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Causality, Connectedness, and Volatility Pass-through among Energy-Metal-Stock-Carbon Markets: New Evidence from the EU

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Summary

The EU carbon market serves as an innovative financial instrument with the primary objective of contributing to mitigate the impacts of climate change. This market demonstrates significant interconnectedness with fossil energy, precious metal, and financial markets, although limited research has focused on the causality, dependency, intensity and direction of time-varying spillover effects. This study aims to investigate the causality direction, degree of dependency structure, and volatility transmission from Brent Oil, UK Natural Gas, Rotterdam Coal, Gold, Silver, Copper, and EuroStoxx600 future prices to EU Allowances during different periods of EU market. To achieve these objectives, this paper proposes a novel methodological approach that combines the most recent econometrics methods, such as Directed Acyclic Graph analysis, C-Vine Copula models, and Time-Varying parameter Vector Auto Regressive models with Stochastic Volatility with the use of a comprehensive sample of daily data from 26 April 2005 to 31 December 2022. The major findings of this study demonstrate that causality predominantly runs from energy, metal, and financial markets to the EU carbon market. The dependency structure, although varying across different sub-periods, shows a strong relationship observed between oil, coal, silver, copper, EuroStoxx600, and CO2 market. Additionally, the oil and copper futures prices exhibit the highest dependence on EUA prices. Furthermore, the study establishes that the EU carbon market is a net receiver of shocks from all other markets, with the energy, metal, and financial markets significantly influencing volatility in EUA prices. The time-varying spillover effect is most pronounced with a one-day lag, and the duration of the spillover effects ranges from 2 to 15 days, gradually diminishing over time. These results have the potential to increase the understanding of the EU carbon market and offer practical guidance for policymakers, investors, and companies involved in this domain.

Keywords: Causality direction, Dependency structure, EU-ETS, Time-varying spillover

JEL Classification: O52, Q43, Q54

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Causality, Connectedness, and Volatility Pass-through among Energy-Metal-Stock-Carbon Markets: New Evidence from the EU

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Abstract

The EU carbon market serves as an innovative financial instrument with the primary objective of contributing to mitigate the impacts of climate change. This market demonstrates significant interconnectedness with fossil energy, precious metal, and financial markets, although limited research has focused on the causality, dependency, intensity and direction of time-varying spillover effects. This study aims to investigate the causality direction, degree of dependency structure, and volatility transmission from Brent Oil, UK Natural Gas, Rotterdam Coal, Gold, Silver, Copper, and EuroStoxx600 future prices to EU Allowances during different periods of EU market. To achieve these objectives, this paper proposes a novel methodological approach that combines the most recent econometrics methods, such as Directed Acyclic Graph analysis, C-Vine Copula models, and Time-Varying parameter Vector Auto Regressive models with Stochastic Volatility with the use of a comprehensive sample of daily data from 26 April 2005 to 31 December 2022. The major findings of this study demonstrate that causality predominantly runs from energy, metal, and financial markets to the EU carbon market. The dependency structure, although varying across different sub-periods, shows a strong relationship observed between oil, coal, silver, copper, EuroStoxx600, and CO2 market. Additionally, the oil and copper futures prices exhibit the highest dependence on EUA prices. Furthermore, the study establishes that the EU carbon market is a net receiver of shocks from all other markets, with the energy, metal, and financial markets significantly influencing volatility in EUA prices. The time-varying spillover effect is most pronounced with a one-day lag, and the duration of the spillover effects ranges from 2 to 15 days, gradually diminishing over time. These results have the potential to increase the understanding of the EU carbon market and offer practical guidance for policymakers, investors, and companies involved in this domain.

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1.Introduction

Global warming is currently a pressing environmental issue that has attracted significant attention. Its increasing severity, stemming from greenhouse gas emissions, presents a formidable challenge to sustainable development, prompting widespread global concern. Carbon dioxide (CO2), primarily emitted through human activities, stands as the principal component of greenhouse gases. The 2022 report by the Intergovernmental Panel on Climate Change (IPCC) highlights that CO2 emissions contribute to 79.2% of global greenhouse gases (e.g. IPCC, and Liu et al., 2022).

As CO2 emissions worsen, an increasing number of countries, including the EU, the US, Australia, Japan, and China, have swiftly established carbon emission trading markets since the Kyoto Protocol. In 2001, the European Commission took the initiative to implement the first and largest cap-and-trade carbon trading scheme. The scheme places an emissions cap on major European CO2 emitters through the allocation of tradable EU Allowances EUA. The European Union Emissions Trading System (EU-ETS) has been structured into four distinct phases: phase I from 2005 to 2007, phase II from 2008 to 2012, phase III from 2013 to 2020, and the recently started last phase from 2021 up to2030. Presently, EU-ETS stands as the world's active, efficient, and largest carbon emissions trading system, covering about 45% of greenhouse gas emissions from the EU (e.g. Jiang and Chen, 2022).

In tandem with its rapid development and consistent expansion in size, liquidity, trading volume, and complexity, the EU-ETS market has demonstrated a progressively strong association with various other markets. Specifically, over the past decade, the EUA has been associated with an increasing price volatility. Upon analyzing the EUA future prices (refer to Figure 1) during the initial phase of the EU-ETS (2005–2007), the prices started at approximately € 17.55 and surged to a peak of € 31.5 on April 18, 2006, subsequently maintaining a range of € 0–20 until December 17, 2007. Notably, the price experienced a significant increase of over 50% in December 2007, settling at around € 22 until the conclusion of phase I. The second phase commenced on January 1, 2008, with EUA future prices fluctuating between € 10 and € 30, peaking on July 1, 2008. Thereafter, prices gradually declined from July 2008 to February 2009, reaching a trough during that period. They continued to fluctuate in the range of € 10–20 until 2011, when a decline began, eventually dropping to less than € 10 in December 2011. Throughout the rest of the second phase, prices remained steady between € 5 and € 10. Transitioning into the third phase on January 1, 2013, EUA prices initiated trading at approximately € 6.37, but, within four months, quickly decreased to around € 3, hitting again a trough. Subsequently, from May 2013 onward, prices gradually increased and remained relatively stable, oscillating between € 3 and € 10 until March 2018. Notably, in early March 2018, the EUA prices experienced a gradual increase from € 11 to € 33, reaching a peak of € 33.29 on December 28, 2020. With the onset of the fourth phase in January 2021, a sharp increase and considerable fluctuations were observed in the EUA future prices, initiating from € 33.56. Additionally, the prices gradually increased throughout 2020, doubling in September 2020 and ultimately reaching a peak of € 97.59 on August 19, 2022. Since the end of 2023, the EUA prices have exhibited volatility, fluctuating within the range of € 60-90.

[FIGURE 1 ABOUT HERE]

The drivers behind such volatility in the carbon market are multifaceted, stemming from internal fluctuations and interactions with other interconnected markets. Several important factors considerably contribute to the heightened volatile behavior of the carbon market. These factors can be broadly grouped into four categories: degree of integration with macroeconomic, financial, and commodity markets; uncertainty concerning carbon allowance demand; fluctuations in energy prices; influence of speculators on the volatility levels of the carbon market. Given the potential interconnections between the carbon market and various other markets, considerable interest has been sparked among scholars, regulators, investors, and risk managers on this topic. As a result, an extensive body of research has been undertaken to explore aspects related to volatility spillover and market interconnectedness (e.g. Wu et al., 2022).

Numerous studies (e.g., Chevallier et al., 2008; Hammoudeh et al., 2014; Rodríguez, 2019; Jiang and Chen, 2022) consistently find that energy prices, particularly coal prices, significantly influence EUA prices due to several reasons. First, lower fossil energy prices can result in increased energy consumption, leading to higher demand for carbon emissions and carbon prices. Secondly, increased fossil energy consumption, driven by global population growth and ongoing economic development, especially in developing countries, lead to higher carbon emissions and carbon prices. Lastly, the sensitivity of energy use to weather changes varies across different seasons.

However, divergent conclusions are drawn regarding the transmission of volatility between financial, metal and carbon markets. Existing research lacks robust methodological foundations to establish the importance of those markets in influencing EUA volatilities. Due to increasing globalization, financialization, and integration of carbon markets with other international markets, there is strong indication that the financial and metal markets are interconnected with EUA prices. In recent years, all markets with an international dimension have witnessed increased uncertainty, and this has led to significant fluctuations in energy, metal, and carbon prices. Given the distinctive financial attributes characterizing energy, metal, and carbon markets, an increase in speculative activities across these markets facilitates their interconnectedness, thereby amplifying the cross-spillover effects. Hence, understanding the connectedness between EUA prices and the financial market is essential, as EUA price fluctuations may impact the economic incentives and cost of manufacturing companies and could be reflected in the stock market. On the other hand, specific metals, such as gold, silver, and copper (used in fuel cells), are essential for the development of clean energy. As a result, the metal market has become a vital source of raw materials for clean energy production. Changes in metal prices affect the cost of industrial manufactures and, consequently, the demand for energy and carbon emissions. Therefore, formal investigations are necessary to determine causality, degree of connectedness, and potential spillover effects between EUA prices and other markets (e.g. Adekoya et al., 2021).

To address the limitation of the existing literature, in this paper we introduce the following novel contributions. First, we test causality using the Directed Acyclical Graph (DAG) non-parametric approach. Second, to gain a clear understanding of the interconnections and the degree of dependencies among the carbon-energy-financial-metal markets, we employ the C-Vine-Copula model to capture information about both upper and lower tail dependencies among the connected markets. Copula functions are able to capture multi-dependence co-movement, different types of dependency structures, and the degree of dependency among markets (Bouri and Kamal, 2023). Third, to assess the spillover effects among the identified interconnected markets, in this paper we use the Time-Varying Parameter Vector Auto Regressive Stochastic Volatility (TVP-VAR-SV) model. This approach allows us to estimate both static and time-varying spillovers, considering the impacts of each markets on all the others and the total pairwise spillovers (Yousaf et al., 2023).

By employing these set of integrated methodologies, we aim to obtain more reliable and comprehensive insights into the dynamics and interconnectedness of the markets under analysis, in order for policymakers and stakeholders to shape more accurate decision-making procedures.

To sum up, this paper conducts in-depth research to understand the direction of causality, degree of connectedness, and the potential spillover effects among energy, metal, financial and carbon markets by employing advanced and comprehensive methodologies. Our results are crucial for interpreting volatility transmission among the carbon-energy-metal-stock markets (CEMS) and promoting the stable establishment of ETS in countries outside the EU. Our results also help policy maker to timely detect and handle financial risks generated in CEMS markets, and provide valuable insights for investors and companies to make more accurate predictions of both returns and volatilities.

The rest of the paper is structured as follows. The relevant literature review is reported in Section 2. Section 3 is devoted to illustrate the essential elements of DAG, C-Vine Copulas, and TVP-VAR-SV models, as well as to describe the dataset. The empirical results are discussed in Section 4. Section 5 concludes.

2.Literature Review

As carbon emission trading has emerged as one of the predominant approaches to contrast climate change globally, an increasing number of scholars have been investigating the potential for cross-market information spillovers among the energy-metal-financial-carbon markets. Table 1 presents a comprehensive overview of existing studies exploring the linkage between the carbon market and other markets. Notably, these studies can be categorized along different dimensions.

In the context of *energy-carbon market connectedness*, several studies have explored the relationship between these markets. Cheavallier et al. (2008) pioneers in investigating the drivers behind the EU-ETS, using a GARCH model and daily data from July 1, 2005, to April 30, 2007. Their results show that carbon prices react to both energy prices and temperature changes. During the first phase of EU-ETS, energy prices, including Brent oil, natural gas, and coal, have a significant and positive effect on EUA prices. Hammoudeh et al. (2014) conduct a study using a Bayesian Structural VAR model and data from August 2006 to September 2011. They focus on explaining the short-term dynamics of carbon prices in response to changes in energy prices of oil, gas, coal, and electricity. Their findings prove that shocks in oil prices have initial positive effects followed by negative effects on carbon prices. However, no spillover effects are found between gas, coal, and carbon markets. As for electricity, a positive shock in the price has a negative impact on the price of EUA in the second phase. At the same time, Reboredo (2014) investigates the volatility spillovers between oil and carbon markets using a Multi-Conditional Auto Regressive Range model. The results suggest the existence of volatility dynamics and leverage effects but no significant volatility spillovers between these markets. Zhang and Sun (2016) employ an MGARCH model to study the dynamic volatility spillover impact from fossil energy prices, including oil, gas, coal, and electricity, to the carbon market from January 2, 2008, to September 30, 2014. The findings suggest a significant unidirectional volatility spillover from coal to the carbon market, while no spillover impacts are found from oil to carbon prices. Additionally, there is a significant correlation between energy and carbon markets. By conducting a multi-phase survey, Dhamija et al. (2017) examine the volatility spillover impact from energy to the carbon market using daily data from 2005 to 2015. Based on BEKK-MGARCH results, they show a high degree of volatility co-movement between carbon and energy prices, specifically Brent oil, coal, and natural gas. The results support the existence of small but significant volatility spillover from energy markets to EUA markets. Chevallier et al. (2019) employ the Vine-Copula approach to capture the conditional correlation between energy and carbon prices between January 1, 2010, and May 19, 2016. The outcomes suggest that carbon prices co-move only weakly with oil, gas, coal, and switch energy prices, and the link to Brent oil and gas is significantly negative. Similarly, Chen et al. (2019) examine the dynamic correlation and volatility spillover between energy and carbon prices by considering an asymmetric BEKK model. They signal a relatively stable and positive correlation between carbon, Brent oil, and natural gas prices, while the correlation between carbon-gas and coal-carbon weaken and become more volatile during the second and third phase of EU-ETS, particularly after the Global Financial Crisis (GFC). Recently, Yoon and Lee (2020) survey time-varying correlations and dynamic spillovers between energy and carbon markets from October 23, 2009, to July 5, 2020. The results from VAR and BEKK-GARCH models demonstrate a weak volatility spillover effect among the markets, while a strong impact exists between carbon and Brent oil prices. Addressing the third phase of EU-ETS, Xiao et al. (2021) analyze the multiscale interplay of higher-order moments between carbon and energy markets using the Barunik-Krehlic model. The estimated results point out weak bidirectional high-order moments spillovers between the carbon and energy markets in the short-term, but it significantly increases in the long-term. During the same period, Ren et al. (2021) examine the marginal effects of energy prices on EUA prices using a Quantile-on-Quantile regression approach for estimation. The empirical results exhibit quasi-monotonic increase and negative impacts of oil and coal prices on carbon prices, with higher absolute values for the gas price effect. In a recent study, Lin et al. (2021) pay attention to the time-varying spillover mechanism between the carbon and energy markets using a TVP-VAR model.

Their outcomes from time-interval and time point response functions reveal time-varying spillover effects from the energy market, particularly coal prices, to the carbon market, but the effect reduces after three weeks.

A limited number of studies has been devoted to the specific analysis of *interactions between financial and carbon markets*. Rodríguez (2019) uncover the causality direction between carbon and EU major indices, including CAC40, DAX, FTSE100, FTSEMIB, and IBEX, for the first, second, and half periods of EU-ETS. The results of the Toda-Yamamoto co-integration test, along with the causality Granger test, demonstrate a causality direction from stock indices to the carbon market. Aslan and Posch (2022) discover the volatility connectedness between FTSE300 and EUA prices, using the Diebold-Yilmaz method for the third and last phase of the EU-ETS. According to the outcomes, the carbon market is a net receiver of volatilities from the stock market, and this connection enhances during the latest energy crisis in the EU.

Based on our knowledge, no prior investigation has been conducted concerning the linkage between the metal-carbon markets and the financial-metal-carbon markets. However, there is research on the interconnectedness between the energy-financial-carbon markets and the energy-metal-carbon markets. The study of Bataller and Keppler (2010) is considered a pioneering work in the context of uncovering the causality direction between carbon-energy-stock markets. Their contribution carries out for the first phase of EU-ETS. The results of Granger causality test imply causality direction are from energy, coal and gas to electricity market, and from electricity to EuroStoxx600 and carbon prices. Using a different approach, Venmans (2015) uncovers the response of the stock market to energy and carbon returns. Daily data from 2008 to 2010 are used, and a BEKK-CCC model is applied for the investigation. The findings show positively weak correlations between EUA and EuroStoxx600 prices. Lovcha et al. (2015) develop a Structural VAR model and use weekly data from the mid-second and first-half periods of EU-ETS to explore the determinants influencing carbon prices. The Stoxx indices are identified as a significant source of carbon price variations, but their impact has diminished recently, whereas the opposite trend is observed for coal prices. More recently, Zhao and Wang (2020) identify the driving factors behind EUA prices by employing a Structural Equation Model and using data from February 2015 to January 2020. The empirical outcomes suggest direct impacts of CAC40, SP500, and SP clean indices on carbon prices. Additionally, energy prices, including oil and gas, affect carbon prices through the stock market. Focusing on the third stage of EU-ETS, Kim et al. (2021) utilize a VAR model and Wavelet analysis to explore the relationship between energy-financial-carbon markets. The findings reveal a negative relationship between coal and carbon prices, while a positive relationship exists between Stoxx50 and EUA prices. Using a time-varying analysis, Yuan et al. (2021), discover the drivers behind EUA in various time periods. A TVP-VAR model is used to capture the time-interval and also time point response of carbon prices to oil, gas, electricity, and EuroStoxx600 prices. Results imply that the carbon price is more sensitive to energy, particularly oil, and stock prices in short-term, however the responses change in mid and long-term. A VAR-DCC-GARCH model is used to conduct the co-movement between EU-ETS, energy and financial markets between January 2010 and February 2021 by Salvador et al. (2021). Regarding the outcomes, the correlation between EUA-gas, EUA-oil, EUA-coal, EUA-EuroStoxx600 are positive, although not strong. Zoynul Abedin et al. (2023) conduct a comprehensive investigation into the causality direction, dynamic conditional correlation, and spillover effects among the energy, stock, and carbon markets spanning the period from December 16, 2010, to December 29, 2022. The findings suggest that the carbon market Granger-causes the stock market. Furthermore, the study highlights that natural gas emerges as the most significant contributor of shocks, whereas the stock market exhibits a comparatively lower impact as a shock contributor. The following study deals with spillover effects, in particular Wei et al. (2023), quantify the time-varying connectedness effects among energy, financial, and carbon markets throughout all phases of the EU-ETS. To achieve this aim, they develop a TVP-VAR model in conjunction with the Diebold-Yilmaz spillover index. The findings indicate that the average total connectedness among the markets is not strong, but it exhibits significant fluctuations during periods such as the GFC and the COVID-19 pandemic.

Another aspect of the literature that has received less attention concerns the *relationship between energy, metal, and carbon markets*. A recent study conducted by Adekoya et al. (2021) delve into the transmission of volatility between carbon-energy-metal markets using weekly data period from October 2009 to October 2020. The researchers apply a Generalized Forecasting Error Variance Decomposition model acts as the net receiver of volatility from energy and metal markets, with the exception of copper. More recently, Wu et al. (2022) address multidimensional risk spillovers among carbon-energy- nonferrous metal markets, utilizing daily data from July 1, 2015, to February 28, 2022. Evidence from GARCH with Skewness and Kurtosis (GARCH-SK) and Quantile VAR (QVAR) models suggests significant spillover effects among these markets. Notably, the coal market plays a central role in the carbon-energy-metal system. Likewise, Liu et al. (2022) employ a QVAR model to capture the dynamic linkage between energy-metal- carbon markets during the period from April 1, 2008, to October 29, 2021. Results indicate a strong linkage between these markets, with an average connectedness of about 51%; however, spillover effects vary between different time periods. In another study, Jiang and Chen (2022) aim to understand the time-frequency connectedness among energy, carbon, and metal markets, specifically considering the impact of COVID-19, during the period from January 1st, 2014, to March 1st, 2022. They employ the Diebold-Yilmaz spillover index in conjunction with the Barunik-Krehlic approach. The copper and silver price demonstrate higher explanatory power for carbon price fluctuations, particularly during the post-COVID-19 period.

Our paper makes significant contributions to various aspects of the extant literature as summarized above. Specifically, our study focuses on exploring causality, connectedness, and spillover effects among carbon-energy-metal-financial markets from multiple perspectives. In contrast to many existing works that limit their research to the entire cycle or specific phases of the EU-ETS, our research covers several time spans, motivated by the different operating periods of the EU-ETS market and general economic conditions. When examining market relationships, many studies rely on Granger causality tests to determine the direction of the links, although it is well known that this approach is not aimed at revealing causality linkages. To analyze the spillover effects between the carbon and other markets, the main methods generally followed by the literature are simple techniques (such as the VAR, the MGARCH model, and the Diebold-Yilmaz variance decomposition spillover, alongside the Barunik-Krehlic approaches). In order to improve the limitations of those methods, our research approach not does only focus on the overall magnitude and direction of volatility spillovers but also sheds light on the dynamic change processes of these spillovers, which have often been overlooked in previous studies. Additionally, we pay careful attention to the time lag and periodicity of the time-varying spillover effect of returns among the markets. Our study also extends the examination of market relationships beyond spillover effects between energy-carbon markets or energy-financial-carbon markets. We delve into the directional linkage between the metal and carbon market, filling a gap in the existing literature. Notably, we observe that the level of connectedness between carbon and metal prices is lower compared to that reported in previous studies.

To address the limitations in the existing literature on the issue of volatility transmission mechanism from one market to the other, we employ a multi-dimensional approach. Firstly, we explore possible cause and effect relationships among the markets contemporaneously using a non-parametric DAG method. Secondly, we quantify the degree of connectedness among the markets employing the Canonical Vine Copula (C-Vine Copula) to identify the structure and intensity of co-movements. Lastly, we construct a TVP-VAR-SV model of EUA, energy (Brent oil, UK natural gas, Rotterdam coal), metal (gold, silver, copper), and financial (EuroStoxx600) returns, combined with Impulse Response Function (IRF) analysis, to assess dynamic spillover effects from various perspectives, including time-varying, time lag, and periodicity. Based on our knowledge and on an extended review of previous research, the investigation of the causality directions and degree of connectedness, together with the measure of volatility transmissions, is relevant to understand how different markets are intertwined and to identify specific risk sources. In order to differentiate the spillover effects and provide a more comprehensive results, we study various combinations of markets, in which the energy and metal market are distinguished including and excluding one component in each combination (e.g. Rodríguez, 2019). This segmentation leads to a more comprehensive analysis of the specific influences and relationships among markets. Finally, the sample used in this paper, namely daily data from 26 April 2005 to 31 December 2022, includes all trading periods of EU-ETS market, and allows us to obtain evidence of whether the volatility spillover transmission changes over time.

