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Price discovery in carbon exchange traded fund markets

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ABSTRACT

In this study, we analyze the price discovery in four carbon exchange-traded funds (ETF) markets: (i) VanEck Low Carbon Energy ETF (Vaneck), (ii) iShares MSCI ACWI Low Carbon Target ETF (iShare), (iii) SPDR MCSI ACWI Climate Paris Aligned ETF (SPDR), and (iv) Xtrackers Emerging Markets Carbon Reduction and Climate Improvers ETF (Xtrackers) using daily closing prices of the four carbon ETFs from December 6, 2018, to November 30, 2022. All four ETF prices are found to have a single unit root implying the efficiency of these ETF markets (LeRoy 1989). However, Johansen's (1991) cointegration test reveals that these four ETFs are driven by not one but three common stochastic trends. Further Analysis reveals that iShares and SPDR markets are driven by the same market force (common stochastic trend). Based on the generalized information share (GIS), we find that approximately 57.89% and 42.11% of the price discovery occurs in the iShares and SPDR markets, respectively. We further analyze the impact of the COVID-19 pandemic by dividing the whole sample into pre-COVID and COVID subsamples. In the pre-COVID period, the GIS measures for the iShares and SPDR are 88.69% and 11.31%, respectively. However, GIS measures for the iShares and SPDR are 1.04% and 98.96%, respectively, in the COVID period indicating a significant impact of COVID-19 on price discovery.

1. Introduction

Acknowledgment and increasing awareness of the unavoidable socio-economic effects of climate change (driven mainly by carbon dioxide (CO2) emissions) have led to several global initiatives to mitigate its adverse consequences. Among these actions, the Kyoto Protocol, which was entered into force in 2005, and the Paris Agreement in 2015 are two of the most noteworthy examples. Due to the legally binding nature of these protocols, various strategies have been implemented to comply with their requirements for governments in developing and developed countries, including imposing a carbon tax and constructing emission trading systems (ETS).[1]

While there are reports on the effectiveness of carbon tax on reducing CO2 emissions and alleviating its environmental impacts (Gupta, Bandyopadhyay, and Singh, 2019; Mardones and Cabello, 2019; Wolde-Rufael and Mulat-weldemeskel, 2022), compelling evidence put forth by comparative studies indicates the outperformance of ETS as compared to other regulatory measures including carbon tax (Bakam, Balana, and Matthews, 2012; Brink, Vollebergh, and van der Werf, 2016).[2] In addition to ETS, a reduction in carbon emissions can also be achieved through a free-market mechanism where investors can invest in firms operating in low-carbon and renewable energy industries. Rather than investing in individual firms, investors can diversify by investing in carbon exchange-traded funds (ETFs). Therefore, carbon ETF markets can play a critical role in reducing CO2 emissions.

The success of ETFs in the reduction of carbon emissions depends on the efficiency of these markets. In a free market economy, price plays a crucial role by facilitating optimal resource allocation through the concept of the "invisible hands," as coined by the famous economists Adam Smith. The efficiency of carbon ETF markets can be analyzed using the price discovery process. The price discovery analysis involves (i) testing for unit root,[3] (ii) finding the number of cointegrating vectors,

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[1] One of the early initiatives on emission trading was taken by the US to deal with its sulfur dioxide (SO2) emissions and acid rains in 1990. Driven by the effective implementation in the US, European Union decided to create a cap-and-trade system for its emissions allowances to comply with the Kyoto Protocol in 2005 known as EU ETS (i.e., European Union Emission Trading System) and is the biggest carbon market worldwide (Huang, Shen, Miao, and Zhang, 2021). Since then, ETS has been adopted and operating in major economies including China.

[2] However, it is worth mentioning that a mixed policy has been reported to be the most effective strategy to deal with climate change (Li and Jia, 2017).

[3] The presence of unit-root is consistent with the martingale principle implied by market efficiency LeRoy (1989)

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and (iii) if the number of cointegrating vectors is equal to the number of series minus one, then computing the generalized information share (GIS) proposed by Lien and Shrestha (2014).[4] A higher value of GIS for a specific ETF market indicates a larger percentage of the price information being disclosed in that ETF market.

In this study, we set out to investigate the price discovery process in four carbon ETFs that include (i) VanEck Low Carbon Energy ETF (VanEck), (ii) iShares MSCI ACWI Low Carbon Target ETF (iShares), (iii) SPDR MCSI ACWI Climate Paris Aligned ETF (SPDR), and (iv) Xtrackers Emerging Markets Carbon Reduction and Climate Improvers ETF (Xtrackers). We use the daily closing prices from December 6, 2018, to November 30, 2022. We find that all four ETFs consist of a single unit root using three different unit-root tests implying the efficiency of all the ETF markets considered. We also find that these series are cointegrated with a single cointegrating vector indicating that these four series are driven by not one but three common stochastic trends. This is a significant result because even though all four ETFs represent low-carbon companies, they differ in some aspects, as discussed in the Data and Results Section and Footnote 10.

