Herding behaviour surrounding the Russo–Ukraine war and COVID-19 pandemic: evidence from energy, metal, livestock and grain commodities

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Abstract

Purpose – This study examines herding behaviour in commodity markets amid two major global upheavals: the Russo–Ukraine conflict and the COVID-19 pandemic.

Design/methodology/approach – By analysing 18 commodity futures worldwide, the study examines herding trends in metals, livestock, energy and grains sectors. The applied methodology combines static and dynamic approaches by incorporating cross-sectional absolute deviations (CSAD) and a time-varying parameter (TVP) regression model extended by Markov Chain Monte Carlo (MCMC) sampling to adequately reflect the complexity of herding behaviour in different market scenarios.

Findings – Our results show clear differences in herd behaviour during these crises. The Russia–Ukraine war led to relatively subdued herding behaviour in commodities, suggesting a limited impact of geopolitical turmoil on collective market behaviour. In stark contrast, the outbreak of the COVID-19 pandemic significantly amplified herding behaviour, particularly in the energy and livestock sectors.

Originality/value – This discrepancy emphasises the different impact of a health crisis versus a geopolitical conflict on market dynamics. This study makes an important contribution to the existing literature as it is one of the first studies to contrast herding behaviour in commodity markets during these two crises. Our results show that not all crises produce comparable market reactions, which underlines the importance of the crisis context when analysing financial market behaviour.

Keywords Energy commodity, Herd behaviour, Russo–Ukraine war, COVID-19, Time-varying parameter (TVP) regression, Markov chain Monte Carlo (MCMC)

Paper type Research paper

1. Introduction

The Russo–Ukraine conflict and the COVID-19 pandemic have profoundly affected the world's financial and commodity markets in recent times. As the pandemic unfolded in January 2020, the S&P 500 index witnessed a steep decline, plummeting from 3,400 to 2,180 within two months. Concurrently, gold prices saw a dramatic ascent, escalating from a low of 1,454 to a record high of 2,070, a rise of 42.3% over eight months. Similarly, the Ukrainian currency, the Hryvnia, experienced a notable devaluation in the months surrounding Russia's

JEL Classification — G01, G10, G15

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invasion of Ukraine, dropping from 0.0383 to 0.0207. Gold demonstrated a bullish trend, surging from 1,795 to 2,070 within two months. This scenario illustrated a stark contrast in the financial and commodity markets, where sectors such as equities and currencies were beleaguered. In contrast, others, particularly gold and precious metals, emerged as perceived safe havens amidst the financial turmoil.

This period of financial instability has given rise to primary research focus areas such as ‘flight-to-safety’ or safe haven investments (Baur and Lucey, 2010; Kinateder *et al.*, 2021; Mohamad, 2022; Sifat *et al.*, 2022). In such scenarios, investors, amidst market chaos, gravitate towards safe assets, thereby shunning riskier investments. This shift towards security or liquidity in uncertain times, as explained by Greenspan (2004), is often characterised by dramatic and collective shifts in investment, akin to herding behaviour. Market declines and bullish trends can indicate herding in a flight-to-safety context (Demirer and Kutan, 2006).

Our motivation for examining herding in commodity markets in the context of the Russo–Ukraine war and the COVID-19 pandemic is threefold. First, early studies on herding argue that herding between commodity markets tends to increase during periods of market stress (Chang *et al.*, 2000; Christie and Huang, 1995), but few studies compare the intensity of herding between two crises. It would be interesting to see if herding behaviour could also be observed in two crises - war and health crises. Secondly, one could argue that herding amongst commodity traders and investors is due to a flight to safety and fear of missing out (FOMO). Others might say that the herding is due to speculation and the financialisation of commodity markets. We believe that regardless of the causes of herding behaviour, the phenomenon of herding is a fascinating research opportunity. This study analyses herding behaviour in different commodity sectors over 100 trading days before and during the two recent crises: the Russo–Ukraine war and the COVID-19 pandemic. Thirdly, herding behaviour and volatility in times of market stress could be triggered by stop-loss orders leading to price cascades (Osler, 2005). Therefore, it would be interesting to investigate whether the prices of different types of commodities cascade, leading to herding behaviour during the two crises, war and pandemic.

Our dataset encompasses 18 of the world’s most traded commodity futures, including the metal, livestock, energy and grain sectors. To evaluate herding intensity, we utilise both static and dynamic measures. Initially, we calculate Chang *et al.*’s (2000) cross-sectional absolute deviations (CSADs) and apply this model across different quantiles. Subsequently, we assess the temporal variability of herding intensity using Nakajima’s (2011) time-varying parameter (TVP) regression with stochastic volatility, implemented via Markov Chain Monte Carlo (MCMC) sampling estimation. Employing Bayesian inference with stochastic volatility, such as TVP regression and MCMC, allows for observing time variations, rendering it an effective method for producing detailed and precise findings.

Further, our study makes an important contribution to the growing literature on herding and commodity markets. To the best of our knowledge, this study is one of the first to examine herding behaviour in commodity markets before and during the two recent crises: the Russo–Ukraine war and the COVID-19 pandemic. Whilst previous studies, such as those by Demirer *et al.* (2015) and Mohamad (2022) have examined herding behaviour in commodity markets and financial assets at specific points in time, what is particularly striking in our study is the different intensity of herding behaviour during the two crises, with the COVID-19 pandemic triggering a significantly higher intensity of herding behaviour compared to the Russia–Ukraine war. Specifically, our static analysis of herding indicates a tendency towards anti-herding in commodity markets before and during the Russo–Ukraine conflict, with only slight herding observed in the livestock commodities preceding the COVID-19 pandemic. Conversely, our dynamic analysis of herding reveals minimal herding around the Russo–Ukraine conflict but a more pronounced herding intensity during the pandemic.

The structure of this paper is as follows: Section 2 reviews the existing literature on herding behaviour in commodity markets. Section 3 details the data and methodology used. Section 4 presents the empirical results and discussion, and Section 5 concludes the paper.

2. Literature review

John Maynard Keynes significantly contributed to the understanding of investor herding by positing an analogy of the stock market to a beauty contest. Herein, judges, rather than relying on their own beliefs and judgements, predict victors based on the anticipated choices of their peers (Keynes, 1936). This concept was elaborated upon by Bikhchandani *et al.* (1992) and Devenow and Welch (1996), who suggested that prevailing fashions and fads substantially influence human inclinations to emulate or mimic others. In financial markets, this manifests as investors frequently imitating the actions of their counterparts (Bikhchandani and Sharma, 2000). Herding transpires when investors disregard their information in favour of that garnered from others, and new information is gradually disseminated across the market (Bikhchandani *et al.*, 1992, 1998; Welch, 1992). Various factors elucidate this convergent behaviour. For instance, investors engage in social learning to refine their decision-making process, investment managers mimic the strategies of senior managers believed to possess superior information and short-term speculators might follow other traders in the absence of sufficient immediate information (Bikhchandani *et al.*, 1998; Scharfstein and Stein, 1990).

Cross-sectional standard deviations (CSSDs) and CSADs, as introduced by Christie and Huang (1995) and further developed by Chang *et al.* (2000), are amongst the most utilised methodologies for analysing herding. Initial empirical research into herding, exemplified by studies by Lakonishok *et al.* (1992), Sias (2004) and Wermers (1999), predominantly focussed on whether institutional investors emulate each other's transactions within the same or subsequent periods, utilising institutional transaction data. Christie and Huang (1995) contend that the cross-sectional dispersion of asset returns during market stress can signal the intensity of herding, thus obviating the necessity for institutional data in herding analysis. Chang *et al.* (2000) further assert that, under the Capital Asset Pricing Model (CAPM), a linear relationship between dispersion and market return is expected. Nevertheless, during periods of herding, particularly in times of market stress, this relationship is anticipated to alter from linear to nonlinear, a shift that their nonlinear model is designed to capture.

The exploration of herding in commodity markets is in its infancy, with most studies relying on daily, monthly and quarterly datasets. The investigation by Pierdzioch *et al.* (2010) marked a pioneering effort in this area. Their research uncovered significant anti-herding behaviour among oil-price forecasters based on quarterly oil price estimates issued by the European Central Bank from 2002 to 2009. Subsequently, Steen and Gjolberg (2013) employed a monthly dataset of 20 commodities from 1986, detecting increased comovements across commodities post-2004, utilising a beta herding model and covariance based on recursive estimation.

Further, Demirer *et al.* (2015) examined herding in the grains market during high-volatility periods, using CSAD static and Markov-switching models on a daily dataset of 19 commodities from January 1995 to November 2012. Similarly, Babalos *et al.* (2015) investigated herding in eight metal commodities, identifying a prevalence of anti-herding behaviour before and after the Global Financial Crisis (GFC). They employed CSAD quantile analysis, rolling-window regressions and a daily dataset from January 1995 to December 2013. In another study, Babalos *et al.* (2015) applied CSAD TVP regression with MCMC estimation and rolling-window regression to a daily dataset of 25 commodity sector indices from January 2002 to December 2014. Their findings indicated an absence of herding based on the static model, but both the TVP and rolling-window regressions revealed brief instances of herding following the 2008 GFC.

In an insightful study, BenMabrouk (2018) utilised a monthly dataset encompassing WTI, the NASDAQ and a fear index (VIX) from January 2000 to October 2018. The author applied Christie's (1982) herding model, which accounts for crisis periods, volatility and investor attitude and discovered that herding behaviour between WTI and the NASDAQ intensifies due to informational deficiencies in one market. Similarly, Júnior *et al.* (2020) employed Hwang and Salmon's (2004) beta herding measure on the daily closing prices of 15 commodities from January 2000 to October 2018. They concluded that herding is more pronounced in food commodities. Additionally, Apergis *et al.* (2020) conducted a study from January 1990 to December 2020, employing CSADs and Cai's (2007) time-varying model on daily prices of 14 commodity futures. Their findings indicate a negative correlation between herding in the commodity futures market and US monetary policy.

Fan and Todorova (2021) executed a CSAD asymmetric model on a daily dataset of 24 commodity futures in China, covering January 2013 to June 2018. Their research reveals a significant presence of herding on days when the market is up. Subsequently, Youssef and Mokni (2021) applied CSADs and the Kalman filter to a daily agricultural, metal and energy commodities dataset from January 2003 to April 2017. They observed time-varying herding in the energy commodity sector after the 2008 GFC, whilst metal commodities exhibited herding tendencies before 2004. Kumar *et al.* (2021) found that herding behaviour varies asymmetrically and is more evident during periods of high volatility, based on their use of CSADs on a daily dataset of three commodity indices from eight Asian nations, spanning January 2010 to March 2020. Youssef (2022) expanded upon earlier research by employing a similar CSAD with the Kalman filter approach across five commodity sectors, the S&P 500 and the EURUSD from January 2003 to April 2007. The study concluded that there is evidence of time-varying herding post the 2008 GFC, with livestock displaying unexpected anti-herding behaviour.

Mohamad (2022) investigated the flight-to-safety phenomenon between safe haven and risky assets and herding behaviour amongst assets with similar characteristics 24 h before and during the Russian invasion of Ukraine. Using a minute-by-minute dataset and TVP regression, the study demonstrated mild time-varying herding between Brent, WTI, gasoline and natural gas, occurring approximately 20% of the time during market upturns and downturns following the invasion's onset. In a more recent study, Mohamad and Fromentin (2023) observed roughly 20% unintentional herding between energy commodities and 15% amongst ethical investment indices, revealing that herding varied across different phases of the COVID-19 pandemic.

Bouri *et al.* (2021) analysed the impact of the COVID-19 pandemic on investor herding behaviour across global stock markets, utilising a newspaper-based index to measure financial uncertainty linked to infectious diseases. They discovered a significant correlation between the uncertainty caused by the pandemic and the development of herding behaviour, with this effect especially marked in emerging markets and several European stock markets. In a related vein, Chang *et al.* (2020) explored herding behaviour within energy stock markets, particularly in the renewable energy sector amidst global crises such as the COVID-19 pandemic, SARS and the GFC. They found that investors are more inclined to exhibit herding behaviour during periods of extremely low oil price returns, notably within the fossil fuel energy sectors.

To summarise, the findings on herding in commodity markets are somewhat inconsistent. The static model often indicates anti-herding, whereas the time-varying model suggests evidence of herding in certain commodities under specific conditions. For instance, more than 50% herding intensity has been noted in grain commodities during high-volatility periods (Demirer *et al.*, 2015), in energy commodities following the 2008 GFC (Youssef, 2022) and briefly in 25 commodities post the 2008 GFC (Babalos *et al.*, 2015).