[TABLE 1 ABOUT HERE]

3. Methodology

The study employs a comprehensive array of econometric and statistical tools, including GARCH models, unit-root tests, DAG, C-Vine Copula models, and TVP-VAR-SV models, to analyze time-series data. This multifaceted approach allows for an in-depth investigation of relationships, dependencies, and dynamic behavior exhibited by the variables which sre the object of this study. The details of each method are thoroughly outlined in Section A of the Online Appendix.

In our analysis each price series is log-transformed. Volatility, a crucial aspect of our data, is assessed using the GARCH model introduced by Bollerslev (1986). In the following, unit-root tests, a vital step in assessing the stationarity of time-series data, are performed. The Augmented Dickey-Fuller (ADF) test, Philips-Perron (PP), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Zivot-Andrews (ZA) tests, are executed to examine mean, variance, and autocorrelation structures over time. A comprehensive comparison of the performance of these tests is presented in Table A.1 of the Online Appendix.

The DAG approach is employed to discover the direction of relationships among variables. While the Granger causality method has historically been used for this purpose, DAG, introduced by Pearl (2000), Spirtes et al. (2000), and Demiralp and Hoover (2003), offers an innovative approach to identify contemporaneous causal relationships.

The degree of connectedness is measured using the C-Vine Copula model, which is acknowledged for its accuracy in quantifying multivariate dependencies among variables. In this respect, it is well known that the Spearman and Pearson correlation coefficient has several limitations, and recent studies (see, among others, Tarantola et al., 2018; Chevallier et al., 2019; Pishbahar et al., 2019; Zhou et al., 2020; Ma 2021; Tan et al., 2022; Man et al., 2023; Ghazani et al., 2023) have demonstrated the superiority of copulas due to their flexibility in modeling correlations as well as structural dependencies. Specifically, C-Vine Copulas have a hierarchical structure and assume a single variable as a root node. Kendall's tau is employed as a measure of dependence structure, that overcomes the inadequacy of linear correlation coefficients to capture non-linear dependences. The tail dependence coefficient, as described by Czado et al. (2022), further characterizes the degree of association.

As far as volatility spillovers, we adopt theTVP-VAR-SV model, pioneered by Primiceri (2005) and Nakajima (2011), which acknowledges the limitations of the VAR approach in representing the dynamic relationships among variables and assumes that parameters follow a stochastic walk process. The estimation of the TVP-VAR-SV model involves Markov Chain Monte Carlo (MCMC) simulation. IRF are derived to analyze the reaction of dependent variables to explanatory variables. This model has been widely employed in economic and financial studies (e.g. Pakrooh and Pishbahar, 2020; Yuan et al., 2021; Lang et al., 2023).

4. Data

Our dataset consists of the future prices of EU carbon allowances (EUR/ton of CO_2), Brent Oil (USD/barrel), UK Natural Gas (USD/Mmbtu), Rotterdam Coal (USD/ton), Gold (USD/t.oz), Silver (USD/t.oz), Copper (USD/Lbs), and StoxxEurope600. Prices, which are expressed in USD, are converted into EUR using the EUR/USD exchange rate. The data are at daily frequencies and are collected from different reliable sources, namely the European Energy Exchange (EEX)[1], Investing[2] and the Trading Economics information financial database[3], from April 25, 2005 to December 30, 2022, a total of 4531 observations (see Table 2). The time period spanned by our data allows us to investigate different economic conditions and regimes, and increases the comparability of our results with several studies published in the literature. However, since data on coal are available only from July 19, 2006, our study analyzes the existence of spillovers between coal and other markets starting from Phase II of the EU-ETS system.

[TABLE 2 ABOUT HERE]

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[1] https://www.eex.com/en/

[2] https://www.investing.com/

[3] https://tradingeconomics.com/

5. Empirical Results and Discussions

5.1. Preliminary analysis

The log returns of carbon, Brent oil, natural gas, coal, gold, silver, copper, and stock prices show volatility clustering from all four phases (see Table B.1 of the Online Appendix). The one-step ahead volatilities are estimated with different GARCH specifications (see Tables B.2 and B.3 of the Online Appendix). The largest volatilities are associated with: coal, and silver prices in Phase I; oil, coal, and silver prices in Phases II and III; coal, copper, and stock prices in Phase IV.

Table 3 shows the preliminary statistics of daily returns (Panel A) and volatilities (Panel B) of all series across different EU-ETS trading periods. The average levels of the returns and volatilities range within the intervals (-0.042, 0.089), and (0.14, 187.48), respectively. The unconditional volatilities vary from 0.034 to 2969.33, with the price of gold exhibiting the lowest variability and proving to be a stable investment opportunity. The price of carbon during Phase I exhibits positive returns with relatively high volatility, which tends to decrease during the next phases. The energy market is also moderately volatile, within the range (0.53, 4.175). Most of the returns are negatively skewed, suggesting a higher probability of large negative, rather than large positive, price dynamics and indicating that coal, oil, and stock markets carry larger risk. The large kurtosis values imply that most of the prices are leptokurtic, that is episodes of extreme volatility movements heavily load the tails of the price distributions. These results are confirmed by the Shapiro-Wilk statistics, which strongly reject the hypothesis of normal distribution for all variables.

Finally, in order to tackle the issue of spurious regressions, we perform a bunch of stationary tests, with different assumptions on the deterministic components (i.e. intercept, trend, intercept and trend) and accounting for potential structural breaks in the four sub-periods (Phases I-IV) of the EU-ETS market. All absolute returns (volatilities) of the series under investigation are stationary according to Augmented Dickey-Fuller (ADF), Philips-Perron (PP), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Zivot-Andrews (ZA) tests, with the hypothesis of a unit-root being rejected at the 5% significance level (see Table B.4 of the Online Appendix).

[TABLE 3 ABOUT HERE]

5.2. DAG Analysis

The main results of the DAG analysis suggest the presence of a contemporaneous relationship among carbon, energy, financial, and metal prices in all sub-periods (see Table 4). A closer look to Phase I demonstrates that stock, gold, silver, copper, oil, and gas prices cause on impact the price of carbon, indicating that energy, financial, and metal markets have contemporaneous relationships with EUA. In other words, changes or any movements in these markets tend to transmit almost immediately to the carbon market. The results are in line with Bataller and Keppler (2010), who point out that the prices of energy, gas and coal Granger-cause the carbon price during Phase I. This pattern persists in Phase II, implying that the relationships among these markets are not transient or episodic. Furthermore, the gas market is the contemporaneous cause of the stock market, that is the fluctuations in natural gas prices can directly affect the price of stock. Actually, the significant gas price drop recorded during the GFC may indicate weaker economic activity and, consequently, a negative effect on the earnings of companies through the stock channel. During periods of financial uncertainty, the coal and oil markets are the contemporaneous cause of metal markets. Changes in energy prices can lead to adjustments in investment strategies, which in turn influence the metal markets. Our findings are in line with Rodriguez (2019), who proves that the causal direction is from stock market to EUA spot prices during both Phase I and Phase II. Moving to Phase III, the contemporaneous relationships among these markets become more complex. According to our results, energy, financial, and metal markets are the contemporaneous cause of the carbon market, although new “bilateral” relationships emerge between energy-stock, metal-stock, and energy-metal markets. This suggests that the interconnection between carbon and other markets has become significantly entangled. Carbon, energy, financial, and metal markets are closely integrated for several possible reasons, including the impact of globalization through trade, financialization, market volatility, and advances in technology. The outcomes from Phase IV suggest that energy, metal, and financial markets continue to have a contemporaneous effect on the carbon market. Similarly to Phase III, the relationships between the pairs of markets metal-stock, energy-stock, energy-metal still persist; however, our analysis does not show the complex causal directions observed in Phase III. The results reveal that changes in energy, stock, metal markets impact directly the carbon market. This evidence is coherent with the conclusion by Abedin et al. (2023) about the Granger causality from oil and gas prices to the EU stock market, although it supports the absence of causality from stock to carbon prices.

[TABLE 4 ABOUT HERE]

5.3. C-Vine Copula Models

Table 5 presents the results based on the parametric C-Vine Copula models, which show that the dependence structure between carbon, energy, financial, and metal markets varies across the sub-periods. In Phase I, the dependence between the carbon market and other markets is dominated by the oil market, which exhibits the stronger negative dependence (Kendall's tau equal to -0.27). Given this asymmetric tail dependence, extreme market fluctuations in the oil market are transmitted to the carbon market. An increase in oil price might have a different impact on the CO2 price compared to a decrease in the oil price of the same magnitude. On the other hand, the silver market is the second largest spillover transmitter to the carbon market, with a Kendall's tau of 0.20, suggesting that both markets tend to move in the same direction. The reasons for this positive correlation include the fact that silver is used in various industries, such as in the production of solar panels, while EUA are tied to industrial emissions. Additionally, volatility in the silver price can reflect changes in energy costs. Conversely, the dependence between the carbon market and other markets is relatively weak and symmetric, that is high (low) prices are associated with high (low) levels of CO2 emissions. Moving to Phase II, it is clear that the financial market shows a stronger dependence with the carbon market. In particular, the stock market (Kendall's tau equal to -0.17) shows the most negative significant connection with the carbon market. Additionally, the coal and silver markets (Kendall's tau equal to 0.14) demonstrate positive and moderate dependence with the carbon market, while the oil, gas, gold, and copper markets show a weak correlation. This is line with Reboredo (2013), who finds a positive average dependence between the oil and carbon prices during Phase II and points out that the carbon market can be the net receiver of shocks from both the stock market and the energy. An increase in stock, silver, and coal prices might have different impacts on CO2 prices, compared to a decrease in the prices of the same magnitude. The results of Phase III are almost similar to the findings in Phases I. The structure of the relationships between carbon and the other related markets is mostly dominated by the link between stock, silver, and oil markets. The connection degree between the carbon market and the silver market is positive (Kendall's tau around 0.19), which implies a moderate asymmetric tail dependence. Likewise, the dependence between carbon and stock markets is positive (Kendall's tau around 0.23). In contrast, a negative asymmetric dependency is observed between the carbon market and the oil market (Kendall's tau around -0.10). These outcomes suggest that shocks originating in oil, coal, stock and silver markets can potentially affect the price of carbon. Our findings are also consistent with the conclusions drawn by Chevallier et al. (2019) about the weak and negative co-movement between oil, gas, and carbon prices in Phase III. During Phase IV, stock and metal markets, particularly the copper market, demonstrate the closest relationship with the carbon market with a Kendall’s tau of 0.27. The carbon market has a positive and strong connection with the copper market, and any fluctuations in the copper prices strongly impact the EUA future prices. A rise in copper prices could have an impact on CO2 prices that is distinct from the effect that a decrease of the same size in copper prices would have on CO2 prices. The coal and stock markets display a moderate correlation with the carbon market (Kendall’s tau values of 0.10 and 0.16, respectively). Based on the asymmetric tail dependencies, the carbon market can be the net receiver of shocks from both the coal and stock markets.

As a consequence, EUA future prices display a strong dependency on energy, stock, and metal markets, particularly oil, stock, and copper, and are the most effective channels of transmission of fluctuations to the carbon market. The intensity of this pass-through varies across sub-periods. The strongest connection is observed between oil and carbon prices in Phase I, followed by stock prices in both Phase II and Phase III, and finally by copper prices in Phase IV. Overall, the degree of dependence between the carbon and oil markets decrease over time, whereas the relationship with gas remain weak, with coal showing a consistently high degree of dependence. Conversely, the gold market presents a weak relationship with the carbon market, whereas the relationships with silver and copper are stronger. The degree of dependence between carbon and stock markets remains consistently strong throughout the sub-periods.

[TABLE 5 ABOUT HERE]

5.4 TVP-VAR-SV Estimation

We apply Bayesian techniques based on the MCMC method to estimate the TVP-VAR-SV models for the market combinations that are most strongly correlated with carbon prices. Specifically, we use the MCMC algorithm to simulate 20000, 2000 of which are burnt out. The final estimation results, including posterior mean, standard deviations, 95% confidence interval, Geweke Converge Diagnostic (CD) absolute value, and invalid influencing factors of the estimated parameters are available in Table 6. Accordingly, the CD statistics stand within the confidence intervals and the null hypothesis of “parameters converging to the posterior distribution” cannot be rejected at conventional significance levels, indicating that the parameters have converged to their posterior distributions. Furthermore, the invalid influencing factors of the parameters are quite small. Actually, the maximum value observed is 286.16, implying that at least 70 unrelated samples can be observed from 20000 simulations. We can also infer that the sample path appears stable and the autocorrelations consistently decrease, suggesting that the MCMC algorithm accurately reproduces samples and parameter distributions. Based on the TVP-VAR-SV models, we provide the time-interval and time-point impulse functions to analyze the time-varying spillover effects between the carbon market and the most correlated markets at different lag periods and specific points in time. Regarding the time-intervals, we select 1, 2, 3 and 4 days, while, as for time-points selection, potential outliers are considered and detected. The time-varying stochastic volatilities of carbon market and different driving forces are presented in Table 6 across the four different phases of the EU market.

5.4.1. Phase I

The time-interval responses of carbon to shocks on Brent oil vary significantly from positive to negative, and as the number of lags increases, the intensity of the carbon response tends to increase. Accordingly, an increase in Brent oil prices has two distinct impacts on economic growth: 1) it limits economic growth by reducing energy demand and, consequently, carbon emissions, or 2) it stimulates economic growth due to the substitution effect of oil, which leads economies to use alternative lower-priced energy sources, such as coal. By comparing the shock effects over time, we find that in case of a four-day lag, oil has the most significant positive shock effect, especially in the second half of 2005 and 2006. However, this effect becomes limited and turns negative when considering the other lags (see green spot line). The possible reasons behind this phenomenon can be reconducted to the introduction of the Kyoto protocol, supply disruptions caused by Hurricane Katrina, and the increasing in global energy demand, driven by China and India. In the case of time-point impulse functions of carbon to Brent oil prices, it is evident that the impacts of the shock vary for up to 15 days, reaching their maximum intensity (-0.065) on the 13th day. These results are aligned with Dhamija et al. (2017)'s findings on the volatility co-movement between markets of EUA and Brent oil, with Cretì et al. (2012), who show that the oil market is a determinant of carbon prices in Phase I, and with Hammoudeh et al. (2014)'s conclusions on the persistent impact of energy price shocks on carbon market during Phase I.

The impacts of stock shocks on EU carbon prices oscillate between positive and negative and exhibit large volatility in the latter part of 2006. The stock market shows its largest shock effect on the carbon market in the four-day lag case (response intensity around 7.0). The early stages of the GFC cause significant financial turbulence, enhancing market uncertainty and volatility due to changes in industrial activity. These effects directly impact carbon prices, in the light of the close link between industrial output and emissions.

Additionally, the impacts of shocks in the silver market on EU carbon prices alternate between positive and negative. However, by increasing the number of time lags, the strength of responses gradually increases, and, in case of four-day lag, the silver market shows its greatest shock effect on the carbon market. By the latter part of 2006, we observed a relevant response intensity (7.5) to silver shocks, suggesting that the GFC exerts a significant impact on silver demand, consequently causing fluctuations in the EUA. Despite the financial crisis, the industrial demand for silver, particularly in the solar industries, remain relatively stable. Stability in industrial demand, coupled with the increased investment demand due to the crisis, causes significant fluctuations in silver prices, which, in turn, affect the EU carbon market. This finding aligns with the conclusions of Liu et al. (2022) regarding the time-varying connectedness between metals, particularly silver, and the carbon market.

5.4.2. Phase II

The response of carbon prices to stock price shocks alternate between positive and negative. The strength and direction of shock effect changes frequently, reaching its maximum in 2009. The short-term impact of stocks on carbon price is greater than the long-term impact. In the case of one-day lag, the stock market has the most significant shock effect, ranging between -0.2 and +0.22. Considering the second half of 2009 and the early part of 2010, the magnitude of the shock impact is significant. This is due to the strong market interconnectedness during the EU Debit Crisis (EDC), as the world economy gradually begins to recover after the GFC. During this period, despite the positive pressure on fossil energy prices, firms' output improves (in particular the performance of leading companies reflects to the stock prices and increases investors' returns), thus the demand for EU allowances increases. These findings are in line with Lin et al. (2021), Yuan et al. (2021), Lovcha et al. (2019), and Venmes (2015), according to whom EuroStoxx600 is a major source of carbon price variations. Additionally, it is noticeable that the time-point responses of carbon to stock shocks last approximately 2-3 days. The responses are positive, reaching a trough at lag 2, and then begin to diminish.

The time-interval responses of carbon prices to silver market shocks vary significantly between positive and negative. As the number of lags increases, the intensity of the carbon response does not follow a clear trend. By comparing the shock effects over time, we find that, with a one-day lag, silver has the most significant positive shock effect, especially before mid-2010. However, this effect becomes limited and turns negative with longer-term lags. After mid-2010, the responses vary between negative and positive, based on their short and long-term impacts. These phenomena can be attributed to the GFC, which leads to decreased economic and industrial activity, particularly in silver mining and demand. Additionally, bearing in mind that silver is a key material in the production of solar panels, an increased demand for silver, driven by investments in renewable energy, can lead to higher carbon prices as the market anticipates larger demand for carbon credits to offset emissions from traditional energy sources. Our conclusions are supported by the findings of Liu et al. (2022), Jiang and Chen. (2002), and Adekoya et al. (2021) on the volatility spillover from silver to the CO2 prices.

Regarding the effects of shocks in the coal market on the carbon market, the strength and direction of these shocks are not constant over time. When the coal price unexpectedly rises, carbon prices typically respond positively, except in late 2009 and early 2010, suggesting that an increase in coal prices leads to greater demand for EUA and, consequently, for coal. The coal market has the greatest impact on carbon prices with a one-day lag before 2010. As the number of lags increases, the strength of the carbon market's response gradually weakens. After early 2010, the coal market shows the largest impact with a three-day lag. In 2011, responses peak, ranging between 0.02 and 0.15, and then experience a dramatic drop until the end of the period. These trends can be explained by the impact of the GFC, which increased demand for coal as an alternative fuel. Additionally, many Eastern and Central European countries heavily depend on coal, and it was the primary fuel for power generation in the EU during that period. From 2010 to mid-2011, two bell-shaped curves with peaks are observed, possibly due to firms' efforts to stimulate economic activity after the GFC, along with the EDC phenomenon. Our results are consistent with the findings reported by Lin et al. (2021) and Hammoudeh et al. (2014) regarding the impacts of coal prices shocks on the EU carbon market.

5.4.3. Phase III

The impacts of stock shocks on EU carbon prices are dominated by positive responses and exhibit large volatility. This suggests that it is not possible to identify a clear pattern between 2013 and 2020. According to our results, an increase in stock prices has two distinct impacts on the carbon market, that is, it can either limit or stimulate the emissions indirectly. Additionally, as the number of lags increases, the degree of the carbon market's response tends to decrease, although these effects persist over time. In the case of one-day lag, the stock market shocks have the greatest effects on the carbon market. In the early years of Phase III, especially between 2013 and 2015, the magnitude of responses is smaller than in the later period. This indicates that the carbon market becomes more sensitive to changes in stock prices, and the information transmission between the markets is more intense. Several factors can explain the volatile response of carbon to stock shocks, including the back-loading structural change in ETS, economic recovery after the EDS crisis, European Central Bank policies to combat inflation, the Brexit referendum in 2016, disruptions in global energy oversupply, and the 2015 Paris agreement on climate change. Regarding the time-point impulse functions of carbon to stock prices, the impacts of the shocks last between 1 and 5 days, reaching their maximum intensity (0.004) on the first day and then gradually diminishing. These outcomes are close to the conclusions of Lovcha et al. (2019), Salvador et al. (2021), Kim et al. (2021).

The response of the carbon market to oil market shocks indicates two types of impacts, one positive, the other occasionally negative. As the number of lags increases, the magnitude of the carbon market response decreases. Due to an oversupply disruption between the end-2014 and mid-2015, the price of Brent oil declines from $ 100 to $ 30. This leads to an improvement of the performance of leading companies via an increase in energy intensity, which raises the demand for EUA. In the last period of Phase III, due to various factors, including green energy transition policies of the EU, OPEC production cuts, geopolitical tensions between the USA and the Middle East, Brexit, and the impact of COVID-19, we document a volatile response of the carbon price to changes in oil prices, with response magnitudes ranging between -0.02 and -0.41. Lin et al. (2021), Yoon and Lee (2019), Adekoya et al. (2021), and Dhamija et al. (2017) study the volatility spillovers between Brent oil and EU carbon prices and come to conclusions very close to our findings.

The response of carbon prices to silver price shocks alternate between positive and negative, although strength and direction of the shock effect change frequently. Accordingly, a bell-shaped pattern of this response, with its maximum magnitude in 2016, is observed, followed by an uncertain and volatile trend. An increase in silver price can either stimulate or dampen carbon prices over time, which aligns with the findings by Jiang and Chen (2022). The intensity of carbon market’s response to changes in silver prices ranges between -0.011 to +0.021. In the case of one-day lag, the silver market shocks have the largest effects on the carbon market. As the number of lags increases, the size of carbon’s response tends to decrease before mid-2015, while the opposite occurs after, a pattern documented also by Liu et al. (2022). This suggests that the carbon market becomes more sensitive after the Paris Agreement in 2015. Additionally, several factors can explain the change in the carbon price response to silver prices, including the EU’s energy and environment concerns, as well as shifts in power generation towards cleaner fuels, which result in an increase in silver mining.

5.4.4. Phase IV

The response of the carbon market to stock market shocks indicates two types of impacts, one positive, the other negative, reaching its maximum in the first quarter of 2021. The long-term impact of stocks on carbon prices is greater than the short-term impact. In the case of four-day lag, the stock market shocks have the most significant effects, ranging between -0.001 and 0.0042. During early 2021, due to the post COVID-19 pandemic and lockdowns, the magnitude of the shock impact is significant. As the world economy gradually begins to recover after widespread vaccination in the EU, the responses diminish considerably. This implies that the stock market shocks, occurring during the COVID-19 pandemic and invasion of Russia into Ukraine, do not persist over time and they are noticeably smaller compared to the effects of the GFC (Pappas et al. 2023). This picture is supported by the time-point response functions of the stock market to the carbon market, which last approximately 1-5 days. The responses are negative, reaching a peak at lag 2, and then start to decline.

