Spillover effect among independent carbon markets: evidence from China’s carbon markets

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Abstract
Carbon pricing is one of the key policy tools in the green recovery of the post-COVID-19 era. As linkages among ETSs worldwide are future trend, the carbon price spillover effects among markets are needed to be explored. This study examines the spillover effects and dynamic linkages of carbon prices using the example of China’s pilot carbon markets during 2015–2019, which are seemingly independent carbon markets. A structural vector error correction model and an improved directed acyclic graph approach are applied. The main results are as follows. First, the linkages among the five pilots demonstrate features of “two small-world networks.” Specifically, these are the Guangdong and Hubei network and the Beijing, Shenzhen and Shanghai network. Second, Shenzhen, Beijing and Hubei ranked as the top three pilots in terms of external spillover effect, accounting for 36.25%, 29.76%, and 25.59%, respectively. Second, Guangdong pilot has increasing influence on the Hubei, Shenzhen and Beijing pilots. Third, trading activities are positive contributors to the spillover, while the allowance illiquidity ratio and volatility are negative factors. The findings imply that to retain an expectable abatement costs in achieving the climate goals in green recovery, carbon prices in other potentially related markets should be considered by the policy maker in addition to its own policy design.

Keywords China’s carbon market · Spillover effect · Improved directed acyclic graph approach · Structural vector error correction model

JEL Classification C01 · C32 · G12 · G14 · Q59
1 Introduction

A green recovery is being called for in the post-COVID-19 era. As stated in the Glasgow Climate Pact (UNFCCC, 2021), climate actions such as carbon neutrality and energy transition are key components of this recovery. Carbon pricing will continue to play a central role in achieving these goals (Jiang et al., 2016; Tan and Wang, 2017; Taghizadeh-Hesary and Yoshino, 2019; Hu et al., 2020; Zhu et al., 2020a; Taghizadeh-Hesary et al., 2022). As a market-based policy tool, the emissions trading system (ETS) has gained popularity worldwide. By 2021, there were already 25 such ETSs in force, covering 17% of global GHG emissions, and 22 further such schemes are planned (ICAP, 2022). To enhance the cooperation of ETSs globally, the COP 26 negotiation reached an agreement to further link the ETSs worldwide, and to establish an international carbon market in the near future (UNFCCC, 2021). Nevertheless, such institutional linking would probably remain in the design stage for years before its actual implementation. However, the implication is that, in the current stage, it would be beneficial to understand how the carbon prices in one ETS are influenced by the spillover effect from other markets (Creti et al., 2012; Ji et al., 2018a; Wang and Guo, 2018). Such knowledge would help fully discover the role of carbon pricing in contributing to a low-carbon transition in the post-COVID era.

Although numerous studies have discussed the possible outcome of institutionally linking independent ETSs at a global level (Li et al., 2019; Li and Duan, 2021; Winkler et al., 2021), the real spillover effects are seldom tested, as currently, there is a lack of practices to do so. Earlier empirical studies focusing on the EU ETS (European Union Emission Trading Scheme) case can only test the spillover effects between EU carbon markets and energy markets (Alberola et al., 2008; Kim et al., 2010; Creti et al., 2012; Aatola et al., 2013; Reboredo, 2014; Yu et al., 2015; Zhang and Sun, 2016; Chang et al., 2017, 2018; Zhao et al., 2018; Ji et al., 2018a;). The later cases of regional carbon market pilots in China give rise to the empirical tests of spillovers among seemingly unrelated carbon markets. Evidence has been found for short-run correlation of carbon prices (Li et al., 2018), the risk spillover effects (Zhu et al., 2020b) and the spillover effects of return and volatility (Guo and Feng, 2021). Methodologically, these studies have investigated the linkages, similarities, transmission characteristics, or integration degree of carbon prices using the VAR-GARCH model with dynamic conditional correlation (Li et al., 2018), the topological measure of networks (Jia et al., 2018; Fan et al., 2019a), the entropy-based correlation measurement (Yin et al., 2019), or the copula-CoES approach (Zhu et al., 2020b). Yet due to the limitation of these methods, the direction, causality and driving forces of such connections are still not fully understood.

According to financial market theories, carbon prices in independent markets may exert an impact upon each other through both the economic fundamental spillover channel and the information spillover channels (McQueen and Roley, 1993; Wang and Guo, 2018). For example, the shocks of economics fundamentals may influence another market through secondary market trading; the behavior of covered entities in one ETS may also influence the expectation or activities of entities in another.
This paper explores these issues by using the case of China’s regional carbon markets, which played the role of pilots for the new national ETS in China. These regional carbon markets include five cities (Shenzhen, Beijing, Shanghai, Tianjin, and Chongqing) and four provinces (Hubei, Guangdong, Sichuan, and Fujian). The markets were launched consecutively, from 2013 to 2017. The case is suitable for the research topic for the following reasons: First, these pilots are de facto independent carbon markets, which have greater divergence in market regimes, including capping rules, coverages, allowance allocation, monitoring, reporting, and verifications (MRV) (Jotzo and Löschel, 2014; Wu et al., 2014; Liu et al., 2015; Yan et al., 2020) (See Appendix 1). There are no explicit direct linkage rules among these pilots in terms of policy design; that is, an allowance in one pilot cannot be traded and used for compliance in another scheme. However, these pilots may still have indirect or soft connections with each other. For example, pilots are allowed a small proportion of offsets from emissions reduction programs in Mainland China. Covered entities in different pilots may also belong to the same company group (such as the power generators) or have close economic relationships with each other. These features generate an expectation that carbon price linkages might exist among these independent markets. This is also a representative case for the mainstream ETSs internationally, such as the EU ETS, WCI (Western Climate Initiative), and RGGI (Regional Greenhouse Gas Initiative). Second, although China’s national ETS was launched in July, only the electricity sector is covered in the current phase. The regional pilots are still operating alongside the national one, regulating sectors outside the national scheme in these provinces and cities. Therefore, the spillover effect among regional carbon markets still contains policy implications in the era of China’s national carbon market.

