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Carbon emission trading and equity markets in China: How liquidity is impacting carbon returns?

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ABSTRACT

This paper aims to investigate the impact of liquidity on the return dynamics between the carbon emission trading market and the stock market in China from 2013 to 2021. In the carbon emission trading market, we find that liquidity on any given day can significantly predict the cross-section returns the next day. Furthermore, we examine the spillover effect between the two markets and find the carbon market has a greater impact on the stock market. We also find evidence that stock market liquidity can significantly improve the liquidity of the carbon market. Finally, we observe that the volatility in the stock market not only deteriorates the liquidity of the stock market but also the carbon market, where the impact for the latter is from decreasing trading volume and increasing prices.

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1. Introduction

Currently, climate change is one of the biggest global issues for the entire world. From the emission of carbon dioxide in various countries, greenhouse gases have increased, which poses a large threat to global ecosystems (Jiao et al., 2021; Umar et al., 2020). This is exactly why the 21st United Nations Climate Change Conference adopted and signed the Paris Agreement. As part of this agreement, countries around the world will reduce greenhouse gas emissions (Umar et al., 2020; Yu et al., 2022). Since China is the largest developing country and the largest carbon emitter in the world (J. Zheng et al., 2019), it has assumed important responsibilities. At the United Nations General Assembly in September 2020, China announced its goal of achieving a carbon peak by 2030 and carbon neutrality by 2060 (Ji et al., 2021; Tao et al., 2022). For this to occur, the establishment of a national carbon emission trading market is required as a major step in controlling and reducing greenhouse gas emissions in China (Wen et al., 2020; Yan et al., 2022).

The carbon emissions trading market is a measurement mechanism for carbon emissions to be capped, traded and priced (Oestreich & Tsiakas, 2015). It is also a

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powerful tool to promote economic development, achieve green and low-carbon transformation, strengthen ecological progress, and fulfil international commitments on emission reduction (Bibi et al., 2021). Since 2011, China has piloted carbon emission trading markets in seven places, such as Beijing, Tianjin and Shanghai, and an increasing number of companies are participating in the carbon market, which has also attracted a large amount of capital injection (R. Wang et al., 2020). Therefore, investors' have become attracted to the carbon emission as an asset class. Meanwhile, as one of the most fundamental factors in markets, liquidity influences asset prices and other asset characteristics (Ielasi et al., 2018; Mirza et al., 2020; Umar et al., 2021). The quality of liquidity is important for investors in their investment planning.

With the improvement of the financial system, the relationships of all markets have become stronger (Kaiser & Welters, 2019; Naqvi et al., 2021). The price or return of a specific market is influenced not only by itself but also by other markets (Li et al., 2020; Liang et al., 2020; Lobato et al., 2021). To the best of our knowledge, the stock market plays a role in the economy as a barometer, which reflects the situation of the whole economy therefore the relationship between the stock market and the carbon emission trading market has become an issue of focus (Itani et al., 2020).

Recently, there has been some research on the correlation between the carbon emission trading market and the stock market. (Jiménez-Rodríguez, 2019) noted that the stock market and the carbon emission trading market are related from a theoretical view. There is an asymmetric relationship between these markets in China (Y. Zheng et al., 2021). (Wen et al., 2020) stated that there is a positive relation between the carbon emission trading market and stock returns. In addition, some research investigated the risk between the carbon market and stock market (Cong & Lo, 2017; Krueger et al., 2020; Lin & Wu, 2022; Zhu et al., 2020). Obviously, the conclusions of these studies are not consistent. We further explore how these two markets affect each other.

In this paper, we investigate the relationship between the carbon emission trading market and the stock market from the perspective of liquidity. We contribute to the literature as follow. First, we enrich the literature on the relationship between the carbon and stock markets. Many studies focus on one market, either the carbon market or the stock market (Bahmani-Oskooee et al., 2020; Behrendt & Schmidt, 2021; Cong & Lo, 2017; Kanamura, 2016; Liang et al., 2020; Liang et al., 2020). Furthermore, this paper sheds light on a new relationship between the carbon and stock markets from the liquidity perspective. We show the spillover effect from the stock market to the carbon market is far greater than anticipated, especially the liquidity spillover effect. Our empirical findings are helpful for investors and companies to better understand and predict the carbon emission trading market and stock market, to enhance market participation, to realize the policy of strengthening the construction of the carbon emission trading market and to help to achieve the goals of 'peak carbon dioxide emissions' and 'carbon neutrality' in the 14th five-year plan.