In examining the response function of the carbon market to coal, it emerges that the response is dominated by positive responses and exhibits large volatility in 2021. As the number of lags increases, the magnitude of the carbon market responses decreases. During the COVID-19 pandemic lockdowns, the magnitude of the shock impacts is large, around 0.16. This value can be attributed to reduced economic activity, which leads to fluctuations in coal demand and disrupts supply, consequently affecting the demand for EUA. By comparing the size of these responses, the coal market is the highest contributor to shocks to the carbon market, while the stock market has the least impact (Wu et al. 2022; Zoynul Abedin et al. 2023). With widespread vaccination and the gradual recovery of the EU economy, these responses diminish slightly. With the beginning of the Russian invasion into Ukraine, the coal rises, due to supply shortages, leading to a decline in demand for both coal and the EUA.

The response of the carbon price to copper market shocks is initially negative, followed by a positive phase. With a one-day lag, copper market shocks exhibit a distinct pattern compared to those associated with mid and long-term lags. Our findings indicate that, before the last quarter of 2021, the long-term positive response of carbon prices to copper market shocks follow a bell curve, peaking during the COVID-19 pandemic lockdowns, a pattern documented also by Jiang and Chen (2022). The magnitude of these shock impacts is around 0.016, and it can be attributed to reduced economic activity leading to fluctuations in copper demand and supply disruptions, consequently affecting the demand for EUA. Additionally, as the number of lags increases, the magnitude of the carbon market's response decreases. This evidence is close to the findings of Wu et al. (2022) and Liu et al. (2022).

[TABLE 6 ABOUT HERE]

6. Robustness Check

In the context of DAG analysis, we employ alternative algorithms (namely, Fast Casual Inference, FCI and Fast Greedy Equivalence Search, FGES) to assess the robustness of the results obtained from the Peter-Clark (PC) max algorithm. The PC max algorithm produces accurate results, as it efficiently handles large datasets, such as the one used in our paper and reduces the risk of false causal inferences. Conversely, both FCI and FGSE methods encounter scalability issues when dealing with large datasets, they require additional assumptions about the distribution of latent variables, and are dependent on turning parameters. Regarding the copula methodology, we apply both R-Vine and D-Vine copulas to ensure that the chosen copula, C-Vine, satisfies the assumptions obtained from the DAG analysis. According to our findings, the complex structures and a large number of estimated parameters in both R- and D-Vine copulas are more challenging. In contrast, the C-Vine copula allows us to select a center variable as a dependent variable when modelling dependencies. This type of vine copula simplifies our estimations and enhances the interpretability of our results. In the context of TVP-VAR-SV models, we increase the lag order and the number of simulations, ranging from 10000 to 30000. Accordingly, we find that lag 1 and 20000 sample simulation provide credible results, that is both statistically significant and consistent with previous findings.

7.Conclusions and Policy Implications

The EU-ETS market, settled to reduce carbon emissions, is influenced by environmental, energy, and economic factors. In the context of EU carbon market, the relationship between carbon, fossil energy, metal, and financial markets has been investigated by many scholars, who have mainly studied the volatility spillover effects between subgroups (typically pairs) of markets. However, according to our knowledge, no study has paid attention to the multiple contemporaneous relationships, size of connectedness, strength and direction of time-varying spillovers, as well as periodicity and time-lags, among carbon, energy, metal and financial markets. Unlike most previous studies, this paper combines TVP-VAR-SV models along with DAG and C-Vine Copula analysis methods to comprehensively analyze the dynamic spillover effects, and net spillover effects in carbon, Brent Oil, UK Natural

Gas, Rotterdam Coal, Gold, Silver, Copper, and EuroStoxx600 future prices over the period from April 25, 2005 to December 30, 2022. The findings of our study shed new insight on the EU-ETS policy design and can be summarized as follow:

1) Long-term, stable, and multiple relationships among carbon, energy, metal, and financial markets do emerge. However, some short-term relationships are observed during different phases of the EU-ETS market. During Phase I, the trial period of EU-ETS, the carbon market is as a net receiver of shocks from oil, gas, coal, gold, silver, copper, and stock markets. Moving to Phase II, all the previous relationships persist, and a short-term relationship is observed between energy-stock and energy-metal markets. During the GFC, volatility in energy prices impacts metal mining, output and, consequently, the financial performance of firms (Pappas et al., 2023). In Phase III, in addition to the previously established relationships, short-term multiple relationships emerge between the pairs of markets energy-stock, metal-stock, and energy-metal, in accordance with Rodríguez (2019). This finding can be attributed to the high volatility in Brent oil prices, which increases the general price level and economic risk. This situation urges investors to seek a safe-haven against economic risks and high inflation (Cheng et al. 2022). Similar to Phase III, during the final phase of the EU-ETS market, all relationships remain consistent, except for the short-term link between metal-stock markets. In conclusion, our results suggest complex but consistent contemporaneous relationships among carbon, energy, financial, and metal markets across sub-periods. Understanding these intricate relationships across different phases of the EU-ETS market is crucial for carbon market participants, investors, and policymakers.
2) In this paper the degrees of connectedness among carbon, energy, metal and financial markets are unveiled and quantified. Our analysis based on C-Vine Copula models reveals that Brent oil prices are one of the significant driving factors of volatility transmissions within the carbon market during Phase I. The GFC triggers an increase in oil prices, which consequently leads to decreased output and increased demand for EUA. Additionally, we observe large co-movements between silver prices and carbon prices during this phase. In Phase II, the carbon market is more sensitive to stock prices, as well as to silver and coal prices, showing a response to changes in these three variables which is negative and positive, respectively. This result can be attributed to the GFC and the EDC, during which many firms either turn to use coal as an alternative fuel or scale down their activities. These findings are consistent with Ren et al. (2021), but contrast with the conclusions by Venmans (2015) on the positive correlation between stock and carbon market during the period 2008-2010. These apparently diverging views can be motivated

by differences in the data periods and methodologies. Moving on to Phase III, EUA prices are found to be positively correlated with stock and silver prices while their link to oil is negative, similar to Kim et al. (2021) and Chevallier et al. (2019). The negative correlation between energy and carbon markets can be attributed to the introduction of back-loading structural change in ETS, EU implementation of Green Energy policies, followed by the 2015 Paris Agreement, Brexit, COVID-19, and disruption in energy supply. In the final phase of our analysis, we find a positive correlation between carbon prices and both stock and copper prices. This change in the direction of the co-movements between coal and carbon markets is influenced by global economic recovery after COVID-19 and Russian-Ukraine conflict.

3) Significant volatility spillover effects are observed among the markets of carbon, oil, coal, silver, copper and stocks, while UK natural gas and gold markets show the lowest explanatory power for carbon prices. The time-varying spillover effects fluctuate fiercely between sub-periods, as noted in Wei et al. (2023). The carbon market is mostly a net receiver of volatility during the GFC and the Russian-Ukraine war, as suggested by Aslan and Posch (2022). Results document reasonable spillover effects between the carbon market and silver, stock, oil, and coal markets. The coal market presents a long-run higher spillover effect, reaching its maximum during Phase IV, in line, among others, with Wu et al. (2022), Yuan et al. (2021), Lin et al. (2021), Zhan and Sun (2016). Findings for Phase I of the EU-ETS point to the existence of volatility spillovers from the silver, stock, and oil market to carbon prices due to several unprecedent events, including supply disruption and increase in global energy demand. This aligns with the results of Chevallier et al. (2008). During Phase II, due to the GFC and the EDC, both the stock market and the coal market exhibit a high degree of volatility spillovers, consistent with Lovcha et al. (2019). Moving to Phase III, weak volatility spillover effects are observed among energy, metal, stock and carbon markets. Finally, EUA future prices react not only to coal prices but also to the copper and stock markets, because of the energy crisis and COVID-19. Regarding the duration of the time-varying spillover effects, we observe that the energy market, demonstrates a persisting shock effect during trading periods of the EU-ETS, lasting between 5 and 15 days, in line with Lin et al. (2021) and Hammoudeh et al. (2014).

Our findings have economic implications for investors, firms, and policy makers interested in predicting the evolution of carbon future prices. Our measures of causality direction, connectedness degree, and time-varying spillover transmissions among the markets can support policy makers in proposing more accurate policies to achieve the 2050 Net Zero Carbon goals. When policy makers design carbon market policies, they should consider the larger volatility spillover effects and risk transmissions from fossil energy, metal, and stock markets. Additionally, policy makers need to pay attention to the magnitude, the frequency, and the direction of shock transmissions to the carbon trading prices, due to its reactivity with fossil energy, metal, and financial markets. Investors, who have assets and derivatives in the EU carbon market in their own portfolios, should precisely monitor volatilities spillover mechanisms in the fossil energy markets, which are unstable, different at different timescales and conditions, in order to develop a more effective hedging strategy and reduce risk. Moreover, investors should be aware of the energy, metal, and financial markets relationships under different unprecedented events, such as GFC and COVID-19, if they wish to timely adjust their investment in the EU carbon market. Furthermore, it seems necessary to stay "tuned" about both short- and long-term trends in energy markets, which may impact the carbon prices. Firms, particularly high energy-intensive industrial companies, should optimize their carbon emissions reduction strategies by adapting their fossil energy consumption patterns in response to any change between fossil fuels markets and EUA. In the past, firms have forecasted carbon prices based on fossil fuel prices, including Brent oil, UK natural gas, and Rotterdam coal, to choose the best energy bundle. However, the EU-ETS affects predictions and marginal costs of fuel conservation. Therefore, firms should not postpone investments on clean-energy technologies facilitating the transition to lower-carbon production modes. For this aim, policies should integrate the dynamics of silver and copper markets to better predict carbon price fluctuations. Given their role in renewable energy, understanding the trends of these markets can help in designing more resilient carbon pricing mechanisms. Policymakers should promote investments in renewable energy technologies that rely on silver and copper. This support can stabilize demand for these metals and reduce volatility in carbon prices, facilitating the transition to a low-carbon economy.

Authors Statement

Parisa Pakrooh: Investigation, Conceptualization, Methodology, Data Curation, Formal Analysis, Writing, Editing

Matteo Manera: Conceptualization, Supervision, Writing, Review and Editing

Conflict of Interest

We declare that we have no known competing financial interest or personal relationships that could have appeared to influence the contents reported in this work.

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Figures and Tables

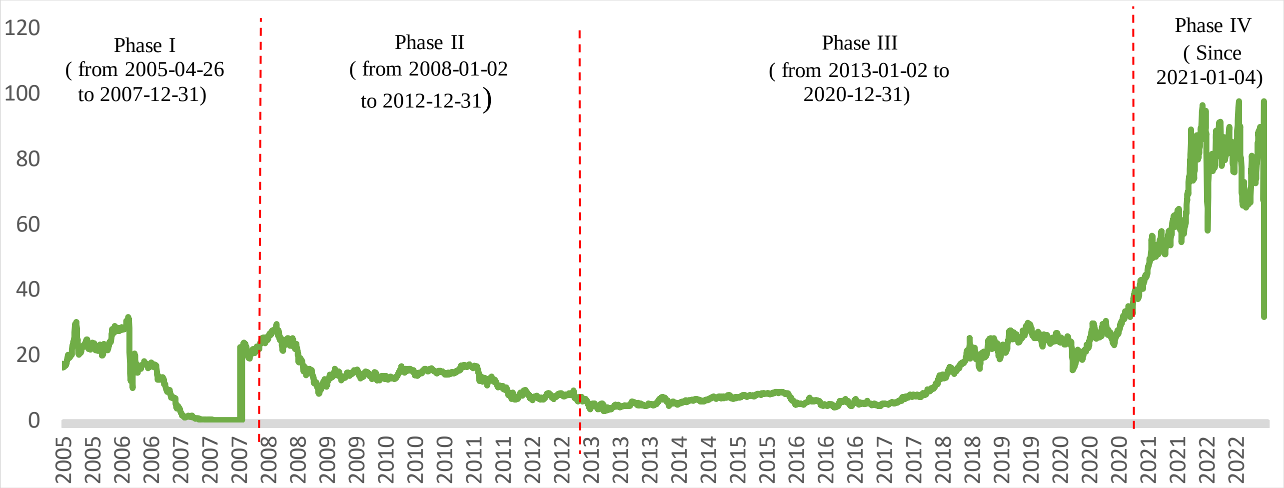


Figure 1. Daily EUA futures prices (€)
(Source: European Environment Agency, EEA 2023)

Table 1. Summary of the literature on linkage between/among energy-metal-financial-carbon markets

Author(s)	Methodology	Main Markets	Period	Major Findings
Wei et al, 2023	TVP-VAR-DY	EUA, MEI index, Brent Oil, Renewable Energy Stock	Monthly data from May 2005 to September 2021	The time-varying total connectedness varies significantly over time, with a focus on short-term.
Zoynul Abedin et al, 2023	Granger causality test, DCC, DY and BK	EUA, Oil, Coal, Gas, European, Shanghai Stock Exchange	Daily data from 16 December 2010 to 29 December 2022	Natural gas contributes the most to shocks, while the European stock exchange contributes the least.
Wu et al., 2022	GARCHSK and QVAR	EUA, Oil, Coal, Gas, Copper, Aluminum, Lead, Zinc, Nickel, Tin	Daily data from July 1, 2015 to February 28, 2022	Significant risk spillover exists among carbon, energy, and nonferrous metal markets, particularly with the coal market as the core of this system.
Liu et al, 2022	QVAR	EUA, Heating Oil, Gas, Brent Oil, Gold, Silver, Copper, Lead, Zinc, Aluminum, Nickel	Daily data from April 1, 2008 to October 29, 2021	The time-varying connectedness between energy, metal, and carbon markets varies over time.
Jiang and Chen., 2022	DY and BK	EUA, Gold, Silver, Copper, Aluminum, WTI Oil, Gas, Coal	From January 1st, 2014 to March 1st, 2022	Copper and silver, particularly copper, show strong explanatory power for carbon price fluctuations notably after the post-COVID-19 outbreak.
Aslan and Posch, 2022	DY	EUA, FTSEE300	From 1st of January 2013 to 1st of Jun 2022	During the recent European energy crisis, the EUA receives volatility from various sectors.
Salvador et al., 2021	VAR-DCC-GARCH	EUA, UK Gas, Brent Oil, Rotterdam Coal, SP Clean, Eurostoxx600	Monthly data from January 2010 to February 2021	The correlation between EUA and other return series is generally positive but weak.
Yuan et al., 2021	TVP-VAR	EUA, Brent Oil, Gas, Phlelix Electricity, STOXX600	Quarterly data from 2008 to 2018	The carbon price shows higher sensitivity to energy prices, along with stock prices in the short-term, while its response to stock price changes in the mid-to-long term.
Ren et al., 2021	QQ	EUA, Brent Oil, Rot. Coal, UK Gas	From 7 Jan 2013 to 30 March 2019	The energy prices reveal an asymmetric and negative impacts on carbon price, in which oil and coal prices indicate

				increasing effects across carbon quantiles.
Kim et al., 2021	VAR and Wavelet	EUA, Coal, Brent Oil, Electricity, ERIX, STOXX50	From January 1 2013 to December 31 2019	Coal and carbon prices share a negative correlation, while carbon and renewable energy stock prices have a positive correlation.
Adekoya et al., 2021	GFEVD, Causality test,	EUA, Crude Oil, Gas, Copper, Silver, Gold, S&P 500, US $	Weekly Data from October 2009 to October 2020	Except for copper and the U.S. currency markets, carbon prices are a net receiver of shocks from various other markets.
Lin et al., 2021	TVP-VAR-SV	EUA, Oil, Gas, Coal	From 1st January 2009 to 31st December 2018	The carbon market is significantly connected with fossil energy markets, particularly coal. Time-varying spillover effects last three weeks and weaken over time.
Xiao et al., 2021	BK	EUA, Brent Oil, Coal, Gas	From January 3 2013 to November 1 2019	There is a bidirectional spillover effects between carbon and energy markets in short-term, while the long-term effect is weak.
Zhao and Wang 2020	SEM	EUA, Brent Oil, Gas, CAC40, DAX, SP Clean, SP500	From February 2015 to January 2020	CAC40, oil, gas have a direct effect on EUA prices, while SP500 and SP clean imply an indirect effect on carbon markets.
Yoon and Lee., 2020	VAR and BEKK-GARCH	EUA, Brent Oil, Biofuels	From 23 October 2009 to 5 July 2020	Volatility spillover exists within the three markets, in which Brent oil showing a strong spillover impact
Rodríguez, 2019	Toda and Yamamoto Cointegration and Granger Causality Tests	EUA, CAC40, DAX, FTSE100, FTSE-MIB, IBEX	Daily data from April 1st, 2005 to December 15, 2015	The causality effect runs from the stock indices to the carbon market.
Lovcha et al., 2019	SVAR	EUA, Oil, Gas, Coal, Electricity, STOXX	Weekly data from 2008 to 2018	STOXX was a main driver of CO2 price fluctuations in the past, but its influence has diminished recently, while coal prices have experienced a contrasting trend.
Chen et al., 2019	Asymmetric BEKK	EUA, Brent Oil, Gas, Coal	From April 22, 2005 to July 17, 2018	A stable, positive correlation exists among EUA, Brent oil, and gas prices, while the EUA's correlation with natural gas and coal weakened and became more volatile after Phase II (particularly after GFC) and III.
Chevallier et al., 2019	ARCH, Vine Copula	EUA, Brent Oil, Gas, Coal, Switch Energy	From 1 January 2010 to 19 May 2016	Carbon prices have a weak correlation with energy prices, showing a negative association with oil and gas.
Dhamija et al., 2017	BEKK-MGARCH	EUA, Brent Oil, Coal, Gas	Daily data from 2005 to 2015	Significant volatility co-movement exists between the EUA and energy markets.
Zhang and Sun, 2016	VAR-DCC-GARCH and BEKK-GARCH	EUA, Coal, Natural Gas, Oil	From 2nd January 2008 to 30th September 2014	An unidirectional volatility spillover emerges from coal to the carbon, while no significant spillover is observed between the carbon and oil.
Venmans, 2015	MGARCH (BEKK-CCC-Diagonal)	EUA, Brent Oil, Gas, Coal, Electricity, StoxxEurope600	Daily data from 2008 to 2010	The carbon market is positively correlated to stock market.
Reboredo, 2014	MCARR	EUA, Brent Oil	Daily data from 2010 to 2014	There is volatility dynamics, leverage effects, and the absence of significant volatility spillovers between the markets.

Hammoudeh et al., 2014	BSVAR	EUA, Oil, Gas, Coal, Electricity	Both daily and monthly data from August 2006 to November 2013	There is a consistent impact between energy to carbon market.
Reboredo, 2013	Copula and ARMA-TGARCH	EUA, Brent Oil	From 3rd January 2008 to 7 September 2011	There is a positive and average symmetric independence between the markets, revealing no contagion effects.
Bataller and Keppler., 2010	Granger Causality test	CO2, Electricity, Coal, Gas, Eurostoxx600, Temperature	From January 2005 to December 2007	Coal and gas prices influence carbon market, subsequently causing Granger effects on electricity, while in the initial year, the direction reverses.
Chavallier et al., 2008	GARCH	EUA, Oil, Gas, Coal, Electricity, Weather Index	From 1st July 2005 to 30 April 2007	EUA respond to both energy prices' forecast errors and unexpected temperature fluctuations during colder events.

Table 2: EU-ETS phases and number of the observations

Trading Periods	Start	End	Number of OBS.
Phase I	2005/04/25	2007/12/31	680
Phase II	2008/01/02	2012/12/31	1285
Phase III	2013/01/02	2020/12/31	2051
Phase IV	2021/01/04	2022/12/30	515

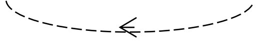
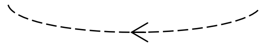
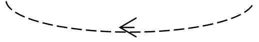
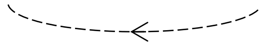
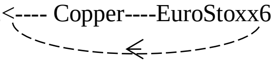
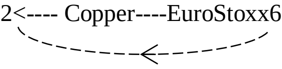
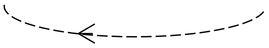
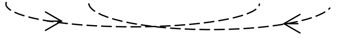
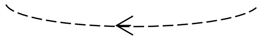
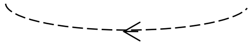
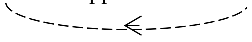
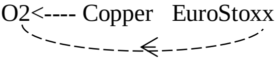
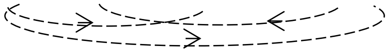
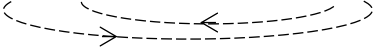
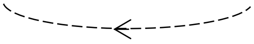
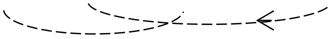
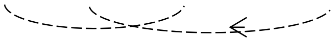
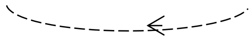
Table 3: Descriptive statistics of daily returns and volatility across the period

Panel A	Returns	OBS	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Shapiro Wilk
I	Carbon	680	0.015	13.67	-60.20	335.12	21.53	532.17	14.51[a]
	Oil	680	0.043	0.867	-2.42	2.91	-0.006	3.23	2.05[a]
	Gas	680	0.010	1.62	-6.47	10.86	0.68	7.42	7.25[a]
	Coal	380	0.010	0.58	-1.88	6.01	3.94	37.77	10.12[a]
	Gold	680	0.049	0.63	-3.42	2.48	-0.48	5.032	5.46[a]
	Silver	680	0.053	0.99	-6.09	3.85	-1.12	9.49	6.09[a]
	Copper	680	0.053	0.94	-3.61	4.83	-0.20	5.20	13.70[a]
	Stock	680	0.021	0.29	-1.15	1.23	-0.52	4.67	6.11[a]
II	Carbon	1285	-0.042	1.18	-5.57	8.76	0.033	7.043	8.57[a]
	Oil	1285	0.0007	1.16	-7.42	7.55	0.10	8.11	9.42[a]
	Gas	1285	-0.032	1.48	-4.37	11.51	0.92	7.82	9.02[a]
	Coal	1285	-0.015	0.91	-10.22	7.02	-1.73	26.33	12.91[a]
	Gold	1285	0.018	0.75	-2.79	4.29	0.03	5.56	7.84[a]
	Silver	1285	0.019	1.25	-8.36	5.92	-0.577	6.884	8.84[a]
	Copper	1285	0.002	1.11	-5.58	5.89	-0.093	5.291	7.32[a]
	Stock	1285	-0.008	3.44	-80.29	80.91	0.23	475.8	16.42[a]
III	Carbon	2051	0.034	1.46	-18.88	10.44	-1.09	20.70	12.15[a]
	Oil	2051	-0.017	1.38	-28.01	17.86	-3.21	109.90	15.24[a]
	Gas	2051	-0.007	1.31	-7.77	8.72	0.25	6.91	9.91[a]
	Coal	2051	-0.007	0.65	-7.87	7.44	0.39	38.93	14.61[a]
	Gold	2051	0.001	0.52	-4.51	2.62	-0.34	7.84	9.748[a]
	Silver	2051	-0.004	0.82	-5.66	3.39	-0.55	8.70	11.30 [a]
	Copper	2051	-0.002	0.58	-2.86	3.01	-0.09	4.69	7.68 [a]
	Stock	2051	0.007	0.38	-3.91	2.32	-1.42	17.25	12.47[a]
IV	Carbon	515	0.075	1.31	-7.69	7.03	-0.69	8.05	7.36[a]

