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Volatility Spillover from Carbon Prices to Stock Prices: Evidence from China's Carbon Emission Trading Markets

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Abstract: The carbon emission trading markets represent an emerging domain within China. The primary objective of this study is to explore whether carbon price volatility influences stock market volatility among companies subject to these emission trading regulations. Employing daily returns data from 293 publicly traded companies regulated by these emission trading markets, this study encompasses the national carbon market and eight pilot regional carbon markets spanning from August 2013 to October 2023. The results demonstrate that volatility in regional carbon prices positively impacts the stock volatility of companies in the corresponding emission trading region, indicating a volatility spillover effect. Moreover, this spillover effect is more pronounced in sectors marked by lesser carbon intensity than those with greater carbon intensity. The volatility transmission is more pronounced in coastal areas than in inland regions. However, no notable distinctions in volatility transmission are discerned between the periods before and throughout the COVID-19 pandemic. Vector autoregression analyses substantiate that lagged carbon price fluctuations possess limited predictive capacity for contemporaneous equity market volatility and vice versa. The robustness of these outcomes is fortified by applying the E-GARCH model, which accounts for the volatility clustering phenomenon. As the first investigation into the volatility spillover effect between China's emission trading market and corresponding stock markets, this study offers valuable insights into the investment strategies of retail investors, the formulation of carbon regulations by policymakers, and the carbon emission strategies of corporate managers.

Keywords: carbon emission trading; stock volatility; volatility spillover; vector autoregression; E-GARCH; China

JEL Classification: G12; G17; Q56; Q58

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1. Introduction

Climate change ranks among the foremost global concerns. Emissions from power generation and energy consumption surpass those from all other human activities, serving as the primary catalyst of global warming (Terhaar et al. 2022). Excessive carbon emissions drive global warming, an essential facet of climate change, necessitating accelerated and substantial emission cuts to rectify the energy equilibrium and avert potential calamities (Pacala and Socolow 2004). In the report by the International Energy Agency (2022), global energy-associated carbon dioxide emissions escalated to 36.8 gigatonnes, with the predominant emitter, China, contributing 12.1 gigatonnes (33%), followed by the United States, accounting for 4.7 gigatonnes (13%). In pursuit of sustaining the global climate and curbing greenhouse gas emissions, nations worldwide inked the United Nations Framework Convention on Climate Change in 1992, an initiative that subsequently led to the signing of the Kyoto Protocol in 1997 (Depledge 2022).

Since then, nations worldwide have established carbon emission trading markets. Specifically, China launched its emission trading scheme (ETS) and implemented multiple regional carbon trading pilots to stimulate emissions mitigation (Chai et al. 2022). As the largest carbon dioxide emitter, China's exports constitute approximately one-third of its GDP, thereby encapsulating a considerable quantum of carbon dioxide emissions (Wu et al. 2022). As a pivotal developing country, China formalized its commitment to emission mitigation at the 2009 Copenhagen Global Climate Conference, pledging an explicit 40% to 45% reduction in carbon emissions per GDP unit by 2020 relative to 2005 levels (Kong and Wang 2022). In forecasts, China's emission reductions are projected to exceed 23 gigatonnes by 2030, surpassing the aggregate reductions of European countries (Zhang 2016). The government's resolute endeavor to institute a national carbon trading market and foster international cooperation carries significant implications for global climate governance and sustainable development.

To evaluate the ramifications of carbon emission trading, the extant literature predominantly investigates the spillover of prices or returns in Chinese pilot ETS markets and global ETS platforms. Yadav et al. (2023) identify a substantial association between carbon emissions indices and equity indices within both the Chinese and European stock markets, incorporating the variables of crude oil and natural gas indices. Aslan and Posch (2022) utilize connectedness network analysis and ascertain that carbon emission allowance futures predominantly function as net recipients of volatility connectedness emanating from European stock market sector indices. Li et al. (2023) examine volatility spillovers across China's eight regional ETS markets, employing a connectedness methodology grounded in the quantile vector autoregression (VAR) framework. They observe that the Guangdong Province and Shanghai pilots primarily act as volatility transmitters, while the Hubei Province pilot has transitioned from a transmitter to a receiver in light of the COVID-19 pandemic. Our research addresses gaps in the carbon market literature by scrutinizing volatility spillovers from China's nine regional ETS markets to the respective individual stocks governed by these same regional ETS platforms. We additionally investigate the moderating impact of varying carbon intensity across sectors and the influence of the COVID-19 pandemic on volatility spillover effects, thereby enriching a more comprehensive understanding of carbon market dynamics.

This investigation probes the impact of carbon price volatility on the stock volatility of firms under the supervision of the same ETS market. From August 2013 to October 2023, our sample encompasses 293 publicly traded companies and their daily equity returns in either the national or eight pilot ETS markets. Utilizing an ordinary least squares (OLS) multivariate framework, we establish that fluctuations in carbon prices positively influence stock volatility among ETS-regulated firms. Moreover, this positive effect is more pronounced in low-carbon-intensity industries than high-carbon-intensity ones and notably stronger in coastal ETS markets than in their inland counterparts. However, the positive volatility spillover effects exhibit no significant variation in the period surrounding the COVID-19 pandemic. VAR analysis suggests that lagged carbon price volatility possesses greater explanatory power for its fluctuations than the corresponding stock volatility, signifying a contemporaneous spillover effect. Lastly, our exponential generalized autoregressive conditional heteroskedasticity (E-GARCH) model substantiates that the volatility spillover from the carbon market to pertinent equities persists even after accounting for lagged volatility and volatility clustering phenomena.

This study enhances the existing literature through five unique contributions. First, the current study enriches the body of literature addressing the ramifications of carbon price volatility. Prior work has primarily focused on the implications of carbon price volatility for financial risk management (Sadorsky 2014), corporate innovation (Mo et al. 2016; Zhu et al. 2022; Yu et al. 2022), trading of emissions permit options (Xu et al. 2016), and stock price volatility of electricity companies in the European ETS market (Tian et al. 2016). Our research explores a neglected aspect: the volatility spillover from carbon pricing to pertinent individual stock volatility. Additionally, it merits attention that antecedent research on the influence of carbon volatility has been predominantly sector-specific (Hassan 2022;

Tian et al. 2016). In contrast, our inquiry centers on the stock volatility of ETS-regulated firms spanning multiple industries.

Secondly, the present study augments the extant literature focusing on the determinants of stock volatility. Previous work has explored macroeconomic drivers such as inflation (Thampanya et al. 2020; Aliyu 2012), business cycles (Corradi et al. 2013; Officer 1973), and exchange rates (Olweny and Omondi 2011; Kennedy and Nourzad 2016). Concurrently, the literature has also examined microeconomic factors influencing stock volatility, including stock trading volume (Sutrisno 2020; Narayan et al. 2013), firm sizes (Mazzucato and Semmler 2002), dividend policies (Baskin 1989; Hashemijoo et al. 2012; Hooi et al. 2015), and capital structure (Christie 1982). The current research enriches this domain by rigorously analyzing the cross-market impacts of carbon ETS markets on stock volatility.

Thirdly, the current investigation extends the scholarly discourse on volatility spillover phenomena. Such spillovers manifest geographically, evidenced by interactions between Chinese and global equity markets (Zhou et al. 2012), within North America (Singh et al. 2010), across regional Asian equity markets (Abbas et al. 2013), across G7 financial markets (Liow 2015), and in global financial markets (BenSaïda et al. 2018), as well as between Nigerian, South African, and global equity markets (Fowowe and Shuaibu 2016). Additionally, these volatility spillovers transpire across distinct financial asset classes, such as the interaction between stock and oil markets (Syed and Bouri 2022), between equities and foreign exchange markets (Jebran and Iqbal 2016), between oil and agricultural commodities (Yip et al. 2020), between crude oil and inflation (Rastogi and Kanoujiya 2022), and between bitcoin and financial markets (Qarni et al. 2019). In the context of volatility spillovers associated with carbon trading markets, prior research has probed into the volatility spillovers between carbon and energy markets (Gong et al. 2021; Ji et al. 2018; Song et al. 2022) and among carbon prices, oil, and natural gas prices, and stock prices (Sadorsky 2014). Further studies have explored volatility spillovers across eight regional Chinese ETS markets (Li et al. 2023) and between carbon prices and European electric equities (Tian et al. 2016). The existing research on carbon market volatility spillover primarily focuses on energy markets, the US markets, and Chinese regional carbon markets; however, none has explored the connection between China's carbon market and its stock market, particularly at the individual stock level. Our study fills in this research gap, concentrating specifically on the stocks of firms subjected to carbon emission quota controls rather than the entirety of publicly traded stocks or stock indices.

Fourthly, the present research enriches our understanding of COVID-19′s impact on the Chinese carbon market. Whereas prior analyses have focused on the pandemic-induced volatility spillovers in China's national and regional carbon markets (Mai et al. 2022), dynamic interactions among green bonds, renewable energy equities, and carbon markets during the COVID-19 era (Tiwari et al. 2022), as well as time–frequency linkages between metal, energy, and carbon markets both pre- and mid-pandemic (Jiang and Chen 2022), our inquiry furnishes unique insights by accentuating that the correlation between carbon volatility and equity volatility remains essentially unchanged amid the COVID-19 pandemic.

Finally, examining China's ETS markets is imperative. As the world's leading emitter of greenhouse gases since 2006, China's initiatives to curtail carbon emissions are integral to global reduction strategies (Zhang et al. 2017). China's ETS is the largest carbon market globally in terms of emissions coverage. Annually, the Chinese ETS accounts for roughly 4.5 billion metric tons of carbon dioxide equivalent, rendering it nearly threefold the size of the second largest ETS, the European ETS (World Bank 2024).

The remainder of this paper is structured as follows:

- Section 2 surveys the extant literature and formulates the research hypotheses.
- Section 3 elucidates the sample and methodologies employed.
- Section 4 furnishes and interprets the empirical findings.
- Section 5 concludes the paper.

2. Literature Review and Hypothesis Development

2.1. Carbon Price Volatility

Lyu et al. (2020) discovered that volatility is more pronounced in the Chinese ETS market than its European counterpart, underlining the imperative for enhancements in the Chinese ETS market. Sun et al. (2020) further elucidated that the European ETS market exhibits a heightened responsiveness to positive news, whereas the Chinese ETS market demonstrates greater sensitivity to negative information. These observations substantiate the premise that the Chinese ETS market remains in a nascent stage and has not successfully incentivized a broader array of entities to engage in the carbon market (Wang et al. 2023). Since the inauguration of the Chinese ETS pilot markets, frequent policy revisions impacting allowance quantities have triggered unanticipated fluctuations in carbon equity valuations. Simultaneously, increasing market turbulence in the emissions sector, coupled with the complexity of the energy industry, has intensified the volatility of carbon pricing (Wang et al. 2022a). Due to marked disparities and uneven development among the Chinese pilot ETS regions, significant volatility continues to prevail, obstructing advancements toward a unified national carbon market valuation (Zhou and Li 2019). Consequently, disclosing carbon market information is indispensable for ensuring its functional efficiency and market equilibrium (Zhao et al. 2016). Nevertheless, Song et al. (2022) asserted that the Chinese carbon trading market utilizes free quota allocation, effectively diminishing the inherent volatility of carbon price dynamics. Consistent with the observations of Zhang et al. (2018), the Chinese carbon market witnessed substantial initial volatility upon the advent of carbon trading and has since generally subsided.