The remainder of the paper is organized as follows. Section 2 describes the methodology. Section 3 shows the data of this paper. In addition, Section 4 presents the empirical results. Section 5 presents the extensions. Section 6 ends this paper.

2. Methodology

2.1. Fama-MacBeth regression

Liquidity is a fundamental financial concept that is abstract and difficult to measure (Amihud & Mendelson, 1986). Some studies employed alternative indicators of liquidity to conduct research on the stock market from three dimensions, including width, depth and price impact (Amihud, 2002; Chordia et al., 2005; Fong et al., 2017; Goldstein & Kavajecz, 2000; Goyenko et al., 2009; Rhee & Wang, 2009). Based on data available in the carbon market, we mainly adopt the trading volume and illiquidity measurements, where the former captures the depth of liquidity and the latter captures the price impact information.

Following the methodology suggested by (Fama & MacBeth, 1973), we test the effect of liquidity on individual carbon market returns using daily frequency data. The cross-sectional model is:

$$R_{i,t} = \alpha + \beta_1 X_{i,t-1} + \beta_2 X_{i,t-2} + \beta_3 X_{i,t-3} + \beta_4 X_{i,t-4} + \beta_5 X_{i,t-5} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ indicates the return of individual carbon market i on day t. X is one measure of trading volume (Vol) and illiquidity of (Amihud, 2002) ($Illiq$). $Vol_{i,t}$ and $Illiq_{i,t}$ denote the trading volume and the illiquidity for individual carbon market i on day t, and both of them take the natural logarithm. In addition, there are total 8 individual carbon emission markets, including Beijing, Shanghai, Guangdong, Shenzhen, Tianjin, Chongqing, Hubei, and Fujian. The regression covers the period of 2013-2021. For each month, we fit the cross-sectional model using the daily data of individual carbon markets before the time-series average for these estimations.

2.2. Vector autoregressive model

We employ the vector autoregressive model designed by (Sims, 1980) to estimate the dynamic relationship between the carbon emission trading market and the stock market. This model is an extension of the AR model, which regresses several lagging variables for all variables with all current variables in the model. The vector autoregressive model is thus:

$$Y_t = c + \sum_{l=1}^{l} A_l Y_{t-l} + \varepsilon_t \tag{2}$$

where Y_t denotes a vector composed of 7 variables: AGGCRet, AGGCVol, AGGCIlliq, MktRV, MKtRet, MktVol and MktIlliq, c is the constant vector, A_l expresses the coefficient matrix, and ε_t represents the residual vector.We then refer to the Bayesian information criterion to determine the lag order, and the lag order is 2.

Based on the above vector autoregressive model, we also conduct the Granger causality analysis to show the spillover effect between the carbon market and the stock market in China. We may infer that there is Granger causality from a given variable (causing variable) to another variable (caused variable) if the null is rejected, where the test is whether the coefficients associated with the 2 lags of the causing variable are jointly 0 in a particular equation with the caused variable as the dependent variable.

Table 1. Descriptive statistics for market variables.

	Mean	Min	Max	Std.dev.	Skewness	Kurtosis	ADF
MktRV	15.121	3.610	102.216	10.883	3.220	14.896	−3.482***
MktRet	0.000	−0.085	0.058	0.014	−0.893	6.490	−7.938***
MktVol	26.079	24.601	27.901	0.596	0.235	0.215	−2.925***
MktIlliq	−31.375	−37.978	−27.758	1.228	−0.852	1.466	−4.633***
AGGCRet	0.001	−0.512	0.717	0.054	1.632	32.631	−7.794***
AGGCVol	14.313	4.603	18.518	1.699	−1.426	4.345	−3.993***
AGGCIlliq	−16.234	−23.614	0.000	4.343	1.945	4.124	−6.972***

Notes: This table reports the descriptive statistics of daily variables, where ADF refers to the statistics of stationary tests. The statistical significance at 1%, 5%, and 10% levels are represented as ***, ** and *, respectively.
Sources: Authors.

3. Data

We use daily data on the carbon market and the stock market, and the sample period is from 18 June 2013 to 12 January 2021, which is obtained from the Oxford Man Institute of Quantitative Finance and the Wind Economic database. Specifically, the extension experiments use weekly data, and the data indicators are uniformly calculated according to the average of daily data within a week.

