Time-Varying Intraday Causality between European Carbon Spot and Futures Prices

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This study examines the spot-futures nexus during Phase IV of the EU-ETS, using a novel time-varying Granger causality test on intraday high-frequency data. The results show that the causality largely runs from carbon futures to spot market. The findings indicate that carbon futures prices reflect the information faster, predominately leading the price formation process, possibly due to higher liquidity and trading volume in the ECX futures market, enhancing its informational content over time. These findings have significant implications for portfolio management. Also, the findings may help policymakers to improve the market microstructure of the EU-ETS and similar carbon markets.

Keywords: Time-Varying Granger Causality; Carbon Markets; EU-ETS; Price Discovery; Spot-Futures Nexus.

1. Introduction

The growing concern for climate change has amplified the importance of market-based approaches, such as emission trading schemes (ETS), to mitigate the climate change risk (Hoque et al., 2023). ETS have emerged as an effective policy instrument to curtail GHG emissions, steering investments towards low-carbon technologies. In 2005, the European Union commenced an EU-wide ETS, called the *"European Union Emission Trading Scheme"* ("EU-ETS", henceforward), to facilitate the trading of *"European Union allowances"* (EUA, henceforward) spot and its derivatives (Liu et al., 2021). The scheme is structured in four distinct phases [Phase 1 (2005-2007), Phase II (2008 -2012), Phase III (2013-2020)], and Phase IV was initiated in 2021. In the last two decades, carbon markets have been scrutinized from the perspective of liquidity, market efficiency, price discovery, price determinants, integration with other financial markets (e.g., stock, cryptocurrencies, green bonds, and energy markets), and its role in portfolio management (Creti et al., 2012; Hoque et al., 2023; Wei et al., 2022; Zhou et al., 2022).

Market efficiency, price discovery, lead-lag relationship, causality, etc., remain hot topics for discussion in the financial literature for the last few decades. In financial markets where the spot and futures prices are interconnected, any movement in the spot prices will be emulated in the futures prices in the presence of stable equilibrium, referred to as 'the spot-future parity' (Sarno & Valente, 2000). In an efficient market, spot and futures returns should be contemporaneously correlated (Kawaller et al., 1987). Although a few studies explore the causal relations between carbon futures and spot prices in the early phases, during the recent phases of the EU-ETS, several important policy changes have been implemented, including (a) market stability reserve, (b) cancellation mechanism, (c) increase in the linear reduction factor, and (d) carbon border adjustment mechanism. As a result, the EU-ETS has experienced exponential growth (in terms of price, volume, and market size), which entices us and makes it imperative to revisit the carbon price dynamics, particularly the carbon spot-futures nexus. (Chan et al., 1991; Hasbrouck, 1995; Protopapadakis & Stoll, 1983). However, only a few studies investigate the causal relations between EUA futures and spot prices during Phase IV (Mondal et al., 2024).

Moreover, the existing literature invariably employs the conventional "*Granger causality"* tests and *"Vector Error Correction Models"* (VECM), which are time-invariant and do not account for the dynamic nature of such relationships. Considering the recently heightened socio-political and economic uncertainty, varying market sentiments, and recent regulatory policy changes, it is of utmost importance to study such relationships under a time-varying framework, particularly in policy-driven markets such as EU-ETS, where the policy changes may significantly impact price dynamics (Fan et al., 2017). To this end, our study addresses the research gap on the dynamic causal relations between EUA futures and spot prices by employing (a) a novel lag-augmented vector autoregressive (LA-VAR) time-varying Granger causality test of Shi *et al.* (2020) and (b) intraday data at 5- and 30-minutes.