Further Analysis of the single cointegrating vector and cointegration tests indicate that iShares and SPDR are driven by a single common stochastic trend.[5] Therefore, we analyze the price discovery by computing the GIS for these two ETF markets.[6] GIS measures indicate that approximately 57.89% of the price discovery occurs in the iShares market, and the remaining 42.11% of the price discovery takes place in the SPDR market. To analyze the possible impacts of COVID-19, we divide the sample into pre-COVID and COVID subsamples. In the pre-COVID period, the GIS measures for the iShares and SPDR are 88.69% and 11.31%, respectively. However, in the COVID period, GIS measures for the iShares and SPDR are 1.04% and 98.96%, respectively. This implies a dramatic shift in price discovery from the iShares market in the pre-COVID period to the SPDR market in the COVID period.

This study contributes to the literature in several ways. Firstly, we establish the four carbon ETF markets are efficient by showing that the logarithm of ETF prices consists of a single unit root. Secondly, we find that the four ETF prices are driven by three common stochastic trends instead of a single one. We discuss the implication of the existence of more than one common stochastic trend for practitioners, investors, and policymakers in dealing with multiple risk factors. Thirdly, we find that two ETFs, e.g., iShares and SPDR ETFs, are driven by a common stochastic trend and compute the GIS for these two markets. Finally, we find a dramatic impact of COVID on price discovery dominance among these two ETF markets. To the best of our knowledge, all the above results are new. Our results have important implications for investors as well as for policymakers.

The remaining part of the paper is organized as follows. In Section 2, we present a brief discussion of the literature review. The methodology will follow this in Section 3. We discuss our empirical results in Section 4. Finally, the paper concludes with conclusions in Section 5.

2. Literature review

One of the most common forms of market friction is the differential trading cost for securities in various venues. It consists of explicit (such as brokerage and clearing fees) or implicit (such as bid and ask spread) costs (Schultz and Swieringa, 2014). The explicit portion of the cost is hard to capture since it is related to market participants' arrangement with the brokerage and membership type. However, these costs are negligible in value compared to implicit trading costs (Rittler, 2012). The implicit costs, largely exogenously determined, lead to different trading costs for identical securities. This issue which Hasbrouck (1995) refers to as the fragmentation (dispersal of trading in security to multiple sites), signifies the importance of identification of the price discovery process in the securities market. In this case, an analysis of price discovery helps identify the trading venues where the fundamental information is incorporated into prices most efficiently (Hasbrouck, 1995). The following section reviews the main methods widely used in price discovery literature.

2.1. Price discovery

Three major approaches were identified in the price discovery literature. The first approach takes into account the lead-lag relationship between the prices on different markets or among different securities. Notable works include Eun & Shim (1989), who use a nine-market vector-autoregressive system on stock market indices' daily rate of return to investigate the international transmission mechanism of stock market movements. Chan (1992) analyzes the intraday lead-lag relationship between returns on the cash market and returns of the stock index futures market. Harris, McInish, Shoesmith, and Wood (1995) estimate an error correction model to investigate the contribution of New York, Pacific, and Midwest stock exchanges to price discovery. And finally, Nam, Oh, Kim, and Kim (2006) analyzed the lead-lag relationship between the Korean stock exchange index, index futures, and the index options markets.

The second approach focuses on the fact that volatility is a source of information and therefore revolves around the role of volatility spillovers in price discovery. Two initial studies include French and Roll (1986) and Ross (1989). French and Roll (1986) analyze the volatility of asset prices and find that volatility is caused by public information, private information, and pricing errors. Ross (1989) shows that in an arbitrage-free economy, the volatility of prices is directly related to the rate of flow of information to the market. Their results link the volatility test to the efficient market hypothesis. More recently, Sehgal, Ahmad, and Deisting (2015) have confirmed the price discovery and volatility spillover between futures and spot and among futures prices in the multi-commodity stock exchange and national stock exchange in India. Their results also indicate that the movement of volatility spillover takes place from futures to spot markets in the short run, while the effect from spot to futures market is observed in the long run. The overall conclusion from these studies and similar research (Booth, Chowdhury, Martikainen, and Tse, 1997; Karolyi, 1995; Koutmos and Tucker, 1996) is that the volatility in one market will spill over to other markets, and this has implications on the process of price discovery.

The third approach, and the most widely used in price discovery research, focuses on how information is transmitted among markets, known as Information Share (IS). Hasbrouck (1995) defined IS associated with a particular market as the proportional contribution of that market's innovation to the innovation in the common efficient prices. At the same time common factor model proposed by Gonzalo and Granger (1995) helps to study the contribution of price discovery from closely related markets. Baillie, Geoffrey Booth, Tse, and Zabotina (2002) examined the relationship between Hasbrouck (1995) and Gonzalo and

[4] All price discovery analyses using information share measures require that the number of cointegrating vectors is equal to number of unit-root series. In this study, this condition is referred to as the *number* condition. If this condition is not satisfied, we cannot implement price discovery analysis. Therefore, price discovery analysis that uses information share measures ignore situations when the *number* condition is not satisfied. However, violation of the *number* condition has some interesting implications, which will be discussed later. This is considered as one of the contributions of this study to the extant literature.

[5] In footnote 10, we mentioned that iShares and SPDR ETFs may represent the same information due to their coverage of large and mid-capitalization companies from developed and emerging markets. Our empirical analysis indicates that this is true.