In addition, the liquidity indicators are presented below. The first indicator is volume (Chordia et al., 2001), which is defined as the total volume of the underlying asset during the day. The second indicator is illiquidity of (Amihud, 2002), specifically:

$$ILLIQ_t = \frac{|R_{i,t}|}{Volume_{i,t}} \tag{3}$$

where $|R_{i,t}|$ is the simple return of underlying asset i on day t.

Table 1 reveals the descriptive statistics of the market variables in this paper. In particular, there are two kinds of market variables, one for the aggregated carbon emission trading market and another for the stock market. The variable AGGCRet represents the carbon market return, AGGCVol indicates the carbon market volume, and AGGCIlliq is the illiquidity of the carbon market. AGGCRet, AGGCVol, and AGGCIlliq are aggregated based on trading-volume weights of 8 individual carbon markets, respectively. In the stock market, MktRV is the realized volatility of the Shanghai Stock Exchange Index, MKtRet, MktVol, and MktIlliq are the return, trading volume, and illiquidity of the Shanghai Stock Exchange Index, respectively.

Additionally, under the augmented Dickey-Fuller (ADF) statistics (Dickey & Fuller, 1981), since the unit root null hypothesis is rejected at the 1% significance level, all variables are stationary.

4. Empirical results

4.1. Liquidity impacts on returns for individual carbon emission trading markets

Table 2 presents the regression results based on the cross-sectional data of all individual carbon markets from the perspective that carbon market liquidity could influence

Table 2. Estimation results of Fama-MacBeth regressions.

Variables	$X = Vol$	$X = Illiq$
Intercept	0.017***	0.017***
t-stat	(2.807)	(2.807)
$X_{i,t-1}$	0.029	−0.025
t-stat	(1.254)	(-1.416)
$X_{i,t-2}$	−0.026*	0.029**
t-stat	(-1.667)	(2.118)
$X_{i,t-3}$	0.006	−0.001
t-stat	(0.957)	(-0.250)
$X_{i,t-4}$	−0.013	0.017
t-stat	(-1.123)	(1.478)
$X_{i,t-5}$	−0.013	0.002
t-stat	(-1.600)	(0.660)

Notes: This table shows the results of the Fama-MacBeth regression estimates. The dependent variable is daily returns of individual carbon market. The sample has daily observations from 2013-2021. The statistical significance at 1%, 5%, and 10% levels are represented as ***, ** and *, respectively.
Sources: Authors.

its return. We mainly explain liquidity through two aspects: trading volume (volume) and price impact (illiquidity).

The results in Table 2 show that carbon market volume and illiquidity are both significant when lagging for two periods. The relationship between trading volume and return of the carbon market is consistent with the relationship between volume and price mentioned in (H. Wang & Boatwright, 2019). In addition, we test the relationship between carbon market liquidity and returns from the perspective of illiquidity. Table 2 shows that the coefficient of $Illiq_{i,t-2}$ is significantly positive (0.029) at the 5% level. In contrast, an increase in trading volume $Vol_{i,t-2}$ will lead to a decrease in return, which is significantly negative (-0.026) at the 10% level. These results show that individual carbon market's illiquidity has a stronger impact on its future return than trading volume. In the next section, we continue to explore the properties of the carbon market from the market-level perspective. Moreover, spillover effects between the aggregate carbon market and the stock market in China are investigated by considering several important asset characteristics, including the return, trading volume, illiquidity, and volatility.

4.2. Spillover effects between the carbon market and the stock market

4.3.1. Equation results of the vector autoregressive model

We investigate the specific relationship between the two markets by introducing the 7 market variables into a VAR model with the lag order of 2. Table 3 shows the VAR's equation results. We find that the three characteristics of the carbon emission trading market have no significant impact on the realized volatility of the stock market (MktRV). The volume of the carbon emission trading market (AGGCVol) with a one-period lag is significantly and negatively related to the return of the stock market (MktRet) at the 10% level. This demonstrates that the increasing trading volumes in the carbon emission trading market could weakly decrease future returns in the stock market. On the future trading volume of the stock market (MktVol), the one-period lagged trading volume of the carbon emission trading market (AGGCVol) has a negative impact, and the two-period lagged one has a positive impact. Three carbon

Table 3. Equation results of VAR(2).