Investigations into carbon price volatility have focused on delineating the intricate nexus between carbon and energy markets, particularly emphasizing the power industry (Ji et al. 2018). Research conducted by Feng et al. (2011) accentuates the importance of comprehending carbon volatility within the electricity sector. They identify a positive correlation between carbon price levels and electricity volumes, noting that the influence of the carbon market exhibits substantial variability depending on temporal factors and jurisdictional context. Aatola et al. (2013) undertook an exhaustive assessment of the ramifications of carbon pricing in the integrated European electricity market, illuminating the nuanced impact of carbon costs on electricity expenditures. Additionally, Mo et al. (2016) showed that carbon price volatility is a formidable deterrent to investment initiatives in wind energy technologies, adversely influencing the expansion of low-carbon energy infrastructures in China. These relationships exhibit bidirectionality; fluctuations in electricity prices reciprocally affect carbon price volatility, establishing a reverse causality between the two variables (Ji et al. 2018). The stock returns of power companies are consistently and significantly influenced by carbon price volatility, which signifies a direct relationship between carbon volatility and power company stock valuations (Tian et al. 2016). Simultaneously, the ramifications of carbon volatility exhibit geographical specificity; Wu et al. (2021) discerned a significant long-term causal relationship, at a 5% threshold, between renewable energy adoption and carbon price volatility, exclusively within the Vietnamese setting.

2.2. Determinants of Stock Volatility

Numerous scholars have rigorously examined the macro-level determinants of stock market volatility, yielding invaluable frameworks for interpreting market behavior and forecasting future volatility. Binder and Merges (2001) identify rational economic factors, including uncertainties surrounding price levels, risk-free interest rates, equity risk premiums, and the ratio of expected profits to expected revenues, as pivotal drivers of stock market volatility. These variables account for over 50% of the variation in market volatility from 1929 to 1989, with coefficients exhibiting temporal variability elucidating an additional 40%. Corradi et al. (2013) focus on business cycle factors, ascertaining their notable impact on both the level and fluctuations in stock market volatility. Touny et al. (2021) examine Middle Eastern countries, identifying inflation, corruption, stock market capitalization, and stock turnover ratios as exerting a positive and significant influence on stock market volatility. Conversely, economic growth, financial freedom, and stock market returns appear to negatively and substantially impact stock market volatility. Nikmanesh and Nor (2016) concentrate on Malaysia and Indonesia, uncovering a substantial correlation between stock market volatility and fluctuations in macroeconomic variables. The findings suggest that macroeconomic instability and trade openness account for 81% of stock market volatility in Malaysia and 75% in Indonesia.

Micro-level determinants also exert an influence on stock price volatility. Sutrisno (2020) examines firms in the Jakarta Islamic Index and discerns a significant positive relationship between trading volume and stock price volatility, whereas firm size is inversely correlated with volatility. Duffee (1995) observes a positive contemporaneous association between firm-level stock returns and stock volatility, notably accentuated among smaller firms and those with lower financial leverage. Intriguingly, this contemporaneous relationship manifests an inverted sign at the aggregate level. Ahmad et al. (2018) demonstrate that both dividend yield and dividend payout are negatively and significantly associated with stock price volatility in the Amman Stock Exchange. Additionally, Hussainey et al. (2011) provide insights into the relevance of firm characteristics, such as growth rate, debt level, size, and earnings, in explaining stock price changes, further emphasizing the significance of corporate dividend policy as a driving force behind price fluctuations. Zainudin et al. (2018) corroborate that earnings volatility significantly accounts for stock price volatility in industrial product firms during the crisis period, while the dividend payout ratio predominantly dictates volatility during pre- and post-crisis subperiods. Mazzucato and Tancioni (2012) link innovation to stock return volatility using firm-level patent data in the pharmaceutical industry. Their study establishes a positive and significant relationship between stock return volatility, research and development intensity, and patent-related measures, particularly for highly innovative firms.

2.3. Volatility Spillover

Firstly, volatility spillover transpires across distinct geographical regions. Ciarreta and Zarraga (2015) document increasing price integration and noteworthy volatility spillover among Spain, Portugal, Austria, Germany, Switzerland, and France within electricity spot markets. Kearney (2000) delved into the determinants of stock market volatility and the spillover impact among international markets, revealing that global stock market volatility is predominantly instigated by fluctuations in the Japanese and US markets, subsequently reverberating into the European market. Employing the frequency–domain causality methodology, Özer et al. (2020) demonstrate that intra- and inter-regional volatility transmission is evident between Southeast European equity markets and emerging and mature markets globally, thereby suggesting limited diversification benefits for international portfolios allocated to these markets. Liu and Pan's (1997) empirical analysis, focusing on the data spanning 1984 to 1991, indicates that the US market exerts a more significant influence than the Japanese market in disseminating returns and volatilities across four Asian markets: Hong Kong, Singapore, Taiwan, and Thailand.

Secondly, volatility spillover manifests across the temporal spectrum. Wang and Wang (2019) contend that frequency spillover plays a pivotal role in predicting equity market volatility, the dynamics of which between oil and equity markets are contingent upon distinct temporal horizons, either short-term or long-term. Yadav et al. (2023) examine volatility spillover from energy commodities to the Shanghai Stock Exchange and European equity markets, identifying persistent volatility in the long-term but not in the short-term duration. Liu et al. (2017) disclose that the volatility linkage between oil and the US equity market is increasingly oriented towards short-term intervals, whereas the connection with the Russian equity market is evolving across all temporal scales. Su and Liu (2021) assert that economic policy uncertainty considerably impacts aggregate inter-sectoral volatility transmission within the Chinese equity market, characterized by notable heterogeneity. Koutmos (2018) investigates return and volatility shocks across 18 cryptocurrencies, revealing that volatility spillovers progressively amplified as these currencies achieved high integration.

Thirdly, cross-asset volatility spillover is observed. Nazlioglu et al. (2013) demonstrate that volatility spillover was undetectable before the food price crisis between oil and agricultural commodity markets. However, oil volatility was transmitted to the wheat, corn, and soybean markets after the food price crisis. Gong et al. (2021) identify pronounced spillover phenomena between the carbon and fossil energy markets, exhibiting both time-variant and asymmetric characteristics in strength and direction. Green et al. (2018) ascertain that positive news in gas and coal markets induces a substantially greater power variance response than negative news. For the carbon market, the relevance of distinguishing between positive and negative news appears considerably less significant. Han et al. (2020) explore volatility spillover dynamics across Australia's regional spot electricity markets and conclude that such spillover effects are markedly impacted by regional proximity and interconnectors.

Fourthly, volatility propagation can manifest as unidirectional or bidirectional phenomena. Morema and Bonga-Bonga (2020) ascertain that South African equity markets predominantly experience unidirectional volatility transmissions from global commodity markets, namely oil and gold, attributable to South Africa's limited influence on international commodity pricing. Vardar et al. (2018) delineate the primary trend in advanced and emerging countries as the bidirectional volatility spillover effect between stock and commodity returns. Notably, significant volatility spillovers between these asset classes escalate during crisis and post-crisis intervals relative to pre-crisis epochs. Tsagkanos et al. (2024) investigate the directional volatility spillover between the business confidence index and equity market indices in Greece, concluding that the business confidence index principally serves as the recipient of volatility transmissions. Wang et al. (2022b) assess the dissemination of returns and volatility across the commodities spectrum amid the Ukraine war. Silver, gold, copper, platinum, aluminum, and sugar emerge as net transmitters of volatility transmission.

Dong et al. (2024) highlight prior research confirming risk correlations and spillover effects between carbon and stock markets. Xu et al. (2022) identified positive cross-correlations between carbon-intensive industry stock returns and carbon allowance price returns in Shenzhen and Shanghai, contrasting with negative correlations in Beijing, Guangdong, and Hubei. Zhang and Zhang (2023) observed that carbon price returns adversely impact firms' stock returns within regional markets, notably in Shenzhen and Guangdong. Dong et al. (2024) revealed that the Chinese carbon and stock markets exhibit significant, asymmetric, and extreme-event-sensitive spillover effects, predominantly positioning the carbon market as an information net recipient. Zhang et al. (2022) highlighted the nascent interconnectivity between China's carbon and stock markets. Dutta et al. (2018) demonstrated a notable volatility linkage between emissions and European clean energy price indices, a phenomenon not mirrored in the US market, indicating that emission return and volatility shocks are distinct across countries or regions. Thus, the volatility spillover between carbon and stock markets in China warrants further exploration.

In addition to the above empirical evidence, the conceptual foundation to link stock price volatility and carbon price volatility is the mechanism of cap-and-trade systems, where governments or regulatory bodies set a cap on the total amount of greenhouse gases that can be emitted and then allow market forces to drive the trading of emission allowances or credits. This market-based approach incentivizes companies to reduce their carbon footprint through innovation and efficiency improvements, as emitting costs become a tangible financial consideration. The transition risk associated with moving towards a low-carbon economy can lead to significant volatility in the valuations of companies not aligned with this transition, thus affecting their stock prices. Companies with high carbon footprints may face increased costs due to higher carbon prices, which can squeeze profit margins and lead to stock price volatility. Conversely, companies that are leaders in reducing emissions or that produce carbon-reducing technologies may benefit from such a transition, experiencing less volatility or even positive revaluations.

A multi-theoretical approach offers profound insights into examining the volatility transmission from carbon markets to stock markets. As articulated by King and Wadhwani (1990), the financial contagion theory provides a foundational perspective on how volatility can traverse between distinct markets. This theory posits that shocks in one market can lead to increased volatility in another through cash flow connectedness, cross-market hedging strategies, or liquidity constraints, suggesting that fluctuations in carbon prices might similarly affect the stock market volatility of ETS-regulated companies. Complementing this, the behavioral finance theory, explored by Shleifer and Summers (1990), delves into the psychological aspects influencing market participants. This theory elucidates how cognitive biases, overreactions, and underreactions to new information can lead to market inefficiencies. In the context of carbon pricing, it implies that investor sentiment and perception regarding future regulatory changes or economic impacts can significantly influence the volatility of related stocks. Lastly, the information signaling and asymmetry theory, presented by Myers and Majluf (1984), examines the impact of information asymmetry between corporate insiders and outside investors. This theory argues that companies with access to insider information might make financing decisions that signal their private knowledge to the market, affecting their stock prices. Regarding carbon pricing volatility, the market could interpret changes in carbon prices as signals about the future profitability or risk profile of ETS-covered firms, thereby influencing their stock price volatility. In light of the preceding empirical and theoretical discussions, we formulate the first hypothesis as follows:

Hypothesis 1. *A positive spillover effect exists from carbon price volatility to the corresponding ETS-covered stock price volatility.*

2.4. Low- and High-Carbon-Intensity Industries

Aslan and Posch (2022) demonstrate that industries with high carbon intensity significantly influence the volatility interconnections between the European equity market and the emission allowance futures price. Zhang and Zhang (2023) demonstrate that the adverse effects of carbon returns on stock returns are more pronounced in industries with high carbon intensity than those with lower carbon intensity. Tian et al. (2016) elucidate an inverse relationship between carbon price returns and electricity stock returns for producers with high carbon intensity, while the converse relationship prevails for low-carbon-intensity producers. Chapple et al. (2013) identify a negative linkage between corporate valuation and carbon intensity, indicating heightened vulnerability for high-carbon-emitting firms prior to the ETS initiation. Bolton and Kacperczyk (2021) find that stocks of firms with higher total carbon dioxide emissions earn higher returns, controlling for size, book-to-market, and other return predictors. Xie et al. (2023) corroborate that carbon emissions trading within China's pilot market can mitigate stock price volatility for high-carbon firms and reduce the risk of stock price collapses resulting from carbon emission reductions.