Research on volatility spillovers and dynamic linkages between commodities has been ongoing since the 1990s. Alhajji and Huettner (2000) explored whether the Organisation of Petroleum Exporting Countries could be considered the leading oil producer in the 2 decades before 1994, concluding that Saudi Arabia aligns with the dominant business paradigm. Numerous studies have probed the relationship between crude oil and other energy commodities, such as natural gas (Batten *et al.*, 2017; Brigida, 2014; Brown and Yücel, 2008; Hartley and Medlock, 2008; Serletis and Herbert, 1999; Villar and Joutz, 2006) and between crude oil, coal and natural gas (Nick and Thoenes, 2014; Vücel and Guo, 1994). Additionally, research has focussed on the volatility spillover between energy commodities (Baruńik *et al.*, 2015; Gong *et al.*, 2021; Li *et al.*, 2019; Lin and Li, 2015; Lin and Su, 2021; Lovcha and Perez-Laborda, 2020; Mensi *et al.*, 2021).

During the COVID-19 pandemic, Lin and Su (2021) and Mensi *et al.* (2021) specifically examined volatility spillovers across energy commodities. Lin & Su used the TVP vector autoregressive (VAR) model on a daily dataset for seven energy commodities from August 2019 to July 2020, finding evidence of heightened interconnections at the pandemic's onset, with effects lasting around two months. Mensi *et al.* used the wavelet technique and the generalised VAR on a daily dataset from January 1997 to February 2021, noting accelerated volatility spillovers during the pandemic, with WTI being the predominant contributor. Gong *et al.* (2021) studied volatility spillovers across four energy commodities using TVP-VAR with MCMC estimation on a daily dataset from October 2005 to April 2019, identifying crude oil and heating oil as the primary transmitters of volatility spillovers, whilst gasoline and natural gas were the primary receivers.

Li *et al.* (2019) and Lovcha and Perez-Laborda (2020) investigated volatility connectivity between WTI and natural gas. The former noted that volatility transmission is unpredictable over short time horizons, whilst the latter found that volatility spillover is time-varying, with natural gas being a net spillover transmitter. Lin and Li (2015) analysed volatility spillovers amongst Brent and WTI crude oil and natural gas from the USA, Europe and Japan, demonstrating spillovers from crude oil to natural gas markets using the vector error correction model (VECM) and multivariate generalised autoregressive conditional heteroscedasticity (MGARCH). Baruńik *et al.* (2015) used a 27-year, five-minute dataset to study volatility spillovers across crude oil, heating oil and gasoline, concluding that volatility spillovers increased post-2001 but decreased after 2008.

Various studies have examined the dynamic linkages between crude oil and natural gas using datasets of different frequencies, such as annual (Vücel and Guo, 1994), monthly (Atil *et al.*, 2014; Villar and Joutz, 2006), weekly (Brigida, 2014; Brown and Yücel, 2008; Nick and Thoenes, 2014) and daily (Batten *et al.*, 2017; Lahiani *et al.*, 2017; Serletis and Herbert, 1999). Vücel and Guo used a 43-year yearly dataset to demonstrate evidence of cointegrating linkages between coal, crude oil and natural gas during 1974–1990, arguing that a single fuel tax would adversely affect these markets. Five studies employing the VECM suggested a cointegrating relationship between crude oil and natural gas (Brigida, 2014; Brown and Yücel, 2008; Hartley and Medlock, 2008; Serletis and Herbert, 1999; Villar and Joutz, 2006). Atil *et al.* (2014) used nonlinear autoregressive distributed lags (NARDL) to analyse the relationships between crude oil, gasoline and natural gas, finding that natural gas and gasoline respond to oil price variations. Nick and Thoenes (2014) employed structural VAR on a weekly dataset, identifying a long-term link between coal, crude oil and natural gas.

Furthermore, the causal relationships between crude oil and natural gas have been a subject of study (Batten *et al.*, 2017). Using the time-frequency causality test, the authors found causation from natural gas to crude oil between 1999 and 2007, but post-2007, the markets appeared independent. Lahiani *et al.* (2017) used quantile autoregressive distributed lags (ARDL) to compare the daily prices of five energy commodities, discovering that crude oil predicts the prices of the other commodities.

Overall, research into volatility spillovers and dynamic links across commodities reveals that crude oil and other energy commodities are dynamically interconnected, with crude oil often being a source of volatility spillovers to other commodities. Furthermore, these volatility spillovers appear to have intensified with the onset of the COVID-19 pandemic.

3. Data and methodology

Our dataset consists of the 18 most traded [1] commodities on the US futures exchanges, comprising grains, energy, livestock and metal, as presented by Barchart. The Chicago Mercantile Exchange (CME) and other US futures exchanges are the top futures exchanges globally, boasting an average daily trading volume of 7.3 million contracts in 2022. The CME group was formed following ten years of consolidation, which involved incorporating the Chicago Board of Trade (CBOT), the New York Mercantile Exchange (NYMEX), the Chicago Mercantile Exchange (COMEX) and the Kansas City Board of Trade (KCBT) [2]. Table 1 presents the list of the futures contracts, exchanges and respective codes. Daily closing prices of the front-month or nearest-to-maturity futures contracts are collected from Refinitiv Eikon and Bloomberg, covering 100 trading days before and 100 trading days during the Russo–Ukraine war (October 2021–July 2022) and the COVID-19 pandemic (September 2019–June 2020). The front-month futures contracts are used because they are usually the most traded contracts (see, for example, Booth *et al.*, 1999; Cabrera *et al.*, 2009; Entrop *et al.*, 2020; Mohamad and Inani, 2023; Zainudin and Mohamad, 2023). 24 February 2022 and 1 February 2020 have been identified as the starting dates of the war and the pandemic [3]. We calculate the natural log return, $r_t = \ln(P_t/P_{t-1})$ and tabulate the descriptive statistics of the daily returns in Table 2. Natural gas is the most volatile commodity, with a 6.38 standard deviation and shows the largest daily gain of 38.17%, whereas oats yield the biggest loss (−34.2%) before and during the Russo–Ukraine war. In contrast, WTI produces the highest standard deviation (6.54), with the greatest daily gain of 31.96%, whilst gasoline registers the biggest daily downfall (−39.73%). We also examine the time series properties of the data using the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. The unit root hypothesis is rejected for all data for both periods, indicating all the time series returns were stationary. Figure 1 displays the time evolution of all commodities under study in terms of US dollars from August 2018 to July 2022. Almost all commodities show an upward trend, except for the metal commodities (gold, silver, copper, platinum and palladium).

In herding research, Table 3 illustrates that many existing studies have utilised the cross-sectional absolute deviation (CSAD) as the primary static metric for assessing herding

Table 1. Futures contracts' exchanges and codes

Grains	Energy	Livestock	Metals
Corn (CBOT; ZC)	Crude oil WTI (NYMEX; CL)	Live cattle (CME; LE)	Gold (COMEX; GC)
Soybean (CBOT; ZS)	Gasoline RBOB (NYMEX; RB)	Feeder cattle (CME; GF)	Silver (COMEX; SI)
Soybean meal (CBOT; ZM)	Natural gas (NYMEX; NG)	Lean hogs (CME; HE)	High-grade copper (COMEX; HG)
Wheat (CBOT; ZW)	Crude oil Brent (NYMEX; QA)		Platinum (NYMEX; PL)
Oats (CBOT; ZO)	Ethanol Chicago (NYMEX; FL)		Palladium (NYMEX: PA)

Note(s): This table presents the futures exchanges and codes for the 18 commodity futures in our sample. CBOT, NYMEX, CME and COMEX stand for Chicago Board of Trade, New York Mercantile Exchange, Chicago Mercantile Exchange and Commodity Exchange, respectively
Source(s): Author's own work

Table 2. Descriptive statistics of daily returns

Commodity	Mean (%)	Median (%)	Max (%)	Min (%)	Stdev	Kurtosis	ADF	PP	Jarque-Bera
Panel A: 100 days before and during Russo-Ukraine war									
Corn	0.05	0.33	5.88	−13.99	2.02	14.61	−14.91***	−14.88***	1248.3***
Soybean	0.08	0.28	3.66	−9.37	1.57	8.54	−14.12***	−14.19***	308.8***
Soybean meal	0.14	0.35	5.68	−14.31	2.37	14.31	−16.13***	−16.13***	1228.7***
Wheat	0.07	−0.01	19.70	−11.30	3.29	9.77	−12.07***	−12.11***	400.2***
Oats	−0.10	−0.04	27.67	−34.20	5.52	15.88	−16.15***	−16.91***	1391.4***
WTI	0.16	0.49	8.02	−14.00	3.17	6.06	−14.05***	−14.05***	109.6***
Gasoline	0.21	0.68	7.63	−13.35	3.03	5.96	−14.64***	−14.65***	107.6***
Natural gas	0.11	0.59	38.17	−30.05	6.38	10.88	−17.36***	−17.43***	519.4***
Brent	0.16	0.50	9.27	−14.04	3.06	6.60	−13.58***	−13.57***	133.2***
Ethanol	0.03	0.08	13.02	−27.01	3.16	35.52	−14.37***	−14.33***	9.4k***
Live cattle	0.06	0.08	2.43	−4.84	0.90	7.25	−12.16***	−14.32***	173.5***
Feeder cattle	0.08	−0.04	7.01	−2.29	1.10	10.53	−13.49***	−13.5***	566.8***
Lean hogs	0.10	−0.02	15.42	−11.93	2.39	17.62	−13.36***	−13.39***	1876.6***
Gold	−0.01	0.05	2.29	−2.69	0.93	3.36	−14.68***	−14.71***	4.96*
Silver	−0.08	0.08	4.70	−5.20	1.72	3.36	−14.73***	−14.72***	1.75

(*continued*)

Commodity	Mean (%)	Median (%)	Max (%)	Min (%)	Stdev	Kurtosis	ADF	PP	Jarque-Bera
Copper	−0.11	−0.13	5.04	−5.51	1.74	3.50	−11.06***	−13.58***	2.18
Platinum	−0.06	0.00	4.87	−6.09	2.01	3.01	−13.81***	−13.81***	0.06
Palladium	−0.01	0.18	10.48	−14.65	3.37	5.09	−12.74***	−12.75***	40.34***
Vix	0.03	−1.50	43.20	−22.04	8.35	6.17	−15.6***	−15.59***	119.2***
Panel B: 100 days before and during Covid-19 pandemic									
Corn	0.00	−0.13	5.77	−4.41	1.36	6.32	−14.61***	−14.69***	110.1***
Soybean	0.02	−0.01	3.34	−3.00	0.89	4.84	−12.49***	−12.41***	29.8***
Soybean meal	0.01	−0.07	3.49	−3.18	0.99	4.23	−11.43***	−11.33***	19***
Wheat	0.01	−0.10	5.13	−3.77	1.39	4.07	−14.12***	−14.12***	19.7***
Oats	0.04	0.08	4.06	−5.30	1.70	3.51	−14.58***	−14.59***	11.4***
WTI	0.09	−0.07	31.96	−28.22	6.54	11.65	−13.48***	−13.5***	618.9***
Gasoline	0.03	0.00	22.71	−39.73	5.79	18.57	−14.11***	−14.14***	2112.1***
Natural gas	−0.26	−0.29	8.51	−9.33	3.25	3.06	−14.11***	−14.56***	0.83
Brent	−0.03	0.14	19.08	−27.58	4.53	11.99	−12.29***	−12.31***	674.4***
Ethanol	0.00	0.00	9.02	−28.92	2.69	69.86	−13.71***	−13.71***	38.1k***
Live cattle	0.01	0.05	6.80	−5.23	1.89	4.81	−12.21***	−12.2***	27.9***

(*continued*)

Table 2.

Table 2.

