“Liquidity spillover from carbon emission trading markets to stock markets in China”

AUTHORS	Xinyuan Yang Jingyao Zhu Hantao Xie Jianing Zhang

ARTICLE INFO	Xinyuan Yang, Jingyao Zhu, Hantao Xie and Jianing Zhang (2023). Liquidity spillover from carbon emission trading markets to stock markets in China. *Investment Management and Financial Innovations*, *20*(4), 227-241. doi:10.21511/imfi.20(4).2023.19
DOI	http://dx.doi.org/10.21511/imfi.20(4).2023.19
RELEASED ON	Thursday, 16 November 2023
RECEIVED ON	Tuesday, 05 September 2023
ACCEPTED ON	Friday, 10 November 2023
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
60	1	8

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

Xinyuan Yang (China), **Jingyao Zhu** (China), **Hantao Xie** (China), **Jianing Zhang** (China)

LIQUIDITY SPILLOVER FROM CARBON EMISSION TRADING MARKETS TO STOCK MARKETS IN CHINA

Abstract

This study delves into China's carbon emissions trading markets, investigating the interplay between carbon price liquidity and stock liquidity. Focusing on 338 companies listed in the national and eight pilot markets of the carbon emissions trading system from August 2013 to October 2023, the empirical finding reveals a positive impact of carbon price liquidity on stock liquidity. Notably, this positive association manifests more robustly in industries characterized by low carbon intensity compared to those with high carbon intensity, is more prominent during the COVID-19 period than in preceding times, and is particularly accentuated in the Hubei Province and Chongqing, as opposed to the remaining seven regions. Intriguingly, both carbon price liquidity and stock liquidity display positive autocorrelations in vector autoregression analysis. The endogeneity concern is alleviated by the two-stage least squares regressions, using lagged carbon price liquidity as instrumental variables. This study contributes to an enhanced comprehension of the dynamic interaction between carbon price liquidity and stock liquidity contextualized within China's evolving carbon market landscape. The insights garnered herein hold substantial value for investors and government stakeholders seeking to navigate this evolving financial terrain.

Received on: 5th of September, 2023
Accepted on: 10th of November, 2023
Published on: 16th of November, 2023

Xinyuan Yang, Undergraduate Student, College of Science, Mathematics and Technology, Wenzhou-Kean University, China.

Jingyao Zhu, Undergraduate Student, College of Business and Public Management, Wenzhou-Kean University, China.

Hantao Xie, Undergraduate Student, College of Science, Mathematics and Technology, Wenzhou-Kean University, China.

Jianing Zhang, Ph.D., Assistant Professor of Finance, College of Business and Public Management, Wenzhou-Kean University, China. (Corresponding author)

Keywords carbon emission trading, stock price, liquidity spillover, vector autoregression, instrumental variable, China

JEL Classification G12, G14, G15, Q56

INTRODUCTION

A suite of ecological challenges, particularly involving the greenhouse effect and climate change, instigated by substantial emissions of greenhouse gases, chiefly carbon dioxide, pose significant hurdles for China and the global environment (Duan et al., 2018, 2022). In the 2015 Paris Agreement, a coalition of 195 countries, including China, endorsed a global climate agreement that, for the first time, outlined a set of measures aimed at limiting global temperature rise to well below two degrees Celsius (Liobikienė & Butkus, 2017). Currently, China is the leading emitter of carbon dioxide, pushing the global climate agenda to a critical inflection point should the nation forgo a transition to a low-carbon economic framework (IEA, 2022; World Bank, 2022). Through targeted regulation of these sectors, China is expected to reach its peak carbon emissions by 2030, in alignment with achieving carbon neutrality before 2060.

The Chinese government has implemented diverse policies to regulate greenhouse gas emissions to accelerate China's path toward environmentally sustainable and low-carbon development and effectively address global climate change demands. This holistic strategy encompasses the launch of China's pilot carbon emissions markets (Zhang

Conflict of interest statement:
Author(s) reported no conflict of interest

& Hao, 2015; Jiang et al., 2016; Wang et al., 2015). In October 2011, a critical milestone was achieved when the National Development and Reform Commission released an ambitious plan outlining China's aim to establish eight provincial carbon trading pilots in critical regions, including Beijing, Tianjin, Shanghai, Chongqing, Guangdong Province, Hubei Province, Shenzhen, and Fujian Province (Zhang & Wang, 2021). Fueled by the abundant reserves of carbon resources in China, the potential for carbon emissions trading rights and their derivative instruments holds significant relevance in the future (Wang et al., 2016). This also substantiates the claim concerning the global importance of China's carbon market.

In financial markets and related spheres, investigations into spillover effects, encompassing intra-market and inter-market dimensions, have emerged as vital endeavors to bridge existing knowledge gaps. The late establishment of China's carbon market compared to its European Union counterpart has created a research void, particularly regarding the firms regulated by the carbon markets (Chang et al., 2018b).

1. LITERATURE REVIEW

The integration of China into the carbon market occurred with a temporal lag relative to the European Union. Nevertheless, by capitalizing on its abundant carbon assets, carbon emission allowances and corresponding derivatives demonstrate significant promise within the Chinese market (Wang et al., 2016). During the maturation of China's carbon market, the path of carbon liquidity has exhibited incremental growth, concomitant with improvements in market infrastructure. However, the existing landscape of carbon liquidity persists in a suboptimal condition. Zhang et al.'s (2020) comprehensive analysis, segmented into three distinct chronological phases, revealed that later stages experienced reduced market efficiency compared to the initial phase. Kalaitzoglou and Ibrahim (2013) have posited evidence supporting that carbon markets characterized by elevated liquidity demonstrate superior responsiveness to market-driven news. Conversely, markets with diminished liquidity tend to manifest a delayed integration of such information. This interrelationship between liquidity and reactivity to market news is inextricably linked with the speed of news dissemination, thereby exerting additional influence on liquidity conditions.

In scrutinizing China's carbon market, Chang et al. (2018a) identified a prominent clustering effect within daily price intervals, in which intraday returns significantly impacted market liquidity. However, the current attributes of China's emergent carbon emissions trading framework reveal features of opacity, protracted inter-trade durations, inefficient resource allocation, market segmentation, and price heterogeneity across trading pilots. These factors collectively give rise to prospective obstacles to liquidity and pricing efficiency within the Chinese carbon market. Song et al. (2017) and Zhang et al. (2019) also emphasize these issues, elucidating the interplay among the over-allocation of carbon emission allowances, the nascent state of China's carbon financial market, and governmental policy deficiencies contributing to this quandary.

Driven by carbon illiquidity, China's carbon market shows pronounced inefficiencies despite regional variations. The initial eight pilot markets reveal a complex efficiency and risk landscape. Shenzhen and Beijing excel in efficiency, yet overall performance remains suboptimal. Among China's key economic regions, the East outperforms, the Central converges fastest, and the West lags in both metrics (Dong et al., 2013). Concurrently, China's carbon market lags behind the European Union's in efficiency metrics, demonstrating less maturity yet higher activity, and displays leverage characteristics. However, a gradual transition from inefficiency to weak efficiency is observed (Sun et al., 2020; Zhao et al., 2017; Zhou et al., 2019; Liu et al., 2019). It is evident that China's carbon market remains nascent, and regulatory deficiencies contribute to its inefficiency (Zhu et al., 2020). While most of China's carbon markets exhibit inefficiencies, select pilot markets like Shenzhen and Beijing have attained weak efficiency. These inefficiencies may be attributable to restricted carbon liquidity. Wu and Qin (2021) illustrate a long-term positive equilibrium

 http://dx.doi.org/10.21511/imfi.20(4).2023.19

correlation between pilot market efficiency and liquidity, indicating that liquidity enhances market efficiency in the short term.