The financial contagion theory (King and Wadhwani 1990) posits that industries with high carbon intensity, due to their reliance on carbon allowances and emissions costs, are inherently more interconnected with the carbon market. This connection renders them more susceptible to the direct impacts of carbon price volatility, potentially leading to significant financial and cash flow implications. Such susceptibility enhances the volatility spillover from the carbon to the stock market within these sectors. Similarly, the behavioral finance theory (Shleifer and Summers 1990) suggests that these industries are subject to increased investor scrutiny, with fluctuations in carbon prices heavily influencing investor perceptions and reactions, thereby amplifying stock price volatility through behavioral overreactions or underreactions. Moreover, the information signaling and asymmetry theory (Myers and Majluf 1984) indicates that volatility in carbon prices serves as a crucial signal to the market regarding the future profitability and risk profiles of high-carbon-intensity companies, exacerbating information asymmetry and, consequently, stock price volatility. This interplay highlights a pronounced effect of carbon price volatility on the stock market volatility of ETS-covered firms in high-carbon-intensity industries. Given this empirical evidence and theoretical analysis, we propose:

Hypothesis 2. *The positive spillover effect from carbon price volatility to ETS-covered stock price volatility is more pronounced for industries with high carbon intensity than those with low carbon intensity.*

2.5. Coastal versus Inland Companies

The financial contagion theory (King and Wadhwani 1990) posits that coastal companies often have operations more directly exposed to environmental and regulatory policies affecting carbon markets, such as stricter emissions regulations or policies targeting maritime and shipping industries. This direct exposure could mean that fluctuations in carbon prices have a more immediate and significant impact on coastal companies' cash flows and hedging activities, leading to a heightened spillover of volatility from the carbon market to their stock prices compared to inland companies. Similarly, the behavioral finance theory (Shleifer and Summers 1990) suggests that coastal companies might be perceived as more vulnerable to the impacts of carbon pricing due to their geographical location and the associated risks of climate change, such as rising sea levels and more stringent environmental regulations. This perception could lead to investor sentiment playing a more prominent role in the volatility of these companies' stocks. Investors may overreact to changes in carbon prices, anticipating more significant regulatory and environmental challenges for coastal companies, thereby amplifying the volatility spillover effect on their stock prices. Moreover, the information signaling and asymmetry theory (Myers and Majluf 1984) indicate that coastal companies on the front lines of environmental impact and regulation might see carbon price volatility as a more critical signal regarding their prospects. This is especially true for companies in areas directly affected by carbon pricing, such as shipping, oil and gas, and coastal tourism. The market might interpret volatility in carbon prices as a more significant indicator of future challenges and opportunities for coastal companies, leading to more significant information asymmetry and, subsequently, more pronounced stock price volatility for these firms. Based on the above theoretical analysis, we propose:

Hypothesis 3. *The positive spillover effect from carbon price volatility to ETS-covered stock price volatility is more pronounced for coastal companies than inland firms.*

2.6. The Impact of COVID-19

During the COVID-19 pandemic, equity markets witnessed significant return declines (Ashraf 2021). Concurrently, the proliferation of COVID-19 engendered heightened market volatility (Zhang et al. 2020). Amidst the pandemic crisis, the nexus of heightened uncertainty and associated economic contractions further intensified stock market fluctuations (Chowdhury et al. 2022). Notably, no antecedent infectious disease event, not even the Spanish Flu, has had a pronounced impact on stock markets as COVID-19 (Baker et al. 2020). Díaz et al. (2022) demonstrate that global equity market volatility exhibits heightened (attenuated) sensitivity to the COVID-19 reproductive number in states of high (low) contagion. Intriguingly, the COVID-19 pandemic catalyzed increased participation of financial investors in cryptocurrency markets, thereby intensifying high-risk asset allocations, magnifying herd tendencies in financial markets, and subsequently intensifying volatility spillover effects (Özdemir 2022). Shahzad et al. (2021) investigate the uneven volatility transmission across sectors of the Chinese stock market amid the COVID-19 pandemic. Their findings reveal the asymmetric effects of good and bad volatilities, which exhibit temporal fluctuations and heightened intensity throughout the COVID-19 era.

According to the financial contagion theory (King and Wadhwani 1990), the pandemic may disrupt supply chains, affect cash flows, and lead to more pronounced liquidity constraints. These factors may have amplified the mechanisms through which volatility is transmitted from carbon markets to stock markets. The economic uncertainties and operational challenges faced by ETS-regulated companies during the pandemic could make the stock market more reactive to changes in carbon prices, enhancing the spillover effect. The COVID-19 era has been marked by significant uncertainty and changes in investor behavior, potentially exacerbating cognitive biases and emotional reactions to new information. According to Shleifer and Summers (1990), such conditions can lead to overreactions or underreactions to carbon price volatility. The pandemic has likely heightened concerns about the future economic landscape, regulatory responses to climate change, and the financial health of companies. This increased sensitivity to news and regulatory announcements related to carbon pricing could result in more pronounced volatility spillovers to the stocks of ETS-regulated firms during the COVID-19 era. Myers and Majluf (1984) discuss how information asymmetry influences stock prices by signaling insider decisions. The COVID-19 pandemic has likely exacerbated information asymmetry between insiders and the market due to the unpredictable economic environment and the rapid changes in corporate prospects. Volatility in carbon prices during this period could be a more potent signal to investors about the future profitability or risk profile of ETS-covered firms. With companies and investors navigating an unprecedented landscape, the market may interpret changes in carbon prices as more significant indicators of corporate resilience or vulnerability, thus magnifying the spillover effect on stock price volatility. In light of the preceding analysis, we formulate the subsequent hypothesis:

Hypothesis 4. *The positive spillover effect from carbon price volatility to ETS-covered stock price volatility is more pronounced in the COVID-19 era than in the pre-COVID period.*

3. Data and Methodology

3.1. Data

This research employs two data sources: (1) the Wind Economic Database (Wind 2024), which provides regional carbon prices, gold prices, oil prices, natural gas prices, coal prices, and the Chicago Board Options Exchange Volatility Index (VIX); and (2) the China Stock Market and Accounting Research Database (CSMAR 2024), encompassing individual stock returns and company information.

In the initial step, we meticulously assembled a list of companies subject to regulation under the national ETS framework as well as eight ETS pilot regions: Shenzhen, Shanghai, Beijing, Guangdong Province, Tianjin, Hubei Province, Chongqing, and Fujian Province. This compilation originates from the official websites of Municipal Ecology and Environment Bureaus within each respective region. The resultant dataset comprises 5526 firms overseen by their respective ETS markets, with a preponderance being private companies. Subsequently, we executed manual queries via Google to cross-reference company names against the roster of publicly traded firms in the CSMAR Database. This exhaustive methodology culminated in the validation of 293 publicly listed entities out of the initial 5526 ETS-regulated firms, of which 179 emanate from the eight regional ETS markets, and 114 are affiliated with the national ETS market.

In the second step, we retrieve daily stock returns for the 293 publicly listed firms from the CSMAR Database from August 2013 to October 2023. The National Development and Reform Commission of China declared in October 2011 that carbon emission trading would be piloted in eight regions (Zhang and Wang 2021). Shenzhen witnessed the debut of China's first ETS on 18 June 2013. A solitary data point exists from June 2013 until 5 August 2013; therefore, our sample starts in August 2013. Concurrently, we acquire stock codes, stock names, and industry classifications. We segregate the 293 publicly listed ETS-regulated entities into two divergent categories: firms with high carbon intensity and those with low carbon intensity. Entities within the petrochemical, building materials, steel, nonferrous metals, paper, electric power, aviation, glass manufacturing, and pharmaceutical sectors are classified as high-carbon-intensity firms. Conversely, the industries of food and beverages, education, sports, entertainment, general manufacturing, wholesale and retail, hospitality, information technology, telecommunications and broadcasting, internet and software services, financial and insurance services, and real estate are deemed to be low-carbon-intensity industries. The underlying rationale for this categorization stems from the primary utilization of natural gas as feedstock in the chemical, electric power, metal, and glass manufacturing industries. Additionally, synthesizing small- and medium-molecule pharmaceuticals relies on chemical constituents derived from crude oil and fossil fuels.

In the third step, we procure daily carbon prices from the Wind Economic Database, spanning the eight pilot regions and the national market. Simultaneously, we compile time-series data for selected control variables from the same source. Daily gold prices (COMEX, ticker code: GC.CMX), crude oil (NYMEX WTI, ticker code: CL.NYM), natural gas (NYMEX, ticker code: NG.NYM), and coal price index (ticker code: JFI.WI) are retrieved. Including these control variables stems from the direct link between fossil fuels (coal, oil, and natural gas) and carbon emissions. The volatility in the prices of these commodities reflects changes in their demand and supply, which, in turn, can impact carbon emissions. For instance, a spike in oil prices might lead to a temporary shift towards more carbon-intensive fuels or vice versa, affecting carbon prices. Hence, the literature extensively documents volatility spillovers between carbon and energy markets (Liu et al. 2023; Song et al. 2022; Wang and Guo 2018). Moreover, gold is traditionally seen as a hedge against currency devaluation and a symbol of economic stability. Its price volatility can indicate broader economic trends that might influence investment and consumption patterns, indirectly affecting carbon emission levels and prices. Additionally, we integrate the VIX index, sourced from the Chicago Board Options Exchange. The VIX represents the annualized implied volatility of a hypothetical S&P 500 equity option with a 30-day expiry, thereby providing investors with a forward-looking volatility forecast. The VIX index, often called the "fear index," measures market risk, sentiment, and stress. A high VIX suggests increased uncertainty and risk aversion among investors, which can lead to broader market volatility. This environment can affect the stock prices of companies, especially those heavily involved in carbon-intensive industries, and by extension, influence carbon pricing mechanisms.

3.2. Methodology

In the initial step, we follow Chen et al. (2013) to quantify the monthly volatility of securities, defined as the standard deviation of daily returns, encompassing stocks, carbon, gold, oil, gas, and coal. Subsequently, in the second step, each ETS region's unique carbon price corresponds to several ETS-regulated stocks. We then compute the average volatility of these stocks for each region and month. Considering that carbon price volatility demonstrates marked variability and the occurrence of notable outliers, we further winsorize the carbon volatility metrics at the upper and lower 1% levels. Our final sample encompasses 293 firms and 800 region–month observations from August 2013 to October 2023. Ideally, we would anticipate 1080 (=120 × 9) region–month observations for the decade-long timeframe. Nevertheless, due to the initiation of the national EST market in 2021, the commencement of the Fujian ETS market in 2017, and the launch of the Hubei and Chongqing ETS markets in 2014, the sample size is diminished to 800 region–month observations.