Financial market literature has deeply intrigued the spot-futures nexus in the conventional markets, e.g., equity, currency, energy, and commodity (Baur & Dimpfl, 2019; Shrestha, 2014; Tse et al., 2006). The extant literature on spot-futures nexus in other financial markets supports the leadership of the futures market and attributes it to numerous reasons, such as inherent leverage benefit, low trading cost, and higher liquidity. Nevertheless, the research on the price formation process in the carbon market is nascent. For example, Stefan and Wellenreuther (2020) find the dominance of ECX futures over EEX futures in the price formation during Phase III of EU-ETS. In contrast, Liu *et al.* (2021) observe a bidirectional causality between futures and spot prices. Recently, Mondal *et al.* (2024) document a strong dynamic correlation between daily carbon spot and futures prices.

Furthermore, advancements in IT and telecom industries and algorithmic trading have enormously contributed to the fast information spillovers and their incorporation into asset prices (O'Hara, 2015). Therefore, the recent discussion on market efficiency, price discovery, lead-lag relationship, causality, etc., has gradually shifted from lower frequencies (e.g., monthly, weekly, daily data) to higher frequencies (e.g., 5- and 30-minute data). In the context of EU carbon markets, only a few studies examine the intraday price discovery during the previous phases of EU-ETS. For example, Benz and Hengelbrock (2008) find ECX futures to be the major contributor to price discovery due to high liquidity and low transaction costs (Schultz & Swieringa, 2014). Similarly, Rittler (2012) finds that ECX carbon futures prices significantly explain the movements in Bluenext spot prices during Phase II of the EU-ETS, and this dominance increased over time. Interestingly, Philip and Shi (2015) observe that information and volatility are transmitted from spot to future before the allowance-submission period. In contrast, the futures prices lead the *"price discovery"* process after the allowance-submission period (Philip & Shi, 2015).

In short, the extant literature on the causal relationships between carbon spot and futures prices shows mixed and contrasting evidence. To our knowledge, this is the first study that examines the causality between European carbon futures and spot prices using a novel time-varying approach on the high-frequency (5- and 30- min) data during Phase IV of EU-ETS.

To study the spot-future nexus during Phase IV of EU-ETS, we employ high-frequency EUA spot and futures prices. Our findings exhibit: (a) EUA spot and futures prices are not contemporaneously correlated, (b) a lead-lag relationship persists, and (c) the information largely transmits from ECX futures to the EEX spot market. Our study contributes to this novel strand of literature on dynamic spot-futures nexus in carbon markets (De Jong & Nijman, 1997; Rittler, 2012).

The rest of the paper proceeds as follows. We briefly discus the methodology and describe the data in section 2. Next, we present the empirical results and discussions in section 3. Finally, we conclude the study in section 4.

2. Methodology and Data

2.1 Methodology

The study first employs the *"linear Granger causality"* test, followed by a novel *"time-varying Granger causality"* framework proposed by Shi *et al.* (2020), which possesses several advantages over other methods. First, it employs a dynamic framework to address the limitations of parametric methods, which often obscure dynamic relationships among the chosen indicators. Second, it doesn't need *"detrending"* or *"differencing"* the data to outline the origin and collapse dates of causality. Next, LA-VAR surpasses the fully modified VAR and VECM because it demonstrates size control properties, ensuring size stability (Shi et al., 2020). Lastly, it considers the presence of heteroscedasticity during the testing process, which is often overlooked in the literature.

Following Hammoudeh et al. (2020), suppose y_t is a k-vector time series, which is deduced with the following model

$$y_t = \alpha_0 + \alpha_1 t + \mu_t \tag{1}$$

where μ_t follows a VAR(p) process:

$$\mu_t = \beta_1 \mu_{t-1} + \cdots + \beta_p \mu_{t-p} + \epsilon_t \tag{2}$$

where ϵ_t denotes the error term. By substituting μ_t using Eq. (2) $\mu_t = y_t - (\alpha_0 + \alpha_1 t)$ into Eq. (1) we get,

$$y_t = \gamma_0 + \alpha\gamma_1 t + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \epsilon_t \tag{3}$$

where γ_i denotes the function of α_i and β_j in which i = 0,1 and j = 1, …, p.