	Oil	515	0.031	1.14	-5.59	3.86	-0.71	5.78	6.37^{a}
	Gas	515	0.036	1.94	-8.27	6.50	-0.36	4.37	4.40^{a}
	Coal	515	0.089	2.05	-23.75	13.80	-2.32	46.93	11.65^{a}
	Gold	515	-0.014	0.51	0.51	2.12	-0.20	5.24	5.46^{a}
	Silver	515	-0.019	0.91	-4.96	3.91	-0.19	7.19	6.79^{a}
	Copper	515	-0.004	0.77	-2.46	4.07	0.16	4.50	3.37^{a}
	Stock	515	0.005	0.37	0.37	1.30	-0.52	5.14	6.05^{a}
Panel B	Volatility	OBS	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Shapiro Wilk
I	Carbon	680	187.48	2969.33	0.632	77453.87	25.96	676.23	14.79^{a}
	Oil	680	0.749	0.109	0.651	1.546	3.184	16.823	12.01^{a}
	Gas	680	2.678	1.522	1.956	36.03	16.41	345.16	14.11^{a}
	Coal	380	0.531	1.732	0.116	40.22	19.29	419.77	14.55^{a}
	Gold	680	0.398	0.068	0.338	1.022	3.712	23.757	12.15^{a}
	Silver	680	0.993	0.714	0.556	11.73	8.541	105.07	13.70^{a}
	Copper	680	0.896	0.450	0.429	3.958	2.975	14.52	11.98^{a}
	Stock	680	0.080	0.034	0.053	0.388	4.917	34.613	13.07^{a}
II	Carbon	1285	1.435	1.262	0.682	29.40	10.79	201.86	15.40^{a}
	Oil	1285	1.444	1.084	0.678	18.07	9.85	128.52	15.67^{a}
	Gas	1285	2.229	0.693	1.756	11.36	6.24	59.97	15.10^{a}
	Coal	1285	1.099	2.832	0.231	75.84	17.33	405.2	16.22^{a}
	Gold	1285	0.555	0.203	0.324	2.74	5.33	42.67	14.71^{a}
	Silver	1285	1.624	0.725	0.877	11.10	5.31	6.72	14.65^{a}
	Copper	1285	1.239	0.756	0.661	11.56	46.52	68.71	15.12^{a}
	Stock	1285	4.443	8.729	0.233	194.6	18.64	385.06	16.26^{a}
III	Carbon	2051	2.178	2.162	0.643	43.69	9.21	128.32	16.77^{a}
	Oil	2051	1.807	10.44	0.331	350.95	26.66	790.12	17.93^{a}
	Gas	2051	1.826	1.487	0.793	25.85	7.12	76.66	16.66^{a}
	Coal	2051	0.748	3.489	0.101	82.94	16.47	322.33	17.74^{a}
	Gold	2051	0.279	0.122	0.160	2.155	5.33	52.91	15.84^{a}
	Silver	2051	0.655	0.206	0.479	3.450	7.18	71.67	16.68^{a}
	Copper	2051	0.347	0.098	0.259	1.567	3.90	28.03	15.46^{a}
	Stock	2051	0.140	0.183	0.056	4.355	14.10	261.70	17.41^{a}
IV	Carbon	515	1.673	1.235	0.853	17.839	7.35	81.24	12.62^{a}
	Oil	515	1.302	0.630	0.850	8.219	6.43	57.53	12.69^{a}
	Gas	515	3.775	1.177	1.966	14.750	3.85	25.67	11.49^{a}
	Coal	515	4.175	1.450	3.915	34.612	18.43	379.42	13.78^{a}
	Gold	515	0.244	0.071	0.166	0.671	2.55	11.48	10.85^{a}
	Silver	515	0.833	0.161	0.756	3.060	8.09	8.093	12.90^{a}
	Copper	515	0.610	0.214	0.480	4.109	9.78	143.90	12.80^{a}
	Stock	515	0.143	0.064	0.080	0.772	4.53	32.90	11.89^{a}

Notes: the superscript “a” indicates the 1% significance level.

Table 4: The contemporaneous causal relationships among Carbon-Energy-Financial-Metal markets

Phases	Markets	Causality Directions
I	CO2-Oil-Gold-EuroStoxx600	Oil---->CO2<---- Gold EuroStoxx600 
	CO2-Gas-Gold-EuroStoxx600	Gas---->CO2<---- Gold EuroStoxx600 
	CO2-Oil-Silver-EuroStoxx600	Oil---->CO2<---- Silver----EuroStoxx600 
	CO2-Gas-Silver-EuroStoxx600	Gas---->CO2<---- Silver----EuroStoxx600 
	CO2-Oil-Copper-EuroStoxx600	Oil---->CO2<---- Copper----EuroStoxx600 
	CO2-Gas-Copper-EuroStoxx600	Gas---->CO2<---- Copper----EuroStoxx600 
II	CO2-Oil-Gold-EuroStoxx600	Oil---->CO2<---- Gold EuroStoxx600 
	CO2-Gas-Gold-EuroStoxx600	Gas---->CO2<---- Gold EuroStoxx600 
	CO2-Coal-Gold-EuroStoxx600	Coal---->CO2<---- Gold EuroStoxx600 
	CO2-Oil-Silver-EuroStoxx600	Oil---->CO2<---- Silver EuroStoxx600 
	CO2-Gas-Silver-EuroStoxx600	Gas---->CO2<---- Silver EuroStoxx600 
	CO2-Coal-Silver-EuroStoxx600	Coal---->CO2<---- Silver EuroStoxx600 
	CO2-Oil-Copper-EuroStoxx600	Oil---->CO2<---- Copper EuroStoxx600 
	CO2-Gas- Copper -EuroStoxx600	Gas---->CO2<---- Copper EuroStoxx600 
	CO2-Coal- Copper -EuroStoxx600	Coal---->CO2<---- Copper EuroStoxx600 
III	CO2-Oil-Gold-EuroStoxx600	Oil--->CO2<--- Gold--->EuroStoxx600 
	CO2-Gas-Gold-EuroStoxx600	Gas--->CO2<---Gold--->EuroStoxx500 
	CO2-Coal-Gold-EuroStoxx600	Coal-->CO2<--Gold--> EuroStoxx600 
	CO2-Oil-Silver-EuroStoxx600	Oil--->CO2<--- Silver --- EuroStoxx600 
	CO2-Gas-Silver-EuroStoxx600	Gas--->CO2<--- Silver --- EuroStoxx600 
	CO2-Coal-Silver-EuroStoxx600	Coal--->CO2<--- Silver --- EuroStoxx600 

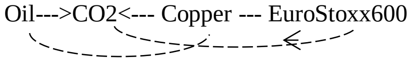
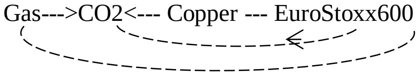
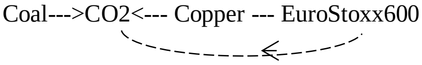
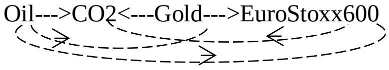
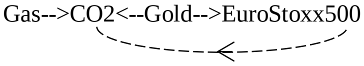
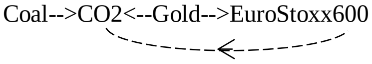
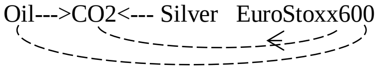
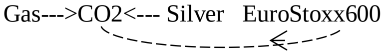
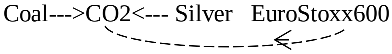
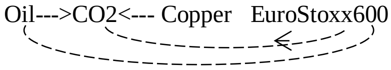
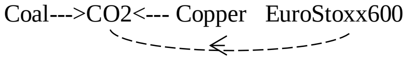
	CO2-Oil-Copper-EuroStoxx600	 Oil--->CO2<--- Copper --- EuroStoxx600
	CO2-Gas- Copper -EuroStoxx600	 Gas--->CO2<--- Copper --- EuroStoxx600
	CO2-Coal- Copper -EuroStoxx600	 Coal--->CO2<--- Copper --- EuroStoxx600
IV	CO2-Oil-Gold-EuroStoxx600	 Oil--->CO2<---Gold--->EuroStoxx600
	CO2-Gas-Gold-EuroStoxx600	 Gas-->CO2<--Gold-->EuroStoxx500
	CO2-Coal-Gold-EuroStoxx600	 Coal-->CO2<--Gold-->EuroStoxx600
	CO2-Oil-Silver-EuroStoxx600	 Oil--->CO2<--- Silver EuroStoxx600
	CO2-Gas-Silver-EuroStoxx600	 Gas--->CO2<--- Silver EuroStoxx600
	CO2-Coal-Silver-EuroStoxx600	 Coal--->CO2<--- Silver EuroStoxx600
	CO2-Oil-Copper-EuroStoxx600	 Oil--->CO2<--- Copper EuroStoxx600
	CO2-Gas- Copper -EuroStoxx600	 Gas--->CO2<--- Copper EuroStoxx600
	CO2-Coal- Copper -EuroStoxx600	 Coal--->CO2<--- Copper EuroStoxx600

Table 5: Results for the C-Vine Copula models

Phases	Markets	Tree, Edge	Family	P1	P2	Kendall's Tau
I	CO2-Oil-Gold-EuroStoxx600	(CO2-Oil)	Rotated-Tawn Type 1, 90^0	-2.07	0.42	-0.27
		(CO2-Gold)	Gaussian	0.08	-	0.05
		(CO2-EuroStoxx600)	Frank	0.7	-	0.08
	CO2-Gas-Gold-EuroStoxx600	(CO2-Gas)	Rotated-Tawn Type 2, 180^0	1.24	0.17	0.06
		(CO2-Gold)	Rotated BB8, 270^0	-1.21	-0.85	-0.05
		(CO2-EuroStoxx600)	Frank	0.7	-	0.08
	CO2-Oil-Silver-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 90^0	-2.07	0.42	**-0.27**
		(CO2-Silver)	Tawn type 2	1.87	0.32	**0.20**
		(CO2-EuroStoxx600)	Frank	0.7	-	**0.08**
	CO2-Gas-Silver-EuroStoxx600	(CO2-Gas)	214, Rotated-Tawn Type 2, 180^0	1.24	0.17	0.06
		(CO2-Silver)	Tawn type 2	1.87	0.32	0.20
		(CO2-EuroStoxx600)	Frank	0.7	-	0.08
	CO2-Oil-Copper-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 90^0	-2.07	0.42	-0.27
		(CO2-Copper)	Rotated Tawn type 1, 90^0	-2.02	0.03	-0.03
		(CO2-EuroStoxx600)	Frank	0.7	-	0.08
	CO2-Gas-Copper-EuroStoxx600	(CO2-Gas)	214, Rotated-Tawn Type 2, 180^0	1.24	0.17	0.06
		(CO2-Copper)	Rotated Tawn type 1, 90^0	-2.02	0.03	-0.03
		(CO2-EuroStoxx600)	Frank	0.7	-	0.08
II	CO2-Oil-Gold-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 180 degree	1.57	0.05	0.04
		(CO2-Gold)	Rotated Tawn type 2, 180 degree	1.35	0.04	0.02
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Gas-Gold-EuroStoxx600	(CO2-Gas)	Survival Joe	1.06	-	0.03
		(CO2-Gold)	Rotated Tawn type 2, 180^0	1.35	0.04	0.02
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Coal-Gold-EuroStoxx600	(CO2-Coal)	Survival BB8	1.36	0.96	0.14
		(CO2-Gold)	Rotated Tawn type 2, 180^0	1.35	0.04	0.02

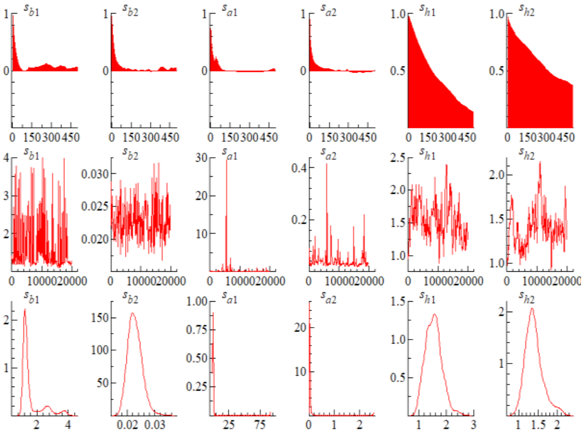
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Oil-Silver-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 180^0	1.57	0.05	0.04
		(CO2-Silver)	Survival BB8	1.32	0.98	0.14
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Gas-Silver-EuroStoxx600	(CO2-Gas)	Survival Joe	1.06	0	0.03
		(CO2-Silver)	Survival BB8	1.32	0.98	0.14
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Coal-Silver-EuroStoxx600	(CO2-Coal)	Survival BB8	1.36	0.96	**0.14**
		(CO2-Silver)	Survival BB8	1.32	0.98	**0.14**
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	**-0.17**
	CO2-Oil-Copper-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 180^0	1.57	0.05	0.04
		(CO2-Copper)	Rotated Tawn type 1, 180^0	1.88	0.02	0.01
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Gas-Copper-EuroStoxx600	(CO2-Gas)	Survival Joe	1.06	0	0.03
		(CO2- Copper)	Rotated Tawn type 1, 180^0	1.88	0.02	0.01
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
	CO2-Coal-Copper-EuroStoxx600	(CO2-Coal)	Survival BB8	1.36	0.96	0.14
		(CO2- Copper)	Rotated Tawn type 1, 180^0	1.88	0.02	0.01
		(CO2-EuroStoxx600)	Rotated Tawn type 1, 90^0	-2.41	0.21	-0.17
III	CO2-Oil-Gold-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 90^0	-1.38	0.22	-0.10
		(CO2-Gold)	Survival Clayton	0.05	-	0.02
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Gas-Gold-EuroStoxx600	(CO2-Gas)	Rotated Tawn type 2, 270^0	-1.56	0.09	-0.06
		(CO2-Gold)	Survival Clayton	0.05	-	0.02
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Coal-Gold-EuroStoxx600	(CO2-Coal)	Rotated Tawn type 1, 90^0	-1.69	0.14	-0.10
		(CO2-Gold)	Survival Clayton	0.05	-	0.02
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Oil-Silver-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 90^0	-1.38	0.22	**-0.10**
		(CO2-Silver)	Survival BB8	3.88	0.43	**0.19**
		(CO2-EuroStoxx600)	t	0.36	3.13	**0.23**
	CO2-Gas- Silver -EuroStoxx600	(CO2-Gas)	Rotated Tawn type 2, 270^0	-1.56	0.09	-0.06
		(CO2-Silver)	Survival BB8	3.88	0.43	0.19
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Coal- Silver -EuroStoxx600	(CO2-Coal)	Rotated Tawn type 1, 90^0	-1.69	0.14	-0.10
		(CO2-Silver)	Survival BB8	3.88	0.43	0.19
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Oil-Copper-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 1, 90^0	-1.38	0.22	-0.10
		(CO2-Copper)	Rotated Tawn type 1, 180^0	1.37	0.07	0.04
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Gas-Copper-EuroStoxx600	(CO2-Gas)	Rotated Tawn type 2, 270^0	-1.56	0.09	-0.06
		(CO2-Copper)	Rotated Tawn type 1, 180^0	1.37	0.07	0.04
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
	CO2-Coal-Copper-EuroStoxx600	(CO2-Coal)	Rotated Tawn type 1, 90^0	-1.69	0.14	-0.10
		(CO2-Copper)	Rotated Tawn type 1, 180^0	1.37	0.07	0.04
		(CO2-EuroStoxx600)	t	0.36	3.13	0.23
IV	CO2-Oil-Gold-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 2, 270^0	-1.51	0.06	-0.04
		(CO2-Gold)	Gaussian	0.1	-	0.06
		(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
	CO2-Gas-Gold-EuroStoxx600	(CO2-Gas)	Rotated Tawn type 2, 90^0	-2.27	0.07	-0.07
		(CO2-Gold)	Gaussian	0.10	-	0.06
		(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
	CO2-Coal-Gold-EuroStoxx600	(CO2-Coal)	Rotated Tawn type 2, 180^0	1.59	0.16	0.10
		(CO2-Gold)	Gaussian	0.10	-	0.06
		(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
	CO2-Oil-Silver-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 2, 270^0	-1.51	0.06	-0.04
		(CO2-Silver)	Survival Clayton	0.03	0	0.02
		(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
	CO2-Gas- Silver -EuroStoxx600	(CO2-Gas)	Rotated Tawn type 2, 90^0	-2.27	0.07	-0.07
		(CO2-Silver)	Survival Clayton	0.03	0	0.02
		(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
	CO2-Coal- Silver -EuroStoxx600	(CO2-Coal)	Rotated Tawn type 2, 180^0	1.59	0.16	0.10
		(CO2-Silver)	Survival Clayton	0.03	0	0.02
		(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
	CO2-Oil-Copper-EuroStoxx600	(CO2-Oil)	Rotated Tawn type 2, 270^0	-1.51	0.06	-0.04

	(CO2-Copper)	Rotated Tawn type 1, 180^0	3.06	0.33	0.27
	(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
CO2-Gas-Copper-EuroStoxx600	(CO2-Gas)	Rotated Tawn type 2, 90^0	-2.27	0.07	-0.07
	(CO2-Copper)	Rotated Tawn type 1, 180^0	3.06	0.33	0.27
	(CO2-EuroStoxx600)	BB7	1.03	0.33	0.16
CO2-Coal-Copper-EuroStoxx600	(CO2-Coal)	Rotated Tawn type 2, 180^0	1.59	0.16	**0.10**
	(CO2-Copper)	Rotated Tawn type 1, 180^0	3.06	0.33	**0.27**
	(CO2-EuroStoxx600)	BB7	1.03	0.33	**0.16**

Table 6: Time-interval impulse response and time-point impulse response results

Phase	Sample Autocorrelations (top), Paths (middle), and Posterior Densities (bottom) of case (CO2-Oil-Silver-EuroStoxx600)	Estimation Results (α,β,h) of case (CO2-Oil-Silver-EuroStoxx600)

I

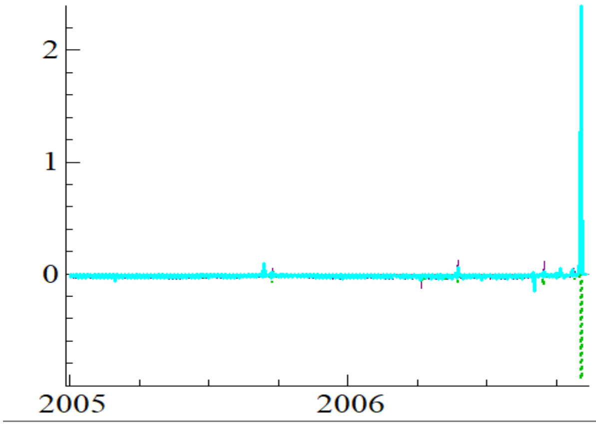


CO2-Oil-Silver-EuroStoxx600

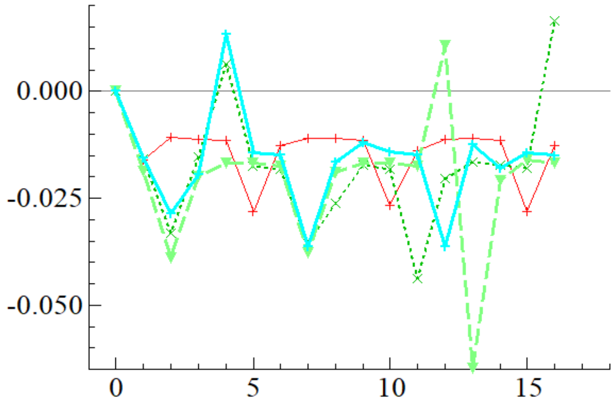
Parameter	Mean (stdev)	Interval [95%L-95%U]	Geweke	Inef.
Sb1	1.61 (0.6954)	[1.1344-3.7114]	0.030	52.36
Sb2	0.02 (0.0026)	[0.0183-0.0284]	0.613	45.81
Sa1	0.22 (1.4327)	[0.0210-1.3220]	0.049	33.49
Sa2	0.04 (0.0565)	[0.0206-0.1376]	0.537	37.02
Sh1	1.53 (0.2995)	[1.0100-2.1661]	0.982	245.65
Sh2	1.39 (0.2304)	[1.0212-1.9837]	0.907	279.51

*The posterior mean value should be within the 95% of confidence interval.
*Geweke value is the convergence value of the parameters does not exceed the critical values of 1.96 at 5% significance level.
*The inefficiency factor measures the effectiveness of sampling, or the number of uncorrelated samples.