	Equations						
Variables	$MktRV_t$	$MktRet_t$	$MktVol_t$	$MktIlliq_t$	$AGGCRet_t$	$AGGCVol_t$	$AGGCIlliq_t$
Intercept	−42.509***	0.425%	0.579***	−6.441***	6.746%	−2.493*	15.824***
t-stat	(-5.550)	(0.236)	(2.854)	(-4.489)	(0.982)	(-1.810)	(3.103)
$MktRV_{t-1}$	0.425***	0.013%**	−0.000	0.025***	−0.014%	−0.012**	0.023***
t-stat	(16.314)	(2.044)	(-0.570)	(5.088)	(-0.619)	(-2.536)	(1.326)
$MktRet_{t-1}$	−108.297***	7.684%***	3.441***	−2.627	6.795%	−2.214	7.956
t-stat	(-9.583)	(2.887)	(11.490)	(-1.241)	(0.671)	(-1.090)	(1.058)
$MktVol_{t-1}$	3.052***	−0.326%	0.644***	−0.824***	−0.120%	0.391**	0.786
t-stat	(3.017)	(-1.367)	(24.035)	(-4.346)	(-0.132)	(2.150)	(1.167)
$MktIlliq_{t-1}$	0.527***	0.080%**	0.006*	−0.015	0.176%	−0.048**	−0.001
t-stat	(4.013)	(2.584)	(1.786)	(-0.610)	(1.495)	(-2.045)	(-0.014)
$AGGCRet_{t-1}$	1.572	−0.224%	0.075	0.257	−16.364%***	−0.031	1.490
t-stat	(0.601)	(-0.363)	(1.078)	(0.526)	(-6.981)	(-0.066)	(0.856)
$AGGCVol_{t-1}$	−0.047	−0.053%*	−0.007**	0.026	0.001%	0.478***	−0.398***
t-stat	(-0.366)	(-1.761)	(-2.065)	(1.068)	(0.006)	(20.801)	(-4.680)
$AGGCIlliq_{t-1}$	0.009	0.000%	−0.000	−0.000	−0.026%	0.000	0.166***
t-stat	(0.253)	(0.000)	(-0.473)	(-0.014)	(-0.804)	(0.006)	(6.858)
$MktRV_{t-2}$	0.348***	−0.019%***	−0.001	0.019***	0.012%	0.008*	0.002
t-stat	(14.012)	(-3.195)	(-0.855)	(4.039)	(0.554)	(1.803)	(0.127)
$MktRet_{t-2}$	37.766***	−2.552%	−0.387	−4.224**	−5.050%	−1.929	−0.280
t-stat	(3.459)	(-0.992)	(-1.339)	(-2.065)	(-0.516)	(-0.983)	(-0.039)
$MktVol_{t-2}$	−0.362	0.412%*	0.331***	−0.194	−0.035%	−0.220	−1.603**
t-stat	(-0.355)	(1.714)	(12.248)	(-1.016)	(-0.038)	(-1.203)	(-2.362)
$MktIlliq_{t-2}$	0.168	−0.003%	−0.009***	−0.018	−0.083%	0.024	−0.053
t-stat	(1.341)	(-0.105)	(-2.577)	(-0.777)	(-0.734)	(1.062)	(-0.629)
$AGGCRet_{t-2}$	2.817	0.025%	0.071	0.349	−0.612%	−0.339	−0.067
t-stat	(1.078)	(0.041)	1.029	(0.712)	(-0.261)	(-0.721)	(-0.038)
$AGGCVol_{t-2}$	−0.044	0.039%	0.007**	−0.026	−0.001%	0.316***	−0.159*
t-stat	(-0.348)	(1.306)	(1.981)	(-1.081)	(-0.007)	(13.732)	(-1.867)
$AGGCIlliq_{t-2}$	0.056	−0.004%	−0.000	0.006	0.005%	−0.018***	0.132***
t-stat	(1.565)	(-0.493)	(-0.343)	(0.849)	(0.139)	(-2.715)	(5.518)

Notes: The sample has daily observations from 2013-2021. The statistical significance at 1%, 5%, and 10% levels are represented as ***, ** and *, respectively.
Sources: Authors.

market variables do not have a significant impact on the illiquidity of the stock market (MktIlliq). This is intuitive because the stock market is more developed and more liquid than the newly established carbon market.