The lag-augmented VAR model of Dolado & Lütkepohl (1996) and Toda & Yamamoto (1995) support to test the causality for a possible integrated variable, y_t can be represented as:

$$Y = \tau\Gamma' + \mathrm{X}\mathrm{A}' + \mathrm{B}\phi' + \epsilon \tag{4}$$

where, $Y = (y_1, \ldots, y_T)_{T\times n'}$, $\tau = (\tau_1, \ldots., \tau_T)_{T\times 2'}, \tau_t = (1, t)_{2\times 1'}$,

$$X = (x_1, \ldots, x_T)_{T\times np'} \text{ , } x_t = \left(y_{t-1'}, \ldots, y_{t-p'}\right)_{np\times 1'} \text{ , } A = \left(\beta_1, \ldots, \beta_p\right)_{n\times np} \text{ ,}$$

$$B = (b_1, \ldots, b_T)_{T\times nd'} \text{ , } b_t = \left(y_{t-1}, \ldots, y_{t-p-d'}\right)_{nd\times 1'}, \phi = \left(\beta_{p+1}, \ldots, \beta_{p+d}\right)_{n\times nd}$$

and $\epsilon = (\epsilon_1, \ldots, \epsilon_T)_{T\times n'}$

Where, d denoted the maximum order of integration for y_t. Then, to test the *"null hypothesis"*: $H_0: R\varphi = 0,$ the *"Wald statistic"* can be expressed as follows:

$$W = (R\hat{\varphi})'\left\{R\left[\hat{\Omega} \otimes (X'QX)^{-1}\right]R'\right\}^{-1}(R\hat{\varphi}) \tag{5}$$

In which, $\hat{\varphi} = \mathrm{vec}(\hat{A})$ is a row vector, $\hat{\Omega} = \frac{1}{T}\hat{\varepsilon}'\hat{\varepsilon}$ and $\otimes$ denotes the Kronecker product, R is a $m \times n^2p$ matrix, here m represents the number of restrictions.

Shi *et al.* (2018, 2020) proposed a real *"time-varying causality"* test based on supremum (sup) *"Wald statistic"* sequences using a *"Forward recursive"* (Thoma, 1994), a *"Rolling window"* (Swanson, 1998), and a *"Recursive evolving"* approach (Phillips et al., 2015b, 2015a).

The *"Wald statistic"* over $[f_1, f_2]$ with a sample size fraction of $f_w = f_2 - f_1 \geq f_0$ is represented by $Wf_2(f_1)$ for the "*recursive evolving approach"* (Shi et al., 2018).

The supremum (sup) Wald test at the point f is followed as

$$SW_f(f_0) = \frac{sup}{(f_1,f_2)\in \wedge_0, f_2=f}\{Wf_2(f_1)\} \tag{6}$$

Where $\wedge_0 = \{(f_1, f_2): 0 < f_0 + f_1 \leq f_2 \leq 1\}$ and $0 \leq f_1 \leq 1 - f_0$ for minimum sample size represented by $f_0 \in (0,1)$ to estimate the VAR (Wu et al., 2021).

The *"Forward procedure"* of Thoma (1994) requires the statistic sequences to be as follows:

$$\hat{f}_e = \frac{inf}{f\in[f_0,1]}\{f: W_f(0) > cv \,.and\,. \hat{f}_f = \frac{inf}{f\in[\hat{f}_e,1]}\{f: W_f(0) < cv \tag{7}$$

The *"Rolling procedure"* of Swanson (1998) requires the statistics sequence as follows:

$$\hat{f}_e = \frac{inf}{f\in[f_0,1]}\{f: W_f(f - f_0) > cv \,.and\,. \hat{f}_f = \frac{inf}{f\in[\hat{f}_e,1]}\{f: W_f(f - f_0) < cv \tag{8}$$