Time impulse graph[1] of ↑ ε $Oil \rightarrow CO2$



Time-point impulse graph[2] of ↑ ε $Oil \rightarrow CO2$



Time impulse graph of ↑ ε $Silver \rightarrow CO2$

Time impulse graph of ↑ ε $EuroStoxx600 \rightarrow CO2$

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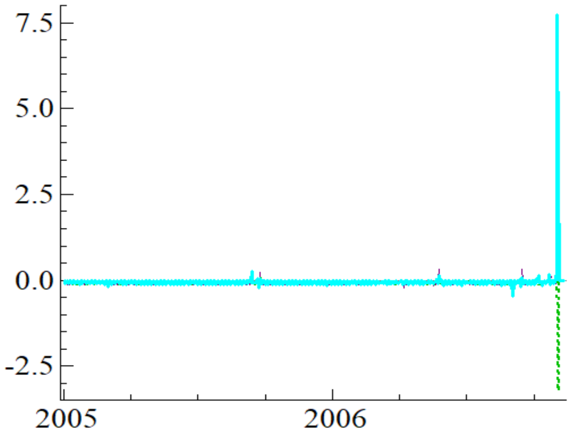
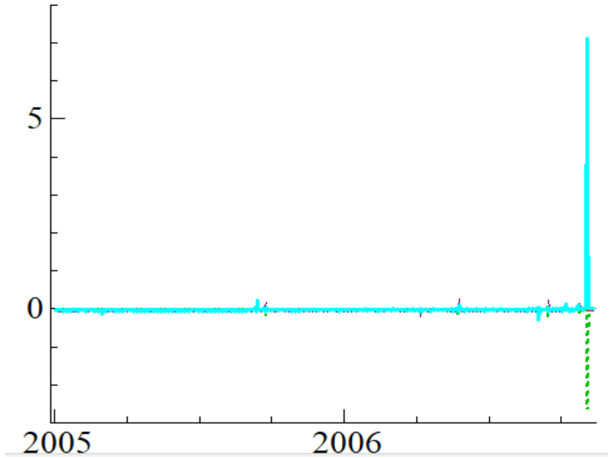
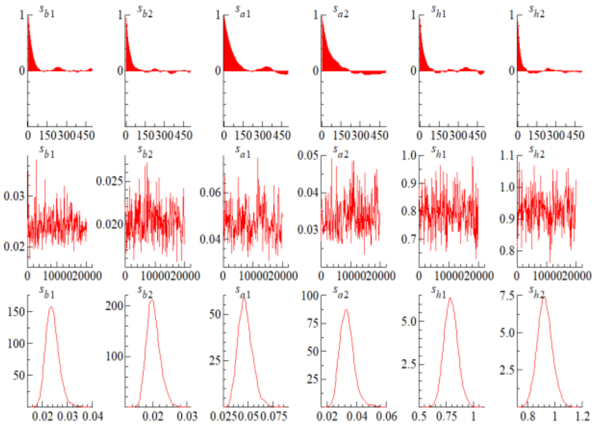
[1] Time impulse graph, response of CO2 to key factors (i.e. multiple market combinations with the highest degree of connection with the carbon market) for 1 (red thin solid line), 2 (purple dashed line), 3 (green spot line), and 4 (blue thick solid line) days ahead. ↑ε indicates a unit-standard deviation positive shock to the volatility of the carbon price.

[2] Time-point impulse graph, response of CO2 to structural break time of key factors (i.e. multiple market combinations with the highest degree of connection with the carbon market). ↑ε indicates a unit-standard deviation positive shock to the volatility of the carbon price.





Phase	Sample Autocorrelations (top), Paths (middle), and Posterior Densities (bottom) of case (CO2-Coal-Silver-EuroStoxx600)	Estimation Results (α,β,h) of case (CO2-Coal-Silver-EuroStoxx600)



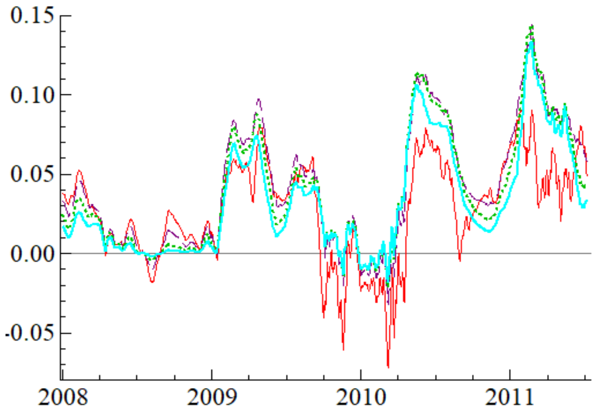
CO2-Coal-Silver-EuroStoxx600

Parameter	Mean (stdev)	Interval [95%L-95%U]	Geweke	Inef.
Sb1	0.02 (0.0026)	[0.0195-0.0298]	0.705	52.98
Sb2	0.02 (0.0020)	[0.0168-0.0245]	0.646	49.89
Sa1	0.04 (0.0073)	[0.0344-0.0634]	0.550	102.66
Sa2	0.03 (0.0049)	[0.0255-0.0447]	0.009	99.38
Sh1	0.79 (0.0624)	[0.6773-0.9236]	0.369	48.43
Sh2	0.92 (0.0550)	[0.8212-1.0395]	0.519	29.04

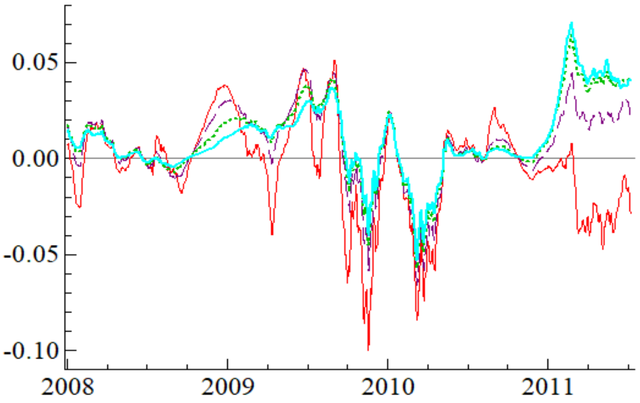
*The posterior mean value should be within the 95% of confidence interval.
*Geweke value is the convergence value of the parameters does not exceed the critical values of 1.96 at 5% significance level.
*The inefficiency factor measures the effectiveness of sampling, or the number of uncorrelated samples.

II

Time impulse graph of ↑ ε $Coal \rightarrow CO2$

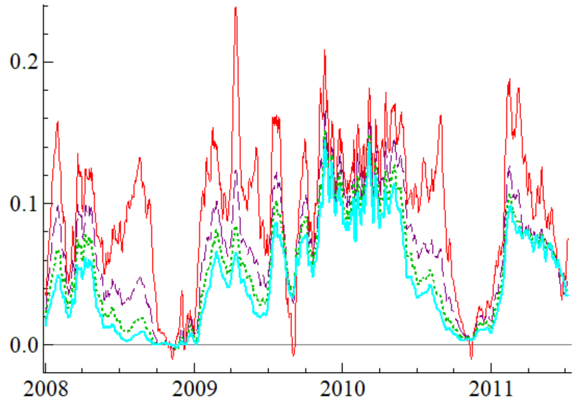


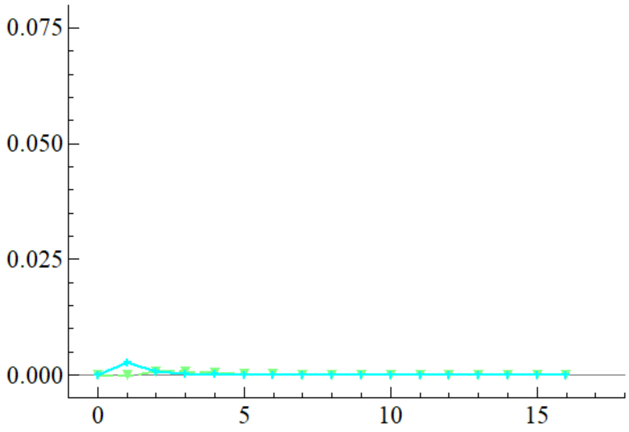
Time impulse graph of ↑ ε $Silver \rightarrow CO2$



Time impulse graph of ↑ ε $EuroStoxx600 \rightarrow CO2$

Time-point impulse graph of ↑ ε $EuroStoxx600 \rightarrow CO2$

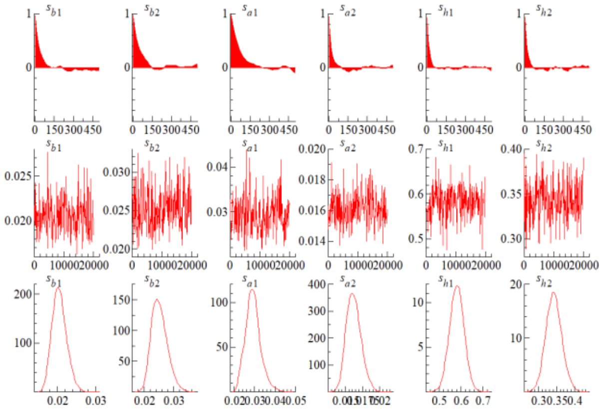




Phase

Sample Autocorrelations (top),
Paths (middle), and Posterior Densities (bottom) of
case (CO2-Oil-Silver-EuroStoxx600)

Estimation Results (α,β,h) of case
(CO2-Oil-Silver-EuroStoxx600)



CO2-Oil-Silver-EuroStoxx600

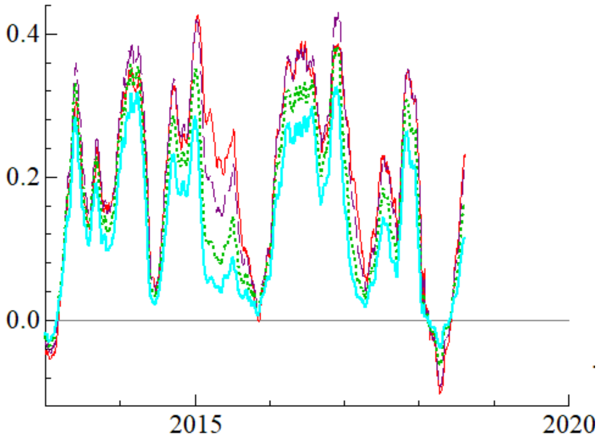
Parameter	Mean (stdev)	Interval [95%L-95%U]	Geweke	Inef.
Sb1	0.02 (0.0019)	[0.0172-0.0246]	0.404	60.55
Sb2	0.02 (0.0027)	[0.0207-0.0310]	0.072	85.10
Sa1	0.02 (0.0038)	[0.0226-0.0378]	0.888	107.89
Sa2	0.01 (0.0011)	[0.0144-0.0185]	0.922	31.58
Sh1	0.58 (0.0332)	[0.5163-0.6463]	0.302	29.75
Sh2	0.34 (0.0217)	[0.3003-0.3870]	0.150	27.76

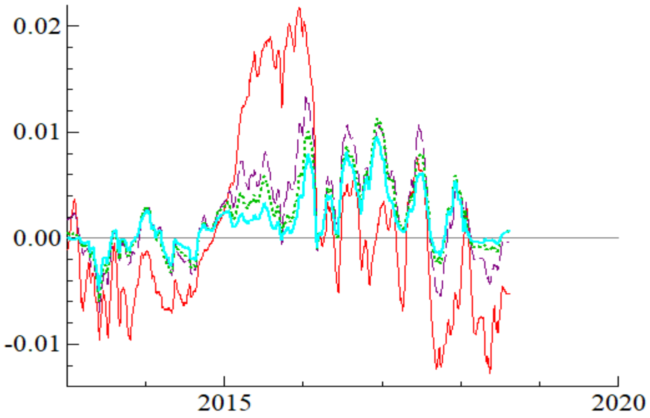
*The posterior mean value should be within the 95% of confidence interval.
*Geweke value is the convergence value of the parameters does not exceed the critical values of 1.96 at 5% significance level.
*The inefficiency factor measures the effectiveness of sampling, or the number of uncorrelated samples.

Time impulse graph of $\uparrow \varepsilon\ Oil \rightarrow CO2$

Time impulse graph of $\uparrow \varepsilon\ Silver \rightarrow CO2$

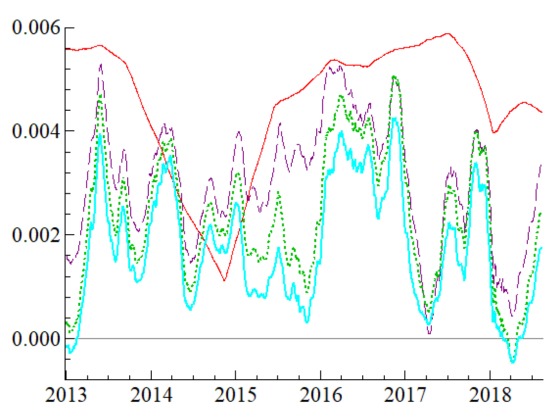
III

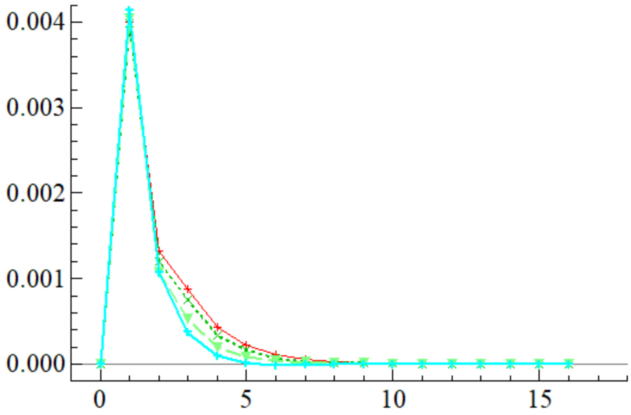




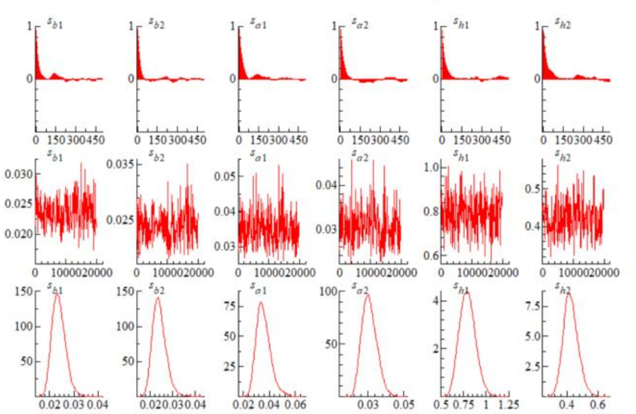
Time impulse graph of $\uparrow \varepsilon\ EuroStoxx600 \rightarrow CO2$

Time-point impulse graph of $\uparrow \varepsilon\ EuroStoxx600 \rightarrow CO2$





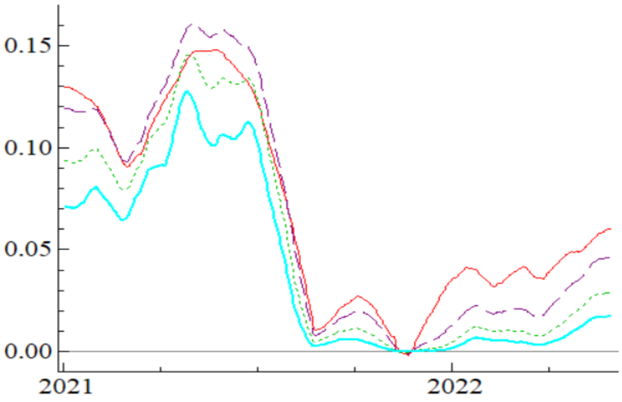
p

Phase	Sample Autocorrelations (top), Paths (middle), and Posterior Densities (bottom) of case (CO2-Coal-Copper-EuroStoxx600)	Estimation Results (α,β,h) of case (CO2-Coal-Copper-EuroStoxx600)
IV		CO2-Coal-Copper-EuroStoxx600

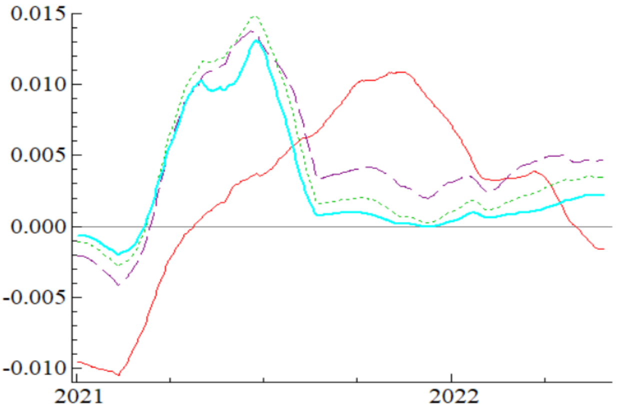
Parameter	Mean (stdev)	Interval [95%L-95%U]	Geweke	Inef.
Sb1	0.02 (0.0028)	[0.0191-0.0299]	0.300	36.55
Sb2	0.02 (0.0030)	[0.0190-0.0308]	0.607	26.10
Sa1	0.03 (0.0055)	[0.0266-0.0485]	0.472	51.36
Sa2	0.03 (0.0041)	[0.0236-0.0395]	0.124	33.98
Sh1	0.79 (0.0879)	[0.6349-0.9756]	0.282	45.17
Sh2	0.42 (0.0473)	[0.3395-0.5253]	0.789	51.03

*The posterior mean value should be within the 95% of confidence interval.
*Geweke value is the convergence value of the parameters does not exceed the critical values of 1.96 at 5% significance level.
*The inefficiency factor measures the effectiveness of sampling, or the number of uncorrelated samples.

Time impulse graph of ↑ ε $Coal \rightarrow CO2$

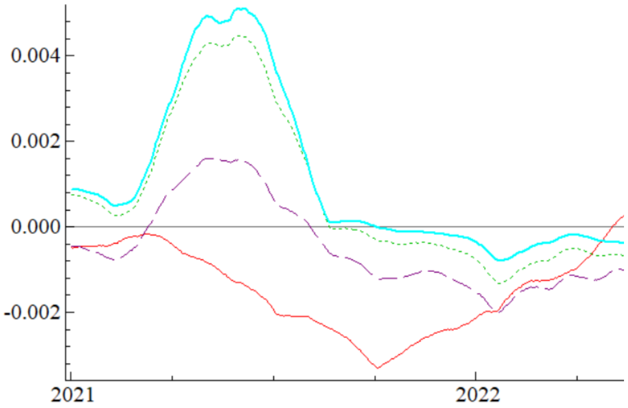


Time impulse graph of ↑ ε $Copper \rightarrow CO2$



Time impulse graph of ↑ ε $EuroStoxx600 \rightarrow CO2$

Time-point impulse graph of ↑ ε $Copper \rightarrow CO2$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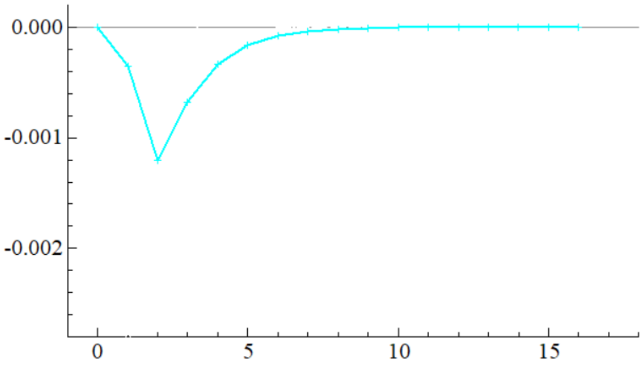
0.002
0.000
-0.002
2021
2022


0.000
-0.001
-0.002
0
5
10
15

Online Appendix

A. Methodology

Returns

As in many other studies in this area (see, e.g., Chen et al., 2021; Lin et al., 2021; Bouri and Kamal, 2023; Abedin et al., 2023), all price variables are transformed (see Eq(A.1)) using natural logarithms, where p_t refers to price at time t and r_t is the returns at time t:

$$r_t = log\left(\frac{p_t}{p_t - 1}\right) \tag{A.1}$$

Volatilities

The GARCH model introduced by Bollerslev (1986) as a generalized version of the ARCH aims at describing volatility associated with financial time-series data. The basic structure of a GARCH(p,q) model is as Eq(A.2).

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{A.2}$$

where ε_t is the error term of the mean equation for returns r_t from Eq(A.1), σ_t^2 is the conditional variance of ε_t, α_0, α_j, and β_j are the model parameters that should satisfy stationary conditions (i.e. be non-negative and cumulatively sum to a value below 1). Notice that p and q are the lag orders of variance σ_t^2 and squared errors ε_t^2 in the GARCH(p,q) (Rodríguez and Hernández, 2021; Aras, 2021; Jung et al. 2021).

Unit-Root Tests

To ascertain the presence of a unit-root in the time-series, the Augmented Dickey-Fuller (ADF) test is used, along with Philips-Perron (PP), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Zivot-Andrews (ZA) tests. The null hypothesis of all tests, except for KPSS, is stationarity (a formal definition of stationarity can be found in Zhu et al., 2019). In order to facilitate a comparison of the performance of the adopted unit-root tests, we have produced Table A.1, where pros and cons of each test are highlighted.

Table A.1: Performance comparison of the unit-root tests

Tests	Merits	Demerits	Suggestion
ADF	1) Reliable for long time-series length	1) Calculates low power for a shorter time-series length	1) Reliable for apt selection of lag number
KPSS	1) A non-parametric test 2) Outcome imply stationary if the series is strongly stationary	1) The test statistic is vulnerable to type-I errors	1) Reliable for short time-series length and recommend to be used along with another test, including ADF and PP
PP	1) Reliable for long time-series length 2) A non-parametric test	1) Low reliability for short and moderately longer time series length	1) Reliable for long time series length

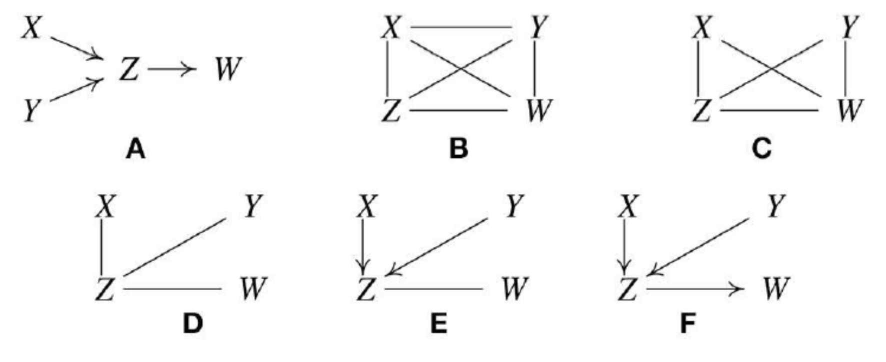
ZA	1) Utilizes the full sample 2) Uses a different dummy variable for each possible break date	1) Assumes a linear dynamic structure over time 2) The test statistic is vulnerable to type-I errors	1) Reliable for long time series length

Sources: Saadi and Rahman (2008); Nelson et al. (2001)

Directed Acyclic Graphs (DAG)

Causation can informally be defined as the connection between two variables, X and Y, where changes in X leads to changes in Y. The main difference between association and causation stands on the issue of confounding. Assume that there is no direct causal link between X and Y, but a third variable Z causes both X and Y. In this way, despite a strong association between X and Y, a change in X will not result in changes to Y, hence Z is called as a confounder. Formally, causation refers to a direct effect between variables X and Y, persisting after accounting for confounding. Confounding can be either observed or unobserved (latent) (Shen et al. 2020). In many previous studies, Granger (1969) causality has been utilized to explore causal relationships among variables. However, this approach may not reveal the true causal relationship. Pearl (2000), Spirtes et al. (2000), and Demiralp and Hoover (2003), among others, have introduced the Directed Acyclic Graph (DAG) technique to identify contemporaneous causal relationships among economic variables. DAGs offer an elegant visual representation of directional or causal connections among nodes. These structures find applications in diverse domains, including energy and environmental economics (Zhang et al., 2021; Rafei and Esmaeili, 2021; Bhatti et al., 2022(a)).

