Herd dynamics around the Russo-Ukraine war and Covid-19 pandemic

Abstract
This paper scrutinises the herding behaviour in commodity markets surrounding the Russo-Ukraine war and Covid-19 pandemic. Utilising both static and time-varying measures, we examine the herding intensity within the following commodity sectors: energy, metal, livestock and grain commodities. We document heterogeneity. The static measure uncovers no herding surrounding the Russo-Ukraine war, and very weak herding within the livestock commodity sector before the pandemic. Contrarily, while the time-varying measure indicates mild herding surrounding the war, it detects considerably stronger herding intensity, particularly within the energy and livestock commodities, during the pandemic. In summary, the war in Ukraine does not result in a strong herding pattern in the commodity markets relative to that during the pandemic – which signals that not all crises produce similar herding intensity.

JEL classification: G14, G15.

Keywords: Herd behaviour; Russo-Ukraine war; Covid-19; Time-varying parameter (TVP) regression; Markov Chain Monte Carlo (MCMC).

1. Introduction

Two of the most recent crises to have wreaked havoc and stirred up the world's financial and commodity markets have been the Russo-Ukraine war and the Covid-19 pandemic. On the eve of the pandemic in January 2020, the S&P 500 tumbled from 3400 to 2180 within two months, while gold soared from a low of 1454 to an all-time high of 2070, an increase of 42.3% in a matter of eight months. In a similar manner, from three months before Russia's invasion of Ukraine, when the news broke, to nine months later, the Ukrainian currency, the Hryvnia, plunged from 0.0383 to 0.0207. On the other hand, gold suddenly became bullish – it surged from 1795 to a high of 2070 in a matter of two months. One man's meat suddenly became another man's poison in the financial and commodity markets, big time. Whereas some markets such as equity and currencies have turned gloomy, other markets like gold and precious metals have been more upbeat and perceived by investors to be safe ports in a financial storm.

Out of the latest financial turbulence, at least three strands of research have emerged. The first concerns the flight-to-safety or safe haven topic (e.g., Baur & Lucey, 2010; Kinateder et al., 2021; Mohamad, 2022; Sifat et al., 2022). In a flight-to-safety situation, when the market is in chaos, investors seek refuge from the financial turmoil. Safe-haven assets, which suddenly become attractive, are sought after, whereas risky assets suddenly become unappealing, and are dumped. Thus, funds will flow from the risky assets to the safe havens. Greenspan (2004) explains this situation as investors, facing uncertainty, disengaging from long-term commitments in favour of safety or liquidity - and not only will the funds flow in a dramatic manner, but they will also tend to move together in herds. A tumbling market can be a sign of herding in a flight-to-safety manner (Rıza Demirer & Kutan, 2006), as can a raging and bullish market.

The second reason why investors herd is because of a fear of missing out (FOMO). Chaos and volatility in financial markets can present excellent opportunities for investors and traders looking for breakouts (Williams, 2011). When certain price levels (support or resistance) are broken, traders may take this as a signal that a profit opportunity is presenting itself and that a market move is going to be explosive. Naturally, traders do not want to miss such opportunities, and FOMO can result in these types of traders entering buying or selling positions in droves, even if the entry level is sub-optimal, as they believe the market is ripe for massive price action (Potsaid & Venkataraman, 2022).

Thirdly, earlier herding research prior to the 2008 Global Financial Crisis (GFC) describes herding as an effect of speculation and the financialisation of commodity markets. As a case in point, hedge fund manager Michael Master testified in the US congress in 2008, claiming that it was index speculators and institutional investors who were crowding the corn and crude oil markets, causing the prices of these commodities to escalate (Masters, 2008). Furthermore, and interestingly, the soaring prices of these commodities coincided with the timing of the introduction of commodity exchange-traded funds (Masters et al., 2008). However, the notion of financialisation is not agreed upon by all researchers. Kilian (2009), for instance, argues that not all price shocks are alike, with commodity prices such as that of crude oil driven mainly by global demand and supply. In addition to that, some behavioural finance researchers, such as Aggarwal (2014) and Mu (2007), opine that the fluctuations in commodity prices are difficult to explain – and could be due to perplexing anomalies, such as psychological predisposition and animal behaviour.

Whether commodity traders and investors move in herds because of a flight-to-safety, FOMO or speculation and the financialisation of commodity markets, or for some other reason, herding behaviour, in our view, is an exciting avenue for research. In this paper, using a daily dataset, we are particularly interested in examining herding within the commodity sectors over 100 trading days before and 100 trading days during the two most recent crises, namely the Russo-Ukraine war and the Covid-19 pandemic. Our dataset covers 18 of the world's most liquid commodity futures, comprising the metal, livestock, energy and grain commodity sectors. To measure herding intensity, we employ both static and time-varying measures. First, we compute Chang et al.'s (2000) cross-sectional absolute deviations (CSADs) and run the model across quantiles. Then, to check whether herding intensity varies across time, we apply Nakajima's (2011) time-varying parameter (TVP) regression with stochastic volatility using Markov Chain Monte Carlo (MCMC) sampling estimation. A Bayesian inference using stochastic volatility, such as TVP regression and MCMC, can observe time variation, and hence is considered a superior method as it can produce detailed and precise results. Our static herding results generally indicate that commodity markets tend to anti-herd before and during the Russo-Ukraine war and show very mild herding within the livestock commodities before the Covid-19 pandemic. On the other hand, our time-varying herding analysis records very mild herding surrounding the Russo-Ukraine war but stronger herding intensity during the pandemic.

We add to the burgeoning herding and commodity markets literature, and our contributions are twofold. First and foremost, we believe our study is among the first to examine herding behaviour in commodity markets before and during the two most recent crises: the Russo-Ukraine war and the Covid-19 pandemic. In previous studies, Demirer et al. (2015) investigate herding in commodity markets over the period of January 1995 to November 2012, while Mohamad (2022) scrutinises herding within commodity and financial assets 24 hours before and after the Russian invasion of Ukraine. We particularly observe heterogeneity in terms of the herding intensity of the commodity markets between the two crises. It appears that the Covid-19 pandemic prompts markedly greater herding intensity in the world's most traded commodity markets than the Russo-Ukraine war. Secondly, our research is among the few studies that utilise both static and Bayesian TVP regression methods to estimate herding intensity before and during periods of market stress. A previous study (Babalos et al., 2015) also employs both static and TVP regression measures to examine herding before and after the 2008 GFC. Seminal work by Geweke (1992) and later research by Nakajima (2011) have motivated our research and espoused the application of Bayesian inference with stochastic volatility, as it can produce sound and reliable results.

The remainder of this paper is organised as follows. Section 2 reviews the literature on herding behaviour in commodity markets. Section 3 describes the data and methodology. Empirical results and discussion are presented in Section 4, and Section 5 offers our conclusion.

2. Literature review

It was John Maynard Keynes who first offered a simple explanation of why investors herd: if the stock market were a beauty contest, the judge would choose the victor by guessing who other judges would choose, rather than relying on her own beliefs and judgements (Keynes, 1936). Early theoretical works (Bikhchandani et al., 1992; Devenow & Welch, 1996) posit that fashion and fads contribute to the human inclination to emulate or mimic the behaviour of others. In a similar vein, within the financial markets, there is a strong temptation among investors to copy other investors' moves (Bikhchandani & Sharma, 2000). Herding can occur when investors suppress their own information in favour of that of others, while new information slowly spreads across the market (Bikhchandani et al., 1992, 1998; Welch, 1992). A variety of factors can explain this convergent behaviour. For example, by watching and interacting with others (social learning), investors aspire to improve their decision-making abilities (Bikhchandani et al., 1998). Second, in order to safeguard their own reputations, investment managers prefer to follow senior managers they consider to hold superior information. Third, even though the acquired knowledge is unrelated to fundamentals, short-term speculators may seek to follow other traders if they lack sufficient information about the near term (Scharfstein & Stein, 1990).

Cross-sectional standard deviations (CSSDs), introduced by Christie & Huang (1995), and CSADs, an enhancement by Chang et al. (2000), are two of the most widely used approaches for assessing herding. Early empirical herding research (e.g., Lakonishok et al., 1992; Sias, 2004; Wermers, 1999) examines whether institutional investors follow one another's transactions in the same or a subsequent period using institutional transaction data. According to Christie and Huang (1995), the cross-sectional dispersion of asset returns during moments of market stress may capture herding intensity, thus eliminating the requirement for institutional data to evaluate herding behaviour. Meanwhile, Chang et al. (2000) reiterate that the dispersion and the market return should have a linear relationship based on the Capital Asset Pricing Model (CAPM). When herding occurs, especially during times of market stress, this relationship should shift from linear to nonlinear, and their nonlinear model will capture this herding behaviour.

The study of herding in commodity markets is still in its infancy, with the majority of the studies relying on daily, monthly and quarterly datasets. Pierdzioch et al. (2010) was the first herding study. The authors discover considerable anti-herding behaviour among oil price forecasters based on quarterly oil price estimates issued by the European Central Bank from 2002 to 2009. Steen & Gjolberg (2013), meanwhile, use a monthly dataset of 20 commodities from 1986 onwards and detect greater comovements across commodities after 2004, using a beta herding model and covariance based on recursive estimation.

Demirer et al. (2015) examine the occurrence of 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 & Stavroyiannis (2015) investigate herding in eight metal commodities. They discover the prevalence of anti-herding behaviour before and after the GFC, using CSAD quantile analysis, rolling-window regressions, and a daily dataset from January 1995 to December 2013. Babalos et al. (2015), in another study, use CSAD TVP regression with MCMC estimation and rolling-window regression, applied to a daily dataset of 25 commodity-sector indices, from January 2002 to December 2014. Their findings show no herding based on the static model, but both the TVP and rolling-window regressions show herding briefly, following the 2008 GFC.

Correspondingly, BenMabrouk (2018) conducts another study that uses a monthly dataset on WTI, the NASDAQ, and a fear index (VIX) from January 2000 to October 2018. The author employs a herding model developed by Christie (1982) to account for crisis times, volatility and investor attitude, and finds that herding behaviour between WTI and the NASDAQ is exacerbated by a lack of information in the other market. Similarly, Júnior et al. (2020) use Hwang & Salmon's (2004) beta herding measure on daily closing prices of 15 commodities from January 2000 to October 2018, and conclude that herding is more intense in food commodities. Furthermore, from January 1990 to December 2020, Apergis et al. (2020) employ CSADs and Cai's (2007) time-varying model on daily prices of 14 commodity futures based on different contract months, and conclude that there is a negative relationship between herding in the commodity futures market and US monetary policy.

Fan & Todorova (2021) run a CSAD asymmetric model on a daily dataset of 24 commodity futures in China from January 2013 to June 2018, and find a substantial presence of herding on up-market days. Later, Youssef & Mokni (2021) apply CSADs and the Kalman filter to a daily dataset of agriculture, metal and energy commodities from January 2003 to April 2017 and observe time-varying herding in the energy commodity sector after the GFC in 2008, whereas metal commodities appear to herd earlier, before 2004. Meanwhile, Kumar et al. (2021) find that herding behaviour varies asymmetrically, and is more prominent during high-volatility times, based on using CSADs on a daily dataset of three commodity indices from eight Asian nations, from January 2010 to March 2020. Finally, Youssef (2022) extends an earlier paper by using a similar CSAD with Kalman filter approach for five commodity sectors, the S&P 500 and the EURUSD from January 2003 to April 2007, arriving at a somewhat similar conclusion, that there is evidence of time-varying herding after the 2008 GFC, but that livestock exhibits surprising anti-herding behaviour.