The *"Recursive procedure"* of Phillips *et al.* (2015a, 2015b) requires the statistics sequence as follows:

$$\hat{f}_e = \frac{inf}{f\in[f_0,1]}\{f: SW_f(f_0) > scv \,.and.\, \hat{f}_f = \frac{inf}{f\in[\hat{f}_e,1]}\{f: SW_f(f_0) < scv \tag{9}$$

2.2 Data

The study employs EUA spot prices from the *"European Energy Exchange (EEX)"* and futures prices from the *"European Climate Exchange (ECX)."* Under the EU-ETS, EUA spot and futures contracts are actively traded on various exchanges; however, the EEX and the ECX account for the substantial trading volume. Therefore, we consider EUA spot prices from EEX and EUA futures prices from ECX. High-frequency data disclose detailed information on the market microstructure that is not well captured at lower frequencies (O'Hara, 2015). Therefore, we employ EUA futures (December-expiry due to their high volume and liquidity.) and spot prices at 5- and 30-minutes from February 2021 to May 2024. The data for EUA spot and futures prices are downloaded from Bloomberg and Barchart (https://www.barchart.com), respectively. **Table 1** reports the descriptive statistics and unit root test results at 5- and 30-minutes. The unit root test results indicate that the price (return) series are non-stationary (stationary), suggesting that variables are order one integrated.

Table 1 *Descriptive Statistics.*

Series	Mean	Std. Dev.	Skewness	Kurtosis	ADF	KPSS
Panel-A: 5-minute						
Spot prices	4.260	0.212	-0.722	2.561	-2.785	16.87***
Futures prices	4.270	0.214	-0.707	2.562	-2.796	18.09***
Spot returns	0.000	0.011	1.031	28.140	-16.38***	0.224
Futures returns	0.000	0.011	0.380	26.680	-16.56***	0.204
Panel-B: 30-minute						
Spot prices	4.259	0.214	-0.754	2.599	-2.778	12.77***
Futures prices	4.270	0.217	-0.741	2.596	-2.802	13.64***
Spot returns	0.000	0.014	0.517	18.470	-14.36***	0.221
Futures returns	0.000	0.013	0.334	17.530	-19.34***	0.199

Note: *Std. Dev.= Standard deviation, ADF = "Augmented Dicky-Fuller," KPSS = "Kwiatkowski-Phillips-Schmidt-Shin."* ***, **,** *and *** denote the levels of statistical significance at 10%, 5%, and 1%.*

3. Empirical Analysis

3.1 Static Granger causality

Table 2 reports the the static "*Granger causality"* test results at 5- and 30-minutes. At 5-minutes, we reject both the null hypotheses shown in **Table 2**. The results indicate bi-directional causality between the EUA spot and the futures market. However, in terms of magnitude, the impact of futures prices (63.004) on the spot prices is much more pronounced. More interestingly, we observe that causality solely runs from EUA futures to the spot market at 30-minutes. Overall, these results suggest that futures prices incorporate the relevant information faster and lead the price formation process.

Table 2. *Linear Granger Causality Test.*

Frequency	Null Hypotheses	F-statistics	P-value
5-minutes	*"EUA spot does not granger cause futures"*	2.149**	0.018
	"EUA futures does not granger cause spot"	63.004***	0.000
30-minutes	*"EUA spot does not granger cause futures"*	1.3402	0.203
	"EUA futures does not granger cause spot"	94.092***	0.000

Note: **, **, and *** denote the levels of statistical significance at 10%, 5%, and 1%.*

3.2 Time-varying Granger causality from futures to spot prices (at 5-minutes)

Next, we examine *"time-varying causality"* under a novel LA-VAR framework (with order of integration as one and two lags based on BIC) using the *"Forward expanding," "Rolling window," and "Recursive evolving"* algorithms. To identify the causality from EUA futures to spot prices at 5-minute intervals, we plot the time-varying *"Wald test statistics"* along with their bootstrapped *"critical values"* in Figure. 1(a), (b), and (c).