Generally, determinants of liquidity fluctuations can be categorized into macroeconomic and microeconomic variables. Stock liquidity is influenced by macroeconomic variables such as oil prices, gold prices, inflation rates, and foreign investment inflows. Oil price volatility and uncertainty exert a discernible influence on stock market liquidity. Zheng and Su (2017) establish that oil price fluctuations significantly affect stock markets: pronounced demand shocks correlate with increased liquidity, whereas the influence of oil price shifts on oil supply and aggregate demand adversely impacts stock liquidity. Zhang and Wong (2023) suggest that heightened oil uncertainty exerts a significant adverse effect on the stock liquidity of publicly traded firms. For sectors extraneous to the oil industry, the ramifications of escalating oil uncertainty are more pronounced for smaller firms than their larger counterparts. Conversely, within the oil and affiliated sectors, the stock liquidity of large oil enterprises exhibits heightened sensitivity to oil price uncertainty.

Foreign investment flows also influence stock market liquidity. Naik and Reddy (2021) indicate that foreign investment inflows and elevated gold prices contribute to decreased stock market liquidity. According to Li et al. (2022), the presence of foreign investors enhances corporate governance mechanisms, thereby mitigating stock liquidity uncertainty. They further posit that the heterogeneity among foreign investors is a pivotal determinant of stock liquidity uncertainty. Similarly, Ng et al. (2016) found that stock liquidity diminishes with increased direct foreign ownership but augments with foreign portfolio ownership. Concurrently, inflation and stock liquidity exhibit a negative correlation. Elevated inflation rates adversely impact equity liquidity and diminish market capitalization (Boyd et al., 1996; Khan, 2004). Furthermore, Jiang (2014) elucidates that rising inflation depresses stock liquidity and amplifies liquidity covariance. This effect is more pronounced for stocks with lower market capitalization and reduced liquidity than other stocks.

From a microeconomic perspective, stock liquidity is principally influenced by firm-specific determinants and certain external variables. Cheng (2007) enumerates six key factors that impact stock liquidity: firm size, ownership concentration, the extent of information asymmetry, engagement in margin trading, investors' perceptions, and the prevailing market liquidity conditions. Among these variables, firm fundamentals substantially influence stock liquidity, encompassing many factors such as profitability, operational management, and innovation. Uncertainty regarding these fundamentals can significantly affect liquidity; firms with diminished profitability often exhibit increased liquidity (Asem et al., 2016). Additionally, robust corporate governance mechanisms enhance liquidity by intensifying managerial oversight and mitigating information asymmetry (Chung et al., 2010; Prommin et al., 2014). In addition, a firm's inventive and innovative activities can contribute positively to its stock liquidity (Chen et al., 2023). Firm size and total outstanding shares also influence stock liquidity. Cheng (2007) posits that both firm size and shareholding composition are pertinent determinants: a positive correlation exists between firm size and liquidity, and greater diversification in shareholding structure is associated with enhanced liquidity. Additionally, the pronounced volatility in liquidity metrics pre- and post-stock splits corroborates the transient influence of stock splits on stock liquidity (Huang et al., 2015).

Regarding liquidity spillovers, intramarket and intermarket spillovers can be observed across various asset classes within a singular financial market. For instance, liquidity spillovers exist among diverse commodities within futures, foreign exchange, and equity markets. Zhang and Ding (2021) indicate that commodity price fluctuations within futures markets are influenced not merely by their liquidity but also by the liquidity of different commodity classes. In the foreign exchange domain, Chang et al. (2022) identify significant liquidity spillovers across currencies, noting that these spillovers are time-variant and are exacerbated by financial constraints and market instability. Recent studies by Zhou and Ye (2023) in the equity market reveal that liquidity and returns of margin-traded equities exert spillover effects on other stocks. Lim and Choi (2022) further corroborate that liquidity spillovers manifest between different industry sectors within the equity market, as evidenced in an analysis of S&P 500 constituents. These studies collectively affirm the existence of liquidity spillovers within specific financial markets.

Beyond the confines of financial markets, there exists a potential for spillovers between these markets and other markets. Wen et al. (2012) identified a contagion effect between crude oil and stock prices. This contagion effect exhibited greater intensity in the United States than in China. Other investigations have elucidated direct risk spillover dynamics and information dissemination across diverse markets. Wen et al. (2019) identified risk spillovers between oil and equity markets, with a discernible shift after the 2008 financial crisis. The realm of carbon markets also experiences risk spillovers. Balcılar et al. (2016) revealed that risks from energy markets, including coal futures, permeate into carbon markets, engendering spillovers. In the context of China's pilot carbon markets, Yao et al. (2022) discerned modest information spillovers with the energy and stock markets, especially coal and oil markets. Notably, Ren et al. (2023) unveiled information spillovers between the stock market and other markets, with the oil market exerting more substantial spillover on the stock market than the inverse, signifying the stock market's propensity to receive information. Liquidity spillovers are also observable across distinct markets, encompassing the foreign exchange and fund markets. These spillovers can also have repercussions on the stock market. Righi and Vieira (2014) uncovered that international stock market returns could be influenced by liquidity spillovers, employing wavelet multiscale methodologies to dissect different time series meticulously. Chan et al. (2008) centered on liquidity spillovers within fund markets, highlighting that the illiquidity of funds and their underlying assets in trading markets can impact share prices. The study suggests that in integrated markets, illiquidity in one market is susceptible to spillovers, consequently influencing other markets. Furthermore, liquidity spillovers manifest in the foreign exchange and stock markets. Karnaukh et al. (2015) illustrated that foreign exchange market liquidity varies with bond and equity markets.

Carbon markets wield an influence over corporations and stock markets, with the Chinese carbon market exerting a significant impact on participating companies and their associated stocks. Zhang and Zhang (2023) show that the carbon price returns negatively affect the stock returns of enterprises covered by the Chinese regional carbon markets. According to Sun et al. (2022), a modest two-way causality is observed between the carbon and stock markets, with a 1% oscillation in one market leading to an approximately 0.15% to 0.3% oscillation in the other. Wen et al. (2020) found that the carbon emission trading market impacts the broader Chinese stock market and industries. Carbon-intensive firms' trajectory hinges on emission trading prices, prompting a distinct long-term asymmetry between the stock market and carbon trading. This is evident in the stock market's heightened responsiveness to carbon price increases versus decreases. Moreover, in China's carbon market, carbon trading positively impacts excess returns for companies involved in carbon allowance trading. These firms, marked by heightened carbon exposure, witness an increasing carbon premium on their stock returns. Variations in carbon allowances can further impact stock returns as companies with elevated carbon emissions confront heightened carbon risks, translating into higher anticipated stock returns (Oestreich & Tsiakas, 2015).

Limited research has explored the liquidity spillover dynamics between carbon and stock markets. Zhang and Han (2022) discerned an asymmetric pattern in liquidity spillovers between these markets. Notably, the one-period lagged trading volume of the carbon emission market negatively affects the future trading volume of the stock market. Nonetheless, their analysis was conducted at an aggregate market level instead of an examination at the individual firm level. In contrast, this paper explores liquidity spillover from Chinese carbon markets to the relevant stock markets at the level of individual firms.

2. METHODOLOGY

This study employs two datasets free from survivorship bias: (1) the Wind Economic Database, encompassing regional carbon, gold, crude oil,

http://dx.doi.org/10.21511/imfi.20(4).2023.19

natural gas, and coal price variables, and (2) the China Stock Market & Accounting Research database, capturing individual stock returns, trading volume, and company information.