In a very recent study, Mohamad (2022) examines the flight-to-safety phenomenon between safe-haven and risky assets, and herding behaviour between assets of similar characteristics, 24 hours before and during the Russian invasion of Ukraine. Utilising a minute-by-minute dataset and TVP regression, the study demonstrates mild time-varying herding between Brent, WTI, gasoline and natural gas, about 20% of the time, during market upturns and downturns after the start of the invasion.

In summary, what we have gathered so far regarding herding in commodity markets is mixed at best. The static model tends to point to anti-herding, whereas the time-varying model appears to yield some evidence of herding (showing more than 50% herding intensity) in certain commodities and conditions, namely grain commodities during high-volatility periods (Demirer et al., 2015), energy commodities after the 2008 GFC (Youssef, 2022), and 25 commodities, briefly, after the 2008 GFC (Babalos et al., 2015).

Beyond herding, research on volatility spillovers and dynamic linkages between commodities has been undertaken since the 1990s. Alhajji & Huettner (2000), for example, investigate whether the Organization of Petroleum Exporting Countries can be classified as the main oil producer in the 20-year period before 1994, and conclude that Saudi Arabia fits the dominant business paradigm. One strand of energy commodity research investigates the relationship between crude oil and other energy commodities, such as between crude oil and natural gas (Batten et al., 2017; Brigida, 2014; Brown & Yücel, 2008; Hartley & Rosthal, 2008; Serletis & Herbert, 1999; Villar & Joutz, 2006), and between crude oil, coal and natural gas (Nick & Thoenes, 2014; Vücel & Guo, 1994), and the volatility spillover between energy commodities (Baruńik et al., 2015; Gong et al., 2021; Li et al., 2019; Lin & Li, 2015; Lin & Su, 2021; Lovcha & Perez-Laborda, 2020; Mensi et al., 2021).

Looking at the period of the Covid-19 pandemic, Lin & Su (2021) and Mensi et al. (2021) explicitly investigate volatility spillovers across energy commodities. The former employs the TVP vector autoregressive (VAR) model on a daily dataset for seven energy commodities from August 2019 to July 2020, and finds evidence of enhanced connections across commodities at the outset of the pandemic, with the impact lasting roughly two months. Meanwhile, the latter looks at dynamic links and volatility spillovers across six energy commodities. The authors discover that the volatility spillovers accelerated during the Covid-19 epidemic, having used the wavelet technique and the generalised VAR on a daily dataset from January 1997 to February 2021, with WTI being the largest contributor to the volatility spillover. In a similar tone, Gong et al. (2021) examine volatility spillovers across four energy commodities, using TVP-VAR with MCMC estimation on a daily dataset from October 2005 to April 2019. Their findings show that crude oil and heating oil are the principal transmitters of volatility spillovers, whereas gasoline and natural gas are the key receivers.

Li et al. (2019) and Lovcha & Perez-Laborda (2020) use daily datasets from January 1997 to November 2017 and January 1994 to February 2018 to examine volatility connectivity between WTI and natural gas. The former records that volatility transmission is unpredictable over short time horizons, while the latter concludes that volatility spillover is time-varying and that natural gas is a net spillover transmitter. Lin & Li (2015) investigate volatility spillovers among crude oil (Brent and WTI) and natural gas from the US, Europe and Japan. The authors demonstrate volatility spillovers from crude oil to natural gas markets using the vector error correction model (VECM) and multivariate generalised autoregressive conditional heteroscedasticity (MGARCH). Correspondingly, Baruńik et al. (2015) use a 27-year five-minute dataset from September 1987 to February 2014 to study volatility spillovers across crude oil, heating oil and gasoline, and conclude that volatility spillovers tend to grow after 2001 but then fall after 2008.

Further, some studies have examined the dynamic linkages between crude oil and natural gas using datasets of different frequencies, namely, annual (Vücel & Guo, 1994), monthly (Atil et al., 2014; Villar & Joutz, 2006), weekly (Brigida, 2014; Brown & Yücel, 2008; Nick & Thoenes, 2014) and daily (Batten et al., 2017; Lahiani et al., 2017; Serletis & Herbert, 1999). Vücel and Guo (1994) use a 43-year yearly dataset from 1947 to 1990 to uncover evidence of cointegrating linkages between coal, crude oil and natural gas during the 1974-1990 period, and they argue that a single fuel tax would harm these three markets. Five studies have used the VECM to investigate the link between crude oil and natural gas; they all suggest that there is a cointegrating relationship or a common trend between the two variables (Brigida, 2014; Brown & Yücel, 2008; Hartley & Rosthal, 2008; Serletis & Herbert, 1999; Villar & Joutz, 2006). Similarly, Atil et al. (2014) examine the links between crude oil, gasoline and natural gas using nonlinear autoregressive distributed lags (NARDL). Natural gas and gasoline respond to variations in oil prices, according to their monthly data analysis from January 1997 to September 2012. Nick & Thoenes (2014), on the other hand, use structural VAR on a weekly coal, crude oil and natural gas dataset, and find a long-term link between the three variables.

Along the same lines, the causal relationships between crude oil and natural gas have been investigated (Batten et al., 2017). Using the time-frequency causality test on a daily dataset from January 1994 to December 2014, the authors discover the existence of causation from natural gas to crude oil from 1999 to 2007, but after 2007, the two markets seem to be independent of one another. Similarly, Lahiani et al. (2017) use quantile autoregressive distributed lags (ARDL) to compare the daily prices of five energy commodities from January 1997 to October 2015, and find that crude oil is a predictor of the other commodities.

The research on volatility spillovers and dynamic links across commodities, on the whole, show that crude oil and other energy commodities have dynamic interactions. Crude oil is also a source of volatility spillovers to other commodities. Furthermore, the volatility spillovers seem to have increased with the commencement of the Covid-19 pandemic.

3. Data and methodology

Our dataset consists of the 18 most traded[1] commodities in the US futures exchanges, comprising grains, energy, livestock and metal commodities. 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 normally the most traded contracts

[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).

(see, for example, Booth et al., 1999; Cabrera et al., 2009; Entrop et al., 2020; Mohamad & Inani, 2022). 24 February 2022 and 1 February 2020 have been identified as the starting dates of the war and the pandemic.[2] 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%, while gasoline registers the biggest daily downfall (-39.73%). 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).

[insert Tables 1 & 2 here]
[insert Figure 1 here]

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 own judgement. Christie & Huang (1995) were among 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 & Huang (1995) could be 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 periods of market stress, reflecting the traders' herding behaviour in following the market consensus (actions of other traders) and disregarding their own judgement. Collective imitations of trading actions would mean greater similarity and would lead to lower return dispersions. We estimate Eq (2) across quantiles to test for asymmetries.

[2] 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 Organization 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.

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:

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

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

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

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 any 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 $h_0 \sim N\left(0, \sigma_\eta^2/(1-\phi^2\right)$ and $|\phi| < 1$. Σ (in the output) denotes a positive-definite matrix.

Next, we run the MCMC algorithm to estimate the Bayesian posterior distribution recursively.[3] We obtain 20,000 samples (iterations), after discarding the initial 2,000 samples from the burn-in period, by assuming the following priors:

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

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

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

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

[3] MCMC is considered one of the most powerful algorithms for recursively sampling from a posterior distribution.

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 the occurrence of 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 3, 4, 5 and 6 present our findings on the 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 across quantiles during up- and down-market days for any of the four commodity types. Mild anti-herding behaviour, meanwhile, is observed for the metal commodities before and during the Russo-Ukraine war, while 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 record no herding using 25 commodities before and during the 2008 GFC.

[insert Tables 3, 4, 5 & 6 here]

Tables 7, 8, 9 and 10 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 7) and energy (Table 9) 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 10 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, among 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 among the livestock commodities, in quantiles 0.4 (0.1564), 0.5 (0.1221) and 0.6 (0.0902).

[insert Tables 7, 8, 9 & 10 here]

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 are generally in line with Babalos et al. (2015), who document a lack of herding within commodity sectors surrounding the GFC, and Júnior et al. (2020), who find evidence of herding among food commodities.

4.2 CSAD time-varying herding result

Figures 2, 3, 4 and 5 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. The top, middle and bottom sections of Panel B 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 in a stable fashion, suggesting the ability of the MCMC algorithm to yield uncorrelated samples efficiently. Table 11 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 posterior distribution hypothesis. Correspondingly, the inefficiency factor for parameter σ_η for the metal commodities displayed in Panel A of Table 11 is 126.5, which points to uncorrelated samples, thus indicating adequacy for the posterior inference.

[insert Figures 2, 3, 4 and 5 here]
[insert Table 11 here]

Figure 2 presents the time-varying alphas for the metal commodities (gold, silver, copper, platinum and palladium). The coefficients α_3 and α_4 appear to be positive, indicating anti-herding behaviour except in the last 30 days during the Russo-Ukraine war. In other words, mild herding intensity is detected among 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 3, 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 4 displays very weak herding intensity among 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 particular finding seems slightly at odds with Mohamad (2022), who observes time-varying herding among energy commodities, of about 20% of the time during market upturns and downturns, 24 hours before and after the Russian invasion of Ukraine. Finally, Figure 5 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.

[insert Table 12 here]

Overall, as can be seen from Table 12, 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 presented in Figures 2, 3, 4 and 5 are generally in line with our static herding results tabulated in Tables 3, 4, 5 and 6. In other words, the war in Ukraine generally has 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 6 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. Contrarily, Figure 7 demonstrates much stronger herding intensity among 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. In a similar vein, Figure 8 reveals strong herding behaviour within the energy commodity sector (WTI, gasoline, natural gas Brent and ethanol). The energy commodities seem to move together about 60% of the time during market upturns and 70% of the time during market downturns, surrounding the Covid-19 pandemic. This finding is in line with Youssef (2022), who documents time-varying herding among energy commodities right after the 2008 GFC. Lastly, in Figure 9, 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 a nutshell, we observe stronger herding intensity, of more than 50% of the time within the energy (65%) and livestock (55%) commodities, as compared to the metal commodities (10%) and grain commodities (30%), before and during the Covid-19 pandemic. Secondly, we uncover that the commodity markets generally show much stronger herding intensity surrounding the Covid-19 pandemic than the Russo-Ukraine war. Put differently, we document heterogeneity in terms of herding behaviour between the two crises, with the pandemic displaying a considerably stronger herding impact than the Russo-Ukraine war. We believe the results could be attributed to the fact that the Covid-19 pandemic produced a greater effect on the whole world, whereas the Russo-Ukraine war appears to have yielded a smaller herding impact on the world's commodity markets, as the conflict is confined to Ukraine, Russia and perhaps the neighbouring Balkan countries. Furthermore, our commodity futures dataset (based on the most active futures) is sourced from a futures exchange located in the US. Thus, a smaller influence from the Russo-Ukraine war on these commodity markets would be expected.

5. Conclusion

Our objective in this paper was to examine herding intensity within the most actively traded commodities futures from the energy, metal, livestock and grain commodity sectors, over 100 trading days before and 100 trading days during two crises, namely the Russo-Ukraine war and the Covid-19 pandemic. We employed both the static CSAD quantile regression method and time-varying namely CSAD TVP regression with stochastic volatility using MCMC estimation, to measure the degree of herding intensity. Comparing the static and time-varying methods, we generally found that the two methods produced quite different results, with the TVP regression method exhibiting a more detailed time-varying analysis and reporting mild herding intensity surrounding the Russo-Ukraine war, but stronger herding behaviour during the Covid-19 pandemic. On the other hand, the static measure generally documented almost non-existent herding before and during the Russo-Ukraine war, and very mild herding among the livestock commodities only before the Covid-19 pandemic. We would like to advocate the use of a time-varying measure to gauge herding intensity as it can show the evolution of herding over time.