Commodity	Mean (%)	Median (%)	Max (%)	Min (%)	Stdev	Kurtosis	ADF	PP	Jarque-Bera
Feeder cattle	0.01	0.02	4.86	−8.12	1.72	6.75	−11.26***	−11.07***	133.2***
Lean hogs	−0.23	−0.16	15.85	−20.01	4.02	9.17	−11.92***	−11.93***	315***
Gold	0.08	0.12	5.78	−4.74	1.28	7.93	−13.23***	−13.44***	204***
Silver	0.00	0.10	7.32	−12.39	2.30	9.12	−7.43***	−11.38***	342.8***
Copper	0.03	−0.01	3.61	−6.93	1.31	6.75	−14.11***	−14.2***	132.6***
Platinum	−0.07	0.22	11.18	−12.35	2.58	9.07	−7.71***	−13.34***	313.8***
Palladium	0.11	0.30	22.60	−23.40	3.67	19.38	−10.59***	−10.59***	2219.5***
Vix	0.31	−0.93	39.17	−26.62	9.51	7.00	−16.04***	−15.95***	201.7***

Note(s): This table shows the descriptive statistic of the daily returns of 18 commodities 100 days before and during the Russo-Ukraine war (October 2021–July 2022) and Covid-19 pandemic (September 2019–June 2020). * and *** denote significance at 10% and 1%, respectively. ADF and PP refer to Augmented Dickey–Fuller and Phillips–Perron unit root tests
Source(s): Author's own work

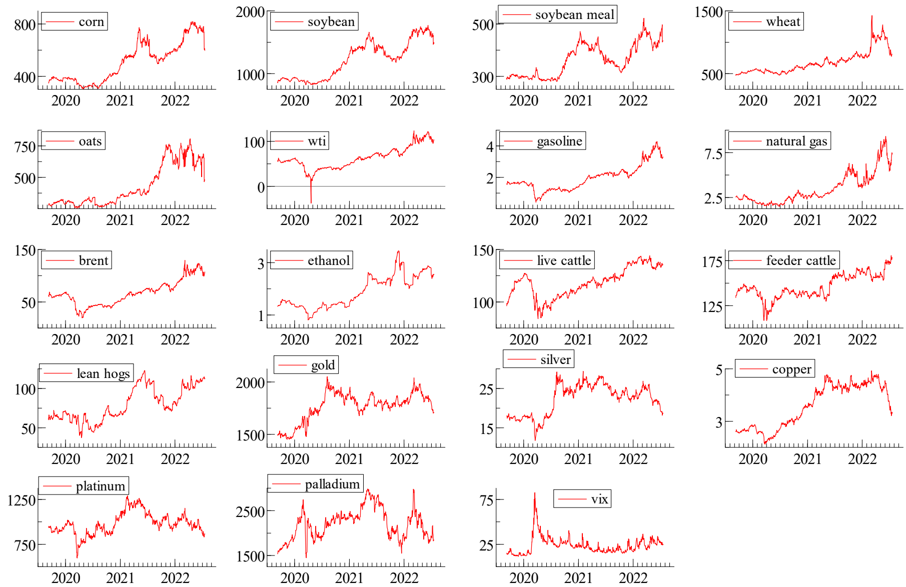

Figure 1.
Time evolution of commodity markets from August 2018 to July 2022

Source(s): Author's own work

intensity in commodity markets. This approach has been adopted in various studies, including those by Apergis *et al.* (2020), Babalos *et al.* (2015), Babalos and Stavroyiannis (2015), BenMabrouk (2018), Riza Demirer *et al.* (2015), Fan and Todorova (2021), Júnior *et al.* (2020), Kumar *et al.* (2021), Mohamad and Fromentin (2023), Pierdzioch *et al.* (2010), Steen and Gjolberg (2013), Youssef (2022) and Youssef and Mokni (2021). Moreover, these studies have explored the time-varying nature of herding intensity utilising diverse methodologies, such as the Kalman filter (Youssef, 2022), TVP regression with MCMC analysis, a technique popularised by Nakajima (2011) and employed in studies like Babalos *et al.* (2015), Mohamad (2024), Mohamad and Fromentin (2023) and Mohamad and Stavroyiannis (2022), rolling-windows regression model (Babalos and Stavroyiannis, 2015), Markov-switching model (Demirer *et al.*, 2015), covariance based on recursive estimations (Steen and Gjolberg, 2013) and Cai's (2007) time-varying model (Apergis *et al.*, 2020).

Informed by this comprehensive survey of the literature, our study has elected to utilise CSAD as the static measure to assess the presence of herding. Additionally, we will incorporate TVP regression with MCMC following Nakajima's (2011) framework as a robustness check to ascertain the presence of time-varying herding. Nakajima posits that TVP regression using MCMC is an efficacious model, as it is adept at detecting temporal fluctuations in the herding coefficient, thereby offering a more precise measure of herding.

3.1 CSAD static herding model

In the finance literature, herding behaviour is defined as behaviour in which traders mimic the actions of other traders, disregarding their judgement. Christie and Huang (1995) were amongst the first to argue that the intensity of herding behaviour could be measured by computing the CSSDs of asset returns during periods of market stress - departing from the need to use institutional data to measure herding behaviour. Later, Chang *et al.* (2000) suggested that the linear relationship in the CSSD of Christie and Huang (1995) could be

No	Author (yr), journal	Data	Method
1	Mohamad and Fromentin (2023, EE)	Daily dataset of 4 energy commodities and 3 investment indices from Aug 2018 to Feb 2023	CSAD and Nakajima (2011) TVP regression with stochastic volatility
2	Youssef (2022, JBF)	Daily dataset of 5 commodity sectors, SnP 500 and EURUSD from Jan 2003 to Apr 2017	CSAD and Kalman filter
3	Kumar *et al.* (2021, FRL)	Daily dataset of 3 aggregate commodity indices (agricultural, metal, energy) of 8 Asian countries from Jan 2010 to Mar 2020	CSAD within subperiods
4	Youssef and Mokni (2021, MF)	Daily dataset of 3 commodity sectors (agriculture, metal, energy) from Jan 2003 to Apr 2017	CSAD and Kalman filter
5	Fan and Todorova (2021, FRL)	Daily dataset of 24 commodity futures in China, roughly from Jan 2013 to Jun 2018	CSAD asymmetric model
6	Apergis *et al.* (2020, AEJ)	Daily dataset of 14 commodities based on different contract months from Jan 1990 to Dec 2020	CSAD based Cai (2007) time-varying model
7	Júnior *et al.* (2020, FRL)	Daily dataset of 15 commodities from Jan 2000 and Oct 2018	Hwang and Salmon (2004) beta herding measure
8	BenMabrouk (2018, MF)	Monthly dataset of WTI, Nasdaq100 and VIX from Jan 2000 to Dec 2016	Use modified CSSD and CSAD to account for crisis periods, vol and investor sentiment
9	Babalos *et al.* (2015, RP)	Daily dataset of 25 commodities sectors from Jan 2002 to Dec 2014	CSAD, Nakajima (2011) TVP regression with stochastic volatility and rolling windows reg
10	Babalos and Stavroyiannis (2015, AE)	Daily dataset of 8 metal commodities from Jan 1995 to Dec 2013	CSAD quantile, t-cDCC and rolling window reg models
11	Demirer *et al.* (2015, IRFA)	Daily dataset of 19 commodities from energy, livestocks, grains and metals from Jan 1995 to Nov 2012	CSAD static and Markov-switching models
12	Steen and Gjolberg (2013, AFE)	Monthly dataset of 20 commodities from 1986 to 2010	Beta herding and covariance based on recursive estimations
13	Pierdzioch *et al.* (2010, EE)	Quarterly oil-price forecasts published by ECB from 2002 to 2009	Based on forecast clustering approach

Note(s): This table shows the data and methods used to measure herding intensity in the previous commodity studies
Source(s): Author's own work

Table 3. Data and herding measures of previous commodity studies

converted into a nonlinear relationship and expressed this nonlinear herding behaviour intensity as the CSAD. Following them, we specify our CSAD model as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{it} - R_{mt}| \tag{1}$$

where R_{it} is defined as the natural log return of commodity i on day t and R_{mt} is the daily commodity sector return, namely grains, energy, livestock or metals.

The CSAD values for each commodity sector derived from Eq (1) are then used to calculate the cross-sectional dispersion of each commodity return around its commodity sector return during up- and down-market days, specified as follows:

$$CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+\left(R_{mt}^{2,+}\right) + \alpha_4^-\left(R_{mt}^{2,-}\right) + \varepsilon_t \tag{2}$$

where $|R_{mt}|$ is the absolute commodity sector return. $R_{mt}^{2,+}$ and $R_{mt}^{2,-}$ denote the commodity sector returns during up- and down-market days, respectively, taking values of 1 if the market registers positive (upturn) and negative (downturn) returns, respectively, and 0 otherwise. Coefficients α_3^+ and α_4^- will take negative values if herding is present and positive values if anti-herding is present. In the presence of herding, coefficients α_3^+ and α_4^- are expected to be negative, suggesting that the CSAD declines during market stress, reflecting the traders' herding behaviour in following the market consensus (actions of other traders) and disregarding their judgement. Collective imitations of trading actions would mean more significant similarity and would lead to lower return dispersions. We estimate Eq (2) across quantiles to test for asymmetries.

3.2 CSAD time-varying herding model

We also examine the existence of time-varying herding by employing a TVP regression with stochastic volatility using the MCMC algorithm. We are particularly motivated by Nakajima (2011), who adopts the TVP regression with MCMC sampling estimation, illustrates the time-varying nature of Japanese macroeconomic components and reiterates the need to incorporate stochastic volatility into the TVP framework. Thus, our TVP regression model is specified as follows:

$$y_t = x_t'\beta + z_t'\alpha_t + \varepsilon_t \tag{3}$$

where y_t is a scalar of response; x_t and z_t are $(k \times 1)$ and $(p \times 1)$ vectors of covariates, respectively; β is a $(k \times 1)$ vector of constant coefficients; α_t is a $(p \times 1)$ vector of time-varying coefficients.

The interactions of the system are given by:

$$\alpha_{t+1} = \alpha_t + u_t \tag{4}$$

where α_t signifies a vector of time-varying coefficients. Meanwhile, the stochastic volatility can be expressed as follows:

$$\sigma_t^2 = \gamma \exp(h_t);\ h_{t+1} = \phi h_t + \eta_t, \eta_t \sim N\left(0, \sigma_\eta^2\right);\ t = 0, \ldots, n-1 \tag{5}$$

where h_t represents stochastic volatility; it is assumed that $\alpha_0 = 0, u_0 \sim N\ (0, \Sigma_0)$, $\gamma > 0$, and $h_0 = 0$.

The time-varying coefficients α_t specified in Eq (4) follow a first-order random walk process, which enables the identification of temporary and permanent shifts. Simultaneously, the drifting coefficient allows us to observe non-linearity, such as a gradual change or structural break. For the log-volatility function in Eq (5), we presume the initial condition for the stationary distribution to be $h_0 \sim N(0, \sigma_\eta^2/(1-\phi^2)$ and $|\phi| < 1$. Σ (in the output) denotes a positive-definite matrix.

Next, we run the MCMC algorithm to recursively estimate the Bayesian posterior distribution [4]. We obtain 20,000 samples (iterations) after discarding the initial 2,000 samples from the burn-in period by assuming the following priors:

$$\beta \sim N(0, 10 \times I);\ \Sigma \sim IW(4, 40 \times I);\ \alpha_i \sim N(0, 10 \times I);\ \frac{\phi+1}{2} \sim \text{Beta}(20, 1.5); \sigma_\eta^2 \sim IG(2, 0.02);$$

$$\text{and}\, \gamma \sim IG(2, 0.02)$$

where IW and IG refer to the inverse-Wishart and inverse-Gamma distributions, whilst $\Gamma_p(.)$ represents a multivariate Gamma distribution, specified as follows:

$$W^{-1}(\Psi, v) = \frac{|\Psi|^{\frac{v}{2}}}{2^{\frac{vp}{2}}\Gamma_p\left(\frac{v}{2}\right)}|X|^{-\frac{v+p+1}{2}} exp\left(-1/2tr\left(\Psi X^{-1}\right)\right) \tag{6}$$

$$f(x;\, a, \beta) = \frac{\beta^a}{\Gamma(a)} x^{-a-1} exp\left(-\beta/x\right) \tag{7}$$

4. Empirical results and discussion

The essence of Chang *et al.*'s (2000) herding model lies in the interpretation of herding as deviations from the CAPM as the benchmark model. In the event of large market movements, the CAPM would suggest the asset returns were more dispersed and hence would move erratically due to the cross-sectional deviation of the asset returns from the benchmark returns. Thus, the coefficients α_3 and α_4 estimated across quantiles in Eq (2) must show significant and negative values to indicate the presence of herding during up- and down-market days. Similarly, in the TVP regression with stochastic volatility in Eq (3), the coefficients α_3 and α_4 estimated using MCMC need to show significant negative values to imply the presence of herding. In contrast, significant positive values of coefficients α_3 and α_4, in either the quantile or TVP regression model, would reveal anti-herding behaviour during market upturns and downturns.

