Information Efficiency of the European CO2 Trading Market in the Period 2008-2021

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Research Article

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Posted Date: December 22nd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1050631/v1

Submitted to Environ Sci Pollut Res – Short Research

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Abstract

This work examined the information efficiency of the European CO_2 trading market for the period 2008-2021. The analysis is based on the singular value decomposition (SVD) approach and the task is to test whether the dynamics of logarithmic price differences are consistent with a random process. The results showed that the information efficiency changes over time and scales, which is in line with adaptive market hypothesis notions. High market efficiency was exhibited in Phase II (2008-2012), but large deviations from efficiency, especially for quarterly scale, were exhibited in Phase III. However, Phase IV has shown a behavior that is consistent with the information efficiency. The findings in the present study suggest that the European carbon market is gradually attaining a state of financial maturity.

Keywords: Emission allowances; European emission trading scheme; information efficiency; entropy; singular value decomposition; market phases.

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1. Introduction

Energy production in the recent two centuries has been strongly based on fossil fuels. Carbon, natural gas and crude oil triggered the impressive technological evolution since the Industrial Revolution, contributing to about 80% of the nowadays world's energy. However, the combustion of fossil fuels for energy production has carried adverse environmental effects. It has been reported that the emission of greenhouse gases, mainly carbon dioxide, has disrupted the thermal atmospheric balance, leading to a fast-rising of average regional and world temperatures (Philipona et al. 2009). In turn, global warming has impacted the incidence of severe droughts (Dai 2011), desertification (Sivakumar 2007), and intense flooding (Mousavi et al. 2011).

The adverse effects of global warming in ecological, social and economic systems have prompted the urgency for actions to reduce the emission of greenhouse gases from fossil fuels. The scientific consensus that global warming is occurring and that human-made greenhouse gases emissions are driving it motivated the 1992 United Nations Framework Convention on Climate Change (UNFCCC) to commit states to reduce greenhouse gas emissions. The Kyoto Protocol adopted on 11 December 1997 was an international treaty that extended the UNFCCC agreements. The Kyoto Protocol entered into force on 16 February 2005, and in 2003 the European Commission established a mandatory cap-and-trade (i.e., emission trading scheme) system for carbon dioxide permits oriented to meet Kyoto Protocol obligations. The European Union Emission Trading Scheme (EU ETS) was the first CO_2 market and one of the largest cap-and-trade targeting schemes for mitigation of greenhouse gases emission (Ghazani and Jafari 2021). Besides, the EU ETS accounts for over 75% of the international carbon dioxide trading. Permits emitted by the EU ETS are increasingly traded in over-the-counter, spot and futures markets.

The EU ETS has transited through four phases. Phase I (2005-2007) was an introductory stage when accurate emission data of facilities were not available, and the emission levels were established by each member state. The lack of strict emission regulations and the absence of bankable allowances led to the collapse of the market, with prices nearing zero at the end of 2007.

In Phase II (2008-2012), the cap levels were set by the National Allocation Plans (NAPs). Despite the relatively starting price (about 30 €/ton), the price showed a sustained negative trend that reached values of about 6 €/ton at the end of 2012. Phase III (2013-2020) faced stricter emission regulations as EU members adhered to the 2030 CEF framework. Emission should be cut by 43% compared to 2005, and from 2021 forward the ceiling should be lowered by at least 2% annually until 2030 (Action 2018). Besides, a Europe-wide emission cap was implemented for Phase III. Phase IV started in 2021 as the Market Stability Reserve (MSR) was adopted to eliminate oversupply systematically and momentarily. The MRS is aimed to improve the market resilience by fine-tuning the number of permits to be auctioned. As a possible consequence of the MSR, the price showed a fast-rising to maximum levels of about 55 €/ton in the recent few months.

The ability of the cap-and-trade scheme to drive a reduction of emissions relies strongly on the fulfillment of the market informational efficiency (Daskalakis 2013). The notion is linked to the so-called efficient market hypothesis (EMH), which in its weak-form establishes that prices should follow a random walk behavior since all publicly available information concerning the underlying price formation is accurately reflected in the price dynamics (Fama 1965; Malkiel and Fama 1970; Lo 1991). In an efficient market, price prediction is not possible based solely on public information. If the carbon market is efficient, prices are constructed based on fundamentals (e.g., marginal abatement costs), and as such polluters can use the prices of the carbon futures traded under the EU ETS as input for the expected future carbon cost (Daskalakis 2013). Several studies have assessed the efficiency of carbon markets, with many of them focusing on the Chinese markets (Zhao et al. 2017; Fan et al. 2018; Chen et al. 2021). The results are controversial as some results found that the markets are becoming more efficient with time, and others reported that the efficiency in Chinese markets is fluctuating as a consequence of still immature operations. The efficiency of the EU ETS scheme has also been explored. Daskalakis and Markellos (2008) studied the efficiency in Phase I (2005-2007) and concluded that the market was far from efficient, an effect that was ascribed to the short history of the market. In the same line, Montagnoli and De Vries (2010) showed that Phase I