The first step is to manually curate a roster of enterprises across eight pilot regional emissions trading system (ETS) markets: Shenzhen, Shanghai, Beijing, Tianjin, Chongqing, Hubei Province, Fujian Province, Guangdong Province, and the national ETS market. This necessitates manual data extraction from pertinent Municipal Ecology and Environment Bureaus. This study identifies 5,246 ETS-regulated companies, predominantly privately owned. Subsequently, a Google search is conducted for each company's name, identifying 338 publicly traded firms – 223 from regional pilot ETS markets and 115 from the national ETS market.

The second step is to extract daily stock returns and trading volumes from the China Stock Market & Accounting Research database for the 338 publicly listed entities spanning the period of August 2013 to October 2023, commensurate with the inception of China's first pilot ETS market in Shenzhen in 2013. Additionally, stock information is retrieved, including stock code, name, and industry classification.

The third step is to acquire daily carbon price and trading volume from the Wind Economic Database for the eight pilot regions and the national market. Concurrently, time series data are compiled for control variables from the same source. Daily gold price (COMEX gold, ticker code: GC.CMX), crude oil price (NYMEX WTI, ticker code: CL.NYM), natural gas price (NYMEX, ticker code: NG.NYM), and coal price index (ticker code: JFI.WI) are retrieved. These control variables are chosen due to their substantial impact on carbon emissions. Fossil energy, encompassing coal, oil, and natural gas, has historically been pivotal for China's industrial production. Additionally, gold is included as it reflects economic trends and serves as a reliable market indicator.

This study follows Amihud (2002) to define security liquidity as the average ratio of the daily absolute return to the trading volume on that day, $\left|R_{jmd}\right| / Vol_{jmd}$. R_{jmd} is the return on security j on day d of month m, and Vol_{jmd} is the daily volume. The liquidity of security j is calculated as the monthly average:

$$Liq_{jm} = \frac{1}{D_{jm}} \sum_{t=1}^{D_{jm}} \frac{\left|R_{jmd}\right|}{Vol_{jmd}}, \tag{1}$$

where D_{jm} is the number of days for which data are available for security j in month m. Equation (1) calculates monthly liquidity measures for stocks, regional carbon, gold, oil, gas, and coal prices.

Next, this study proceeds to calculate the mean liquidity for these stocks as follows:

$$StockLiq_t = \frac{1}{N_t} \sum_{t=1}^{N_t} Liq_{jm}, \tag{2}$$

where N_t is the number of ETS-covered stocks in month t, and $StockLiq_t$ is the average stock liquidity in month t. A similar approach calculates the mean carbon price liquidity across nine distinct regions. Given that the liquidity measures exhibit pronounced volatility and the presence of significant outliers, this study winsorizes the liquidity measures at the top 5% to mitigate the influence of these extreme observations. The final sample encompasses 338 firms and 123 monthly observations from August 2013 to October 2023.

Finally, this study employs the ordinary least squares regression to elucidate the linear association between the two pivotal variables: carbon price liquidity and stock liquidity. The basic model equation is as follows:

$$StockLiq_t = \beta_0 + \beta_1 CarbonLiq_t + \varepsilon_t, \tag{3}$$

where $CarbonLiq_t$ denotes carbon price liquidity in month t. β_0 is the intercept term, β_1 is the regression coefficient, and ε_t is the error term with $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma^2$.

Subsequently, the control variables impacting stock liquidity are included. The multivariate regression is as follows:

$$\begin{aligned} StockLiq_t &= \beta_0 + \beta_1 CarbonLiq_t + \\ &+ \beta_2 GoldLiq_t + \beta_3 OilLiq_t + \beta_4 GasLiq_t + \\ &+ \beta_5 CoalLiq_t + \varepsilon_t, \end{aligned} \tag{4}$$

where $GoldLiq_t$ denotes gold price liquidity in month t, $OilLiq_t$ denotes crude oil price liquidity in month t, $GasLiq_t$ denotes natural gas price liquidity in month t, and $CoalLiq_t$ denotes coal price liquidity in month t.

3. RESULTS

Table 1 presents the descriptive statistics for all examined variables. The average liquidity of stocks is quantified at 0.0257, over twice its standard deviation, measured at 0.0099. In contrast, the average liquidity of carbon pricing is 0.0850, nearly equivalent to its standard deviation of 0.0768, signifying a substantial degree of variation compared to stock liquidity. Gold price liquidity exhibits an average of 0.0130, twice its standard deviation of 0.0069, indicative of lesser variability. The liquidity averages for crude oil, natural gas, and coal are documented at 0.0452, 0.0410, and 0.0031, respectively, with all averages approximating their respective standard deviations.

Table 2 presents the pairwise correlations among the variables under investigation. Stock price liquidity is positively associated with carbon liquidity, yielding a correlation coefficient of 0.2125, significant at the 5% significance level. Conversely, stock price liquidity is inversely correlated with the liquidity of gas and coal prices, exhibiting coefficients of –0.1742, significant at the 10% level, and –0.3699 at the 1% level, respectively. The empirical evidence suggests that a decline in carbon price liquidity is positively linked to reduced liquidity in ETS-covered stock prices.

Table 3 elucidates the baseline regressions, employing Equations (3) and (4). The dependent variable is the mean liquidity of the 338 ETS-covered stocks, with carbon price liquidity as the primary explanatory variable. The estimated coefficient for carbon price liquidity registers at 0.0275, achieving statistical significance at the 5% level. Upon the inclusion of control variables, namely the liquidity of gold price, coal price, natural gas price, and crude oil price, the coefficient of carbon price liquidity adjusts to 0.0247, retaining statistical significance at the 5% level. This adjustment substantiates the robustness of the baseline findings after accounting for relevant commodity price liquidity. The paper thus posits a positive influence of car-

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std.Dev.	Min	P25	Median	P75	Max
StockLiq	123	0.0257	0.0099	0.0105	0.0188	0.0226	0.0322	0.0551
CarbonLiq	123	0.0850	0.0768	0.0004	0.0176	0.0648	0.1337	0.3225
GoldLiq	123	0.0130	0.0069	0.0045	0.0078	0.0104	0.0167	0.0367
OilLiq	123	0.0452	0.0460	0.0122	0.0213	0.0339	0.0510	0.3508
GasLiq	123	0.0410	0.0405	0.0120	0.0224	0.0301	0.0442	0.3059
CoalLiq	123	0.0031	0.0031	0.0003	0.0007	0.0015	0.0049	0.0117

Note: This table presents descriptive statistics for 338 firms across nine ETS markets, spanning August 2013 to October 2023.

Table 2. Pairwise correlations between variables

Variable	StockLiq	CarbonLiq	GoldLiq	OilLiq	GasLiq	CoalLiq
StockLiq	1.0000					
CarbonLiq	0.2125**	1.0000				
	(0.0183)					
GoldLiq	0.0881	–0.4066***	1.0000			
	(0.3325)	(0.0000)				
OilLiq	0.0131	–0.1170	0.3998***	1.0000		
	(0.8859)	(0.1975)	(0.0000)			
GasLiq	–0.1742*	–0.1866**	0.2662***	0.2809***	1.0000	
	(0.0540)	(0.0388)	(0.0029)	(0.0016)		
CoalLiq	–0.3699***	–0.2440***	–0.0867	–0.0104	0.1973**	1.0000
	(0.0000)	(0.0065)	(0.3401)	(0.9095)	(0.0287)	

Note: This table shows the pairwise correlations between variables. The *p*-values are reported in parentheses below the correlation coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

http://dx.doi.org/10.21511/imfi.20(4).2023.19

bon price liquidity on the liquidity of ETS-covered stocks. Economically, given the coefficient value of 0.0275, a one standard deviation fluctuation in carbon liquidity, 0.0768, induces a change in stock liquidity of 0.0021, approximately 8% of its mean value of 0.0257. Hence, carbon price exerts a substantive spillover effect on correlated stock liquidity. In market turbulence instigated by unforeseen variables such as policy alterations, investors may utilize ETS market carbon liquidity as a leading indicator for situational awareness.