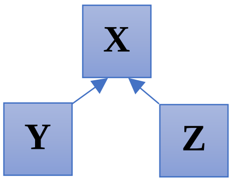
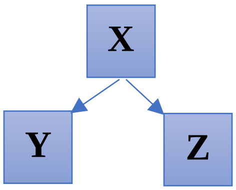
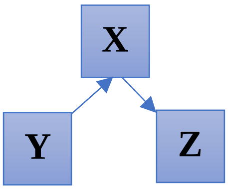
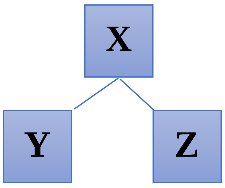
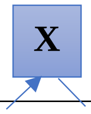
Generally, DAG analysis uses graphs to illustrate contemporaneous causal relationships among variables. Arrows in the graph indicate causal connections between variables. The development of Directed Acyclic Graph (DAG) analysis provides an effective tool for examining contemporaneous relationships among N variables without loops, consisting of variable nodes connected by directed edges (He et al., 2022). For instance, $X \rightarrow Y$ ($X \leftarrow Y$) implies a unidirectional contemporaneous causality from X to Y (from Y to X). $X \leftrightarrow Y$ shows bidirectional contemporaneous causality between X and Y, while $X - Y$ indicates uncertain directional contemporaneous causality. $X\ Y$ suggests the absence of contemporaneous causality between X and Y (Qi et al., 2020; Shen et al., 2020; Bhatti et al., 2022). The Tetrad program offers numerous algorithms for directed graph analysis. The core idea behind constraint-based causal discovery algorithms is that distinct causal structures imply different independence relationships. Peter and Clark (PC)'s causality algorithm, introduced by Spirtes et al. (2000) as the Graph Theoretic Approach (GTA), provides a statistical and mathematical method to identify causality in observational data (see Figure A.1). Initially, this algorithm connects variables with directionless edges, then utilizes correlation tests to remove edges without correlations (zero-order) or with high-order partial correlations. The algorithm, based on this approach, eliminates edges between variables with a zero-conditional correlation from the first order. If there are *N* variables, the PC max algorithm assesses conditional correlations up to the *N-2* order between variables (Bouri et al., 2018; Qi et al., 2020; Bhatti et al., 2022(a); Bhatti et al., 2022(b)). In Table A.2, we present a comprehensive example of all possible graphs with interpretations for three variables.

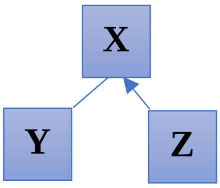
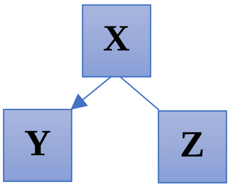
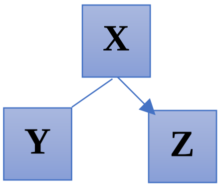


A) Primary causal graph, B) PC max algorithm starts to modify the graph, C) The *X*→*Y* edge is removed due to loop, D) Both *X*→*W* and *Y*→*W* edges are removed due to loop, E) After finding structures among variables, F) Final causal graph, after orientation dissemination

Figure A.1. Visualization of how PC max algorithm works in DAG
Source: Zhang et al. (2019).

Table A.2: The contemporaneous causal relationships among 3 variables in the DAG analysis

All Possible Graphs	Interpretation of graph output
	There are edges connecting *Y* and *Z* to *X*. *Y* and *Z* cause *X*. There are two contemporaneous causal relationships *Y*→*X* and *Z*→*X*.
	There are edges connecting *X* to *Y* and *Z*. *X* causes both *Y* and *Z*. There are two contemporaneous causal relationships *X*→*Y* and *X*→*Z*.
	There are edges connecting *Y* to *X* and *X* to *Z*. *X* causes *Z* and *Y* causes *X*. There are two contemporaneous causal relationships *Y*→*X* and *X*→*Z*.
	*X* causes both *Y* and *Z*. Both *Y* and *Z* cause *X*. *X* causes both *Y* and *Z*. There is causal relationship between variables but we cannot determine the direction of the relationship.
	There is an edge connecting *Y* to *X*. *Y* causes *X*. *X* causes *Z*. *Z* causes *X*. There is contemporaneous causal relationship *Y*→*X*.

	There is a causal relationship between *X* and *Z* but we cannot determine the direction of the relationship.
	There is an edge connecting *Z* to *X*. *Z* causes *X*. *Y* causes *X*. *X* causes *Y*. There is contemporaneous causal relationship *Z*→*X*. There is causal relationship *Y*→*X*, but we cannot determine the direction of the relationship.
	There is an edge connecting *X* to *Y*. *Z* causes *X*. *X* causes *Y*. *X* causes *Z*. There is contemporaneous causal relationship *X*→*Y*. There is causal relationship *X*→*Z*, but we cannot determine the direction of the relationship.
	There is an edge connecting *X* to *Z*. *Y* causes *X*. *X* causes *Y*. *X* causes *Z*. There is contemporaneous causal relationship *X*→*Z*. There is causal relationship *Z*→*Y*, but we cannot determine the direction of the relationship.

Sources: references in Section 3.4, and Tetrad 7.1.2 program user's guide.

Canonical Vine (C-Vine) Copulas

Numerous tools have been introduced for measuring dependencies between variables. Recent studies (Tarantola et al., 2018; Chevallier et al., 2019; Pishbahar et al., 2019; Zhou et al., 2020; Ma, 2021; Tan et al., 2022; Man et al., 2023; Ghazani et al., 2023) have proved that copulas have several merits, which include high flexibility in modeling and estimating marginal distributions, constancy under uniform transformations, and representation of the structure of dependencies (Pishbahar et al., 2019).

Formally, if (X_1, X_2, …, X_d) is a d-dimensional random vector and the marginal Cumulative Distribution Functions (CDF) $F_i(x_i) = P(X_i<x_i)$, i=1,…,d, are continuous, then the random vector

$$(U_1, U_2, ..., U_d) = (F_1(x_1), F_2(x_2), ..., F_d(x_d))$$

has marginals that are uniformly distributed on the interval [0,1].

The copula of $(X_1, X_2, ..., X_d)$, $C(.)$, is the joint CDF of $(U_1, U_2, ..., U_d)$, that is:

$$C(U_1, U_2, ..., U_d) = P(U_1\leq u_1;\ U_2\leq u_2;\ ...;\ U_d\leq u_d) = P(X_1\leq F_1^{-1}(u_1);\ X_2\leq F_2^{-1}(u_2);\ ...;\ X_d\leq F_d^{-1}(u_d)) \quad \text{(A.3)}$$

In Eq(A.3), the copula $C(.)$ contains all information on the dependence structure between the components $(X_1, X_2, ..., X_d)$, while the marginal CDFs $F_i(.)$ contain all information on the marginal distributions of X_i.

Sklar (1959)'s theorem shows that every multivariate CDF $H(x_1, x_2, ..., x_d) = P(X_1 \leq x_1, X_2 \leq x_2, ..., X_d \leq x_d)$ of a random vector $(X_1, X_2, ..., X_d)$ can be expressed in terms of its marginals and a copula $C(.)$, that is:

$$H(x_1, x_2, ..., x_d) = C(F_1(x_1), F_2(x_2), ..., F_d(x_d))$$

and

$$h(x_1, x_2, ..., x_d) = c(F_1(x_1), F_2(x_2), ..., F_d(x_d))\, f_1(x_1)\, f_2(x_2) \,....\, f_d(x_d) \tag{A.4}$$

By assuming that the marginals and copula function are distinguishable, Eq(A.4) is the density representation of $C(.)$. Specifically, $f_i(x_i)$, i=1,…,d, are the marginal densities and $c(.\ )$ is the copula density, which can be written as Eq(A.5) (Chevallier et al., 2019; Bouri and Kamal, 2023).

$$\mathrm{c}(\mathrm{u}_1, \mathrm{u}_2, \dots \dots, \mathrm{u}_\mathrm{d}\ ) = \frac{\partial^d \mathrm{C}(\mathrm{u}_1, \mathrm{u}_2, \dots \dots, \mathrm{u}_\mathrm{d},)}{\partial u_1 \partial u_2 \dots . \partial u_d} \tag{A.5}$$

In other words, the structure of dependence is represented by the product of the multivariate density, which serves as the output of the marginal densities, and the multivariate copula density. This characteristic involves decoupling univariate marginal distributions from dependence estimation. Copula functions are categorized into two main groups: elliptical and Archimedean. The first group has a definite functional form, such as Gaussian and t-student, while Archimedean copulas are obtained from generative functions, including Clayton, Gambel, Frank, Joe, BB, etc. However, copulas have limitations in modeling multivariate dependence for a large number of variables. To overcome this problem, Vine Copulas, including Regular, Canonical, and Drawable Vine copulas, have been introduced (Joe, 1997). These copulas have been developed to measure and describe multivariate dependencies by using a cascade of pair copulas and their hierarchical structure, capturing Conditional Dependence (CD) between variables. In our paper we focus on a particular type of Vine models that has been extensively employed in empirical studies, namely C-Vine copulas. The multivariate density of a C-Vine copula is defined as follows:

$$\mathrm{f}(x_1, x_2, \dots .., x_d) = \prod_{k=1}^{d} f_k(x_k) \prod_{h=2}^{d} C_{1,h}\big(F_1(x_1), F_h(x_h)\big) \prod_{j=2}^{d-1} \prod_{i=1}^{d-j} C_{jj+1}\, |1, \dots j - 1(F\big(x_j | x_1, \dots x_{j-1}\big), (F\big(x_{j+1} | x_1, \dots x_{j-1}\big). \tag{A.6}$$

According to Joe (1997), the CD between two variables, x_i and x_j, can be represented by Eq(A.7).

$$f_{i|j}(x_i|x_j) = c_{i|j}[F_i(x_i), F_j(x_j)] = \frac{\partial C_{ij}[F_i(x_i), F_j(x_j)]}{\partial F_j(x_j)} \tag{A.7}$$

where, $c_{i|j}$ refers to the CD of variable *i* given variable *j* with a joint distribution function C_{ij}. The parameters of the model and the marginal distribution parameters are estimated using Maximum Likelihood (MLE) (Pishbahar et al., 2019; Czado et al., 2022; Uddin et al., 2018).

The dependence structure can be visually represented through a hierarchical tree. C-Vine Copula trees exhibit a "star" structure (see Figure A.2), wherein the initial tree (T1) has its first root node capturing the relationship between two random variables through bivariate copulas, as depicted by the connecting edge between the associated nodes. In the subsequent trees, the edges from the preceding stage transition into the nodes of the successive trees. At each stage, a single variable assumes the primary role as the root node, chosen as the node with the highest value of Kendall's tau (τ) (Brechmann and Schepsmeier, 2013).

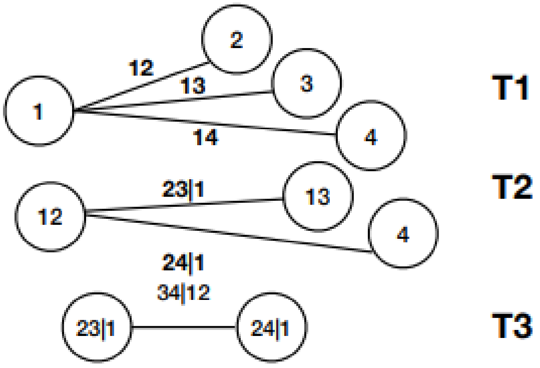


Figure A2. Example of 4-dimensional C-Vine Copula
Source: Liu et al. (2019)

τ is often used to measure the dependence structure, as linear correlation coefficients are inappropriate for capturing non-linear dependence. It can be defined as in Eq (A.8):

$$\tau(X_1, X_2) = P\big((X_{11} - X_{21})(X_{21} - X_{22}) > 0\big) - P\big((X_{11} - X_{21})(X_{21} - X_{22}) < 0\big) \tag{A.8}$$

where both $(X_{11} - X_{21})$ and$(X_{21} - X_{22})$ are independent, and $\tau(X_1, X_2)$ is invariant. The tail dependence coefficient (λ) describes the degree of association (Czado et al., 2022):

$$\lambda^{upper} = \lim_{t\to1^-} P(X_2 > F_2^{-1}(t)|\, X_1 > F_1^{-1}(t)) = \lim_{t\to1^-} \frac{1-2t+C(t,t)}{1-t} \tag{A.9}$$

$$\lambda^{Lower} = \lim_{t\to0^+} P(X_2 \leq F_2^{-1}(t)|\, X_1 \leq F_1^{-1}(t)) = \lim_{t\to0^+} \frac{C(t,t)}{t} \tag{A.10}$$

Time-Varying Vector Parameter Autoregressive models with Stochastic Volatility (TVP-VAR-SV model)

Structural Vector AutoRegressive (SVAR) models are widely used to represent the dynamic relationships among multiple time series and deal with the problem of endogeneity. Unfortunately, SVAR models are not designed to deal with non-linear relationships. A number of authors (see, among others, Primiceri, 2005 and Nakajima, 2011) have generalized the SVAR models to Time-Varying Parameter Vector Auto Regressive models incorporating Stochastic Volatility (TVP-VAR-SV), which assume that all parameters follow random walk processes. This class of models is commonly used in energy economics and finance (see, e.g., Pakrooh and Pishbahar, 2020; Yuan et al. 2021; Lang et al., 2023; Lin et al., 2023; He, 2023; Lu et al., 2023; Thanh et al., 2022; Lin et al., 2021; Yuan et al., 2021; Gang and Liu, 2020).

Following Primiceri (2005) and Nakajima (2011), a TVP-VAR-SV model is based on the SVAR structure of Eq(A.11):

$$AY_t = F_1 Y_{t-1} + \cdots .. + F_s Y_{t-s} + u_t \qquad t=s+1,\ldots.,n \tag{A.11}$$

where Y_t is $k\times 1$ dimensional column vector of observed endogenous variables, and $A, F_1, \ldots, F_s$ are $k\times k$ dimensional coefficient matrices. u_t denotes a $k\times 1$ structural shock vector which is assumed to normally distributed, i.e. $u_t \sim N(0, \Sigma)$, with Σ diagonal.

To ensure the simultaneity of structural shocks, A is lower triangular.

We can solve for Y_t in Eq(A.11) and obtain the reduced form:

$$Y_t = B_1 Y_{t-1} + \cdots .. + B_s Y_{t-s} + A^{-1}\Sigma\varepsilon_t \qquad \varepsilon_t \sim N(0, I_k), \qquad t = s+1, \ldots ., n \tag{A.12}$$

where $B_i = A^{-1}F_i$, i=1,2,…s. Define $X_t = I_k \otimes (y_t', \ldots, y_s')$, with $\otimes$ indicating the Kronecker product. Then, Eq(A.12) can be written as:

$$Y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t \tag{A.13}$$

Assume that all parameters in Eq(A.13) can change over time. Hence, the reduced form SVAR of Eq(A.13) becomes:

$$Y_t = X_t\beta_t + A_t^{-1} \tag{A.14}$$

β_t, A_t, and Σ_t are time varying coefficients; $\alpha_t = (\alpha_{21}, \ldots\ldots\ldots\ldots, \alpha_{k,k-1})$ is the low-triangular accumulation vectors of matrix A_t, and $h_t = (h_{1t}, \ldots\ldots, h_{kt}), h_{jt} = \log \sigma_{jt}^2$, j=1,…,k, t=$s+1$,…..,n. The parameters in Eq(A.14) are subject to the following random walk processes:

$$\beta_{t+1} = \beta_t + u_{bt}$$

$$\alpha_{t+1} = \alpha_t + u_{at} \tag{A.15}$$

$$h_{t+1} = h_t + u_{ht}$$

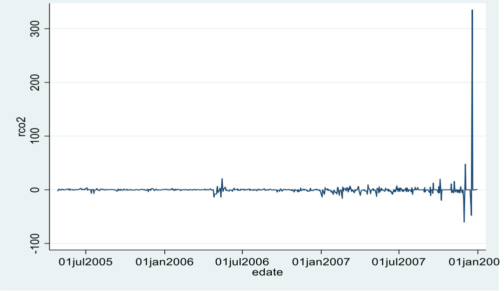
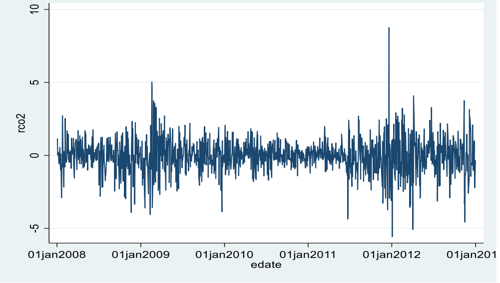
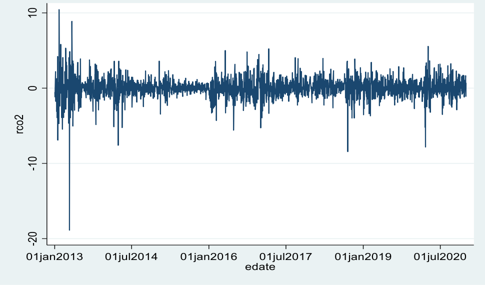
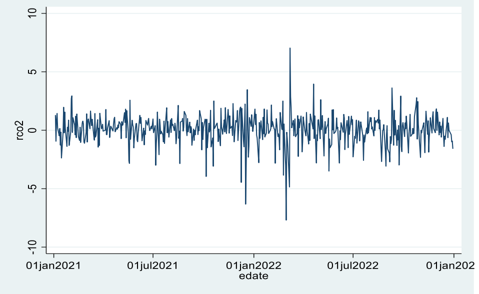
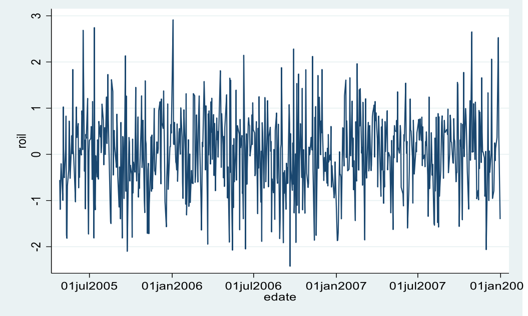
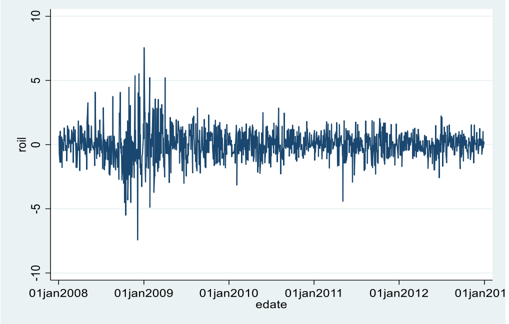
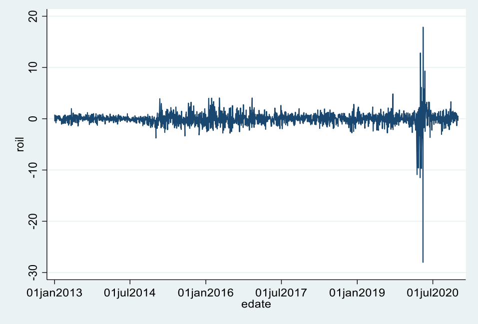
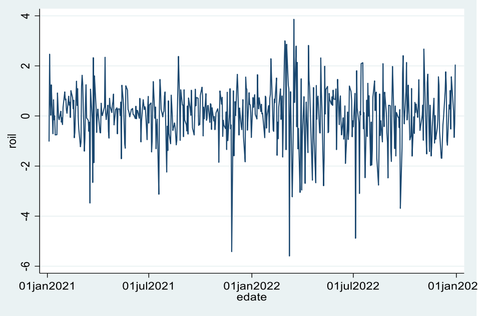
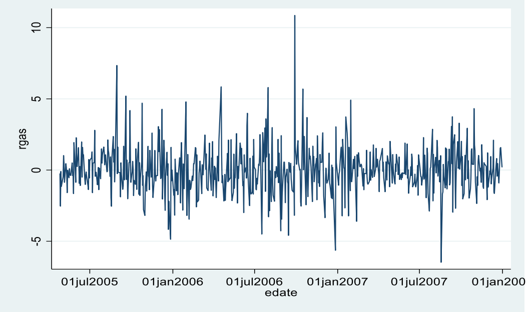
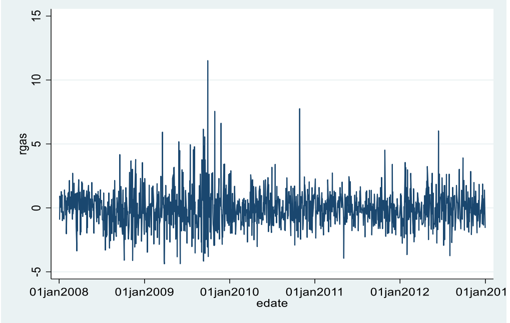
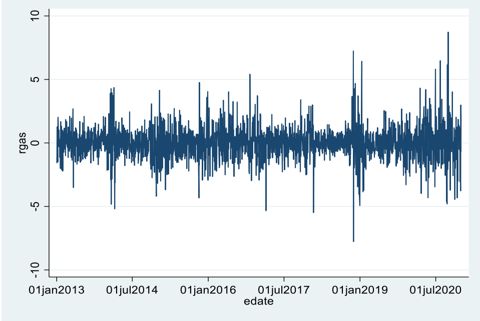
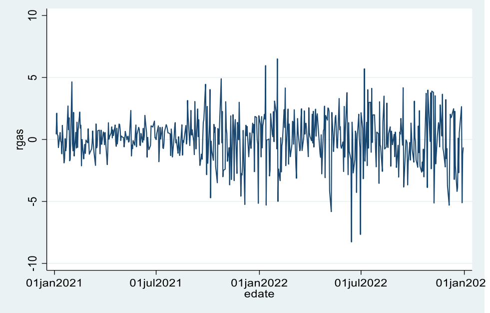
$$\begin{pmatrix} u_{\beta t} \\ u_{\alpha t} \\ u_{ht} \end{pmatrix} \sim N \begin{pmatrix} \Sigma_\beta & 0 & 0 \\ 0 & \Sigma_\alpha & 0 \\ 0 & 0 & \Sigma_h \end{pmatrix}$$