In the third step, we utilize the OLS regression to elucidate the linear relationship between carbon volatility and stock volatility while adjusting for variables that affect stock volatility. The OLS multivariate regression model is delineated as follows:

$$\begin{aligned} StockVol_{i,t} &= \beta_0 + \beta_1 CarbonVol_{i,t} + \beta_2 GoldVol_t + \beta_3 OilVol_t + \beta_4 GasVol_t \\ &\quad + \beta_5 CoalVol_t + \beta_6 VIX_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $StockVol_{i,t}$ represents the ETS-covered stock volatility in month t and region i, $CarbonVol_{i,t}$ represents the carbon price volatility in month t and region i, $GoldVol_t$ denotes gold price volatility in month t, $OilVol_t$ denotes crude oil price volatility in month t, $GasVol_t$ denotes natural gas price volatility in month t, $CoalVol_t$ denotes coal price volatility in month t, and VIX_t signifies the Chicago Board Options Exchange Volatility Index in month t. β is the regression coefficient, and $\varepsilon_{i,t}$ represents a disturbance term with $E(\varepsilon_{i,t}) = 0$ and $Var(\varepsilon_{i,t}) = \sigma^2$.

We also employ the VAR model to examine the dynamic interactions among multiple variables and their lagged values (Cummins 2013):

$$X_t = \phi_0 + \phi_1 X_{t-1} + \varepsilon_t \quad (2)$$

$$X_t = (StockVol_t \quad CarbonVol_t \quad GoldVol_t \quad OilVol_t \quad GasVol_t \quad CoalVol_t \quad VIX_t)^T \quad (3)$$

where the superscript T transposes the row vector X_t to a column vector, ϕ_0 is a column vector of constants, and ϕ_1 is a matrix of coefficients, and ε_t is a column vector of error terms. $StockVol_t$ represents the mean volatility of $StockVol_{i,t}$ across nine regions for month t; $CarbonVol_t$ denotes the mean volatility of $CarbonVol_{i,t}$ over the same nine regions during month t.

We also employ the E-GARCH model (Nelson 1991) to accommodate volatility clustering and asymmetric innovations as follows:

$$\ln\left(\sigma_t^2\right) = \alpha_0 + \alpha_1 Z_{t-1} + \alpha_2[|Z_{t-1}| - E(|Z_{t-1}|)] + \alpha_3 \ln\left(\sigma_{t-1}^2\right) \quad (4)$$

where ${\sigma_t}^2$ is the conditional variance of ε_t in Equation (1), Z_t equals ε_t divided by σ_t and represents the standardized error term. α_0 serves as the ARCH constant, α_1 corresponds to L.EARCH and captures the asymmetric impact of previous shocks on current volatility, α_2 is identified as L.EARCH_A and gauges the symmetric influence of the absolute magnitude of past shocks on current volatility, and α_3, designated as L.EGARCH, signifies the persistence of volatility over time.

During the preparation of this work, the authors used ChatGPT-4 for the purposes of grammatical refinement and stylistic augmentation. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the variables under investigation. The mean of stock volatility is 0.0250. In contrast, the mean for carbon price volatility is 0.0946. These observations suggest higher volatility in carbon prices compared to stock volatility. These data are consistent with Xu et al.'s (2022) assertion that carbon markets tend to be riskier, more volatile, and less efficient than stock markets. Contrary to previous investigations in selected ETS pilot markets (Fu and Zheng 2020; Zhang et al. 2018), the current study employs a comprehensive dataset, integrating a national market with all eight pilot ETS markets. The mean volatility of gold prices is quantified at 0.0087, which is lower than the mean volatility of crude oil, recorded at 0.0239. The mean volatility of natural gas is documented at 0.0332, while that of coal prices is 0.0195. The average VIX measure stands at 0.1850, the most elevated among all variables under analysis. The skewness of all volatility measures is positive, indicating that a few exceptionally high volatility values extend the distribution to the right.

Table 1. Description statistics.

	Obs.	Mean	Std.Dev.	Min	P25	Median	P75	Max	Skew
StockVol	800	0.0250	0.0097	0.0101	0.0186	0.0229	0.0284	0.0760	1.9755
CarbonVol	800	0.0946	0.1389	0.0003	0.0232	0.0540	0.1068	0.9576	3.8414
GoldVol	800	0.0087	0.0031	0.0046	0.0068	0.0083	0.0100	0.0248	1.9125
OilVol	800	0.0239	0.0159	0.0056	0.0158	0.0209	0.0274	0.1455	4.6967
GasVol	800	0.0332	0.0179	0.0109	0.0198	0.0283	0.0417	0.1252	1.7494
CoalVol	800	0.0195	0.0087	0.0049	0.0134	0.0184	0.0246	0.0561	1.1150
VIX	800	0.1850	0.0690	0.1025	0.1371	0.1698	0.2217	0.5774	2.0956

Notes: This table reports descriptive statistics for 293 ETS-covered firms in eight pilot ETS markets and a national ETS market from August 2013 to October 2023.

Table 2 delineates the pairwise correlation coefficients among the variables. The correlation coefficient between stock and carbon volatilities is 0.0775, significant at the 5% level, indicating a strong positive relationship between stock and carbon volatilities. Regarding control variables, gold price volatility, oil price volatility, and the VIX index demonstrate positive correlation coefficients of 0.1291, 0.1518, and 0.1642 with stock volatility, respectively, each significant at the 1% level. In contrast, the correlation coefficient between stock volatility and coal price volatility is significantly negative at −0.1927.

Table 2. Pairwise correlations between variables.

	StockVol	*CarbonVol*	*GoldVol*	*OilVol*	*GasVol*	*CoalVol*	*VIX*
StockVol	1						
CarbonVol	0.0775 **	1					
	(0.0284)						
GoldVol	0.1291 ***	−0.0315	1				
	(0.0003)	(0.3731)					
OilVol	0.1518 ***	−0.0020	0.5164 ***	1			
	(0.0000)	(0.9558)	(0.0000)				
GasVol	−0.0491	−0.0382	0.2167 ***	0.2953 ***	1		
	(0.1652)	(0.2808)	(0.0000)	(0.0000)			
CoalVol	−0.1927 ***	0.0518	−0.0889 **	−0.0151	0.1999 ***	1	
	(0.0000)	(0.1434)	(0.0119)	(0.6706)	(0.0000)		
VIX	0.1642 ***	0.0239	0.5761 ***	0.6766 ***	0.4729 ***	0.0182	1
	(0.0000)	(0.5003)	(0.0000)	(0.0000)	(0.0000)	(0.6073)	

Notes: 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.

4.2. Baseline Regressions

Table 3 presents the baseline OLS regression analyses utilizing Equation (1). The dependent variable is the regional average volatility of the 293 ETS-covered stocks, observed at a monthly frequency, and the independent variable is the regional carbon price volatility. The coefficient associated with carbon price volatility is 0.0054, achieving statistical significance at the 5% level. Upon the inclusion of control variables such as volatilities of gold, crude oil, natural gas, and coal prices, along with the VIX index, the coefficient of carbon price volatility persists at 0.0055 and maintains significance at the 5% level. Consequently, we validate Hypothesis 1, positing that carbon price volatility positively influences the stock volatility of ETS-covered firms. From an economic perspective, given that the coefficient is 0.0055, a one-standard-deviation variation in carbon volatility of 0.1389 would alter stock volatility by approximately 0.00076, or about 3% of its mean value of 0.0250. Forecasting volatility across markets proves challenging, as evidenced by minimal R^2 values. Zhang and Zhang (2023) disclosed R^2 between 0.003 and 0.009 in their analysis linking individual stock returns to carbon price returns. Likewise, Yang et al. (2023) presented an adjusted R^2 of 0.037 when examining liquidity spillover from carbon to stock markets. Tian et al. (2016) reported an R^2 of 0.055 in their study correlating individual stock returns with European carbon returns. Xie et al. (2023) identified an adjusted R^2 of 0.022 in their regression of down-to-up volatility against a set of control variables, including the volatility of abnormal returns. Nevertheless, the studies above have primarily focused on the return spillover effects between stock and carbon markets, as opposed to the volatility spillover effect examined here. For example, Xu et al. (2022) demonstrate that the stock returns of carbon-intensive industries and carbon allowance price returns exhibited positive cross-correlation in the Shenzhen and Shanghai pilot markets. Our empirical results are valuable in scenarios where unforeseen variables influence stock performance, enabling investors to proactively evaluate the situation through carbon market volatility, thus employing it as a predictive indicator.

The results in Table 3 are also aligned with theoretical predictions. Financial contagion theory posits that carbon price volatility, as systemic risk, transmits uncertainty to ETS-regulated stock markets, leading to heightened volatility. Behavioral finance theory suggests that investor reactions to carbon price fluctuations are amplified by psychological biases, affecting stock market volatility as investors adjust to perceived risks and regulatory impacts. Information signaling theory argues that changes in carbon prices serve as market signals, informing investors about the future performance and risk profiles of ETS-covered firms, thus influencing their stock volatility.

Table 3. Baseline regressions.

	(1) *StockVol*	(2) *StockVol*
CarbonVol	0.0054 **	0.0055 **
	(0.0025)	(0.0024)
GoldVol		0.0306
		(0.1332)
OilVol		0.0374
		(0.0288)
GasVol		−0.0606 ***
		(0.0214)
CoalVol		−0.1948 ***
		(0.0389)
VIX		0.0241 ***
		(0.0075)
Constant	0.0244 ***	0.0246 ***
	(0.0004)	(0.0014)
Observations	800	800
$Adj\text{-}R^2$	0.005	0.077

Notes: This table shows the baseline regressions of ETS-covered stock volatility on carbon price volatility 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.

4.3. Low- and High-Carbon-Intensity Industries

Table 4 delineates regression outputs for stock volatility across low- and high-carbon-intensity sectors. In firms operating within low-carbon-intensity sectors, the coefficient associated with *CarbonVol* registers at 0.0128 and achieves statistical significance at the 1% confidence level. In contrast, within high-carbon-intensity sectors, the corresponding coefficient is 0.0049, achieving significance at the 10% level. These empirical results underscore a more marked positive association between carbon price volatility and stock volatility in sectors with low carbon intensity relative to those with high carbon intensity, contradicting Hypothesis 2.

Per the financial contagion theory (King and Wadhwani 1990), industries with high carbon intensity are closely linked to the carbon market, necessitating reliance on carbon allowances and emissions costs. Consequently, such industries may implement advanced hedging strategies or modify operational practices to mitigate carbon price volatility risks. This proactive approach could attenuate the spillover impact of carbon price fluctuations on their stock prices compared to lower carbon intensity sectors, which may be less adept at navigating abrupt carbon pricing shifts. Similarly, following the behavioral finance theory (Shleifer and Summers 1990), investors in high-carbon-intensity sectors likely forecast these industries' vulnerability to carbon price changes, influencing their investment decisions and stock valuations. Thus, market responses to carbon price variations in these sectors may be subdued, as such volatility is anticipated and potentially already accounted for in stock prices. In the context of the information signaling and asymmetry theory (Myers and Majluf 1984), for high-carbon-intensity sectors, carbon price shifts may not significantly alert the market to the firms' future profitability or risk profiles, considering these outcomes are presumed and predicted. Conversely, carbon price volatility in low-carbon-intensity sectors could unveil novel insights or uncertainties about forthcoming regulatory expenses and profitability, prompting a more pronounced stock price realignment as the market integrates this fresh information. Overall, companies in high-carbon-intensity industries might commence improvements to their infrastructures in response to increased demands for carbon emission reductions, thus becoming less prone to volatility shocks from the carbon market. Tian et al. (2016) delineate a negative relationship between carbon price returns and electricity stock returns in high-carbon-intensity firms, while an opposite relation exists for low-carbon-intensity firms. Yang et al. (2019) suggest that when confronted with rising business costs of environmental regulations, firms pursue a beneficial approach, strengthening internal governance, boosting operational efficiency, and spurring innovation rather than choosing the adverse option of cross-regional relocation. Cheng et al. (2019) assert that the growth of the service industry can facilitate the transformation of high-carbon-intensity regions into areas with lower carbon emissions, facilitating the realization of environmentally sustainable and low-carbon economic growth.