was inefficient, although the initial part of Phase II showed signs of restoring market efficiency. Daskalakis (2013) considered the Phase II period (2008-2011) and concluded that the EU ETS from 2010 onwards is consistent with weak market efficiency, which suggested that the European carbon market was gradually attaining a state of maturity. However, Aatola et al. (2014) found evidence of profitable opportunities in the European Union carbon market for 2008-2010. Yang et al. (2018) used Lo-MacKinlay several variance ratio tests and reported that Phase II behavior is consistent with a Martingale process, whereas Phase I and Phase III failed the test of the EMH. Recently, Ghazani and Jafari (2021) used a generalized spectral and automatic portmanteau test over a roller window and showed that the efficiency of the European market is dependent on both time and scale, a result that is in line with the adaptive market hypothesis (AMH) (Lo 2005).

The recent results on the efficiency of the EU ETS are controversial and still inconclusive. Further studies are required to elucidate the evolution of the EU ATS market efficiency over time and at different scales (Ghazani and Jafari 2021). The present work studied the efficiency of the EU ETS market for the period 2008-2021, containing phases II, II and the start of Phase IV. The approach is based on the computation of the singular value decomposition (SVD) entropy (Sabatini 2000; Caraini 2014) over rolling windows of different sizes, which in turn defines the scale or time horizon. The results showed that the efficiency is not uniform, displaying important variations over time and scales. Phase II exhibited a higher efficiency degree, whereas Phase III exhibited large deviations from efficiency. Phase IV shows an apparent recovery of the information efficiency, which suggests that the carbon trading market is becoming more efficient.

2. Methods

Let $\{X(t_i)\}$ be a discrete-time process with $X(t_i)$ be the value produced by a given run of the process at time t_i. By some abuse of notation, take a subsequence of size n with leading time t_i:

$$\boldsymbol{X}(t_i; n) = \{X(t_{i-n+1}), \dots, X(t_{i-1}), X(t_i)\} \quad (1)$$

The problem under analysis is to decide whether the subsequence was extracted from a process containing serial correlations. If the process is affected by serial correlations, then the subsequence (1) shares some similarity with past subsequences of the same size. The following approach is proposed to address such a question. Construct the following square symmetric matrix of n lagged subsequences:

$$\boldsymbol{M}_X(t_i;n) = \begin{bmatrix} \boldsymbol{X}(t_i;n) \\ \boldsymbol{X}(t_{i-1};n) \\ \dots \\ \boldsymbol{X}(t_{i-n+1};n) \end{bmatrix} \tag{2}$$

If the rows of $\boldsymbol{M}_X(t_i;n)$ are similar, Eq. (2) corresponds to a correlated random matrix. Although a correlated matrix $\boldsymbol{M}_X(t_i;n)$ may be a full-rank matrix ($rank(\boldsymbol{M}_X(t_i;n)) = n$), the presence of correlation implies that most information is aggregated in a sub-space of reduced dimension. In contrast, the absence of correlations implies that dimensionality reduction can lead to important information loss. That is, all row vectors in a non-correlated matrix contain the same amount of information, and as such no one-row vector can be discarded without important information loss. Fig. 1.a shows the plot of $X(t_i)$ versus $X(t_{i-1})$ for 1000 points of uncorrelated white noise. The points are distributed uniformly about the origin, without preferential radial or angular direction. In contrast, Fig. 1.b shows a similar plot for (correlated) 1/f-noise. In this case, the distribution of points shows an ellipsoidal geometry with many points concentrated along a preferential direction. This suggests the existence of a principal direction where most information on the dynamical process was concentrated.