Generally speaking, our results point to heterogeneity between the two crises. The commodities, particularly from the livestock and energy sectors, tend to herd considerably more during the Covid-19 pandemic than the Russo-Ukraine war. We interpret this finding as follows - the war that has taken place in a Balkan country, the Ukraine, has not had such a strong herding impact on the commodity markets as the Covid-19 pandemic. It is interesting to note that, while the recent Russian blockade of Odessa has prevented Ukraine cargo ships from leaving the ports, and resulted in increases to wheat prices of more than 50%, this incident is not reflected in the herding behaviour within the grain commodity sector (corn, soybean, soybean meal and wheat) [4]. Surprisingly, even precious metals like gold, silver, high-grade copper, platinum and palladium flock together (herd) at only about 10% of the time, surrounding the Russo-Ukraine

[4] See https://www.economist.com/the-economist-explains/2022/05/27/why-is-odessa-important-to-both-ukraine-and-russia

war. This brings us to our recommendation for future studies – future researchers might want to explore the impact of the Russo-Ukraine war on the herding intensity of the commodity markets by looking at the commodity futures exchanges located in Ukraine and Russia, to properly capture the impact of this war on local commodity markets. All in all, our herding patterns detected within the livestock and energy sectors during the Covid-19 pandemic also mean that anti-herding behaviour is observed in other commodity sectors such as grains and metals - which is at odds with Demirer et al. (2015), who document herding within the grain commodities using a 1995 to 2012 dataset. Our results, however, are more in line with those of Júnior et al. (2020), Youssef (2022) and Youssef & Mokni (2021).

Compliance with Ethical Standards Declarations

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REFERENCES

Aggarwal, R. (2014). Animal spirits in financial economics: A review of deviations from economic rationality. *International Review of Financial Analysis*, *32*, 179–187. https://doi.org/https://doi.org/10.1016/j.irfa.2013.07.018

Alhajji, A. F., & Huettner, D. (2000). OPEC and world crude oil markets from 1973 to 1994: Cartel, oligopoly, or competitive? *Energy Journal*, *21*(3), 31–60. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol21-No3-2

Apergis, N., Christou, C., Hayat, T., & Saeed, T. (2020). U.S. Monetary Policy and Herding: Evidence from Commodity Markets. *Atlantic Economic Journal*, *48*(3), 355–374. https://doi.org/10.1007/s11293-020-09680-4

Atil, A., Lahiani, A., & Nguyen, D. K. (2014). Asymmetric and nonlinear pass-through of crude oil prices to gasoline and natural gas prices. *Energy Policy*, *65*, 567–573. https://doi.org/https://doi.org/10.1016/j.enpol.2013.09.064

Babalos, V., & Stavroyiannis, S. (2015). Herding, anti-herding behaviour in metal commodities futures: a novel portfolio-based approach. *Applied Economics*, *47*(46), 4952–4966. https://doi.org/10.1080/00036846.2015.1039702

Babalos, V., Stavroyiannis, S., & Gupta, R. (2015). Do commodity investors herd? Evidence from a time-varying stochastic volatility model. *Resources Policy*, *46*, 281–287. https://doi.org/10.1016/j.resourpol.2015.10.011

Baruńik, J., Kočenda, E., & Vácha, L. S. (2015). Volatility spillovers across petroleum markets. *Energy Journal*, *36*(3), 309–329. https://doi.org/10.5547/01956574.36.3.jbar

Batten, J. A., Ciner, C., & Lucey, B. M. (2017). The dynamic linkages between crude oil and natural gas markets. *Energy Economics*, *62*, 155–170. https://doi.org/https://doi.org/10.1016/j.eneco.2016.10.019

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, *45*(2), 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

BenMabrouk, H. (2018). Cross-herding behavior between the stock market and the crude oil market during financial distress: Evidence from the New York stock exchange. *Managerial Finance*, *44*(4), 439–458. https://doi.org/10.1108/MF-09-2017-0363

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992–1026. https://doi.org/10.1086/261849

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1998). Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades. *Journal of Economic Perspectives*, *12*(3), 151–170. https://doi.org/10.1257/jep.12.3.151

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers*, *47*(3), 279–310. https://www.scopus.com/inward/record.uri?eid=2-s2.0-0010015080&partnerID=40&md5=3a3181083bdd9eb9d87764d4054d00d2

Booth, G. G., So, R. W., & Tse, Y. (1999). Price discovery in the german equity index derivatives markets. *Journal of Futures Markets*, *19*(6), 619–643. https://doi.org/10.1002/(SICI)1096-9934(199909)19:6<619::AID-FUT1>3.0.CO;2-M

Brigida, M. (2014). The switching relationship between natural gas and crude oil prices. *Energy Economics*, *43*, 48–55. https://doi.org/https://doi.org/10.1016/j.eneco.2014.01.014

Brown, S. P. A., & Yücel, M. K. (2008). What Drives Natural Gas Prices? *The Energy Journal*, *29*(2), 45–60. http://www.jstor.org/stable/41323156

Cabrera, J., Wang, T., & Yang, J. (2009). Do futures lead price discovery in electronic foreign exchange markets? *Journal of Futures Markets*, *29*(2), 137–156. https://doi.org/10.1002/fut.20352

Cai, Z. (2007). Trending time-varying coefficient time series models with serially correlated errors. *Journal of Econometrics*, *136*(1), 163–188. https://doi.org/https://doi.org/10.1016/j.jeconom.2005.08.004

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking and Finance*, *24*(10), 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics*, *10*(4), 407–432.

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal*, *51*(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Demirer, Riza, Lee, H.-T., & Lien, D. (2015). Does the stock market drive herd behavior in commodity futures markets? *International Review of Financial Analysis*, *39*, 32–44. https://doi.org/10.1016/j.irfa.2015.02.006

Demirer, Rıza, & Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets? *Journal of International Financial Markets, Institutions and Money*, *16*(2), 123–142. https://doi.org/https://doi.org/10.1016/j.intfin.2005.01.002

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, *40*(3), 603–615. https://doi.org/https://doi.org/10.1016/0014-2921(95)00073-9

Entrop, O., Frijns, B., & Seruset, M. (2020). The determinants of price discovery on bitcoin markets. *Journal of Futures Markets*, *40*(5), 816–837. https://doi.org/10.1002/fut.22101

Fan, J. H., & Todorova, N. (2021). A note on the behavior of Chinese commodity markets. *Finance Research Letters*, *38*. https://doi.org/10.1016/j.frl.2019.101424

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculations of posterior moments. *Bayesian Statistics*, *4*, 641–649.

Gong, X., Liu, Y., & Wang, X. (2021). Dynamic volatility spillovers across oil and natural gas futures markets based on a time-varying spillover method. *International Review of Financial Analysis*, *76*, 101790. https://doi.org/https://doi.org/10.1016/j.irfa.2021.101790

Greenspan, A. (2004). Risk and Uncertainty in Monetary Policy. *American Economic Review*, *94*(2), 33–40. https://doi.org/10.1257/0002828041301551

Hartley, P. R., & Rosthal, K. B. M. I. I. I. and J. E. (2008). The Relationship of Natural Gas to Oil Prices. *The Energy Journal*, *Volume 29*(3), 47–66. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol29-No3-3

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*, *11*(4), 585–616. https://doi.org/https://doi.org/10.1016/j.jempfin.2004.04.003

Júnior, G. D. S. R., Palazzi, R. B., Klotzle, M. C., & Pinto, A. C. F. (2020). Analysing herding behavior in commodities markets – an empirical approach. *Finance Research Letters*, *35*. https://doi.org/10.1016/j.frl.2019.08.033

Keynes, J. M. (1936). The General Theory of Employment, Interest and Money. *Mac Millan, Houndsmills, UK.*

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053–1069. https://doi.org/10.1257/aer.99.3.1053

Kinateder, H., Campbell, R., & Choudhury, T. (2021). Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2021.101951

Kumar, A., Badhani, K. N., Bouri, E., & Saeed, T. (2021). Herding behavior in the commodity markets of the Asia-Pacific region. *Finance Research Letters, 41*. https://doi.org/10.1016/j.frl.2020.101813

Lahiani, A., Miloudi, A., Benkraiem, R., & Shahbaz, M. (2017). Another look on the relationships between oil prices and energy prices. *Energy Policy*, *102*, 318–331. https://doi.org/https://doi.org/10.1016/j.enpol.2016.12.031

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, *32*(1), 23–43. https://doi.org/https://doi.org/10.1016/0304-405X(92)90023-Q

Li, X., Sun, M., Gao, C., & He, H. (2019). The spillover effects between natural gas and crude oil markets: The correlation network analysis based on multi-scale approach. *Physica A: Statistical Mechanics and Its Applications*, *524*, 306–324. https://doi.org/10.1016/j.physa.2019.04.141

Lin, B., & Li, J. (2015). The spillover effects across natural gas and oil markets: Based on the VEC–MGARCH framework. *Applied Energy*, *155*, 229–241. https://doi.org/https://doi.org/10.1016/j.apenergy.2015.05.123

Lin, B., & Su, T. (2021). Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities? *Research in International Business and Finance*, *56*, 101360. https://doi.org/https://doi.org/10.1016/j.ribaf.2020.101360

Lovcha, Y., & Perez-Laborda, A. (2020). Dynamic frequency connectedness between oil and natural gas volatilities. *Economic Modelling*, *84*, 181–189. https://doi.org/https://doi.org/10.1016/j.econmod.2019.04.008

Masters, M. W. (2008). Testimony before the Committee on Homeland Security and Governmental Affairs, United States Senate. *Washington, DC*, *20*.

Masters, M. W., Kaplan, P., Blitzer, P. D., Israelsen, C., & Gastineau, G. (2008). Are Index Investors Driving Up Commodity Prices. *Journal of Indexes*, *11*(6).

Mensi, W., Rehman, M. U., & Vo, X. V. (2021). Dynamic frequency relationships and volatility spillovers in natural gas, crude oil, gas oil, gasoline, and heating oil markets: Implications for portfolio management. *Resources Policy*, *73*, 102172. https://doi.org/https://doi.org/10.1016/j.resourpol.2021.102172

Mohamad, A. (2022). Safe flight to which haven when Russia invades Ukraine? A 48-hour story. *Economics Letters*, *216*, 110558. https://doi.org/https://doi.org/10.1016/j.econlet.2022.110558

Mohamad, A., & Inani, S. K. (2022). Price discovery in bitcoin spot or futures during the Covid-19 pandemic? Evidence from the time-varying parameter vector autoregressive model with stochastic volatility. *Applied Economics Letters*, *0*(0), 1–9. https://doi.org/10.1080/13504851.2022.2106030

Mu, X. (2007). Weather, storage, and natural gas price dynamics: Fundamentals and volatility. *Energy Economics*, *29*(1), 46–63. https://doi.org/10.1016/j.eneco.2006.04.003

Nakajima, J. (2011). Time-Varying Parameter VAR Model with Stochastic Volatility: An Overview of Methodology and Empirical Applications. *Monetary and Economic Studies*, *29*, 107–142. https://econpapers.repec.org/RePEc:ime:imemes:v:29:y:2011:p:107-142

Nick, S., & Thoenes, S. (2014). What drives natural gas prices? — A structural VAR approach. *Energy*

Economics, *45*, 517–527. https://doi.org/https://doi.org/10.1016/j.eneco.2014.08.010

Pierdzioch, C., Rülke, J. C., & Stadtmann, G. (2010). New evidence of anti-herding of oil-price forecasters. *Energy Economics*, *32*(6), 1456–1459. https://doi.org/https://doi.org/10.1016/j.eneco.2010.05.014

Potsaid, T., & Venkataraman, S. (2022). Trading restrictions and investor reaction to non-gains, non-losses, and the fear of missing out: Experimental evidence. *Journal of Behavioral and Experimental Finance*, *33*, 100597. https://doi.org/https://doi.org/10.1016/j.jbef.2021.100597

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *American Economic Review*, *80*(3), 465–479.