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

	(1) **Low-Carbon-Intensity Industries** ***StockVol***	**(2)** **High-Carbon-Intensity Industries** ***StockVol***
CarbonVol	0.0128 ***	0.0049 *
	(0.0032)	(0.0028)
GoldVol	−0.0440	0.0566
	(0.1717)	(0.1579)
OilVol	0.0337	0.0294
	(0.0365)	(0.0341)
GasVol	−0.0588 **	−0.0815 ***
	(0.0281)	(0.0254)
CoalVol	−0.2778 ***	−0.0824 *
	(0.0506)	(0.0461)
VIX	0.0223 **	0.0274 ***
	(0.0097)	(0.0089)
Constant	0.0269 ***	0.0231 ***
	(0.0017)	(0.0016)
Observations	617	800
$Adj\text{-}R^2$	0.090	0.040

Notes: This table shows the regression of ETS-covered stock volatility on the carbon price volatility 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.

4.4. Subregional Markets

In Table 5, we partition ETS-covered stocks into two geographically delineated categories: coastal and inland ETS markets. The coastal ETS markets consist of Shenzhen, Shanghai, Guangdong Province, Tianjin, Fujian Province, and the national market in Shanghai. Conversely, the inland ETS markets include Beijing, Hubei Province, and Chongqing. Contrary to Felice et al. (2023), who distinguish between coastal and inland provinces, our analysis incorporates singular city and assorted provincial markets. Column 1 of Table 5 indicates that the regression coefficient for carbon volatility in the coastal ETS markets is 0.0051, attaining statistical significance at the 5% level. In contrast, the coefficient in inland ETS markets does not achieve statistical significance. This evidence suggests that the positive volatility spillover from carbon pricing to stock volatility is more accentuated in coastal ETS environments than inland ETS landscapes, lending support to Hypothesis 3. The above observations align with the prediction of theoretical frameworks. Financial contagion theory suggests coastal firms are more exposed to carbon market shifts due to stringent environmental policies, potentially affecting their stock volatility more than inland companies. Behavioral finance theory posits that perceptions of higher risk from carbon pricing and climate change might amplify coastal firms' stock volatility through investor sentiment. Additionally, information signaling theory argues that carbon price volatility is critical for coastal companies' future prospects, influencing market perceptions and possibly leading to greater stock price volatility due to information asymmetry.

Table 5. Coastal versus inland markets.

	(1) Coastal ETS Markets *StockVol*	(2) Inland ETS Markets *StockVol*
CarbonVol	0.0051 **	0.0117
	(0.0025)	(0.0103)
GoldVol	0.0775	−0.0796
	(0.1655)	(0.2262)
OilVol	0.0737 **	−0.0232
	(0.0369)	(0.0460)
GasVol	−0.0818 ***	−0.0211
	(0.0269)	(0.0355)
CoalVol	−0.2102 ***	−0.1728 ***
	(0.0492)	(0.0651)
VIX	0.0163 *	0.0388 ***
	(0.0096)	(0.0124)
Constant	0.0259 ***	0.0223 ***
	(0.0017)	(0.0022)
Observations	506	294
Adj-R^2	0.090	0.061

Notes: This table shows the regression of ETS-covered stock volatility on the carbon price volatility and a series of control variables for two categories of regional markets: coastal and inland ETS markets. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denotes statistical significance levels of 1%, 5%, and 10%, respectively.

4.5. Subperiod Analysis

Table 6 exhibits regression results spanning two subperiods: the pre-COVID-19 pandemic epoch (August 2013–November 2019) and amid the COVID-19 pandemic interval (December 2019–October 2023). The coefficient associated with carbon price volatility is 0.0071, showing statistical significance at the 10% level in the pre-COVID-19 period, but it shifts to 0.0056, reaching statistical significance at the 5% level during the pandemic.

Given the closeness of the numbers and significance levels, we conduct Chow's (1960) test to ascertain the presence of significant disparities in the coefficients of two linear regressions among two subgroups. We assign the variable $Covid_t$ a value of one for the months commencing from December 2019 onwards and zero for all preceding months. Following this, Chow's test is implemented through the incorporation of numerous interactions with the $Covid_t$ dummy variable:

$$\begin{aligned} StockVol_{i,t} &= \beta_0 + \beta_1 CarbonVol_{i,t} + \beta_2 GoldVol_t + \beta_3 OilVol_t \\ &+\beta_4 GasVol_t + \beta_5 CoalVol_t + \beta_6 VIX_t \\ &+\theta_0 Covid_t + \theta_1(Covid_t \times CarbonVol_{i,t}) + \theta_2(Covid_t \times GoldVol_t) \\ &+\theta_3(Covid_t \times OilVol_t) + \theta_4(Covid_t \times GasVol_t) \\ &+\theta_5(Covid_t \times CoalVol_t) + \theta_6(Covid_t \times VIX_t) + \varepsilon_{i,t} \end{aligned} \quad (5)$$

Our analysis aims to elucidate the distinct effect of carbon volatility, assessing the null hypothesis that θ_1 is equal to zero. The obtained F-value is 0.11, and the p-value is 0.73, suggesting the disparity between the two coefficients is insignificant.

These results fail to lend support to Hypothesis 4. Mai et al. (2022) investigated volatility spillovers between national and regional carbon markets, partitioning the temporal subsegment into three phases: antecedent to, concurrent with, and after the COVID-19 pandemic. During the pandemic phase, the magnitudes of spillover effects were considerably elevated. As Tan et al. (2022) point out, the COVID-19 pandemic constitutes a substantial exogenous perturbation affecting the supply-side dimensions of economies on both national and global scales. Financial contagion theory suggests that the pandemic intensified systemic risks, leading to more extraordinary transmission of uncertainty from carbon to stock markets. Behavioral finance theory indicates that COVID-19 heightened investor sensitivities to carbon price fluctuations due to increased psychological biases towards perceived pandemic-related risks and regulatory changes. Information signaling theory posits that during COVID-19, shifts in carbon prices were more significant as signals to investors about the altered performance and risk profiles of ETS-covered firms, reflecting the unique economic and regulatory landscape induced by the pandemic. Notwithstanding the empirical evidence and theoretical predictions, our analysis reveals no substantial variation in volatility spillover preceding and throughout the COVID-19 pandemic.

Table 6. Subperiod analysis.

	(1) **Pre-COVID** ***StockVol***	(2) **During-COVID** ***StockVol***
CarbonVol	0.0071 *	0.0056 **
	(0.0037)	(0.0025)
GoldVol	−0.3316	0.0329
	(0.2090)	(0.1510)
OilVol	0.3951 ***	−0.0549 **
	(0.0764)	(0.0264)
GasVol	−0.1759 ***	−0.0227
	(0.0458)	(0.0211)
CoalVol	−0.4605 ***	0.1565 ***
	(0.0616)	(0.0436)
VIX	0.0487 ***	0.0390 ***
	(0.0163)	(0.0090)
Constant	0.0245 ***	0.0134 ***
	(0.0029)	(0.0020)
Observations	446	354
$Adj\text{-}R^2$	0.285	0.096

Notes: This table shows the regression of ETS-covered stock volatility on the carbon price volatility and a series of control variables during subperiods: before the COVID-19 pandemic (August 2013–November 2019) and during the COVID-19 pandemic (December 2019–October 2023). The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denotes statistical significance levels of 1%, 5%, and 10%, respectively.

The volatility coefficients for oil, gas, and coal exhibit variations from pre-COVID to amid-COVID. Coal consumption in China has consistently increased during the COVID-19 pandemic, whereas oil consumption markedly decreased in 2022. As highlighted in a CNBC news report, China has no choice but to rely on coal power for now (Cheng 2021).

4.6. VAR Analysis

This study computes the average volatility across 293 stocks from August 2013 to October 2023 to construct a time series of stock volatility. Similarly, carbon volatility is averaged across nine regions. The resulting dataset includes 123 monthly observations. Table 7 presents the results of VAR following Equations (2) and (3). Empirical data reveals strong positive auto-correlations in the volatilities of stock, carbon, gold, natural gas, coal, and the VIX index, exhibiting coefficients of 0.7546, 0.4606, 0.2295, 0.4381, 0.6331, and 0.6933, respectively, each achieving statistical significance at the 1% or 5% level. In contrast, lagged carbon price volatility exhibits negligible explanatory power for contemporaneous stock volatility and vice versa. These insights suggest that volatility spillover mechanisms are primarily contemporaneous rather than inter-temporal.

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

Table 7. VAR analysis.

	(1) *StockVol*	(2) *CarbonVol*	(3) *GoldVol*	(4) *OilVol*	(5) *GasVol*	(6) *CoalVol*	(7) *VIX*
L.StockVol	0.7546 ***	−0.2811	0.0568 *	0.3053 **	0.0023	−0.0435	1.2166 **
	(0.0584)	(0.7430)	(0.0311)	(0.1278)	(0.1448)	(0.0700)	(0.5050)
L.CarbonVol	0.0033	0.4606 ***	−0.0061 *	−0.0254 *	−0.0121	0.0163 **	−0.0133
	(0.0066)	(0.0834)	(0.0035)	(0.0143)	(0.0163)	(0.0079)	(0.0567)
L.GoldVol	0.0585	−0.1805	0.2295 **	0.9079 **	1.3727 ***	0.1969	0.1378
	(0.1843)	(2.3456)	(0.0981)	(0.4034)	(0.4572)	(0.2211)	(1.5942)
L.OilVol	0.0039	0.2137	−0.0337	0.1269	−0.3034 ***	−0.0688	−0.4337
	(0.0418)	(0.5314)	(0.0222)	(0.0914)	(0.1036)	(0.0501)	(0.3612)
L.GasVol	−0.0318	−0.4895	−0.0036	−0.1139	0.4381 ***	0.0419	0.5392 *
	(0.0322)	(0.4098)	(0.0171)	(0.0705)	(0.0799)	(0.0386)	(0.2785)
L.CoalVol	−0.1249 **	−0.0207	−0.0265	0.1017	0.2456 *	0.6331 ***	−0.0597
	(0.0582)	(0.7402)	(0.0310)	(0.1273)	(0.1443)	(0.0698)	(0.5031)
L.VIX	−0.0102	0.1487	0.0168 ***	0.1121 ***	0.0804 ***	0.0024	0.6933 ***
	(0.0111)	(0.1412)	(0.0059)	(0.0243)	(0.0275)	(0.0133)	(0.0960)
Constant	0.0105 ***	0.0495	0.0043 ***	−0.0110 **	−0.0047	0.0045	0.0188
	(0.0024)	(0.0312)	(0.0013)	(0.0054)	(0.0061)	(0.0029)	(0.0212)
Observations	122	122	122	122	122	122	122

Notes: This table shows the VAR analysis of ETS-covered stock volatility, carbon price volatility, a series of control variable volatilities, and their one-month lagged values. The standard errors are reported in parentheses below the estimated coefficients. ***, **, and * denotes statistical significance levels of 1%, 5%, and 10%, respectively.

