatory companies issued by the Shenzhen Carbon Emissions Exchange, 52 listed companies are identified for participating in carbon emissions trading and receiving free carbon allowances over the sample period. This group, for which the market value-weighted dynamic portfolio's monthly returns are constructed, forms our "dirty" portfolio (Dai and Wen, 2018). We further identify 245 listed companies that do not receive carbon allowances and do not participate in the Shenzhen pilot ETS to form the "clean" portfolio. In addition, we extend the models of Oestreich and Tsiakas (2015) and Zhang and Gregory-Allen (2018) to ensure the robustness of the empirical results.

Based on Oestreich and Tsiakas (2015) and Zhang and Gregory-Allen (2018), we examine the market value-weighted portfolio returns based on overall means, standard deviations, and risk models chosen from CAPM, Fama-French 3- and 5-factor models and extended-factor models. In all cases, we examine dirty, clean and "clean-dirty" portfolios (Dai et al., 2016).

$$r_{j,t}-r_{f,t} = \alpha_j + \beta_{j1}(r_{M,t}-r_{f,t}) + \varepsilon_t \tag{2}$$

$$r_{j,t}-r_{f,t} = \alpha_j + \beta_{j1}(r_{M,t}-r_{f,t}) + \beta_{j2}SMB_t + \beta_{j3}HML_t + \varepsilon_t \tag{3}$$

$$r_{j,t}-r_{f,t} = \alpha_j + \beta_{j1}(r_{M,t}-r_{f,t}) + \beta_{j2}SMB_t + \beta_{j3}HML_t + \beta_{j4}RMW_t + \beta_{j5}CMA_t + \varepsilon_t \tag{4}$$

$$r_{j,t}-r_{f,t} = \alpha_j + \beta_{j1}(r_{M,t}-r_{f,t}) + \beta_{j2}SMB_t + \beta_{j3}HML_t + \beta_{j4}RMW_t + \beta_{j5}CMA_t + \beta_{j6}ILLIQ_t + \varepsilon_t \tag{5}$$

$$r_{j,t}-r_{f,t} = \alpha_j + \beta_{j1}(r_{M,t}-r_{f,t}) + \beta_{j2}SMB_t + \beta_{j3}HML_t + \beta_{j4}RMW_t + \beta_{j5}CMA_t + \beta_{j6}ILLIQ_t + \beta_{j7}DMC_t + \varepsilon_t \tag{6}$$

where $r_{j,t}$ is the monthly return of portfolio j at time t. $r_{f,t}$ is the monthly risk-free rate at time t. $r_{M,t}$ is the market portfolio at time t. SMB_t is the "small-minus-big" size factor. HML_t is the "high-minus-low" value factor. RMW_t is the "robust-minus-weak" profitability factor. CMA_t is the "conservative-minus-aggressive" investment factor. $ILLIQ_t$ is the liquidity factor. DMC_t is the carbon risk factor. $\varepsilon_{j,t}$ is a normal error term.

Table 7 reports the results of the first portfolio classification approach, which mostly shows the results of the carbon premium. According to the method of Oestreich and Tsiakas (2015), we define the carbon premium as abnormal return (alpha) of the "dirty-minus-clean" portfolio. The empirical results of the five models show a high degree of consistency, indicating that our results are robust. Shenzhen Pilot ETS commenced operations in June 2013.The sample period of the CAPM model is from June 2009 to June 2018. However, because the data are unavailable, the sample period of the remaining four factor models is from June 2009 to November 2016.

It is clear from the results that the abnormal return (alpha) of the "dirty-minus-clean" portfolio is significantly negative during the sample period. After the establishment of China's carbon market, the carbon premium has increased. Furthermore, for all instances, we employ the price data to generate a time series of the return of each variable. For instance, we calculate the return of the SZA as $r_{SZA,\ t+1} = \mathrm{Ln}(P_{SZA,\ t+1}) - \mathrm{Ln}(P_{SZA,\ t})$, where $P_{SZA,\ t}$ denotes the SZA price series at time t. Next, we employ the dirty-minus-clean portfolio returns to estimate the factor models with the additional explanatory variable. The related results are presented in Table 7. We observe that the sensitivity (beta) of the SZA is not significant and it cannot influence the alpha of the regression (i.e., the carbon premium).