The illustrative example in Fig. 1 indicated that the information on the dynamics of a process can be preferentially contained in a subspace. In this regard, the singular-value decomposition (SVD) is suitable to address the question of whether the matrix $\boldsymbol{M}_X(t_i;n)$ is not correlated. Indeed, the SVD is a factorization or real or complex matrices that generalizes the eigen-factorization to any $m \times n$ matrix using an extension of the polar decomposition. The SVD entropy is a powerful tool to analyze the complexity of financial signals (Caraini 2014; Gu et al. 2015,

2016). In particular, it provides an index of the order content in a time series (Busu and Busu 2019). In the case of the matrix given by Eq. (2), the SVD leads to factorization of the form

$$\boldsymbol{M}_X(t_i;n) = \boldsymbol{U}(t_i;n)\boldsymbol{\Lambda}_X(t_i;n)\boldsymbol{V}(t_i;n)^{\boldsymbol{T}} \quad (3)$$

where $\boldsymbol{U}(t_i;n)$ is a $n \times n$ unitary orthogonal matrix, $\boldsymbol{\Lambda}(t_i;n)$ is a $n \times n$ diagonal matrix with non-negative real numbers on the diagonal, and $\boldsymbol{V}(t_i;n)$ is a $n \times n$ unitary orthogonal matrix. The diagonal entries $\lambda_{jj}(t_i;n) = \boldsymbol{\Lambda}_{jj}(t_i;n) \geq 0$ of the matrix $\boldsymbol{\Lambda}(t_i;n)$ are the singular values of the matrix $\boldsymbol{M_X}(t_i;n)$**.** The number of non-zero singular values corresponds to the rank of the matrix $\boldsymbol{M_X}(t_i;n)$**.** The columns of $\boldsymbol{U}(t_i;n)$ and $\boldsymbol{V}(t_i;n)$ are the left-singular and right-singular vectors of $\boldsymbol{M_X}(t_i;n)$, respectively. The SVD is essentially a change of coordinates via rotations ($\boldsymbol{U}(t_i;n)$ and $\boldsymbol{V}(t_i;n)$) and rescaling ($\boldsymbol{\Lambda}(t_i;n)$). In particular, the singular values of a matrix $\boldsymbol{M_X}(t_i;n)$ can be seen as quantifying the geometry of the transformation $\boldsymbol{M_X}(t_i;n)\boldsymbol{B}$, where $\boldsymbol{B}$ is the unit ball. In general, the transformed ball is an ellipsoid where the singular values correspond to the length of its principal axes.

The singular values of the matrix $\boldsymbol{M_X}(t_i;n)$ strongly reflect the correlation information of the time series X_t for a time horizon of n discrete times. In turn, such information should decide the tendency of the time series. The entropy is commonly used to make an index of the degree of interdependence of the row/columns of a matrix (Sabatini 2000). Succinctly, the entropy is an index reflecting the average information contained in a process and is a measure of the degree of randomness in the matrix. The higher the entropy, the higher the information required to reconstruct the process dynamics. Entropy is estimated from the distribution of the singular values of the matrix $\boldsymbol{M_X}(t_i;n)$. In a first step, the singular values are normalized as follows:

$$\lambda_j^*(t_i;n) = \frac{\lambda_j(t_i;n)}{\sum_{j=1}^{n}\lambda_j(t_i;n)} \quad (4)$$

Subsequently, the entropy of the matrix $\boldsymbol{M_X}(t_i;n)$ is computed by

$$\mathrm{S}_X(t_i;n) = -\frac{1}{\ln(n)}\sum_{j=1}^{n}\lambda_j^*(t_i;n)\ln(\lambda_j^*(t_i;n)) \quad (5)$$

For a perfectly non-correlated process (e.g., white noise), there are no preferential directions of information accumulation (see Fig. 1.a) and $\lambda_j^*(t_i;n) = 1/n$, $j = 1, \dots n$, such that $\mathrm{S}_X(t_i;n) = 1$. For a matrix containing correlations and reflecting preferential information directions (see Fig. 1.b), one should have that $\mathrm{S}_X(t_i;n) < 1$.

The entropy value $\mathrm{S}_X(t_i;n) = 1$ for uncorrelated sequences is a theoretical reference that holds asymptotically (i.e., for very long sequences). In practice, the analysis of entropy should deal with sequences of finite size. Also, one would like to explore the entropy for short sequences associated with relatively small scales (e.g., days for financial time series). In this way, the SVD entropy depends on the scale and should be smaller than one for sequences of finite size.