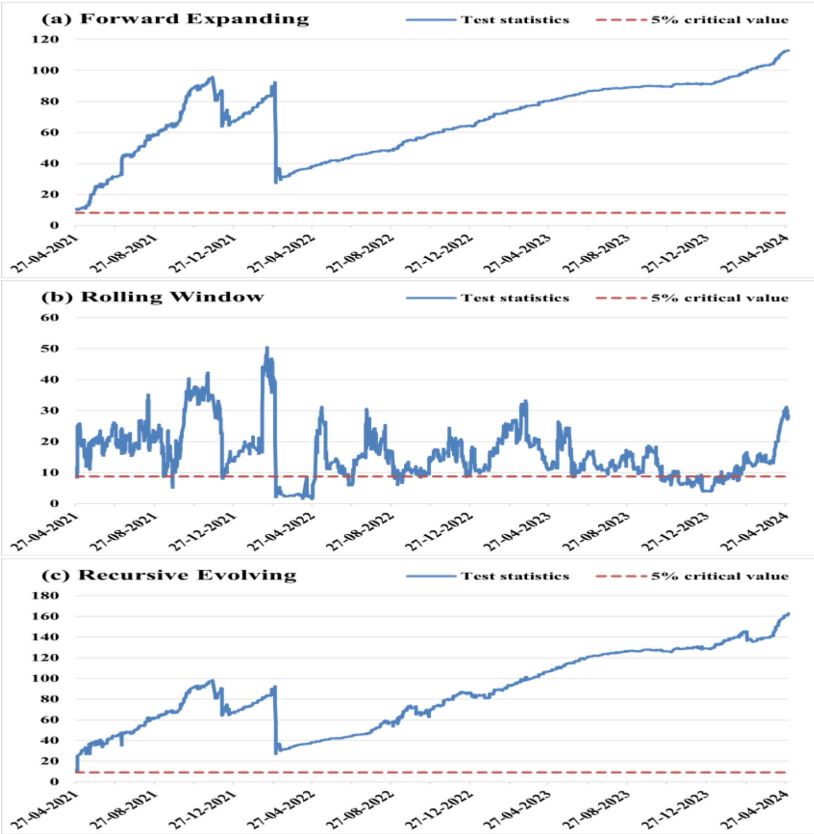

Figure. 1 *Futures Causing Spot (5-Minutes).*

Note: *Figure. 1 shows the "time-varying Granger causality" from the ECX futures to the EEX spot at 5-minutes. Figs. 1 (a), (b), and (c) show "Wald test statistics" using "forward expanding", "rolling window", and "recursive evolving" approaches, respectively. The estimation method uses a novel LA-VAR model with two lags and reports heteroscedasticity-robust test statistics. The 5% critical values are derived through bootstrapping with a rolling window of 200 observations. The results are qualitatively similar using the "rolling window" of 250 and 300 observations (not reported for brevity; however, results are available upon request from corresponding author).*

We observe that test statistics values exceed the *"critical values at the 5% significance level"* for all three algorithms. Therefore, we reject the *"null hypothesis"* of no "*Granger causality"* from EUA futures to spot prices. Interestingly, we observe a sharp decline in the test statistics in all three cases during the Russia-Ukraine war around Feb 2022. During this period, due to the high uncertainty about the gas supply from Russia to Europe, European carbon prices dropped significantly, and positions in EUA futures were liquidated heavily (Refinitiv, 2023). However, we observe insignificant test statistics at some points in the case of *"Rolling window"* approach, especially during the Russia-Ukraine war and around the compliance (allowance submission) periods. A plausible reason could be the higher trading activity in the EUA spot market around the compliance periods (Philip & Shi, 2015). These findings suggest that EUA futures prices predominately lead the price formation process.