Thus, the paper examines the spillover effect of the carbon price of China’s ETS pilots. This is achieved using an improved directed acyclic graph approach, designed especially for the direction and causality of the dynamic linkages. The paper does find clear evidences of such linkages among these seemingly independent markets. First, two small networks of carbon price linkages exist, which are the Guangdong–Hubei network and the Beijing–Shenzhen–Shanghai network. Second, the average carbon price spillover during the sample period was 20.83%, among which the carbon prices in Shenzhen, Beijing and Hubei had the most powerful influences (external spillover effect) on prices in the other pilots. It thereby enriches the existing understanding of carbon market linkages, whether institutionally or non-institutionally (Anger, 2008; Li et al., 2019; Li and Duan, 2021; Winkler et al., 2021).

The potential contribution to existing literature is two-fold. First, it accurately unveils the causal relationship and capture the price linkage among the pilots by applying an updated method of the SVECM (structure vector error correction model), with a directed acyclic graph (DAG) structure. These methods enable the examination of the causality, direction and sizes of the static and dynamic spillover effects, which are missing in the existing literature. Second, the paper also explores the possible driving factors behind the spillovers, a topic which has rarely been empirically tested in related studies (Li et al., 2018; Guo and Feng, 2021; Zhu et al., 2020b).
The rest of the paper is organized as follows: Sect. 2 introduces the theoretical background. Section 3 presents the methodologies and data. In Sect. 4, the paper shows the main empirical results and analysis, discusses the dynamic spillover effects and empirically tests the mechanism. Finally, Sect. 5 presents the conclusions and implications.

2 Theoretical background

Unlike traditional financial markets, an ETS includes three tiers of markets: the primary market (known as the distribution market of allowances), the secondary market (known as the spot market) and the derivative market (See Fig. 1). The primary market creates the total supply (the cap of allowances) and initially allocate the emission allowances to covered entities. The secondary market is the hub of the whole carbon market and caters for the spot trading of allowances. The derivatives market functions as the price discovery and risk management with carbon futures, options and other carbon financial derivatives. Currently, China’s national and pilot ETSs only introduce the primary market and secondary market. Therefore, this paper focuses on the spillover effect of carbon prices among secondary markets. The mechanism includes two channels: the fundamental spillover and the information spillover. The
former can be explained by the Economic Fundamentals (EF) Hypothesis (McQueen and Roley, 1993), while the latter can be explained by the Market Contagion (MC) Hypothesis (King and Wadhwani, 1990).

2.1 The economic fundamentals spillover channel

According to the EF Hypothesis, larger correlation of economic fundamentals among carbon markets would enhance the spillover effect. We illustrate the mechanism behind in Fig. 1, which shows intuitively two representative regions (A and B). Carbon prices of the two regions could influence each other via two channels.

The first channel is through the interaction of commodity prices of the two regions (See Paths ①-⑧). The carbon prices would affect the production costs, thus the commodity prices. Contrarily, the commodity markets could also influence the carbon markets as the prosperity of the former would determine the demand of the latter (See Path ⑦ and ⑧). As commodity prices could be easily transmit through transactions and related economic activities between regions (See Path ⑨), it will result in the spillover of carbon prices. The second channel is through common economic fundamental shocks of these two regions. Carbon markets in different regions might face a series of basic fundamental economic factors, such as common shocks in terms of economic growth, industrial structure, and energy mix (Taghizadeh-Hesary and Yoshino, 2015). It would lead to the cross-region spillover effect of carbon prices (See Paths ① & ⑨).

In terms of the cases of China’s pilot carbon markets, there do exists similar economic fundamental factors that would impact the commodity prices and thus the carbon prices (Appendix 2). As for the economic structure, HB\(^1\) and GD provinces are both with high proportion of secondary industry and, in particular, heavy industries; while BJ and SH have higher proportion of services and some manufacturing. As for the energy consumption, power generation, and SO\(_2\) emission per unit of GDP, HB and GD are much larger than that of SZ, BJ, and SH. The economic growth and market circumstances of HB and GD (compared with SZ, BJ, and SH) also share obvious similarities. Therefore, according to the EF hypothesis, HB and GD carbon markets might form a “small world network” (Fan et al., 2019b).

2.2 Information spillover channels

The MC hypothesis believes that economic fundamentals are not sufficient to fully explain the cross-market carbon price spillover effect. When fundamentals do not change significantly, the price fluctuations in one regional market may have an impact on another, in which the compliance attitude and behaviors of participants

\(^1\) HB (short for Hubei carbon market pilot and hereafter) and GD (short for Guangdong carbon market pilot and hereafter) are well-developing provinces. BJ (short for Beijing carbon market pilot and hereafter) is China’s capital; SH (short for Shanghai carbon market pilot and hereafter) is China’s economic center and municipality, and SZ (short for Shenzhen carbon market pilot and hereafter) is the most developed special economic zone.
may both play important roles. When carbon prices fluctuate significantly in one market, participants in other pilots will make corresponding expectations by adjusting their trading and compliance behaviors. This channel of transmission could be further executed via herd behavior in the market, causing price linkage and risk transmission among carbon markets.

Similarities and diversities in terms of the institutional features exist in China’s regional carbon markets, which might cause spillover effects explained by the MC hypothesis. As shown in Appendix 2, HB and GD have the largest amount of cap, that is, the total carbon emission allowances (compared to SZ, BJ, and SH). They also have considerable different number of covered entities in different sectors. Notably, covered sectors in HB and GD are dominated by heavy industries, such as electric power, steel, and cement, while SZ, BJ, and SH have more services and lighter manufacturing included. It may also lead to “small world network” from the channel of market information spillover.

3 Methodologies and data

The paper applies an improved DAG (Directed Acyclic Graphs) approach first introduced by Chakraborty and Zhang (2019), to explore the contemporaneous causality of carbon prices among different carbon markets. This DAG analysis provides a data-driven solution to the contemporaneous casual structure of VECM residuals (SVECM model). A forecast error variance decomposition of the SVECM model is also applied, to quantitatively explore the time-varying and dynamic effect. Then, this time and spatial dimension are used to measure the dynamic linkages among carbon pilots markets. This method can accurately depict the strength of the spillover effect among the carbon markets and the direction of the spillover path. It can also identify the role of each carbon pilot market in the spillover process. The driving factors of the spillover effect are also empirically examined.