4.1 CSAD static herding result

We proceed with the estimation of the quantile regression of the CSAD static measure from Eq (2), over 100 days before and 100 days during the Russo–Ukraine war, for each sector. Tables A1, A2, A3 and A4 present our findings on metal, livestock, energy and grain commodities. No significant negative values are recorded for the coefficients α_3 and α_4 across quantiles, suggesting no herding behaviour during up- and down-market days for any of the four commodity types. Meanwhile, mild anti-herding behaviour is observed for metal commodities before and during the Russo–Ukraine war. In contrast, stronger anti-herding is noticed for the other three commodity types, particularly before the war. Our static CSAD results are generally consistent with Babalos *et al.* (2015), who recorded no herding using 25 commodities before and during the 2008 GFC.

Tables A5, A6, A7 and A8 exhibit the CSAD static herding results for the metal, livestock, energy and grain commodities before and during the COVID-19 pandemic. We observe mild anti-herding behaviour for the metal (Table A5) and energy (Table A7) commodities, as indicated by positive significant values of the coefficients α_3 and α_4 for a few quantiles. The findings for the grain commodities tabulated in Table A8 do not show evidence of herding but weak evidence of anti-herding, as displayed for quantile 5, where the coefficient α_3 has a value of 0.4368. Contrarily, we uncover the only evidence of herding, albeit with mild intensity, amongst the livestock commodities before the COVID-19 pandemic, during down-market days, in quantiles 0.6 (−0.083) and 0.8 (−0.1546). Interestingly, mild anti-herding behaviour is also detected during up-market days amongst the livestock commodities, in quantiles 0.4 (0.1564), 0.5 (0.1221) and 0.6 (0.0902).

Utilising a static herding measure (CSAD) for both crises, the Russo–Ukraine war and the COVID-19 pandemic, we observe almost non-existent herding behaviour before and during the crises for all commodity sectors except livestock, which shows mild herding intensity during market downturns before the pandemic. Our results generally align with Babalos *et al.* (2015), who document a lack of herding within commodity sectors surrounding the and Júnior *et al.* (2020), who find evidence of herding amongst food commodities.

4.2 CSAD time-varying herding result

Figures A1, A2, A3 and A4 delineate the time-varying herding behaviour based on the CSADs using Bayesian TVP regression with the MCMC algorithm over 100 days before and 100 days during the Russo–Ukraine war. If herding were present during up- or down-market days, we would expect the coefficients α_3 (during upturns) and α_4 (during downturns) exhibited in Panel A to be negative. In contrast, if anti-herding were observed, we would expect the coefficients α_3 and α_4 displayed in Panel A to be positive. The MCMC sampling results are shown in Panel B. Panel B's top, middle and bottom sections show the sample autocorrelations, sample paths and posterior distribution, respectively. The sample paths for each commodity sector surrounding the Russo–Ukraine war appear stable, and the sample autocorrelations seem to decline stably, suggesting the ability of the MCMC algorithm to yield uncorrelated samples efficiently. Table A9 shows posterior means, standard deviations (Stdev), 95% credible intervals (upper and lower bounds), convergence diagnostics (Geweke, 1992) and inefficiency factors (Inef) based on the MCMC estimations of the TVP regressions for both the Russo–Ukraine war and the COVID-19 pandemic. Comparing the posterior means and 95% credible intervals, we can observe that, for all the samples, i.e. commodity sectors, surrounding both crises, the posterior means lie within the credible intervals, suggesting a non-rejection of the convergence of the posterior distribution hypothesis. Correspondingly, the inefficiency factor for parameter σ_η for the metal commodities displayed in Panel A of Table A9 is 126.5, which points to uncorrelated samples, thus indicating adequacy for the posterior inference.

Figure A1 presents the time-varying alphas for the metal commodities (gold, silver, copper, platinum and palladium). The coefficients α_3 and α_4 appear positive, indicating anti-herding behaviour except in the last 30 days during the Russo–Ukraine war. In other words, mild herding intensity is detected amongst the metal commodities only at the end of the sample period, for about 10% of the time, during both up- and down-market days. Meanwhile, the livestock commodities (live cattle, feeder cattle and lean hogs), as depicted in Figure A2, show milder time-varying herding, at about 2% of the time, which occurs during down-market days on the eve of the Russo–Ukraine war. Similarly, Figure A3 displays very weak herding intensity amongst the energy commodities (WTI, gasoline, natural gas Brent and ethanol), at about 3% of the time during market upturns and occurring on day 50 before the Russo–Ukraine war. This finding seems slightly at odds with Mohamad (2022), who observes time-varying herding amongst energy commodities about 20% of the time during market upturns and downturns, 24 h before and after the Russian invasion of Ukraine. Finally, Figure A4 exhibits the faintest time-varying herding, of less than 1% of the time, for the grain commodities (corn, soybean, soybean meal and wheat) during down-market days, with anti-herding behaviour dominating at more than 99% of the time for this commodity sector.

Overall, as can be seen from Table A10, we observe very mild herding or strong anti-herding across the commodity sectors in the 100 days before and during the Russo–Ukraine war. Our time-varying herding results in Figures A1, A2, A3 and A4 generally align with our static herding results tabulated in Tables A1, A2, A3 and A4. In other words, the war in Ukraine has typically not resulted in herding in the commodity markets, a finding that is broadly consistent with Babalos *et al.* (2015), who observe no herding in the commodity markets using a static model but uncover some evidence of time-varying herding briefly following the 2008 GFC.

We re-run the CSAD time-varying herding analysis using TVP regression and MCMC for the four commodity types before and during the COVID-19 pandemic. Figure A6 shows the time-varying alphas for the metal commodities (gold, silver, copper, platinum and palladium). There is mild herding intensity indicated by the coefficients α_3 (on day 50 during the pandemic on up-market days) and α_4 (on day 50 before the pandemic during down-market days), about 10% of the time. On the other hand, Figure A6 demonstrates much stronger herding intensity amongst the livestock commodities (live cattle, feeder cattle and lean hogs). These livestock commodities appear to herd about 40% of the time during upturns and 70%

of the time during downturns, as shown by the coefficients α_3 and α_4. Similarly, Figure A7 reveals strong herding behaviour within the energy commodity sector (WTI, gasoline, natural gas Brent and ethanol). The energy commodities move together about 60% of the time during market upturns and 70% during market downturns surrounding the COVID-19 pandemic. This finding aligns with Youssef (2022), who documents time-varying herding amongst energy commodities after the 2008 GFC. Lastly, in Figure A8, we can observe weaker time-varying herding in the grain commodity sector (corn, soybean, soybean meal and wheat), as indicated by the coefficients α_3 and α_4. The grain commodities herd together about 30% of the time during market upturns and downturns. Our time-varying herding results for the grain commodities generally agrees with Demirer *et al.* (2015), who observe the presence of herding based on a Markov-switching model during high-volatility periods.

In summary, our analysis reveals a notable increase in herding behaviour, surpassing 50% of the time, within the energy (65%) and livestock (55%) sectors, compared to the metal (10%) and grain (30%) sectors, both before and during the COVID-19 pandemic. Furthermore, we find that commodity markets demonstrate significantly stronger herding during the COVID-19 pandemic compared to the Russo–Ukraine conflict. Put differently, there is a clear discrepancy in herding behaviour between these two crises, with the pandemic exerting a much more significant influence than the Russo–Ukraine conflict. This difference likely arises from the global impact of the COVID-19 pandemic, whereas the impact of the Russo–Ukraine conflict appears more localised, primarily affecting Ukraine, Russia and possibly nearby Balkan countries. Additionally, our analysis is based on commodity futures data sourced from US-based exchanges, suggesting a diminished influence of the Russo–Ukraine conflict on these markets.

5. Conclusion

This study examined the intensity of herding behaviour in the most actively traded commodity futures from the energy, metal, livestock and grain sectors over 100 trading days before and during two major crises: the Russo–Ukraine war and the COVID-19 pandemic. To this end, we used a dual approach: the static quantile regression method of cross-sectional absolute deviation (CSAD) and a dynamic model, specifically the CSAD regression with TVPS with stochastic volatility using MCMC estimation.

Our results reveal remarkable differences between the two methods. The TVP regression method, which provides a more detailed time-varying analysis, showed low herding intensity during the Russo–Ukraine war but increased herding behaviour during the COVID-19 pandemic. In contrast, the static model predominantly showed negligible herding associated with the Russo–Ukraine war, whilst only low herding was observed in livestock populations prior to the COVID-19 outbreak. This discrepancy emphasises the effectiveness of time-varying measures in depicting the evolution of herd formation over time.

Further, our analysis suggests different herding patterns during the two crises, with commodities, particularly from the livestock and energy sectors, showing more pronounced herding behaviour during the COVID-19 pandemic than during the Russo–Ukraine war. This observation is intriguing as, unlike the pandemic, the Russo–Ukraine war had a limited impact on herding behaviour in commodity markets. In particular, the recent Russian blockade of Odessa, which led to a significant increase in wheat prices, has not impacted the herding behaviour of grain commodities such as corn, soybeans, soybean meal and wheat [5]. For precious metals such as gold, silver, high-grade copper, platinum and palladium, herding only occurred in around 10% of cases during the Russo–Ukraine war.

Our study provides important insights to commodity traders, investors, academics and policy makers. First, the time-varying herding behaviour in energy and livestock commodities during the COVID-19 pandemic suggests a simultaneous movement amid a health crisis. This observation calls for a strategy for investors in these commodities to diversify their portfolios into other commodities to mitigate risk. A lack of diversification in the face of an impending pandemic could lead to significant financial losses. Secondly, regardless of the nature of the crisis - be it a pandemic or a war - energy commodities always exhibit increased volatility. This behaviour can be seen in the individual energy commodities' minimum and maximum daily returns. Against this background, commodity futures exchanges should consider increasing margin requirements for energy commodities, especially when news about pandemics or wars affects the markets. Third, our study argues in favour of including time-varying models such as TVP regression with stochastic volatility in academic and scientific analyses. These models provide more detailed results than static herd instinct analyses, allowing for a more accurate representation of market dynamics. Our findings reveal marked herding tendencies in the livestock and energy sectors during the COVID-19 pandemic whilst indicating anti-herding behaviour in areas such as grains and metals. These results stand in contrast to the observations made by Demirer *et al.* (2015) yet align more closely with the research of Júnior *et al.* (2020) and Youssef (2022).

However, our study is not without limitations. For example, we could not investigate the determinants of herding behaviour in more detail, particularly whether it originates from institutional or retail investors/traders. This investigation would require access to commodity brokers' order books and proprietary data not readily available in financial databases. Consequently, certain aspects of herd intensity remain elusive and represent a suitable area for future research.

Notes

1. The most actively traded futures contracts by sector can be seen on the Barchart website (see https://www.barchart.com/futures/most-active/all?orderBy=volume&orderDir=desc).
2. See US Securities and Exchange Commission. "CME Group, Form 10-K, For the Fiscal Year Ended December 31, 2021," p5. https://investor.cmegroup.com/static-files/afdab443-a828-46c8-97fc-5f407512a5de
3. The first blasts on Kyiv, which marked the start of the Russo–Ukraine war, were heard around 5am, 24 February 2022 (see, for example, Mohamad, 2022). The World Health Organisation declared the COVID-19 outbreak as a public health emergency of international concern on 30 January 2020. Hence, we use 1 February 2020 as the start of the COVID-19 pandemic.
4. MCMC is considered one of the most powerful algorithms for recursively sampling from a posterior distribution.
5. See https://www.economist.com/the-economist-explains/2022/05/27/why-is-odessa-important-to-both-ukraine-and-russia

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Appendix

Table A1. CSAD quantile regression on metal commodities before and during Russo-Ukraine war

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$

Parameter	Quantile	100 days before Russo-Ukraine war Coefficient	*t*-stat	Prob	100 days during Russo-Ukraine war Coefficient	*t*-stat	Prob
α_1	0.2	0.6076	4.19	0.0001	0.5865	5.39	0
	0.4	0.7816	4.86	0	0.6853	4.99	0
	0.5	0.9255	6.54	0	0.6937	4.86	0
	0.6	1.0641	7.29	0	0.8815	6.16	0
	0.8	1.1514	8.09	0	1.2513	6.47	0
α_2	0.2	−0.1558	−0.66	0.5119	−0.0810	−0.50	0.6204
	0.4	−0.0851	−0.31	0.7603	0.0089	0.04	0.9654
	0.5	−0.0983	−0.44	0.6599	0.0855	0.36	0.7223
	0.6	−0.0654	−0.29	0.7741	−0.0130	−0.07	0.9455
	0.8	0.1153	0.39	0.6998	−0.1449	−0.66	0.5127
α_3	0.2	0.1122	1.41	0.1627	0.1069	2.38	0.0192
	0.4	0.0762	0.75	0.4545	0.0863	1.51	0.1354
	0.5	0.1330	2.33	0.022	0.0658	0.98	0.3293
	0.6	0.1163	2.00	0.0479	0.0787	1.54	0.1264
	0.8	0.0661	0.84	0.4005	0.1580	1.55	0.1253
α_4	0.2	0.1793	2.49	0.0145	0.0855	2.00	0.0488
	0.4	0.1402	1.61	0.1099	0.0621	1.12	0.2654
	0.5	0.1303	1.86	0.0654	0.0831	0.97	0.3352
	0.6	0.1103	1.57	0.1202	0.1124	2.70	0.0082
	0.8	0.0972	0.40	0.6925	0.1354	3.14	0.0022