For the spillover effect from the stock market to the carbon emission trading market, we find the stock market variables have no significant impact on the future return of the carbon market (AGGCRet). However, the realized volatility, trading volume, and illiquidity of the stock market significantly impact the trading volume of the carbon market, and the realized volatility and trading volume of the stock market also show significant coefficients on the carbon market illiquidity. These results indicate that: first, the stock market liquidity can significantly improve the liquidity of the carbon emission trading market; second, higher stock market volatility deteriorates not only the liquidity within the stock market but also the carbon market liquidity, where the impact for the latter is from two aspects of decreasing trading volume and increasing the price impact.

Within the system of the carbon market, both the trading volume and illiquidity do not predict future aggregate carbon market returns. The relation between liquidity and return at the carbon market level is inconsistent with the previous evidence from individual carbon markets. This suggests that due to the presence of liquidity

Table 4. Ganger causality tests from VAR model.

Causing	Caused	*F*-Stat.	*p*-Value
Panel A: Granger causalities from the stock market to the carbon market			
MktRV	AGGCRet	0.203	0.816
MktRV	AGGCVol	3.217**	0.040
MktRV	AGGCIlliq	2.109	0.121
MktRet	AGGCRet	0.399	0.671
MktRet	AGGCVol	0.975	0.377
MktRet	AGGCIlliq	0.571	0.565
MktVol	AGGCRet	0.121	0.886
MktVol	AGGCVol	5.147***	0.006
MktVol	AGGCIlliq	7.493***	0.001
MktIlliq	AGGCRet	1.375	0.253
MktIlliq	AGGCVol	2.630*	0.072
MktIlliq	AGGCIlliq	0.198	0.820
Panel B: Granger causalities from the carbon market to the stock market			
AGGCRet	MktRV	0.674	0.510
AGGCRet	MktRet	0.071	0.931
AGGCRet	MktVol	0.954	0.385
AGGCRet	MktIlliq	0.340	0.712
AGGCVol	MktRV	0.386	0.680
AGGCVol	MktRet	1.565	0.209
AGGCVol	MktVol	2.456*	0.086
AGGCVol	MktIlliq	0.692	0.501
AGGCIlliq	MktRV	1.377	0.252
AGGCIlliq	MktRet	0.126	0.882
AGGCIlliq	MktVol	0.208	0.812
AGGCIlliq	MktIlliq	0.371	0.690

Notes: The sample has daily observations from 2013-2021. The statistical significance at 1%, 5%, and 10% levels are represented as ***, ** and *, respectively.
Sources: Authors.

differences across individual carbon markets, investors will demand additional liquidity compensation in some individual carbon markets that lack liquidity.

Overall, the transmission between the two markets is non-symmetrical from the above evidence, and the spillover effect from the stock market to the carbon market is greater than the one from the carbon market to the stock market. The positive liquidity spillover effect from the stock market to the carbon market could be due to high investor sentiment. Intuitively, when investor sentiment is higher in the stock market, these investors are easier to participate in other asset markets due to their high tolerance, especially when they have profited from the stock market. From the risk perspective, within an interconnected economic system, risks from large asset markets are more easily transmitted to small asset markets. Therefore, the increasing price uncertainty in the stock market also deteriorates the quality of liquidity in the carbon market.

4.3.2. Granger causality based on the vector autoregressive model

The above equation results of VAR show specific impacts of the lagged individual variable on an underlying variable. Table 4 further presents the Granger causality results between the carbon market and the stock market to directly demonstrate the significance of the overall impact of a market characteristic from the stock market to the carbon market, or from the carbon market to the stock market. This table shows the F-statistics and p-values from the causal correlation for these carbon and stock market variables. In Panel A, we report the results from the stock market to the carbon

Table 5. Descriptive statistics for market variables: Weekly results.