[6] It is important to note that the GIS can only be computed where there is a single common stochastic trend, i.e., where the *number* condition is satisfied. Therefore, due to three common stochastic trends, we could not compute GIS for the four ETFs. However, when we consider only the iShares and SPDR ETFs, we find one common stochastic trend and we could compute GIS for these two series.

Granger (1995). They find that these two models complement each other and provide different views of the price discovery process between markets. The IS method has been used in various studies, such as by Fricke and Menkhoff (2011), who analyze the price discovery in the Euro bond futures market. They found that among the markets, Bund (the 10-year Euro bond futures contract on German sovereign debt) is the most important market in incorporating permanent price changes first. Most recently, Alexander and Heck (2020) analyzed the multidimensional information share in the Bitcoin market across various instruments, including futures, perpetual and spot prices. They use minute-by-minute transaction data and find a strong dominance of unregulated exchanges over regulated exchanges.

2.2. Generalized information share (GIS)

Although the applications of IS are important in broadening our understanding of the price discovery process, it is associated with one weakness the IS measure provides upper and lower bounds instead of a unique measure. In the first attempt to overcome these issues, Lien and Shrestha (2009) modify the information share to yield a unique measure termed modified IS (MIS). However, it still had the limitation of being only applicable in situations where the cointegrating relationship is required to be one-to-one. To resolve this, Lien and Shrestha (2014) extend the IS and MIS in a way that could be applied to situations where the cointegrating relationship is not necessarily one-to-one. The extended technique is known as generalized information share (GIS). In a recent structural study, Alexander and Heck (2020) point to the non-uniqueness problem of IS and use the GIS to overcome this issue. Reiterating the advantages of GIS, Chau, Han, and Shi (2018) employ this technique to investigate the dynamics and drivers of credit risk discovery between stock and credit default swap markets in the US. They indicate that when GIS is employed, the relative informational dominance becomes less extreme as compared to IS. Their results indicate that the financial condition index and funding cost are potential drivers of credit risk price discovery.

Referring to the flexibility of the GIS measure, Chen, Lin, and Shiu (2019) examine the price discovery of the Taiwan futures market and found that despite the relatively low trading volume of futures contracts, these trades significantly contribute to price discovery. Fernandez-Perez, Frijns, Gafiatullina, and Tourani-Rad (2018) also used GIS as an alternative measure of price discovery to investigate the intraday price discovery of VIX short-term futures. They find that trading costs and market liquidity are significant determinants of price discovery. Hu, Hou, and Oxley (2020) point to GIS as a new measure of information sharing to resolve the ordering problem of Hasbrouck (1995). They investigate the casual relationships, cointegration, and price discovery between spot and futures markets for Bitcoin and conclude that futures prices dominate the price discovery process. In line with these results, Shrestha, Subramaniam, and Thiyagarajan (2020) employ the GIS to explore the contribution of the futures market to the price discovery process of seven agricultural commodities. They report that most price discovery takes place in the futures market except for Cocoa which emphasizes the significance of futures markets in the price discovery process.

2.3. Price discovery in carbon market

Carbon prices are found to have implications such as influencing high-quality innovation activities to induce clean technologies and companies' decisions to conduct green production (Lin, Wang, Wu, and Qi, 2018; Wu, Li, and Tang, 2022; Zhu, Fan, Deng, and Xue, 2019), influencing prices in other energy markets such as crude oil spot price and natural gas spot prices (Chevallier, 2011; Kanamura, 2016; Soliman and Nasir, 2019; Wu, Wang, and Tian, 2020), affecting decisions in green investment markets (Brauneis, Mestel, and Palan, 2012; Liao and Shi, 2018; Ohlendorf, Flachsland, Nemet, and Steckel, 2022), impacting stock markets (Tian, Akimov, Roca, and Wong, 2016; Wen, Zhao, He, and Yang, 2020; Zhu et al., 2019). Therefore, accurate pricing in the carbon market is crucial for companies in their decision makings regarding adopting new abatement strategies and allocating necessary budgets. On the other hand, without a clear long-term price signal, the ETSs may be unable to achieve emission abatement targets (Cason and Gangadharan, 2011; Clò, Battles, and Zoppoli, 2013).

Since the launch of carbon markets and the expansion of carbon credit trading, most carbon price-related research has focused on identifying its determinants (e.g., Creti, Jouvet, and Mignon, 2012; Daskalakis, Psychoyios, and Markellos, 2009; Paolella and Taschini, 2008). Other research also looks into the implications of speculation as a driver of the carbon price and its volatility in the market (e.g., Balietti, 2016; Lucia, Mansanet-Bataller, and Pardo, 2015).