3.3 Time-Varying Granger Causality from Spot to Futures Prices (at 5-minutes)

Next, the results for causality from EUA spot to futures prices at 5-minutes [reported in Figs. 2 (a), (b), and (c)] show that the test statistics are largely insignificant, implying no "*Granger causality"* from EUA spot to futures prices. However, we notice a few spikes where the test statistics exceed the *"critical values at the 5% significance level"* in the case of "*Rolling window*" and "*Recursive evolving*" approach, particularly during the Russia-Ukraine conflict and compliance periods. Additionally, we observe that the highest spike in the test statistics is around April 2024. Again, this could be due to the higher trading activity in the spot market before the allowance submission to meet regulatory compliances (Philip & Shi, 2015).

Figure. 2 *Spot Causing Futures (5-Minutes).*

Note: *Figure. 2 shows the "time-varying Granger causality" from the EEX spot to the ECX futures at 5-minutes. Figs. 2 (a), (b), and (c) show "Wald test statistics" using "forward expanding", "rolling window", and "recursive evolving" approaches, respectively.*

3.4 Time-varying Granger causality from futures to spot prices (at 30-minutes)

Next, we examine the *"time-varying Granger causality"* between EEX spot and ECX futures at 30-minutes. We observe that the test statistics (for all three specifications) for causality from futures to spot (reported in Fig. 3) are mostly significant throughout the sample period, implying that EUA futures Granger causes spot.

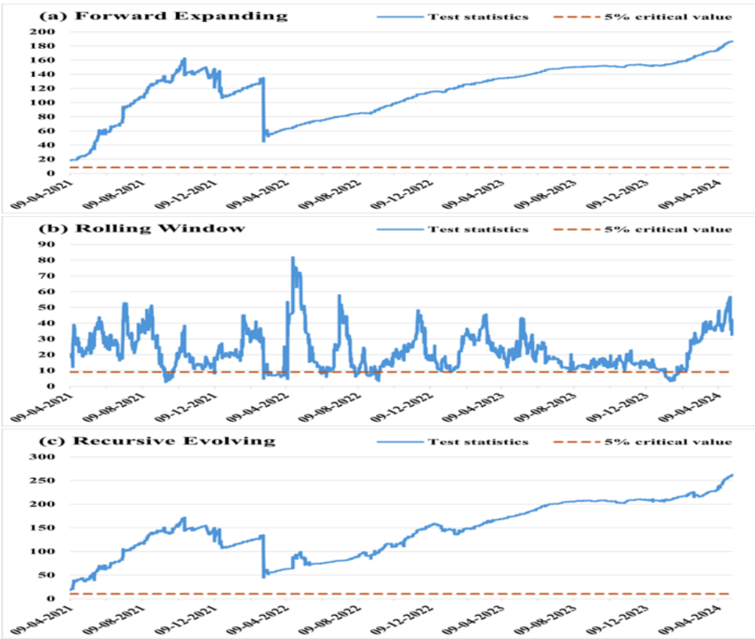

Figure. 3 *Futures Causing Spot (30-Minutes).*

Note: *Figure. 3 shows the "time-varying Granger causality" from the ECX futures to the EEX spot at 30-minutes. Figs. 3 (a), (b), and (c) show "Wald test statistics" using "forward expanding", "rolling window", and "recursive evolving" approaches,* *respectively. The estimation method uses a novel LA-VAR model with two lags and reports heteroscedasticity-robust test statistics. The 5% critical values are derived through bootstrapping with a rolling window of 100 observations. The results are qualitatively similar using the "rolling window" of 80 and 120 observations (not reported for brevity; however, results are available upon request from corresponding author).*

3.5 Time-varying Granger causality from spot to futures prices (at 30-minutes)

Next, the test statistics (for all three specifications) for causality from spot to futures (reported in Fig. 4) are predominantly insignificant, except during compliance periods and the Russia-Ukraine war (for *"Rolling window"* and *"Recursive evolving"* approaches). Overall, the results at 30-minutes corroborate with and support our previous findings at 5-minutes.