	Mean	Min	Max	Std.dev.	Skewness	Kurtosis	ADF
MktRV	14.998	5.792	87.606	9.789	2.908	12.112	−2.889**
MktRet	0.001	−0.028	0.021	0.006	−0.601	2.801	−17.701***
MktVol	26.066	24.679	27.731	0.588	0.235	0.222	−3.322***
MktIlliq	−31.362	−33.292	−29.705	0.720	−0.040	−0.402	−3.655***
AGGCRet	0.001	−0.100	0.137	0.024	1.126	8.325	−7.118***
AGGCVol	14.273	6.655	16.902	1.521	−1.215	2.836	−5.244***
AGGCIlliq	−16.131	−22.169	0.000	3.092	1.711	5.446	−4.500***

Notes: This table reports the summary statistics for weekly market variables. There are 383 weekly observations. ADF refers to the statistics of stationary tests, and *** represents the statistical significance at the 1% level.
Sources: Authors.

market and show that the trading volume of the stock market (MktVol) significantly causes the carbon market liquidity, both for illiquidity (AGGCIlliq) and trading volume (AGGCVol). This is consistent with the above findings in specific equation results. The stock market realized volatility (MktRV) also causes the trading volume of the carbon market (AGGCVol) with an F-statistic of 3.217. Panel B reports the results from the carbon market to the stock market. However, F-statistics are not significant only excluding the impact of the carbon market trading volume on the stock market trading volume, where AGGCVol weakly causes MktVol with a p-value of 0.086. These results indicate that the impacts from the carbon market to the stock market are weak.

Overall, the spillover effect from the stock market to the carbon market is stronger than the opposite situation, especially for the role of trading activities and price uncertainty of the stock market.

5. Extensions

Our main empirical analysis using daily data expresses the short-term connection between two markets. We further conduct the same analysis with using weekly data to investigate the long-term connection. Table 5 reports the descriptive statistics of the weekly market variables, and they are all stationary. We fit a VAR(1) model with the 7 market variables by using weekly data. The specific equation results are shown in Table 6, and we find there is no significant impact from the return and liquidity of the carbon market to the stock market. The stock market presents a persistently significant impact on the carbon market at a weekly frequency. Specifically, the trading volume of the stock market negatively and significantly predicts the weekly return of the carbon market, where the t-statistic is −2.355. The weekly return of the stock market also has a significant impact on the illiquidity of the carbon market. In particular, in the carbon market, the weekly trading volume and illiquidity positively predict future market returns. Their predictive impact could be driven by different mechanism, specifically, the positive volume-return and illiquidity-return relations could be based on the role of investor sentiment and liquidity compensation, respectively. The Granger causality results in Table 7 further reveal the impacts from the stock market to the carbon market.

In conclusion, the relations between the stock market and the carbon market distinct from the daily and weekly frequencies. The stock market still shows a stronger role in the carbon market from the perspectives of its trading volume and returns.

Table 6. Equation results of VAR(1): Weekly results.

	Equations						
Variables	$MktRV_t$	$MktRet_t$	$MktVol_t$	$MktIlliq_t$	$AGGCRet_t$	$AGGCVol_t$	$AGGCIlliq_t$
Intercept	−56.996***	1.320%	1.674***	−9.542***	10.954%	−2.523	10.445
t-stat	(-3.656)	(0.704)	(3.171)	(-5.714)	(1.527)	(-1.015)	(1.562)
$MktRV_{t-1}$	0.686***	0.002%	−0.001	0.028***	0.028%	−0.003	−0.002
t-stat	(15.754)	(0.307)	(-0.570)	(6.038)	(1.401)	(-0.376)	(-0.132)
$MktRet_{t-1}$	61.757	10.552%*	8.830***	−13.166***	18.082%	1.937	−36.198*
t-stat	(1.334)	(1.895)	(5.637)	(-2.656)	(0.849)	(0.262)	(-1.824)
$MktVol_{t-1}$	4.185***	−0.073%	0.945***	−0.701***	−0.889%**	0.185	−0.165
t-stat	(5.099)	(-0.735)	(34.012)	(-7.970)	(-2.355)	(1.412)	(-0.467)
$MktIlliq_{t-1}$	1.422***	−0.020%	0.009	0.125**	−0.282%	−0.019	0.276
t-stat	(2.707)	(-0.321)	(0.501)	(2.215)	(-1.168)	(-0.224)	(1.227)
$AGGCRet_{t-1}$	14.889	−1.467%	0.153	1.049	−1.975%	0.947	−2.656
t-stat	(1.345)	(-1.101)	(0.409)	(0.884)	(-0.388)	(0.537)	(-0.560)
$AGGCVol_{t-1}$	−0.100	−0.001%	0.002	0.009	0.329%***	0.733***	−0.452***
t-stat	(-0.450)	(-0.036)	(0.255)	(0.369)	(3.206)	(20.621)	(-4.726)
$AGGCIlliq_{t-1}$	0.086	0.002%	−0.002	0.012	0.102%**	−0.061***	0.444***
t-stat	(0.789)	(0.124)	(-0.486)	(1.042)	(2.024)	(-3.480)	(9.493)

Notes: This table presents the results of weekly data for VAR equations in OLS. The sample is from 2013-2021. The statistical significance at 1%, 5%, and 10% levels are represented as ***, ** and *, respectively.
Sources: Authors.