Table 3. Baseline regression

Variable	(1) StockLiq	(2) StockLiq
CarbonLiq	0.0275**	0.0247**
	(0.0115)	(0.0124)
GoldLiq		0.2522*
		(0.1472)
OilLiq		−0.0004
		(0.0201)
GasLiq		−0.0317
		(0.0223)
CoalLiq		−0.8973***
		(0.2865)
Constant	0.0234***	0.0244***
	(0.0013)	(0.0029)
Observations	123	123
Adj-R^2	0.037	0.148

Note: This table shows the baseline regression of ETS-covered stock liquidity on the carbon price liquidity and a series of control variables. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

Table 4 presents the regression results of stock liquidity across sectors distinguished by their respective carbon intensity levels. In entities within sectors of low carbon intensity, the coefficient linked to carbon liquidity is recorded at 0.0282, attaining statistical significance at the 5% level. Conversely, in sectors characterized by high carbon intensity, the analogous coefficient stands at 0.0225, achieving significance at 10%. These findings accentuate a stronger positive correlation between carbon liquidity and stock liquidity in sectors with diminished carbon intensity, in contrast to those with elevated carbon intensity. It can be conjectured that firms operating in industries with high carbon intensity may initiate upgrades to their facilities in reaction to heightened demand for carbon emissions, thereby rendering them less susceptible to liquidity shocks emanating from the carbon market.

Table 4. Low- and high-carbon-intensity industries

Variable	(1) Low-carbon-intensity industries StockLiq	(2) High-carbon-intensity industries StockLiq
CarbonLiq	0.0282**	0.0225*
	(0.0114)	(0.0133)
GoldLiq	0.2702**	0.2366
	(0.1352)	(0.1568)
OilLiq	−0.0087	0.0052
	(0.0185)	(0.0214)
GasLiq	−0.0302	−0.0324
	(0.0204)	(0.0237)
CoalLiq	−0.6538**	−1.0481***
	(0.2630)	(0.3052)
Constant	0.0217***	0.0262***
	(0.0027)	(0.0031)
Observations	123	123
Adj-R^2	0.137	0.152

Note: This table shows the regression of ETS-covered stock liquidity on the carbon price liquidity and a series of control variables for two subsamples: the subsample firms in the low-carbon-intensity industries and the subsample firms in high-carbon-intensity industries. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

Table 5 explicates the regression results connecting stock liquidity with carbon price liquidity across nine ETS markets, complemented by a series of control variables. The affirmative liquidity spillover from carbon pricing to stock is exclusively observable in two nascent regional ETS markets: Hubei Province and Chongqing, which are inland instead of coastal regions. A plausible rationale for this phenomenon could be that these particular markets primarily rely on the manufacturing, construction, and transportation sectors. This reliance potentially renders them more susceptible to variations in carbon price liquidity.

Table 6 delineates regression results spanning two distinct temporal subperiods: the pre-COVID era (August 2013 to November 2019) and the period after its onset (December 2019 to October 2023). In the pre-COVID interval, the coefficient tied to carbon price liquidity stands at 0.0362, attaining statistical significance at 10%. Conversely, the corresponding coefficient registers at 0.0286 during the COVID era, reaching statistical significance at 1%. These results suggest that the emergence of the COVID-19 pandemic serves to amplify the liquidity

Table 5. Different ETS markets

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Shenzhen	Shanghai	Beijing	Guangdong Province	Tianjin	Hubei Province	Chongqing	Fujian Province	National market
	StockLiq	StockLiq	StockLiq	StockLiq	StockLiq	StockLiq	StockLiq	StockLiq	StockLiq
CarbonLiq	−0.0006	0.0040	−0.0051	−0.0159	−0.1738	0.0712**	0.0153***	0.0054	0.0561
	(0.0037)	(0.0056)	(0.0074)	(0.0115)	(0.1060)	(0.0313)	(0.0055)	(0.0042)	(0.3679)
GoldLiq	0.0397	0.2267	0.0023	−0.5853***	−0.1242	−0.2391	−0.6148**	−0.8578*	−0.7357*
	(0.1404)	(0.1486)	(0.1023)	(0.1638)	(0.2023)	(0.1522)	(0.2903)	(0.4697)	(0.4080)
OilLiq	−0.0109	−0.0011	0.0028	0.0456*	0.0448	0.0259	0.0533*	0.1207	0.1176
	(0.0205)	(0.0237)	(0.0164)	(0.0262)	(0.0312)	(0.0214)	(0.0284)	(0.0850)	(0.0806)
GasLiq	−0.0389*	−0.0225	−0.0213	−0.0261	−0.0537	−0.0082	−0.0018	−0.0246	−0.0163
	(0.0224)	(0.0252)	(0.0167)	(0.0267)	(0.0352)	(0.0216)	(0.0470)	(0.0399)	(0.0198)
CoalLiq	−0.3922	−0.6751**	−0.8701***	−0.8395***	−0.4628	−1.0663***	−0.3369	0.5708	0.1043
	(0.2756)	(0.2942)	(0.2212)	(0.3079)	(0.5065)	(0.2680)	(0.4089)	(0.3505)	(0.3226)
Constant	0.0266***	0.0252***	0.0210***	0.0358***	0.0361***	0.0294***	0.0293***	0.0253***	0.0242***
	(0.0023)	(0.0023)	(0.0015)	(0.0022)	(0.0039)	(0.0021)	(0.0037)	(0.0041)	(0.0038)
Observation	123	107	109	116	67	113	72	65	28
Adj-R^2	0.020	0.062	0.136	0.176	0.061	0.183	0.193	0.043	−0.033

Note: This table shows the regression of ETS-covered stock liquidity on the carbon price liquidity and a series of control variables in the eight regional and national markets. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

spillover effects transpiring from the carbon market to the equity market. This could be attributed to a depletion in stock market liquidity and an intensification of cross-market systematic risk induced by the pandemic.

Table 6. Subperiod analysis

Variable	(3)	(4)
	Pre COVID	During-COVID
	StockLiq	StockLiq
CarbonLiq	0.0362*	0.0286***
	(0.0187)	(0.0094)
GoldLiq	0.4058**	−0.2023
	(0.1998)	(0.2186)
OilLiq	0.0055	0.0300*
	(0.0345)	(0.0151)
GasLiq	−0.0303	−0.0294
	(0.0292)	(0.0211)
CoalLiq	−3.2488***	0.0225
	(0.7358)	(0.2082)
Constant	0.0253***	0.0221***
	(0.0041)	(0.0025)
Observations	76	47
Adj-R^2	0.230	0.243