Table 8 shows the results of the second approach with matched industry characteristics for the dirty and clean portfolios, resulting in 52 dirty companies and 125 clean companies. In this approach, compared with Table 7, the carbon premium has the similar increase after establishing China's carbon market. In brief, carbon emission allowances do bring higher expected returns for companies involved in carbon emissions trading.

Following Oestreich and Tsiakas (2015) and Gong et al. (2017), we assess carbon risk by the "dirty-minus-clean" (DMC) risk factor. The DMC factor is the expected return of the dirty-minus-clean portfolio. In Tables 7 and 8, we observe that the sensitivity (beta) of the DMC is positively significant. We can reasonably infer that, for this sample, the companies participating in the carbon market have higher carbon exposures. In general, our empirical results do support hypothesis (H2) that the stock returns exist a carbon premium, and a carbon risk factor can also explain a part of the cross-sectional variation of stock returns.

Our other empirical finding is illustrated in Fig. 5. It shows a plot of the abnormal return (alpha) of dirty, clean and dirty-minus-clean portfolios for a rolling window of three years during the entire sample period. Fig. 5 indicates that due to the lag of policy effect, the carbon premium of the CAPM model shows a steady upward trend after 2014. It indicates that the uncertainty of the price of carbon emission

Table 8
Results of the second portfolio classification approach.

	CAPM-α	FF3-α	FF5-α	ILLIQ-α	DMC-α
2009.8–2013.5	−0.214***	−0.266***	−0.250***	−0.247***	−0.188***
	(−8.32)	(−9.22)	(−8.35)	(−7.73)	(−11.08)
2013.6–2018.6 (2013.6–2016.11)	−0.142***	−0.189***	−0.167***	−0.176***	−0.129***
	(−6.46)	(−6.56)	(−6.04)	(−5.55)	(−5.49)
	CAPM+SZA-α	FF3+SZA-α	FF5+SZA-α	ILLIQ+SZA-α	DMC+SZA-α
2013.6–2018.6 (2013.6–2016.11)	−0.142***	−0.189***	−0.166***	−0.176***	−0.128***
	(−6.75)	(−6.39)	(−5.83)	(−5.37)	(−5.35)
β_{SZA}	0.063	−0.0147	0.024	0.024	0.040
	(0.80)	(−0.16)	(0.26)	(0.26)	(0.63)
β_{DMC}					0.997***
					(5.95)

Notes: the "dirty" portfolio contains 52 companies that are involved in carbon emissions trading and receive the free carbon allowance over the sample period. According to the industry characteristics of 52 companies, 125 of the 245 companies that do not receive any carbon allowance and do not participate in the Shenzhen pilot ETS are matched as the "clean" portfolio. The return of dirty-minus-clean portfolio is the return of the "dirty" portfolio less that of the "clean" portfolio. All portfolios are market value-weighted. CAPM- α is the alpha of a CAPM regression. FF3- α is the alpha of the Fama-French three-factor model regression. FF5-α is the alpha of the Fama-French five-factor model regression. ILLIQ-α is the alpha of the regression model with a liquidity factor based on the Fama-French five-factor model. DMC-α is the alpha of the regression model with a risk factor. SZA is the spot price of carbon emissions in the Shenzhen Pilot Emissions Trading Scheme. T-statistics are in parentheses.
Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