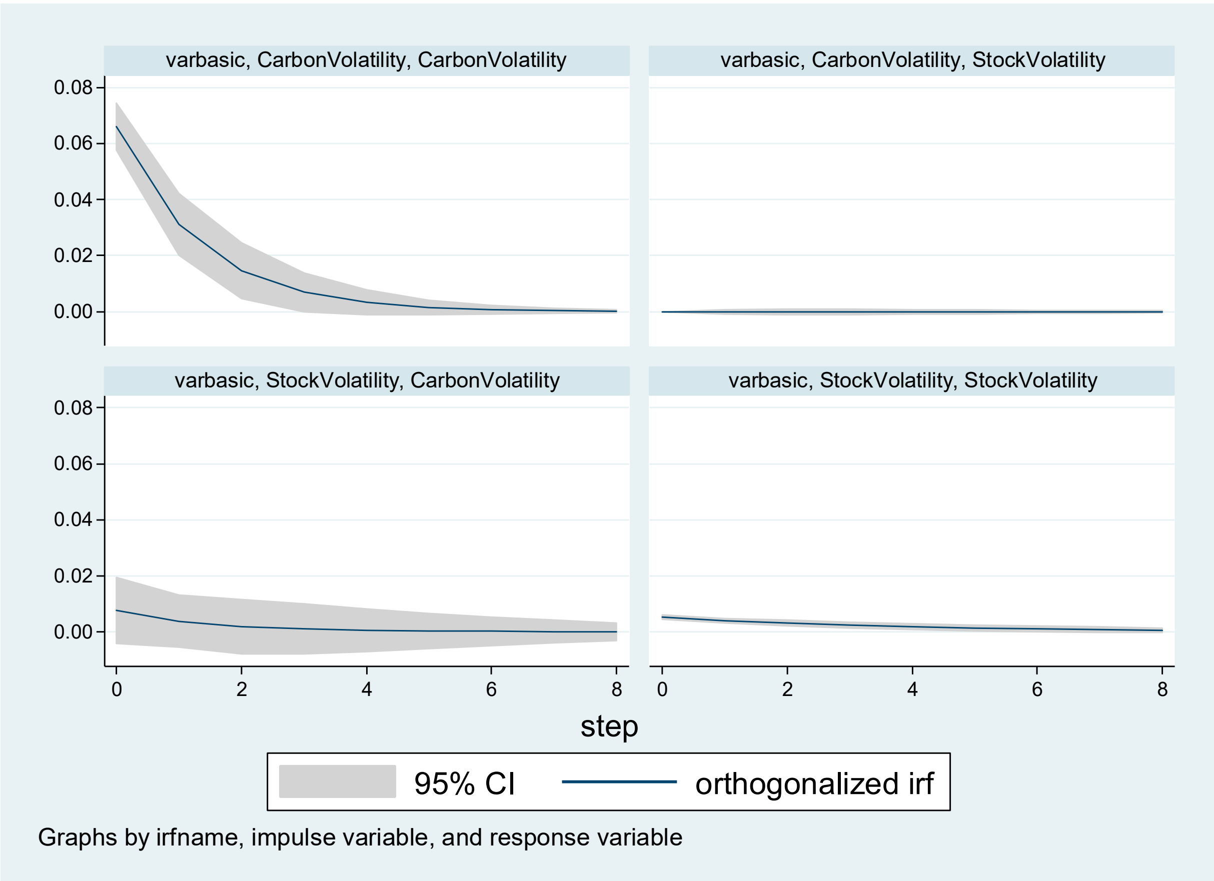

Figure 1. Impulse response function of vector autoregression. Note: after implementing vector autoregression analysis, this figure shows the impulse response function and the evolving trajectory between stock and carbon price volatility.

4.7. E-GARCH Analysis

Table 8 displays outcomes derived pursuant to Equation (4), wherein Nelson's (1991) E-GARCH model is utilized to integrate an innovation sign approach. Although well-established, the E-GARCH model may not reflect the most recent developments in volatility modeling. Our selection was driven by the model's proficiency in detecting volatility asymmetries, which is essential for the context of our study. It is noted that financial time series data frequently present characteristics like volatility clustering, leverage effects, and fat tails. As a preliminary test, we employed the E-GARCH model to mitigate the effects of volatility clustering. Again, the time series dataset consolidates all nine regional markets into a single composite of China's ETS market from August 2013 to October 2023. As depicted in Table 8, the positive coefficient on *L.EARCH* suggests that positive innovations (unexpected price increases) have a more significant destabilizing impact than negative innovations. This effect is pronounced (0.5959) and surpasses the symmetric effect (0.5568). In essence, the ramifications of favorable news surpass those of adverse news. Our principal coefficient on carbon volatility persists at 0.0193 and 0.0139, attaining statistical significance at the 5% and 1% thresholds, respectively, corroborating that our baseline findings remain robust after accommodating for volatility clustering phenomena, non-negligible volatility inclinations, and asymmetries in positive and negative shocks, as embedded by the E-GARCH model.

Table 8. E-GARCH analysis.

	(1) ***StockVol***	**(2)** ***StockVol***
CarbonVol	0.0193 **	0.0139 ***
	(0.0078)	(0.0052)
GoldVol		−0.0238
		(0.1521)
OilVol		−0.0591
		(0.0472)
GasVol		−0.0689 ***
		(0.0249)
CoalVol		0.0749 *
		(0.0446)
VIX		0.0539 ***
		(0.0090)
Constant	0.0222 ***	0.0141 ***
	(0.0010)	(0.0014)
L. EARCH	0.0787	0.5959 ***
	(0.0989)	(0.1443)
L. EARCH_A	0.5140 ***	0.5568 **
	(0.1679)	(0.2363)
L. EGARCH	0.8080 ***	0.5727 ***
	(0.0738)	(0.0984)
ARCH Constant	−1.9525 ***	−4.5717 ***
	(0.7571)	(1.0263)
Observations	123	123

Notes: This table shows the E-GARCH result of ETS-covered stock volatility on carbon price volatility 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.

5. Conclusions

This study investigates the volatility spillover effects of carbon pricing on ETS-covered equities in the Chinese market. We identify a statistically robust, positive spillover impact from carbon price volatility onto corresponding equity volatility utilizing an exhaustive dataset comprising 293 publicly traded, ETS-affected firms across nine distinct Chinese markets from August 2013 to October 2023. Subsample scrutiny reveals that the positive volatility spillover is more pronounced in low-carbon-intensity industries than in their high-carbon-intensity analogs. Geographical examination substantiates that the volatility spillover effect is significantly more prevalent in coastal ETS markets than in inland ETS markets, manifesting regional heterogeneity. Temporal bifurcation demonstrates that the spillover impact remains predominantly unchanged during the COVID-19 era compared to preceding periods. Vector autoregressive assessments affirm that volatility spillovers are predominantly contemporaneous instead of inter-temporal. Our baseline findings remain resilient when utilizing the E-GARCH model to control for volatility clustering phenomena.

This study provides several enrichments to the extant literature. First, it expands the corpus of research dedicated to the evolution and efficacy of China's carbon emissions trading markets, delineating a direct mechanism by which policy impacts equity markets. Second, introducing a novel inter-market spillover channel amplifies the discourse on determinants of stock volatility. Finally, the present study advances the academic dialogue on the volatility spillover effect within carbon ETS arenas. These spillovers are discernible geographically, as demonstrated by volatility transfers among eight regional carbon ETS markets in China (Li et al. 2023). Furthermore, such volatility spillovers extend across various classes of financial assets, exemplified by the correlation between carbon pricing and energy stocks (Tian et al. 2016; Gong et al. 2021; Ji et al. 2018; Song et al. 2022; Sadorsky 2014). Nevertheless, the volatility spillover between China's carbon market and the equity market remains unexplored, especially in the individual stock level. Our investigation addresses this lacuna, focusing on the equities of companies under carbon emission quota regulation. It furnishes novel empirical evidence on the cross-market volatility dynamics between carbon and stock markets, thus bridging a significant gap in the literature.

Despite its contributions, this research is subject to several limitations that pave the way for future inquiries. Primarily, the study's dataset, confined to a timeframe commencing with initiating ETS pilots in 2013, would benefit substantially from a longitudinal expansion. An extended temporal analysis could yield more robust empirical findings as these markets evolve, capturing the full spectrum of market dynamics over time. Moreover, future studies should consider separating systematic volatility from idiosyncratic volatility to provide a clearer understanding of the sources of volatility in ETS-regulated stock markets. This distinction is critical for accurately attributing volatility to market-wide shocks versus firm-specific events. Exploring beyond volatility impacts to examine alternative interaction mechanisms between carbon and equity markets, such as regulatory announcements or investor sentiment, could deepen insights into their complex relationship. Enhancing the analysis with additional regional-level control variables alongside macroeconomic indicators would offer a more nuanced perspective on the influence of external factors. Additionally, investigating the effects of technological innovations and comparing different ETS jurisdictions could highlight adaptive strategies and inform policy in emerging markets, providing a holistic view of carbon trading's economic implications globally.

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References

Aatola, Piia, Markku Ollikainen, and Anne Toppinen. 2013. Impact of the carbon price on the integrating European electricity market. *Energy Policy* 61: 1236–51. [CrossRef]

Abbas, Qaisar, Sabeen Khan, and Syed Zulfiqar Ali Shah. 2013. Volatility transmission in regional Asian stock markets. *Emerging Markets Review* 16: 66–77. [CrossRef]

Ahmad, Muhannad Akram, Ashraf Mohammad Salem Alrjoub, and Hussein Mohammed Alrabba. 2018. The effect of dividend policy on stock price volatility: Empirical evidence from Amman Stock Exchange. *Academy of Accounting and Financial Studies Journal* 22: 1–8.