2.1. Randomness test

The weak form of the EMH involves testing if a given sequence was generated by a random process. In terms of the SVD approach described above, one should decide whether the entropy of a tested sequence $\boldsymbol{X}(t_i;n)$ corresponds to the entropy of a random sequence. If the probability distribution $P(\boldsymbol{X})$ that generated the values of the sequence $\boldsymbol{X}(t_i;n)$ is available, an approach is to generate many random sequences of size n and to compute the statistics of the SVD entropy to obtain the confidence intervals (CI). However, the exact distribution is hardly available in practice for a given process. Bootstrapping estimates can be used by considering an approximate (i.e., empirical) distribution. In this way, the following procedure based on iso-distributional surrogate data (Theiler et al. 1992) is proposed to estimate the CI for randomness: a) Compute N_{sh} shuffled sequences $\boldsymbol{X}_{sh}(t_i;n)$ from the original sequence $\boldsymbol{X}(t_i;n)$. In principle, shuffling destroys serial correlations while retaining the statistical distribution of values. That is, the sequences $\boldsymbol{X}_{sh}(t_i;n)$ and $\boldsymbol{X}(t_i;n)$ were generated from a common distribution $P(\boldsymbol{X})$. b) Compute the SVD entropy for the shuffled sequences $\boldsymbol{X}_{sh}(t_i;n)$, which reflects the entropy of a random sequence. c) Carry out the

statistical analysis of the N_{sh} SVD entropy values to obtain the corresponding CI for randomness. In the sequel, $N_{sh} = 5000$ randomized samples were employed to compute the confidence intervals.

2. Data

The present work considered daily variations of the CO_2 spot price (€/ton) of European Union Allowance (EUA) units. The purchase of an EUA gives the holder the right to emit one ton of carbon dioxide, or the equivalent amount of two more powerful greenhouse gases, nitrous oxide (N_2O) and perfluorocarbons (PFCs). The period under scrutiny is from 4 January 2008 to 31 October 2021, containing the so-called Phase II (2088-2012), Phase III (2013-2020) and beginning of the Phase IV (2021-date) of the EU ETS. The spot prices were obtained from www.sendeco2.com (accessed on 31 October 2021) and its behavior is shown in Fig. 2.a. Phase II was characterized by a continuous decline of the spot prices, from maximum values of about 28 €/ton in 2008:Q2 to minimum values of about 5 €/ton in 2012:Q4. The spot prices remained at low levels (4-7 €/ton) in the first five years of Phase III, reflecting a low demand scenario. The stricter EU regulations on carbon emissions and the recent COP26 Climate Summit have triggered a bearish dynamic starting by 2018:Q1, which increased the spot prices to levels of 65 €/ton in the recent months. The SVD entropy analysis will be conducted for the logarithmic return $r(t)$ (Fig. 2.b), which is given by

$$r(t) = \log(p(t)) - \log(p(t-1)) \quad (6)$$

Here, $p(t)$ is the spot price at time t. The values of the mean and standard deviation are 1.08×10^{-4} and 0.013, respectively, estimated over 3521 observations. The return exhibit negative skewness (-0.869). The level of kurtosis is remarkable (14.68), which is linked to leptokurtic behavior (Ghazani and Jafari, 2021). The normality of the return distribution is rejected at a 5% decision level via the Kolmogorov-Smirnov test (0.0746).

3. Results and discussion

The SVD entropy was computed for moving windows of 5, 21, 63 and 265 observations (business days), corresponding to week, month and quarter scales. The number of observations determines the dimension of the lagged matrix given by Eq. (2). By doing this, the variation of the SVD entropy over different time scales can be monitored. In contrast to other entropy computations (e.g., approximate entropy) where the entropy estimates are obtained by averaging over the replication of patterns over the window, the SVD entropy is directly obtained by the distribution of singular values that reflects the aggregation of information along with preferential directions.

Fig. 3 exhibits the behavior of the SVD entropy for weekly scales (5 business days). The gray ban denotes the region where the SVD entropy corresponds to a random sequence with a 95% confidence interval. Over weekly scales, the CO_2 market was informationally efficient most of the time in Phase II as no departures from randomness were displayed. Phase III presented three isolated deviations from randomness. The first one occurred in 2013:Q4 and reflected the sluggish recovery of the European economy from the 2011-2012 debt crisis (Benczes and Szent-Ivanyi 2015). The other two deviations from randomness occurred in the early months of 2020, an effect that could be induced by the COVID-19 economic lockdown. The starting of Phase IV contained two large deviations, which might be reflecting the adaptation of the market participants to updated and strictest emission regulations. However, the CO_2 has recovery the information efficiency in the second 2021 semester.