allowances is growing. As discussed in OT, Goulder et al. (2016) and elsewhere, the carbon premium is based on two economic mechanisms: (1) the effect of cash flow and (2) the effect of carbon risk. First, the significance of the cash-flow effect mainly depends on the amounts of free certificates and on how much a firm is able to pass-through emissions costs to output prices. In some industries the pass-through rates are large. For instance, Fabra and Reguant (2014) find the average pass-through rates in the Spanish electricity market to be above 80%, implying that a 1 EUR increase in emissions costs translates, on average, into a more than 80 cents increase in electricity price. When all required carbon allowances are allocated freely, ETS can lead to massive windfall profits which can inform a positive cash flow effect. Second, in term of the carbon risk effect, recent contributions by Weitzman (2009), Litterman (2013) and Pindyck (2013) suggest that carbon emissions firms are exposed to carbon risk because they might face a higher price for carbon allowances in the future as a result of catastrophic climate change. In short, carbon risk is based on uncertainty about the future price for carbon allowances. As a result, carbon emissions firms will require higher expected returns relative to firms with no carbon emissions. Carbon premium has an increasing trend. In other words, the uncertainty faced by carbon emission companies has an increasing trend in the future no matter from the perspective of expectation or risk premium. Furthermore, the carbon premium in the Fama-French factor models also shows a similar trend.

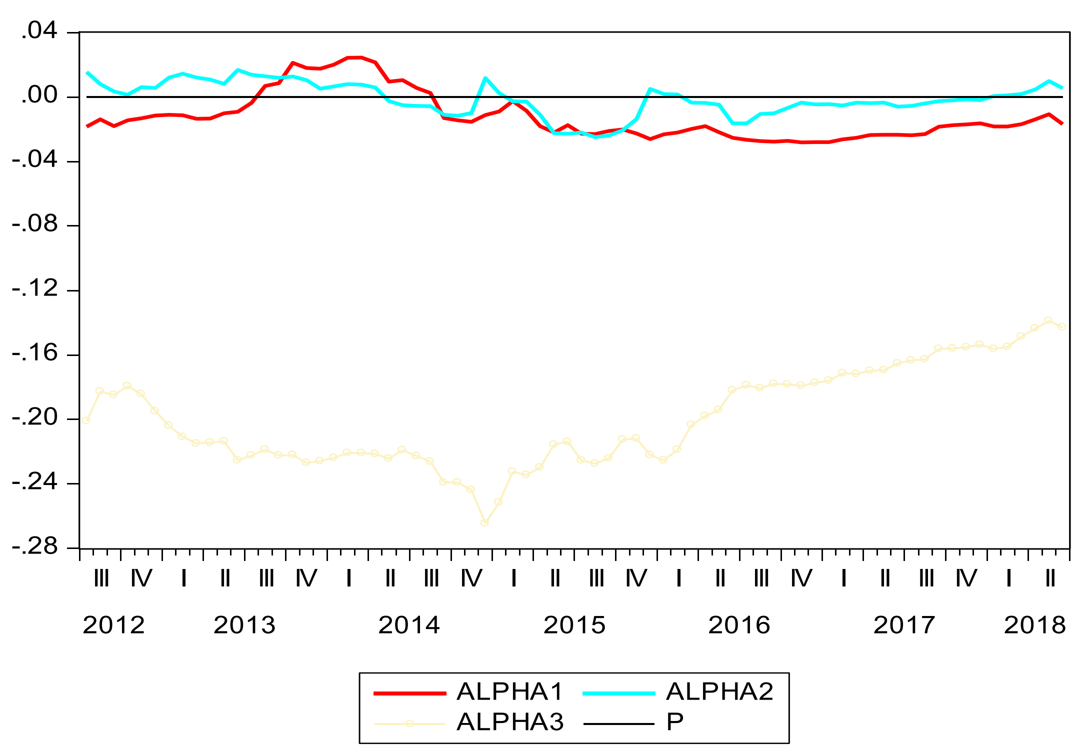

Fig. 5. Abnormal return (alpha) of the CAPM model. Notes: the figure shows a plot of the abnormal return (alpha) of the dirty (red line), clean (blue line) and dirty-minus-clean portfolios (yellow line) for the sample period from August 2009 to June 2018.The black line represents *p*-values of the carbon premium.