Serletis, A., & Herbert, J. (1999). The message in North American energy prices. *Energy Economics*, *21*(5), 471–483. https://doi.org/https://doi.org/10.1016/S0140-9883(99)00015-8

Sias, R. W. (2004). Institutional Herding. *The Review of Financial Studies*, *17*(1), 165–206. https://doi.org/10.1093/rfs/hhg035

Sifat, I., Mohamad, A., Zhang, H. C., & Molyneux, P. (2022). Reevaluating the risk minimisation utility of Islamic stocks and bonds (Sukuk) in international financial markets. *European Journal of Finance*. https://doi.org/10.1080/1351847X.2022.2032242

Steen, M., & Gjolberg, O. (2013). Are commodity markets characterised by herd behaviour? *Applied Financial Economics*, *23*(1), 79–90. https://doi.org/10.1080/09603107.2012.707770

Villar, J. A., & Joutz, F. L. (2006). The relationship between crude oil and natural gas prices. *Energy Information Administration, Office of Oil and Gas*, 1–43.

Vücel, M. K., & Guo, S. (1994). Fuel Taxes and Cointegration of Energy Prices. *Contemporary Economic Policy*, *12*(3), 33–41. https://doi.org/10.1111/j.1465-7287.1994.tb00432.x

Welch, I. (1992). Sequential Sales, Learning, and Cascades. *The Journal of Finance*, *47*(2), 695–732. https://doi.org/https://doi.org/10.1111/j.1540-6261.1992.tb04406.x

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance*, *54*(2), 581–622. https://doi.org/10.1111/0022-1082.00118

Williams, L. (2011). *Long-term secrets to short-term trading*. John Wiley & Sons.

Youssef, M. (2022). Do Oil Prices and Financial Indicators Drive the Herding Behavior in Commodity Markets? *Journal of Behavioral Finance*, *23*(1), 58–72. https://doi.org/10.1080/15427560.2020.1841193

Youssef, M., & Mokni, K. (2021). Asymmetric effect of oil prices on herding in commodity markets. *Managerial Finance*, *47*(4), 535–554. https://doi.org/10.1108/MF-01-2020-0028

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: 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.

Table 2. Descriptive statistics of daily returns.

	Panel A: 100 days before & during Russo-Ukraine war						Panel B: 100 days before & during Covid-19 pandemic					
	Mean (%)	Median (%)	Max (%)	Min (%)	Stdev	Jarque-Bera	Mean (%)	Median (%)	Max (%)	Min (%)	Stdev	Jarque-Bera
Corn	0.05	0.33	5.88	-13.99	2.02	1248.3***	0.00	-0.13	5.77	-4.41	1.36	110.1***
Soybean	0.08	0.28	3.66	-9.37	1.57	308.8***	0.02	-0.01	3.34	-3.00	0.89	29.8***
Soybean meal	0.14	0.35	5.68	-14.31	2.37	1228.7***	0.01	-0.07	3.49	-3.18	0.99	19***
Wheat	0.07	-0.01	19.70	-11.30	3.29	400.2***	0.01	-0.10	5.13	-3.77	1.39	19.7***
Oats	-0.10	-0.04	27.67	-34.20	5.52	1391.4***	0.04	0.08	4.06	-5.30	1.70	11.4***
WTI	0.16	0.49	8.02	-14.00	3.17	109.6***	0.09	-0.07	31.96	-28.22	6.54	618.9***
Gasoline	0.21	0.68	7.63	-13.35	3.03	107.6***	0.03	0.00	22.71	-39.73	5.79	2112.1***
Natural gas	0.11	0.59	38.17	-30.05	6.38	519.4***	-0.26	-0.29	8.51	-9.33	3.25	0.83
Brent	0.16	0.50	9.27	-14.04	3.06	133.2***	-0.03	0.14	19.08	-27.58	4.53	674.4***
Ethanol	0.03	0.08	13.02	-27.01	3.16	9.4k***	0.00	0.00	9.02	-28.92	2.69	38.1k***
Live cattle	0.06	0.08	2.43	-4.84	0.90	173.5***	0.01	0.05	6.80	-5.23	1.89	27.9***
Feeder cattle	0.08	-0.04	7.01	-2.29	1.10	566.8***	0.01	0.02	4.86	-8.12	1.72	133.2***
Lean hogs	0.10	-0.02	15.42	-11.93	2.39	1876.6***	-0.23	-0.16	15.85	-20.01	4.02	315***
Gold	-0.01	0.05	2.29	-2.69	0.93	4.96*	0.08	0.12	5.78	-4.74	1.28	204***
Silver	-0.08	0.08	4.70	-5.20	1.72	1.75	0.00	0.10	7.32	-12.39	2.30	342.8***
Copper	-0.11	-0.13	5.04	-5.51	1.74	2.18	0.03	-0.01	3.61	-6.93	1.31	132.6***
Platinum	-0.06	0.00	4.87	-6.09	2.01	0.06	-0.07	0.22	11.18	-12.35	2.58	313.8***
Palladium	-0.01	0.18	10.48	-14.65	3.37	40.34***	0.11	0.30	22.60	-23.40	3.67	2219.5***

Note: 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.

Table 3. CSAD quantile regression on metal commodities before & during Russo-Ukraine war

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

		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	0.6076	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

Table 4. CSAD quantile regression on livestock commodities before & during Russo-Ukraine war

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

		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	0.3527	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

Table 5. CSAD quantile regression on energy commodities before & during Russo-Ukraine war

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

		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

Table 6. CSAD quantile regression on grain commodities before & during Russo-Ukraine war

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

		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

Table 7. CSAD quantile regression on metal commodities before & 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

Table 8. CSAD quantile regression on livestock commodities before & 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

Table 9. CSAD quantile regression on energy commodities before & 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	0.3957	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

Table 10. CSAD quantile regression on grain commodities before & 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	0.5027	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

Table 11. Time-varying parameter (TVP) regression estimation results

Panel A: Metal commodities before & during Russo-Ukraine war

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.006	0.0037	0.0019	0.0156	0.574	56.71
Σ_{22}	0.0083	0.0065	0.0023	0.0268	0.649	71.78
Σ_{33}	0.0043	0.0022	0.0016	0.0098	0.706	46.17
Σ_{44}	0.0034	0.0016	0.0015	0.0074	0.188	32.85
ϕ	0.865	0.099	0.6109	0.9894	0.802	34.75
σ_η	0.1311	0.0616	0.061	0.2973	0.656	126.5
γ	0.133	0.0317	0.0682	0.1882	0.307	57.54

Panel B: Livestock commodities before & during Russo-Ukraine war

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0063	0.004	0.0021	0.0163	0.958	65.12
Σ_{22}	0.0115	0.0122	0.0026	0.0468	0.006	115.64
Σ_{33}	0.017	0.0127	0.0039	0.0494	0.974	101.82
Σ_{44}	0.0084	0.0076	0.0022	0.0282	0.185	114.68
ϕ	0.8993	0.0761	0.6965	0.9867	0.932	35.47
σ_η	0.1979	0.0969	0.0755	0.4333	0.866	122.21
γ	0.1586	0.0422	0.0691	0.242	0.679	43.16

Panel C: Energy commodities before & during Russo-Ukraine war

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0098	0.0088	0.0023	0.0349	0.411	75.91
Σ_{22}	0.008	0.0066	0.0022	0.024	0.523	84.78
Σ_{33}	0.0028	0.0012	0.0013	0.0059	0.93	38.9
Σ_{44}	0.0036	0.0015	0.0016	0.0074	0.148	32.38
ϕ	0.8621	0.0997	0.6067	0.9909	0.037	65.43
σ_η	0.2073	0.1109	0.0739	0.509	0.098	154.14
γ	0.6932	0.1818	0.2107	1.0129	0.31	108.56

Panel D: Grain commodities before & during Russo-Ukraine war

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0061	0.0042	0.002	0.0168	0.716	70.71
Σ_{22}	0.0084	0.0073	0.0022	0.0282	0.879	91.95
Σ_{33}	0.0039	0.002	0.0016	0.0093	0.8	45.16
Σ_{44}	0.0048	0.0025	0.002	0.0115	0.075	47.94
ϕ	0.7411	0.1203	0.4619	0.9317	0.455	85.31
σ_η	0.949	0.2205	0.565	1.4309	0.64	93.98
γ	0.2256	0.0971	0.0866	0.4128	0.31	70.01

Panel E: Metal commodities before & during Covid-19 pandemic

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0055	0.003	0.0019	0.0134	0.96	33.2
Σ_{22}	0.0076	0.0055	0.0022	0.0226	0.847	71.69
Σ_{33}	0.0062	0.0035	0.0021	0.0147	0.707	54.57
Σ_{44}	0.0044	0.0023	0.0017	0.0104	0.019	42.85
ϕ	0.9308	0.0544	0.7918	0.9936	0.871	105.15
σ_η	0.4737	0.1774	0.1909	0.8621	0.721	113.02
γ	0.0978	0.0638	0.0104	0.244	0.478	132.47

Panel F: Livestock commodities before & during Covid-19 pandemic

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0062	0.0033	0.0022	0.0146	0.71	42.32
Σ_{22}	0.013	0.0119	0.0029	0.0452	0.109	111.08
Σ_{33}	0.0047	0.0024	0.0018	0.0109	0.259	57.57
Σ_{44}	0.0061	0.0037	0.0022	0.015	0.114	50.51
ϕ	0.9622	0.0375	0.8569	0.9973	0.677	150.71
σ_η	0.3287	0.158	0.1448	0.7495	0.437	190.42
γ	0.15	0.1396	0.0129	0.4253	0.324	130.94

Panel G: Energy commodities before & during Covid-19 pandemic

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0116	0.0077	0.003	0.0319	0.166	57.89
Σ_{22}	0.0091	0.0062	0.0025	0.026	0.903	55.43
Σ_{33}	0.0027	0.0012	0.0013	0.0056	0.24	26.33
Σ_{44}	0.0028	0.0011	0.0013	0.0056	0.534	23.89
ϕ	0.9793	0.0231	0.9154	0.9991	0.561	145.56
σ_η	0.2102	0.0761	0.0974	0.3891	0.794	108.82
γ	0.1464	0.1504	0.0075	0.4956	0.474	242.03

Panel H: Grain commodities before & during Covid-19 pandemic

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef
Σ_{11}	0.0041	0.0019	0.0017	0.0089	0.036	40.08
Σ_{22}	0.0088	0.0068	0.0022	0.0284	0.809	88.74
Σ_{33}	0.0092	0.0066	0.0024	0.0271	0.467	60.87
Σ_{44}	0.0089	0.0066	0.0024	0.0274	0.377	65.56
ϕ	0.8485	0.1065	0.5799	0.9835	0.912	28.69
σ_η	0.1329	0.0559	0.0631	0.2759	0.453	96.02
γ	0.1034	0.0189	0.0635	0.1401	0.165	22.61

Note: This table shows the TVP regression estimation results based on 95% Bayesian credible interval. Geweke is the Bayesian convergence diagnostic (Geweke, 1992), while Inef refers to inefficiency factor.