Source(s): Author’s own work

Table A2. CSAD quantile regression on livestock commodities before and during Russo-Ukraine war

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$

Parameter	Quantile	100 days before Russo-Ukraine war Coefficient	*t*-stat	Prob	100 days during Russo-Ukraine war Coefficient	*t*-stat	Prob
α_1	0.2	0.3527	4.05	0.0001	0.1987	1.79	0.0763
	0.4	0.4982	5.34	0	0.4028	3.47	0.0008
	0.5	0.5186	5.38	0	0.5428	4.34	0
	0.6	0.6011	6.14	0	0.6498	5.06	0
	0.8	0.7993	7.09	0	0.7879	6.37	0
α_2	0.2	−0.3155	−1.56	0.1228	−0.0721	−0.27	0.7853
	0.4	−0.1556	−0.76	0.4485	0.0092	0.04	0.9704
	0.5	−0.0616	−0.28	0.7784	−0.0806	−0.31	0.7583
	0.6	−0.0111	−0.05	0.9619	−0.0691	−0.26	0.799
	0.8	0.4114	1.42	0.1587	0.2557	0.95	0.3444
α_3	0.2	0.2895	7.22	0	0.3515	6.43	0
	0.4	0.2493	5.83	0	0.3240	6.32	0
	0.5	0.2286	4.98	0	0.3369	6.30	0
	0.6	0.2143	4.43	0	0.3293	5.95	0
	0.8	0.1166	2.03	0.0454	0.2517	4.50	0
α_4	0.2	0.3607	7.62	0	0.0539	0.31	0.7547
	0.4	0.3134	6.30	0	0.0908	0.99	0.3271
	0.5	0.2895	5.46	0	0.1051	1.12	0.2662
	0.6	0.2724	4.87	0	0.0861	0.90	0.372
	0.8	0.1585	2.31	0.0231	−0.0423	−0.47	0.6423

Source(s): Author’s own work

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2\lvert R_{mt}\rvert + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$							
		100 days before Russo-Ukraine war			100 days during Russo-Ukraine war		
Parameter	Quantile	Coefficient	*t*-stat	Prob	Coefficient	*t*-stat	Prob
α$_1$	0.2	0.8447	1.61	0.1097	0.9239	4.21	0.0001
	0.4	1.1540	3.90	0.0002	1.2508	4.84	0
	0.5	1.5023	5.30	0	1.6036	6.29	0
	0.6	2.0317	6.93	0	1.7763	6.82	0
	0.8	2.3041	8.14	0	2.4348	7.91	0
α$_2$	0.2	−0.3716	−0.36	0.7177	−0.0465	−0.25	0.8052
	0.4	−0.4175	−1.33	0.1855	0.0783	0.35	0.7294
	0.5	−0.4570	−1.51	0.1336	−0.0286	−0.16	0.876
	0.6	−0.7179	−2.22	0.0288	−0.0550	−0.30	0.7651
	0.8	−0.1898	−0.50	0.6183	−0.0676	−0.33	0.7427
α$_3$	0.2	0.2049	0.55	0.586	0.0342	1.35	0.1812
	0.4	0.2614	6.22	0	0.0129	0.41	0.6857
	0.5	0.2604	6.42	0	0.0208	0.84	0.4047
	0.6	0.2860	6.69	0	0.0213	0.87	0.3881
	0.8	0.2094	4.21	0.0001	0.0122	0.47	0.6378
α$_4$	0.2	0.2233	1.41	0.1609	0.0365	1.20	0.2346
	0.4	0.2286	4.92	0	0.0388	0.77	0.4452
	0.5	0.2265	4.92	0	0.0588	2.42	0.0174
	0.6	0.4196	4.97	0	0.0637	2.70	0.0081
	0.8	0.3096	3.48	0.0007	0.0555	2.38	0.0195

Source(s): Author's own work

Table A3. CSAD quantile regression on energy commodities before and during Russo-Ukraine war

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2\lvert R_{mt}\rvert + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$							
		100 days before Russo-Ukraine war			100 days during Russo-Ukraine war		
Parameter	Quantile	Coefficient	*t*-stat	Prob	Coefficient	*t*-stat	Prob
α$_1$	0.2	0.8342	8.49	0	0.7047	4.75	0
	0.4	1.0389	8.32	0	0.8822	5.51	0
	0.5	1.0900	7.88	0	1.1445	7.36	0
	0.6	1.1749	8.07	0	1.3892	8.64	0
	0.8	1.5111	8.97	0	1.3393	4.75	0
α$_2$	0.2	−0.6170	−3.73	0.0003	0.0115	0.08	0.936
	0.4	−0.6438	−3.61	0.0005	0.0943	0.70	0.4864
	0.5	−0.5044	−2.45	0.0161	0.0188	0.14	0.8905
	0.6	−0.3798	−1.73	0.0867	−0.0435	−0.32	0.7499
	0.8	−0.3242	−1.30	0.1959	0.6253	1.00	0.3219
α$_3$	0.2	0.2560	8.29	0	0.0568	1.21	0.2289
	0.4	0.2541	7.81	0	0.1003	6.81	0
	0.5	0.2273	6.22	0	0.1055	6.97	0
	0.6	0.2020	5.24	0	0.1094	7.31	0
	0.8	0.1809	4.29	0	0.0598	0.16	0.8703
α$_4$	0.2	0.2144	2.04	0.0437	0.0313	3.29	0.0014
	0.4	0.2982	6.31	0	0.0249	2.74	0.0074
	0.5	0.2407	4.16	0.0001	0.0288	3.12	0.0024
	0.6	0.2204	3.97	0.0001	0.0319	3.47	0.0008
	0.8	0.1833	3.27	0.0015	−0.0130	−0.31	0.756

Source(s): Author's own work

Table A4. CSAD quantile regression on grain commodities before and during Russo-Ukraine war

Table A5.
CSAD quantile regression on metal commodities before and during Covid-19 pandemic

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$

		100 days before Covid-19			100 days during Covid-19		
Parameter	Quantile	Coefficient	*t*-stat	Prob	Coefficient	*t*-stat	Prob
α_1	0.2	0.4085	5.61	0	0.5196	5.73	0
	0.4	0.5416	3.78	0.0003	0.6970	6.12	0
	0.5	0.5652	6.99	0	0.7789	6.76	0
	0.6	0.7514	7.48	0	0.9352	7.72	0
	0.8	1.0379	7.15	0	1.3406	6.81	0
α_2	0.2	0.0989	0.38	0.7076	0.2435	2.70	0.0082
	0.4	0.0319	0.04	0.9673	0.2442	1.66	0.0994
	0.5	0.1693	0.61	0.543	0.2382	1.98	0.0511
	0.6	−0.2668	−0.83	0.4105	0.2729	2.18	0.0315
	0.8	−0.4766	−1.14	0.2555	0.3427	1.89	0.0612
α_3	0.2	0.0043	0.02	0.9861	0.0250	1.45	0.1512
	0.4	0.0277	0.04	0.9679	0.0561	0.58	0.5654
	0.5	−0.0130	−0.04	0.9647	0.0907	2.17	0.0321
	0.6	0.3309	1.63	0.1056	0.0745	1.73	0.0863
	0.8	0.3469	1.48	0.141	0.0477	1.04	0.2989
α_4	0.2	0.2206	1.92	0.0583	0.0297	3.40	0.001
	0.4	0.2961	0.42	0.6775	0.0281	1.88	0.0627
	0.5	0.1819	1.30	0.1968	0.0280	2.30	0.0238
	0.6	0.4864	2.32	0.0223	0.0233	1.84	0.0687
	0.8	0.5265	2.24	0.0274	0.0132	0.78	0.438

Source(s): Author's own work

Table A6.
CSAD quantile regression on livestock commodities before and during Covid-19 pandemic

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$

		100 days before Covid-19			100 days during Covid-19		
Parameter	Quantile	Coefficient	*t*-stat	Prob	Coefficient	*t*-stat	Prob
α_1	0.2	0.2020	2.73	0.0076	0.4200	3.53	0.0006
	0.4	0.2142	3.19	0.0019	0.6620	4.29	0
	0.5	0.2285	3.55	0.0006	0.6603	3.76	0.0003
	0.6	0.2311	3.72	0.0003	0.6515	3.06	0.0029
	0.8	0.3741	4.94	0	0.7995	3.61	0.0005
α_2	0.2	0.0897	0.44	0.6629	−0.0091	−0.06	0.9536
	0.4	0.5581	2.97	0.0038	0.0573	0.32	0.7518
	0.5	0.7265	4.56	0	0.2627	1.19	0.2355
	0.6	0.8850	5.85	0	0.5460	1.63	0.1056
	0.8	1.1349	5.52	0	0.9907	2.39	0.0187
α_3	0.2	0.2508	6.11	0	0.0173	0.52	0.6076
	0.4	0.1564	4.12	0.0001	0.0036	0.10	0.9193
	0.5	0.1221	3.83	0.0002	−0.0208	−0.51	0.6145
	0.6	0.0902	3.02	0.0032	−0.0695	−1.22	0.2256
	0.8	0.0344	0.82	0.4126	−0.0031	−0.04	0.9713
α_4	0.2	0.1181	2.41	0.0178	0.0185	0.62	0.5349
	0.4	0.0000	0.00	0.9998	0.0104	0.36	0.7188
	0.5	−0.0431	−1.04	0.299	−0.0206	−0.61	0.5428
	0.6	−0.0830	−2.08	0.0404	−0.0536	−1.17	0.2453
	0.8	−0.1546	−3.04	0.0031	−0.1022	−1.28	0.203

Source(s): Author's own work

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$

Parameter	Quantile	100 days before Covid-19 Coefficient	*t*-stat	Prob	100 days during Covid-19 Coefficient	*t*-stat	Prob
α_1	0.2	0.3957	3.66	0.0004	0.6366	2.62	0.0102
	0.4	0.6843	5.67	0	1.0752	5.12	0
	0.5	0.7821	6.22	0	1.2080	5.27	0
	0.6	0.8809	6.40	0	1.2765	5.03	0
	0.8	1.2220	7.28	0	2.0063	3.85	0.0002
α_2	0.2	0.1874	1.32	0.1906	0.1760	0.83	0.408
	0.4	0.1927	1.20	0.2325	0.1301	1.06	0.2906
	0.5	0.1449	0.88	0.381	0.2594	1.81	0.0732
	0.6	0.2689	1.38	0.1696	0.3308	1.95	0.0539
	0.8	0.3858	1.52	0.1317	0.4779	1.23	0.2206
α_3	0.2	0.0441	2.80	0.0062	0.0378	1.36	0.1775
	0.4	0.0396	2.19	0.031	0.0426	4.00	0.0001
	0.5	0.0438	2.37	0.0199	0.0353	3.26	0.0016
	0.6	0.0283	1.31	0.1939	0.0296	2.36	0.0203
	0.8	0.0103	0.37	0.7121	0.0147	0.54	0.5897
α_4	0.2	0.0630	1.85	0.0676	0.0275	1.42	0.1584
	0.4	0.0376	0.89	0.3753	0.0414	5.23	0
	0.5	0.0560	1.41	0.1621	0.0324	3.56	0.0006
	0.6	0.0236	0.52	0.6073	0.0275	2.60	0.0109
	0.8	−0.0193	−0.36	0.7198	0.0158	0.67	0.5036

Source(s): Author's own work

Table A7. CSAD quantile regression on energy commodities before and during Covid-19 pandemic

CSAD augmented model Eq (x): $CSAD_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3^+(R_{mt}^{2,+}) + \alpha_4^-(R_{mt}^{2,-}) + \varepsilon_t$