However, limited research is dedicated to examining carbon markets' efficiency and price discovery process. For instance, Cason and Gangadharan (2011) use laboratory methods to evaluate linked emissions trading markets' efficiency and pricing performance. They report that prices more accurately show a common cross-market abatement cost when a link exists between the markets. They also point out that intermediation in the carbon market can significantly increase the transaction cost, eventually leading to decreased trading and lower efficiency, particularly in larger emissions markets. Rittler (2012) investigates the relationship between spot and futures prices in European ETS (EU-ETS) during the second commitment period. He particularly looks into information transmission in first and second conditional movements. He reports the futures market to be the leader in the long-run price discovery process while confirming a close relationship between the volatility dynamics of both markets. Ibikunle, Gregoriou, and Pandit (2013) investigate the EU-ETS efficiency by testing the link between trading volumes of permit contracts and their impact on price discovery. They find that more liquid permit instruments are traded more efficiently. They also report the higher trading volume per minute and greater price efficiency for after-hours compared to regular trading hours.

Emphasizing the location and driving factors of price discovery, Schultz and Swieringa (2014) evaluate the contemporaneity of returns in EU-ETS using a regression approach and investigate the contribution of each security to the long-term price equilibrium using the information share. They also look into the identity and effect of market frictions on price discovery. Their results confirm the superiority of futures contracts as the main source of price discovery in both the short and long run. They also report the trading costs to be major factors in price discovery, while leverage and market segmentation are found to have a negligible role. Aiming to evaluate the effect of carbon trading policies on the Shanghai Emission Allowance (SHEA) price in the context of the Shanghai Emissions trading scheme pilot, Song, Liang, Liu, and Song (2018) use Cox-Ingersoll-Ross (CIR) model and find that the SHEA price has the price discovery function among other things. They report that carbon price has the mean reversion property, implying its predictability. They confirm the effectiveness of related policies on carbon prices through supply and demand and participants' sentiments. And finally, Stefan and Wellenreuther (2020) focus on two futures for European carbon emission allowances traded on the ICE in London and the FEX in Leipzig. They use a vector error correction model to investigate price discovery in these markets and found that the price discovery occurs on the ICE in London.

3. Methodology

In this section, we briefly discuss the GIS method. Here the time series considered are logarithms of the ETF price series. Before computing the GIS, we need to establish that all the series considered are unit-root or random-walk series. This condition implies that all the series are consistent with the martingale principle implied by market efficiency (LeRoy (1989)), i.e., all the ETF markets are efficient. After establishing that all the series are unit-root, we need to confirm further that the unit-root series are cointegrated with the number of cointegrating vectors equal to one less than the number of series considered, i.e., if we are considering n series, there should be $(n-1)$ cointegrating vectors in to be able to compute the GIS measure.[7]

Let Y_t be an $n \times 1$ vector of n unit-root or random walk series, where it is assumed that there are $(n-1)$ cointegrating vectors with a single common stochastic trend (Stock and Watson, 1988). Under the given assumption of $(n-1)$ cointegrating vectors, the data generating process can be represented by the following vector error-correction (VEC) representation (Engle and Granger, 1987):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t, \Pi = \alpha\beta^T \& E\left[\varepsilon_t \varepsilon_t^T\right] = \Omega \tag{1}$$

where β and α are $n \times (n-1)$ matrices of rank $(n-1)$. The columns of β consist of the $(n-1)$ cointegrating vectors, and each column of α consists of the adjustment coefficients. The matrix Π is decomposed in such a way that $\beta^T Y_t$ represents the vector of $(n-1)$ stationary series. Following Stock and Watson (1988), eq. (1) can be transformed into the following equivalent vector moving average (VMA) representations (Hasbrouck, 1995):

$$\Delta Y_t = \Psi(L)\varepsilon_t \tag{2}$$

$$Y_t = Y_0 + \Psi(1)\sum_{i=1}^{t} \varepsilon_i + \Psi^*(L)\varepsilon_t \tag{3}$$

Then, the Engle-Granger representation theorem (Engle and Granger, 1987) implies the following (De Jong, 2002; Lehmann, 2002):

$$\beta^T \Psi(1) = 0 \text{ and } \Psi(1)\alpha = 0 \tag{4}$$

Then, $\Psi(1)\varepsilon_t$ represents the long-run impact of innovations on the unit-root series (Hasbrouck, 1995). Different information share measures considered by Hasbrouck (1995), Lien and Shrestha (2009), and Lien and Shrestha (2014) are based on this term. Let ψ_1^r be the first row of $\Psi(1)$. Let Λ be a diagonal matrix containing the eigenvalues of the innovation correlation matrix on the diagonal, where the corresponding eigenvectors are given by the columns of matrix G. Then, the GIS of j^{th} series or market (S_j^G) is given by:

$$S_j^G = \frac{\left(\psi_j^G\right)^2}{\psi_1^r \Omega \psi_1^{rT}} \tag{5}$$

where $\psi^G = \psi_1^r F^M$, $F^M = [G\Lambda^{-1/2}G^T V^{-1}]^{-1}$ and ψ_j^G is the j^{th} element of ψ^G. It can be shown that the GIS measure is independent of ordering. Therefore, the GIS method leads to a unique information share, unlike the upper and lower bound for Hasbrouck's IS measure.[8]

As mentioned above, in the computation of GIS measure, we require the *number* condition to be satisfied, i.e., there are $(n-1)$ cointegrating vectors among n unit-root series. However, in empirical analyses, we may encounter situations where there are fewer than $(n-1)$ cointegrating vectors among n unit-root series depending on the series considered. We cannot compute GIS measures in such situations, and the price discovery literature has ignored such situations. However, we argue that such situations are worth analyzing and have some implications for investors and policymakers, as discussed below.