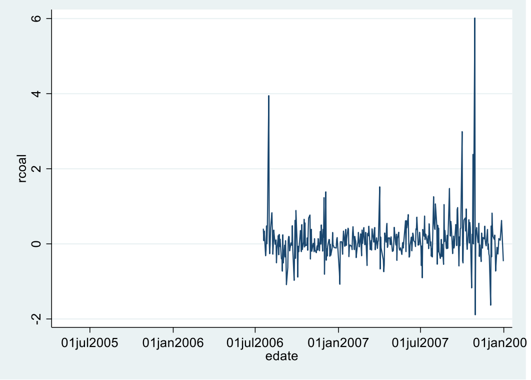
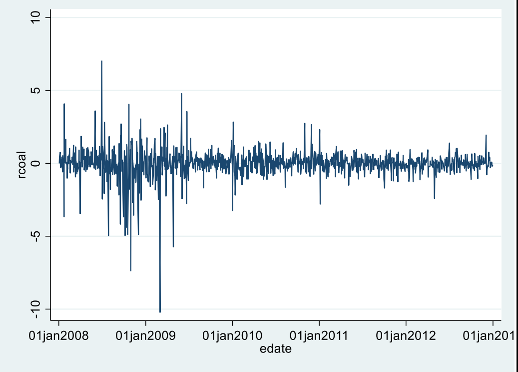
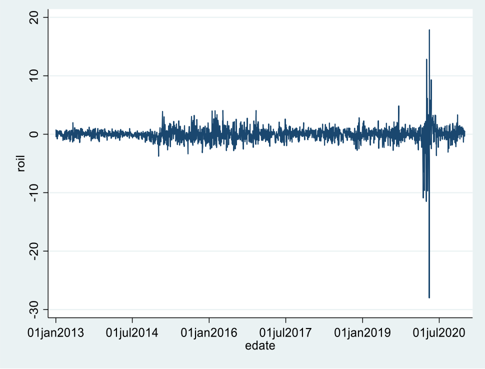
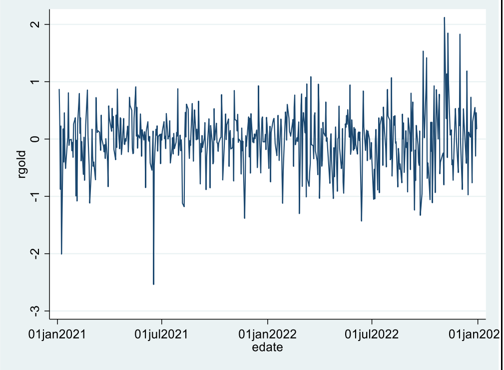
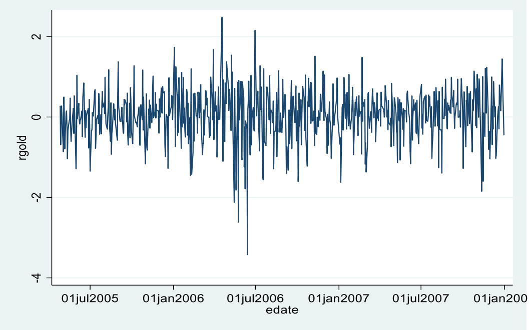
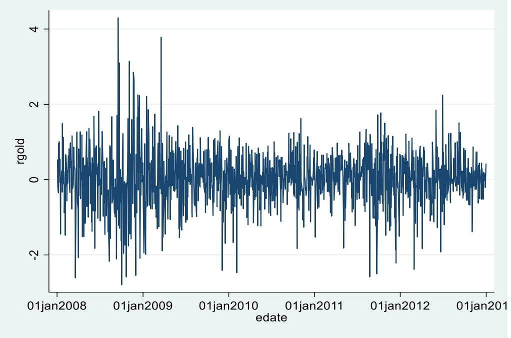
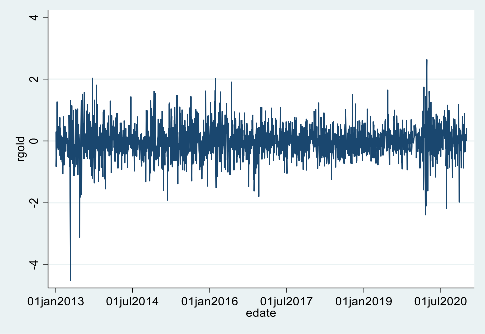
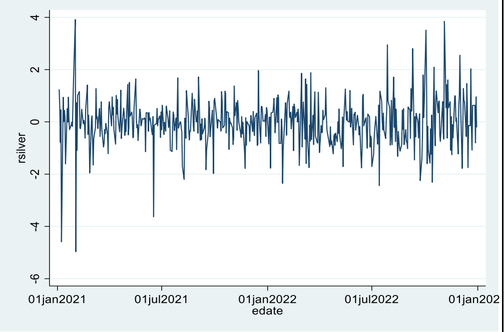
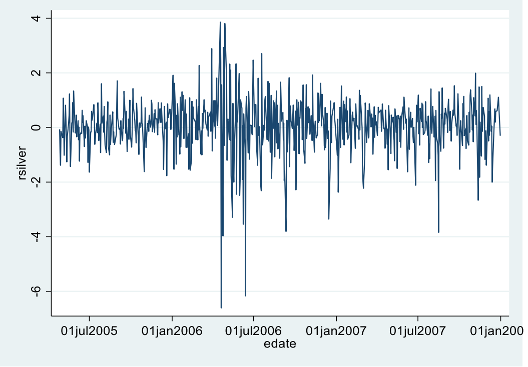
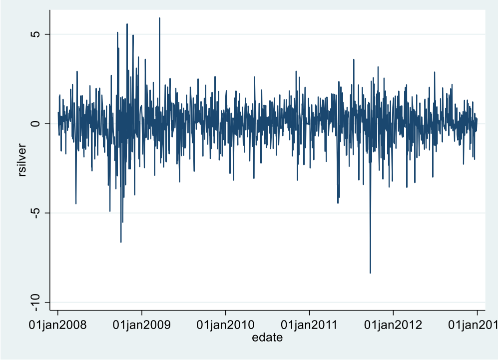
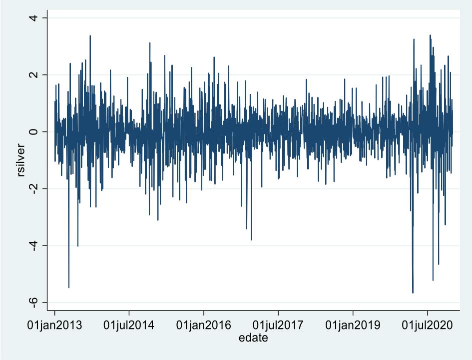
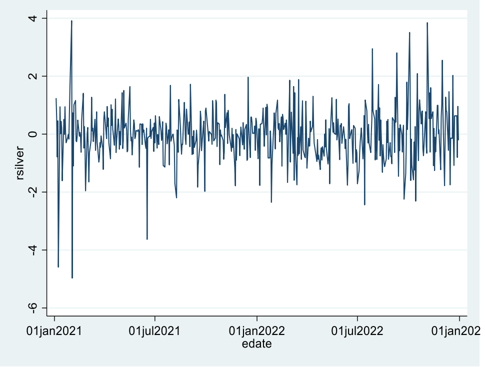
where $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $\alpha_{s+1} \sim N(\mu_{\alpha_0}, \Sigma_{\alpha_0})$, and $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$.

The TVP-VAR-SV model can be estimated by using the Markov Chain Monte Carlo (MCMC) simulation sampling method. With this method, we can obtain the estimated constant and time-varying parameters. Based on the estimated parameters, we can calculate impulse response functions, including time-point and equal-interval impulse responses (Primiceri, 2005; Nakajima, 2011; Gong and Liu, 2020; Lin et al., 2021; He, 2023; Lin et al., 2023).

B.Results

Table B.1: Returns

Markets	I: 2005-04-24 – 2007-12-31	II: 2008-01-02-2012-12-31	III: 2013-01-02- 2020-12-31	IIII:2021-01-04- 2022-12-30
CO2				
Oil				
Gas				

Coal				
Gold				
Silver				

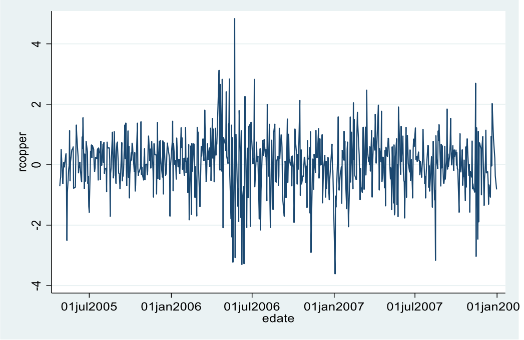
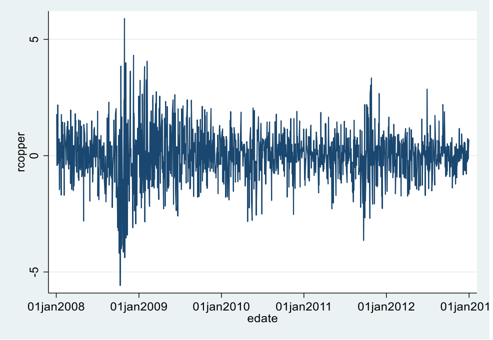
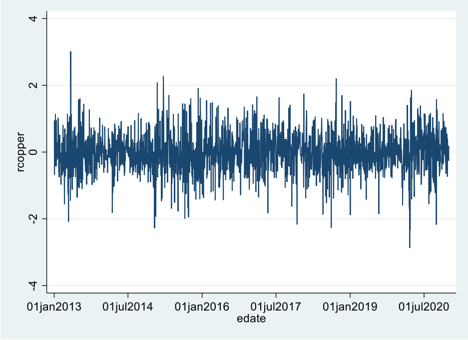
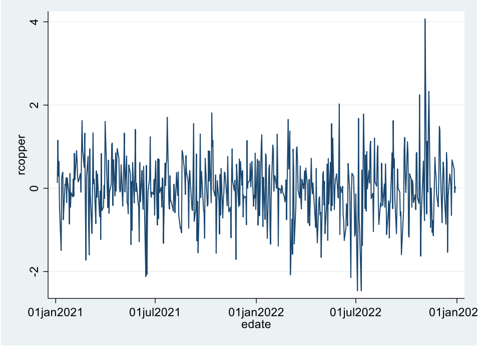
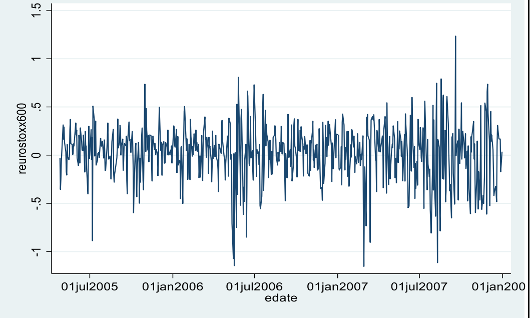
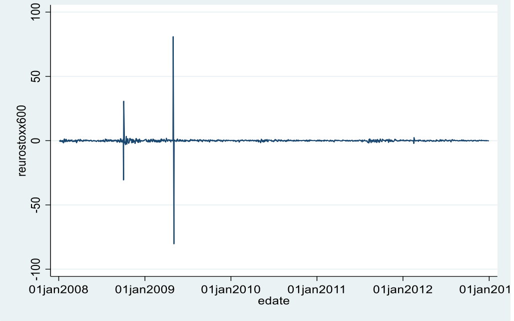
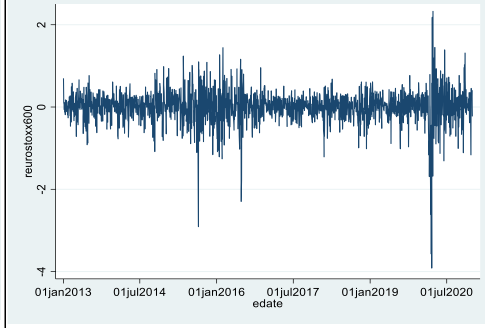
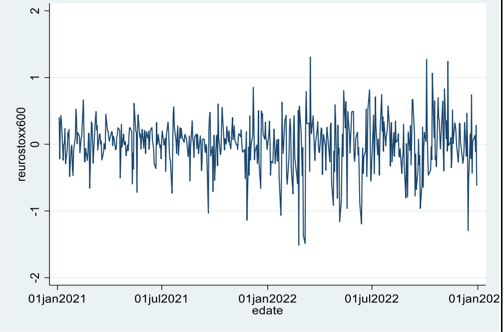
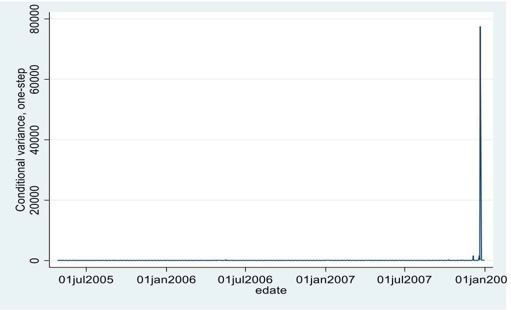
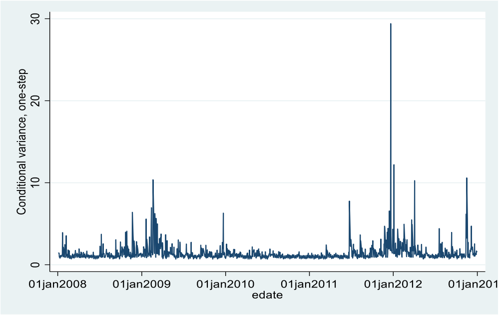
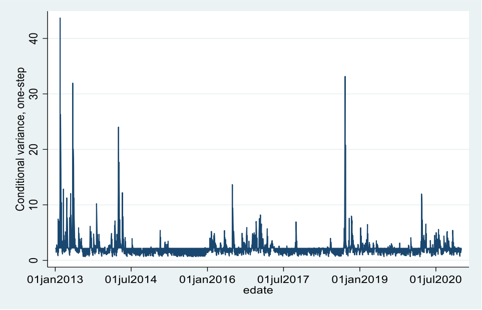
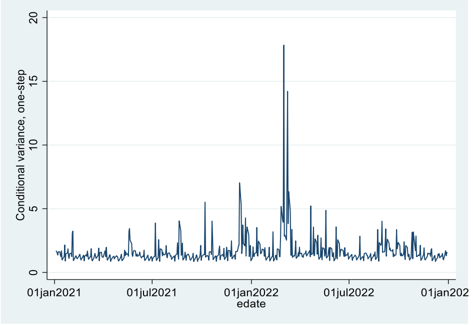
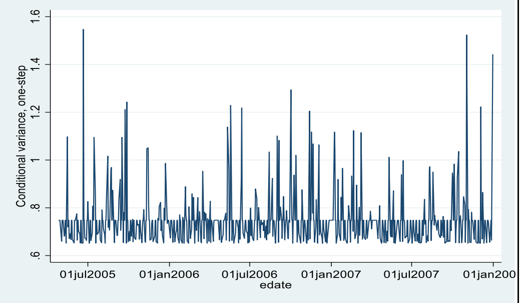
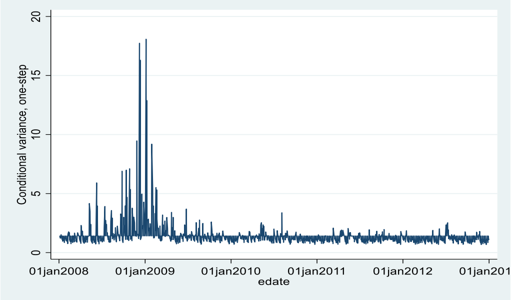
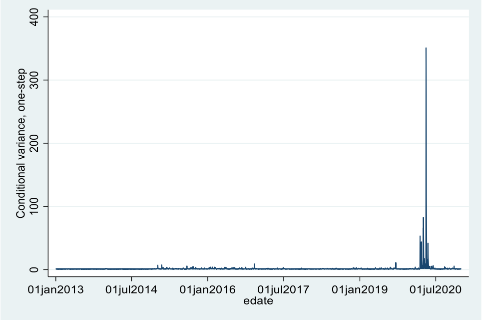
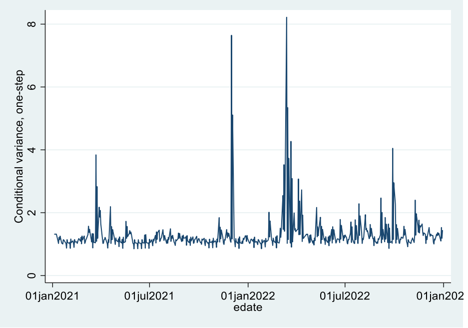
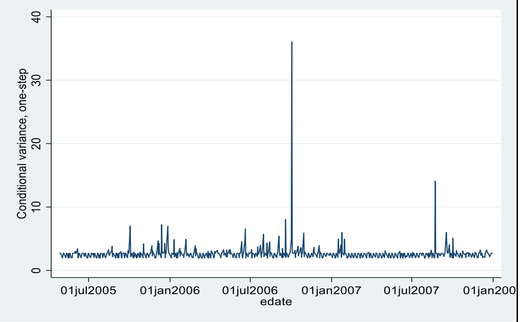
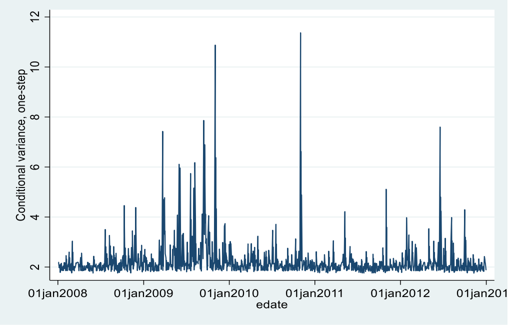
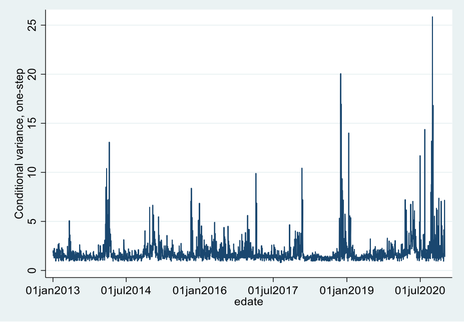
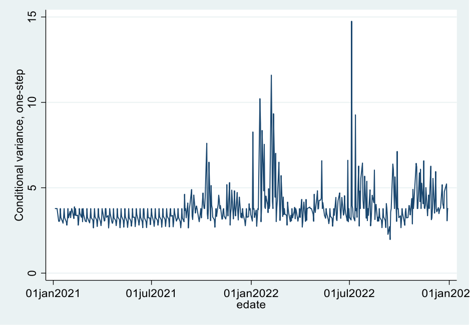
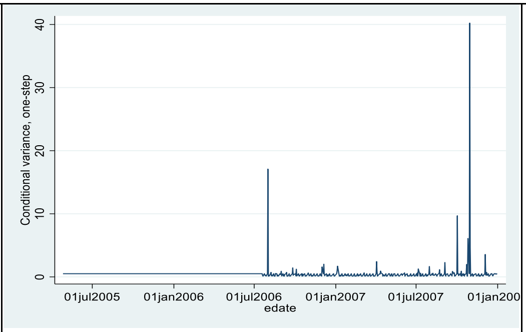
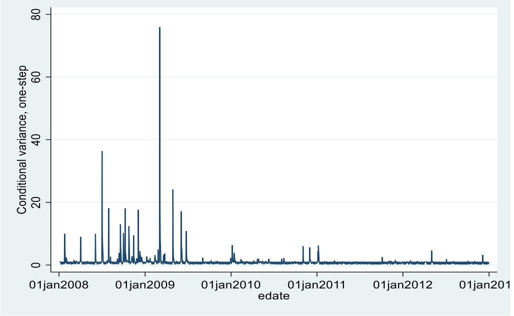
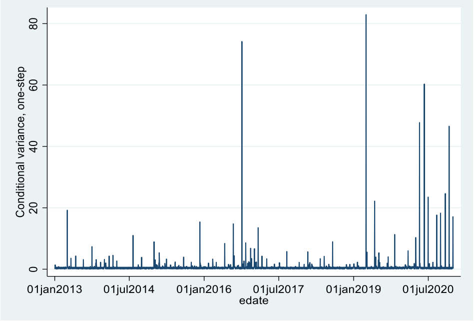
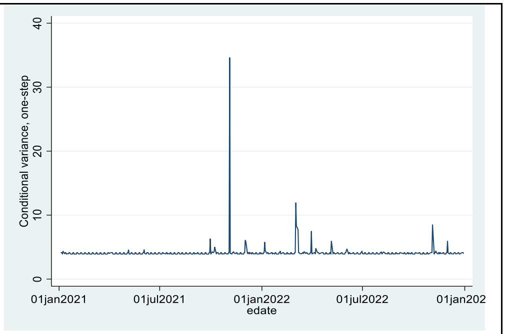
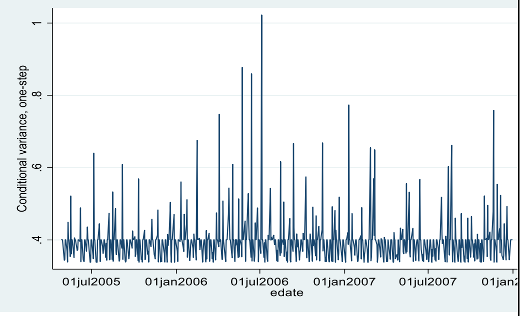
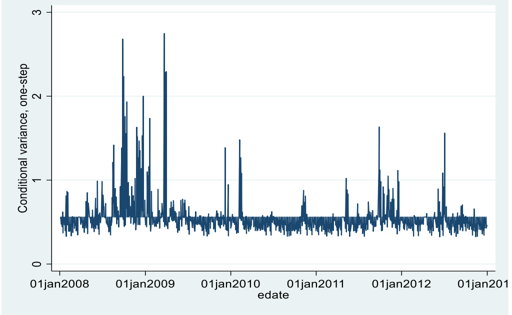
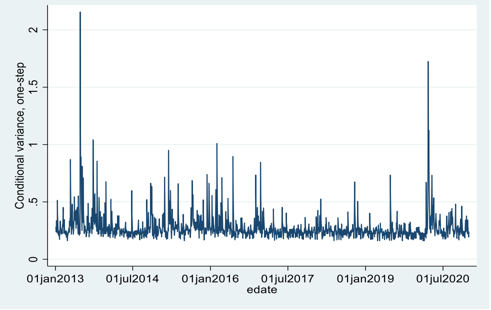
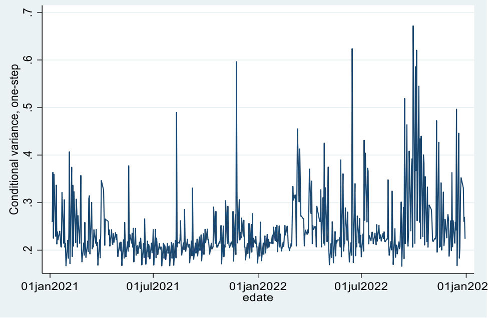
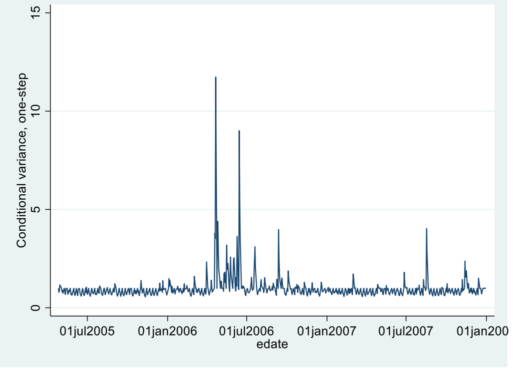
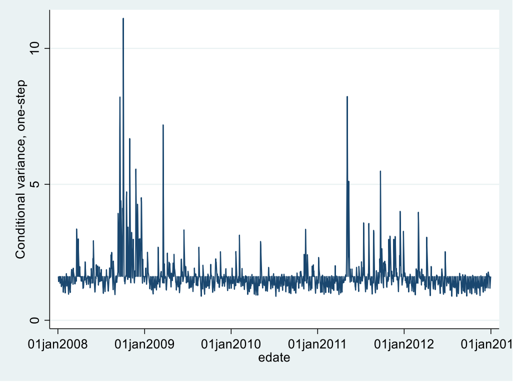
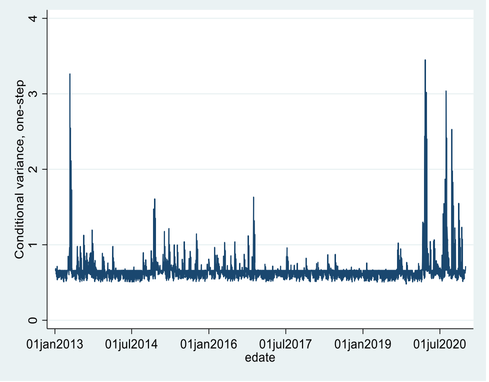
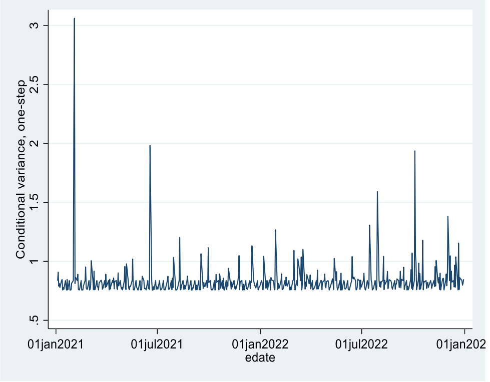
Copper				
Stock				