3.1 A VECM based DAG

The empirical analysis of this paper is based on the forecast error variance decomposition of the SVECM (structured VECM) with DAG constraints. SVECM could quantitatively analyse the carbon prices in different carbon markets without losing intercept terms and the trend information. After premising the full integration test, the cointegration coefficient and adjustment coefficient estimated could reveal the long-term equilibrium relationship between carbon prices in different carbon markets, as well as the correction speed of carbon prices when they deviate from the equilibrium relationship. However, the method of Cholesky decomposition applied by SVECM is criticized as being subjective and arbitrary by some studies (Yang and Zhou, 2017). Thus, the paper needs to use the DAG method to overcome these restrictions by identifying the contemporaneous causal structure fully driven by the data (Pearl, 1995; Swanson and Granger, 1997; Pearl, 2000).
The DAG method builds on the insight that contemporaneous causal relations are deduced by examining the correlation structure. DAG seeks to create a causal map linking of data-driven variables. This statistically eliminates uncorrelated linkages between variables and applies logic arguments to direct the remaining links. However, the traditional DAG methods, such as the PC algorithm (Sprites et al., 2000), which only identify the graph’s Markov equivalence class based on conditional independence tests, leaving some links undirected (Peters et al., 2014). Thus, the paper applied the structural equation models with an additive noise structure to identify the correct graph, following Peters et al. (2014), and Chakraborty and Zhang (2019), as follows:

$$X_j = \sum_{k \in \text{Par}(j)} f_{j,k}(X_k) + \varepsilon_j, j = 1, 2, \ldots, d$$

(1)

where the $X_j$ corresponds to the direct parents of $X_j$, $\text{Par}(j)$ denotes the index associated with the parents of the $j$th node, and the noise variables $\varepsilon_1, \ldots, \varepsilon_d$ are jointly independent variables.

This paper follow Chakraborty and Zhang (2019)’s improved method. Their approach has advantages in quantifying the joint dependence when there are more than two different possible causal directions for each pair of variables, compared with previous methods such as Peters et al. (2014) (Gretton et al., 2005, 2006). The following steps are performed to identify the correct DAG model.

First, the PC algorithm proposed by Spirtes et al. (2000) is used to build DAG models. The paper begins with a diagram of the five pilot markets, interconnected with each other by straight lines, representing undirected linkages. The links for markets in which prices are statistically uncorrelated are then eliminated, with remaining linkages turned into arrows via a two-stage, logic-based algorithm. The different significance levels of DAG selection may vary and there are no unified standards. In the present study, the DAG models are calculated at the 5%, 10%, 15%, 20%, 25%, and 30% significance levels.

Second, if one link is undirected in a DAG model, the graph would split into two graphs, because the undirected link would split into two different possible causal directions. Similarly, if there are $n$ links undirected, the graph will split into $2^n$ graphs. From this process the paper obtains all the candidates of DAG models, and then discovers which candidate corresponds to the largest p-values. Based on all candidates, it then employs high-order distance metrics to measure joint dependence for DAG model selection.

Third, based on a series of tests recommended by Chakraborty and Zhang (2019), a DAG model with the maximum p-value can be correctly selected. These generated metrics are robust to outliers and follow a heavy-tailed distribution. This is another appealing feature of the new metrics, particularly when the PC algorithm is to some extent sensitive to the distribution of data. Thus, whether or not the time series of

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2 For example, Spirtes et al. (2000) recommended a 10% significance level, while in their study, Awokuse and Bessler (2003) found that a significance level of up to 30% presented a clear DAG structure.
carbon prices are normal distributed has less important influence on the valid inference in the DAG analysis.3

### 3.2 Measurements of spillover effect in the contemporaneous period

The spillover index measures the contribution of the mutual spillover effect among the carbon price to overall prediction error variance. The index reflects the overall correlation of carbon prices in China’s regional pilot markets rather than that of a specific market. The spillover indicators follow the forecast error variance decomposition approach employed by Diebold and Yılmaz (2014). This approach of variance decomposition was derived from the data-driven DAG-based SVECM, adopting Bernanke decomposition to forecast the intensity of each variable in order to explain the variation of another variable. Table 1 summarizes the various spillover measures and their relationships, in which each variable in the first row indicates its level of spillover to others. Also, each variable in the first column indicates its spillover from other variables. In particular, $d_{i\rightarrow j}^H$ measures pairwise directional spillovers based on variance decomposition results:

| Variables | $X_1$ | $X_2$ | … | $X_k$ | IN (From others) |
|-----------|-------|-------|---|-------|----------------|
| $X_1$     | $d_{1\rightarrow 1}^H$ | $d_{1\rightarrow 2}^H$ | … | $d_{1\rightarrow k}^H$ | $\sum_{i=1}^k d_{1\rightarrow j}^H, j \neq 1$ |
| $X_2$     | $d_{2\rightarrow 1}^H$ | $d_{2\rightarrow 2}^H$ | … | $d_{2\rightarrow k}^H$ | $\sum_{i=1}^k d_{2\rightarrow j}^H, j \neq 2$ |
| …         | …     | …     | … | …     | …              |
| $X_k$     | $d_{k\rightarrow 1}^H$ | $d_{k\rightarrow 2}^H$ | … | $d_{k\rightarrow k}^H$ | $\sum_{i=1}^k d_{k\rightarrow j}^H, j \neq k$ |
| Out (to others) | $\sum_{i=1}^k d_{i\rightarrow 1}^H, i \neq 1$ | $\sum_{i=1}^k d_{i\rightarrow 2}^H, i \neq 2$ | … | $\sum_{i=1}^k d_{i\rightarrow k}^H, i \neq k$ | |

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3 Many studies believe that deviation from the normality assumption does not appear to seriously affect the inference of cointegration (Gonzalo, 1994; Lee and Tse, 1996; Bessler and Yang, 2003; Yang and Bessler, 2008). Scheines et al. (1994) and Scheines et al. (1996) argued that although DAG method is based on normal hypothesis, non-normal distribution still could be applied in practical application. For instance, Ji and Fan (2015) and Ji et al. (2018b) employed the DAG approach to a series of variables that showed non-normal distributions (according to Jarque–Bera test). Then, VECM linked with a DAG method was used in the discussion of the energy economics issue. Similarly, when the DAG approach has been applied in other research on financial markets (Awokuse and Bessler, 2003; Yang et al., 2006; Wang, 2010; Yang and Zhou, 2017) or energy economics (Chen et al., 2009; Yang and Zhao, 2014), the distributions of the variables were not considered.
where $\sum_{h=0}^{H-1} a_{ij,l}^2$ is the contribution to the H-step-ahead error variance in the forecasting pilot $i$, due to pilot $j$, and $\sum_{l=0}^{H-1} \text{trace}(A_i A_l)$ is the total H-step-ahead error variance. The ratio is the percentage of pilot $i$ variations explained by pilot $j$ innovations and thus is a general measurement of spillover intensity from pilot $j$ to pilot $i$. The element in column $j$ in the OUT row indicates the spillover effect from pilot $j$ to the other carbon pilot markets, and the element in row $i$ of the IN column indicates the spillover effect from other carbon pilot markets to pilot $i$.