The variation of the SVD entropy for monthly scales is displayed in Fig. 4. The price return in Phase II exhibited behavior that is consistent with a random pattern, except for a large peak at about 2011:Q2. The origin of this significant deviation from the EMH is not clear at all, although financial and economic events might be underlying the carbon market disruption. The 2011 European debt crisis as well as concerns over the slow economic growth of the United States and its credit rating being downgraded might affect the efficiency of the CO_2 market. Phase III showed a more complex pattern, with several deviations from the information efficiency. The largest peak at about 2018:Q3 might be attributed to the herding effect induced by the stellar rise in EUA prices in

2018, more than tripling from 8 to 25 €/ton, and the overall market value increased about 250%, to 144 €/ton. Interestingly, the COVID-19 economic lockdown hardly affected the information efficiency for monthly scales. The incipient Phase IV has shown a stable evolution of information efficiency.

The quarterly scale offered a more interesting picture of the CO_2 market, with more frequent deviations from the randomness behavior (Fig. 5). In general, the hallmark of the market for quarterly scales is the volatile behavior in terms of efficiency. Phase II contains three relatively small deviations from the EMH. However, Phase III exhibited several important deviations, with about 42% of the time out of the 95% CI. The large deviation in 2016:Q1 might reflect the reaction of the market to the Paris Agreement adopted at the Paris Climate Conference (COP21) in December 2015. The deviation of medium magnitude in 2020:Q2 might be linked to the economic downturn and social lockdown by COVID-19, which led to a sudden price decrease from about 24 to 15 €/ton. The market recovered in the subsequent months to achieve the present boom to prices as high as 65 €/ton. After a short transient, Phase IV showed the apparent recovered of the information efficiency.

3.1. Discussion

The results described above showed that the EU CO_2 market is generally efficient for short and medium-time scales. Except for short-timed deviations from randomness, the SVD entropy fluctuated into the 90% band most of the time for Phases II and Phases III over weekly and monthly scales. The deviations from randomness can be seen as adjustments of the market to changing conditions. In this way, the dynamics of the EU CO_2 market are consistent with the adaptive market hypothesis (AMH). According to Lo (2005), the AMH implies that market participants are generally rational, but can overreact during periods of heightened market volatility. Also, market participants aim to meet their interests, sometimes make mistakes, and tend to adapt and learn from them.

A somewhat different scenario was displayed for quarterly scales as the market exhibited several periods of inefficiency. Whereas the inefficiency time was not higher than 5% for weekly and monthly scales, the inefficiency time was about 42% for the scrutinized period. Although the market is mostly unpredictable over short and medium time horizons, windows of certain predictability degrees are opened for quarterly time horizons. The oscillatory behavior of the SVD entropy with frequent deviations from randomness suggests that the market still meets the AMH where participants take actions to adapt to changing conditions. However, it also suggests that the EU CO_2 market is insufficiently mature to forbid price predictability for quarterly and longer horizons. The deviations from randomness exhibited in Phase III suggest prospects for profitable opportunities by bidding over relatively long-time horizons. However, the evolution of Phase IV suggests that the information efficiency is gradually recovering in recent months.

The results obtained with the SVD entropy approach complemented the existing results in the recent literature. Aatola et al. (2014) showed that the EU ETS market exhibited periods with no informational efficiency for the period 2008-2010. Yang et al. (2018) used several variance ratio tests (e.g., Lo-MacKinlay) to show that only the rate of return in Phase II follows a martingale process, implying a weak form of the EMH. In contrast, Phase III failed to possess the features of an efficient market. These findings are in line with the results for the quarterly scale in Fig. 5 where Phase III exhibited several deviations from randomness. Daskalakis (2013) also showed that the EU ETS market is consistent with the EMH in the period 2008-2011 (Phase II) and suggested that the market is gradually reaching a state of maturity. However, our results and those of Yang et al. (2018) contradict such asseveration since important deviations from randomness were exhibited in Phase III. In the same line, Ghazani and Jafari (2021) used generalized spectral and automatic portmanteau tests to show that the EU ETS market was in general consistent with the AMH in the Phase III.

4. Conclusions

This paper aimed to investigate the information efficiency of the European carbon market for the period 2008-2021, which includes Phase II, Phase III and the starting of Phase IV. The aim was undertaken by examining the randomness behavior of the logarithmic price differences using the SVD entropy over different salient scales. The results showed that the market efficiency changes with time and scales, which is in line with the concepts underlying the adaptive market hypothesis. Phase II exhibited a low level of randomness in line with market efficiency, whereas Phase III displayed large deviations from efficiency, especially for the quarterly scale. However, the incipient Phase IV seems to evolve along with the information efficiency hypothesis. In this way, the results in this study suggest that the European carbon market is becoming more efficient with time. Overall, the results suggest that the carbon market lacks sufficient maturity to guarantee informational efficiency over time and scales. Maybe, the carbon market is still subjected to the effects of political shocks and decisions, which inhibit the enrollment of participants that are not directly linked to emission-intensive firms. The increasing inclusion of the carbon market in the financial system (e.g., investment funds, investment portfolios, secondary and derivative markets) should diversify the market dynamics. Also, the flexibilization of the supply side of the allowance allocation might lead to a more resilient market.