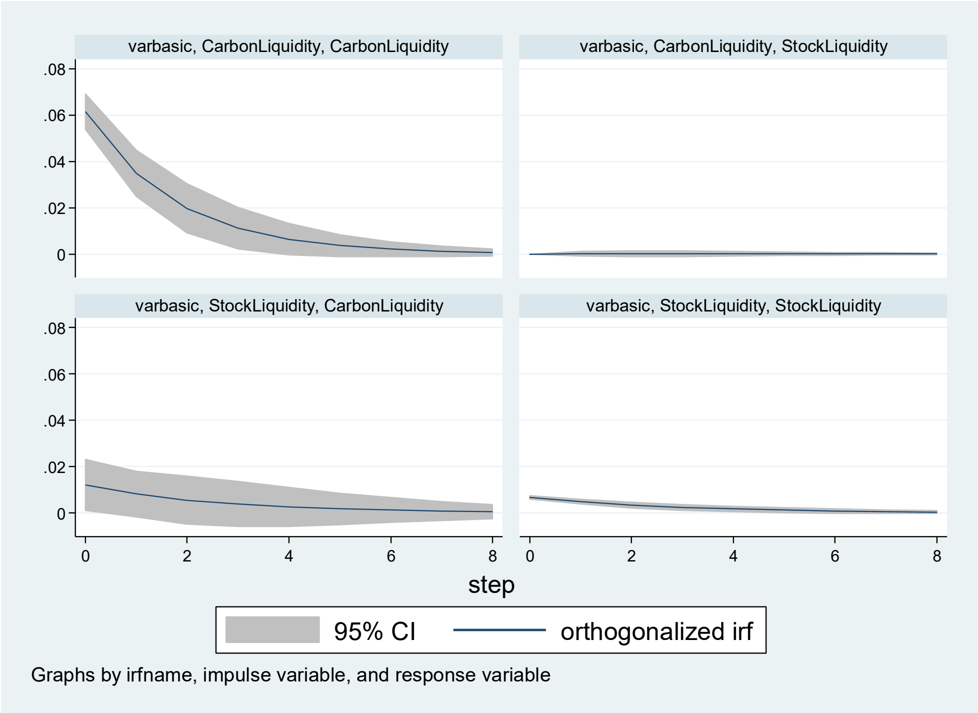
Note: This table shows the regression of ETS-covered stock liquidity on the carbon price liquidity and a series of control variables during subperiods: before the COVID-19 pandemic (2013.8–2019.11) and during the COVID-19 pandemic (2019.12–2023.10). The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

Table 7 presents the results of vector autoregressions. The results indicate robust positive auto-correlations for the liquidity in equity, carbon, gold, oil, and coal markets, with coefficients of 0.6498, 0.4324, 0.6649, 0.2842, and 0.9027, respectively, achieving statistical significance at the 1% level. Conversely, lagged carbon liquidity lacks significant explanatory prowess to contemporaneous stock liquidity and vice versa. These results suggest that liquidity spillovers are primarily synchronous rather than spanning across different periods.

Figure 1 displays impulse response functions delineating the interrelations between stock liquidity and carbon price liquidity after executing vector autoregression analyses. These graphical outcomes corroborate the empirical evidence presented in Table 7. The impulse response function gradually decays when quantifying auto-correlations in carbon price liquidity. Conversely, the impulse response function exhibits rapid attenuation when assessing the cross-relationship explanatory power between carbon price liquidity and equity liquidity.

Endogeneity issues emerge in the baseline regression specified by Equation (4). Reverse causality is conceivable, wherein elevated levels of stock illiquidity induce corporate distress,

http://dx.doi.org/10.21511/imfi.20(4).2023.19



Note: This figure shows the impulse function and changing trend between stock liquidity and carbon price liquidity after applying the vector autoregression analysis.

Figure 1. Vector autoregression impulse function

Table 7. Vector autoregression analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	StockLiq	**CarbonLiq**	**GoldLiq**	**OilLiq**	**GasLiq**	**CoalLiq**
L.StockLiq	0.6498***	0.0604	0.0887*	0.0920	−0.2105	−0.0180
	(0.0666)	(0.6046)	(0.0478)	(0.4112)	(0.4035)	(0.0134)
L.CarbonLiq	−0.0010	0.4324***	−0.0104	0.0744	−0.0346	−0.0014
	(0.0091)	(0.0826)	(0.0065)	(0.0562)	(0.0552)	(0.0018)
L.GoldLiq	0.0307	−2.8609***	0.6649***	2.1135***	0.5609	−0.0046
	(0.1073)	(0.9735)	(0.0770)	(0.6622)	(0.6497)	(0.0215)
L.OilLiq	−0.0023	0.1501	0.0001	0.2842***	0.0500	−0.0006
	(0.0144)	(0.1309)	(0.0104)	(0.0890)	(0.0874)	(0.0029)
L.GasLiq	−0.0276*	0.0153	−0.0130	−0.0275	0.0054	−0.0077**
	(0.0161)	(0.1462)	(0.0116)	(0.0995)	(0.0976)	(0.0032)
L.CoalLiq	−0.4149*	−4.5705**	0.0432	0.9309	0.5609	0.9027***
	(0.2176)	(1.9752)	(0.1563)	(1.3435)	(1.3182)	(0.0436)
Constant	0.0111***	0.0909***	0.0033*	−0.0055	0.0379**	0.0014**
	(0.0026)	(0.0240)	(0.0019)	(0.0163)	(0.0160)	(0.0005)
Observations	122	122	122	122	122	122

Note: This table shows the vector autoregression of ETS-covered stock liquidity, carbon price liquidity, and a series of control variables. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively

precipitating withdrawal from regional ETS markets and amplifying carbon price illiquidity. Alternatively, latent third-party attributes could concomitantly elevate both carbon price illiquidity and stock illiquidity, thereby engendering a spurious positive correlation. The present study deploys a two-stage least squares estimation framework to mitigate the endogeneity issue, utilizing lagged carbon price liquidity as the instrumental variable.

$$CarbonLiq_t = \beta_0 + \beta_1 CarbonLiq_{t-1} + \\ +\beta_2 CarbonLiq_{t-2} + \beta_3 GoldLiq_t + \\ +\beta_4 OilLiq_t + \beta_5 GasLiq_t + \beta_6 CoalLiq_t + \varepsilon_t, \quad (5)$$

$$StockLiq_t = \beta_0 + \beta_1 PredCarbonLiq_t + \\ +\beta_2 GoldLiq_t + \beta_3 OilLiq_t + \beta_4 GasLiq_t + \\ +\beta_5 CoalLiq_t + \varepsilon_t. \quad (6)$$

In the first step, Equation (5) regression predicts the current carbon price liquidity using the one- and two-month lagged carbon price liquidity as the instrumental variables. The second step employs the first-step predicted value to forecast stock liquidity in Equation (6). From prior research, lagged independent variables may be considered valid instrumental variables (Heckman, 1997).

Table 8 delineates the results of the two-stage least squares regression, utilizing lagged carbon price liquidity as the instrumental variables. The first-stage findings, consistent with Equation (5), indicate that the coefficient associated with the one-month lagged carbon liquidity stands at 0.3734 and achieves statistical significance at the 1% level, thus mitigating concerns of weak instrument variables. Following Equation (6), the second-stage findings reveal a statistically significant, positive association between the predicted carbon liquidity and stock liquidity, manifesting a coefficient of 0.0493 that is statistically significant at the 10% level. These two-stage least squares regression outcomes are congruent with the antecedent regression results.