### 3.3 The model of factors driving the time-varying spillover effect

To identify the driving factors of carbon price spillover channels within the clustered groups, an estimation is designed to show the mutual influence between the pilots onto the dynamic spillover effect. The estimation of the time-varying spillover effect is based on rolling forecast error variance decomposition. This paper selects the market features of liquidity metrics (allowance illiquidity ratios), trading activity (allowance trading volume), emission allowance substitute (CCER trading volume), and market fluctuations (allowance price volatility) as the driving factors of the spillover effect and estimates their contribution with the following model:

$$
\text{Spillover}_{it} = \beta_0 + \beta_1 \text{Iliq}_{it} + \beta_2 \text{Volume}_{it} + \beta_3 \text{Lnccer}_{it} + \beta_4 \text{Volatility}_{it} + \text{Pilot}_i + \text{Year}_t + \epsilon_{it}
$$

(3)

where $\text{Spillover}_{it}$ is the level of the spillover effect of pilot $i$ in 80-week rolling-sample windows; $\text{Iliq}_{it}$, $\text{Volume}_{it}$, $\text{Lnccer}_{it}$, and $\text{Volatility}_{it}$ refer to the illiquidity ratio, allowance trading activity, CCER trading volume and allowance price volatility, respectively; $\text{Pilot}_i$ and $\text{Year}_t$ denote the fixed effect of the regional pilots and time, and $\epsilon_{it}$ is the error term. The independent variables are defined as follows: $\text{Iliq}_{id}$: The daily market illiquidity ratio is as suggested by Amihud (2002) as $\text{Iliq}_{id} = |R_{id}|/V_{id}$. Then, the 80-week rolling-sample period illiquidity ratio is calculated as $\text{Iliq}_{it} = 1/N_i \sum_{d=1}^{N_i} \text{Iliq}_{id}$, where $R_{id}$ is the allowance daily return; $V_{id}$ is the allowance daily trading value, and $N$ denotes the number of trading days within 80 weeks. To facilitate the comparison of the pilots’ illiquidity, we replace daily market illiquidity ratio with the highest illiquidity ratio of the pilots when the trading volume is 0. A larger illiquidity ratio implies that the market is highly illiquid, if the emissions allowance price moves significantly in response to little volume.

$\text{Volume}_{it}$ is calculated as the sum of the daily allowance volumes divided by the number of covered entities, reflecting the carbon pilot markets’ trading intensity.

$\text{Lnccer}_{it}$ is the logarithm of the sum of daily CCER volumes during the 80-week rolling-sample period, reflecting the substitute’s trading activity.
Volatility\(_i\) indicates the standard deviation of the weekly allowance price during the 80-week rolling-sample period. High price volatility products have large price movement uncertainty or indicate a high degree of risk.

### 3.4 Sample selection, data description and tests results

#### 3.4.1 Sample selection and data description

The paper selects the prices of the emissions allowance products of Hubei (HBEA), Guangdong (GDEA), Shenzhen (SZA), Beijing (BEA), and Shanghai (SHEA) as the samples.\(^5\) The cumulative trading volumes of them are accounted for 31%, 31%, 12%, 8%, and 7%, respectively.\(^6\) The weekly prices are calculated by dividing the weekly trading values by the weekly trading volume. To eliminate the estimation deviation caused by the inconsistency of accession time, the sample interval is selected from January 1st, 2015, to December 1st, 2019. The weekly trading volumes and prices of the five pilots are presented in Fig. 2.\(^7\)

Table 2 summarizes the statistics of the carbon prices of the five pilots. As Table 2 shows, BEA’s mean price and standard deviation are the highest, with CNY 55.49 and 13.656/ton, respectively. Meanwhile, GDEA and HBEA have the lowest prices and the lowest standard deviations, respectively.

#### 3.4.2 Unit root test and cointegration test results

Unit root tests and cointegration tests are required before conducting the DAG analysis. The results of the unit root and cointegration tests are given in Appendix 3. First, the ADF and PP tests indicate that all the variables are integrated of order one, I (1).\(^8\) Second, the Bayesian information criterion (BIC) needs to be employed to select the number of lags (1) for the VAR. The results of the cointegration test with an intercept term show compelling evidence of two cointegrating vectors linking the five pilots’ carbon prices at the 5% significance level. As allowance prices will follow unit root processes and contain two cointegrating vectors, a VECM model

\(^{4}\) In contrast to other pilots with only one emissions allowance, SZA includes SZA-2013, SZA-2014, SZA-2015, SZA-2016, SZA-2017, SZA-2018, and SZA-2019 products. The relatively small number of daily transactions for each SZA product makes them poorly representative (Chang et al., 2018a), and thus, SZA was represented by their average weekly price.

\(^{5}\) The emissions allowance products of Chongqing (CQEA), Tianjin (TJEA), and Fujian (FJEA) products were excluded from the sample, because these pilots have sparse trading activities, and their trading volume accounts for less than 5% of the total of all pilots. Correlations between allowances prices are provide in Appendix 4.

\(^{6}\) The daily traded volume and traded value were obtained from www.tanpaifang.com and the Wind database. Traded values and volumes of the eight China’s ETS allowance products are provided in Appendix 5.

\(^{7}\) Chongqing and Tianjin pilots’ trading data are not included, as the data are insufficient to analyze using the DAG approach.

\(^{8}\) To be robust, the paper also conducts a recursive estimation of the ADF and PP unit root tests with an intercept term and finds there are always some price series that are nonstationary over time.
Fig. 2  Weekly prices and weekly trading volume of the five pilots
should be constructed. A BIC is used to test the optimal model. According to it, an intercept is included, and the optimal number of lags with the maximum number is set to 8. The VECM model and the innovation correlation matrix are estimated before the DAG analysis, thus a causal structure is derived from the data.