Table B.2: Volatilities

Markets	I: 2005-04-24 – 2007-12-31	II: 2008-01-02-2012-12-31	III: 2013-01-02- 2020-12-31	IIII:2021-01-04- 2022-12-30

CO2	Conditional variance, one-step 0 20000 40000 60000 80000 01jul2005 01jan2006 01jul2006 01jan2007 01jul2007 01jan200 edate	Conditional variance, one-step 0 10 20 30 01jan2008 01jan2009 01jan2010 01jan2011 01jan2012 01jan201 edate	Conditional variance, one-step 0 10 20 30 40 01jan2013 01jul2014 01jan2016 01jul2017 01jan2019 01jul2020 edate	Conditional variance, one-step 0 5 10 15 20 01jan2021 01jul2021 01jan2022 01jul2022 01jan202 edate
Oil	Conditional variance, one-step .6 .8 1 1.2 1.4 1.6 01jul2005 01jan2006 01jul2006 01jan2007 01jul2007 01jan200 edate	Conditional variance, one-step 0 5 10 15 20 01jan2008 01jan2009 01jan2010 01jan2011 01jan2012 01jan201 edate	Conditional variance, one-step 0 100 200 300 400 01jan2013 01jul2014 01jan2016 01jul2017 01jan2019 01jul2020 edate	Conditional variance, one-step 0 2 4 6 8 01jan2021 01jul2021 01jan2022 01jul2022 01jan202 edate
Gas	Conditional variance, one-step 0 10 20 30 40 01jul2005 01jan2006 01jul2006 01jan2007 01jul2007 01jan200 edate	Conditional variance, one-step 2 4 6 8 10 12 01jan2008 01jan2009 01jan2010 01jan2011 01jan2012 01jan201 edate	Conditional variance, one-step 0 5 10 15 20 25 01jan2013 01jul2014 01jan2016 01jul2017 01jan2019 01jul2020 edate	Conditional variance, one-step 0 5 10 15 01jan2021 01jul2021 01jan2022 01jul2022 01jan202 edate

Coal				
Gold				
Silver				

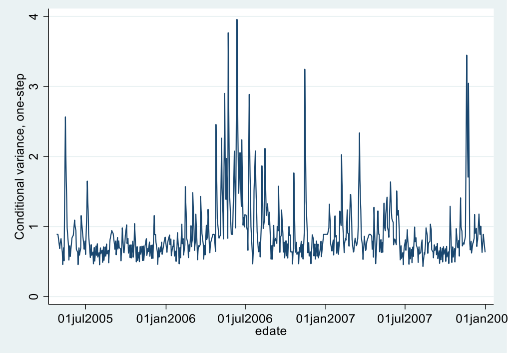
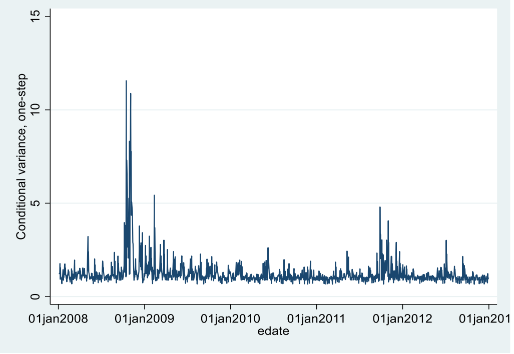
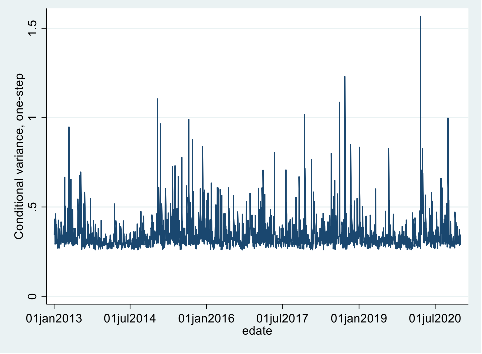
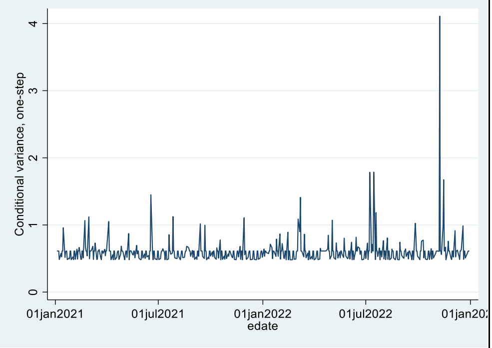
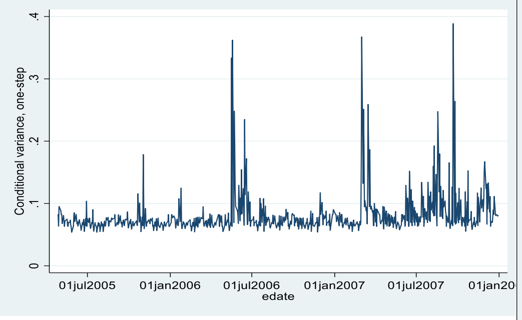
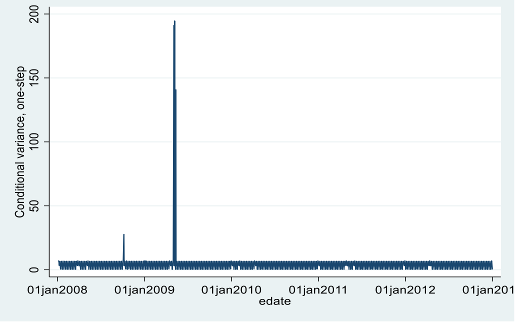
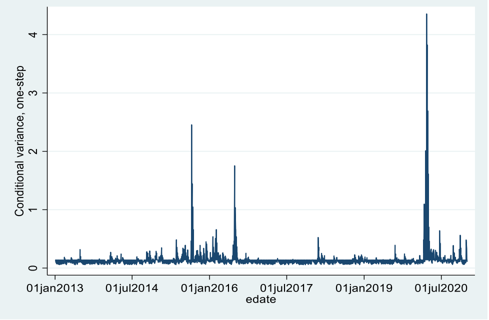
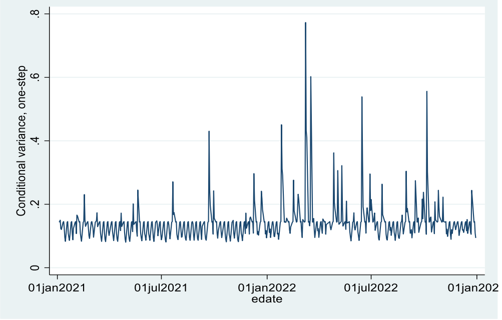
Copper				
Stock				

Table B.3: GARCH Models

Phases	Volatility	ARCH lag order (p)	GARCH lag order (q)	Model
I	CO2	2	1	GARCH(2,1)
	Oil	4	-	ARCH(4)
	Gas	5	-	ARCH(5)
	Coal	1	-	ARCH(1)
	Gold	5	-	ARCH(5)
	Silver	1	1	GARCH(1,1)
	Copper	4	1	GARCH(4,1)
	Eurostoxx600	2	4	GARCH(2,4)
II	CO2	4	3	GARCH(4,3)
	Oil	1	1	GARCH(1,1)
	Gas	1	5	GARCH(1,5)
	Coal	1	-	ARCH(1)
	Gold	5	1	GARCH(5,1)
	Silver	3	4	GARCH(3,4)
	Copper	1	3	GARCH(1,3)
	Eurostoxx600	3	4	GARCH(3,4)
III	CO2	1	3	GARCH(1,3)
	Oil	3	3	GARCH(3,3)
	Gas	4	2	GARCH(4,2)
	Coal	2	1	GARCH(2,1)
	Gold	4	4	GARCH(4,4)
	Silver	1	1	GARCH(1,1)
	Copper	5	2	GARCH(5,2)
	Eurostoxx600	3	5	GARCH(3,5)
IIII	CO2	1	3	GARCH(1,3)
	Oil	5	2	GARCH(5,2)
	Gas	5	4	GARCH(5,4)
	Coal	1	-	ARCH(1)
	Gold	2	4	GARCH(2,4)
	Silver	1	-	ARCH(1)
	Copper	4	-	ARCH(4)
	Eurostoxx600	2	1	GARCH(2,1)

[1] Order of ARCH model

[2] Order of GARCH model

Table B.4: Unit-root tests

Volatility	Time period	ADF			PP			KPSS		Zandrews			
		Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	Intercept	Trend	Intercept and Trend	Break Points
CO2	Phase I	7.12 (1.00)	7.07 (1.00)	2.01 (0.98)	-25.95*** (0.00)	-26.06*** (0.00)	-25.87*** (0.00)	0.36*	0.13*	-26.16 (0.15)	-26.69*** (0.00)	-26.87** (0.04)	2006-11-23 2006-11-23 2006-11-23
Oil	Phase I	-25.06*** (0.00)	-25.04*** (0.00)	-0.18 (0.62)	-25.06*** (0.00)	-25.04*** (0.00)	-2.38*** (0.01)	0.05	0.05	-25.18*** (0.01)	-25.06 (0.21)	25.32*** (0.00)	2006-08-14 2006-11-15 2005-08-12
Gas	Phase I	-25.57*** (0.00)	-24.55*** (0.00)	1.18 (0.21)	-24.57*** (0.00)	-24.55*** (0.00)	-12.36*** (0.00)	0.17	0.17	-24.95*** (0.00)	-24.77* (0.09)	-25.02*** (0.00)	2006-05-16 2006-04-27 2006-05-16
Coal	Phase I	-23.97*** (0.00)	-23.99*** (0.00)	-14.43*** (0.00)	-24.07*** (0.00)	24.09*** (0.00)	23.99*** (0.00)	0.17	0.12*	-16.31** (0.02)	-16.32** (0.02)	-16.33 (0.36)	2006-11-23 2006-10-22 2006-11-19
Gold	Phase I	-25.56*** (0.00)	-25.54*** (0.00)	-0.21 (0.60)	-25.56*** (0.00)	-25.54*** (0.00)	-1.91** (0.05)	0.24	0.25***	-25.91*** (0.00)	-25.87*** (0.00)	-26.17*** (0.00)	2005-10-22 2006-01-24 2006-02-23
Silver	Phase I	-11.22*** (0.00)	-11.21*** (0.00)	-3.31*** (0.00)	-18.53*** (0.00)	-18.52*** (0.00)	-9.84*** (0.00)	0.30	0.29***	-8.61*** (0.00)	-8.39*** (0.00)	-9.12*** (0.00)	2005-12-19 2006-01-02 2006-02-09
Copper	Phase I	-10.38*** (0.00)	-10.37*** (0.00)	-0.99 (0.28)	-13.41*** (0.00)	-13.40*** (0.00)	-3.99*** (0.00)	0.26	0.25***	-11.51*** (0.00)	-11*** (0.00)	-11.64*** (0.00)	2006-01-03 2006-02-05 2006-01-03
Eurostoxx600	Phase I	-9.40*** (0.00)	-9.89*** (0.00)	-1.51 (0.12)	-26.86*** (0.00)	-26.62*** (0.00)	-6.76*** (0.00)	0.85***	0.05	-9.99*** (0.00)	-9.69 (0.38)	-9.99*** (0.00)	2006-02-16 2006-05-30 2006-02-14
CO2	Phase II	-6.90*** (0.00)	-6.97*** (0.00)	-2.92*** (0.00)	-34.86*** (0.00)	-34.81*** (0.00)	-24.84*** (0.00)	0.31	0.20**	-10.86*** (0.00)	-10.45*** (0.00)	-11.33*** (0.00)	2010-06-13 2009-12-27 2010-09-28
Oil	Phase II	-2.51 (0.11)	-2.99 (0.13)	-0.83 (0.35)	-40.86*** (0.00)	-39.24*** (0.00)	-26.72*** (0.00)	1.39***	0.21**	-11.10*** (0.00)	-10.87 (0.71)	-14.13*** (0.00)	2008-10-12 2008-07-28 2008-10-06
Gas	Phase II	-10.83*** (0.00)	-10.92*** (0.00)	-1.22 (0.20)	-39.72*** (0.00)	-39.61*** (0.00)	-6.90*** (0.00)	0.52**	0.28***	-10.88** (0.03)	-10.82 (0.15)	-11.97*** (0.00)	2008-10-30 2008-12-29 2009-04-22
Coal	Phase II	-6.92*** (0.00)	-6.97*** (0.00)	-2.95*** (0.00)	-34.86*** (0.00)	-34.81*** (0.00)	-24.84*** (0.00)	0.31	0.20**	-10.86*** (0.00)	-10.45*** (0.00)	-11.33*** (0.00)	2010-06-13 2009-12-27 2010-09-28
Gold	Phase II	-7.03*** (0.00)	-7.49*** (0.00)	-0.91 (0.32)	-45.00*** (0.00)	-43.97*** (0.00)	-10.01*** (0.00)	1.00***	0.21***	-10.85*** (0.00)	-10.45*** (0.00)	-12.08*** (0.00)	2008-11-17 2008-11-17 2008-11-17
Silver	Phase II	-6.08***	-6.31***	-1.52	-26.22***	-25.93***	-6.15***	0.58**	0.15**	-9.98***	-9.34***	-11.50***	2008-09-07

		(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)	2008-09-07 2008-09-07
Copper	Phase II	-7.16*** (0.00)	-7.41*** (0.00)	-1.92*** (0.05)	-37.75*** (0.00)	-38.01*** (0.00)	-14.74*** (0.00)	0.62**	0.10	-8.68*** (0.00)	-8.67*** (0.00)	-10.17*** (0.00)	2008-10-13 2008-07-22 2008-08-10
Eurostoxx600	Phase II	-6.02*** (0.00)	-6.08*** (0.00)	-3.20** (0.04)	-39.45*** (0.00)	-39.39*** (0.00)	-44.27*** (0.00)	0.17	0.05	-8.76*** (0.00)	-8.60*** (0.00)	-9.42*** (0.00)	2008-12-17 2008-12-09 2008-12-17
CO2	Phase III	-7.98*** (0.00)	-8.18*** (0.00)	-3.62*** (0.00)	-41.87*** (0.00)	-41.62*** (0.00)	-34.46*** (0.00)	0.63**	0.30***	-11.30*** (0.00)	-11.47*** (0.00)	-11.87*** (0.00)	2013-11-23 2014-01-21 2013-11-23
Oil	Phase III	-8.35*** (0.00)	-8.51*** (0.00)	-7.85*** (0.00)	-22.03*** (0.00)	-22.15*** (0.00)	-21.25*** (0.00)	0.53**	0.11	-17.50*** (0.00)	-17.36** (0.05)	-17.55*** (0.00)	2017-10-11 2017-02-12 2017-10-11
Gas	Phase III	-12.18*** (0.00)	-12.39*** (0.00)	-4.04*** (0.00)	-44.73*** (0.00)	-44.49*** (0.00)	-31.38*** (0.00)	0.50**	0.15**	-12.66*** (0.00)	-12.90*** (0.00)	-13.03*** (0.00)	2017-10-11 2017-10-11 2017-04-08
Coal	Phase III	-40.88*** (0.00)	-41.07*** (0.00)	-39.29*** (0.00)	-40.85*** (0.00)	-40.98*** (0.00)	-40.69*** (0.00)	1.10***	0.11	-41.22*** (0.00)	-41.19*** (0.00)	-41.24*** (0.00)	2015-11-19 2017-10-10 2015-11-19
Gold	Phase III	-19.98*** (0.00)	-20.29*** (0.00)	-2.51** (0.01)	-19.98*** (0.00)	-20.31*** (0.00)	-7.68** (0.01)	0.98***	0.16**	-14.37*** (0.00)	-14.35*** (0.00)	-14.41*** (0.00)	2017-10-09 2017-04-19 2015-11-06
Silver	Phase III	-9.16*** (0.00)	-9.25*** (0.00)	-1.40 (0.14)	-51.38*** (0.00)	-51.23*** (0.00)	-5.49*** (0.00)	0.44*	0.31***	-12.06*** (0.00)	-12.18*** (0.00)	-12.21 (0.18)	2017-09-03 2017-06-25 2017-09-03
Copper	Phase III	-16.06*** (0.00)	-16.07*** (0.00)	-1.41 (0.14)	-38.52*** (0.00)	-38.50*** (0.00)	-5.24*** (0.00)	0.13	0.09	-16.23*** (0.00)	-16.51*** (0.00)	-16.46*** (0.00)	2014-05-08 2014-05-08 2014-05-08
Eurostoxx600	Phase III	-9.04*** (0.00)	-9.13*** (0.00)	-4.57*** (0.00)	-50.51*** (0.00)	-50.41*** (0.00)	-44.98*** (0.00)	0.26	0.11	-9.75*** (0.00)	-9.44*** (0.00)	-9.76*** (0.00)	2015-06-22 2017-04-26 2015-06-22
CO2	Phase IV	-5.37*** (0.00)	-5.40*** (0.00)	-2.32*** (0.01)	-18.88*** (0.00)	-18.79*** (0.00)	-9.95*** (0.00)	0.26	0.16**	-6.03*** (0.00)	-5.83*** (0.00)	-6.17* (0.07)	2021-11-10 2021-11-02 2021-10-28
Oil	Phase IV	-7.13*** (0.00)	-7.25*** (0.00)	-1.54*** (0.01)	-25.76*** (0.00)	-25.59*** (0.00)	-7.77*** (0.00)	0.33	0.07	-7.82*** (0.00)	-7.60*** (0.00)	-8.14*** (0.01)	2021-11-01 2021-11-10 2021-11-01
Gas	Phase IV	-5.62*** (0.00)	-6.35*** (0.00)	-0.57 (0.46)	-22.16*** (0.00)	-21.85*** (0.00)	-3.19*** (0.00)	1.08***	0.12*	-6.97*** (0.00)	-6.63*** (0.00)	-7.06*** (0.00)	2021-10-30 2021-10-05 2021-10-30
Coal	Phase IV	-21.62*** (0.00)	-21.61*** (0.00)	-0.97 (0.29)	-21.62*** (0.00)	-21.61*** (0.00)	-3.97*** (0.00)	0.14	0.13*	-21.88*** (0.01)	-21.79*** (0.01)	-21.97*** (0.01)	2021-08-09 2021-08-10 2021-08-09
Gold	Phase IV	-9.35***	-10.05***	-0.84	-26.30***	-26.08***	-3.53***	1.06***	0.18**	-10.63***	-10.65***	-11.01***	2022-03-15

		(0.00)	(0.00)	(0.34)	(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)	2022-05-03 2022-03-16
Silver	Phase IV	-17.68*** (0.00)	-17.68*** (0.00)	-0.41 (0.53)	-17.58*** (0.00)	-17.58*** (0.00)	-1.71* (0.08)	0.18	0.12*	-17.82*** (0.00)	-16.31*** (0.00)	-17.90*** (0.00)	2021-05-03 2021-05-03 2021-03-29
Copper	Phase IV	-7.58*** (0.00)	-7.76*** (0.00)	-1.16 (0.22)	-22.57*** (0.00)	-22.62*** (0.00)	-5.21*** (0.00)	0.39*	0.05	-7.88*** (0.00)	-7.84*** (0.00)	-7.87 (0.31)	2022-01-30 2021-08-16 2021-01-30
vrEurostoxx600	Phase IV	-15.42*** (0.00)	-15.69*** (0.00)	-0.99 (0.28)	-15.43*** (0.00)	-15.69*** (0.00)	-4.26*** (0.00)	0.84***	0.18**	-9.04*** (0.00)	-8.86*** (0.00)	-9.49*** (0.00)	2021-10-05 2021-11-09 2021-10-07

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