4. DISCUSSION

The paper posits a robustly positive association between the liquidity of stocks and carbon prices. The baseline regression results presented in Table 3 corroborate this association, establishing a positive linkage between the two variables above. Consequently, the hypothesis garners empirical support, implying that a lack of liquidity in carbon price markets precipitates concurrent illiquidity in the stock prices of firms regulated under the ETS. These findings are consistent with extant literature documenting spillover effects across disparate markets (Chang et al., 2022; Wen et al.,

Table 8. Two-stage least squares regression results

Variable	(1) First stage	(2) Second stage
	CarbonLiq	StockLiq
Lag1 CarbonLiq	0.3734***	
	(0.0910)	
Lag2 CarbonLiq	0.1438	
	(0.0926)	
Predicted CarbonLiq		0.0493*
		(0.0266)
GoldLiq	–2.3740**	0.3393*
	(1.0067)	(0.1856)
OilLiq	–0.0201	–0.0086
	(0.1540)	(0.0225)
GasLiq	–0.0501	–0.0267
	(0.1500)	(0.0225)
CoalLiq	–3.6228*	–0.6962**
	(1.9178)	(0.3285)
Constant	0.0865***	0.0206***
	(0.0199)	(0.0049)
Observations	121	121
Adj-R^2	0.375	0.116

Note: This table presents the results derived from the two-stage least squares regressions, examining the association between carbon liquidity and stock liquidity, utilizing one- and two-period lagged carbon price liquidity as the instrumental variables. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

http://dx.doi.org/10.21511/imfi.20(4).2023.19

2012; Wen et al., 2019). Wen et al. (2020) find that the inception of China's carbon emissions trading market positively influences the excess returns of firms engaged in carbon emission allowances trading. Concurrently, Zhang and Zhang (2023) document a detrimental impact of carbon price returns on the stock returns of ETS-regulated firms. Extending this line of inquiry, Zhang and Han (2022) explore the interplay between liquidity and return dynamics within China's carbon emission trading and stock markets over 2013–2021, concluding that daily liquidity levels significantly forecast cross-sectional returns on the subsequent day. Contrarily, Yao et al. (2022) highlight the modest nature of information spillover effects between China's pilot carbon markets, the energy market, and the stock market. In the context of the European Union ETS, Oestreich and Tsiakas (2015) ascertain that German firms benefiting from gratuitous carbon emission allowances exhibit positive excess stock returns.

Table 4 elucidates a more robust positive correlation between carbon liquidity and stock liquidity in sectors with lower carbon intensity than those with higher carbon intensity. This phenomenon presents an intuitive dissonance, considering that enterprises with substantial carbon emissions are typically obligated to procure carbon permits to meet their energy requirements, resulting in elevated production costs and implications for cash flows. Tian et al. (2016) explicate a reciprocal relationship between carbon price returns and electricity stock returns for entities with high carbon intensity, whereas this relationship is inverted for entities with low carbon intensity. In concordance, Xie et al. (2023) validate that participation in China's pilot carbon ETS provides a buffer against stock price volatility for firms with substantial carbon footprints, concurrently mitigating the risk of stock price devaluations associated with reductions in carbon emissions. Yang et al. (2019) theorize that faced with incremental enterprise costs due to environmental regulatory measures, corporations elect a constructive trajectory, fortifying internal governance, enhancing operational efficiency, and catalyzing innovation rather than opting for the detrimental strategy of trans-regional relocation. This strategic choice culminates in an augmentation of output and benefits. In a related vein, Cheng et al. (2019) contend that the expansion of the service sector acts as a catalyst for the conversion of regions with high carbon intensity to locales with reduced carbon emissions, thereby facilitating the advent of environmentally sustainable and low-carbon economic development. These empirical insights collectively provide a potential rationale for the observed amplification of liquidity spillover effects in industries marked by lower carbon intensity.

Table 5 delineates a more pronounced relationship between stock and carbon price liquidity in Hubei Province and Chongqing. Intriguingly, Chang et al. (2018b) identify the carbon product in Hubei Province as possessing the highest liquidity. Furthermore, Hubei Province and Chongqing represent some of the more recent additions to regional carbon markets, in contrast to their counterparts, and are situated inland, as opposed to other markets located along the coast. A plausible interpretation of these phenomena is that these two markets predominantly rely on businesses such as manufacturing, construction, and transportation, making them more susceptible to variations in carbon price liquidity. Notably, the national market does not exhibit a discernible spillover effect, a phenomenon potentially ascribable to the constraints of a limited sample period. Collectively, these observations highlight regional disparities in the liquidity spillover effects under scrutiny.

Table 6 reveals an intensification of the positive liquidity spillover effect during COVID-19 compared to the pre-pandemic era, a finding that aligns with extant scholarly works. Chang et al. (2022) document a substantial augmentation in liquidity spillover within foreign exchange markets during periods of financial turmoil. Utilizing a spillover model, Lim and Choi (2022) analyze liquidity spillovers across various sectors in the U.S. during the global financial crisis and the COVID-19 pandemic, discovering that liquidity spillovers were notably more pronounced during both crisis periods. Similarly, Wen et al. (2019) observed a strengthened risk spillover between oil and stock markets after the 2008 financial crisis, whereas the spillover effect was markedly attenuated before the crisis.

Table 8 delineates that the predominant direction of liquidity spillover is from carbon markets to stock markets, a conclusion that is intuitively sound and corroborated by existing literature. Ren et al. (2023) explore the dynamics of spillovers and information transmission across carbon, crude oil, and stock markets during the third phase of the European Union ETS, demonstrating that information flows robustly from the crude oil market to the stock market under normal conditions but dissipates in extremely bearish or bullish stock market scenarios. Concurrently, Sun et al. (2022) uncover a modest bidirectional causality between Chinese carbon prices and four energy-intensive stock indices, quantifying the impact of a 1% fluctuation in one market as inducing a 0.15%–0.3% fluctuation in the other. In a related study, Zhang and Han (2022) scrutinize the spillover effects between these two markets, concluding that the carbon market exerts a more substantial influence on the stock market.

CONCLUSION

This study explores the liquidity spillover effects of carbon pricing on ETS-covered stocks in China. Leveraging a comprehensive dataset of 338 publicly listed, ETS-covered firms spanning nine distinct markets in China from 2013 to 2023, this study documents a statistically significant, positive spillover effect from carbon price liquidity to associated equity liquidity. Notably, this positive liquidity spillover effect exhibits a greater magnitude in industries with lower carbon intensity than those with higher carbon intensity. Regional analysis reveals that the liquidity spillover phenomenon is significantly manifest solely within Hubei Province and Chongqing, thus evincing regional heterogeneity. Temporal partitioning indicates that the spillover effect is more prominent during COVID-19 relative to early epochs. Vector autoregressive analyses corroborate that liquidity spillovers are chiefly concurrent rather than inter-temporal. The outcomes of the two-stage least squares estimations effectively mitigate endogeneity concerns.

This study offers multiple contributions to existing literature. Firstly, it augments the body of work focused on the development and effectiveness of China's carbon emission trading markets, elucidating a direct conduit through which policy influences the equity market. Secondly, introducing an innovative inter-market spillover channel enhances the literature on stock liquidity determinants. Lastly, the study fortifies the overarching literature on liquidity spillovers across diverse markets. It furnishes novel empirical insights into the cross-market liquidity dynamics between carbon and equity markets in China, bridging a significant research gap.

In summary, the present research is pivotal in elucidating the interconnected dynamics between China's nascent carbon markets and its equity market. As global carbon pricing mechanisms proliferate, the prospect for additional scholarly inquiry is pronounced. Grasping these complex interlinkages is imperative for regulatory entities, investment practitioners, and corporate actors steering the course of energy transformation and climate risk mitigation. Nevertheless, the study has limitations that future research could redress. The dataset, confined to a temporal window commencing with initiating the ETS pilots in 2013, could benefit from longitudinal expansion as these markets evolve, potentially yielding more robust empirical findings. Moreover, scrutinizing liquidity spillover effects across different industries may furnish supplementary insights. Additionally, the merit exists for exploring alternative transmission conduits between carbon and equity markets, extending beyond solely liquidity effects.

AUTHOR CONTRIBUTIONS

Conceptualization: Jianing Zhang.
Data curation: Xinyuan Yang, Jingyao Zhu, Hantao Xie, Jianing Zhang.
Formal analysis: Xinyuan Yang, Jingyao Zhu, Hantao Xie, Jianing Zhang.
Funding acquisition: Jianing Zhang.
Investigation: Xinyuan Yang, Jingyao Zhu, Hantao Xie, Jianing Zhang.

http://dx.doi.org/10.21511/imfi.20(4).2023.19

Methodology: Xinyuan Yang, Jingyao Zhu, Hantao Xie, Jianing Zhang.
Project administration: Jianing Zhang.
Resources: Xinyuan Yang, Jingyao Zhu, Hantao Xie.
Software: Xinyuan Yang, Hantao Xie.
Supervision: Jianing Zhang.
Validation: Xinyuan Yang, Jingyao Zhu, Jianing Zhang.
Visualization: Xinyuan Yang.
Writing – original draft: Xinyuan Yang, Jingyao Zhu, Hantao Xie.
Writing – review & editing: Jianing Zhang.