### 4 Result analysis

#### 4.1 The causality and direction based on the DAG analysis

The DAG results show that the carbon prices in most pilots were either directly or indirectly influenced by other pilot markets (Fig. 3) in the study period. Their connection seems to have the characteristics of two “small-world networks”: GDEA links with HBEA, while BEA and SZA link with SHEA. Specifically, there is a direct link from GDEA to HBEA, indicating that the GDEA innovation correlation matrix has an external impact on HBEA. Moreover, there are direct links from BEA to SZA and SHEA, and from SZA to SHEA. It means that BEA have a direct influence on SZA and SHEA, and SZA directly influences SHEA. The later implies that BEA also has an indirect impact on SHEA via SZA.

#### 4.2 The level of carbon price spillovers based on a variance decomposition of SVECM with DAG structure

The carbon prices of each carbon market were put into the spillover index model to obtain the spillover index from the variance decomposition (Table 3). These results confirm the existence of the two “small-world networks” of carbon price spillovers. Moreover, they quantify the sizes of spillovers. In the GDEA – HBEA network, 97.26% of the HBEA price, and 100% of the GDEA price are explained by the price variance of themselves at the initial day 0. Later at the 10-week horizon, the

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**Table 2** Statistics of allowance prices

| Variable | N   | Mean  | Std dev | Min   | P50  | Maximum | Skewness | Kurtosis |
|----------|-----|-------|---------|-------|------|---------|----------|----------|
| HBEA     | 256 | 22.133| 7.245   | 22.695| 51.715| 10.494  | 0.706    | 3.382    |
| GDEA     | 256 | 16.531| 4.786   | 15.058| 32.480| 7.873   | 0.979    | 3.349    |
| SZA      | 256 | 27.140| 9.786   | 28.239| 47.273| 3.868   | −0.445   | 2.427    |
| BEA      | 256 | 55.493| 13.656  | 51.535| 87.172| 30.968  | 0.889    | 3.115    |
| SHEA     | 256 | 27.463| 12.742  | 32.069| 46.836| 3.878   | −0.582   | 1.883    |

Later on, the logarithm of allowance prices is employed in the empirical analysis.

Fig. 3 The “small-world networks” among pilot carbon prices
contribution of price variance of other market increases. That is, GDEA price variance contributes 7.3% to the HBEA price, and conversely, HBEA contributes 25.03% to GDEA. Relatively, SZA, BEA, and SHEA had minor influence on HBEA. In the BEA – SZA – SHEA network, BEA and SZA share the strongest influences to each other. That is, 20.45% from BEA price variance to SZA price at the 10-week horizon, and 31.42% conversely. Aside from it, no other pilots have significant impacts on SZA or BEA. In addition, SHEA is modestly impacted by SZA and BEA.

The spillover index then quantifies the impact of one pilot to other pilots in a network, that is, the spillover effect (Table 4). Overall, the average level of the carbon price spillover index of China’s carbon market during the sample period is 20.83%. This finding means that more than one-fifth of carbon prices in a market are influenced by other regional carbon markets. The results also indicate that carbon prices could be easily transmitted through pilot markets without interregional allowances trade. Individually, the price spillover direction among pilot markets is also
asymmetric. Shenzhen, Beijing and Hubei rank the top three in terms of external spillover effect, indicating that these three markets have high information transmission efficiency and are located in the information-leading position among China’s regional carbon markets. Specifically, SZA’s influence on BEA is stronger than BZA’s influence on SZA. Finally, SHEA is the least central pilot among the five pilots with the lowest in and out spillover index indicators.

### 4.3 Robustness test: dynamic recursive analysis

Although the analysis of the full-sample spillover effect provides on average a good characterization of the price linkages, the analysis only indicates the rough connection for the whole time period. To test whether the above conclusions obtained by variance decomposition between prices are robust, here a recursive forecast error variance decomposition is conducted. For example, the first decomposition is made on the 80 weekly samples from January 2015, to 15 June 2016. Then, the second decomposition is made on the 81 weekly samples from January 2015, to 22 June 2016. Thus, the variance decomposition was estimated recursively each week with an expanding sample.

Figure 4 plots the recursive variance decomposition results of the five regional markets at a 10-week horizon. Clearly, the spillover effects between HBEA and GDEA, and between SZA and BEA are relatively stable. In short, the variance decomposition results stay relatively steady, and the findings of this paper are robust.

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**Table 4 Spillover index for the 2015 to 2019 period**

| Variables | HBEA  | GDEA  | SZA   | BEA   | SHEA  | IN   |
|-----------|-------|-------|-------|-------|-------|------|
| HBEA      | 0.9170| 0.0730| 0.0064| 0.0033| 0.0004| 0.0830|
| GDEA      | 0.2503| 0.6752| 0.0222| 0.0367| 0.0156| 0.3248|
| SZA       | 0.0036| 0.0160| 0.7728| 0.2045| 0.0032| 0.2272|
| BEA       | 0.0014| 0.0110| 0.3142| 0.6706| 0.0027| 0.3294|
| SHEA      | 0.0006| 0.0037| 0.0197| 0.0531| 0.9230| 0.0770|
| OUT       | 0.2559| 0.1037| 0.3625| 0.2976| 0.0219|
| NET       | 0.1729| −0.2211| 0.1353| −0.0318| −0.0551|

The upper-left $5 \times 5$ sub-matrix elements are the variance of variables in rows 1–5 explained by variables in columns 2–6 at the 10-week ahead horizon. The element in column j of the IN row indicates the spillover effect from pilot j to other pilots. The element in row i of the OUT column indicates the spillover effect from other pilots to pilot i. NET is calculated by OUT minus IN, indicating net spillover.

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9 Shenzhen, Beijing and Hubei account for 36.25%, 29.76% and 25.59%, respectively.