Aliyu, Shehu Usman Rano. 2012. Does inflation have an impact on stock returns and volatility? Evidence from Nigeria and Ghana. *Applied Financial Economics* 22: 427–35. [CrossRef]

Ashraf, Badar Nadeem. 2021. Stock markets' reaction to COVID-19: Moderating role of national culture. *Finance Research Letters* 41: 101857. [CrossRef]

Aslan, Aydin, and Peter N. Posch. 2022. Does carbon price volatility affect European stock market sectors? A connectedness network analysis. *Finance Research Letters* 50: 103318. [CrossRef]

Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin. 2020. The unprecedented stock market reaction to COVID-19. *Review of Asset Pricing Studies* 10: 742–58. [CrossRef]

Baskin, Jonathan. 1989. Dividend policy and the volatility of common stocks. *Journal of Portfolio Management* 15: 19. [CrossRef]

BenSaïda, Ahmed, Houda Litimi, and Oussama Abdallah. 2018. Volatility spillover shifts in global financial markets. *Economic Modelling* 73: 343–53. [CrossRef]

Binder, John J., and Matthias J. Merges. 2001. Stock market volatility and economic factors. *Review of Quantitative Finance and Accounting* 17: 5–26. [CrossRef]

Bolton, Patrick, and Marcin Kacperczyk. 2021. Do investors care about carbon risk? *Journal of Financial Economics* 142: 517–49. [CrossRef]

Chai, Shanglei, Ruixuan Sun, Ke Zhang, Yueting Ding, and Wei Wei. 2022. Is emissions trading scheme (ETS) an effective market-incentivized environmental regulation policy? Evidence from China's eight ETS pilots. *International Journal of Environmental Research and Public Health* 19: 3177. [CrossRef]

Chapple, Larelle, Peter M. Clarkson, and Daniel L. Gold. 2013. The cost of carbon: Capital market effects of the proposed emission trading scheme (ETS). *Abacus* 49: 1–33. [CrossRef]

Chen, Zhian, Jinmin Du, Donghui Li, and Rui Ouyang. 2013. Does foreign institutional ownership increase return volatility? Evidence from China. *Journal of Banking & Finance* 37: 660–69.

Cheng, Evelyn. 2021. China Has 'No Other Choice' but to Rely On Coal Power for Now, Official Says. Available online: https://www.cnbc.com/2021/04/29/climate-china-has-no-other-choice-but-to-rely-on-coal-power-for-now.html (accessed on 9 March 2024).

Cheng, Jinhua, Jiahui Yi, Sheng Dai, and Yan Xiong. 2019. Can low-carbon city construction facilitate green growth? Evidence from China's pilot low-carbon city initiative. *Journal of Cleaner Production* 231: 1158–70. [CrossRef]

Chow, Gregory C. 1960. Tests of equality between sets of coefficients in two linear regressions. *Econometrica* 28: 591–605. [CrossRef]

Chowdhury, Emon Kalyan, Bablu Kumar Dhar, and Alessandro Stasi. 2022. Volatility of the US stock market and business strategy during COVID-19. *Business Strategy & Development* 5: 350–60.

Christie, Andrew A. 1982. The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics* 10: 407–32. [CrossRef]

Ciarreta, Aitor, and Ainhoa Zarraga. 2015. Analysis of mean and volatility price transmissions in the MIBEL and EPEX electricity spot markets. *Energy Journal* 36: 41–60. [CrossRef]

Corradi, Valentina, Walter Distaso, and Antonio Mele. 2013. Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics* 60: 203–20. [CrossRef]

CSMAR. 2024. Available online: https://data.csmar.com (accessed on 8 March 2024).

Cummins, Mark. 2013. EU ETS market interactions: The case for multiple hypothesis testing approaches. *Applied Energy* 111: 701–9. [CrossRef]

Depledge, Joanna. 2022. The "top-down" Kyoto Protocol? Exploring caricature and misrepresentation in literature on global climate change governance. *International Environmental Agreements: Politics, Law and Economics* 22: 673–92. [CrossRef]

Dong, Qingli, Yanzhi Zhao, Xiaojun Ma, and Yanan Zhou. 2024. Risk spillover between carbon markets and stock markets from a progressive perspective: Measurements, spillover networks, and driving factors. *Energy Economics* 129: 107228. [CrossRef]

Duffee, Gregory R. 1995. Stock returns and volatility: A firm-level analysis. *Journal of Financial Economics* 37: 399–420. [CrossRef]

Dutta, Anupam, Elie Bouri, and Md Hasib Noor. 2018. Return and volatility linkages between CO_2 emission and clean energy stock prices. *Energy* 164: 803–10. [CrossRef]

Díaz, Fernando, Pablo A. Henríquez, and Diego Winkelried. 2022. Stock market volatility and the COVID-19 reproductive number. *Research in International Business and Finance* 59: 101517. [CrossRef]
Felice, Emanuele, Iacopo Odoardi, and Dario D'Ingiullo. 2023. The Chinese Inland-Coastal Inequality: The Role of Human Capital and the 2007–2008 Crisis Watershed. *Italian Economic Journal* 9: 761–88. [CrossRef]
Feng, Zhen-Hua, Le-Le Zou, and Yi-Ming Wei. 2011. Carbon price volatility: Evidence from EU ETS. *Applied Energy* 88: 590–98. [CrossRef]
Fowowe, Babajide, and Mohammed Shuaibu. 2016. Dynamic spillovers between Nigerian, South African and international equity markets. *International Economics* 148: 59–80. [CrossRef]
Fu, Yang, and Zeyu Zheng. 2020. Volatility modeling and the asymmetric effect for China's carbon trading pilot market. *Physica A: Statistical Mechanics and Its Applications* 542: 123401. [CrossRef]
Gong, Xu, Rong Shi, Jun Xu, and Boqiang Lin. 2021. Analyzing spillover effects between carbon and fossil energy markets from a time-varying perspective. *Applied Energy* 285: 116384. [CrossRef]
Green, Rikard, Karl Larsson, Veronika Lunina, and Birger Nilsson. 2018. Cross-commodity news transmission and volatility spillovers in the German energy markets. *Journal of Banking & Finance* 95: 231–43.
Han, Lin, Nino Kordzakhia, and Stefan Trück. 2020. Volatility spillovers in Australian electricity markets. *Energy Economics* 90: 104782. [CrossRef]
Hashemijoo, Mohammad, Aref Mahdavi Ardekani, and Nejat Younesi. 2012. The impact of dividend policy on share price volatility in the Malaysian stock market. *Journal of Business Studies Quarterly* 4: 111–29.
Hassan, Aminu. 2022. Does clean energy financial market reflect carbon transition risks? Evidence from the NASDAQ clean energy stock volatility. *Journal of Sustainable Finance & Investment*. *forthcoming*. [CrossRef]
Hooi, Sew Eng, Mohamed Albaity, and Ahmad Ibn Ibrahimy. 2015. Dividend policy and share price volatility. *Investment Management and Financial Innovations* 12: 226–34.
Hussainey, Khaled, Chijoke Oscar Mgbame, and Aruoriwo M. Chijoke-Mgbame. 2011. Dividend policy and share price volatility: UK evidence. *Journal of Risk Finance* 12: 57–68. [CrossRef]
International Energy Agency. 2022. CO_2 Emissions in 2022. Available online: https://iea.blob.core.windows.net/assets/3c8fa115-35c4-4474-b237-1b00424c8844/CO2Emissionsin2022.pdf (accessed on 10 November 2023).
Jebran, Khalil, and Amjad Iqbal. 2016. Dynamics of volatility spillover between stock market and foreign exchange market: Evidence from Asian Countries. *Financial Innovation* 2: 1–20. [CrossRef]
Ji, Qiang, Dayong Zhang, and Jiang-bo Geng. 2018. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production* 198: 972–78. [CrossRef]
Jiang, Wei, and Yunfei Chen. 2022. The time-frequency connectedness among metal, energy and carbon markets pre and during COVID-19 outbreak. *Resources Policy* 77: 102763. [CrossRef]
Kearney, Colm. 2000. The determination and international transmission of stock market volatility. *Global Finance Journal* 11: 31–52. [CrossRef]
Kennedy, K., and Farrokh Nourzad. 2016. Exchange rate volatility and its effect on stock market volatility. *International Journal of Human Capital in Urban Management* 1: 37–46.
King, Mervyn A., and Sushil Wadhwani. 1990. Transmission of volatility between stock markets. *Review of Financial Studies* 3: 5–33. [CrossRef]
Kong, Feng, and Yifei Wang. 2022. How to understand carbon neutrality in the context of climate change? With special reference to China. *Sustainable Environment* 8: 2062824. [CrossRef]
Koutmos, Dimitrios. 2018. Return and volatility spillovers among cryptocurrencies. *Economics Letters* 173: 122–27. [CrossRef]
Li, Zheng-Zheng, Yameng Li, Chia-Yun Huang, and Adelina Dumitrescu Peculea. 2023. Volatility spillover across Chinese carbon markets: Evidence from quantile connectedness method. *Energy Economics* 119: 106542. [CrossRef]
Liow, Kim Hiang. 2015. Volatility spillover dynamics and relationship across G7 financial markets. *North American Journal of Economics and Finance* 33: 328–65. [CrossRef]
Liu, Jian, Yue Hu, Li-Zhao Yan, and Chun-Ping Chang. 2023. Volatility spillover and hedging strategies between the European carbon emissions and energy markets. *Energy Strategy Reviews* 46: 101058. [CrossRef]
Liu, Xueyong, Haizhong An, Shupei Huang, and Shaobo Wen. 2017. The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH–BEKK model. *Physica A: Statistical Mechanics and Its Applications* 465: 374–83. [CrossRef]
Liu, Y. Angela, and Ming-Shiun Pan. 1997. Mean and volatility spillover effects in the US and Pacific-Basin stock markets. *Multinational Finance Journal* 1: 47–62. [CrossRef]
Lyu, Jingye, Ming Cao, Kuang Wu, Haifeng Li, and Ghulam Mohi-ud-din. 2020. Price volatility in the carbon market in China. *Journal of Cleaner Production* 255: 120171. [CrossRef]
Mai, Te-Ke, Aoife M. Foley, Michael McAleer, and Chia-Lin Chang. 2022. Impact of COVID-19 on returns-volatility spillovers in national and regional carbon markets in China. *Renewable and Sustainable Energy Reviews* 169: 112861. [CrossRef]
Mazzucato, Mariana, and Massimiliano Tancioni. 2012. R&D, patents and stock return volatility. *Journal of Evolutionary Economics* 22: 811–32.

Mazzucato, Mariana, and Willi Semmler. 2002. The determinants of stock price volatility: An industry study. *Nonlinear Dynamics, Psychology, and Life Sciences* 6: 197–216. [CrossRef]

Mo, Jian-Lei, Paolo Agnolucci, Mao-Rong Jiang, and Ying Fan. 2016. The impact of Chinese carbon emission trading scheme (ETS) on low carbon energy (LCE) investment. *Energy Policy* 89: 271–83. [CrossRef]

Morema, Kgotso, and Lumengo Bonga-Bonga. 2020. The impact of oil and gold price fluctuations on the South African equity market: Volatility spillovers and financial policy implications. *Resources Policy* 68: 101740. [CrossRef]

Myers, Stewart C., and Nicholas S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13: 187–221. [CrossRef]

Narayan, Paresh Kumar, Sagarika Mishra, Susan Sharma, and Ruipeng Liu. 2013. Determinants of stock price bubbles. *Economic Modelling* 35: 661–67. [CrossRef]

Nazlioglu, Saban, Cumhur Erdem, and Ugur Soytas. 2013. Volatility spillover between oil and agricultural commodity markets. *Energy Economics* 36: 658–65. [CrossRef]

Nelson, Daniel B. 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica* 59: 347–70. [CrossRef]

Nikmanesh, Lida, and Abu Hassan Shaari Mohd Nor. 2016. Macroeconomic determinants of stock market volatility: An empirical study of Malaysia and Indonesia. *Asian Academy of Management Journal* 21: 161.