ACKNOWLEDGMENT

This research was supported by the Summer Student Partnering with Faculty Research Program of Wenzhou-Kean University (WKUSSPF202304), the Wenzhou Association for Science and Technology – Service and Technology Innovation Program (jczc0254), and the Department of Education of Zhejiang Province – General Program (Y202353438).

REFERENCES

1. Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31-56. https://doi.org/10.1016/S1386-4181(01)00024-6
2. Asem, E., Chung, J., Cui, X., & Tian, G. Y. (2016). Liquidity, investor sentiment and price discount of SEOs in Australia. *International Journal of Managerial Finance, 12*(1), 25-51. https://doi.org/10.1108/IJMF-10-2013-0106
3. Balcılar, M., Demirer, R., Hammoudeh, S., & Nguyen, D. K. (2016). Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. *Energy Economics, 54,* 159-172. https://doi.org/10.1016/j.eneco.2015.11.003
4. Boyd, J. H., Levine, R., & Smith, B. D. (1996). *Inflation and Financial Market Performance* (Working Paper, 96-17). Retrieved from https://fraser.stlouisfed.org/files/docs/historical/frbclev/wp/frbclv_wp1996-17.pdf
5. Chan, J. S., Jain, R., & Xia, Y. (2008). Market segmentation, liquidity spillover, and closed-end country fund discounts. *Journal of Financial Markets, 11*(4), 377-399. https://doi.org/10.1016/j.finmar.2008.01.005
6. Chang, K., Chen, R., & Chevallier, J. (2018a). Market fragmentation, liquidity measures and improvement perspectives from China's emissions trading scheme pilots. *Energy Economics, 75,* 249-260. https://doi.org/10.1016/j.eneco.2018.07.010
7. Chang, K., Lu, S., & Song, X. (2018b). The impacts of liquidity dynamics on emissions allowances price: Different evidence from China's emissions trading pilots. *Journal of Cleaner Production, 183,* 786-796. https://doi.org/10.1016/j.jclepro.2018.02.150
8. Chang, Y. T., Gau, Y. F., & Hsu, C. C. (2022). Liquidity spillover in foreign exchange markets. *Finance Research Letters, 44,* 102105. https://doi.org/10.1016/j.frl.2021.102105
9. Chen, Z., Xiao, Y., & Jiang, K. (2023). Corporate green innovation and stock liquidity in China. *Accounting & Finance, 63,* 1381-1415. https://doi.org/10.1111/acfi.13027
10. Cheng, J., Yi, J., Dai, S., & Xiong, Y. (2019). Can low-carbon city construction facilitate green growth? Evidence from China's pilot low-carbon city initiative. *Journal of Cleaner Production, 231,* 1158-1170. https://doi.org/10.1016/j.jclepro.2019.05.327
11. Cheng, S. R. (2007). A study on the factors affecting stock liquidity. *International Journal of Services and Standards, 3*(4), 453-475. https://doi.org/10.1504/IJSS.2007.015227
12. Chung, K., Elder, J., & Kim, J. (2010). Corporate governance and liquidity. *Journal of Financial and Quantitative Analysis, 45*(2), 265-291. https://doi.org/10.1017/S0022109010000104
13. Dong, F., Li, X., Long, R., & Liu, X. (2013). Regional carbon emission performance in China according to a stochastic frontier model. *Renewable and Sustainable Energy Reviews, 28,* 525-530. https://doi.org/10.1016/j.rser.2013.08.009
14. Duan, H., Mo, J., Fan, Y., & Wang, S. (2018). Achieving China's energy and climate policy targets in 2030 under multiple uncertainties. *Energy Economics, 70,* 45-60. https://doi.org/10.1016/j.eneco.2017.12.022
15. Duan, H., Yuan, D., Cai, Z., & Wang, S. (2022). Valuing the impact of climate change on China's economic growth. *Economic Analysis and Policy, 74,* 155-174. https://doi.org/10.1016/j.eap.2022.01.019
16. Heckman, J. (1997). Instrumental variables: A study of implicit

behavioral assumptions used in making program evaluations. *Journal of Human Resources, 32*(3), 441-462. https://doi.org/10.2307/146178

17. Huang, G. C., Liano, K., & Pan, M. S. (2015). The effects of stock splits on stock liquidity. *Journal of Economics and Finance, 39,* 119-135. https://doi.org/10.1007/s12197-013-9250-6

18. IEA (2022). *World energy outlook 2022.* Retrieved from https://www.iea.org/reports/world-energy-outlook-2022

19. 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. *Applied Energy, 178,* 902-917. https://doi.org/10.1016/j.apenergy.2016.06.100

20. Jiang, L. (2014). Stock liquidity and the Taylor rule. *Journal of Empirical Finance, 28,* 202-214. https://doi.org/10.1016/j.jempfin.2014.07.001

21. Kalaitzoglou, I., & Ibrahim, B. M. (2013). Does order flow in the European Carbon Futures Market reveal information? *Journal of Financial Markets, 16*(3), 604-635. https://doi.org/10.1016/j.finmar.2012.11.002

22. Karnaukh, N., Ranaldo, A., & Söderlind, P. (2015). Understanding FX liquidity. *Review of Financial Studies, 28*(11), 3073-3108. https://doi.org/10.1093/rfs/hhv029

23. Khan, K. N. (2004). Inflation and stock market performance: A case study for Pakistan. *Savings and Development, 28*(1), 87-101. https://www.jstor.org/stable/25830851

24. Li, Y., Han, M., Faff, R., & Zhang, H. (2022). Foreign ownership and stock liquidity uncertainty. *Journal of International Financial Markets, Institutions and Money, 81,* 101673. https://doi.org/10.1016/j.intfin.2022.101673

25. Lim, S. Y., & Choi, S. Y. (2022). Impact of liquidity spillovers among industrial sectors on stock markets during crisis periods: Evidence from the S&P 500 index. *PLoS One, 17*(11), e0277261. https://doi.org/10.1371/journal.pone.0277261

26. Liobikienė, G., & Butkus, M. (2017). The European Union's possibilities to achieve targets of Europe 2020 and Paris agreement climate policy. *Renewable Energy, 106,* 298-309. https://doi.org/10.1016/j.renene.2017.01.036

27. Liu, X., Zhou, X., Zhu, B., He, K., & Wang, P. (2019). Measuring the maturity of carbon market in China: An entropy-based TOPSIS approach. *Journal of Cleaner Production, 229,* 94-103. https://doi.org/10.1016/j.jclepro.2019.04.380

28. Naik, P., & Reddy, Y. V. (2021). Determinants of stock market liquidity – a macroeconomic perspective. *Macroeconomics and Finance in Emerging Market Economies*, published online. https://doi.org/10.1080/17520843.2021.1983705

29. Ng, L., Wu, F., Yu, J., & Zhang, B. (2016). Foreign investor heterogeneity and stock liquidity around the world. *Review of Finance, 20*(5), 1867-1910. https://doi.org/10.1093/rof/rfv048

30. Oestreich, A. M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of Banking & Finance, 58,* 294-308. https://doi.org/10.1016/j.jbankfin.2015.05.005