Table 12. Summary of herding intensity results using the TVP regression with MCMC

Panel A. 100 days before & during the Russo-Ukraine war

	Fig 2 (Metal)	Fig 3 (Livestock)	Fig 4 (Energy)	Fig 5 (Grain)
During market upturns	10%	-	3%	-
During market downturns	10%	2%	-	1%

Panel B. 100 days before & during the Covid-19 pandemic

	Fig 6 (Metal)	Fig 7 (Livestock)	Fig 8 (Energy)	Fig 9 (Grain)
During market upturns	-	40%	60%	30%
During market downturns	10%	70%	70%	30%

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

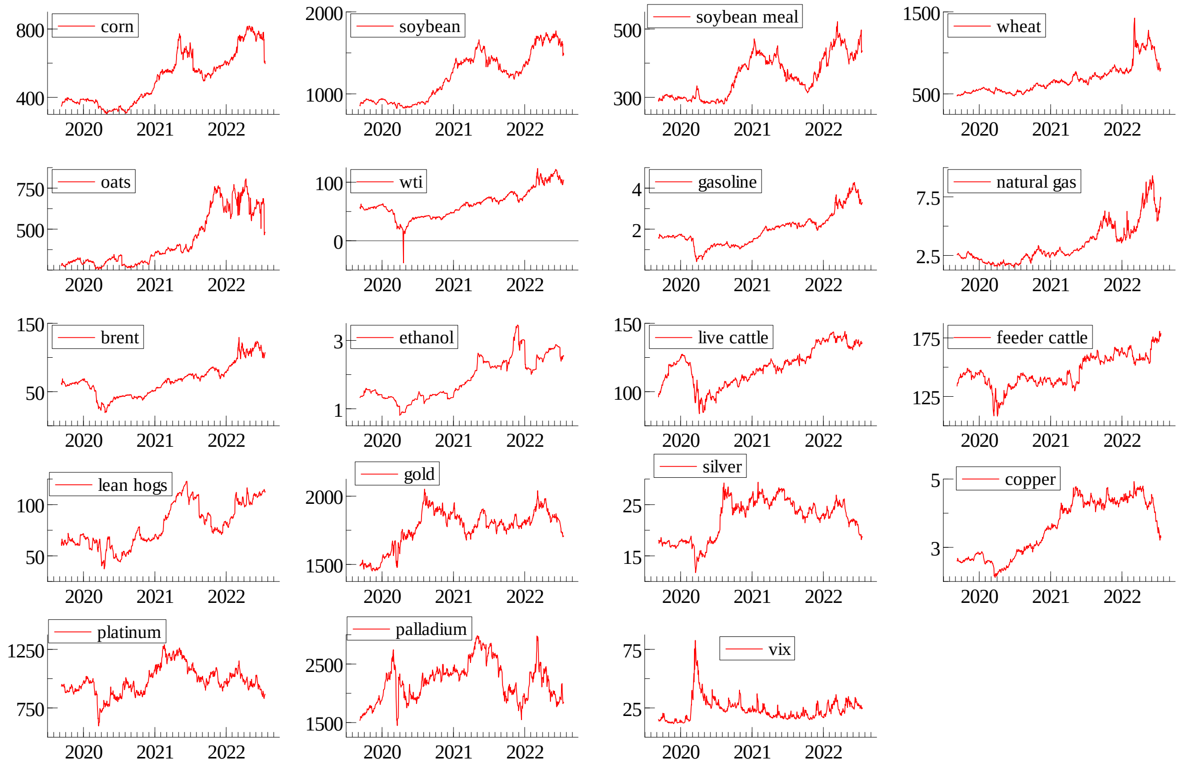
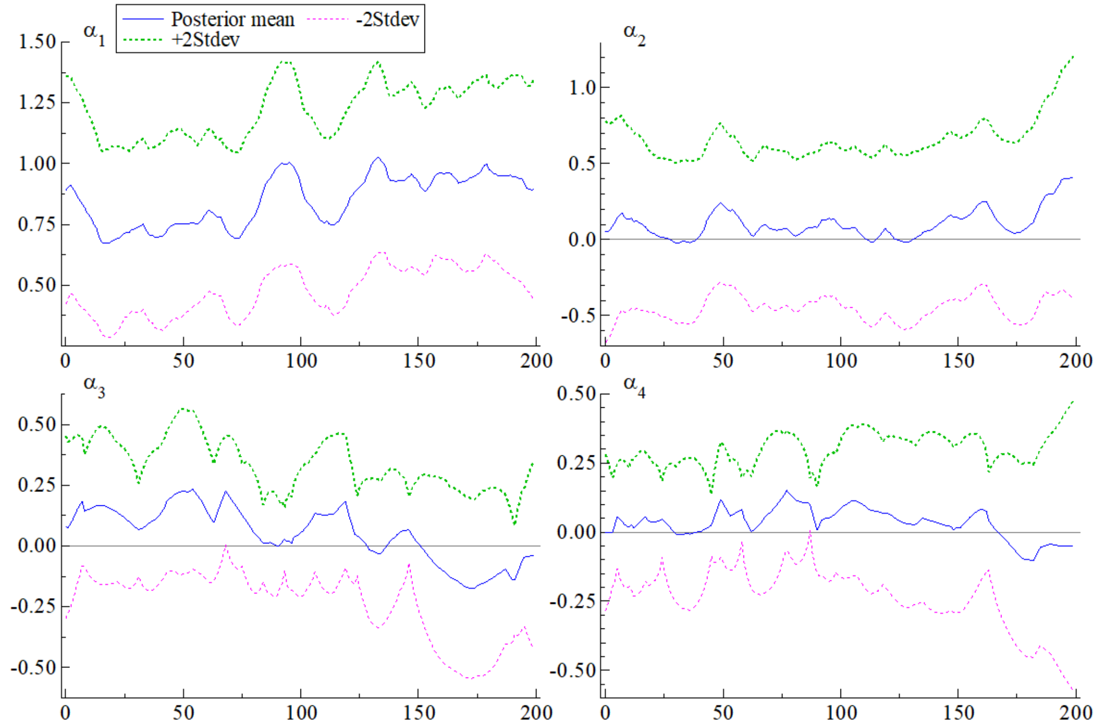


Figure 1. Time evolution of commodity markets from August 2018 to July 2022.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

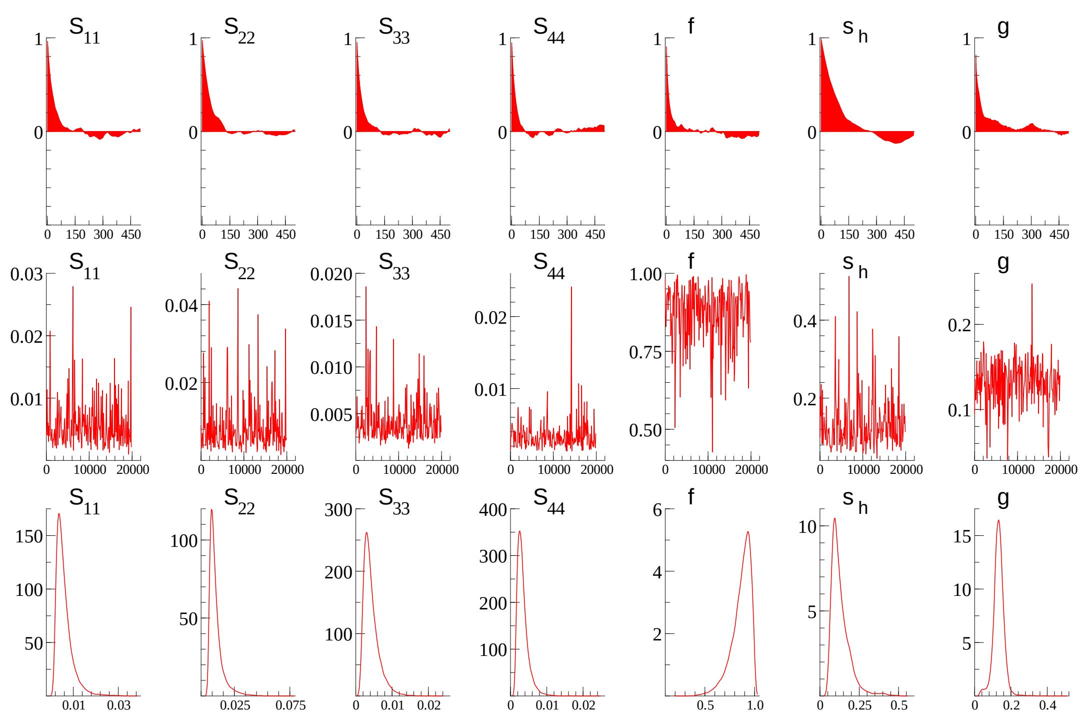
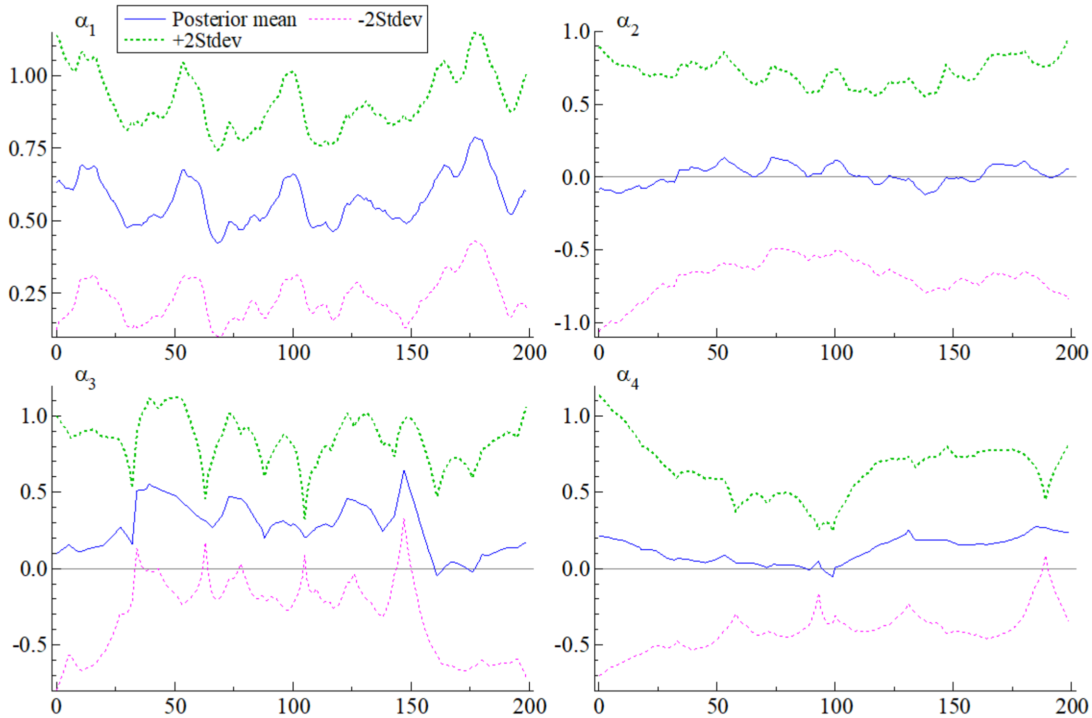