Table 7. Ganger causality tests from VAR model: Weekly results.

Causing	Caused	*F*-Stat.	*p*-Value
Panel A: Granger causalities from the stock market to the carbon market			
MktRV	AGGCRet	1.962	0.161
MktRV	AGGCVol	0.141	0.707
MktRV	AGGCIlliq	0.017	0.895
MktRet	AGGCRet	0.721	0.396
MktRet	AGGCVol	0.069	0.793
MktRet	AGGCIlliq	3.327*	0.068
MktVol	AGGCRet	5.547**	0.019
MktVol	AGGCVol	1.994	0.158
MktVol	AGGCIlliq	0.219	0.640
MktIlliq	AGGCRet	1.364	0.243
MktIlliq	AGGCVol	0.050	0.822
MktIlliq	AGGCIlliq	1.506	0.220
Panel B: Granger causalities from the carbon market to the stock market			
AGGCRet	MktRV	1.808	0.179
AGGCRet	MktRet	1.213	0.271
AGGCRet	MktVol	0.167	0.683
AGGCRet	MktIlliq	0.782	0.377
AGGCVol	MktRV	0.202	0.653
AGGCVol	MktRet	0.001	0.971
AGGCVol	MktVol	0.065	0.799
AGGCVol	MktIlliq	0.136	0.713
AGGCIlliq	MktRV	0.622	0.430
AGGCIlliq	MktRet	0.015	0.901
AGGCIlliq	MktVol	0.237	0.627
AGGCIlliq	MktIlliq	1.085	0.298

Notes: This table presents the results of Granger causality tests from a VAR(1) model using the weekly data. The lag order of the VAR model is determined by the Bayesian information criterion (BIC). The sample is from 2013-2021. The statistical significance at 1%, 5%, and 10% levels are represented as ***, ** and *, respectively.
Sources: Authors.

6. Conclusion

In this paper, we investigate the relationship between the carbon emission trading market and the stock market from the perspective of liquidity. The following are some noteworthy findings. First, within the carbon emission trading market, the illiquidity of the individual carbon markets positively predicts the cross-sectional carbon returns in the next day, and in terms of liquidity depth, the trading volume has a negatively predictive role. Second, considering the relationship between the carbon market and the stock market, we find that the transmission between the two markets is non-symmetrical, and the spillover effect from the stock market to the carbon market is greater than the one from the carbon market to the stock market. Specifically, the trading volume of the stock market can significantly improve the liquidity of the carbon market. In particular, the increasing price uncertainty in the stock market also deteriorates the quality of liquidity in the carbon market. Risks from large asset markets are more easily transmitted to small asset markets.

China is the biggest carbon emitter in the world. Therefore, China has a strong responsibility to manage the carbon emission trading market. This paper investigates the relationship between carbon market liquidity and returns on the basis of price-volume relationship theory (Behrendt & Schmidt, 2021). Meanwhile, we further understand the relationship and impact of the carbon emission trading market and the stock market. The flow of capital between the two markets is asymmetric, which is also a concern for investors as market entities. Therefore, it is necessary to scientifically explore carbon prices for policy-makers when adjusting the industrial structure, developing emission reduction technologies, and strengthening environmental governance. At the same time, regulators should pay attention to observations of market liquidity and improve the carbon emission trading system to ensure the stable operation of each market.

At present, the research is mainly about the relationship between the carbon emission trading market and the energy market. Although the markets involved are different, most of the methods are similar (Aatola et al., 2013; Gong et al., 2021; Hintermann et al., 2020; Kanamura, 2016; Liang et al., 2020; Xu, 2021). For future research, the use of intraday high-frequency data and complex nonlinear forecasting models (such as neural network models) to predict prices, returns and volatility between different markets, as well as research on new energy pricing and hedging, may become a possible future research direction.

Disclosure statement

No potential conflict of interest was reported by the authors

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