7. Conclusion

China's carbon market has been established in consideration of the historical experience, characteristics of the current stage and the future direction of reform. It is also combined with the international experience based on the challenges of the current economic and social development. This paper aims to evaluate the influence of the establishment and operation of China's carbon market on stock returns and to provide a new perspective on assessing the financial performance of the carbon market.

The empirical findings indicate that China's carbon emissions trading market has a positive impact on companies' stock returns. After establishing China's carbon market, the carbon premium experiences a positive increase, and the coefficient of carbon risk factor is significantly positive. The empirical results support hypothesis (H2) that the stock returns exist a carbon premium, which can be explained by the fact that companies participating in the carbon market have higher carbon exposures. Moreover, the carbon premium has an increasing trend, indicating that the uncertainty faced by carbon emission companies has an increasing trend in the future no matter from the perspective of expectation or risk premium. Companies involved in carbon emissions trading market will be exposed to carbon risk as they might face a higher carbon price in the future due to the catastrophic climate change. Meanwhile, carbon risk is non-diversifiable, which will generate risk premium determined by societal risk aversion.

Overall, from the perspective of financial performance, the effect of China's carbon emissions trading market is positive. As a market-based emissions reduction policy tool, the carbon market can guide the companies to reduce carbon emissions to some extent. However, as the carbon market improves, it also needs specific supporting conditions for its effective operation. First, the degree of marketization of the entire economic system directly determines the efficiency and effectiveness of the carbon market. Theoretically, market operations could form equilibrium carbon price signals. While considering the heterogeneity of each pilot development levels and the influence of local trade policy, appropriate direct policy intervention is essential. Second, the strict laws and regulations are important for the construction and effective operation of the carbon market. Compared with the relatively mature carbon trading system in the world, laws and regulations of China's carbon market are relatively lacking. The legal structure and mechanism of the carbon market system are mutually supportive. Moreover, strengthening the connection between Chinese and global carbon market can bring enormous economic and political benefits.

Acknowledgments

The authors would like to express their sincere gratitude for the support of the National Natural Science Foundation of China (Nos. 71873146, 71701176, 71873147, 71431008), Fundamental Research Funds for the Central Universities (No. 2072019029), and Social Science Planning Project of Fujian Province (No. FJ2017C075).

Appendix A

Table A1
Sample description.

	Company	Ticker	Industry	Ownership
1	SKJ	000021	Computer Hardware	State
2	SZNY	000027	Power	State
3	ZXTX	000063	Communications Equipment	Private
4	HRSJ	000999	Pharmaceutical manufacturing	State
5	TZDZ	002052	Household Electric Appliances	Private
6	DRDZ	002055	Electronics	Private
7	LBGK	002106	Electronics	State
8	KLDZ	002121	Electric Power Grid	Private
9	WEHC	002130	Electric Power Grid	Private
10	SLDZ	002138	Electronics	Private
11	TRXN	002218	Semiconductor	Private
12	TCLX	002243	Packaging	State
13	YSDZ	002289	Electronics	Private
14	XLT	002294	Pharmaceutical manufacturing	Private
15	MYS	002303	Packaging	Private
16	LXJM	002475	Electronics	Private
17	HND	002583	Communications Equipment	Private
18	BYD	002594	Automotive	Private
19	DBKJ	002618	Electronics	Private
20	FDKJ	002681	Household Electric Appliances	Private
21	WZXC	002735	Packaging	Private
22	YBSX	002786	Industrial Machinery	Private
23	KZJM	002823	Electric Power Grid	Private
24	CYJM	300115	Electronics	Private
25	DFKJ	300134	Communications Equipment	Private
26	CHKJ	300151	Industrial Machinery	Private
27	XWD	300207	Electric Power Grid	Private
28	XYCZ	300568	Chemical	Private
29	KTSW	300601	Biotechnology	Private
30	JWDZ	603228	Electronics	Private
31	SKJA	000016	Household Electric Appliances	State
32	ZGCC	000066	Computer Hardware	State
33	HQCA	000069	Real Estate	State
34	DZJG	002008	Electronics	Private
35	XLJK	002105	Leisure Products	Private
36	TBGF	002139	Electronics	Private
37	ZHSX	002163	Building Materials	State
38	ZTDZ	002197	Computer Hardware	Private
39	HPR	002399	Pharmaceutical manufacturing	Private