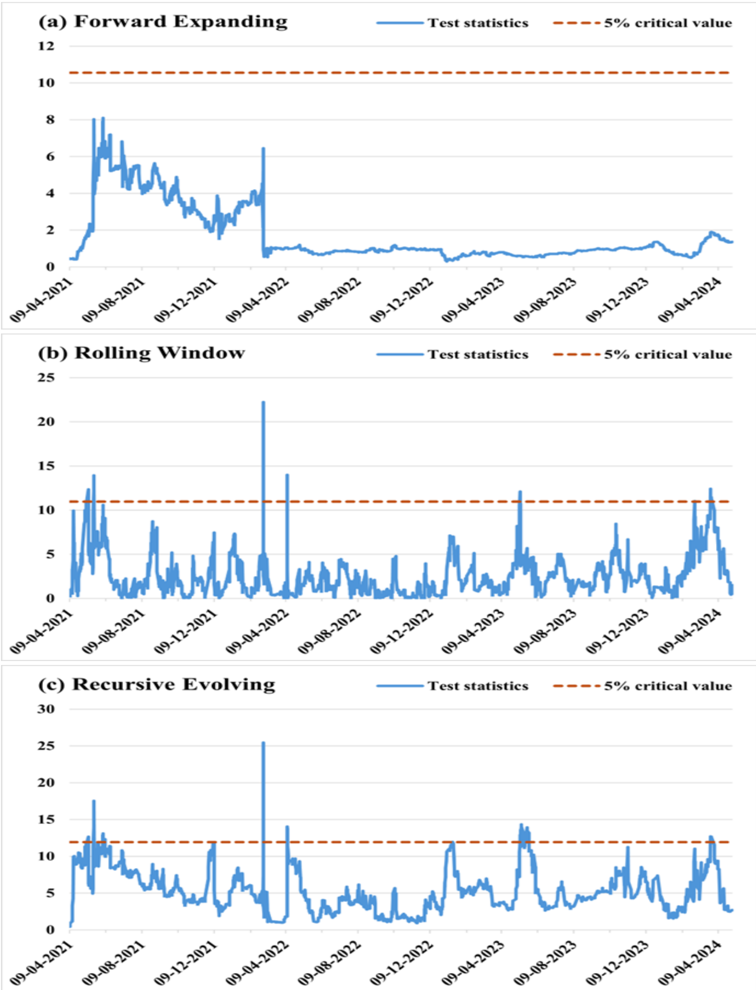

Figure. 4 *Spot Causing Futures (30-Minutes).*

Note: *Figure. 4 shows the "time-varying Granger causality" from the EEX spot to the ECX futures at 30-minutes. Figs. 4 (a), (b), and (c) show "Wald test statistics" using "forward expanding", "rolling window", and "recursive evolving" approaches, respectively.*

The findings from all three testing procedures suggest that EUA futures prices predominantly "*Granger cause"* spot prices. This shows that the relevant information is first reflected in EUA futures prices and then gets transmitted to the spot prices. Notably, the ECX futures market takes the lead in the market, and spot prices lack the ability to predict ECX future prices. This can be ascribed to the relatively low trading volume in the spot market, and thus, poor liquidity has detrimental effects on price formation (Benz & Hengelbrock, 2011).

4. Conclusion

We examine the dynamic causal relationship between EUA spot and futures prices using high-frequency intraday data under a novel time-varying framework proposed by Shi *et al.* (2020). The results indicate that EUA futures prices reflect the relevant information faster and predominantly lead the pricing formation process in the European carbon market. The findings have significant implications for institutional investors and informed traders and may help them with portfolio rebalancing, hedging, and effective trading strategy formulation. Also, the research outcomes may assist arbitragers in comprehending the price formation process and identifying arbitrage opportunities in the EU-ETS. Lastly, these findings can be useful for regulators and policymakers seeking to improve the market microstructure of the EU-ETS and similar carbon markets across the world.

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