Officer, Robert R. 1973. The variability of the market factor of the New York Stock Exchange. *Journal of Business* 46: 434–53. [CrossRef]

Olweny, Tobias, and Kennedy Omondi. 2011. The effect of macro-economic factors on stock return volatility in the Nairobi stock exchange, Kenya. *Economics and Finance Review* 1: 34–48.

Özdemir, Onur. 2022. Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: Evidence from DCC-GARCH and wavelet analysis. *Financial Innovation* 8: 12. [CrossRef] [PubMed]

Özer, Mustafa, Sandra Kamenković, and Zoran Grubišić. 2020. Frequency domain causality analysis of intra-and inter-regional return and volatility spillovers of South-East European (SEE) stock markets. *Economic Research-Ekonomska Istraživanja* 33: 1–25. [CrossRef]

Pacala, Stephen, and Robert Socolow. 2004. Stabilization wedges: Solving the climate problem for the next 50 years with current technologies. *Science* 305: 968–72. [CrossRef]

Qarni, Muhammad Owais, Saqib Gulzar, Syeda Tamkeen Fatima, Majid Jamal Khan, and Khurram Shafi. 2019. Inter-markets volatility spillover in US bitcoin and financial markets. *Journal of Business Economics and Management* 20: 694–714. [CrossRef]

Rastogi, Shailesh, and Jagjeevan Kanoujiya. 2022. The volatility spillover effect of macroeconomic indicators and strategic commodities on inflation: Evidence from India. *South Asian Journal of Business Studies*. *published online*. [CrossRef]

Sadorsky, Perry. 2014. Carbon price volatility and financial risk management. *Journal of Energy Markets* 7: 83–102. [CrossRef]

Shahzad, Syed Jawad Hussain, Muhammad Abubakr Naeem, Zhe Peng, and Elie Bouri. 2021. Asymmetric volatility spillover among Chinese sectors during COVID-19. *International Review of Financial Analysis* 75: 101754. [CrossRef]

Shleifer, Andrei, and Lawrence H. Summers. 1990. The noise trader approach to finance. *Journal of Economic Perspectives* 4: 19–33. [CrossRef]

Singh, Priyanka, Brajesh Kumar, and Ajay Pandey. 2010. Price and volatility spillovers across North American, European and Asian stock markets. *International Review of Financial Analysis* 19: 55–64. [CrossRef]

Song, Xiang, Dingyu Wang, Xuantao Zhang, Yuan He, and Yong Wang. 2022. A comparison of the operation of China's carbon trading market and energy market and their spillover effects. *Renewable and Sustainable Energy Reviews* 168: 112864. [CrossRef]

Su, Xiaqing, and Zhe Liu. 2021. Sector volatility spillover and economic policy uncertainty: Evidence from China's stock market. *Mathematics* 9: 1411. [CrossRef]

Sun, Limei, Meiqi Xiang, and Qing Shen. 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. [CrossRef]

Sutrisno, Bambang. 2020. The determinants of stock price volatility in Indonesia. *Economics and Accounting Journal* 3: 73–79. [CrossRef]

Syed, Qasim Raza, and Elie Bouri. 2022. Spillovers from global economic policy uncertainty and oil price volatility to the volatility of stock markets of oil importers and exporters. *Environmental Science and Pollution Research* 29: 15603–13. [CrossRef]

Tan, Ling, Xianhua Wu, Ji Guo, and Ernesto D. R. Santibanez-Gonzalez. 2022. Assessing the impacts of COVID-19 on the industrial sectors and economy of China. *Risk Analysis* 42: 21–39. [CrossRef]

Terhaar, Jens, Thomas L. Frölicher, Mathias T. Aschwanden, Pierre Friedlingstein, and Fortunat Joos. 2022. Adaptive emission reduction approach to reach any global warming target. *Nature Climate Change* 12: 1136–42. [CrossRef]

Thampanya, Natthinee, Junjie Wu, Muhammad Ali Nasir, and Jia Liu. 2020. Fundamental and behavioural determinants of stock return volatility in ASEAN-5 countries. *Journal of International Financial Markets, Institutions and Money* 65: 101193. [CrossRef]

Tian, Yuan, Alexandr Akimov, Eduardo Roca, and Victor Wong. 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: 1619–26. [CrossRef]

Tiwari, Aviral Kumar, Emmanuel Joel Aikins Abakah, David Gabauer, and Richard Adjei Dwumfour. 2022. Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. *Global Finance Journal* 51: 100692. [CrossRef]

Touny, Mahmoud Abdelaziz, Mostafa Ahmed Radwan, and Mahmoud M. Hussein Alayis. 2021. Macro determinants of stock market volatility: Evidence from Middle East region. *Afro-Asian Journal of Finance and Accounting* 11: 376–91. [CrossRef]

Tsagkanos, Athanasios, Dimitrios Koumanakos, and Michalis Pavlakis. 2024. Business activity and business confidence: A new volatility transmission relationship. *Journal of Economic Studies* 51: 408–23. [CrossRef]
Vardar, Gülin, Yener Coşkun, and Tezer Yelkenci. 2018. Shock transmission and volatility spillover in stock and commodity markets: Evidence from advanced and emerging markets. *Eurasian Economic Review* 8: 231–88. [CrossRef]
Wang, Tian, Xuantao Zhang, Yuhe Ma, and Yong Wang. 2023. Risk contagion and decision-making evolution of carbon market enterprises: Comparisons with China, the United States, and the European Union. *Environmental Impact Assessment Review* 99: 107036. [CrossRef]
Wang, Xiao-Qing, Chi-Wei Su, Oana-Ramona Lobonţ, Hao Li, and Moldovan Nicoleta-Claudia. 2022a. Is China's carbon trading market efficient? Evidence from emissions trading scheme pilots. *Energy* 245: 123240. [CrossRef]
Wang, Xunxiao, and Yudong Wang. 2019. Volatility spillovers between crude oil and Chinese sectoral equity markets: Evidence from a frequency dynamics perspective. *Energy Economics* 80: 995–1009. [CrossRef]
Wang, Yudong, and Zhuangyue Guo. 2018. The dynamic spillover between carbon and energy markets: New evidence. *Energy* 149: 24–33. [CrossRef]
Wang, Yihan, Elie Bouri, Zeeshan Fareed, and Yuhui Dai. 2022b. Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. *Finance Research Letters* 49: 103066. [CrossRef]
Wind. 2024. Available online: https://www.wind.com.cn/mobile/EDB/en.html (accessed on 8 March 2024).
World Bank. 2024. Carbon Pricing Dashboard. Available online: https://carbonpricingdashboard.worldbank.org/map_data (accessed on 8 March 2024).
Wu, Ran, Tao Ma, and Enno Schröder. 2022. The contribution of trade to production-based carbon dioxide emissions. *Structural Change and Economic Dynamics* 60: 391–406. [CrossRef]
Wu, Shu, Majed Alharthi, Weihua Yin, Qaiser Abbas, Adnan Noor Shah, Saeed Ur Rahman, and Jamal Khan. 2021. The carbon-neutral energy consumption and emission volatility: The causality analysis of Asean region. *Energies* 14: 2943. [CrossRef]
Xie, Zeyu, Mian Yang, and Fei Xu. 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: 71. [CrossRef]
Xu, Lin, Chenyang Wu, Quande Qin, and Xiaoying Lin. 2022. Spillover effects and nonlinear correlations between carbon emissions and stock markets: An empirical analysis of China's carbon-intensive industries. *Energy Economics* 111: 106071. [CrossRef]
Xu, Li, Shi-Jie Deng, and Valerie M. Thomas. 2016. Carbon emission permit price volatility reduction through financial options. *Energy Economics* 53: 248–60. [CrossRef]
Yadav, Miklesh Prasad, Taimur Sharif, Shruti Ashok, Deepika Dhingra, and Mohammad Zoynul Abedin. 2023. Investigating volatility spillover of energy commodities in the context of the Chinese and European stock markets. *Research in International Business and Finance* 65: 101948. [CrossRef]
Yang, Fei, Beibei Shi, Ming Xu, and Chen Feng. 2019. Can reducing carbon emissions improve economic performance—Evidence from China. *Economics* 13: 20190047. [CrossRef]
Yang, Xinyuan, 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: 227–41. [CrossRef]
Yip, Pick Schen, Robert Brooks, Hung Xuan Do, and Duc Khuong Nguyen. 2020. Dynamic volatility spillover effects between oil and agricultural products. *International Review of Financial Analysis* 69: 101465. [CrossRef]
Yu, Hongxin, Yaohui Jiang, Zhaowen Zhang, Wen-Long Shang, Chunjia Han, and Yuanjun Zhao. 2022. The impact of carbon emission trading policy on firms' green innovation in China. *Financial Innovation* 8: 55. [CrossRef]
Zainudin, Rozaimah, Nurul Shahnaz Mahdzan, and Chee Hong Yet. 2018. Dividend policy and stock price volatility of industrial products firms in Malaysia. *International Journal of Emerging Markets* 13: 203–17. [CrossRef]
Zhang, Dayong, Min Hu, and Qiang Ji. 2020. Financial markets under the global pandemic of COVID-19. *Finance Research Letters* 36: 101528. [CrossRef]
Zhang, Junru, Kamrul Hassan, Zhuochen Wu, and Dominic Gasbarro. 2022. Does corporate social responsibility affect risk spillovers between the carbon emissions trading market and the stock market? *Journal of Cleaner Production* 362: 132330. [CrossRef]
Zhang, Qiongqiong, and Jianing Zhang. 2023. Carbon pricing and stock performance: Evidence from China's emissions trading scheme pilot regions. *Review of Pacific Basin Financial Markets and Policies* 26: 2350024. [CrossRef]
Zhang, Yue-Jun, and Wei Wang. 2021. How does China's carbon emissions trading (CET) policy affect the investment of CET-covered enterprises? *Energy Economics* 98: 105224. [CrossRef]
Zhang, Yue-Jun, Yu-Lu Peng, Chao-Qun Ma, and Bo Shen. 2017. Can environmental innovation facilitate carbon emissions reduction? Evidence from China. *Energy Policy* 100: 18–28. [CrossRef]
Zhang, Yinpeng, Zhixin Liu, and Yingying Xu. 2018. Carbon price volatility: The case of China. *PLoS ONE* 13: e0205317. [CrossRef]
Zhang, Zhongxiang. 2016. Making the transition to a low-carbon economy: The key challenges for China. *Asia & The Pacific Policy Studies* 3: 187–202.
Zhao, Xin-gang, Gui-wu Jiang, Dan Nie, and Hao Chen. 2016. How to improve the market efficiency of carbon trading: A perspective of China. *Renewable and Sustainable Energy Reviews* 59: 1229–45. [CrossRef]
Zhou, Kaile, and Yiwen Li. 2019. Influencing factors and fluctuation characteristics of China's carbon emission trading price. *Physica A: Statistical Mechanics and Its Applications* 524: 459–74. [CrossRef]

Zhou, Xiangyi, Weijin Zhang, and Jie Zhang. 2012. Volatility spillovers between the Chinese and world equity markets. *Pacific-Basin Finance Journal* 20: 247–70. [CrossRef]

Zhu, Rui, Liyu Long, and Yinghua Gong. 2022. Emission trading system, carbon market efficiency, and corporate innovations. *International Journal of Environmental Research and Public Health* 19: 9683. [CrossRef] [PubMed]