Author contribution Monica Meraz: conceptualization, investigation, methodology. Jose Alvarez-Ramirez: calculation, review, editing. Eduardo Rodriguez: visualization, formal analysis.

Data availability The datasets used or analyzed during the current study are available upon request.

Ethical approval Not applicable

Conflict of interest The authors declare no conflict of interest

Consent to participate All authors agreed to participate in the study

Consent for publication All authors agreed to submit the manuscript to Environmental Science and Pollution Research

Funding Not applicable

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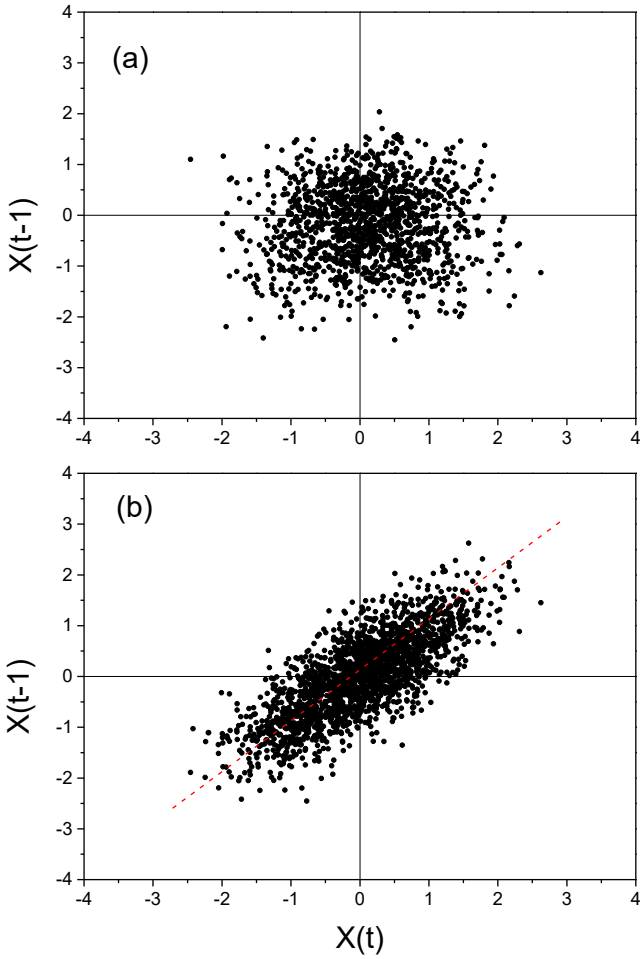

Fig. 1 Phase portrait of current and lagged values of (a) uncorrelated (white noise) and (b) correlated (1/f-noise) sequences. The uncorrelated sequence did not show a preferent direction of distribution. In contrast, the correlated sequence was distributed preferentially along the 45 degrees direction. The dotted red line denotes the preferential direction of information aggregation.