Based on Stock and Watson (1988), if there are n unit-root series with r cointegrating vectors with $r \le n$, then the unit-root series are driven by $(n-r)$ common stochastic trends. When $r < (n-1)$, the unit-root series are driven by not one but more than one common stochastic trend. It is important to note that existing cointegration methodology can tell us how many common stochastic trends drive the unit-root series. However, the methodology does not tell us what these trends are unless, in special cases, e.g., when there is a single common stochastic trend, i.e., when the *number* condition is satisfied.[9]

4. Data and results

4.1. Sample and descriptive statistics

In this study, we use four Carbon ETF indices: (i) *VanEck Low Carbon Energy ETF* (VanEck)*, (ii) iShares MSCI ACWI Low Carbon Target ETF (iShares), (iii) SPDR MCSI ACWI Climate Paris Aligned ETF (SPDR),* and *(iv) Xtrackers Emerging Markets Carbon Reduction and Climate Improvers ETF (Xtrackers)*.[10] The daily prices (P_t) were extracted from the Thomson Reuters Datastream database covering the period of December 6, 2018 to November 30, 2022.[11] More detailed information on these ETFs regarding country distribution, asset value and number of firms is presented in Table 1.

Following the convention, we use the logarithm of prices to represent the series. The summary statistics for the log prices are given in Table 2. Based on the median and mean, iShares has the highest value, and VanEck has the lowest value. The standard deviation is highest for VanEck and lowest for Xtrackers. All log prices have negative skewness

[7] All price discovery studies find this condition that there are $(n-1)$ cointegrating vectors among n series to be satisfied. In this study, we refer this condition as the *number* condition. If the *number* condition is not satisfied,the price discovery measures like IS, MIS, and GIS cannot be computed. In what follows, we assume that this condition is satisfied when discussing the computation of GIS. At the end of the section, however, we will discuss some interesting conclusions that can be made when the *number* condition is not satisfied, especially, when there are less than $(n-1)$ cointegrating vectors. To the best of our knowledge, this issue has not been analyzed in the existing empirical studies.

[8] See Lien and Shrestha (2009) and Lien and Shrestha (2014) for detail on this issue.

[9] To the best of our knowledge, the methodology to analyze price discovery in situations where there is more than one common stochastic trend has not been developed. However, such situations have important implications for practitioners, investors and policymakers because the common stochastic trends can be related to risk factors. For example, suppose that the three energy-related commodities like crude oil, heating oil and natural gas are driven by a single common stochastic trend which can be referred to as energy price. Under such a situation, investors, producers and consumers of these three commodities face a single source of risk, e.g., energy price risk and policymakers as well as practitioners can concentrate on this single source of risk. However, if these three commodities are instead driven by three different stochastic trends, this involves three different sources of risk and a lot more complicated risk environment.

[10] Since high carbon emissions are a global issue, we use these ETFs representing firms operating globally. However, these carbon ETFs differ from one another in some specific aspects. For example, the first ETF, VanEck, represents the largest and most liquid companies in the global low-carbon energy industry. Here the low-carbon energy industry includes wind, solar, hydro, hydrogen, bio-fuel, geothermal technology, lithium-ion batteries, electric vehicles, waste-to-energy production, smart grid technologies, etc. The iShares ETF represents large and mid-capitalization companies from developed and emerging markets with lower carbon exposure than the broad market. The third ETF, SPDR ETF, represents large and mid-capitalization securities across 23 Developed Markets (DM) and 24 Emerging Markets. Finally, the fourth ETF, Xtrackers, represents large and mid-capitalization companies in emerging markets countries that meet certain ESG criteria and/or have committed to greenhouse gas emissions reduction targets. Therefore, these four ETFs may represent different aspects of the low-carbon industry, even though the second (iShares) and the third (SPDR) ETFs may represent the same information due to their coverage of large and mid-capitalization companies from developed and emerging markets. The inclusion of these ETFs is also based on having sufficient observations for the analysis.

[11] The start date of our sample is based on the availability of prices on all four ETFs from Datastream.

Table 1
Country distribution, asset value and number of firms: This table summarizes the country distribution base on the top 10 percentages of net asset value. It also summarizes the total asset value (in million) and the number of firms.

VanEck[a]		iShares[b]		SPDR[c]		Xtrackers[d]	
Country	% Net assets	Country	% Net assets	Country	% Net assets	Country	% Net assets
U.S.	35.71	U.S.	59.97	U.S.	60.10	China	30.82
China	16.02	Japan	5.48	Japan	5.04	Taiwan	18.51
Denmark	8.85	China	3.94	Canada	4.91	India	13.22
Spain	8.38	Canada	3.73	China	3.76	South Korea	10.74
Italy	7.26	UK	3.58	France	3.63	Brazil	4.06
South Korea	5.58	France	2.92	Switzerland	3.55	South Africa	3.52
Sweden	2.93	Switzerland	2.39	UK	2.44	Saudi Arabia	2.72
Canada	2.83	Germany	1.79	Australia	1.29	UAE	2.69
Brazil	2.77	Australia	1.77	Germany	1.17	Mexico	2.42
New Zealand	1.94	Korea	1.46	Spain	1.16	Indonesia	2.24
Total	92.28	Total	87.03	Total	87.05	Total	90.94
Asset value	$214.1		$895.8		$241.3		$495.8
No. of firms	70		1358		799		1293