Figure 2. CSAD TVP regression for metal commodities 100 days before and 100 days during the Russo-Ukraine war.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

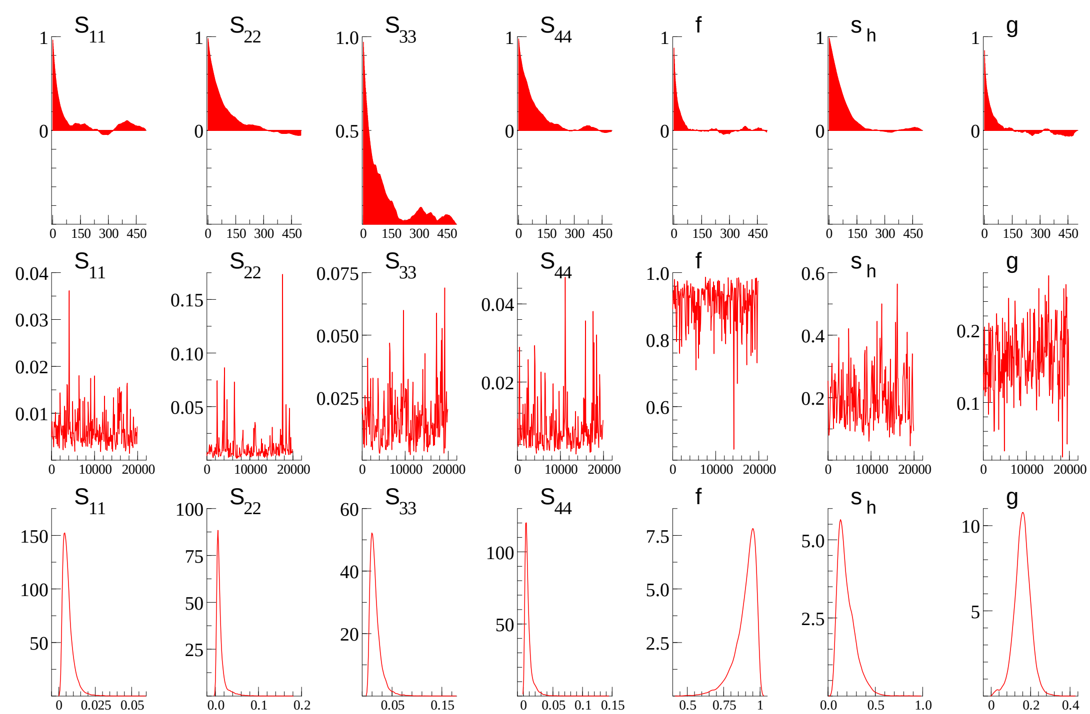
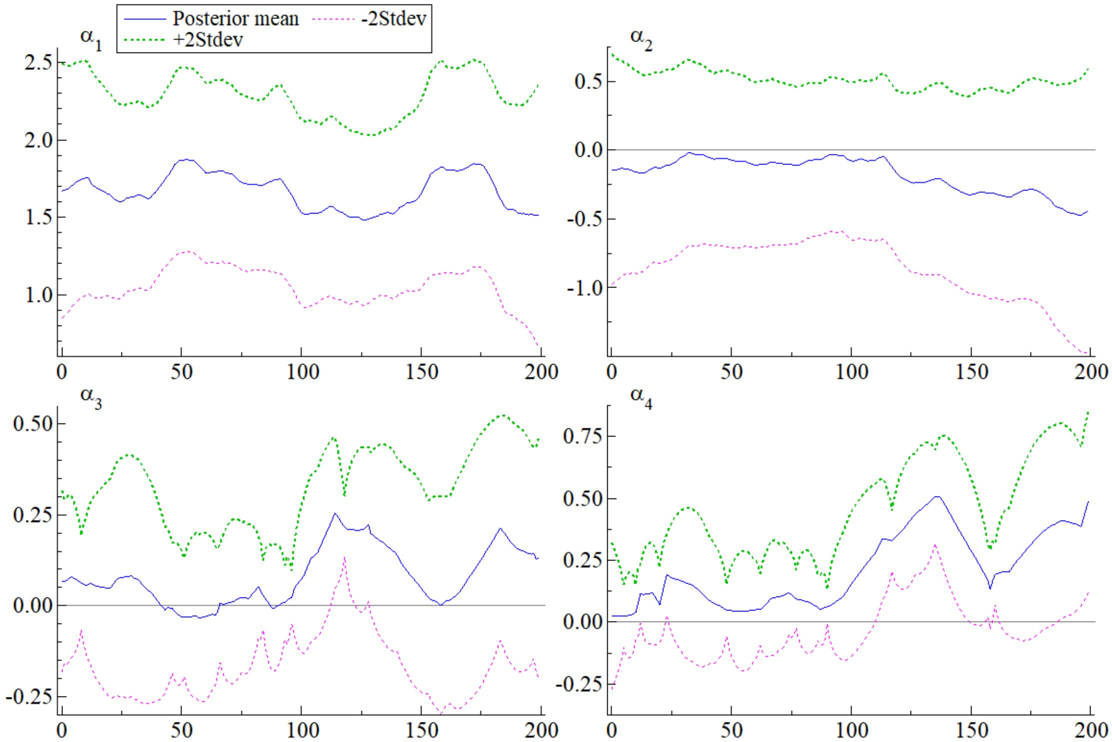


Figure 3. CSAD TVP regression for livestock commodities 100 days before and 100 days during the Russo-Ukraine war.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

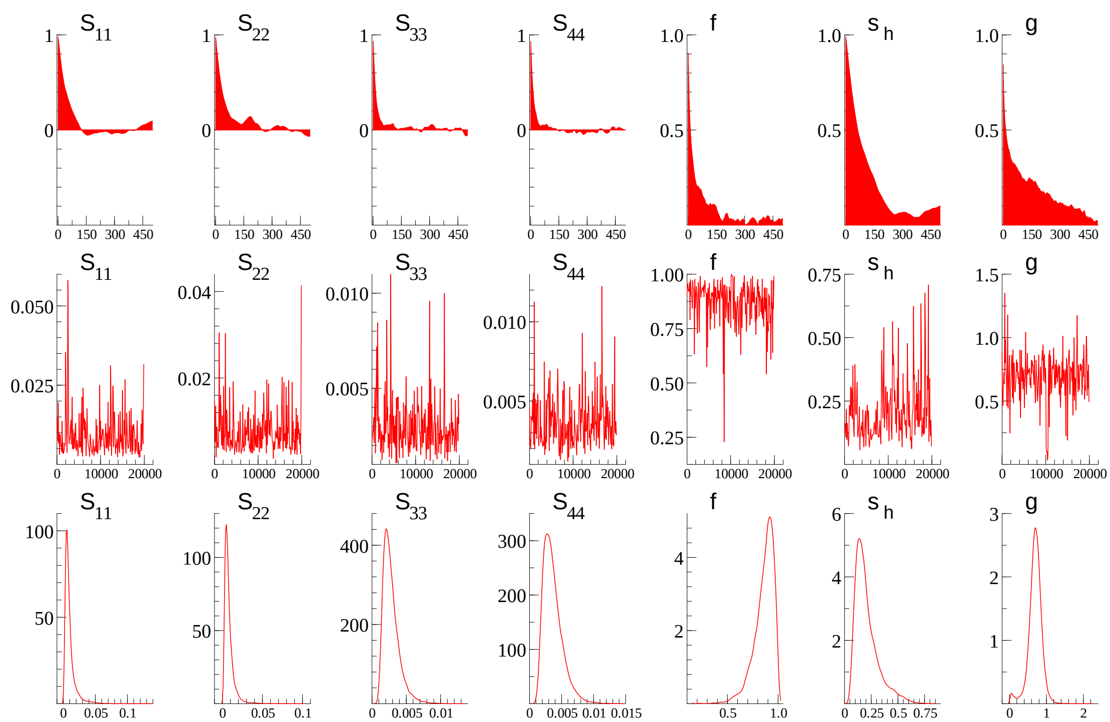
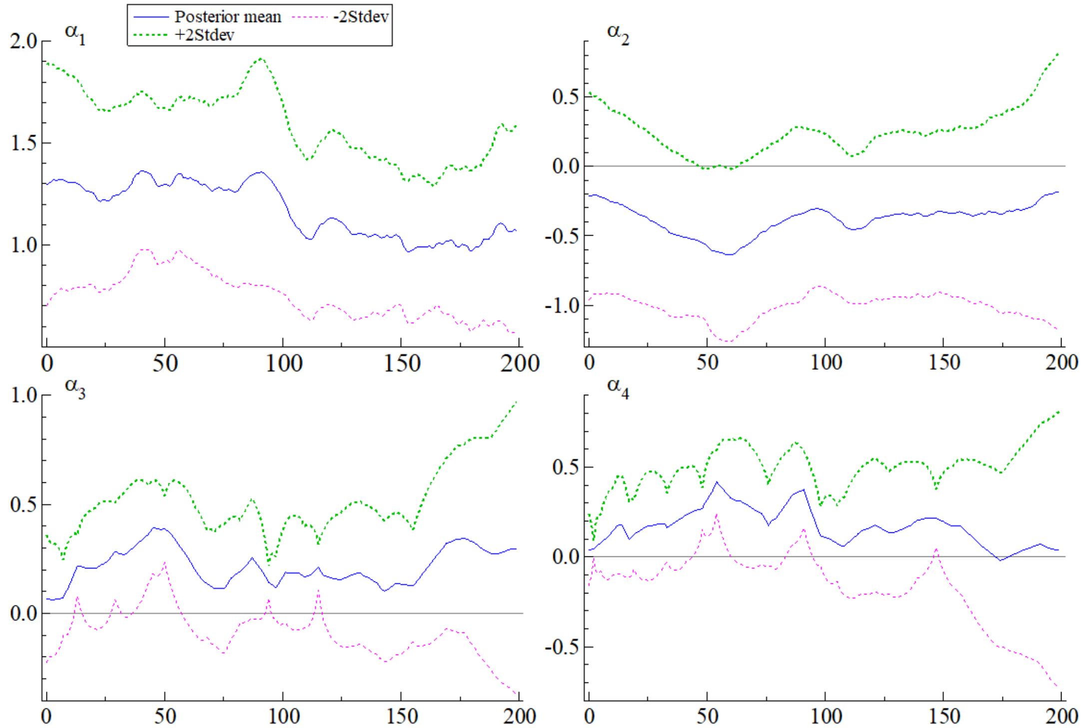


Figure 4. CSAD TVP regression for energy commodities 100 days before and 100 days during the Russo-Ukraine war.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