10 The net indicator of SZA was 13.53%, compared to 3.18% for BEA.

11 For example, the first decomposition is made on the 80 weekly samples from January 2015, to 15 June 2016. Then, the second decomposition is made on the 81 weekly samples from January 2015, to 22 June 2016. Thus, the variance decomposition was estimated recursively each week with an expanding sample.
4.4 Time-varying features of spillover effect based on the rolling-window approach

Here a rolling estimation window approach is used to explore the dynamic effect comparing with the static effect in the previous subsection. This method has the advantages of great simplicity and coherence, which shows the dynamic effect of carbon prices by estimating potential time-varying parameters. (Diebold and Yılmaz, 2014). To track the time-varying spillover effect in real-time, the recursive variance was replaced with rolling variance, sweeping through the sample at each period, using only the most recent 80-week periods to estimate the variance decomposition and calculate the spillover indicators. Therefore, the time-varying spillover effect is given by the rolling forecast error variance decomposition. The results are plotted over 80-week rolling-sample windows (Fig. 5). The main results are as follows.

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**Fig. 4** Recursive forecast error variance decomposition results: Carbon price of a market explained by the price variances of different pilots
Firstly, GDEA’s impact is increasing, not only on HBEA and itself, but also on SZA and BEA. The trading volume of GDEA caught up with and gradually surpassed HBEA (as in Fig. 2); this is the possible reason for GDEAs’ growing centrality. Besides, the active trading of institutional and individual investors is the key reason for a high proportion of transactions in the GD pilot.\(^\text{12}\) According to Fig. 2, the trading volume in 2018 increased by 199.07% from the previous compliance year, with 64.43% contributed by institutional investors.

Secondly, the compliance date might be the key reason behind the pattern changes shown in Fig. 5. One pattern is that the contribution of HBEA to its own price had an increasing trend before May 2019. Then it sharply declined while the contribution GDEA dramatically increased after that date. Meanwhile, the contribution

\(^{12}\) Guangdong Carbon Market 2018 Annual Transaction Data Report (2018/06/21–2019/06/20), http://www.cnemission.com/article/jydt/scyj/201907/20190700001702.shtml.
of GDEA to its own price also increased. Another pattern is that SZA exerted a decreasing influence on itself and BEA, while BEA had a growing impact on itself and SZA before December 2017, and after March 2019. Moreover, the GDEA explained approximately 10% to 20% of the variance in SZA and BEA after March 2019. These are all around compliance date of different pilots. Figure 2 shows that the pilots tend to have centralized trading from May to July each year, which can be called a "compliance effect" (Zhao et al., 2016; Zhang et al., 2018). Almost all of GDEA’s centralized trading occurs before July each year, while HBEA’s centralized trading appears after July. This is in accordance with the compliance periods of GD and HB.13

4.5 Factors driving the spillover effect

Table 5 shows the key determinants of the carbon price spillover effect,14 as follows. The signs of the impacts on \( OUT \) and \( NET \) are consistent with each other, while the signs of the impacts on \( OUT \) and \( IN \) are opposite, which are due to different meaning of these indicators as explain in Sect. 3.2.

First, The illiquidity ratio has a significant negative impact on \( OUT \), implying that a higher liquidity pilot is more likely to have a greater influence on other pilots. Market liquidity is strongly related to market efficiency (Ibikunle et al., 2016). Higher liquidity in a pilot results in higher pricing efficiency, which implies that the information flow can be promptly reflected in that pilot’s carbon price, thus being less influenced by others. This may explain why there is a direct link from GDEA to HBEA, but HBEA exerts a greater spillover effect on GDEA.

Second, trading activity was positively related to \( OUT \), implying that increased trading activity may induce a significantly higher spillover effect on others. The CCER trading volume was significantly positive during the study period. Therefore, a higher trading volume of the emission allowance substitute here contributes to a higher spillover effect on other pilots’ prices. Emission allowances that are traded more frequently have lower price spreads. Then the information flow and liquidity shocks have a significant impact on carbon prices (Chang et al., 2018c).

Third, the CCER offset ratio has a significant positive impact on \( IN \) and \( OUT \). As CCER products can be traded across regional pilots, it may promote co-movement between pilots (Li et al., 2018). Volatility had a significant negative impact on \( OUT \). It means that greater volatility leads to a significantly lower spillover effect on others. Higher price fluctuations indicate market instability and greater uncertainty, therefore, prices in such markets would be easily affected by external markets. The empirical results also show the feature of “small-world network,” for instance, the spillover effect in group A is more sensitive to illiquidity ratios, while group B is more sensitive to the allowance and CCER trading volumes.

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13 The compliance date data are from the official websites of GDEA (http://www.cnemission.cn/) and HBEA (http://www.hbets.cn/).
14 The summary statistics of these variables are provided in Appendix 6.
### Table 5  Determinants of the spillover effect based on spillover measures

|                | Five pilots | Group A: HB & GD | Group B: SZ & BJ & SH |
|----------------|-------------|------------------|-----------------------|
|                | IN          | OUT              | NET                   | IN        | OUT          | NET                   |
| Illiq          | 0.223***    | −0.267***        | −0.490***             | 0.528***  | −0.747***    | −1.275***             | 0.300***  | −0.274***    | −0.574***             |
|                | (12.08)     | (−15.99)         | (−15.33)              | (12.45)   | (−12.44)     | (−14.48)              | (12.07)   | (−12.18)     | (−13.12)              |
| Volume         | −0.009***   | 0.017***         | 0.026***              | −0.008*   | 0.013***     | 0.020***              | −0.311*** | 0.223***     | 0.535***              |
|                | (−3.07)     | (5.46)           | (4.65)                | (−1.82)   | (3.11)       | (2.66)                | (−5.40)   | (5.33)       | (5.74)                |
| Lnccer         | −0.122***   | 0.176***         | 0.298***              | −0.074*** | 0.117***     | 0.190***              | −0.133*** | 0.214***     | 0.347***              |
|                | (−7.82)     | (13.82)          | (11.35)               | (−4.00)   | (9.40)       | (7.09)                | (−4.58)   | (10.04)      | (7.17)                |
| Volatility     | 0.030***    | −0.024***        | −0.054***             | 0.011*    | −0.009       | −0.021*              | 0.034***  | −0.021***    | −0.055***             |
|                | (15.11)     | (.8)             | (−17.37)              | (1.80)    | (−1.46)      | (−1.89)               | (13.23)   | (−11.27)     | (−13.25)              |
| Constant       | 1.973***    | −2.328***        | −4.301***             | 1.299***  | −1.379***    | −2.678***             | 2.380***  | −3.120***    | −5.500***             |
|                | (8.14)      | (−11.61)         | (−10.46)              | (4.75)    | (−6.65)      | (−6.34)               | (5.38)    | (−9.43)      | (−7.40)               |
| Year           | YES         | YES              | YES                   | YES       | YES          | YES                   | YES       | YES          | YES                   |
| Pilot          | YES         | YES              | YES                   | YES       | YES          | YES                   | YES       | YES          | YES                   |
| N              | 885         | 885              | 885                   | 354       | 354          | 354                   | 531       | 531          | 531                   |
| adj. R-sq      | 0.484       | 0.712            | 0.517                 | 0.656     | 0.564        | 0.633                 | 0.464     | 0.836        | 0.566                 |