[a] https://www.vaneck.com/us/en/investments/low-carbon-energy-etf-smog/holdings/
[b] https://www.ishares.com/us/products/271054/ishares-msci-acwi-low-carbon-target-etf
[c] https://www.ssga.com/us/en/intermediary/etfs/funds/spdr-msci-acwi-climate-paris-aligned-etf-nzac
[d] https://etf.dws.com/en-us/EMCR-emerging-markets-carbon-reduction-and-climate-improvers-etf/

Table 2
Summary statistics for log-prices.

	VanEck	iShares	SPDR	Xtrackers
Min.	3.7424	4.5390	4.5020	4.3783
Q1	4.0128	4.8383	4.8095	4.6784
Median	4.5799	4.9470	4.9152	4.7380
Mean	4.4541	4.9656	4.9365	4.7634
Q3	4.8154	5.1111	5.0814	4.8963
Max.	5.0676	5.2176	5.1874	4.9850
Std. Dev.	0.3878	0.1528	0.1522	0.1238
Skewness	−0.2026	−0.0731	−0.0635	−0.0203
Kurtosis	1.4758	1.9727	1.9663	2.2526

Table 3
Correlation for log-prices.

	VanEck	iShares	SPDR	Xtrackers
VanEck	1.0000			
iShares	0.9313***	1.0000		
SPDR	0.9306***	0.9997***	1.0000	
Xtrackers	0.8090***	0.9147***	0.9187***	1.0000

Note: *, **, and *** indicate significance at the 10, 5 and 1% levels, respectively.

Table 4
Summary statistics of log-returns.

	VanEck	iShares	SPDR	Xtrackers
Min.	−0.11441	−0.11756	−0.10747	−0.10952
Q1	−0.00848	−0.00494	−0.00538	−0.00591
Median	0.00000	0.00067	0.00069	0.00000
Mean	0.00073	0.00027	0.00027	0.00010
Q3	0.01133	0.00630	0.00654	0.00669
Max.	0.11702	0.07708	0.08803	0.08242
Std. Dev.	0.02020	0.01326	0.01336	0.01337
Skewness	−0.35487	−1.10046	−0.82695	−0.93302
Kurtosis	7.63015	16.04627	14.96731	15.32620

Table 5
Correlation of log return.

	VanEck	iShares	SPDR	Xtrackers
VanEck	1.0000			
iShares	0.8054***	1.0000		
SPDR	0.7991***	0.9741***	1.0000	
Xtrackers	0.7927***	0.8958***	0.8793***	1.0000

Note: *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

and kurtosis <3. The pairwise Spearman correlations are summarized in Table 3. All correlations are highly significant and positive. The maximum correlation is between iShares and SPDR. As shown later, all series are unit-root series. Therefore, the high pairwise correlations could be spurious. This is why we perform cointegration analysis for unit-root series.

Since starting prices, therefore log prices, are different for different ETFs and are unit-root series, it is more meaningful to consider the summary statistics for the log returns computed by the first-differenced log prices.[12] The summary statistics for the log returns are given in Table 4. Based on the mean log return, VanEck has the highest mean log return, and Xtrackers has the lowest mean log return. However, the median log return for SPDR is the maximum, with VanEck and Xtrackers having the minimum log return. All four log returns have negative skewness and kurtosis higher than 3. All Spearman pairwise correlations, reported in Table 5, are positive and highly significant even at the 1% level. The highest correlation is between iShares and SPDR (97.41%). These are the two series for which the requirement of the computation of GIS, i.e., the *number* condition, is met, i.e., they are both unit-root processes with one cointegrating vector.

4.2. Empirical results

To compute the GIS measures, we first need to establish that each of the series considered consists of a single unit root. This study applies three different unit-root tests: (i) the Philips-Perron (PP) (Phillips and Perron, 1988), (ii) the augmented Dickey-Fuller (ADF), and (iii) KPSS

[12] As shown later, the log-returns, i.e., first-differenced log prices, are found to be stationary. Therefore, summary statistics can be interpreted in normal way unlike the summary statistics for unit-root series.

Table 6
Unit-root test.

	PP test		ADF test		KPSS test	
Series	Level	Differenced	Level	Differenced	Level	Differenced
VanEck	−1.473	−32.482***	−1.422	−6.195***	3.700***	0.198
iShares	−1.736	−37.370***	−1.818	−9.309***	3.189***	0.101
SPDR	−1.760	−37.156***	−1.788	−7.855***	3.144***	0.107
Xtrackers	−1.931	−37.121***	−1.709	−11.398***	1.619***	0.144

Note: *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

(Kwiatkowski, Phillips, Schmidt, and Shin, 1992) tests.[13] The results of the unit-root tests are summarized in Table 6. The results show that the PP test for each series is insignificant, indicating that each series is non-stationary because we cannot reject the null hypothesis even at the 10% level. However, the PP test on each of the first-differenced series is significant even at the 1% level rejecting the null hypothesis of unit-root in favor of the stationary. Based on PP tests, we establish that each of the series consists of a single unit root. The augmented Dickey-Fuller (ADF) tests lead to the same conclusion. Similarly, KPSS test rejects the null hypothesis of stationarity even at the 1% level in favor of unit-root. Finally, the KPSS tests on the first-differenced series do not reject the null hypothesis of stationarity even at the 10% level. Thus, all three tests indicate that each carbon ETF series used in this study has a single unit root. The results suggest that all four ETF markets are efficient in the sense that the log prices are martingale (LeRoy, 1989).