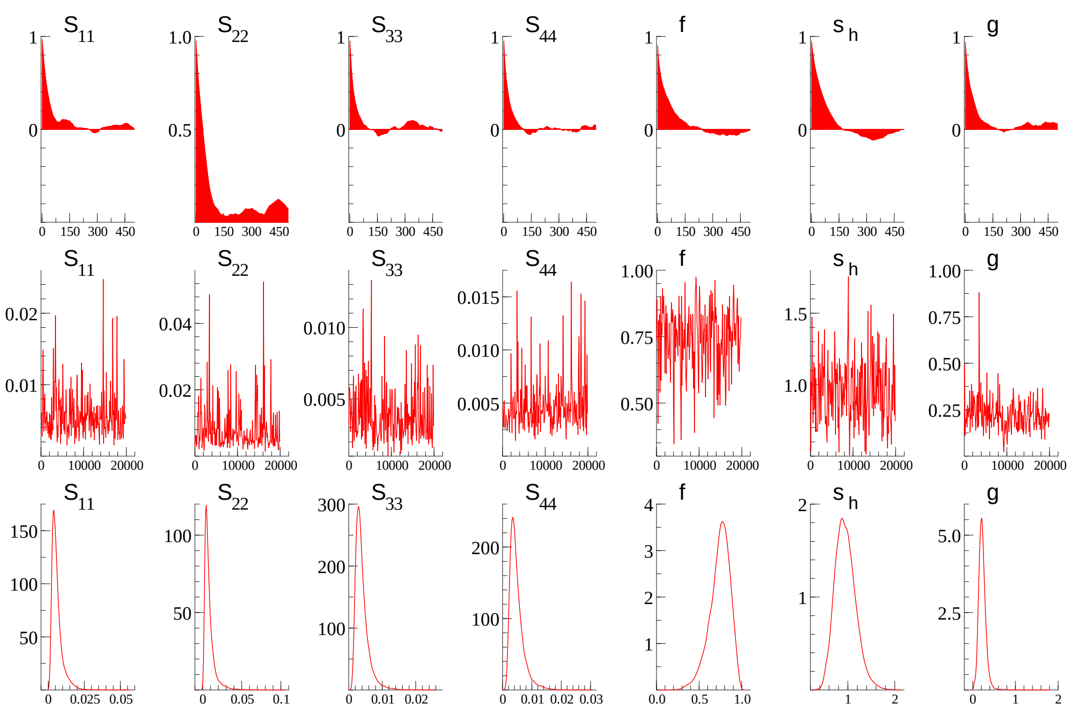
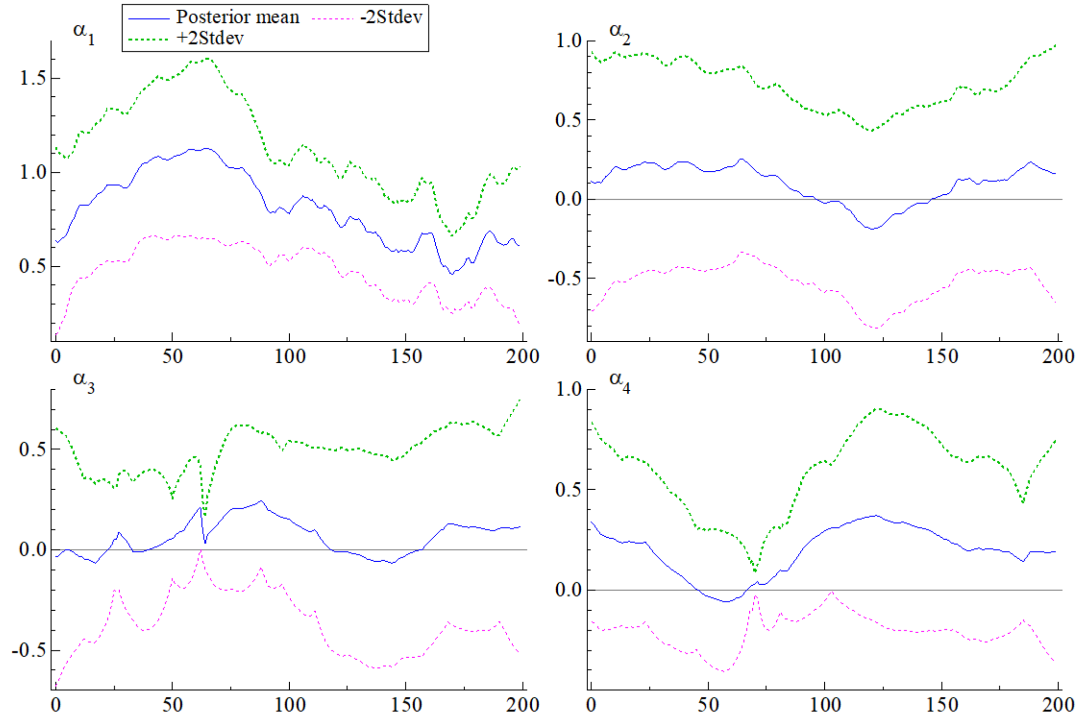


Figure 5. CSAD TVP regression for grain commodities 100 days before and 100 days during the Russo-Ukraine war.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

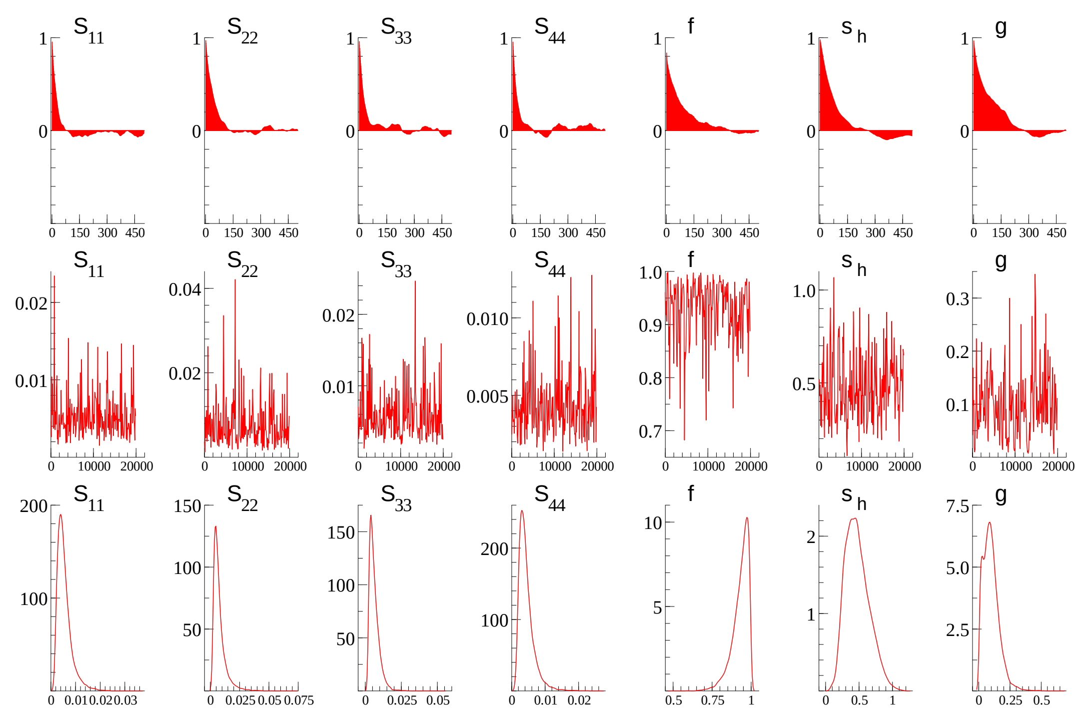
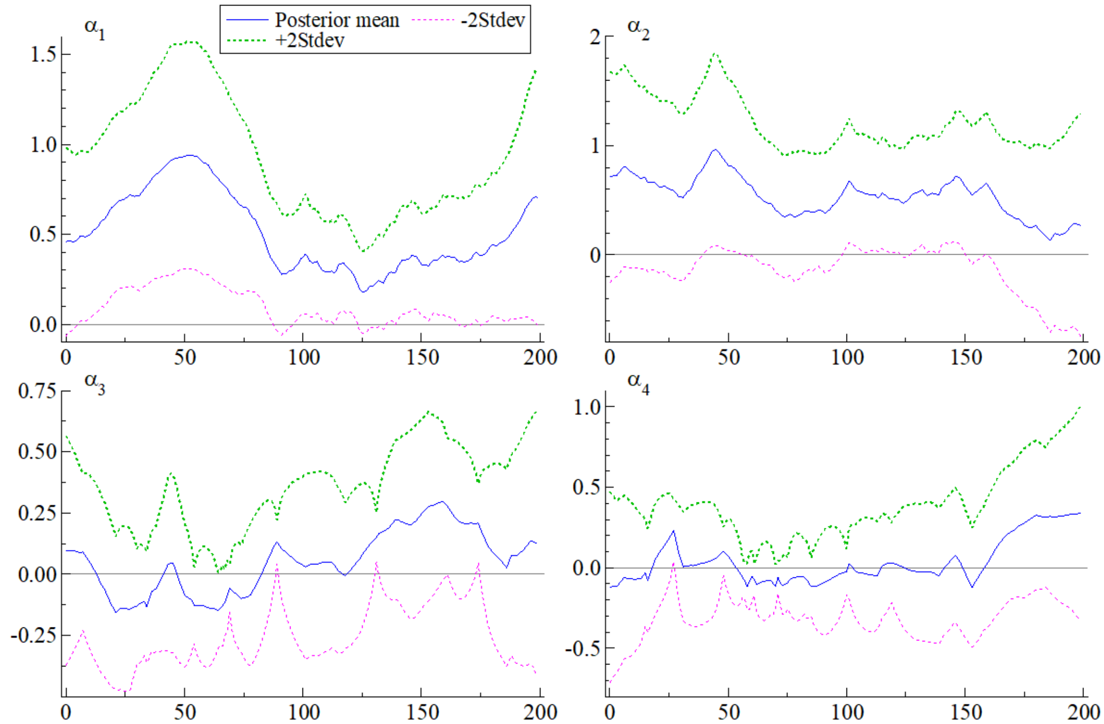


Figure 6. CSAD TVP regression for metal commodities 100 days before and 100 days during the Covid-19 pandemic.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