31. Prommin, P., Jumreornvong, S., & Jiraporn, P. (2014). The effect of corporate governance on stock liquidity: The case of Thailand. *International Review of Economics & Finance, 32,* 132-142. https://doi.org/10.1016/j.iref.2014.01.011

32. Ren, X., Dou, Y., Dong, K., & Yan, C. (2023). Spillover effects among crude oil, carbon, and stock markets: Evidence from nonparametric causality-in-quantiles tests. *Applied Economics, 55*(38), 4486-4509. https://doi.org/10.1080/00036846.2022.2128297

33. Righi, M. B., & Vieira, K. M. (2014). Liquidity spillover in international stock markets through distinct time scales. *PloS one, 9*(1), e86134. https://doi.org/10.1371/journal.pone.0086134

34. Song, Y., Liu, T., Li, Y., & Liang, D. (2017). Region division of China's carbon market based on the provincial/municipal carbon intensity. *Journal of Cleaner Production, 164,* 1312-1323. https://doi.org/10.1016/j.jclepro.2017.07.026

35. Sun, L., Xiang, M., & Shen, Q. (2020). A comparative study on the volatility of EU and China's carbon emission permits trading markets. *Physica A: Statistical Mechanics and its Applications, 560,* 125037. https://doi.org/10.1016/j.physa.2020.125037

36. Sun, X., Fang, W., Gao, X., An, H., Liu, S., & Wu, T. (2022). Complex causalities between the carbon market and the stock markets for energy intensive industries in China. *International Review of Economics & Finance, 78,* 404-417. https://doi.org/10.1016/j.iref.2021.12.008

37. Tian, Y., Akimov, A., Roca, E., & Wong, V. (2016). Does the carbon market help or hurt the stock price of electricity companies? Further evidence from the European context. *Journal of Cleaner Production, 112,* 1619-1626. https://doi.org/10.1016/j.jclepro.2015.07.028

38. Wang, K., Wei, Y. M., & Huang, Z. (2016). Potential gains from carbon emissions trading in China: A DEA based estimation on abatement cost savings. *Omega, 63,* 48-59. https://doi.org/10.1016/j.omega.2015.09.011

39. Wang, P., Dai, H. C., Ren, S. Y., Zhao, D. Q., & Masui, T. (2015). Achieving Copenhagen target through carbon emission trading: Economic impacts assessment in Guangdong Province of China. *Energy, 79,* 212-227. https://doi.org/10.1016/j.energy.2014.11.009

40. Wen, D., Wang, G. J., Ma, C., & Wang, Y. (2019). Risk spillovers between oil and stock markets: A VAR for VaR analysis. *Energy Economics, 80,* 524-535. https://doi.org/10.1016/j.eneco.2019.02.005

41. Wen, F., Wu, N., & Gong, X. (2020). China's carbon emissions trading and stock returns. *Energy*

http://dx.doi.org/10.21511/imfi.20(4).2023.19

Economics, 86, 104627. https://doi.org/10.1016/j.eneco.2019.104627

42. Wen, X., Wei, Y., & Huang, D. (2012). Measuring contagion between energy market and stock market during financial crisis: A copula approach. *Energy Economics, 34*(5), 1435-1446. https://doi.org/10.1016/j.eneco.2012.06.021
43. World Bank. (2022). *China's transition to a low-carbon economy and climate resilience needs shifts in resources and technologies*. Retrieved from https://www.worldbank.org/en/news/press-release/2022/10/12/china-s-transition-to-a-low-carbon-economy-and-climate-resilience-needs-shifts-in-resources-and-technologies
44. Wu, R., & Qin, Z. (2021). Assessing market efficiency and liquidity: Evidence from China's emissions trading scheme pilots. *Science of The Total Environment, 769,* 144707. https://doi.org/10.1016/j.scitotenv.2020.144707
45. Xie, Z., Yang, M., & Xu, F. (2023). Carbon emission trading system and stock price crash risk of heavily polluting listed companies in China: based on analyst coverage mechanism. *Financial Innovation, 9*(1), 71. https://doi.org/10.1186/s40854-023-00475-5
46. Yang, F., Shi, B., Xu, M., & Feng, C. (2019). Can reducing carbon emissions improve economic performance – evidence from China. *Economics, 13*(1), 20190047. https://doi.org/10.5018/economics-ejournal.ja.2019-47
47. Yao, Y., Tian, L., & Cao, G. (2022). The information spillover among the carbon market, energy market, and stock market: A case study of China's pilot carbon markets. *Sustainability, 14*(8), 4479. https://doi.org/10.3390/su14084479
48. Zhang, J., & Han, W. (2022). Carbon emission trading and equity markets in China: How liquidity is impacting carbon returns? *Economic research-Ekonomska istraživanja, 35*(1), 6466-6478. https://doi.org/10.1080/1331677X.2022.2049010
49. Zhang, L., Zeng, Y., & Li, D. (2019). China's emissions trading scheme: First evidence on pilot stage. *Polish Journal of Environmental Studies, 28*(2), 543-551. https://doi.org/10.15244/pjoes/84871
50. Zhang, Q., & Wong, J. B. (2023). The influence of oil price uncertainty on stock liquidity. *Journal of Futures Markets, 43*(2), 141-167. https://doi.org/10.1002/fut.22383
51. Zhang, Q., & Zhang, J. (2023). Carbon pricing and stock performance: Evidence from China's emissions trading scheme pilot regions. *Review of Pacific Basin Financial Markets and Policies,* forthcoming. https://doi.org/10.1142/S0219091523500248
52. Zhang, S., Jiang, K., Wang, L., Bongers, G., Hu, G., & Li, J. (2020). Do the performance and efficiency of China's carbon emission trading market change over time?. *Environmental Science and Pollution Research, 27,* 33140-33160. https://doi.org/10.1007/s11356-020-09168-3
53. Zhang, Y. J., & Hao, J. F. (2015). The allocation of carbon emission intensity reduction target by 2020 among provinces in China. *Natural Hazards, 79,* 921-937. https://doi.org/10.1007/s11069-015-1883-7
54. Zhang, Y. J., & Wang, W. (2021). How does China's carbon emissions trading (CET) policy affect the investment of CET-covered enterprises? *Energy Economics, 98,* 105224. https://doi.org/10.1016/j.eneco.2021.105224
55. Zhang, Y., & Ding, S. (2021). Liquidity effects on price and return co-movements in commodity futures markets. *International Review of Financial Analysis, 76,* 101796. https://doi.org/10.1016/j.irfa.2021.101796
56. Zhao, X. G., Wu, L., & Li, A. (2017). Research on the efficiency of carbon trading market in China. *Renewable and Sustainable Energy Reviews, 79,* 1-8. https://doi.org/10.1016/j.rser.2017.05.034
57. Zheng, X., & Su, D. (2017). Impacts of oil price shocks on Chinese stock market liquidity. *International Review of Economics & Finance, 50,* 136-174. https://doi.org/10.1016/j.iref.2017.03.021
58. Zhou, J., Huo, X., Jin, B., & Yu, X. (2019). The efficiency of carbon trading market in China: Evidence from variance ratio tests. *Environmental Science and Pollution Research, 26,* 14362-14372. https://doi.org/10.1007/s11356-019-04778-y
59. Zhou, S., & Ye, Q. (2023). Margin trading and spillover effects: Evidence from the Chinese stock markets. *Emerging Markets Review, 54,* 101005. https://doi.org/10.1016/j.ememar.2023.101005
60. Zhu, B., Zhou, X., Liu, X., Wang, H., He, K., & Wang, P. (2020). Exploring the risk spillover effects among China's pilot carbon markets: A regular vine copula-CoES approach. *Journal of Cleaner Production, 242,* 118455. https://doi.org/10.1016/j.jclepro.2019.118455