Parameter	Quantile	100 days before Covid-19 Coefficient	*t*-stat	Prob	100 days during Covid-19 Coefficient	*t*-stat	Prob
α_1	0.2	0.5027	5.78	0	0.4202	4.76	0
	0.4	0.6768	6.86	0	0.4571	5.73	0
	0.5	0.6997	7.45	0	0.5093	6.05	0
	0.6	0.7982	8.79	0	0.5910	6.94	0
	0.8	0.9252	9.68	0	0.8586	6.65	0
α_2	0.2	−0.0868	−0.25	0.8037	0.1266	0.29	0.7712
	0.4	−0.2138	−0.52	0.6066	0.4184	1.58	0.1172
	0.5	−0.1646	−0.46	0.6436	0.5615	2.07	0.0408
	0.6	−0.0669	−0.18	0.8556	0.5481	2.03	0.0453
	0.8	0.6126	1.37	0.1733	0.5000	1.34	0.1836
α_3	0.2	0.2715	0.91	0.3662	−0.0349	−0.12	0.9061
	0.4	0.3405	0.90	0.3692	−0.0455	−0.41	0.6793
	0.5	0.4368	1.84	0.0696	−0.0803	−0.72	0.4723
	0.6	0.3428	1.45	0.1512	−0.0877	−0.80	0.4275
	0.8	−0.0852	−0.31	0.7563	−0.1103	−0.77	0.4425
α_4	0.2	0.2933	1.24	0.2178	0.1237	0.34	0.7375
	0.4	0.3151	1.09	0.2802	0.1065	0.66	0.5105
	0.5	0.2752	1.11	0.2706	0.0321	0.20	0.8436
	0.6	0.1753	0.69	0.4942	0.0160	0.10	0.9185
	0.8	−0.3005	−1.14	0.2571	0.0748	0.28	0.783

Source(s): Author's own work

Table A8. CSAD quantile regression on grain commodities before and during Covid-19 pandemic

Table A9.
Time-varying parameter (TVP) regression estimation results

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef	Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Panel A: Metal commodities before and during Russo-Ukraine war							*Panel E: Metal commodities before and during Covid-19 pandemic*						
Σ_{11}	0.006	0.0037	0.0019	0.0156	0.574	56.71	Σ_{11}	0.0055	0.003	0.0019	0.0134	0.96	33.2
Σ_{22}	0.0083	0.0065	0.0023	0.0268	0.649	71.78	Σ_{22}	0.0076	0.0055	0.0022	0.0226	0.847	71.69
Σ_{33}	0.0043	0.0022	0.0016	0.0098	0.706	46.17	Σ_{33}	0.0062	0.0035	0.0021	0.0147	0.707	54.57
Σ_{44}	0.0034	0.0016	0.0015	0.0074	0.188	32.85	Σ_{44}	0.0044	0.0023	0.0017	0.0104	0.019	42.85
ϕ	0.865	0.099	0.6109	0.9894	0.802	34.75	ϕ	0.9308	0.0544	0.7918	0.9936	0.871	105.15
σ_η	0.1311	0.0616	0.061	0.2973	0.656	126.5	σ_η	0.4737	0.1774	0.1909	0.8621	0.721	113.02
γ	0.133	0.0317	0.0682	0.1882	0.307	57.54	γ	0.0978	0.0638	0.0104	0.244	0.478	132.47
Panel B: Livestock commodities before and during Russo-Ukraine war							*Panel F: Livestock commodities before and during Covid-19 pandemic*						
Σ_{11}	0.0063	0.004	0.0021	0.0163	0.958	65.12	Σ_{11}	0.0062	0.0033	0.0022	0.0146	0.71	42.32
Σ_{22}	0.0115	0.0122	0.0026	0.0468	0.006	115.64	Σ_{22}	0.013	0.0119	0.0029	0.0452	0.109	111.08
Σ_{33}	0.017	0.0127	0.0039	0.0494	0.974	101.82	Σ_{33}	0.0047	0.0024	0.0018	0.0109	0.259	57.57
Σ_{44}	0.0084	0.0076	0.0022	0.0282	0.185	114.68	Σ_{44}	0.0061	0.0037	0.0022	0.015	0.114	50.51
ϕ	0.8993	0.0761	0.6965	0.9867	0.932	35.47	ϕ	0.9622	0.0375	0.8569	0.9973	0.677	150.71
σ_η	0.1979	0.0969	0.0755	0.4333	0.866	122.21	σ_η	0.3287	0.158	0.1448	0.7495	0.437	190.42
γ	0.1586	0.0422	0.0691	0.242	0.679	43.16	γ	0.15	0.1396	0.0129	0.4253	0.324	130.94
Panel C: Energy commodities before and during Russo-Ukraine war							*Panel G: Energy commodities before and during Covid-19 pandemic*						
Σ_{11}	0.0098	0.0088	0.0023	0.0349	0.411	75.91	Σ_{11}	0.0116	0.0077	0.003	0.0319	0.166	57.89
Σ_{22}	0.008	0.0066	0.0022	0.024	0.523	84.78	Σ_{22}	0.0091	0.0062	0.0025	0.026	0.903	55.43
Σ_{33}	0.0028	0.0012	0.0013	0.0059	0.93	38.9	Σ_{33}	0.0027	0.0012	0.0013	0.0056	0.24	26.33
Σ_{44}	0.0036	0.0015	0.0016	0.0074	0.148	32.38	Σ_{44}	0.0028	0.0011	0.0013	0.0056	0.534	23.89
ϕ	0.8621	0.0997	0.6067	0.9909	0.037	65.43	ϕ	0.9793	0.0231	0.9154	0.9991	0.561	145.56
σ_η	0.2073	0.1109	0.0739	0.509	0.098	154.14	σ_η	0.2102	0.0761	0.0974	0.3891	0.794	108.82
γ	0.6932	0.1818	0.2107	1.0129	0.31	108.56	γ	0.1464	0.1504	0.0075	0.4956	0.474	242.03
Panel D: Grain commodities before and during Russo-Ukraine war							*Panel H: Grain commodities before and during Covid-19 pandemic*						
Σ_{11}	0.0061	0.0042	0.002	0.0168	0.716	70.71	Σ_{11}	0.0041	0.0019	0.0017	0.0089	0.036	40.08
Σ_{22}	0.0084	0.0073	0.0022	0.0282	0.879	91.95	Σ_{22}	0.0088	0.0068	0.0022	0.0284	0.809	88.74
Σ_{33}	0.0039	0.002	0.0016	0.0093	0.8	45.16	Σ_{33}	0.0092	0.0066	0.0024	0.0271	0.467	60.87
Σ_{44}	0.0048	0.0025	0.002	0.0115	0.075	47.94	Σ_{44}	0.0089	0.0066	0.0024	0.0274	0.377	65.56
ϕ	0.7411	0.1203	0.4619	0.9317	0.455	85.31	ϕ	0.8485	0.1065	0.5799	0.9835	0.912	28.69
σ_η	0.949	0.2205	0.565	1.4309	0.64	93.98	σ_η	0.1329	0.0559	0.0631	0.2759	0.453	96.02
γ	0.2256	0.0971	0.0866	0.4128	0.31	70.01	γ	0.1034	0.0189	0.0635	0.1401	0.165	22.61

Note(s): This table shows the TVP regression estimation results based on 95% Bayesian credible interval. Geweke is the Bayesian convergence diagnostic (Geweke, 1992), whilst Inef refers to inefficiency factor
Source(s): Author's own work

	Figure A1 (Metal)	Figure A2 (Livestock)	Figure A3 (Energy)	Figure A4 (Grain)
Panel A. 100 days before and during the Russo-Ukraine war				
During market upturns	10%	–	3%	–
During market downturns	10%	2%	–	1%
	Figure A5 (Metal)	Figure A6 (Livestock)	Figure A7 (Energy)	Figure A8 (Grain)
Panel B. 100 days before and during the Covid-19 pandemic				
During market upturns	–	40%	60%	30%
During market downturns	10%	70%	70%	30%

Note(s): This table shows the summary of herding intensity results 100 days before and during the crises in percentage using TVP regression with MCMC

Source(s): Author's own work

Table A10. Summary of herding intensity results using the TVP regression with MCMC

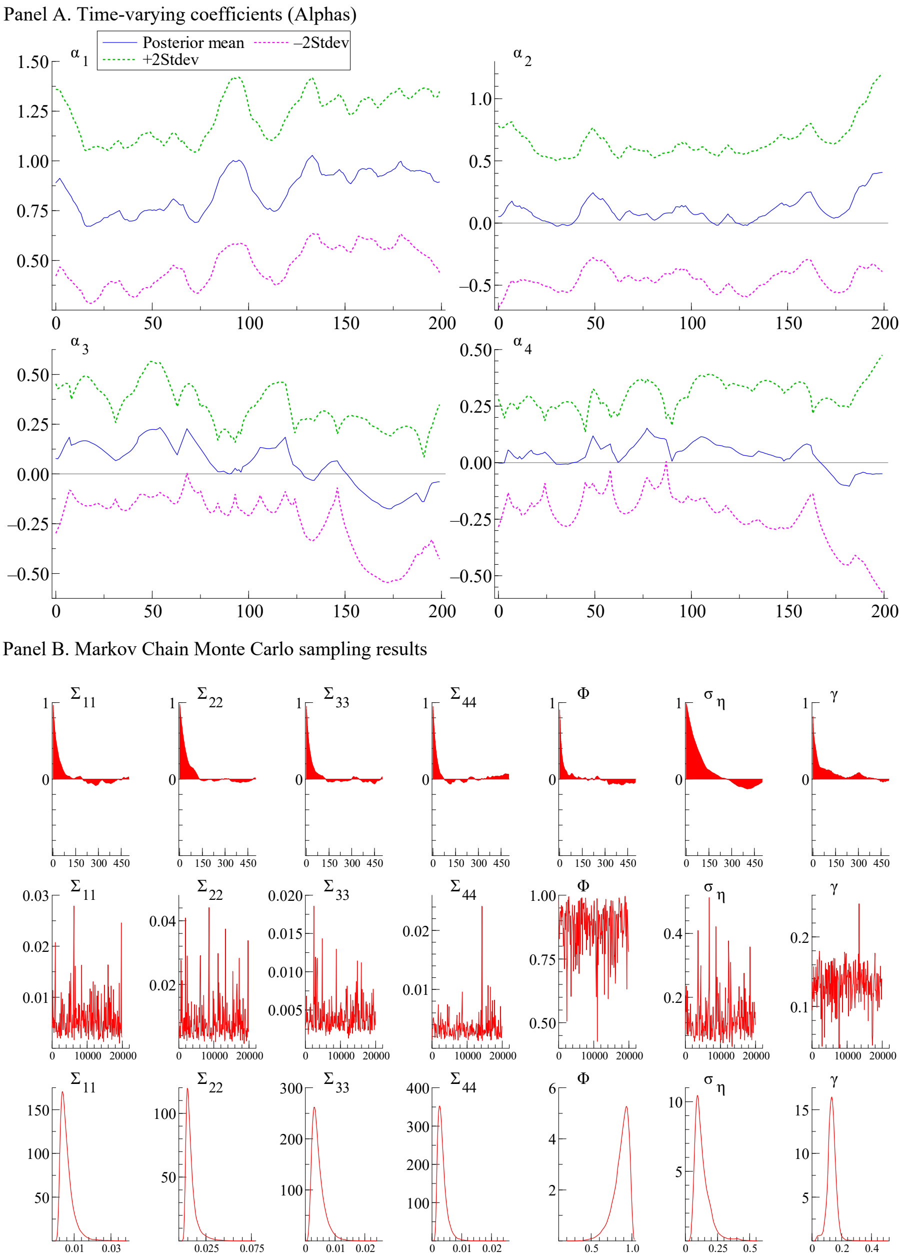
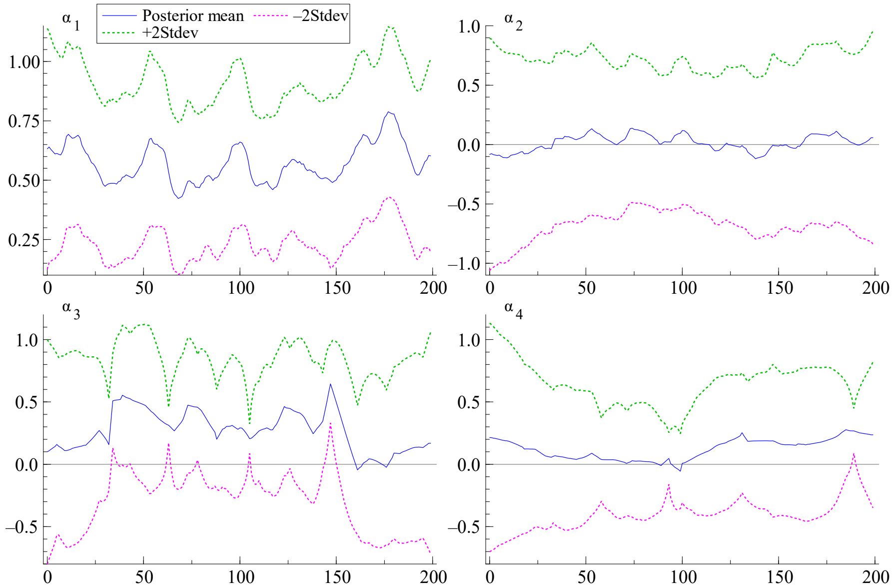