(continued on next page)

Table A1 (*continued*)

	Company	Ticker	Industry	Ownership
40	ZCGF	002429	Household Electric Appliances	Private
41	LPKJ	002577	Computer Hardware	Private
42	KDL	002850	Industrial Machinery	Private
43	WGSW	002880	Biotechnology	Private
44	MGZN	002881	Electronics	Private
45	JLY	002882	Electric Power Grid	Private
46	SNDL	002916	Electronics	State
47	HYYY	300199	Biotechnology	Private
48	RFGD	300241	Semiconductor	Private
49	CFJT	300301	Semiconductor	Private
50	JFGD	300303	Semiconductor	Private
51	DLJS	300679	Electronics	Private
52	MYDL	300739	Electronics	Private

Notes: the table reports the descriptive statistics for 52 treatment group stocks over the sample period from August 2009 to June 2018. Among them, the first 30 companies have been involved in carbon emissions trading. The table also reports the industry characteristics and ownership (the ownership of the companies is up to date).

References

Aatola, P., Ollikainen, M., Toppinen, A., 2013. Price determination in the EU ETS market: theory and econometric analysis with market fundamentals. Energy Econ. 36 (3), 380–395.

Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on observed and unobserved variables: assessing the effectiveness of catholic schools. J. Polit. Econ. 113 (1), 151–184.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5, 31–56.

Anger, N., Oberndorfer, U., 2008. Firm performance and employment in the EU emissions trading scheme: an empirical assessment for Germany. Energy Policy 36 (1), 12–22.

Chang, K., Lu, S., Song, X., 2018. The impacts of liquidity dynamics on emissions allowances price: different evidence from China's emissions trading pilots. J. Clean. Prod. 183, 786–796.

Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proc. Natl. Acad. Sci. 110 (32), 12936–12941.

Chevallier, J., 2011a. A model of carbon price interactions with macroeconomic and energy dynamics. Energy Econ. 33 (6), 1295–1312.

Chevallier, J., 2011b. Macroeconomics, finance, commodities: interactions with carbon markets in a data-rich model. Econ. Model. 28 (1–2), 557–567.

Chevallier, J., Pen, Y.L., Sévi, B., 2011. Options introduction and volatility in the EU ETS. Resourch and Energy Economics 33, 855–880.

Cong, R., Lo, A.Y., 2017. Emission trading and carbon market performance in Shenzhen, China. Appl. Energy 193, 414–425.

Dai, Z., Wen, F., 2018. Some improved sparse and stable portfolio optimization problems. Financ. Res. Lett. 27, 46–52.

Dai, Z., Li, D., Wen, F., 2016. Worse-case conditional value-at-risk for asymmetrically distributed asset scenarios returns. Journal of Computational Analysis & Applications 20 (1), 237–251.

Dong, F., et al., 2019. Can a carbon emission trading scheme generate the Porter effect? Evidence from pilot areas in China. Sci. Total Environ. 653, 565–577.

Duan, H., et al., 2018. Achieving China's energy and climate policy targets in 2030 under multiple uncertainties. Energy Econ. 70, 45–60.

Ebenstein, A., Fan, M., Greenstone, M., He, G., Zhou, M., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. Proc. Natl. Acad. Sci. 114 (39), 10384–10389.

Fabra, N., Reguant, M., 2014. Pass-through of emissions costs in electricity markets. Am. Econ. Rev. 104 (9), 2872–2899.

Fama, E.F., French, K.R., 2004. The capital asset pricing model: theory and evidence. J. Econ. Perspect. 18 (3), 25–46.

Fama, E.F., French, K.R., 2006. The value premium and the CAPM. J. Financ. 61 (5), 2163–2185.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22.

Fell, H., Hintermann, B., Vollebergh, H., 2015. Carbon content of electricity futures in phase II of the EU ETS. Energy J. 61–83.