*, **, and *** denote significance at the 10%, 5%, and 1% levels. The t-statistic is given in parentheses.
5 Conclusions and implications

Green recovery needs to be realized through market-based approaches, which have proven to be an effective tool in striking a balance between economic growth and ecosystem sustainability (Jiang et al., 2016; Tan and Wang, 2017; Taghizadeh-Hesary et al., 2022). The carbon price, as a key instrument of ETS, will play a vital role in balancing emission reductions and sustainable economic development, especially after the devastating COVID-19 pandemic (Jiang et al., 2016; Tan and Wang, 2017; Hu et al., 2020; Zhu et al., 2020a). The study examines the spillover effects and dynamic linkages of carbon prices from the years 2015 to 2019, among seemingly independent carbon markets. This is achieved by using a structural vector error correction model and an improved directed acyclic graph approach.

The main results are as follows. Firstly, the connections among the five pilots seem to present the feature of a “small-world network.” Secondly, the paper finds that GDEA not only has a significantly increasing influence on HBEA, but also has a growing impact on SZA and BEA. The reasons behind this finding may be the time sequence of the “yearly compliance” fulfilled by enterprises, as well as the GDEA pilot’s rapid improvement in trading activity. Thirdly, a pilot’s allowances and CCER trading activities have significant positive impact on the spillover effect. In addition, the allowance illiquidity ratio and volatility of a pilot exert a significant negative influence on the spillover effect from that pilot to others.

Based on the empirical results, the paper presents the following policy implications. First, carbon price spillover effects have brought new challenges and opportunities to regulators, even for seemingly unrelated ETSs, in the era of green recovery. To achieve the stated emissions reduction or carbon neutrality goals with expectable abatement costs, the policy maker needs to consider not only its own policy design, but also the price fluctuation in other carbon markets which have potential linkage. Carbon markets in countries or regions with more interactive economic environments or financial markets may have stronger spillover effects to each other.

Second, it is necessary to consider the important impact of the joint action of the spillover effect and the institutional elements of the ETS on carbon prices. In the design of the institutional elements, the policy maker is expected to pay more attention to the negative consequences of the allowance illiquidity ratio and the volatility of the spillover effect from itself to others. The ETS should set an appropriate and reasonable interval of the two indicators, in order to minimize the transmission of risks.

Third, it also yields some implications to China’s national ETS. To prevent abnormal fluctuations in the transmission of carbon prices among the regional pilot markets, national ETS designers need to pay more attention to market transactions efficiencies. It is also important to improve the response speed during the compliance period. Moreover, it would be helpful to expand the coverage of participating entities, reduce information asymmetry, and improve the discovery of carbon prices.

In future works, the linkages or spillover effects of carbon prices among China’s national ETS and other ETSs deserve further explored. For the influence factors
behind the spillover effects, policy factors that are due to the incomplete information disclosure and the exchange activities could be discussed.

Appendix 1

See Table 6.

Appendix 2: Economic fundamentals and institutional features among pilot regions

See Figs. 6 and 7.

Appendix 3: Results of unit root tests and cointegration tests

See Tables 7 and 8.

Appendix 4: Correlations between allowances prices

Table 9 further calculates the correlations between allowances prices, showing them to be significantly positive or negative, indicating their close co-movement. The correlation between SZA prices and other regional pilot prices are significantly negative, whereas the correlation between other regional pilots’ prices are all significantly positive. Moreover, the correlation coefficient between HBEA and GDEA, SZE A and BJ EA, and BJ EA and SHE A exceed 0.50.

Appendix 5: Traded values and volumes of the eight China’s ETS allowance products

See Table 10.

Data source: the network of carbon emissions trading in China (www.tanpafang.com); the time period is from January 2015 to December 2019 (FJEA is launched at the end of 2016).

Appendix 6: Summary statistics of market features

Table 11 provides the summary statistics of the spillover measures and the market features of the five pilots. As shown, the maximum of the OUT indicator is 0.894, indicating that there is a pilot that has a pronounced impact on other pilots.
| Pilots | Emitters admitted to ETS | ETS mechanism design | Quota allocation | Offset credit | Punishment |
|--------|--------------------------|----------------------|-----------------|--------------|------------|
|        | Number(2018) | Coverage thresholds | Sectoral coverage |               |            |
| Beijing | 1528 | emission $\geq$ 5000 tons CO2/year | Industries: electricity power, heat supply, steel, cement, construction material, chemical industry, papermaking, water supply, automobile, equipment manufacturing | rail transit industry, service sectors | Grandfather method + benchmark method, allowing for dynamic adjustment | Maximum upper limit of CCER is 5% and 50% should be projects within the city | In the case of unreported certification, a fine of less than 50,000 yuan shall be imposed; in the case of quota not submitted, a fine of 3–5 times of market price shall be imposed |
| Shanghai | 850 | industries: energy consumption $\geq$ 10,000 standard coal/year; aviation, port and building: energy consumption $\geq$ 5000 standard coal/year; waterborne: energy consumption $\geq$ 50,000 standard coal/year | – | aviation, airport, port, waterborne, railway, hotel, business office building | Maximum upper limit of CCER is 5% with no geographic limitations | In the case of unreported certification, a fine of 10,000 to 30,000 shall be imposed; in the case of quota not submitted, a fine of 5–10 times of market price shall be imposed |
| Tianjin | 107 | emission $\geq$ 20,000 tons CO2/year | – | – | Maximum upper limit of CCER is 10% with no geographic limitations | Mandatory rectification in a limited period, open criticism notice, deprivation of the right to incentives |
| Pilots      | Number(2018) | Coverage thresholds          | Sectoral coverage | ETS mechanism design | Quota allocation | Offset credit | Punishment |
|------------|--------------|-----------------------------|-------------------|----------------------|------------------|---------------|------------|
| Chongqing  | 197          | emission ≥ 20,000 tons CO2/year |                   |                       | Maximum upper limit of CCER is 8% with no geographic limitations |               |            |
| Hubei      | 338          | energy consumption ≥ 10,000 standard coal/year |                   | Grandfather method + benchmark method + auction method, allowing for dynamic adjustment | Maximum upper limit of CCER is 10% and 100% should be projects within the city |               |            |
| Guangdong  | 288          | emission ≥ 20,000 tons CO2/year or energy consumption ≥ 5000 standard coal/year | civil aviation |                       | In the case of quota not submitted, a fine of 1–3 times of market price shall be imposed with 150,000 yuan top; in the case of absent report, a fine of 10,000 to 30,000 shall be imposed and the right to incentives shall be deprived | Maximum upper limit of CCER is 10% and 70% should be projects within the city | In the case of absent report or certification, a fine of 1–3 times of market price shall be imposed based on average price in recent 6 months |
Table 6 (continued)