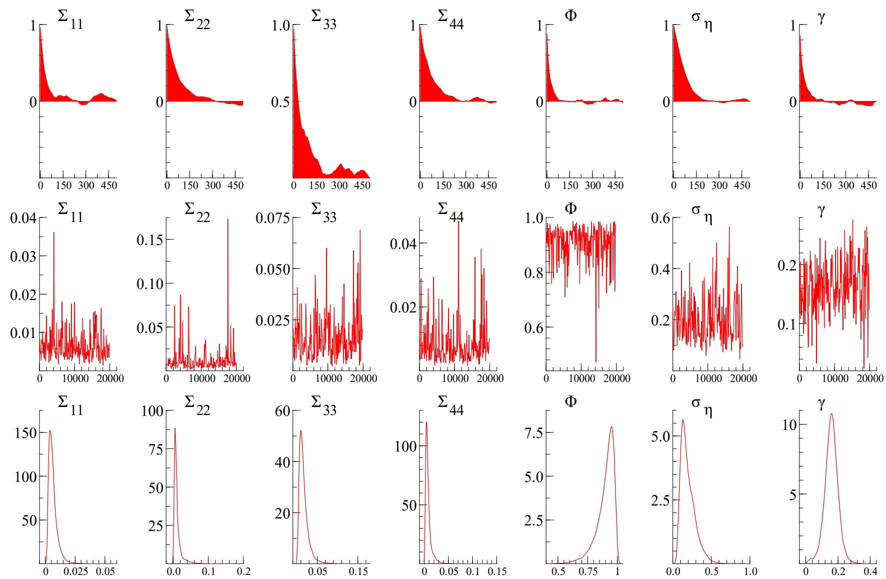
Figure A1.
CSAD TVP regression for metal commodities 100 days before and 100 days during the Russo-Ukraine war

Source(s): Author’s own work

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results



Source(s): Author's own work

Figure A2.
CSAD TVP regression for livestock commodities 100 days before and 100 days during the Russo-Ukraine war

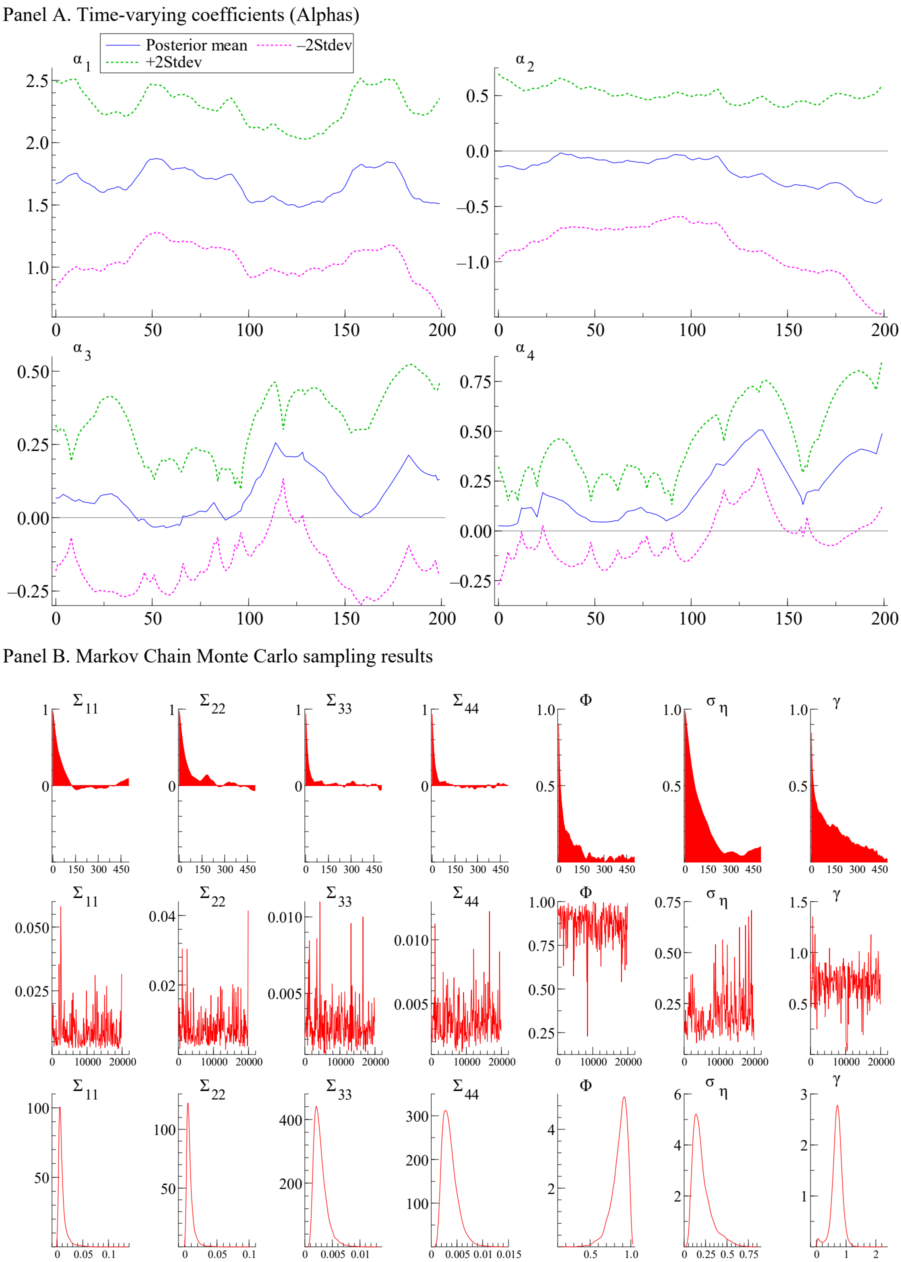
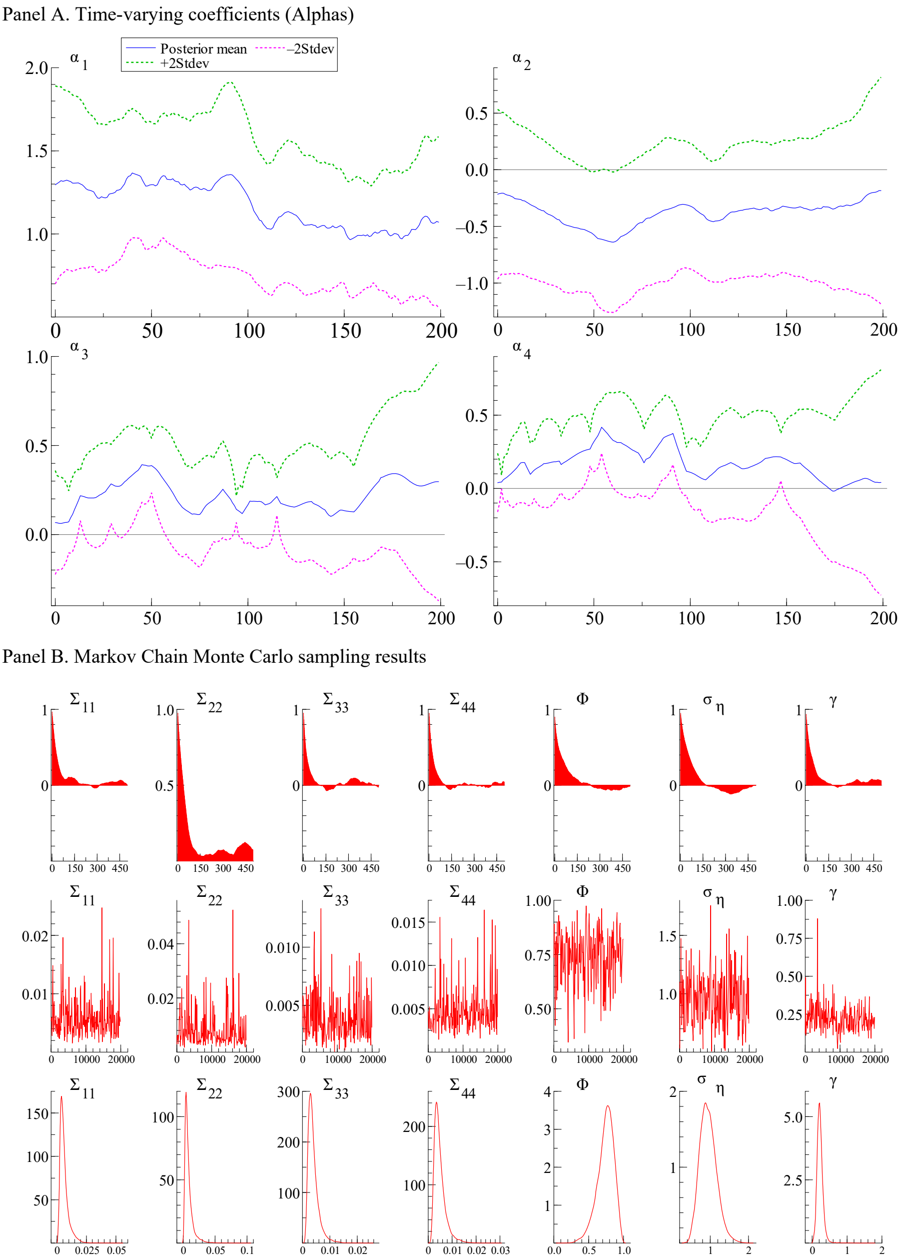


Figure A3.
CSAD TVP regression for energy commodities 100 days before and 100 days during the Russo-Ukraine war

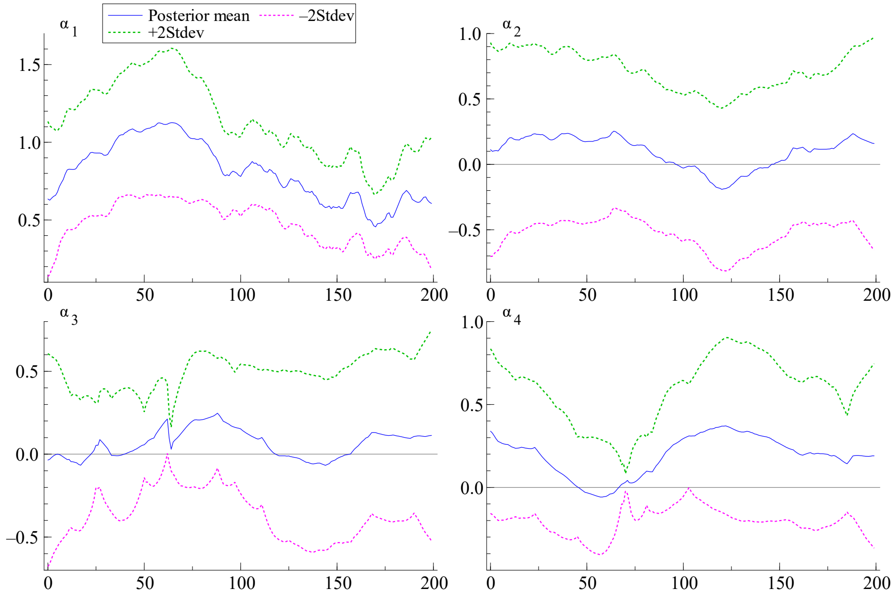
Source(s): Author's own work



Source(s): Author's own work

Figure A4.
CSAD TVP regression for grain commodities 100 days before and 100 days during the Russo-Ukraine war