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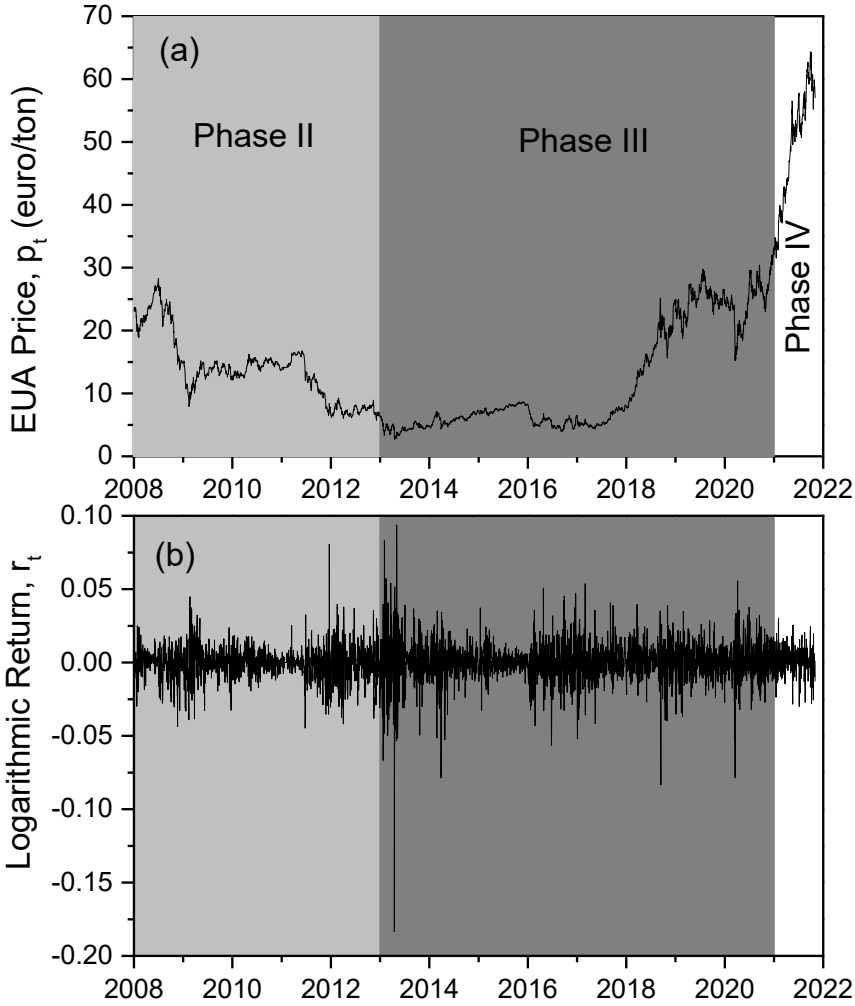

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388 **Fig. 2** (a) carbon allowance price and (b) logarithmic price difference of the European carbon

389 market. Phases II and III and the starting of Phase IV are highlighted.

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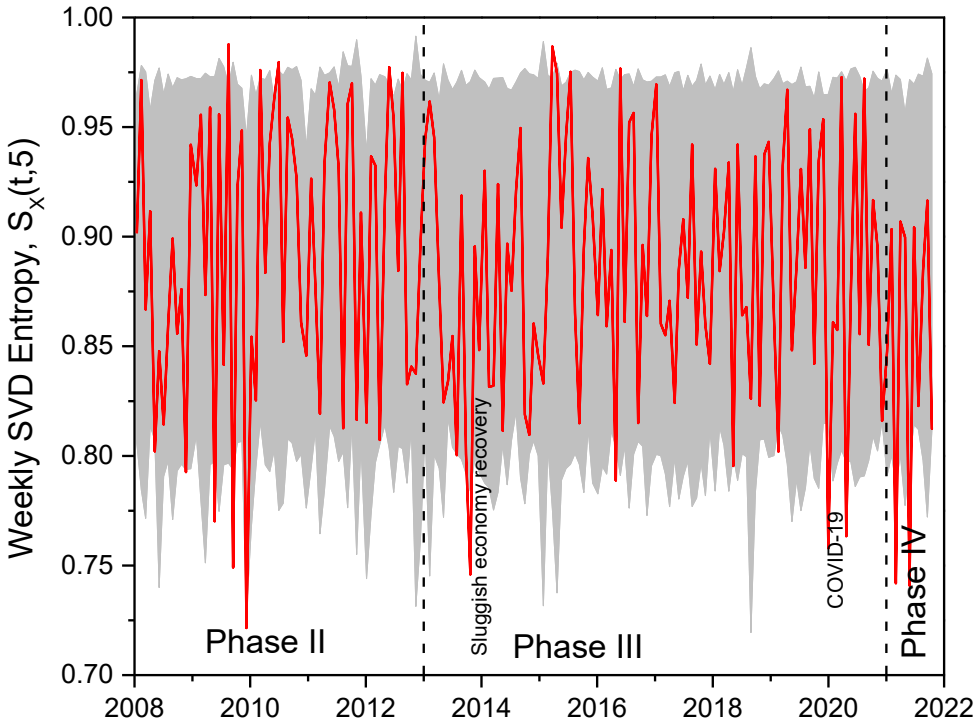

Fig. 3 The behavior of the SVD entropy for weakly time scale (5 observations). The gray band denotes the 95% CI for randomness.