Gong, X., Lin, B., 2018. The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. Energy Econ. 74, 370–386.

Gong, X., Wen, F., Xia, X.H., Huang, J., Pan, B., 2017. Investigating the risk-return trade-off for crude oil futures using high-frequency data. Appl. Energy 196, 152–161.

Goulder, L. H., Mathai, K., 2010. Optimal CO2 abatement in the presence of induced technological change. In Technological change and the environment (pp. 216–256). Routledge.

Goulder, L.H., Hafstead, M.A., Williams III, R.C., 2016. General equilibrium impacts of a federal clean energy standard. Am. Econ. J. Econ. Pol. 8 (2), 186–218.

Hintermann, B., 2016. Pass-through of CO_2 emission costs to hourly electricity prices in Germany. J. Assoc. Environ. Resour. Econ. 3 (4), 857–891.

Hu, C., et al., 2018. Asymmetric impact of oil price shock on stock market in China: a combination analysis based on SVAR model and NARDL model. Emerg. Mark. Financ. Trade 54 (8), 1693–1705.

International Carbon Action Partnership, 2016. ETS Map. Available from. https://icapcarbonaction.com/en/ets-map.

Jensen, M.C., 1986. Agency costs of free cash flow, corporate finance. and takeovers. The American Economic Review 76 (2), 323–329.

Jiang, J., Xie, D., Ye, B., Shen, B., Chen, Z., 2016. Research on China's cap-and-trade carbon emission trading scheme: overview and outlook. Appl. Energy 178, 902–917.

Jiménez-Rodríguez, R., 2019. What happens to the relationship between EU allowances prices and stock market indices in Europe? Energy Econ. 81, 13–24.

Koch, N., Mama, H.B., 2019. Does the EU Emissions Trading System induce investment leakage? Evidence from German multinational firms. Energy Econ. 81, 479–492.

Lin, B., Jia, Z., 2019. What will China's carbon emission trading market affect with only electricity sector involvement? A CGE based study. Energy Econ. 78, 301–311.

Litterman, B., 2013. What is the right price for carbon emissions. Regulation 36, 38.

Liu, L., Chen, C., Zhao, Y., Zhao, E., 2015. China' s carbon-emissions trading: overview, challenges and future. Renew. Sust. Energ. Rev. 49, 254–266.

Ma, D., et al., 2015. Assessment of energy-saving and emission reduction potentials in China's ammonia industry. Clean Technologies & Environmental Policy 17 (6), 1633–1644.

Michalopoulos, S., Papaioannou, E., 2016. The long-run effects of the scramble for Africa. Am. Econ. Rev. 106 (7), 1802–1848.

Moser, P., Voena, A., 2012. Compulsory licensing: evidence from the trading with the enemy act. Am. Econ. Rev. 102 (1), 396–427.

Munnings, C., Morgenstern, R.D., Wang, Z., Liu, X., 2016. Assessing the design of three carbon trading pilot programs in China. Energy Policy 96, 688–699.

Nunn, N., Wantchekon, L., 2011. The slave trade and the origins of mistrust in Africa. Am. Econ. Rev. 101 (7), 3221–3252.

Oestreich, A.M., Tsiakas, I., 2015. Carbon emissions and stock returns: evidence from the EU emissions trading scheme. J. Bank. Financ. 58, 294–308.

Pastor, L., Veronesi, P., 2012. Uncertainty about goverment policy and stock prices. J. Financ. 67 (4), 1219–1264.

Pindyck, R.S., 2013. Climate change policy: what do the models tell us? J. Econ. Lit. 51 (3), 860–872.

Tan, X., Liu, Y., Cui, J., Su, B., 2018. Assessment of carbon leakage by channels: an approach combining CGE model and decomposition analysis. Energy Econ. 74, 535–545.

Tanaka, S., 2015. Environmental regulations on air pollution in China and their impact on infant mortality. J. Health Econ. 42 (3), 90–103.

Tang, L., et al., 2015. Carbon emissions trading scheme exploration in China: a multi-agent-based model. Energy Policy 81, 152–169.