| Pilots | Emitters admitted to ETS | ETS mechanism design |
|--------|--------------------------|----------------------|
| Shenzhen | 794 industries: emission ≥ 5000 tons CO2/year; public architecture: areas ≥ 20,000 m²; national office buildings: ≥ 10,000 m² | building, bus, port, subway |
|        |                          | Maximum upper limit of CCER is 10% with no geographic limitations |
|        |                          | In the case of quota not submitted, a fine of 3 times of market price shall be imposed based on average price in recent 6 months |

All pilots allow institutional and individual investors to participate in trading.
Fig. 6 Economic and industrial structure of pilot regions. Note: A unit of GDP is CNY 100 million
**Table 7** Unit root tests

| Variable | ADF Without intercept | PP Without intercept | ADF With intercept | PP With intercept |
|----------|-----------------------|----------------------|-------------------|------------------|
| HBEA     | −0.049                | −0.079               | −1.474            | −1.691           |
| SHEA     | −0.208                | −0.174               | −1.468            | −1.357           |
| GDEA     | 0.057                 | −0.262               | −1.357            | −2.935**         |
| SZA      | −1.039                | −0.935               | −1.165            | −2.789*          |
| BEA      | 0.262                 | 0.078                | −1.924            | −3.411**         |
| Δ HBEA   | −20.610***            | −20.705***           | −20.570***        | −20.664***       |
| Δ SHEA   | −18.402***            | −18.418***           | −18.367***        | −18.383***       |
| Δ GDEA   | −14.361***            | −21.519***           | −14.333***        | −                 |
| Δ SZA    | −13.690***            | −22.445***           | −13.714***        | −                 |
| Δ BEA    | −10.617***            | −17.881***           | −10.610***        | −                 |

Δ before each variable represents its first differences; optimal lag choice according to Bayesian information criterion (BIC); *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 8** Cointegration test

| Number of cointegrating vectors | Trace statistic | P statistic | Max-Eigen statistic | P statistic |
|-------------------------------|----------------|-------------|---------------------|-------------|
| 0                             | 126.755        | 0.001       | 55.846              | 0.001       |
| 1                             | 70.909         | 0.001       | 46.075              | 0.001       |
| 2                             | 24.834         | 0.168       | 18.069              | 0.127       |
| 3                             | 6.765          | 0.635       | 5.008               | 0.749       |
| 4                             | 1.757          | 0.185       | 1.757               | 0.185       |

The number of cointegrating vectors was tested using the trace test and max-eigenvalue test with the trend and intercept terms at the 5% level.
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Data availability The datasets used during the current study are available from the corresponding author on reasonable request.

Table 9 Correlations between variables

| Variable | HBEA | GDEA | SZA | BEA | SHEA |
|----------|------|------|-----|-----|------|
| HBEA     | 1.000|      |     |     |      |
| GDEA     | 0.759*| 1.000|     |     |      |
| SZA      | −0.424*| −0.428*| 1.000|     |      |
| BEA      | 0.394*| 0.443*| −0.639*| 1.000|      |
| SHEA     | 0.258*| 0.467*| −0.391*| 0.531*| 1.000|

Table 10 Traded values and volumes of the eight China’s ETS allowance products

| Pilot   | Trade volume (10⁶ tons) | Percentage of volume | Trade value (CNY 10⁶) | Percentage of value |
|---------|-------------------------|----------------------|-----------------------|---------------------|
| HBEA    | 54.07                   | 0.31                 | 1118.22               | 0.29                |
| GDEA    | 52.68                   | 0.31                 | 839.52                | 0.22                |
| SZA     | 21.45                   | 0.12                 | 597.83                | 0.15                |
| SHEA    | 13.36                   | 0.08                 | 359.03                | 0.09                |
| BEA     | 12.19                   | 0.07                 | 733.15                | 0.19                |
| CQEA    | 8.10                    | 0.05                 | 35.25                 | 0.01                |
| FJEA    | 8.03                    | 0.05                 | 163.74                | 0.04                |
| TJEA    | 2.04                    | 0.01                 | 21.16                 | 0.01                |

Table 11 Summary statistics of market features

| Variable | N   | Mean | Std dev | Min  | P50  | Max   | Skewness | Kurtosis |
|----------|-----|------|---------|------|------|-------|----------|----------|
| IN_{it}  | 885 | 0.285| 0.178   | 0.007| 0.276| 0.716 | 0.266    | 2.023    |
| OUT_{it} | 885 | 0.285| 0.207   | 0.013| 0.265| 0.894 | 0.444    | 2.377    |
| NET_{it} | 885 | 0.000| 0.317   | −0.662| −0.015| 0.840 | 0.226    | 2.478    |
| Illiq_{it}| 885 | 0.607| 0.460   | 0.018| 0.482| 2.402 | 1.102    | 3.851    |
| Volume_{it} | 885 | 5.545| 5.636   | 0.227| 2.587| 18.696| 0.768    | 2.079    |
| Lnccer_{it} | 885 | 15.968| 0.904   | 13.690| 15.962| 17.565| −0.148   | 2.063    |
| Volatility_{it} | 885 | 5.632| 3.209   | 1.353| 4.870| 14.469| 0.989    | 3.478    |
Declarations

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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