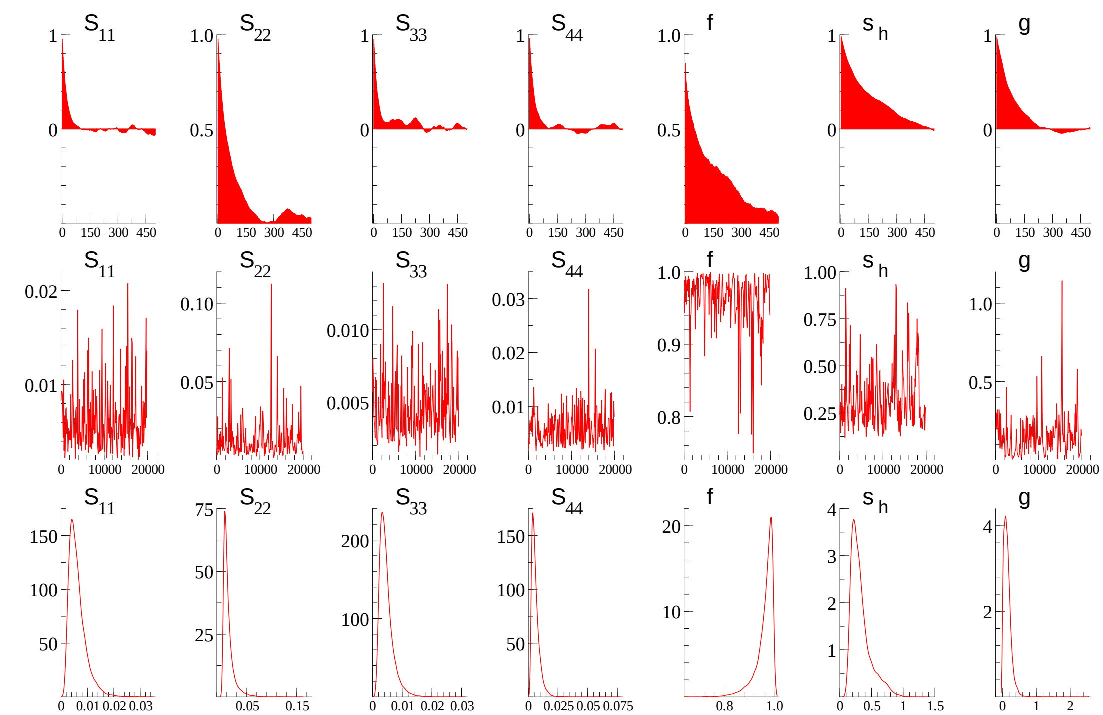
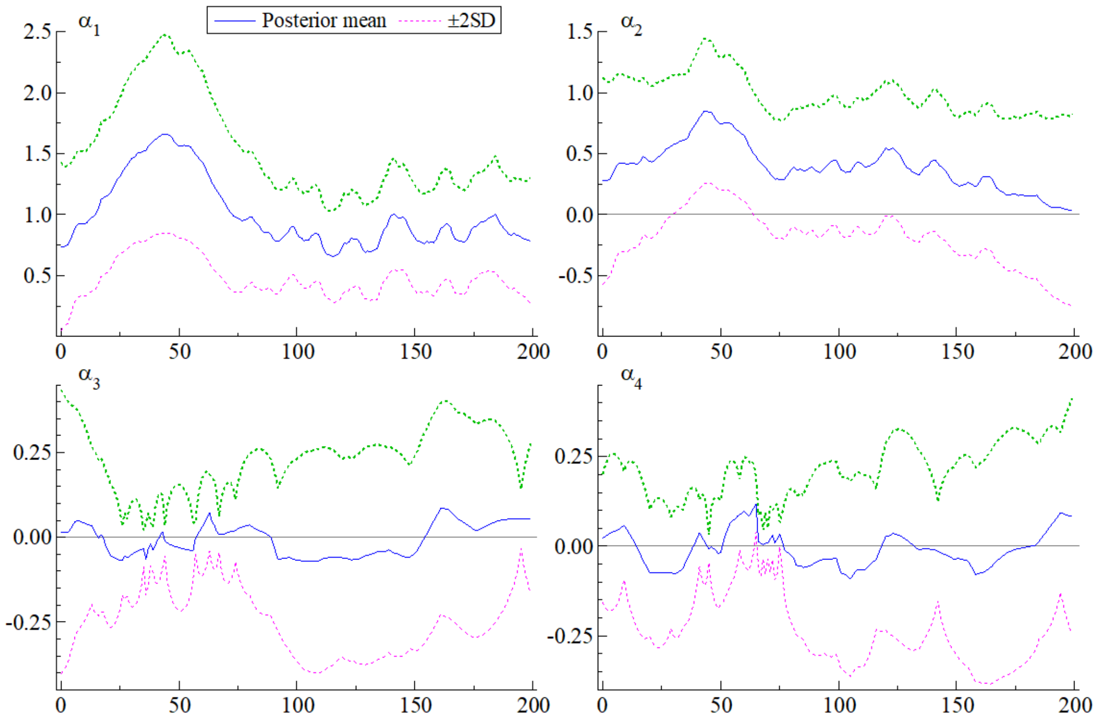


Figure 7. CSAD TVP regression for livestock commodities 100 days before and 100 days during the Covid-19 pandemic.

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

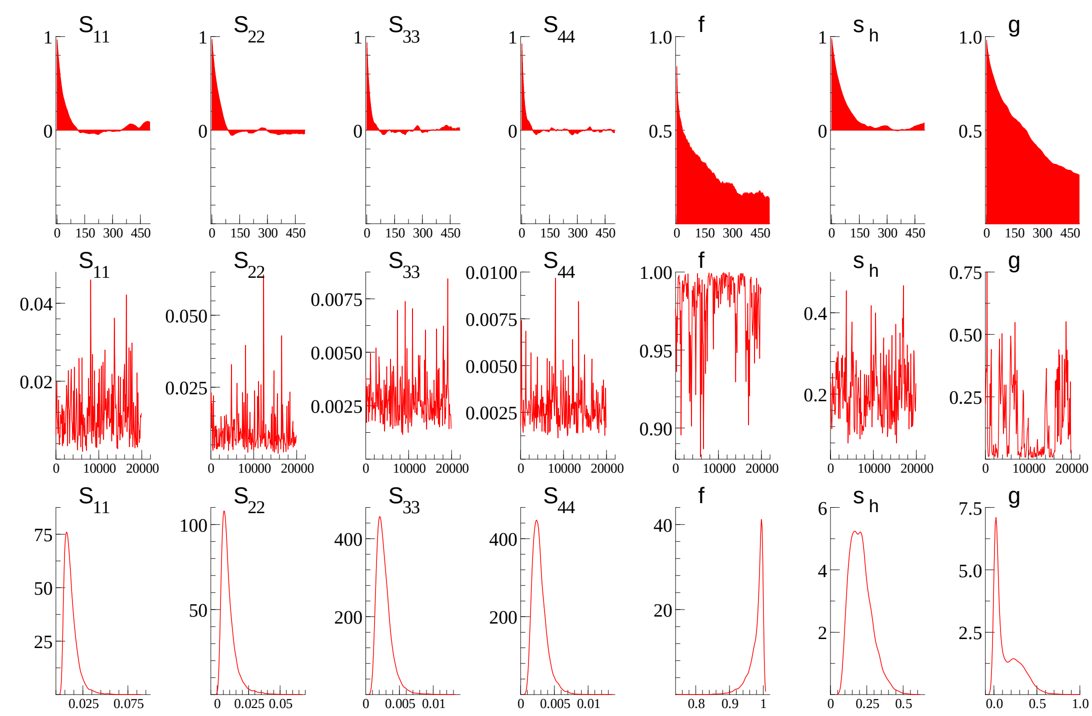
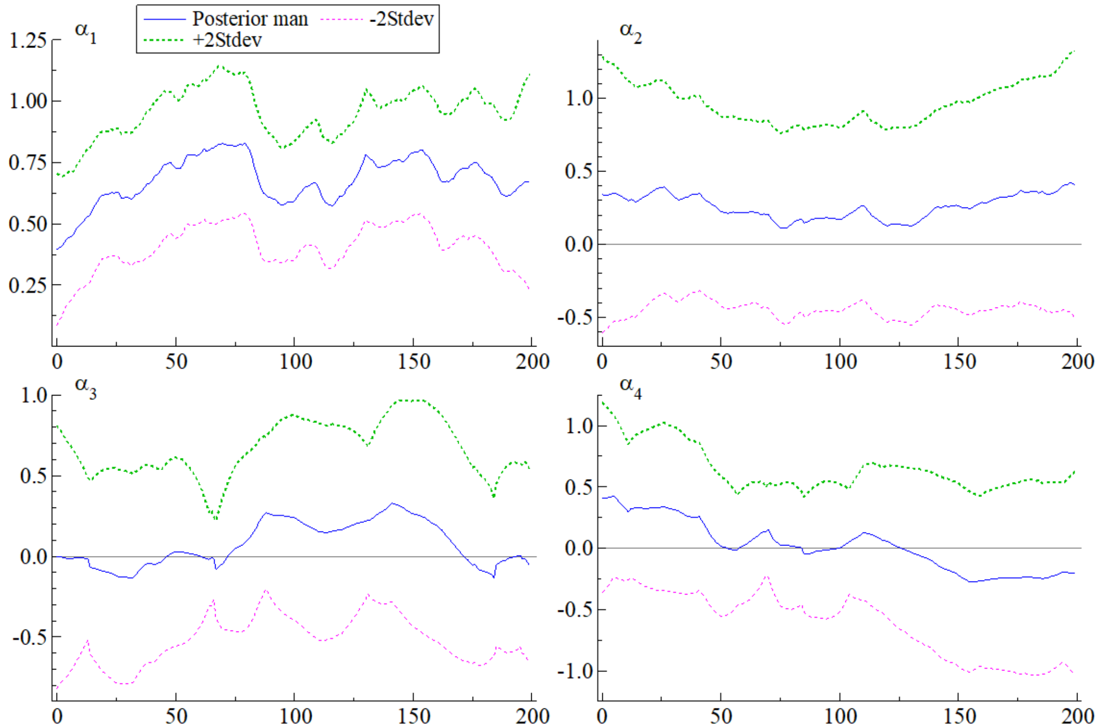


Figure 8. CSAD TVP regression for energy commodities 100 days before and 100 days during the Covid-19 pandemic

Panel A. Time-varying coefficients (Alphas)



Panel B. Markov Chain Monte Carlo sampling results

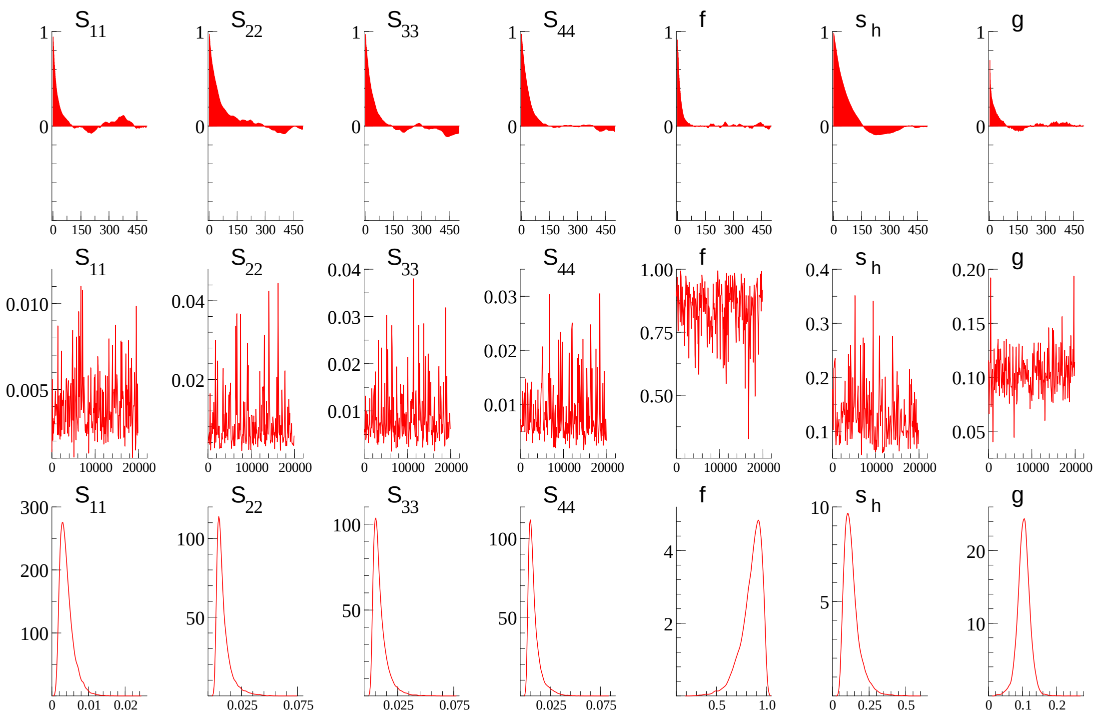


Figure 9. CSAD TVP regression for grain commodities 100 days before and 100 days during the Covid-19 pandemic