Tian, Y., et al., 2015. Does the carbon market help or hurt the stock price of electricity companies? Further evidence from the European context. J. Clean. Prod. 112, 1619–1626.

Veith, S., Werner, J.R., Zimmermann, J., 2009. Capital market response to emission rights returns: evidence from the European power sector. Energy Econ. 31 (4), 605–613.

Weitzman, M.L., 2009. On modeling and interpreting the economics of catastrophic climate change. Rev. Econ. Stat. 91 (1), 1–19.

Wen, F., He, Z., Dai, Z., Yang, X., 2014. Characteristics of investors' risk preference for stock markets. Economic Computation & Economic Cybernetics Studies & Research 48 (3), 235–254.

Wen, F., Gong, X., Cai, S., 2016. Forecasting the volatility of crude oil futures using HAR-type models with structural breaks. Energy Econ. 59, 400–413.

Wen, F., Xiao, J., Huang, C., Xia, X., 2018a. Interaction between oil and US dollar exchange rate: nonlinear causality, time-varying influence and structural breaks in volatility. Appl. Econ. 50 (3), 319–334.

Wen, F., Ye, Z., Yang, H., Li, K., 2018b. Exploring the rebound effect from the perspective of household: an analysis of China's provincial level. Energy Econ. 75, 345–356.

World Bank, 2016. State and Trends of Carbon Pricing 2016. World Bank Group, Washington, D.C.

Wu, R., Dai, H., Geng, Y., et al., 2016. Achieving China's INDC through carbon cap-and-trade: insights from Shanghai. Appl. Energy 184, 1114–1122.

Wu, Y., Chau, K.W., Lu, W., Shen, L., Shuai, C., Chen, J., 2018. Decoupling relationship between economic output and carbon emission in the Chinese construction industry. Environ. Impact Assess. Rev. 71, 60–69.

Xiao, J., Zhou, M., Wen, F., et al., 2018. Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market conditions: evidence from oil volatility index. Energy Econ. 74, 777–786.

Xiong, L., Shen, B., Qi, S.Z., 2017. The allowance mechanism of China's carbon trading pilots: a comparative analysis with schemes in EU and California. Appl. Energy 185, 1849–1859.

Zhang, Z., 2016. Making the transition to a low-carbon economy: the key challenges for China. Asia & the Pacific Policy Studies 3 (2), 187–202.

Zhang, M., Gregory-Allen, R.B., 2018. Carbon emissions and stock returns: evidence from the Chinese pilot emissions trading scheme. Theoretical Economics Letters 8 (11), 2082–2094.

Zhang, J., Wang, C., 2011. Co-benefits and additionality of the clean development mechanism: an empirical analysis. Journal of Environmental Economics & Management 62 (2), 140–154.

Zhang, H., Zhu, X., Guo, Y., Liu, H., 2018. A separate reduced-form volatility forecasting model for nonferrous metal market: evidence from copper and aluminum. J. Forecast. 37 (7), 754–766.

Zhao, X., Jiang, G., Nie, D., Chen, H., 2016. How to improve the market efficiency of carbon trading: a perspective of China. Renew. Sust. Energ. Rev. 59, 1229–1245.

Zhao, X., Han, M., Ding, L., Kang, W., 2018. Usefulness of economic and energy data at different frequencies for carbon price forecasting in the EU ETS. Appl. Energy 216, 132–141.

Zhou, M., Liu, X., Pan, B., Yang, X., Wen, F., Xia, X., 2017. Effect of tourism building investments on tourist revenues in China: a spatial panel econometric analysis. Emerg. Mark. Financ. Trade 53 (9), 1973–1987.

Zhu, B., Chevallier, J., 2017. Forecasting carbon price with empirical mode decomposition and least squares support vector regression. Appl. Energy 191, 521–530.

Zhu, B., Wang, P., Chevallier, J., Wei, Y., 2015. Carbon Price analysis using empirical mode decomposition. Comput. Econ. 45 (2), 195–206.