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

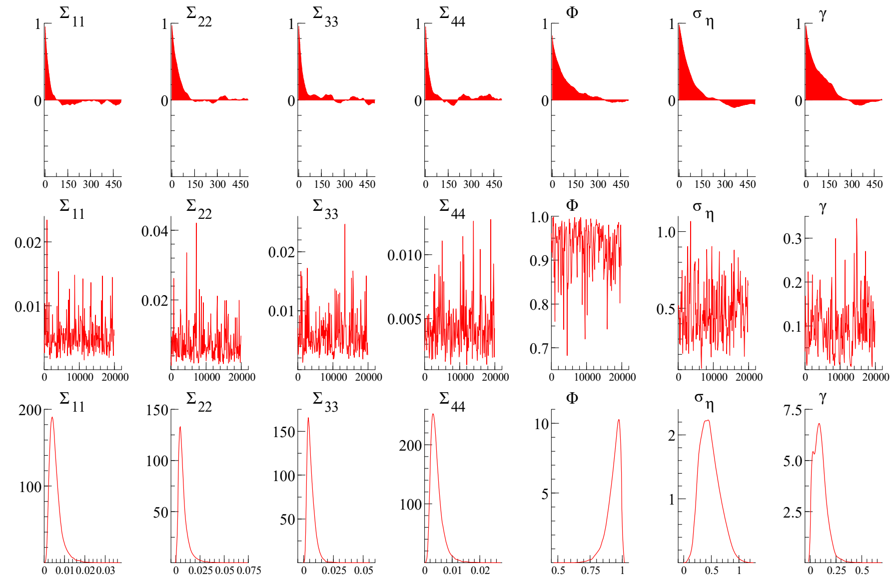
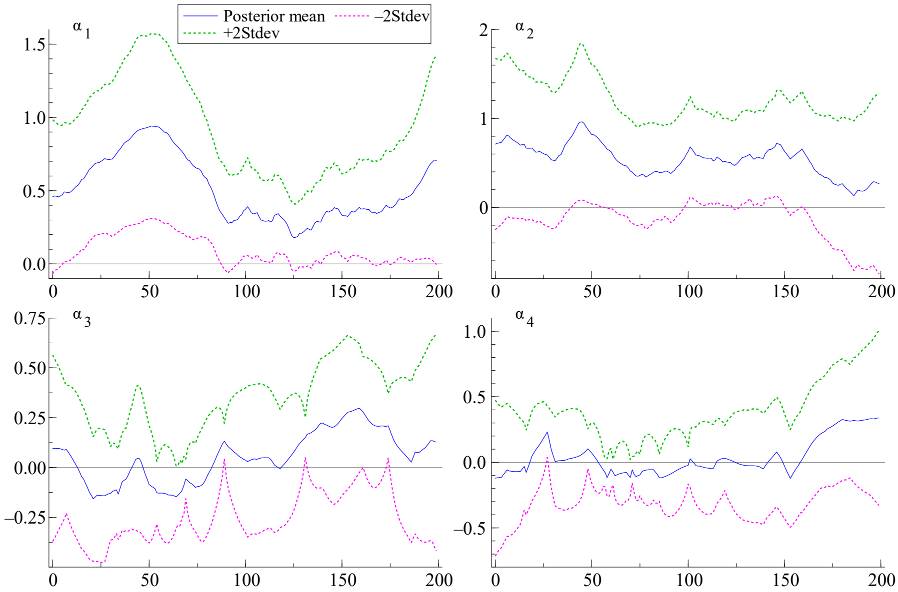


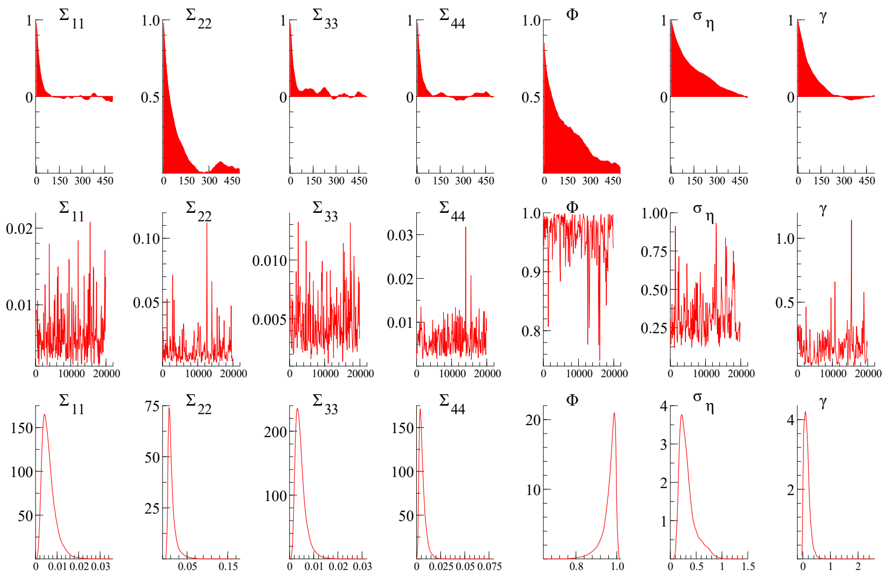
Figure A5.
CSAD TVP regression for metal commodities 100 days before and 100 days during the Covid-19 pandemic.

Source(s): Author’s own work

Panel A. Time-varying coefficients (Alphas)



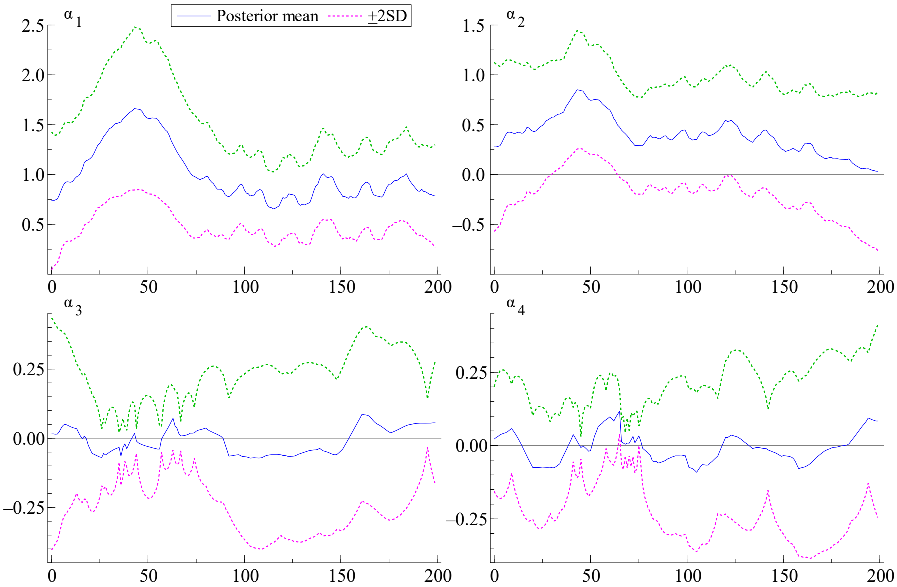
Panel B. Markov Chain Monte Carlo sampling results



Source(s): Author's own work

Figure A6.
CSAD TVP regression for livestock commodities 100 days before and 100 days during the Covid-19 pandemic

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

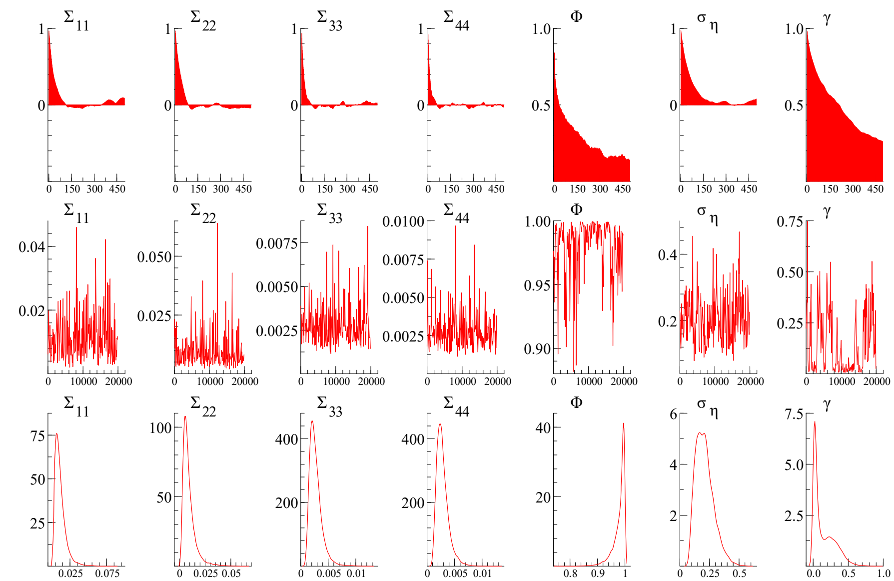
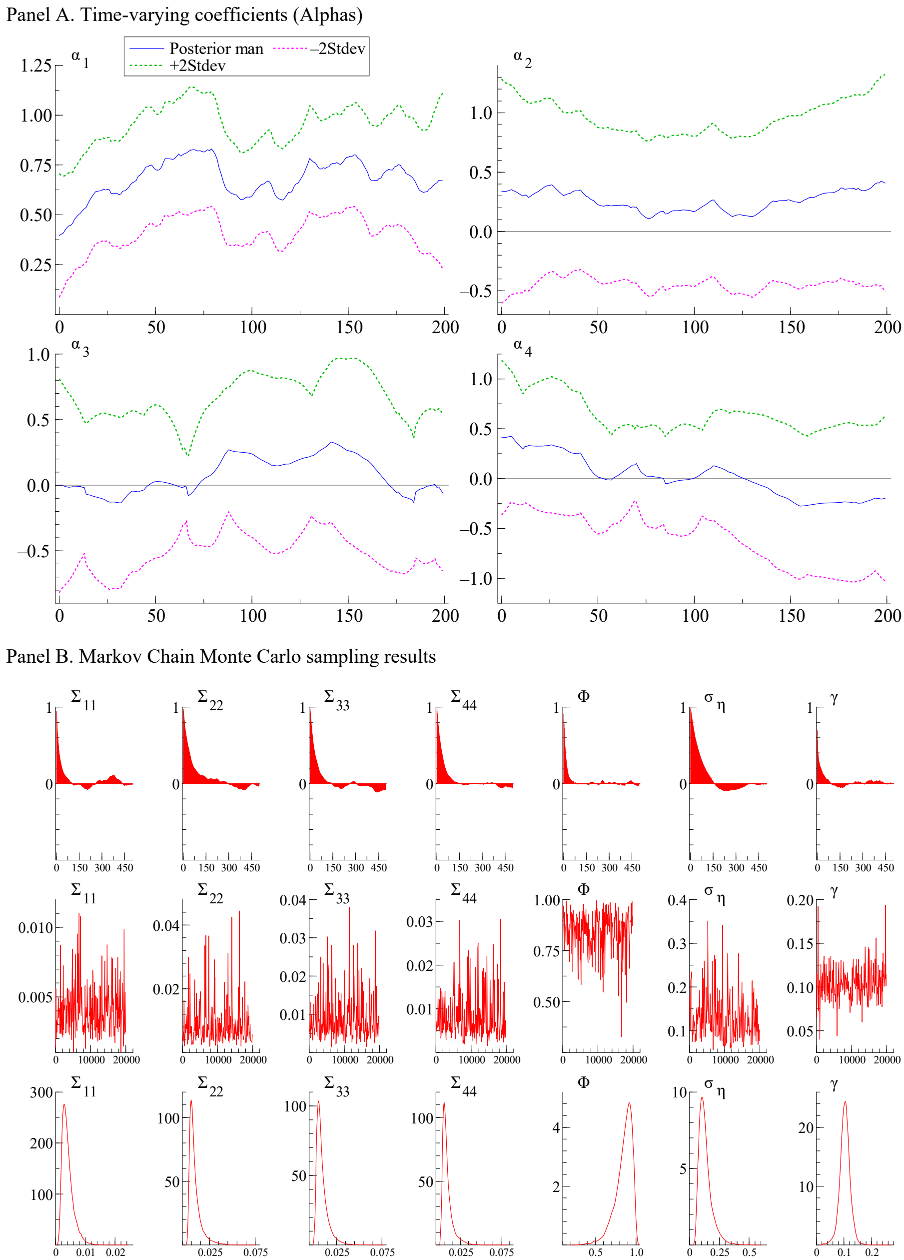


Figure A7.
CSAD TVP regression for energy commodities 100 days before and 100 days during the Covid-19 pandemic

Source(s): Author's own work



Source(s): Author's own work

Figure A8.
CSAD TVP regression for grain commodities 100 days before and 100 days during the Covid-19 pandemic