After ensuring each series has a single unit root, the Johansen (1991) cointegration test is performed to examine the existence of cointegrating relationships and the number of cointegrating relationships, i.e., the number of cointegrating vectors. The Johansen (1991) test results are summarized in Table 7. The results show that there is a single cointegrating vector. Therefore, the *number* condition necessary for the computation of GIS is not satisfied. This indicates that there are three common stochastic trends driving the four ETF series instead of a single stochastic trend. This result regarding the number of common stochastic trends has important implications for practitioners, investors, and policymakers in the sense that they will be dealing with three risk factors instead of one. Even though all four ETFs represent firms operating in the low-carbon industry, they represent three different risk factors represented by three different common stochastic trends. This could be due to differences in geographical coverage, country-level development (developed and emerging markets), capitalization (large capitalization and mid-capitalization), and industry subclassification (wind, solar, hydro, biofuel, etc.).

In order to compute the GIS measures, we require (n − 1) cointegrating vectors among n unit-root series, i.e., the *number* condition needs to be satisfied. Here we consider four unit-root series and find not three but only one cointegrating vector. Therefore, we try to see if a subgroup of ETFs exists where the *number* condition is satisfied for the computation of the GIS measure to perform the price discovery analysis. We look at the single cointegrating vector for some clue as to which subgroup of ETFs may meet this condition. The normalized cointegrating vector is given in Table 8. The coefficients of VanEck and Xtrackers are negligible compared to those of the other two series. Therefore, this indicates that iShares and SPDR could be driven by a single common stochastic trend. We perform the Johansen (1991) cointegration tests on these two ETF series, i.e., iShares and SPDR. The cointegration test results for the two series are summarized in Table 9. The results indicate that there is one cointegrating vector, and the *number* condition is satisfied. Therefore, these two series are driven by a common stochastic trend. The normalized cointegrating vector is summarized in Table 10. Based on the information given in Table 10, the long-run relationship between these two series is as follows

$$log(iShares) = 0.0076 + 1.004 log(SPDR)$$

Since these two series are driven by a single common stochastic trend, we can perform the price discovery analysis by computing the GIS measures for these two series using Eq. (5). The GIS measures computed using Eq. (5) are reported in the first row of Table 11. The GIS measures show that 57.89% of the price discovery occurs in the iShares market, and the remaining 42.11% occurs in the SPDR market. Therefore, between these two markets, the iShares market seems to be the dominant market. However, the SPDR market also significantly contributes to the price discovery process.

There is empirical evidence that the functioning of ETF markets is influenced by crises like COVID-19 (Bhattacharya and O'Hara, 2020; Evans and Barrett, 2019; Pagano, Serrano, and Zechner, 2019 and Saha, Madhavan, and Chandrashekhar, 2022).[14] Since our sample period includes both pre-COVID and COVID periods, to evaluate the effects of COVID, we separate the sample into pre-COVID and COVID periods. Regarding the start of COVID-19, on January 30, 2020, World Health Organization (WHO) declared a "Public Health Emergency of International Concern (PHEIC), and on March 11, 2020, WHO announced COVID-19 as a pandemic. We choose the pre-COVID period to end on January 29, 2020, and the COVID period to start on March 12, 2020, and end on September 16, 2022. We assume the COVID period to end on September 16, 2022, because President Biden declared Covid-19 to be over in the U.S. on September 18, 2022, on CBS '60 Minutes' program. We exclude data from January 30 to March 11, 2020, due to the uncertainty of pandemic status. The GIS measures for the pre-COVID and COVID periods are shown in the second and third rows of Table 11, respectively. We see a dramatic shift in price discovery from the iShares market in the pre-COVID period to the SPDR market in the COVID period. For the pre-COVID period, the GIS measures for the iShares and SPDR are 88.69% and 11.31%, respectively. However, for the COVID period, the GIS measures for the iShares and SPDR are 1.04% and 98.96%, respectively. The results clearly indicate the impact of COVID on the price discovery in these two ETF markets.

The empirical results and their implications can be summarized as follows. Firstly, all four ETF markets are found to be efficient due to the existence of a single unit root. Therefore, investors should feel confident in investing in these ETFs. The message to the policymakers is that the ETF markets can contribute to reducing carbon emissions because efficiency leads to an efficient allocation of resources. Secondly, we find that three common stochastic trends drive the four ETFs. Therefore, the investors face three different risks. The policymakers should keep in mind when making policy decisions that a single factor does not drive these low-carbon ETFs. Instead, they are driven by three factors, i.e., not all low-carbon ETFs are the same. Therefore, they face a fairly complex system. Thirdly, iShares and SPDR markets are driven by a single stochastic trend, and investors face a single risk factor. This result can also

[13] We use three unit-root tests because there does not exist a *uniformly most powerful* test for the unit-root. Also, the PP and ADF tests have unit-root as the *null* hypothesis whereas the KPSS test assumes stationary as the *null* hypothesis. To establish the existence of a single unit-root, we need to establish the series is non-stationary and that the differenced series is stationary.