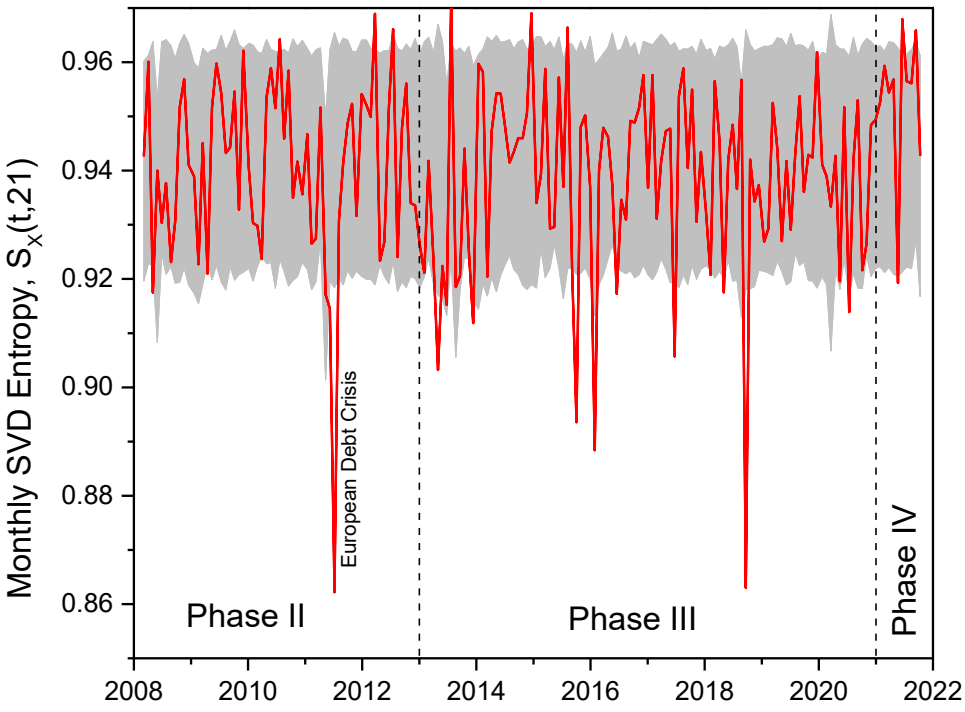

Fig. 4 The behavior of the SVD entropy for monthly time scale (21 observations). The gray band denotes the 95% CI for randomness.

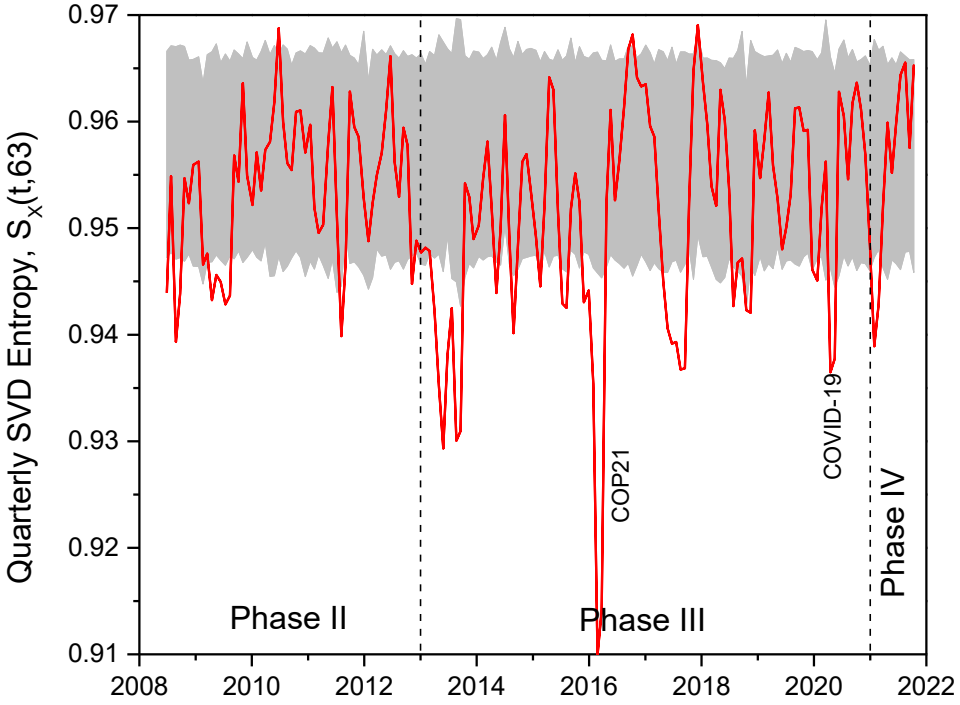

Fig. 5 The behavior of the SVD entropy for quarterly time scale (63 observations). The gray band denotes the 95% CI for randomness.