[14] We would like to thank the anonymous reviewer for pointing this out.

Table 7
Johansen cointegration test.

Number of cointegrating vectors (r)	Trace	Lmax
$r \leq 3$	2.21	2.21
$r \leq 2$	5.27	3.06
$r \leq 1$	15.49	10.22
$r = 0$	69.61***	54.12***

Note: *, ** and *** indicate significance at the 10, 5 and 1% level respectively.

Table 8
Cointegrating vector.

VanEck	iShares	SPDR	Xtrackers	Constant
0.0015	1	−1.0363	0.0405	−0.0501

Table 9
Johansen cointegration test.

Number of cointegrating vectors (r)	Trace	L-Max
$r \leq 1$	3.739	3.739
$r = 0$	51.132***	54.871***

Note: *, ** and *** indicate significance at the 10, 5 and 1% level respectively.

be useful for policymakers and investors. Finally, we find that iShares market played the price leadership role in the pre-COVID period, whereas SPDR market played the leadership role in the COVID period. Therefore, investors and policymakers should be aware of the impact of future pandemics.

5. Conclusion

In this paper, we analyze the price discovery in four carbon ETF markets: (i) VanEck Low Carbon Energy ETF (VanEck), (ii) iShares MSCI ACWI Low Carbon Target ETF (iShares), (iii) SPDR MCSI ACWI Climate Paris Aligned ETF (SPDR), and (iv) Xtrackers Emerging Markets Carbon Reduction and Climate Improvers ETF (Xtrackers). We use the daily closing prices of the four carbon ETFs from December 6, 2018, to November 30, 2022. To test for the presence of a unit-root, we use three different unit-root tests. These include (i) the Philips-Perron (PP) (Phillips and Perron, 1988), (ii) the augmented Dickey-Fuller (ADF), and (iii) KPSS (Kwiatkowski et al., 1992) tests, where the first two tests assume unit-root as the null hypothesis and the third assumes stationarity as the null hypothesis. We find that all four carbon ETFs consist of a single unit-root based on all three unit-root tests implying that all four ETF markets are efficient because the log-prices follow martingale principle (LeRoy, 1989).

Next, we apply Johansen (1991) cointegration test to find the existence and number of cointegrating relationships. The test reveals that there exists a single cointegrating relationship among the four ETF series. This suggests that these ETFs are driven by three common stochastic trends or risk factors. This implies that even though these ETFs represent firms operating in a low-carbon industry, they are driven by not just a single risk factor but by three different risk factors. Further Analysis reveals that iShares and SPDR are driven by the same market force (common stochastic trend or risk factor). Based on the GIS measures, we find that approximately 57.89% of the price discovery takes place in the iShares market, and the remaining 42.11% takes place in the SPDR market.

We further analyze the impact of the COVID-19 pandemic by dividing the whole sample into pre-COVID and COVID subsamples. We see a dramatic shift in price discovery from the iShares market in the pre-COVID period to the SPDR market in the COVID period. In the pre-COVID period, the GIS measures for the iShares and SPDR are 88.69% and 11.31%, respectively. However, in the COVID period, GIS measures for the iShares and SPDR are 1.04% and 98.96%, respectively.

Table 10
Cointegrating vector.

iShares	SPDR	Constant
1	−1.0044	−0.0076

Table 11
Generalized Information Share.

	iShares	SPDR
Whole	0.5789	0.4211
Pre-COVID	0.8869	0.1131
COVID	0.0104	0.9896

Note: The whole sample period starts from December 6, 2018 and ends on November 30, 2022. The Pre-COVID period starts from from December 6, 2018 and ends on January 29, 2020. Finally, the COVID period covers March 12, 2020 to September 16, 2022.

Our results have important implications for policymakers, investors, and market participants in general. All four ETF markets are found to be efficient. Therefore, investors should be confident in investing in these markets. Policymakers should expect these markets to contribute to the reduction of carbon emissions. Even though these four carbon ETFs represent firms operating in a low-carbon industry, they are not driven by single common stochastic trends. They are, instead, driven by three common stochastic trends representing three different risk factors. Policymakers, investors, and market participants need to keep this in mind when making investment and policy decisions. Finally, market practitioners and policymakers should be aware of the impact of future pandemics on the price discovery process.

Finally, to the best of our knowledge, the analytical techniques used in situations with more than one common stochastic trend are not yet developed. Therefore, we cannot identify these stochastic trends. Future researchers can develop tools to investigate price discovery in such situations. These tools may also help to determine the common stochastic trends. Future research can also further analyze the reason behind the impact of COVID on the change in the dominance of price discovery between iShares and SPDR.

Declaration of Competing Interest

None.

Authors have no competing interests to declare.

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